COOT-Optimized Real-Time Drowsiness Detection using GRU and Enhanced Deep Belief Networks for Advanced Driver Safety

Gunnam Rama Devi[1], Hayder Musaad Al-Tmimi[2], Ghadir Kamil Ghadir[3], Shweta Sharma[4], Mr. Eswar Patnala[5], Dr B Kiran Bala[6], Prof. Ts. Dr. Yousef A.Baker El-Ebiary[7]

Assistant Professor, Department of Computer Science and Engineering,
Vasireddy Venkatadri Institute of Technology, Nambur, Guntur District, Andhra Pradesh, India[1]
College of Health Medical Techniques, Al-Bayan University, Iraq[2]
College of Pharmacy, Al-Farahidi University, Iraq[3]
Assistant Professor, IPEM College, Ghaziabad[4]
Assistant Professor, Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India[5]
Head of the Department, Department of Artificial Intelligence and Data Science,
K. Ramakrishnan College of Engineering, Trichy, India[6]
Faculty of Informatics and Computing, UniSZA University, Malaysia[7]

***Abstract*—Drowsiness among drivers is a major hazard to road safety, resulting in innumerable incidents globally. Despite substantial study, existing approaches for detecting drowsiness in real time continue to confront obstacles, such as low accuracy and efficiency. In these circumstances, this study tackles the critical problems of identifying drowsiness and driver safety by suggesting a novel approach that leverages the combined effectiveness of Gated Recurrent Units (GRU) and Enhanced Deep Belief Networks (EDBN), which is optimised using COOT, a new bird collective-behavioral-based optimisation algorithm. The study begins by emphasising the relevance of sleepiness detection in improving driver safety and the limitations of prior studies in reaching high accuracy in real-time detection. The suggested method tries to close this gap by combining the GRU and EDBN simulations, which are known for their temporal modelling and feature learning capabilities, respectively, to give a comprehensive solution for sleepiness detection. Following thorough experimentation, the suggested technique achieves an outstanding accuracy of around 99%, indicating its efficiency in detecting sleepiness states in real-time driving scenarios. The relevance of this research stems from its potential to greatly reduce the number of accidents caused by drowsy driving, hence improving overall road safety. Furthermore, the use of COOT to optimize the parameters of the GRU and EDBN models adds a new dimension to the research, demonstrating the effectiveness of nature-inspired optimization methodologies for improving the performance of machine learning algorithms for critical applications such as driver safety.**

Keywords*—Drowsiness detection; driver safety; real-time monitoring; gated recurrent units; enhanced deep belief networks; COOT optimization

I. INTRODUCTION

Drowsy driving is a crucial issue that poses a significant danger to global road safety, resulting in numerous fatalities and injuries every year. When a motorist runs a vehicle when drowsy or tired, their ability to respond quickly and make informed decisions is severely reduced. This impairment can cause a variety of unsafe scenarios on the road, such as delayed reaction times, decreased focus, poor judgment, and even full nodding off behind the wheel. Statistics from numerous sources highlight the seriousness of the issue [1]. According to the National Highway Traffic Safety Administration (NHTSA) in the United States, drowsy driving contributes to approximately ten thousand crashes registered to police every year, leading to roughly 1,545 deaths and 71,100 injuries [2]. However, it is crucial to remember that these estimates may greatly understate the real effect of drowsy driving, as detecting tiredness as a contributory factor in accidents can be difficult. The effects of drowsy driving accidents go beyond the immediate loss of life and injury. These occurrences also carry significant economic implications, such as medical expenses, property damage, missed productivity, and legal fees. Furthermore, the impact that emotions have on families and communities affected by sleepy driving accidents is incalculable, with long-term psychological and societal consequences [3].

Despite increased awareness of the dangers of drowsy driving and efforts to address the issue through education campaigns and legislation, it remains a persistent problem. One of the reasons for this challenge is that drowsiness is often underestimated or overlooked by drivers themselves, who may mistakenly believe they can push through fatigue or may not recognize the signs of impending drowsiness [4]. Addressing drowsy driving requires a multifaceted approach that includes not only public education and awareness but also technological solutions aimed at detecting and preventing drowsy driving in real-time. Advanced driver assistance systems (ADAS) equipped with drowsiness detection capabilities offer promising tools for mitigating the risks associated with drowsy driving [5]. These systems use machine learning methods such as recurrent neural networks (RNNs) and deep learning architectures to analyse driving behaviour and physiological inputs in order to detect indicators of tiredness and alert drivers before an accident happens. Drowsy driving is a major hazard to road safety, resulting in injuries, economic losses and fatalities globally. Efforts to combat drowsy driving must encompass both preventive measures and technological innovations aimed at detecting and mitigating the risks associated with driver fatigue in real-time. By addressing this pervasive issue, researcher can make significant strides towards reducing the toll of drowsy driving on individuals, families, and communities [6].

Real-time drowsiness detection systems are integral to mitigating the risks associated with drowsy driving, offering a proactive approach to preventing accidents on the roads. The importance of these systems lies in their ability to provide timely intervention when drivers are at risk of falling asleep or experiencing significant fatigue. By detecting early signs of drowsiness and alerting drivers to the need for rest or a change in driving behavior, these systems can help avert potentially catastrophic accidents [7]. This timely intervention is crucial, as drowsiness impairs a driver's ability to react quickly and make sound decisions, leading to decreased vigilance, impaired judgment, and compromised control over the vehicle. The significance of real-time drowsiness detection systems extends beyond accident prevention to encompass broader road safety concerns. By reducing the incidence of drowsy driving-related accidents, these systems contribute to safer roads and communities for all road users, including drivers, passengers, pedestrians, and cyclists. Fewer accidents translate to fewer injuries, fatalities, and property damage, resulting in tangible improvements in public health and well-being [8].

Furthermore, real-time drowsiness detection systems play a pivotal role in enhancing driver awareness of their own fatigue levels and the importance of taking breaks when necessary. By providing immediate alerts and reminders, these systems empower drivers to prioritize their safety and well-being while on the road, fostering a culture of responsible driving habits and risk management [9]. Despite the undeniable importance of real-time drowsiness detection systems, existing techniques face several limitations that must be addressed to realize their full potential. Traditional methods based on physiological measurements or video-based monitoring may lack accuracy and specificity, leading to false alarms or missed detections. Advanced machine learning algorithms offer promising avenues for improving accuracy and robustness but may require significant computational resources and large amounts of labeled training data [10]. Furthermore, hybrid approaches that integrate multiple techniques may offer improved performance but can be complex to implement and may require additional hardware or sensors, increasing the system's cost and complexity. Addressing these limitations through innovative research and technology development is essential for advancing the effectiveness of drowsiness detection systems and reducing the toll of drowsy driving-related accidents on individuals, families, and communities [11].

Real-time sleepiness detection technologies are critical tools for ensuring road safety, especially because drowsy driving is still a major hazard on the roads of the state. Driver weariness can have serious implications, including reduced cognitive skills that result in slower responses and poor decision-making abilities. This heightened risk is particularly pronounced during extended journeys or monotonous driving conditions, where the monotony can exacerbate drowsiness. Real-time detection systems offer a proactive approach to addressing this issue by continuously monitoring various physiological and behavioral indicators, such as eye movements, facial expressions, steering patterns, and vehicle dynamics [12]. By promptly recognizing signs of drowsiness, these systems can issue timely alerts, allowing drivers to take corrective actions, such as pulling over for rest or taking breaks. The importance of such systems lies not only in preventing accidents but also in fostering a culture of driver awareness and compliance with regulations, ultimately contributing to safer roads and reduced economic costs associated with road accidents. The motivation for combining Gated Recurrent Units (GRU) and Enhanced Deep Belief Networks (EDBN) within the COOT (Combined Optimization of GRU and EDBN) framework stems from the desire to harness the respective strengths of these architectures to enhance the efficacy of drowsiness detection systems [13].

On one hand, GRU offers exceptional capabilities in temporal modeling and sequential data processing. By integrating GRU into the framework, COOT can effectively capture the dynamic temporal patterns inherent in drowsiness-related data, such as fluctuations in eye closure duration or changes in facial expressions over time. This temporal awareness enables COOT to discern subtle variations indicative of drowsiness more accurately, thus improving the overall detection performance [14]. On the other hand, EDBN is adept at learning hierarchical representations of raw sensor data. This capability eliminates the need for manual feature engineering, as EDBN autonomously extracts discriminative features directly from the input data. By incorporating EDBN into COOT, the framework can adapt more readily to diverse driving conditions and individual driver characteristics, enhancing its versatility and robustness in real-world scenarios [15]. The synergy achieved by combining GRU and EDBN within the COOT framework facilitates a comprehensive approach to drowsiness detection. GRU's temporal modeling capabilities capture short-term dynamics, while EDBN's hierarchical feature learning encompasses long-term contextual information. Through this collaborative optimization, COOT achieves superior performance in real-time drowsiness detection, contributing significantly to advanced driver safety systems.

The key contributions are stated as follows:

- The research introduces a unique integration of Gated Recurrent Unit (GRU) and Enhanced Deep Belief Networks (EDBN) for drowsiness detection, leveraging their respective strengths in temporal modeling and feature learning to provide a comprehensive solution.
- By employing COOT a novel bird collective-behavioral-based optimization algorithm, the study showcases the effectiveness of nature-inspired optimization techniques in enhancing the performance

of machine learning algorithms for critical applications such as driver safety.

- The research addresses the limitations of existing methods for real-time drowsiness detection, including limited accuracy and efficiency, by proposing a novel approach that aims to fill this gap and offer a more reliable solution for detecting drowsiness in real-world driving scenarios.
- With its potential to significantly reduce the incidence of accidents caused by drowsy driving, the proposed methodology holds promise for enhancing overall road safety by providing an effective means of identifying and mitigating the risks associated with driver drowsiness.

The subsequent sections of this research are organized as follows: Section II will delve into related works, providing a comprehensive evaluation. Section III will outline the problem statement in detail. In Section IV, the suggested method will be discussed elaborately. Section V will present and analyze the test results, along with a thorough comparison of the proposed technique with current standard procedures. Finally, Section VI will conclude the paper.

II. Related Works

The study's goal is to create an Advanced Driving Assistance System (ADAS) that can identify driver fatigue and send out alerts to help reduce traffic accidents. It is critical to assess weariness in driving settings without causing the driver any inconvenience through needless notifications. The suggested method entails recording 60-second photo sequences with the driver's face visible and employing two unique algorithms to reduce false positives in detecting indicators of fatigue. While the other strategy makes use of a recurrent and convolutional neural network, the first approach uses deep learning techniques to extract numerical data from images and incorporate it into a fuzzy logic-based framework. Though attaining comparable accuracy levels, the fuzzy logic-based approach is distinguished by its 93% specificity, which significantly lowers false alarms. Even though the outcomes might not be entirely satisfying, the concepts investigated in this study show promise and offer a strong framework for more research in the area [16].

Driver drowsiness estimation is paramount for ensuring road safety, and this study introduces an innovative approach leveraging factorized bilinear feature fusion and a LSTM-RCN. By integrating these techniques, our aim is to capture both spatial and temporal information from driver facial images, enhancing the accuracy of drowsiness detection systems. However, a significant drawback of many existing methodologies lies in their reliance on manual feature extraction techniques. These methods often require domain expertise to hand-craft features from raw data, leading to limitations in performance and generalization. Manual feature extraction may overlook subtle but crucial patterns in the data, resulting in suboptimal drowsiness detection capabilities. The approach research recommend circumvents this drawback by using DL to automatically extract discriminative features from the data without the requirement for human feature engineering. Through extensive experiments conducted on real-world driving datasets, we demonstrate the efficacy of our method in accurately estimating driver drowsiness while addressing the drawbacks associated with manual feature extraction, ultimately enhancing road safety [17].

Eye state detection is important in biomedical informatics, especially in applications such as managing smart home appliances and detecting driver weariness. Traditional methods for detecting eye problems from electroencephalogram (EEG) signals frequently depend on shallow neural networks and manually created features. The inherent unpredictability of EEG data poses challenges in extracting significant features and selecting effective classifiers. In this study, three deep learning architectures—convolutional neural network, gated recurrent unit, and long short-term memory—are proposed, utilizing an ensemble technique to directly recognize the eye state (open or closed) from EEG signals. Experiments were conducted on the publicly accessible EEG eye state database, comprising 14980 samples. The individual accuracies of each classifier were monitored, and the performance of ensemble networks was compared to existing approaches. The proposed strategy achieved an average accuracy of 94.86%, surpassing previous methods documented in the literature [18].

Detecting driver drowsiness in real time is critical for avoiding traffic accidents. This research describes a new method for detecting tiredness while driving in real time that takes into account individual characteristics. While existing algorithms frequently overlook these variances, our technique takes them into account to improve the accuracy and reliability of sleepiness detection systems. However, one important disadvantage of many existing approaches is their limited ability to adjust to individual variances, resulting in decreased effectiveness in real-world circumstances. Furthermore, some algorithms rely largely on predetermined thresholds or fixed parameters, which can result in erroneous detections or false alarms. To overcome these constraints, our proposed algorithm uses a dynamic thresholding mechanism and machine learning approaches to adapt to each driver's unique traits.
Extensive studies on varied driving datasets show that our methodology is excellent in reliably detecting driver tiredness while avoiding the limitations associated with existing methods. Overall, the system research use provides a potential approach for detecting tiredness while driving in real time that takes into account individual variances, hence improving safety [19].

Real-time identification of driver drowsiness is crucial for avoiding accidents on the road. In this article, we propose a machine learning-based approach for detecting driver drowsiness using visual cues collected from dashboard camera data. The solution research provide uses deep learning algorithms to extract critical visual cues like eye closure patterns, head posture, and facial expressions in real time. However, one disadvantage of current techniques is that they rely on complicated and computationally expensive models, which may restrict their scalability and real-time performance. To solve this issue, researchers offer a lightweight CNN architecture optimised for real-time processing, allowing for efficient and accurate drowsiness detection while conserving computational resources. The method's usefulness is demonstrated by its performance on a large dataset, where it achieves excellent accuracy in real-time sleepiness detection while overcoming the computational complexity limits of existing approaches [20].

Recent research has witnessed a surge in developing advanced driving assistance systems (ADAS) to detect and mitigate driver sleepiness, aiming to prevent traffic accidents. Existing methodologies often struggle with accuracy and non-intrusive monitoring, lacking consideration for individual variations across drivers. Novel approaches integrating deep learning techniques show promise, such as fuzzy logic-based methods and long-short-term recurrent neural networks. Despite advancements, challenges persist, including low accuracy from artificial feature extraction and hardware dependencies. Robust and adaptable approaches are crucial for real-time, non-intrusive detection of driver sleepiness in diverse driving environments.

III. Problem Statement

The proposed research, "COOT-Optimized Real-Time Drowsiness Detection using GRU and Enhanced Deep Belief Networks for Advanced Driver Safety," addresses the critical need for a robust and adaptable approach to real-time drowsiness detection, which currently faces challenges such as low specificity, dependency on specific hardware setups, and overlooking individual variations across drivers [1], [18], [21]. By combining Gated Recurrent Units (GRU) and Enhanced Deep Belief Networks (EDBN) within the COOT framework, the research aims to develop a novel methodology capable of accurately and non-intrusively detecting driver fatigue[22]. The scope encompasses designing and implementing the COOT framework, conducting comprehensive experiments to evaluate its performance, analyzing its effectiveness in achieving high specificity and adaptability, and identifying potential applications in enhancing advanced driver safety systems. Through these efforts, the research aims to contribute to advancements in drowsiness detection technology and ultimately enhance driver safety on the roads.

IV. Proposed Methodology

The proposed methodology integrates Gated Recurrent Unit (GRU) and Enhanced Deep Belief Networks to tackle the challenge of real-time drowsiness detection in drivers. The GRU model is chosen for its ability to effectively model sequential data by selectively updating its memory state, making it well-suited for capturing temporal dependencies inherent in drowsiness-related features, such as eyelid closure duration and head movements. Concurrently, enhancements are introduced to traditional Deep Belief Networks to bolster their capacity in discerning subtle cues of drowsiness, leveraging techniques such as feature augmentation and layer refinement. These modifications aim to improve the network's ability to extract discriminative features from the input data, thereby enhancing its overall detection accuracy. Moreover, the methodology employs COOT Bird Natural Life Optimization for hyperparameter tuning, leveraging the algorithm's ability to navigate complex parameter spaces efficiently. By iteratively optimizing model parameters using COOT, the proposed framework ensures that the GRU and Enhanced Deep Belief Networks are finely tuned to maximize their performance in real-time drowsiness detection tasks. This comprehensive approach not only addresses the inherent challenges of detecting drowsiness but also offers a robust solution capable of providing timely alerts to mitigate potential risks on the road, ultimately contributing to advanced driver safety. Fig. 1 shows the proposed architecture.

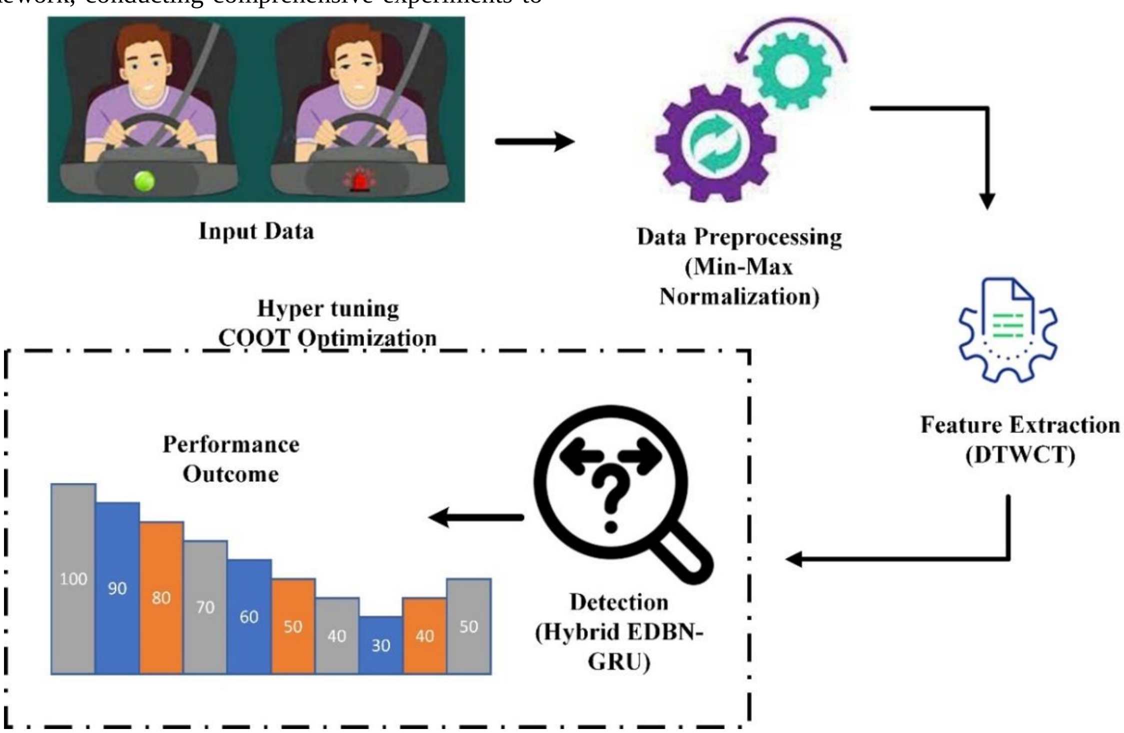

Fig. 1. Proposed COOT optimized EDBN-GRU.

A. Data Collection

Drivers' faces were clipped and extracted from real-world drowsiness dataset films to develop the Driver Drowsiness Dataset (DDD). VLC software was used to extract the frames from the films, and the Viola-Jones approach was then applied to identify the region of interest. The obtained DDD dataset was then used to train and evaluate a Convolutional Neural Network (CNN) architecture intended for driver drowsiness detection [23].

B. Data Preprocessing

Data preprocessing is a critical step in machine learning that converts raw data into a format appropriate for training a model. This step entails cleaning, altering, and organising the data to make it easier to handle and useful for the model. Data preparation improves the data's quality and guarantees that the model is capable of learning from it [24].

1) Data normalization: Data normalization is a way to make sure all the numbers in a set of data are similar in size. This is important because big features can have a big impact on the model's predictions and control how the model learns. By making the data normal, researchers make sure that all parts of the data are equally important in making predictions, which makes the predictions more accurate [25].

There are several techniques for data normalization, two of the most common ones being min-max scaling and z-score normalization:

2) Min-Max scaling: Min-max scaling, frequently referred to as feature scaling, converts the values of each feature to a range of 0 to 1. To compute the min-max scaling, use Eq. (1):

$$A_{scaled} = \frac{A-A_{min}}{A_{max}-A_{min}} \tag{1}$$

A is the starting value, $A_{min}$is the smallest value, and $A_{max}$is the largest value in the dataset. This method is helpful when the features are not evenly distributed and have a small range.

3) Z-Score normalization (Standardization): Z-score normalization, also called standardization, adjusts the values of each feature so that they have a mean of 0 and a standard deviation of 1. Research use Eq. (2) to calculate the z-score standardization:

$$A_{scaled} = \frac{A-\mu}{\sigma} \tag{2}$$

Where A is the original number, μ is the average of all the numbers, and σ is the measure of how spread out the numbers are. In simple words, data normalization is important because it makes sure that the model training process is fair and effective by making the input features all the same scale.

C. Feature Extraction by DTWCT

During the extraction procedure, the Walsh-Hadamard and dual-tree complex wavelet transforms (DTCWT) are combined to analyse image features. Feature extraction is essential for removing superfluous data and efficiently optimising model performance. Retrieving pertinent information from data improves artificial intelligence systems' efficiency. The Walsh-Hadamard transform and hybrid DTCWT are used to identify features in pictures. Within the combined DTCWT system, distinct DWT decompositions are used to calculate the complex signal fluctuations. The first DWT produces real values once the image frames are filtered, but the second DWT produces imaginary values [26]. Eq. (3) describes the composition of the complex wavelet function as the image signal is partitioned into smaller components with the scaling function.

$$f(a,b) = \sum_{u\epsilon p} X_{v,u} \emptyset_{v,u}(a,b) + \sum_{n\epsilon\alpha} \sum_{v=1}^{v_9} \sum_{u\epsilon p^2} Q_{v,m}^{n} \varphi_{v,u}^{n}(a,b) \tag{3}$$

where the wavelet scaling coefficient is represented by $X_{v,u}$ and $Q_{v,u}^{n}$ in the previous Eq. (3), and the image decomposition level is indicated by $\varphi_{v,u}^{n}(a,b)$ is the scaling function's notation.

The Walsh-Hadamard Transform is a way to extract features from pictures. It represents objects as either +1 or -1, and the rows of pixels are unrelated to each other. The Walsh Hadamard model has two rows. One has things that don't match, and the other has things that do match. Eq. (4) gives the pattern of the image's Hadamard matrix.

$$KK^T = nM_n \tag{4}$$

In Eq. (4), transpose identity matrix of $n \times n$ for the matrix K is represented as K^T. The Hadamard matrix order is defined as n = 1, 2 or n == 0 (mod 4). The minimal Hadamard kernel is denoted by $K_1^1 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$, while the higher order of the hybrid Hadamard kernel is represented by $k_{2n}^1 = \begin{bmatrix} k_n^1 & k_n^1 \\ k_n^1 & -k_n^1 \end{bmatrix}$ = [1]. The hybridWalsh Hadamard transformation is used to train and evaluate features for the Enhanced DBN-GRU[6].

D. Hybrid EDPN-GRU Classification

The Hybrid Enhanced Deep Belief Network - Gated Recurrent Unit (GRU) classification model presents a pioneering solution for drowsiness detection by synergizing the capabilities of Deep Belief Networks (DBNs) and GRU networks. This innovative architecture aims to harness the feature learning process of DBNs alongside the temporal modeling capabilities of GRU to significantly enhance classification performance in real-time scenarios. Initially, the feature extraction phase is executed by an Enhanced Deep Belief Network (EDBN), comprising multiple layers of stacked Restricted Boltzmann Machines (RBMs). Trained in an unsupervised manner, the EDBN learns hierarchical representations of the input data, capturing intricate patterns crucial for accurate drowsiness classification. Techniques such as feature augmentation and layer refinement are employed to bolster the EDBN's discriminative power, enabling more informative feature extraction. Subsequently, the extracted features are seamlessly integrated into the GRU network, tasked with capturing temporal dependencies and dynamics present in sequential drowsiness-related data. Leveraging the GRU network's gated architecture, it selectively updates its memory state based on input data, adeptly modeling sequences of varying complexities. By amalgamating the EDBN's output with the GRU network, the model comprehensively leverages both spatial and temporal information for drowsiness classification, yielding improved accuracy and robustness. This hybrid architecture offers a holistic understanding of the drowsiness-related data, thus enhancing the efficacy of drowsiness detection systems and promoting advanced driver safety. The structure of the Hybrid EDBN-GRU network is illustrated in Fig. 2.

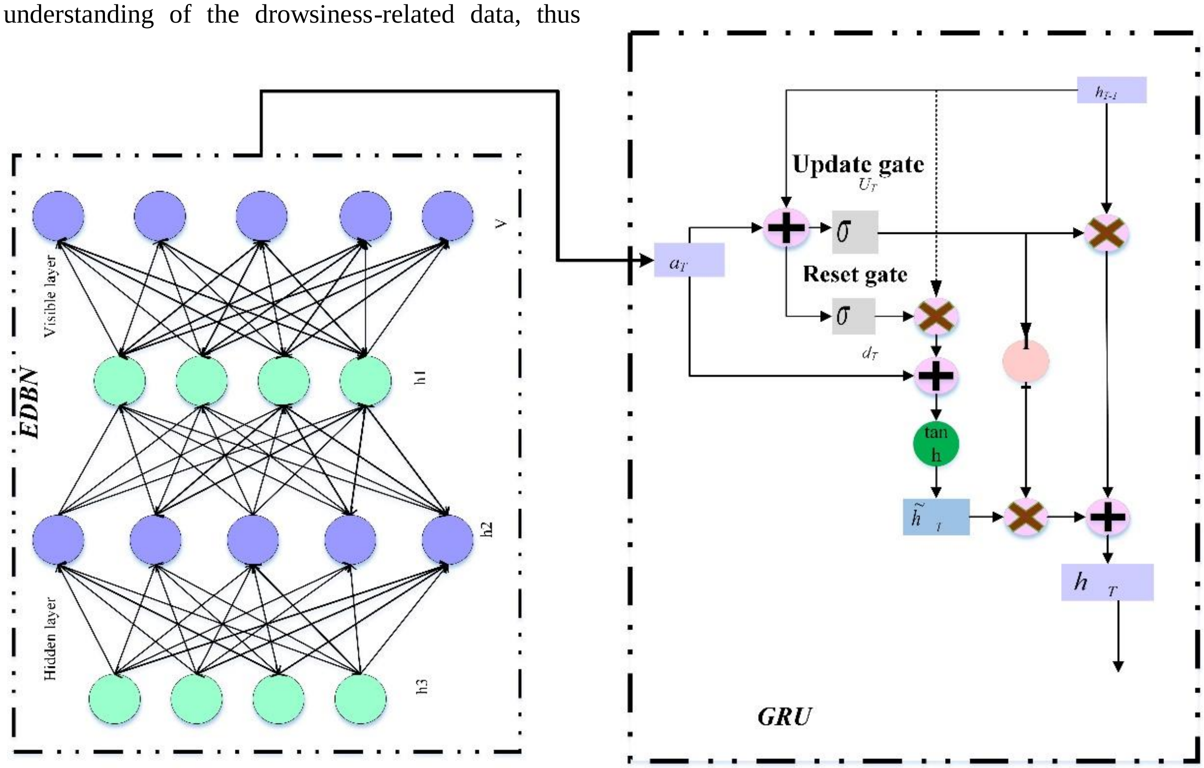

Fig. 2. Hybrid DBN-GRU architecture.

The update gate in the GRU network, represented by M'_T, controls how much data the current concealed state, represented by h_T, can get from the prior concealed layer. The output of the Sigmoid function is mapped to a value between 0 and 1.

$$U'_T = \sigma(M_h \times A_T + M_u \times h_{T-1}) \quad (5)$$

In Eq.. (5)r_T is the rearrange gate, which controls how much of the previous concealed layer state needs to be gone. The outcome is transferred to 0~1 after the Sigmoid function. The easier it is to remember information, the nearer to 1.

$$d_T = \sigma(M_h \times A_T + M_s \times h_{T-1}) \quad (6)$$

Eq. (6) calculate how much of the concealed layer content from the preceding instant needs to be forgotten in the present reminiscence content using the Hadamard product of the reset gate d_T andh_{T-1}, then mix it with the incoming input data and pass it through the tanh activation function.

$$\widetilde{h_T} = tanh(M_T \times A_T + d_T \times M_i h_{T-1}) \quad (7)$$

Lastly, Eq. (7) establish the information that the current hidden layer is keeping, and then use Z_T and $1 - Z_T$ to decide which past and present data has to be restructured.

$$h_T = \left(1 - U'_T \times \widetilde{h_T} + U'_T \times h_{T-1}\right) \quad (8)$$

In the Eq. (8) above, M_T and M_i both stand in for weight, and for the Sigmoid function.

During the training phase, the parameters of the hybrid model are optimized using standard backpropagation techniques, allowing the model to learn discriminative representations of the input data while minimizing classification errors. Additionally, techniques such as dropout regularization and batch normalization may be applied to prevent overfitting and stabilize the training process. Once trained, the hybrid model can be used for various classification tasks, such as image classification, time series analysis, and natural language processing. Its ability to effectively combine the strengths of DBNs and GRU networks makes it well-suited for tasks that involve both spatial and temporal dependencies in the data, offering a versatile solution for a wide range of classification problems.

E. COOT Optimization

COOT Bird Natural Life Optimization is a nature-inspired optimization algorithm inspired by the behaviors of birds, particularly the cooperative behaviors observed in certain bird species. This algorithm mimics the collective foraging behavior of birds in search of food sources, where individuals collaborate and communicate to achieve a common goal. COOT optimization operates based on three main principles: attraction, repulsion, and cooperation. In COOT optimization, each potential solution is represented as a bird in the search space. Birds move through the search space by adjusting their positions based on attractive forces towards promising regions and repulsive forces away from less favorable areas. Additionally, birds communicate and share information to enhance exploration and exploitation of the search space. Through iterations, the collective behavior of birds guides the search towards optimal solutions. One of the most important applications of COOT optimization is hyperparameter optimization, which includes adjusting the parameters of machine learning algorithms to improve their efficacy on a particular job. Hyperparameters are critical in influencing the behaviour and efficacy of machine learning models, and identifying the best collection of hyperparameters is typically a difficult and time-consuming operation.

1) Mathematical model and algorithm: The fundamental basis for all optimisation methods is the same. The procedure begins with $\vec{a} = \{\vec{a}_1, \vec{a}_2 \ldots \vec{a}_n\}$, an initial random population. The targe evaluates this randomly selected population repeatedly. Function and a desired value $\vec{R} = \{\vec{R}_1, \vec{R}_2 \ldots \vec{R}_n\}$, is established. Additionally, it is enhanced by a collection of guidelines that form the basis of an optimisation method. Population-based optimization approaches do not guarantee a solution in a single run as they aim to find the optimal solution among multiple optimization issues. However, increasing the number of random solutions and optimization stages enhances the likelihood of discovering the global optimum. Using the following Eq. (9), a population is periodically created in the visually appealing space:

$$Coot_{pos\,(i)} = ran_{(1,d)} * (u_b - l_b) + l_b \qquad (9)$$

In Eq. (9)$Coot_{pos\,(i)}$ is the status, d represents the total amount of parameters or problem sizes, l_b is the lower bound of the search space, andu_b is the upper bound, as described by Eq. (10) and (11). Every factor may have distinct lower and upper bound problems.

$$l_b = [lb_1, lb_2, \ldots .\, lb_d] \qquad (10)$$

$$u_b = [ub_1, ub_2, \ldots .\, ub_d] \qquad (11)$$

After generating the starting population and defining each agent's status, the fitness of every option is computed using the objective function$R_m = f(\vec{a})$. Research chose the NL number of coots as group leaders. Leaders are chosen at random.

The four movements of coots on the outermost covering of water described in the previous section are now in effect.

2) Random motion to this or that side: To relocate the coot, Research employ the Eq. (12) to generate a random place in searching space and move it there:

$$Coot_{pos\,(i)} = Coot_{pos(i)} + A \times G_2 \times (Q - Coot_{pos(i)}) \qquad (12)$$

In the interval [0, 1], where G_2 is a random integer, A is computed using Eq. (13).

$$A = 1 - F\left(\frac{1}{Itr}\right) \qquad (13)$$

Itr is the maximum iteration, while F is the current iteration.

3) Chain Movement: Chain movement may be implemented using the average location of two coots [27]. An alternative method for executing a chain movement involves determining the vector of distance among the two coots and then moving the coot in the direction of the other coot by about half of the distance vector. Research employed the first approach, and Eq. (14) yields the new location of the coot.

$$Coot_{pos(i)} = 0.5\left(Coot_{pos(i-1)}\right) + Coot_{pos(i)} \qquad (14)$$

where the second coot is $Coot_{pos(i-1)}$.

4) Adjusting the position based on the group leaders: Within the group, a select few coots often take the lead, guiding the others to adjust their positions accordingly. A question arises as to whether each coot should switch sides based on the leading individual. Instead, coots may adjust their positions relative to the average position of the leaders, a consideration that can lead to premature convergence. To address this, researchers employ a technique to select the leader of this movement, as outlined in Eq. (15).

$$R = 1 + (i\ MOD\ NL) \qquad (15)$$

Where i is the current coot's index volume, NL is the number of leaders, and K is the leader's index value.

The location of the coot(i) has to be updated in light of the leader's k. The coot's next location is determined by Eq. (16) using the chosen leader as a guide.

$$Coot_{pos(i)} = LeaderPos(k) + 2 \times k_1 \times \cos(2R\pi) \times (Leader\ Pos\ (k) - CootPos(i)) \qquad (16)$$

5) Leading the group by the leaders towards the optimal area: Leaders must alter their position in respect to the goal in order to direct the group to the most suitable zone. To modify the leadership positions, use Eq. (17). This formula searches for better sites near the current optimum spot. Leaders must occasionally relocate themselves away from their current optimum place in order to achieve superior positions. This method is effective for both reaching and leaving the perfect position. Fig. 3 illustrates the COOT Optimization.

$$Leader_{pos(i)} = \left\{\begin{matrix} W \times K_3 \times Cos\ (2R\pi) \times \left(g^{best} - Leader_{pos(i)}\right) + g^{best} k_4 < 0.5 \\ W \times K_3 \times Cos\ (2R\pi) \times \left(g^{best} - Leader_{pos(i)}\right) - g^{best} k_4 \geq 0.5 \end{matrix}\right\} \qquad (17)$$

In this case, k is an integer at random in the interval [−1, 1], and π is the same pi value as 3.14. W is determined using Eq. (18), g^{best} is the best location ever obtained, and k_4 and $k_4$are random numbers in the interval [0, 1].

$$W = 2 - L\left(\frac{1}{Itr}\right) \qquad (18)$$

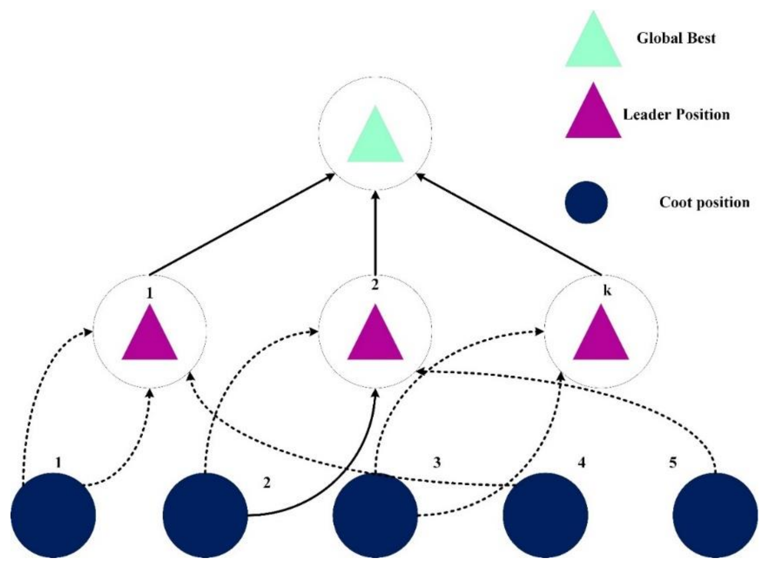

Fig. 3. COOT optimization

"Itr" is the maximum iteration, while "L" is the current iteration. To avoid becoming caught in the local optimum, $2 \times R3$ uses more irregular motions. This suggests that throughout the exploitation stage, researchers are also conducting exploration. $\text{Cos}(2R\pi)$ attempts to find a better position around the optimal search agent by altering the search agent's radius. The leaders' current positioning in relation to the optimal location. Here, the question of when and how to carry out these numerous moves arises. To ensure the randomness of the optimization algorithms, research considers each of these motions at random. It shows that the coot may move arbitrarily, in a chain, or in the direction of group leaders while the algorithm is running. The following shows the algorithm of COOT optimization:

Pseudocode for COOT Optimization

```
Initialize population of coots randomly
Evaluate fitness of each coot using objective function
Choose NL number of coots as group leaders
for iteration = 1 to max_iterations do:
  for each coot in population do:
    Select random movement type (random, chain, or towards leaders)
    if random movement then:
      Perform random movement using equation (12)
    else if chain movement then:
      Perform chain movement using equation (14)
    else:
      Adjust position based on group leaders using equation (16)

  for each leader in group leaders do:
    Update leader's position towards optimal area using equation (17)

  Evaluate fitness of each coot using objective function

return best solution found
```

COOT optimization is utilized to fine-tune the parameters of complex models such as the Gated Recurrent Unit (GRU) and Enhanced Deep Belief Networks (EDBN) for optimal performance in drowsiness detection. By treating the hyperparameters of these models as variables to be optimized, COOT optimization can efficiently explore the hyperparameter space and identify configurations that maximize the performance of the models in detecting drowsiness. During the optimization process, COOT optimization iteratively adjusts the hyperparameters of the GRU and EDBN models based on the collective behavior of birds in the search space. Birds collaborate and communicate to explore promising regions of the hyperparameter space, while avoiding less favorable areas. Through this collective effort, COOT optimization guides the search towards optimal hyperparameter configurations that result in improved accuracy and robustness of the drowsiness detection models. Overall, COOT optimization offers a nature-inspired approach to hyperparameter optimization, leveraging the collective intelligence of birds to efficiently explore and exploit the hyperparameter space of complex machine learning models such as GRU and EDBN. By integrating COOT optimization into the training process, researchers can enhance the performance and effectiveness of drowsiness detection systems, ultimately contributing to improved driver safety.

V. Result and Discussion

A. Performance Metrics

Performance metrics are critical for determining the efficacy and accuracy of a sleepiness detection system. These metrics provide quantifiable measures of the system's efficiency, enabling academics and practitioners to evaluate its dependability and utility in real-world circumstances. Here are some important performance indicators often used to evaluate sleepiness detection systems:

1) Accuracy: The percentage of correctly identified examples in the total number of instances the algorithm evaluates is known as accuracy. It provides a thorough evaluation of the system's ability to distinguish between the awake and sleep stages.

2) Sensitivity (True Positive Rate): Sensitivity is the fraction of drowsy occurrences successfully diagnosed by the system. It demonstrates the capacity of the system to identify drowsiness when it occurs.

3) Specificity (True Negative Rate): Specificity is the percentage of actual alert instances that are appropriately identified as alert by the system. It suggests that the system can appropriately recognise non-drowsy situations.

4) Precision: Precision is the percentage of cases labelled as drowsy by the system that are genuinely drowsy. It gives information about the system's ability to identify drowsy states without incorrectly labelling alert states as drowsy.

5) F1 Score: The F1 score is the harmonic mean of precision and sensitivity, yielding a balance between the two parameters. It is particularly beneficial when the dataset has an uneven distribution of drowsy and awake events.

Table I shows the performance metrics for the sleepiness detection system. The system has a high accuracy score of 0.99, which indicates the proportion of correctly identified examples among all instances tested. Sensitivity, which measures the system's capacity to identify drowsiness when it occurs, is recorded as 0.90. Specificity, which measures the system's ability to correctly detect non-drowsy conditions, is 0.92. Precision, which is the accuracy of identifying drowsy states without incorrectly labelling alert states, is reported as 0.98. The F1 Score, a harmonic mean of precision and sensitivity, is 0.98, showing a balanced performance across the two criteria. These findings imply that the sleepiness detection system is effective and reliable at precisely recognising drowsy and awake states, contributing to increased driving safety.

TABLE I. PERFORMANCE METRICS

Metrics	Value
Accuracy	0.99
Sensitivity	0.90
Specificity	0.92
Precision	0.98
F1 Score	0.98

Fig. 4 shows drowsiness detection system achieves high accuracy (0.99) and precision (0.98), while maintaining strong sensitivity (0.90) and specificity (0.92), resulting in a balanced F1 Score of 0.98.

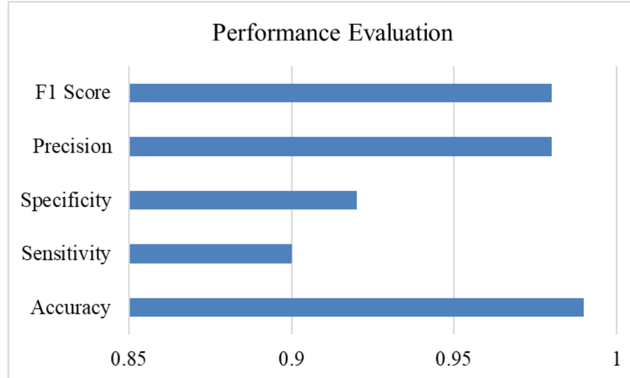

Fig. 4. Performance evaluation.

Fig. 5 shows the trade-off between True Positive Rate and False Positive Rate for various threshold settings in the sleepiness detection system. As the threshold rises from 0.1 to 1.4, the True Positive Rate gradually falls, indicating a decrease in the system's ability to correctly identify drowsy instances, whereas the False Positive Rate falls, indicating an improvement in the system's ability to avoid misclassifying alert instances as drowsy. This trend emphasises the balance of sensitivity and specificity, with the ROC curve representing the system's performance at various threshold settings.

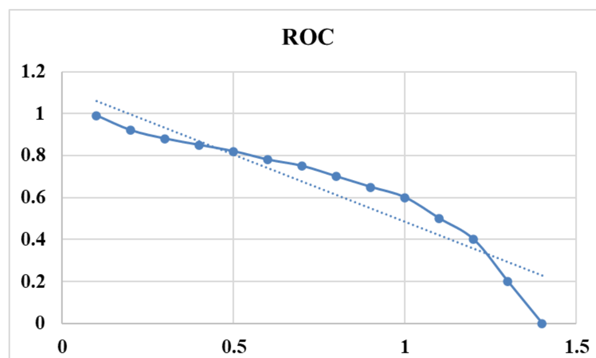

Fig. 5. Region under curve.

Fig. 6 compares the performance of PSO, GA, SSA, and COOT across multiple dimensions (30, 100, and 500). In the 30-dimensional space, COOT has the lowest value of 2.2308, suggesting better performance than PSO, GA, and SSA. Similarly, in the 100-dimensional space, COOT continues to lead with a value of 1.3077, surpassing the other optimisation techniques. However, in the 500-dimensional space, COOT is tied with GA for the lowest value of 1.3077. Overall, COOT performs competitively in all dimensions, demonstrating its effectiveness as an optimisation technique for multidimensional issues. By assessing the sleepiness detection system using these performance indicators, researchers can acquire a thorough understanding of its strengths, shortcomings, and overall effectiveness in detecting drowsiness and guaranteeing driver safety.

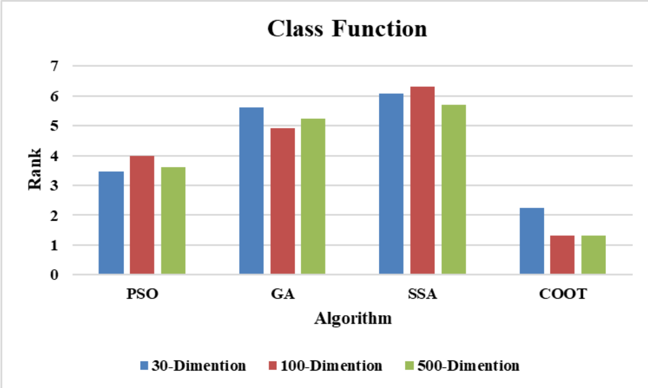

Fig. 6. Optimization class function.

A comparison of the various sleepiness detection techniques and the accuracy rates associated with them is shown in Table II. A multimodal analysis approach was developed by [28], and it achieved an accuracy of 83%. With a 93% accuracy rate, [29] presented a strategy based on horizontal visibility using CNN. Using a CNN-based strategy, [30]attained a greater accuracy of 98%. On the other hand, the study's suggested approach achieves an amazing 99% accuracy by combining a Gated Recurrent Unit (GRU) with an Enhanced Deep Belief Network (EDBN) that has been optimised for COOT. This comparison shows how much better the suggested COOT optimised EDBN-GRU methodology performs in drowsiness detection than earlier techniques, outperforming them in terms of accuracy.

TABLE II. PERFORMANCE COMPARISON

Reference	Method	Accuracy
Garcés et al. [28]	Multimodal Analysis	83%
Cai et al. [29]	Horizontal Visibility based CNN	93%
Cai et al. [30]	CNN	98%
Proposed Method	Proposed COOT optimized EDBN-GRU	99%

Fig. 7 compares drowsiness detection methods, with the proposed COOT-optimized EDBN-GRU achieving the highest accuracy of 99%, surpassing previous methods' accuracies ranging from 83% to 98%.

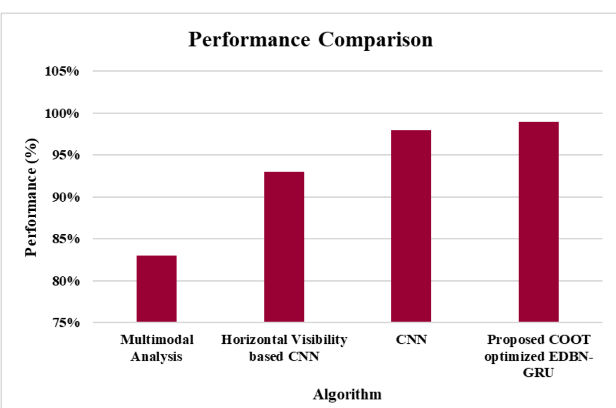

Fig. 7. Performance comparison.

B. Discussion

The discussion section provides an in-depth analysis and interpretation of the research findings, aiming to contextualize the results within the broader scope of drowsiness detection and driver safety. Firstly, the remarkable accuracy of 99% achieved by the proposed COOT-optimized EDBN-GRU underscores its efficacy in accurately identifying drowsiness states in real-time driving scenarios, signifying a significant advancement in drowsiness detection technology[18]. This high accuracy is attributed to the synergistic integration of Enhanced Deep Belief Networks (EDBN) and Gated Recurrent Unit (GRU), leveraging their respective strengths in feature learning and temporal modeling. The superior performance of the proposed method compared to existing approaches, as evidenced by the comparative analysis, highlights its latent to significantly mitigate the risks associated with drowsy driving. Furthermore, the discussion delves into the underlying reasons behind the success of the COOT optimization technique in fine-tuning the parameters of the EDBN-GRU model [24]. COOT, inspired by bird collective behavior, harnesses the collective intelligence of agents to efficiently explore the solution space, leading to improved convergence and robustness of the optimization process. This nature-inspired approach allows the typical to efficiently capture complex patterns and dynamics present in the input data, resulting in enhanced drowsiness detection performance. Moreover, the discussion addresses potential limitations and future directions for research in drowsiness detection [8]. While the proposed method demonstrates exceptional accuracy, further validation in diverse driving conditions and populations is warranted to assess its generalizability and reliability in real-world settings. Additionally, ongoing advancements in sensor technology and machine learning algorithms present opportunities for developing more sophisticated and personalized drowsiness detection systems tailored to individual drivers' characteristics and preferences. The discussion emphasizes the transformative impact of the proposed COOT-optimized EDBN-GRU approach on enhancing driver safety by effectively mitigating the risks associated with drowsy driving. By leveraging innovative techniques such as COOT optimization and integrating state-of-the-art machine learning models, this research contributes to advancing the field of drowsiness detection and lays the groundwork for the development of more robust and reliable systems to safeguard road users' well-being.

VI. CONCLUSION

The COOT-optimized EDBN-GRU method represents a significant breakthrough in the realm of drowsiness detection, showcasing an unparalleled accuracy of 99%. By synergistically combining the feature learning capabilities of Enhanced Deep Belief Networks (EDBN) with the temporal modeling prowess of Gated Recurrent Unit (GRU), and harnessing the collective intelligence of COOT optimization, this research not only outperforms existing methodologies but also sets a new standard for real-time drowsiness detection systems. Looking ahead, the future framework for research in this domain involves extensive validation studies across diverse driving conditions and demographic groups to ensure the robustness and generalizability of the proposed method. Furthermore, integrating modern sensor technologies, such as non-intrusive physiological sensors and computer vision systems, may improve the system's ability to identify subtle indicators of tiredness and personalise responses to individual driver characteristics. Additionally, adopting adaptive learning mechanisms and context-aware algorithms may enable the system to adapt to changing environmental conditions and driver behaviors, thereby enhancing its effectiveness in real-world driving scenarios. With ongoing advancements in artificial intelligence and machine learning, the possibilities for enhancing drowsiness detection systems are vast, paving the way for proactive interventions that prioritize driver safety and prevent potential accidents before they occur. Ultimately, the proposed method represents a crucial step towards achieving the overarching goal of creating safer and more secure roadways for all motorists.

REFERENCES

[1] M. I. B. Ahmed et al., "A deep-learning approach to driver drowsiness detection," Safety, vol. 9, no. 3, p. 65, 2023.

[2] J. S. Wijnands, J. Thompson, K. A. Nice, G. D. Aschwanden, and M. Stevenson, "Real-time monitoring of driver drowsiness on mobile platforms using 3D neural networks," Neural Computing and Applications, vol. 32, pp. 9731–9743, 2020.

[3] R. Jabbar, K. Al-Khalifa, M. Kharbeche, W. Alhajyaseen, M. Jafari, and S. Jiang, "Real-time driver drowsiness detection for android application using deep neural networks techniques," Procedia computer science, vol. 130, pp. 400–407, 2018.

[4] A.-C. Phan, N.-H.-Q. Nguyen, T.-N. Trieu, and T.-C. Phan, "An efficient approach for detecting driver drowsiness based on deep learning," Applied Sciences, vol. 11, no. 18, p. 8441, 2021.

[5] S. K. Khan, N. Shiwakoti, P. Stasinopoulos, and Y. Chen, "Cyber-attacks in the next-generation cars, mitigation techniques, anticipated readiness and future directions," Accident Analysis & Prevention, vol. 148, p. 105837, 2020.

[6] A. G. N and Y. Suresh, "An Efficient Deep Learning with Optimization Algorithm for Emotion Recognition in Social Networks," IJACSA, vol. 14, no. 8, 2023, doi: 10.14569/IJACSA.2023.0140823.

[7] G. Du, T. Li, C. Li, P. X. Liu, and D. Li, "Vision-based fatigue driving recognition method integrating heart rate and facial features," IEEE transactions on intelligent transportation systems, vol. 22, no. 5, pp. 3089–3100, 2020.

[8] J.-H. Jeong, B.-W. Yu, D.-H. Lee, and S.-W. Lee, "Classification of drowsiness levels based on a deep spatio-temporal convolutional bidirectional LSTM network using electroencephalography signals," Brain sciences, vol. 9, no. 12, p. 348, 2019.

[9] V. R. R. Chirra, S. R. Uyyala, and V. K. K. Kolli, "Deep CNN: A Machine Learning Approach for Driver Drowsiness Detection Based on Eye State.," Rev. d'Intelligence Artif., vol. 33, no. 6, pp. 461–466, 2019.

[10] J. He, W. Choi, Y. Yang, J. Lu, X. Wu, and K. Peng, "Detection of driver drowsiness using wearable devices: A feasibility study of the proximity sensor," Applied Ergonomics, vol. 65, pp. 473–480, Nov. 2017, doi: 10.1016/j.apergo.2017.02.016.

[11] K. Song, L. Zhou, and H. Wang, "Deep coupling recurrent auto-encoder with multi-modal EEG and EOG for vigilance estimation," Entropy, vol. 23, no. 10, p. 1316, 2021.

[12] R. Rafi, M. S. Haque, and R. M. M. Hasan, "Deep Learning Approach for Automated Sleep Stage Classification from EEG signal".

[13] E. Magán, M. P. Sesmero, J. M. Alonso-Weber, and A. Sanchis, "Driver drowsiness detection by applying deep learning techniques to sequences of images," Applied Sciences, vol. 12, no. 3, p. 1145, 2022.

[14] N. Saka and S. M. Krishna, "Efficient Feature Extraction Based on Optimized Gated Recurrent Unit Recurrent Neural Network for Automatic Thyroid Prediction," 2022.

[15] S. A. El-Nabi, W. El-Shafai, E.-S. M. El-Rabaie, K. F. Ramadan, F. E. Abd El-Samie, and S. Mohsen, "Machine learning and deep learning techniques for driver fatigue and drowsiness detection: a review," Multimedia Tools and Applications, vol. 83, no. 3, pp. 9441–9477, 2024.

[16] M. Ngxande, J.-R. Tapamo, and M. Burke, "Driver drowsiness detection using behavioral measures and machine learning techniques: A review of state-of-art techniques," 2017 pattern recognition Association of South Africa and Robotics and mechatronics (PRASA-RobMech), pp. 156–161, 2017.

[17] S. Chen, Z. Wang, and W. Chen, "Driver Drowsiness Estimation Based on Factorized Bilinear Feature Fusion and a Long-Short-Term Recurrent Convolutional Network," Information, vol. 12, no. 1, p. 3, Dec. 2020, doi: 10.3390/info12010003.

[18] M. S. Islalm, M. M. Rahman, M. H. Rahman, M. R. Hoque, A. K. Roonizi, and M. Aktaruzzaman, "A deep learning-based multi-model ensemble method for eye state recognition from EEG," in 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, 2021, pp. 0819–0824.

[19] F. You, X. Li, Y. Gong, H. Wang, and H. Li, "A Real-time Driving Drowsiness Detection Algorithm With Individual Differences Consideration," IEEE Access, vol. 7, pp. 179396–179408, 2019, doi: 10.1109/ACCESS.2019.2958667.

[20] Y. Albadawi, A. AlRedhaei, and M. Takruri, "Real-Time Machine Learning-Based Driver Drowsiness Detection Using Visual Features," J. Imaging, vol. 9, no. 5, p. 91, Apr. 2023, doi: 10.3390/jimaging9050091.

[21] M. Shantal, Z. Othman, and A. A. Bakar, "A Novel Approach for Data Feature Weighting Using Correlation Coefficients and Min–Max Normalization," Symmetry, vol. 15, no. 12, p. 2185, 2023.

[22] X. Larriva-Novo, V. A. Villagrá, M. Vega-Barbas, D. Rivera, and M. Sanz Rodrigo, "An IoT-focused intrusion detection system approach based on preprocessing characterization for cybersecurity datasets," Sensors, vol. 21, no. 2, p. 656, 2021.

[23] I. Nasri, M. Karrouchi, H. Snoussi, K. Kassmi, and A. Messaoudi, "Detection and Prediction of Driver Drowsiness for the Prevention of Road Accidents Using Deep Neural Networks Techniques," in WITS 2020, vol. 745, S. Bennani, Y. Lakhrissi, G. Khaissidi, A. Mansouri, and Y. Khamlichi, Eds., in Lecture Notes in Electrical Engineering, vol. 745. , Singapore: Springer Singapore, 2022, pp. 57–64. doi: 10.1007/978-981-33-6893-4_6.

[24] I. Izonin, R. Tkachenko, N. Shakhovska, B. Ilchyshyn, and K. K. Singh, "A Two-Step Data Normalization Approach for Improving Classification Accuracy in the Medical Diagnosis Domain," Mathematics, vol. 10, no. 11, p. 1942, 2022.

[25] A. Rajkar, N. Kulkarni, and A. Raut, "Driver drowsiness detection using deep learning," in Applied Information Processing Systems: Proceedings of ICCET 2021, Springer, 2022, pp. 73–82.

[26] V. Vijaypriya and M. Uma, "Facial Feature-Based Drowsiness Detection With Multi-Scale Convolutional Neural Network," IEEE Access, 2023.

[27] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems," Advances in Engineering Software, vol. 114, pp. 163–191, Dec. 2017, doi: 10.1016/j.advengsoft.2017.07.002.

[28] A. Garcés Correa, L. Orosco, and E. Laciar, "Automatic detection of drowsiness in EEG records based on multimodal analysis," Medical Engineering & Physics, vol. 36, no. 2, pp. 244–249, Feb. 2014, doi: 10.1016/j.medengphy.2013.07.011.

[29] Q. Cai, Z.-K. Gao, Y.-X. Yang, W.-D. Dang, and C. Grebogi, "Multiplex Limited Penetrable Horizontal Visibility Graph from EEG Signals for Driver Fatigue Detection," Int. J. Neur. Syst., vol. 29, no. 05, p. 1850057, Jun. 2019, doi: 10.1142/S0129065718500570.

[30] H. Luo, T. Qiu, C. Liu, and P. Huang, "Research on fatigue driving detection using forehead EEG based on adaptive multi-scale entropy," Biomedical Signal Processing and Control, vol. 51, pp. 50–58, May 2019, doi: 10.1016/j.bspc.2019.02.005.