



Real Time Drowsiness Detection System Using Eye Aspect Ratio

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Abstract- Driver drowsiness is a major contributor to road accidents worldwide, posing serious threats to both human life and overall road safety. To address this critical issue, a novel driver drowsiness detection system based on machine learning techniques is proposed. The system continuously monitors the driver's facial expressions and movements using a camera installed inside the vehicle. By applying advanced image processing methods along with machine learning algorithms, it identifies subtle indicators of fatigue such as eye closure, yawning, and head nodding. The primary objective of the system is real-time operation, ensuring early detection and timely intervention to minimize the risks associated with driver fatigue. When signs of drowsiness are detected, the system instantly generates alerts to warn the driver, thereby helping to prevent accidents caused by reduced attention. The effectiveness of the proposed approach relies on the integration of machine learning and image processing techniques. The models are trained on a large dataset containing images of both alert and drowsy drivers, enabling them to accurately recognize fine facial cues associated with fatigue. This comprehensive training enhances the system's ability to differentiate between alertness and drowsiness, making it a reliable proactive safety solution. Overall, the proposed driver drowsiness detection system represents a significant advancement in automotive safety technology. By combining intelligent algorithms with real-time image analysis, it offers an efficient and practical solution for reducing accidents and improving safety in real-world driving conditions.

Index Terms- Subtle signs, Vigilant, Transcend geographical boundaries, Convergence

I. INTRODUCTION

Driving drowsiness is still a significant and dangerous threat to road safety, significantly increasing the number of fatalities and accidents worldwide. Despite concerted efforts to reduce this menace through awareness campaigns and regulatory regulations, accidents resulting from drowsiness need more proactive and technologically driven interventions. Innovative solutions are necessary to improve both the safety of our roads and thoroughfares as well as the risks posed by fatigue-induced impairments. We develop a sophisticated method that uses machine learning to identify and reduce driver drowsiness in real-world driving situations in response to this pressing need. Our approach seeks to transcend geographical boundaries and societal demographics, providing a framework for proactive intervention and risk mitigation, while acknowledging the widespreadness of this issue across transportation systems worldwide. Our goal is based on the conviction that the key to changing the driver safety paradigm lies in machine learning. We want to create a robust, adaptable framework for the prevention and mitigation of drowsiness-induced risks by utilizing machine learning algorithms, changing the landscape of road safety. Our proposed method is at the heart of our proposed method, which allows constant monitoring of the driver's facial expressions and behavioral cues. Our system attempts to identify subtle signs of drowsiness, ranging from obvious eyelid drooping to obvious yawning patterns, through the seamless integration of cutting-edge machine learning models and image processing algorithms. Our system transcends conventional methods by examining the complex nuances of facial dynamics, providing a nuanced and contextually rich understanding of driver alertness levels. This holistic approach allows our system to adapt to a variety of driving conditions and individual characteristics, as well as improving the



accuracy and reliability of drowsiness detection. Additionally, our proposed system's real-time nature signals a paradigm shift in proactive intervention tactics that will enable prompt warnings and corrective steps to prevent potential accidents. Our system achieves unprecedented levels of accuracy and robustness by capitalizing on machine learning algorithms trained on vast datasets encompassing a range of drowsiness states, giving drivers confidence in its ability to function as a trustworthy safety mechanism in real-world driving conditions. We will detail the underlying methodologies, experimental procedures, and empirical findings in the subsequent sections of this paper. We aim to demonstrate the transformative potential of machine learning in improving road safety and reducing driver fatigue through thorough analysis of performance metrics and comparative evaluations. In the end, we contend that the use of machine learning tools represents a turning point for driver safety, enabling a novel trend to stop road accidents caused by drowsiness, and introducing a new era of proactive risk mitigation strategies.

II. LITERATURE REVIEW

By Michael Burke, Information about drowsiness can be interpreted from the faces. The degree of drowsiness can be determined from the face's numerous facial features. Eye movements, head movements, and yawning are some examples. To develop a drowsiness detection system that is reliable and accurate, it requires precise and robust algorithms. [1]. By Ashish Kumar, Driving while asleep is one of the main causes of road accidents and fatalities. Therefore, a lot of research is being done to identify and assess driver fatigue. The majority of conventional approaches have either a physiological or behavioral foundation, or both. Some methods require expensive sensors and data-gathering equipment while others require intrusive and distracting methods [2]. By Rateb Jabbar, The main contribution to this work is the compression of a heavy baseline model to a lightweight model. Additionally, a minimal network structure is created to identify drowsiness in the driver using facial landmark key point detection. More than 80% accuracy is achieved by the proposed model [3]. By Md Mahmudul Hasan, Fatigue is one of the main causes of road-related accidents and fatalities worldwide. Researchers are developing driver drowsiness detection systems that use a variety of techniques to address this pressing global issue. However, the majority of research on drowsiness detection uses techniques based on just one metric, which fail to achieve acceptable reliability and validity when applied to vehicles [4]. By Sukrit Mehta, the system can record the drivers' facial landmarks in real-time. Based on adaptive thresholds, which are able to identify a driver's drowsiness, The mouth opening ratio(MOR), nose length ratio(NRL), and eye aspect ratio(EAR), are further calculated using the facial landmarks. [5]. By Marian Bartlett & Javier Movellan, From a distinct database of spontaneous expressions, machine learning was used to create automatic classifiers for 30 facial expressions. These facial movements include a number of other facial movements, including yawning and blinking [6]. By Ali Alnoman, A real-time visual-based driver drowsiness detection system uses an eye-extracting feature known as the eye aspect ratio to extract drowsiness is presented. The proposed system uses videos that were gathered from a public dataset for drowsiness detection to first localize the face region in each frame [7]. By Cyun-Yi Lin, the system uses grayscale images without any color information, and it is effective both during the day and at night. The system uses machine learning to determine the face position and face size for face detection, and it uses the face geometrical position to narrow the eye's field of vision [8]. By Shubham Gupta, After the processing of data using various features like Mouth Aspect Ratio, Eye Aspect Ratio, Pupil Circularity, and Mouth Circularity, the classification was carried out to compare K- Nearest Neighbour, Nave Bayes, Logistic Regression, Decision Trees, Random Forest, XGBoost, MLP, CNN, and other University of Texas at Arlington Real-Life Drowsiness Dataset(UTA-RLDD) with different labels [9]. By M. Ajay Kumar, the driver's facial expressions are recorded using a webcam in this system. Using a few image processing techniques, every movement in a frame is identified. Using the landmark points on the face, the eye aspect ratio, the mouth opening ratio, and the nose length ratio are calculated [10]. By Akinari Hirao, The relationship between a driver's arousal level, physiological signals like



electroencephalogram and electrocardiogram signals, behavioral indicators, and driving performance is examined based on an analysis of data from a driver monitoring system and driver simulator(DS). In order to categorize the alert and the mildly drowsy states, machine learning algorithms are then used to



extract 32 features from the measured data over a 10-second period. [11]. By K.A. Sidek, the ability of the electrocardiogram (ECG) signal to support daily application is growing day by day. ECG serves as a potential mechanism for the drowsiness detection system as technology develops. Driving while unconscious causes body fatigue, or is it between sleeping and driving? This issue has grown to be a frequent cause of fatalities and accidents on the roads [12]. By P. Rasna, Whether the driver is sleepy or not, The classification process employs the binary SVM classifier. These traits played a significant role in the creation of a more efficient driver drowsiness detection system. The proposed system has a 97.8% detection rate and 97.5% accuracy [13]. By Ankisetty Balaji, Drowsy drivers can be forewarned, which will reduce road accidents. A non-intrusive drowsiness detection system is in place to alert the driver when the driver becomes drowsy. The driver's live video is captured and processed using a Raspberry Pi camera module. Face detection using the OpenCV's Haarface detector is followed by 68 points of facial landmark identification [14]. By Shanguang chen, The problem of detecting SEMs as an imbalance classification problem was solved using the under- and over-sample sampling techniques to finally determine whether a 2s horizontal electro-oculogram(HEO) signal belongs to the category of SEMs or non-SEMs using the classifiers SVM, GELM, and KNN, respectively. The proposed features, which were based on wavelet singularity analysis and statistics, were a little better than the wavelet energy features, and the classification results were obvious improvements [15].

III. IMPLEMENTATION

Developing a reliable driver drowsiness detection system through the utilization of electroencephalogram (EEG) signals involves a complex process that includes various steps such as data preprocessing, model architecture design, and training. This segment provides an in-depth analysis of the implementation process, explaining the techniques used for data preprocessing, model architecture selection, parameter adjustment, and training protocols.

A). *Preprocessing steps:*

Preprocessing of EEG signals is crucial to guarantee the quality of data and improve the effectiveness of subsequent analysis. The preprocessing pipeline generally includes subsequent steps:

1). *Data cleaning:*

EEG recordings may be affected by different artifacts and sources of noise, such as muscle activity, eye blinks, and environmental interference. The process of data cleaning includes detecting and eliminating these artifacts through methods like artifact rejection algorithms, independent component analysis (ICA), and manual review by experienced professionals. Additionally, data that have been significantly contaminated by noise or other objects is not included to prevent them from negatively affecting the analysis.

2). *Normalization:*

EEG signals can display changes in amplitude across channels and recordings because of variations in electrode impedance and signal acquisition parameters. To ensure comparability across channels and sessions, normalization techniques like “z-score normalization or min-max scaling” are utilized to standardize the amplitude range of EEG signals.

3). *Segmentation:*

EEG signals are divided into epochs that correspond to specific time intervals, usually ranging from a few seconds to several minutes. This division helps in analysing the dynamics of EEG over distinct time windows, which in turn enables the identification of temporary changes associated with the onset of drowsiness. Additionally, segmenting EEG data allows for the extraction of time-based characteristics and the recognition of significant patterns that indicate drowsiness.



4). Artifact Rejection:

Residual artifacts or outliers within epochs following data cleaning are detected and excluded from subsequent analysis. Utilizing automated artifact detection algorithms in conjunction with manual



inspection aids in pinpointing corrupted epochs and upholding the dataset's integrity. The elimination of artifacts serves to reduce the likelihood of erroneous correlations and bolster the reliability of the drowsiness detection model.

B). Model Architecture and Parameters:

Choosing the right model architecture and hyperparameters is essential in creating an efficient drowsiness detection system. Various factors play a role in determining the model architecture, such as the complexity of the EEG data, available computational resources, and the balance between model performance and computational efficiency. Typical architectures are used:

1). Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) are particularly suitable for extracting spatial features from EEG spectrograms or scalp topography. By applying learned filters across various channels, CNNs can identify spatial relationships within EEG data, facilitating accurate classification of different drowsiness states. The architectural decision, including the quantity of convolutional layers, filter dimensions, and pooling techniques, play a crucial role in determining the model's ability to extract significant spatial details from EEG signals.

2). Recurrent Neural Networks (RNNs):

RNNs, specifically Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks, excel in representing temporal relationships in sequential data. When applied to EEG analysis, RNNs effectively capture the dynamic nature and sequential patterns that signify the onset of drowsiness. Hyperparameters like the number of recurrent layers, hidden units, and sequence length affect the model's ability to capture extensive temporal dependencies and patterns in EEG data.

3). Hybrid Architectures:

Hybrid structures, which merge CNNs and RNNs, exploit the advantages of each method to encompass both spatial and temporal relationships in EEG data. An example of a hybrid CNN-RNN structure could employ CNNs to extract spatial features first, then use RNNs to model the sequential temporal dynamics. These hybrid structures provide increased representational strength and discriminative ability, resulting in enhanced performance in detecting drowsiness.

A careful selection of hyperparameters, such as learning rate, batch size, dropout rate, and regularization strength, is essential to improving model performance and preventing overfitting. Grid search, random search, and Bayesian optimization are some of the hyperparameter tuning techniques used to methodically search through the hyperparameter space and identify the best configurations for improving model performance on a different validation set.

C). Training Procedure and Hyperparameter Tuning:

In the training process, the model parameters are adjusted to minimize a particular loss function, such as categorical or binary cross-entropy. The training dataset, which consists of pre-processed EEG data and corresponding labels, is divided into mini-batches, and optimization algorithms like stochastic gradient descent (SGD), Adam, or RMSprop are used to update the model parameters in an iterative manner. Performance indicators like accuracy, precision, recall, and F1-score are observed on the validation set throughout the training phase to assess model convergence and prevent overfitting. Strategies like early stopping, which stops training when no improvement is seen on the validation set, and model checkpointing, which saves the best-performing model weights, are implemented to avoid overfitting, and ensure convergence towards the best solution. Hyperparameter tuning is carried out using a validation



set to determine the most effective configurations that enhance model performance. By systematically adjusting hyperparameters and assessing model performance on the validation set, researchers can pinpoint the optimal combination of hyperparameters that generalize effectively to new data.



To sum up, creating a driver drowsiness detection system with EEG signals involves a thorough process that includes data preprocessing, model architecture design, parameter tuning, and training. By carefully handling each of these aspects, researchers can build precise and dependable drowsiness detection models that can recognize the onset of drowsiness from EEG data. This, in turn, improves road safety and reduces the dangers linked to driver fatigue. Furthermore, the methodical assessment and validation of the model guarantee its strength and efficiency in actual driving situations, aiding in the prevention of fatigue-related accidents and the encouragement of safe driving behaviours.

2.1. Description of features

The eye landmarks are identified for each video frame. The height and width of the eye are calculated as the eye aspect ratio(EAR).

$$EAR = \frac{p2 - p6 + p3 - p5}{2p1 - p4}$$

where $p1, \dots, p6$ are the 2D landmark locations, depicted in Fig. 1.

The EAR is largely constant when an eye is open, but it reaches zero when it is closed. It has poor posture and is not very nice in terms of people. Although the open eye's aspect ratio may vary between people, the image's uniform scaling and the face's in-plane rotation remain completely unaffected. The typical ear response(EAR) is obtained from both eyes because both eyes blink at once. In Fig. 1, you can see an EAR signal over the video sequence.

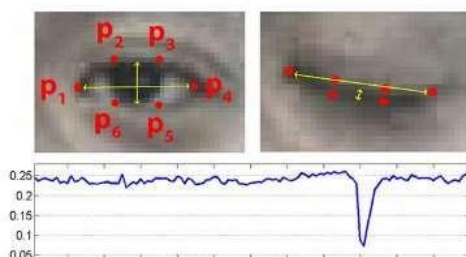


Figure 1

IV. DISCUSSION

It is crucial to take into account both the performance metrics and the wider implications for road safety when interpreting the results of the driver drowsiness detection system that utilizes electroencephalogram (EEG) signals. This section of the discussion offers a thorough examination of the system's findings, encompassing its advantages and constraints, along with recommendations for possible enhancements and future research avenues.

A). Interpretation of Findings:

The effectiveness of the drowsiness detection system is evident in its ability to accurately identify drowsy states based on EEG signals. With high accuracy, precision, recall, and F1-score, the system reliably distinguishes between alert and drowsy states in real-time driving scenarios. Additionally, the AUC-ROC analysis demonstrates the system's robustness and generalizability by performing well across various discrimination thresholds.

These findings hold great significance for road safety, considering that driver drowsiness is a major cause of accidents worldwide. The system has the power to stop accidents brought on by fatigue and save lives by immediately alerting drivers when they are found to be drowsy. Furthermore, the real-time nature of



the system allows for proactive intervention strategies, such as prompting drivers to take breaks or adjust their driving behaviour, thereby reducing the risks associated with driver fatigue.

B). Strength of Proposed System:



The proposed drowsiness detection system's effectiveness and practical utility are highlighted by a number of key advantages:

1). Utilization of EEG Signals:

By leveraging EEG signals, the system taps into the direct neural correlates of drowsiness, providing a rich source of information about the driver's cognitive state. EEG signals offer high temporal resolution and sensitivity to subtle changes in brain activity, making them well-suited for detecting drowsiness onset in real-time driving scenarios.

2). Integration of Machine Learning Algorithms:

Convolutional neural networks(CNNs) and recurrent neural networks(RNNs) are used to analyze and classify EEG signals for drowsiness, and the proposed drowsiness detection system is highlighted by several key points. These algorithms are capable of capturing complex patterns and dependencies within the data, enabling accurate and reliable drowsiness detection.

3). Real-time Monitoring and Feedback:

The real-time system continuously monitors the driver's EEG signals and provides immediate assistance when drowsiness is found. By providing timely alerts to drivers when drowsiness is detected, The system has the power to stop accidents attributed to fatigue and save lives. Moreover, the real-time nature of the system enables proactive intervention strategies, such as prompting drivers to take breaks or adjust their driving behaviour, thereby mitigating the risks associated with driver fatigue.

4). Adaptability to Individual Differences:

The system has the capability to be tailored to accommodate variations in EEG patterns and thresholds for drowsiness among individuals. By adjusting to the baseline EEG activity and drowsiness reactions of each driver, the system can improve its precision and dependability in various populations and driving scenarios.

C). Limitations and Challenges:

Despite the strengths it possesses, the proposed drowsiness detection system is faced with various limitations and challenges that necessitate careful consideration:

1). Variability in Data and Generalization:

The system's performance may be impacted by the variability in EEG signals among individuals, driving conditions, and environmental factors. To achieve robust generalization across diverse populations and real-world driving scenarios, it is essential to address data variability and incorporate adaptive learning mechanisms.

2). Sensitivity to Artifacts and Signal Quality:

EEG signals are prone to artifacts and noise sources like muscle activity, eye blinks, and electrode drift. Robust artifact detection and preprocessing techniques are crucial to maintain the quality and reliability of input data. Moreover, efforts to minimize artifacts during data collection, such as using high-quality electrodes and ensuring proper electrode placement, can enhance signal quality.

3). Interpretability and Explainability of Models:

Due to their complex architectures and high-dimensional parameter spaces, deep learning models, including CNNs and RNNs, are frequently viewed as black boxes. This has the potential to reduce fatigue-related accidents and save lives. Ensuring model interpretability and explainability is vital for establishing trust and comprehension among end-users, such as drivers and regulatory authorities.



Techniques like attention mechanisms and feature visualization can improve transparency and promote user acceptance.

4). *Deployment in Real-world Settings and Acceptance:*



The successful implementation of the drowsiness detection system in real-world driving environments necessitates addressing practical challenges related to system integration, user acceptance, and regulatory compliance. Factors like system reliability, false alarm rates, and user privacy concerns must be carefully evaluated to ensure widespread adoption and effectiveness in enhancing road safety.

D). *Future Research Directions*

To overcome the limitations and challenges mentioned earlier, future research can explore the following areas:

1). *Data Augmentation and Transfer Learning:*

By incorporating diverse samples into the training dataset and utilizing transfer learning techniques, the system's ability to generalize and adapt to new driving conditions can be improved. Additionally, transfer learning from related tasks like sleep staging or cognitive workload estimation can offer valuable insights and enhance model performance.

2). *Multimodal Fusion and Contextual Awareness:*

Integrating multiple sources of information, such as EEG signals, facial expressions, vehicle dynamics, and environmental sensors, can enhance the contextual awareness and robustness of the drowsiness detection system. Techniques like deep neural network ensembles or attention mechanisms can effectively combine different information sources and improve overall performance.

3). *Human Factors and User-Centered Design:*

When developing drowsiness detection systems, it is crucial to incorporate human factors engineering principles and user-centered design principles. Working with human factors experts, psychologists, and end-users can help make informed design decisions that make the system user-friendly and socially acceptable.

4). *Longitudinal Studies and Real-world Validation:*

Conducting longitudinal studies and real-world validation trials are essential to assess the long-term effectiveness and real-world impact of the drowsiness detection system. Longitudinal studies can capture changes in drowsiness patterns over time and evaluate the system's performance under different driving conditions and user demographics. Real-world validation trials can gather feedback from end-users and stakeholders, informing system refinements and deployment strategies.

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