Utilizing Neutrosophic Logic in a Hybrid CNN-GRU Framework for Driver Drowsiness Level Detection with Dynamic Spatio-Temporal Analysis Based on Eye Aspect Ratio

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Abstract

Driver drowsiness has been identified as a major cause of roadway accidents globally. Efficiently determining the extent of drowsiness can greatly enhance preventive measures. This study proposes a novel approach, combining convolutional neural networks (CNN) and Gated Recurrent Units (GRU) to dynamically evaluate both the presence of drowsiness and its severity based on the Eye Aspect Ratio (EAR). By bridging spatial features extracted by CNNs with temporal sequences through GRU, our model offers a robust and real-time assessment of drowsiness levels, paving the way for enhanced safety measures in vehicular systems. Incorporating Neutrosophic Logic enables a more robust representation of uncertainty and ambiguity in the data and enhances the accuracy of driver drowsiness level detection within the Hybrid CNN-GRU framework. The model's hybrid CNN-GRU structure combines CNN layers to extract spatial information from Human eye Images and GRU units to represent temporal correlations between frames. In-car cameras and sensors must be integrated to implement the suggested system in real-time and enable continuous driver behavior monitoring. The system alerts early warnings and takes action when drowsiness is detected, lowering the likelihood of accidents caused by weary drivers. The CNN-GRU hybrid architecture accurately detects fatigue during real-time driving. Performance metrics, including accuracy, recall, and F1-score, are provided for comparative research utilizing baseline models. Model behavior may be understood by visualizing tiredness detection and carefully examining false positives and negatives. The proposed CNN-GRU framework outperforms traditional methods such as SVM, KNN, and BPNN by achieving a significantly higher accuracy of 99.5%. It increases the recognition of driver tiredness by proposing a trustworthy and adaptable hybrid CNN-GRU deep learning system. This project is implemented in Python; it offers a practical and versatile solution for real-time driver drowsiness level detection. The proposed technology has the potential to dramatically increase traffic safety by sending out early warnings and taking steps to lessen the risks related to driver fatigue.

Keywords: Driver drowsiness; Spatio-temporal analysis; Machine learning, Neural Networks; Gated Recurrent Unit; Neutrosophic Logic; Eye Aspect Ratio.

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1 Introduction

Real-world driver drowsiness based on eye-aspect ratio monitoring is a critical use of technology to enhance road safety for identifying and alerting drivers who are dangerously drowsy or weary while operating a vehicle. This tool is essential for lowering crashes and fatalities caused by fatigued driving.[1] It is now feasible to identify indicators of tiredness in real-time by using techniques including computer vision, involving cameras inside the car watching the driver's behavior, particularly eyelid movement, head attitude, and facial expressions. EAR is a facial feature often used in computer vision applications. In drowsiness detection, EAR can monitor changes in the driver's eye state (e.g., blink rate, eye closure) as a potential indicator of drowsiness. This not only encourages traffic safety but also improves drivers' general health and well-being by lowering the likelihood of collisions brought on by diminished cognitive and motor abilities.[2] Reducing accidents and the resulting downtime can improve the effectiveness of commercial vehicle operations.[3] Convolutional neural networks and gated recurrent units are two types of deep learning architecture that operate well together for various applications, especially in computer vision and sequential data analysis.[4] Gated Recurrent Units (GRUs) and Convolutional Neural Networks are two separate neural network topologies that excel in particular data analysis areas.

CNNs were created largely for spatial data, especially photographs. They have a remarkable talent for identifying spatial patterns and characteristics in data. CNNs are the best choice for applications like image classification, object identification, and picture segmentation because they autonomously learn hierarchical representations for data using convolutional layers and pooling layers. Examining and interpreting data and events in terms of both place (geographical or spatial dimension) and time (temporal dimension) is known as spatiotemporal analysis.[5] It examines how phenomena, patterns, and occurrences change across time and place and how they interact. Various academic disciplines, including geography, environmental science, epidemiology, and computer vision, frequently utilize this approach. Recognize and comprehend the trends or patterns that develop over time and in various spatial contexts. For instance, it can entail researching animal migratory patterns or the spread of toxins in environmental science.[6] Utilize previous spatiotemporal data to forecast upcoming occurrences or patterns. For instance, epidemiology can include predicting disease outbreaks based on historical trends. Determine whether any strange or unexpected occurrences or changes in the spatiotemporal data could need more research. This can entail identifying odd behaviors over time through anomaly detection or image monitoring.[7] Enhance decision-making or resource allocation procedures using spatiotemporal analysis. For instance, real-time traffic data can effectively manage traffic flow in the transportation sector. Data from several sources, such as satellite imaging, sensor data, GPS data, and many more, are frequently used in spatiotemporal analysis. Improved analysis and interpretation of spatiotemporal data require advanced techniques such as GIS, machine learning, and deep learning. It may be used for various real-world purposes, including better urban planning, public health initiatives, and comprehension of climate change.[8]

GRUs is a member of the RNN family and is particularly adept at processing sequential input. GRUs, as opposed to CNNs, can detect temporal connections in sequences by considering the data's context and order. They are effective in time series analysis, speech recognition, and natural language processing. CNNs make up the model's first layers. These layers extract relevant spatial properties like edges, textures, and object representations from incoming data like photographs. These characteristics are crucial for comprehending the input's content. GRUs capture the temporal dependencies throughout the data after the CNN layers. They examine how these attributes change over time using the spatial information the CNN retrieved as input. The model can now comprehend the data's sequential character, making it appropriate for jobs involving time series or image data.[9] The GRU layer output is merged with the spatial characteristics the CNN has learned. The fusion of spatial and temporal information produces a comprehensive representation of the data that considers both spatial and sequential patterns. Applications for hybrid CNN-GRU models may be found in many fields, such as image analysis, action recognition, and driving behavior analysis. They are especially useful for jobs that call for comprehension of the data's spatial content (spatial content) and the time context (temporal context). The CNN-GRU hybrid model is a deep learning architecture that seamlessly merges spatial and temporal data processing, enabling it to perform very well in tasks that combine both elements.[10]

Neutrosophic Logic, a novel extension of classical two-valued and fuzzy logic, introduces a third value, indeterminacy, to better capture and represent uncertainties and ambiguities within a given framework.[11] This logic framework has applications in a wide range of fields, especially when decision-making relies on incomplete or vague information.[12] The research utilizes Neutrosophic Logic as a fundamental component of our approach.

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It intends to address and represent the intricate and multidimensional nature of driver drowsiness level detection by introducing this logic system into the framework. Neutrosophic Logic enables us to quantitatively assess the degrees of truth, indeterminacy, and falsity in the information this research gathers, facilitating a more accurate and nuanced understanding of driver drowsiness.[13] Integrating Neutrosophic Logic within the hybrid CNN-GRU framework enhances the precision and reliability of our drowsiness level detection system, ultimately contributing to improved road safety.

Data collection, gathering various image recordings comprising traffic scenarios or specialized automobile-related events, is the first step in recognizing automotive image datasets. Sources for these images include dashcams, traffic cameras, and publically accessible datasets. Once the films are gathered, they are preprocessed to provide a consistent dataset. The preprocessing stage involves converting the image format, extracting frames, and standardizing the resolution.[14] The next critical step is manual or automatic annotation, which entails labeling and annotating automobile instances or pertinent items of interest inside the Human eye Image using bounding boxes or related metadata. This stage is crucial for developing and testing machine learning models. Inter-rater reliability tests and data augmentation strategies may be used to guarantee dataset quality.[15] The annotated dataset is divided into training, validation, and test sets to create accurate and reliable automobile identification models for real-world applications like autonomous driving traffic management. To efficiently monitor and recognize sleepiness indicators, A model for detecting driver fatigue, which combines the strengths of a Convolutional Neural Network and Gated Recurrent Unit, was created using CNN-GRU.[16] The CNN component of the model is in charge of extracting spatial features, such as facial emotions and eye movements, from the human eye image in this situation. A recurrent neural network variant called the GRU is made to recognize temporal relationships in sequential input. The GRU examines the temporal evolution of the spatial information retrieved by CNN in its surroundings of driver sleepiness detection. For instance, it may spot drowsiness-indicating patterns of head nodding or eyelid drooping across a series of Human eye Images. The hybrid model gets skilled at identifying subtle and progressive sleepiness indicators by fusing the spatial data obtained by the CNN alongside the temporal environment modeled by the GRU. It can recognize when a driver's concentration begins to lapse or when symptoms of weariness begin to appear. The model's output may result in prompt warnings or interventions, such as alarms or notifications, aiding in the reduction of accidents brought on by fatigued driving. The CNN-GRU model effectively detects driver sleepiness in the real world because it combines spatial and temporal analysis. The key contributions of the research study are as follows:

1. The study employs data preprocessing for driver drowsiness detection. It involves multiple steps, including extracting images from the Human eye Image dataset collected, data augmentation, and extracting landmark coordinates from images
2. The integration of Neutrosophic Logic to remove uncertainties in the obtained data and enhances the system's ability to effectively represent the ambiguities
3. This framework combines Convolutional Neural Networks (CNN) for spatial analysis and Gated Recurrent Units (GRU) for temporal analysis
4. Rigorous performance evaluation is conducted to assess the effectiveness of the proposed CNN-GRU framework
5. The study's primary contribution lies in providing a more accurate and robust solution for real-world driver drowsiness detection. By combining spatial and temporal analysis in a hybrid model and optimizing the data preprocessing pipeline, the study enhances the accuracy of detecting drowsy drivers, thereby contributing to road safety.

Section 1 provides an overview of the paper. Section 2 reviews existing literature and emphasizes the gap in addressing individual driver differences in drowsiness detection. Section 3 defines the central research problem concerning driver drowsiness detection complexities. Section 4 outlines data collection, preprocessing, feature extraction, and the integration of Hybrid CNN-GRU. Section 5 presents empirical findings, compares classifier performance, and explores implications and future research directions, solidifying the research's significance in driver drowsiness detection.

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2 Related Work

Zhang et al.[17] focus on sleepiness detection via federated learning while protecting the anonymity of drivers' data, addressing a crucial challenge in driving safety technologies. To improve the effectiveness and security of the system, this study introduces a unique technique dubbed PFTL-DDD that combines transfer learning with privacy-preserving protocols. The paper's advantages are clear in several ways. First, it addresses a real issue with driver sleepiness detection while recognizing the value of maintaining privacy using data from multiple industrial groups. Despite the lack of sufficient driver face data, fine-tuning transfer learning in the initial model of a federated learning system is a practical way to improve model performance. A major novelty is the inclusion of the CKKS-based security-preserving protocol, which protects drivers' private information during parameter exchange. The experimental results presented in the study demonstrate that the PFTL-DDD technique outperforms classical federated learning in terms of accuracy and efficiency as assessed on the NTHU-DDD and YAWDD datasets. This empirical evidence highlights the practical usefulness of the suggested strategy. Practitioners would benefit from knowing how to address prospective computational or resource limitations while applying the CKKS-based privacy protocol. By tackling privacy issues in driver drowsiness detection and offering improved model accuracy and efficiency, the study "Privacy-Preserving Federated Transfer Learning for Driver Drowsiness Detection" makes a significant addition to the area. It is advised to do more study and practical testing to evaluate its applicability and scalability thoroughly.

Siddiqui et al.[18] state that identifying driver sleepiness assists in avoiding accidents caused by fatigue-related driving, which is a key issue in road safety. An ultra-wideband radio impulsive radio radar was used in the study's non-contact, non-invasive methodology to track the chest motions of 40 participants and collect data on their breathing rates. For the categorization of sleepy and non-drowsy driving states, various machine learning models are trained using the gathered structured data. With an accuracy rating of 87%, the Support Vector Machine stands out among the evaluated models as the most accurate. This study deserves praise for its creative use of non-intrusive IR-UWB radar technology in sleepiness detection. Since sleepy states frequently go hand in hand with changes in breathing patterns, physiological research supports focusing on respiration rate as a crucial predictor of sleepiness. Given that age might affect sleepiness patterns, using a structured dataset with age as an extra attribute is a clever approach. The empirical findings, especially the high accuracy attained using SVM, point to the potential usefulness of this strategy in real-world settings. Road accidents & their corresponding repercussions might be drastically decreased with accurate sleepiness detection. However, it's critical to recognize certain possible areas for more research and development. The results may not be as generalizable as they may be due to a relatively small sample of 40 individuals. However, diversifying the dataset's demographics and driving circumstances could increase the study's validity. It would also be helpful to describe the computation and hardware specifications for the real-time deployment of the IR-UWB radar system to comprehend its viability. The study offers a potential and ground-breaking method for detecting driver drowsiness, which has important implications for traffic safety. The relevance and application of this study in real-world circumstances might be further improved by extending the dataset and considering actual implementation constraints.

Magán et al.[19] aim to build an Advanced Driving Assistance System centered on drowsiness detection to reduce road traffic accidents caused by driver exhaustion, which tackles a crucial issue in road safety. To avoid unduly upsetting drivers, the authors stress the significance of non-intrusiveness in sleepiness detection while minimizing false alerts. The method uses 60-second picture sequences that capture the driver's face to determine whether or not they are drowsy. This difficult problem is addressed by two approaches, one utilizing a recurrent and convolutional neural network and the other deep learning methods followed by a fuzzy logic-based feature extraction system. While both systems' accuracy (about 65% on overall training data and 60% on test data) is average, the second strategy stands out for its excellent specificity (93%) in preventing false alarms. This study deserves praise for tackling the important problem of driver sleepiness detection and for offering an original method utilizing visual sequences. In real-world applications, minimizing false positives is crucial to ensuring that drivers are not overly bothered when they are not tired. Using fuzzy logic and deep learning for feature extraction and Making decisions requires careful consideration and striking a balance between deep learning's broad capabilities and interpretability. However, the authors agree there is potential for improvement given the moderate accuracy rates obtained using training and test data. The model's performance may be improved by enlarging the dataset, investigating alternate data sources, and considering more contextual data. A more thorough understanding of the suggested system's viability in real-world driving would also result from analyzing the implementation's practical difficulties, such as hardware requirements and real-time processing capabilities. An effective and non-intrusive basis for sleepiness detection is presented in this paper.

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Deng and Wu[20] demonstrate a novel method of detecting driver weariness without extra body-mounted equipment. The authors present DriCare, a system that uses facial movements and variables like blinking, yawning frequency, and the length of eye closure to evaluate a driver's level of weariness from image pictures. This non-intrusive method is important because it enables real-time detection without putting the driver under extra equipment stress. Implementing a novel face-tracking algorithm to improve tracking accuracy is one of the paper's noteworthy strengths. This development is essential for accurately identifying face characteristics linked to driver sleepiness. 68 key points enabling facial region recognition and evaluation are also reliable since they catch a wide range of characteristics that may be symptomatic of driver weariness. The trial findings, which show a 92% accuracy rate, are highly encouraging and show how effective the DriCare technology is. The development of real-time drowsiness detection is a significant achievement. Such a high degree of accuracy and shows how feasible the suggested technique is. The study presents a viable and efficient method for detecting driver weariness utilizing facial expressions. The system is a useful addition to automobile safety technology because of its high degree of accuracy and because it is non-intrusive, with potential uses in cars to stop accidents brought on by fatigued driving. It needs more investigation and validation in practical settings before its robustness and utility can be determined.

You et al.[21] examine a key topic in traffic safety, concentrating on identifying drowsy driving from a novel angle: individual variations among drivers. Even though current sleepiness detection techniques frequently strive for universality, this study emphasizes the value of adjusting identification to individual drivers. The suggested technique uses landmarks from the driver's facial characteristics to build a deep cascaded convolutional neural network for recognizing faces, doing away with the necessity for human feature extraction. Notably, including the "Eyes Aspect Ratio" parameter offers a fresh method for determining tiredness in real time. The algorithm also considers differences in the size of the driver's eyes, which led to the creation of two modules: offline training and internet-based monitoring. This method performs better than current approaches in simulated driving applications in accuracy and speed, obtaining a remarkable 94.80% accuracy at over 20 frames per second (fps). By recognizing the critical importance of individual variability in sleepiness detection, this research significantly contributes to intelligent transportation systems and traffic safety. The creative application of deep learning in conjunction with the Eyes Aspect Ratio parameter demonstrates a promising strategy for accurately detecting driver weariness. A useful and practical feature is the emphasis on real-time detection, including a variable to evaluate the progressive onset of tiredness. An innovative and promising method for detecting driver intoxication is presented in this research. It deserves praise for its ability to adjust to individual driver characteristics and provide great accuracy and speed. More study and field testing are advised to verify its efficacy and usefulness in various driving situations.

Darwish, Salah, and Elzoghabi[22] handle indoor object detection, a key component of technological assistance for those with vision impairments. Given the complexity of background disruption occlusions and different views, navigating interior places can be extremely difficult for those who are blind or visually impaired. The research investigates the combination of neutrosophic logic that enhances conventional fuzzy logic by allowing indeterminate membership principles with a rotating ultrasonic array. The study's strategy focuses on estimating obstacle lengths and assisting those who are blind in navigating their environment. The method relies on varying degrees of veracity, determinacy, and falsification to provide orientation, enabling movement in one of three directions: forward, right, or left, depending on the sensor data. The study provides a mean average precision accuracy rate of 97.2% and 1%. The suggested system's ability to recognize interior items and aid the mobility of visually impaired people is demonstrated by the high degree of accuracy. Such accuracy is essential for boosting the security and freedom of people with visual impairments in enclosed spaces. The application of neutrosophic logic in this setting exemplifies the creative use of mathematical frameworks to address practical issues. This research has the potential to lead to the creation of reliable mobility-assistive technology for blind people, improving their freedom and quality of life.

Abdubrani, Mustafa, and Zahari[23] propose a thorough and creative solution to the critical problem of electroencephalogram (EEG) signal-based driver tiredness identification. The study starts by recognizing the difficulties with EEG signal processing, including artifacts such as muscle movements, eye blinking, and noise that can make reliable tiredness diagnosis difficult. To address these problems, the authors efficiently preprocessed the EEG data obtained from young driver simulation participants using an independent component analysis (ICA) technique. This study is unique because it combines multichannel EEG analysis and feature extraction using an enhanced modified z-score. It also uses machine learning classifiers such as convolutional neural networks, recurrent neural networks, artificial neural networks with long short-term memory, and support vector machines to analyze the data. With a 96.07% average accuracy rate across classifiers, the ANN classifier stands

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out with a precision of 99.65%, which is an astounding finding. The area under the curve (AUC) and receiver operating characteristic (ROC) analyses further confirm the recommended framework's superior performance. By addressing various important issues and offering a thorough solution, this study significantly advances the field of driver tiredness detection. The accuracy of sleep stage recognition, a vital element for accurate tiredness monitoring, is improved by applying the technique of multichannel EEG analysis. A significant advancement in feature extraction is the addition of an improved modified z-score, which enhances the durability of classification by managing outlier values. The inclusion and exceptional performance of multiple machine learning classifiers highlight the proposed framework's potency and adaptability. The study might, however, go into further depth on potential restrictions and difficulties that can arise in realistic deployments, in addition to the computational resources needed for such deployments. A more diversified participant pool would also let the study evaluate how well the framework can be applied to various driving situations and demographics. The study presents a thorough and extremely promising method for identifying driver weariness. It makes an important contribution to advancing intelligent transport systems to maintain driver safety and lower the hazards associated with sleepy driving because of its exceptional accuracy and resilience.

3 Problem Statement

The problem addressed in the above-studied literature is driver drowsiness, which poses a significant threat to road safety. Driver drowsiness can lead to accidents, injuries, and fatalities, making it imperative to develop effective detection systems. Existing methods often struggle with data privacy, accuracy, and real-time monitoring. Therefore, the problem statement revolves around a robust, privacy-preserving, and accurate driver drowsiness detection system that can operate in real-world conditions, addressing individual variability among drivers and protecting sensitive data.[24] The study aims to overcome these challenges by proposing a dynamic spatio-temporal analysis framework that combines the power of deep learning, specifically CNN and GRU models, to provide an efficient and privacy-preserving solution for real-world driver drowsiness detection.

4 Proposed Hybrid CNN-GRU for Earthquake Prediction through Spatio-Temporal Analysis

The methodology of this study follows a systematic flow designed to address the challenge of real-world driver drowsiness detection, represented in Figure 1. It begins with data preprocessing, involving extracting images from the Human eye Image, data augmentation to enhance the dataset, and extracting facial landmark coordinates from the images. These preprocessing steps ensure the input data is properly prepared for analysis. The research provides a more sophisticated approach for resolving the underlying problems in driver sleepiness detection by including Neutrosophic Logic in this research. Next, the study introduces a hybrid deep learning framework, combining Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU) for dynamic spatiotemporal analysis. CNNs are employed for spatial analysis to capture local features, while GRUs handle temporal analysis to understand the evolving drowsiness patterns over time. The hybrid CNN-GRU architecture enhances the accuracy of drowsiness detection by considering both spatial and temporal aspects. Finally, the methodology concludes with a thorough performance evaluation of real-world datasets, comparing the proposed framework's accuracy and efficiency against conventional methods. This systematic approach ensures the development of an effective and practical solution for real-world driver drowsiness detection.

4.1 Data collection

The Drowsiness Detection Dataset is a comprehensive dataset curated by combining the MRL and Closed Eyes in Wild (CEW) datasets with a unique dataset created by the researchers. This extensive dataset contains a wide range of human eye images with closed and open eyes, primarily intended for eye detection tasks. It can also be extended for drowsiness detection applications. The dataset incorporates images captured under various conditions, ensuring diversity in lighting conditions, distances, resolutions, face, and eye angles. This parameter diversity enhances the dataset's utility by reducing the likelihood of encountering low accuracy issues in subsequent tasks. The dataset is available in multiple versions; Version 1 comprises 10,000 images, evenly divided into 5,000 images featuring closed eyes and 5,000 images featuring open eyes. Version 2

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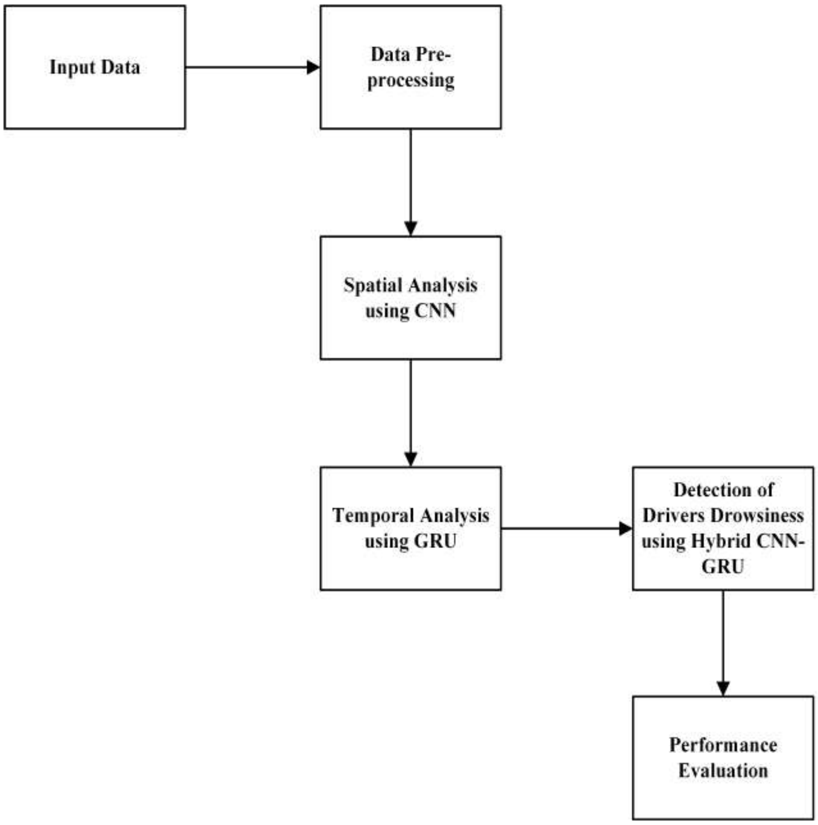

Figure 1: Framework for Proposed Method.

contains 5,000 images, with 2,500 images depicting closed eyes and another 2,500 images displaying open eyes. In Version 3, another collection of 10,000 images is equally distributed between 5,000 images with closed eyes and 5,000 with open eyes. The fourth version of the dataset, known as Version 4, contains 4,000 images, with 2,000 images of closed eyes and 2,000 of open eyes. These versions cater to various research and development needs, accommodating various scales of experimentation and evaluation for eye and drowsiness detection tasks. Researchers and developers can choose the version that best suits their specific requirements, benefitting from the extensive and well-annotated image data provided in each version.[25]

4.2 Removal of Un-certainties in Data through Neutrosophic Logic

Neutrosophic Logic allows quantifying the uncertainty inherent in the data by providing degrees of truth, indeterminacy, and falsity. This quantification helps understand the levels of uncertainty within the dataset. Neutrosophic Logic extends classical two-valued logic and fuzzy logic by introducing a third membership value, indeterminacy, to address the complexities of uncertain and ambiguous information. Each statement in neutrosophic logic has three properties: truth (T), indeterminacy (I), and falsity (F). These numbers describe how truthful, ambiguous, and untrue a statement is. The representation of a neutrosophic statement is (T, I, F), satisfying the constraint $T + I + F \leq 1$. The following equations illustrate the core concepts:

T (Truth) represents the degree to which a statement is true, $0 \leq T \leq 1$

I (Indeterminacy) indicates the degree of uncertainty or neither truth nor falsity,$0 \leq I \leq 1$

F (Falsity) It quantifies the degree, to which a statement is false, $0 \leq F \leq 1$

The complement of a neutrosophic proposition can be calculated as follows:

$$Complement\ (\neg A) :\ (F,\ I,\ T) \tag{1}$$

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Neutrosophic Logic is built on these mathematical equations, which allow for the systematic representation and manipulation of uncertain and ambiguous data, making it an invaluable tool in various modeling and decision-making scenarios.

4.3 Data Preprocessing

Step1: Data Augmentation

Deep learning models benefit from an abundance of diverse training data. We employ data augmentation techniques to ensure that our model captures the full spectrum of nuances and variations in facial expressions. Specifically, this approach utilizes Codebox to generate augmented images. These augmented images are created by applying a set of predefined operations to the extracted images. Data augmentation is crucial in enhancing the model's ability to generalize effectively.[26]

Step2: Extracting Landmark Coordinates from Images

Facial landmarks, including the eyes, mouth, nose, and jawline, are pivotal in identifying and tracking salient facial features. These landmarks are essential for various tasks, such as head pose estimation, blink detection, and yawning detection, which are integral to driver drowsiness prediction. To obtain these facial landmarks, we employ the open-source C++ library Dlib, which provides pre-written functions for facial landmark extraction. Dlib can detect the x and y coordinates of 68 facial landmarks, allowing us to effectively map the intricate facial structure. The library leverages OpenCV's Haar Cascades for facial landmark detection, a technique initially introduced by Paul Viola and Michael Jones. This technique is grounded in machine learning, utilizing labeled images to identify the presence of specific objects, in our case, human faces. Through this process, the algorithm can accurately detect and map facial landmarks in new facial images processed by the model.

The preprocessing workflow ensures that our dataset is prepared comprehensively for the subsequent stages of driver drowsiness prediction, where these facial landmarks and augmented image data will contribute significantly to the model's ability to discern signs of drowsiness.

4.4 Utilization of Cascade Classifiers

Cascade classifiers are typically trained using positive and negative samples. Positive samples are images containing the object of interest (in this case, eyes), and negative samples are images that don't contain the object. Cascade classifiers are valuable tools in computer vision for pinpointing the region of the eye. These classifiers are trained using datasets comprising positive samples (images containing eyes) and negative samples (images without eyes). You can leverage pre-trained cascade classifiers designed for eye detection or train custom ones. To apply a cascade classifier for eye detection, start by preprocessing the input image or image frame by converting it to grayscale and resizing it to an appropriate size. Then, the loaded cascade classifier will be used to identify the eyes in the image, returning the coordinates (bounding boxes) of the detected eyes. Obtained coordinates can easily extract the eye regions from the image by cropping the region defined by the bounding box. This extracted eye region can be further used for various tasks, such as calculating the eye aspect ratio (EAR) or analyzing the driver's eye state in applications like driver drowsiness detection.

4.5 Feature Extraction Using Convolutional Neural Network

In the context of drowsiness detection, the CNN (Convolutional Neural Network) model plays a crucial role in capturing and analyzing relevant features from the Human eye Image; the architecture of CNN is represented in Figure 2. CNN models are designed to process visual data efficiently and are particularly adept at recognizing patterns within images, making them well-suited for this task. In the first segment of the proposed model, the research employs convolution layers to extract local trends and changes in the Human eye Image, a key characteristic of CNNs that enables us to focus on specific regions of interest without being overly influenced by uncertainties.

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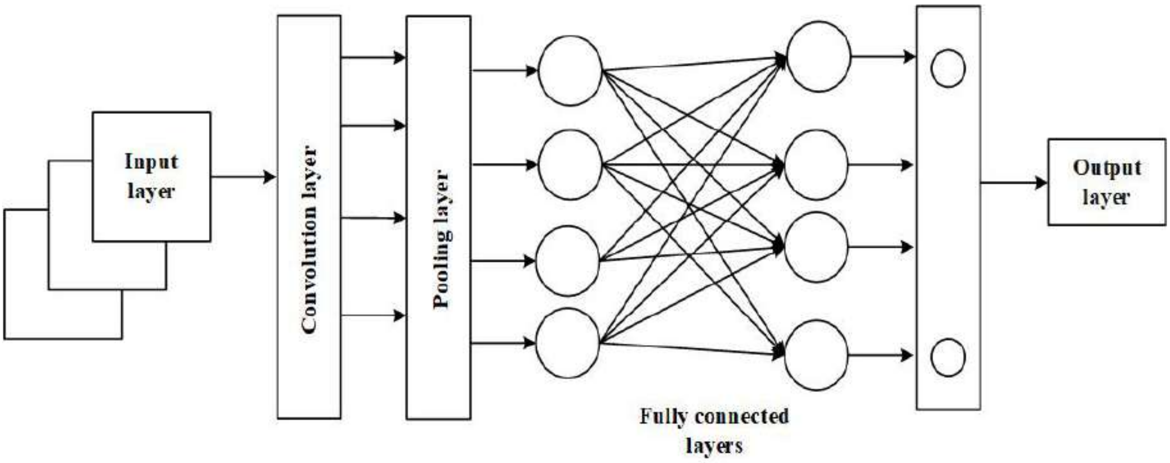

Figure 2: CNN Architecture.

This is vital for identifying subtle facial cues indicative of drowsiness. The CNN component comprises three one-dimensional (1D) convolution layers and one 1D max pooling layer, designed to process the temporal aspects of the human eye image efficiently. The research employs scaled exponential linear units (SELU) as the activation function to activate the neurons within our CNN. This choice is advantageous over traditional activation functions like Rectified Linear Units (ReLU).

$$SELU = \lambda \begin{cases} x \quad if x > 0 \\ \alpha e^{x} - \alpha \quad Otherwise \end{cases} \tag{2}$$

$$ReLU = \max(0, x) \tag{3}$$

The equations for ReLU and SELU are represented in Equation 2 and Equation 3. SELU offers improved convergence properties, enhancing the model's training process. It mitigates the issue of gradient vanishing, which can be particularly beneficial in drowsiness detection, where subtle changes in facial expressions and features must be effectively captured and analyzed.

4.6 Hybrid CNN-GRU Model Architecture

Encouraged by the promising outcomes of the CNN-GRU model, the research constructs a hybrid architecture meticulously designed for real-time driver drowsiness detection from image data. This innovative hybrid model, featured in Figure 3 during the training phase, seamlessly integrates Convolutional Neural Networks (CNNs) with a multi-layered Gated Recurrent Unit (GRU) model customized to the specific image data context. CNNs, initially designed for image classification tasks, have demonstrated versatility and effectiveness in handling one-dimensional data, making them apt for processing image sequences. Through weight-sharing principles, CNNs are well-suited to address complex, non-linear patterns inherent in image data, akin to time series analysis. The essential components within CNN–GRU architecture involve convolution and pooling layers, as illustrated in Figure 3. Convolution operations transform human eye images while pooling layers abstract, resulting in feature maps that are more manageable for interactions between hidden layers and memory cells. In the context of the image data, the research recognizes the significance of temporal dependencies. Gated Recurrent Units (GRUs), known for their efficacy in handling sequences, are deployed to address this. GRUs offer two pivotal gate layers: a reset gate (Y) and an update gate (Z). The general equations of GRU cells are shown in Equations 4-7.

$$At = \sigma(W_a . [h_{t-1}, x_t] + b_a) \tag{4}$$

$$rt = \sigma(W_r . [h_{t-1}, x_t] + b_r) \tag{5}$$

$$\tilde{h}t = tanh(W_a . [rt * h_{t-1}, x_t] + b_a) \tag{6}$$

$$ht = (1 - At) * h_{t-1} + At * \tilde{h}t \tag{7}$$

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The update gate ensures the retention of earlier image frame information. In contrast, the reset gate governs the fusion of input sequences from the subsequent frame with the memory of the preceding one. These architectural features significantly capture temporal nuances within the image data, a crucial aspect of driver drowsiness detection in real-time scenarios. Importantly, a multi-layer GRU configuration is chosen, a choice that expedites training due to its reduced parameter complexity, making it particularly suited to image data analysis.

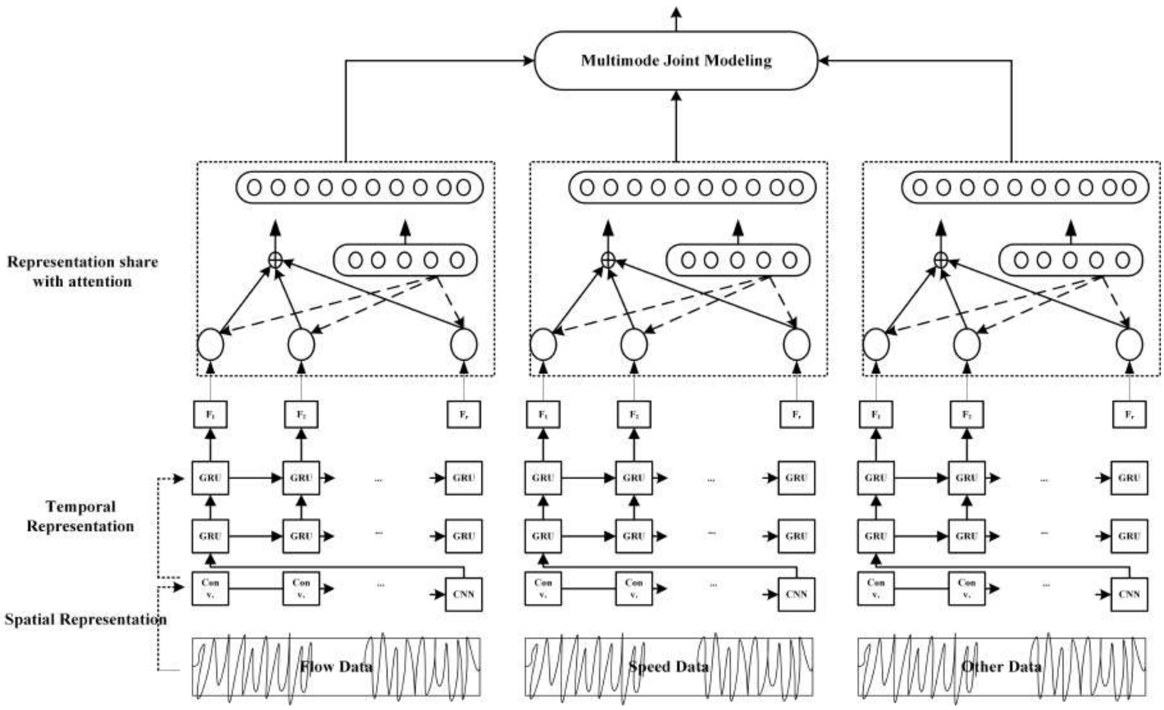

Figure 3: CNN-GRU Architecture.

4.7 Classification using Hybrid CNN-GRU for Predicting Drivers Drowsiness

Based on the spatial and temporal data combination, the model classifies the drowsiness state and quantifies its severity through EAR values. Classification using CNN-GRU is a powerful technique that leverages the capabilities of Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs) for accurate and dynamic classification tasks. This approach employs CNNs for spatial feature extraction, which are well-suited for image and image data. CNNs analyze the spatial information within each input data frame, identifying important patterns, features, and details. The sequence of EAR values derived from consecutive frames is fed into a GRU network to capture the temporal patterns of eye closures, which specializes in handling the temporal aspects of the data. GRUs are recurrent neural networks that capture sequential dependencies and patterns over time**.** They maintain a memory of past information, making them ideal for tasks involving dynamic changes, such as time-series data or sequences of images.

The CNN-GRU model can analyze the spatial features of each frame, recognizing key patterns and structures. Simultaneously, the GRU component processes these spatial features over a sequence of frames, capturing the temporal dynamics and changes in the data. This combined approach allows for the effective classification of sequences or image data, where both spatial and temporal information are essential. Classification using CNN-GRU combines the strengths of spatial and temporal analysis, making it highly effective for tasks such as action recognition in images, sentiment analysis in sequences of text, or drowsiness detection in drivers, in the case mentioned earlier. The model's ability to capture the data's static and dynamic aspects enhances its classification accuracy and robustness.

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5 Results and Discussion

The results section provides a comprehensive overview of the outcomes and findings from the experimental evaluation of the driver drowsiness detection model. It includes detailed accuracy percentages for various data categories, such as Talking Face, Eyeblink8, and Eye Image 1, achieved by different methods, emphasizing the proposed CNN-GRU framework. These accuracy metrics serve as critical performance indicators, demonstrating the model's effectiveness in distinguishing between alert and drowsy states. The results section also highlights the strengths and limitations of each method, shedding light on areas for improvement and future research directions in driver monitoring and safety.

5.1 Dataset

In Figure 4, both open-eye and closed-eye pictures were successfully gathered for the dataset. This dataset is essential for training and evaluating machine learning models focusing on eye-related tasks, such as driver drowsiness detection, eye blink recognition, or gaze tracking. The dataset includes various images featuring individuals with their eyes in different states—both fully open and fully closed, as well as intermediate states, such as half-open eyes or varying degrees of eyelid closure. The data was collected from various individuals across different age groups, genders, and ethnicities to ensure diversity and robustness. Images were captured under various lighting conditions and angles to account for real-world variability.

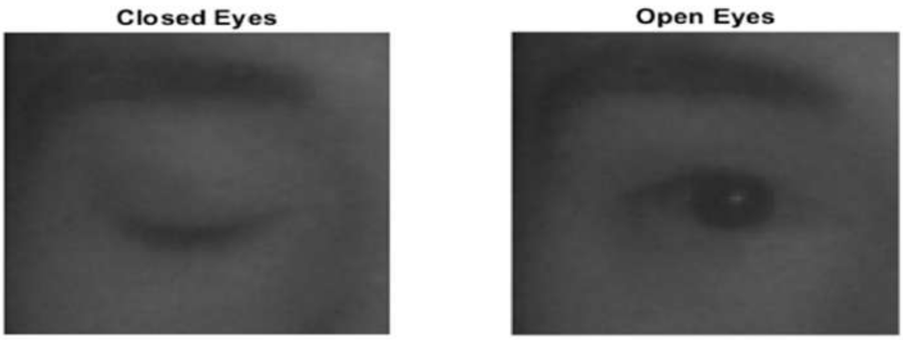

Figure 4: Eye Blink Recognition.

5.2 Blink Detection Threshold

In Figure 5, a threshold can be applied to the duration or intensity of eye closures to determine when a blink has occurred. For example, if the eyes remain closed for a duration exceeding a certain threshold, it can be considered a blink event.

5.3 Gaze Tracking Threshold

Figure 6 represents the gaze tracking applications; thresholds can be used to determine when a person is looking in a particular direction. You can identify gaze shifts or fixations by analyzing eye movements and applying thresholds to gaze angle or pupil position. Tracking the eye closure region involves monitoring changes in the eyelids and surrounding areas to determine when the eyes are open or closed in image or image sequences. This process is pivotal for applications like driver drowsiness detection and blink analysis. It begins with eye detection and defining a region of interest (ROI) around the eyes. Relevant features, such as intensity changes or shape patterns, are extracted from this ROI. A threshold is applied to these features to classify the eye state (open or closed). Temporal analysis of frame sequences helps detect eye blinks and prolonged closures.

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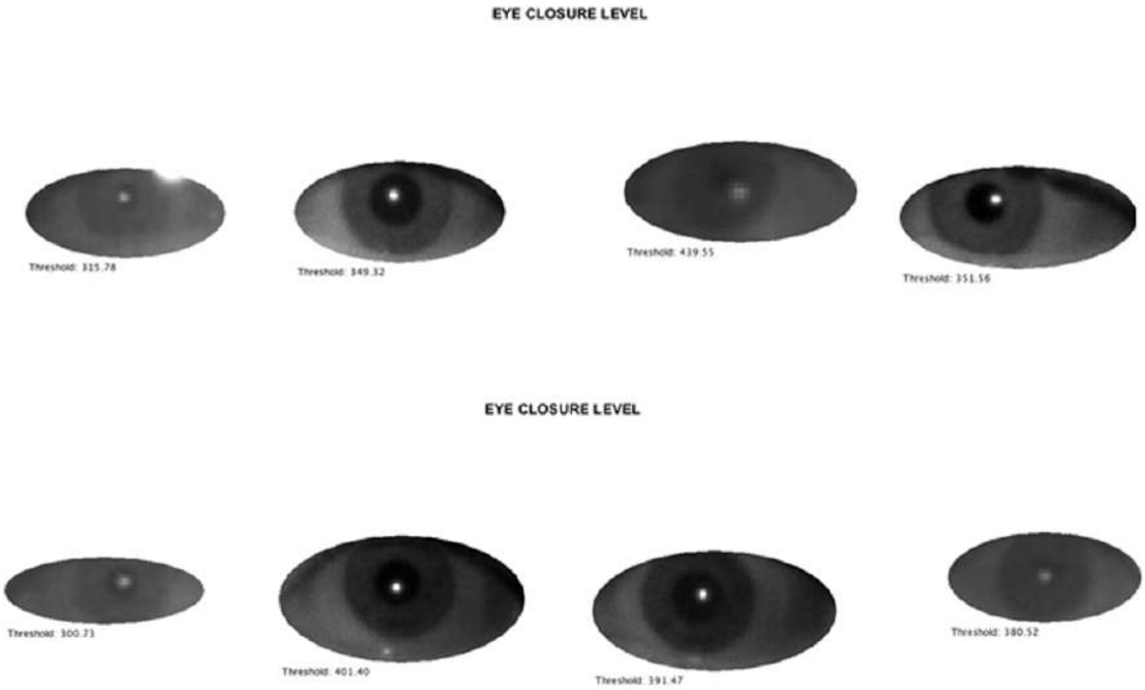

Figure 5: Threshold for Eye Closure Level.

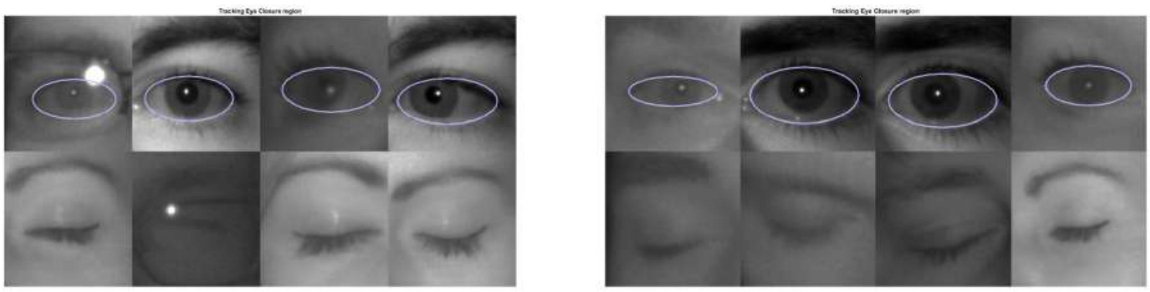

Figure 6: Statistics for Prediction and Test Sets (Eye Blink Dataset).

The histogram in Figure 7 visualizes the distribution of pixel intensity values within an Open and closed-eye image, essentially depicting the brightness levels across the image. It provides information about how the pixel intensities are distributed, revealing the predominant brightness levels and allowing you to assess contrast. For instance, a narrow histogram suggests low contrast, while a wide one implies high contrast.

EAR is a common metric calculated based on the relative positions of facial landmarks around the eyes. Setting a specific EAR threshold can classify eye states as "open" or "closed." For instance, if the EAR falls below a certain value, it can be considered a threshold for detecting closed eyes.

5.4 Performance Metrics Evaluation and Comparison

Figure 8 displays performance metrics by class, including accuracy, precision, recall, and F1 score, which provide a detailed breakdown of the system's effectiveness for each category. Accuracy, represented by the height of the bars, reflects the overall system correctness.

These metrics separate for drowsy and non-drowsy classes, and you gain insights into the model's performance for each class independently. This granularity is essential, particularly in scenarios where the consequences of

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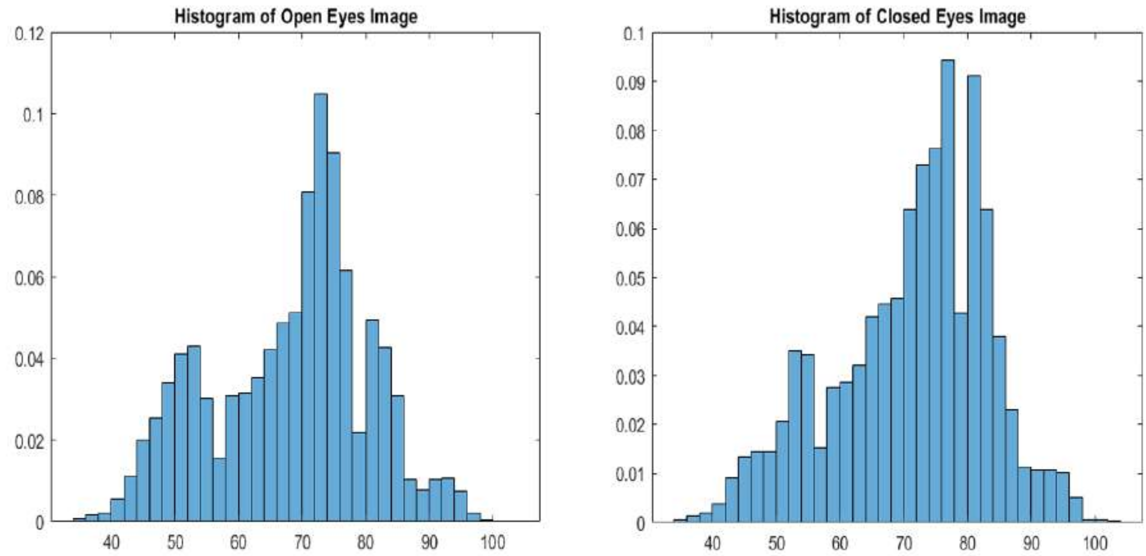

Figure 7: Histogram of Open and Closed Eye Image.

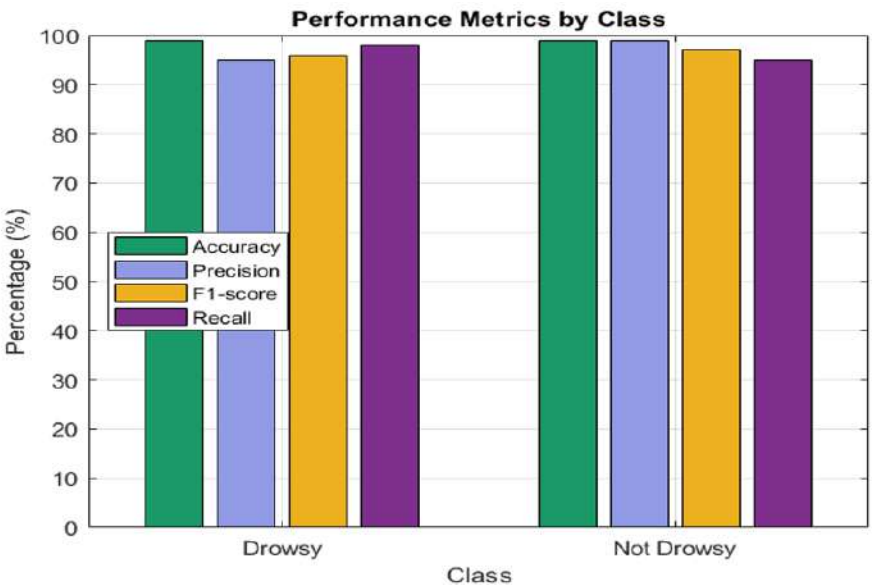

Figure 8: Performance Metrics by Class for Drowsy and Non-Drowsy.

misclassification may vary significantly between classes, such as in driver drowsiness detection, where failing to identify a drowsy driver can lead to accidents, making recall a critical metric.

ROC curve in Figure 9 is a graphical representation used to assess the performance of binary classification models. It depicts the trade-off between sensitivity (the true positive rate) and specificity (1 minus the false positive rate) across various decision thresholds.

In Figure 10, the confusion matrix provided, with 1985 True Positives (correctly identified drowsy drivers), 5 False Negatives (missed drowsy drivers), 15 False Positives (incorrectly labeled non-drowsy drivers as drowsy), and 1995 True Negatives (accurately recognized non-drowsy drivers), serves as a comprehensive evaluation tool for assessing the performance of a classification model, particularly in tasks related to driver drowsiness detection. These values represent the model's ability to distinguish between drowsy and non-drowsy states. With this information, various performance metrics, such as accuracy, precision, recall, and F1

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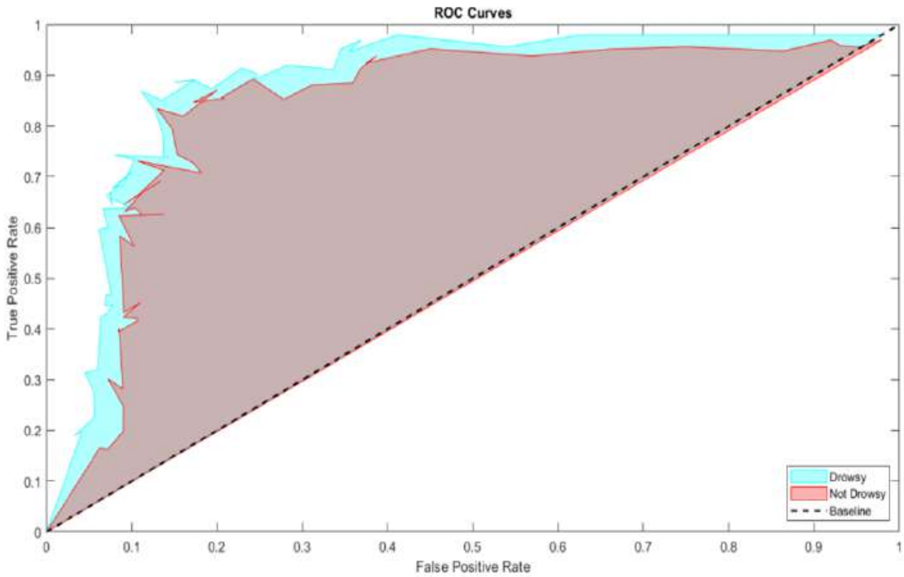

Figure 9: ROC curve.

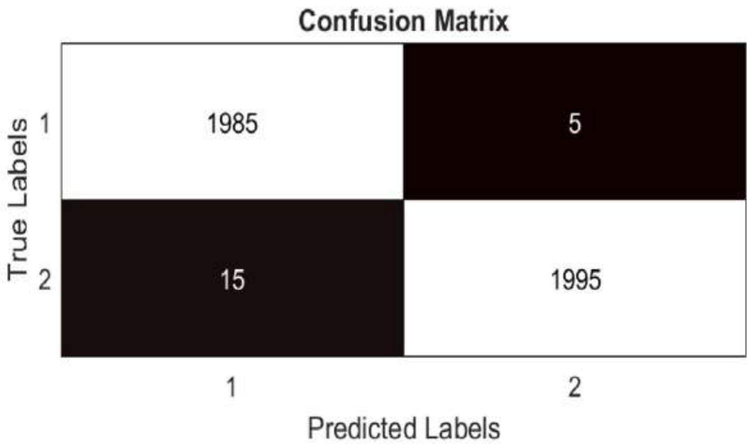

Figure 10: Confusion Matrix.

score, can be computed to provide a more nuanced understanding of the model's effectiveness and potential for real-world applications in road safety.

Table 1: Comparison of Accuracy with Datasets.

Methods	**Accuracy (%)**		
	Talking Face	**Eyeblink8**	**Eye Image 1**
[27]	92.20	79.00	-
[28]	95.00	94.69	-
Proposed CNN-GRU	98.10	98.70	95.00

Table 1 presents the accuracy percentages of different methods in three categories: Talking Face, Eyeblink8, and Eye Image 1.

In Figure 11, the proposed CNN-GRU method demonstrates the highest accuracy across all three categories,

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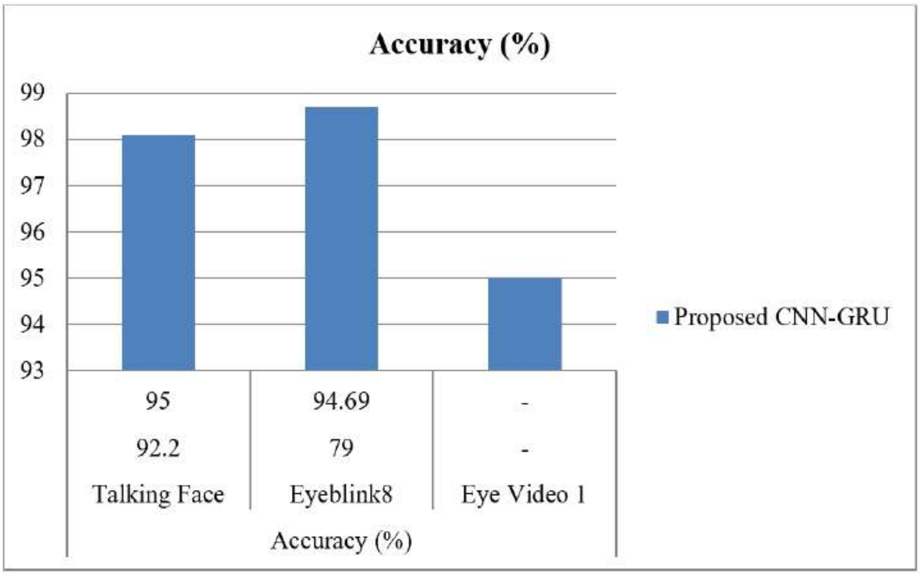

Figure 11: Accuracy Graph.

with 98.10% accuracy for Talking Face, 98.70% for Eyeblink8, and 95.00% for Eye Image 1.

Table 2: Comparison of Proposed Method with Existing Approaches.

Methods	Accuracy	Precision	Recall
SVM	96.72	92.14	97.56
KNN	93.30	93.28	95.2
BPNN	93.10	96.98	97.5
Proposed CNN-GRU (Average)	99.5	98.64	98.93

Table 2 summarizes the performance metrics, including accuracy, precision, and recall, for several methods, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Back Propagation Neural Networks (BPNN), and the proposed CNN-GRU framework. The results indicate that the proposed hybrid CNN-GRU approach outperforms the other methods, achieving an impressive average accuracy of 99.5%, precision of 98.64%, and recall of 98.93%. This underscores the efficacy of incorporating Neutrosophic Logic within the CNN-GRU framework for drowsiness detection, highlighting its potential for improving road safety by accurately identifying driver drowsiness levels in real-time with dynamic spatiotemporal analysis based on eye aspect ratio.

5.5 Discussion

The evaluation results of different driver drowsiness detection methods present a promising outlook for driver monitoring and safety. The comparative analysis reveals substantial progress over the years, with the proposed CNN-GRU method showcasing exceptional performance. With an accuracy of 98.10% for the Talking Face category, 98.70% for Eyeblink8, and 95.00% for Eye Image 1, the CNN-GRU model surpasses prior methods and demonstrates its versatility in handling various data categories. These results highlight the potential of deep learning techniques, particularly the integration of Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs), in effectively capturing intricate patterns associated with driver drowsiness. Such advancements are promising for real-world applications, including in-vehicle drowsiness detection systems and safety enhancement mechanisms. The suggested hybrid CNN-GRU strategy exceeds other approaches by obtaining astounding average accuracy, precision, and recall values of 99.5%, 98.64%, and 98.93%.

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6 Conclusion and Future Work

The results obtained in this project represent a significant advancement in driver drowsiness detection. The remarkable performance figures underscore the potential of deep learning techniques in effectively identifying and responding to driver drowsiness. It's important to acknowledge that real-world implementation and validation are essential in translating these results into practical, life-saving systems. Considering the complexities of driving scenarios, data variability, and robustness requirements, these findings provide a strong foundation for developing more advanced and reliable driver monitoring solutions, ultimately enhancing road safety and driver well-being. The study demonstrates Neutrosophic Logic's capacity to reduce data ambiguity and highlights its effectiveness in the CNN-GRU framework for drowsiness detection. Examples include creating real-time in-car systems with multi-modal sensor integration for improved accuracy, investigating adaptive thresholding methods, using sophisticated machine learning architectures, and incorporating tiredness detection into ADAS. More longitudinal studies, ethical issues, and human factors research should be addressed to guarantee the efficiency, user acceptability, and privacy compliance of these systems. Rigorous validation in real-world scenarios is crucial to assess the robustness of drowsiness detection models across varied driving environments. By pursuing these avenues, future research can create more resilient, user-friendly, and proactive systems that enhance road safety by mitigating the risks associated with driver fatigue.

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