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REAL-TIME DRIVER DROWSINESS DETECTION USING CNN-GRU MODEL WITH FACIAL FEATURES AND BEHAVIOURAL ANALYSIS

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***Abstract*—Drowsiness during driving is a significant contributor to road accidents, especially during prolonged travel or under low visibility conditions. To address this, the proposed study presents a real-time drowsiness detection system based on a deep learning hybrid model combining Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU). The model analyzes behavioral features such as eye aspect ratio (EAR), mouth aspect ratio (MAR), and head pose, extracted using facial landmark detection through MediaPipe. To ensure robustness in variable lighting conditions, Retinex theory is applied for image preprocessing, enhancing contrast and correcting illumination inconsistencies. This improves the reliability of visual feature extraction. The CNN component is responsible for learning spatial features from facial images, while the GRU captures temporal patterns across video frames. This allows the system to detect signs of fatigue such as prolonged eye closure, yawning, and head nodding over time. The hybrid design leverages both spatial and temporal cues for more accurate classification. The model is trained and evaluated on a labeled dataset and demonstrates strong performance across precision, recall, and accuracy metrics. By integrating temporal modeling and illumination correction, the system adapts effectively to real-world environments. This contributes to early and accurate detection of driver fatigue. Ultimately, the approach enhances road safety by providing timely alerts and reducing accident risk**

***Index Terms*—CNN, GRU, BLIP, Retinex Theory, OpenCV, Facial Landmark Extraction, ADHE, MediaPipe**

I. INTRODUCTION

Driver drowsiness is one of the major contributors to road accidents worldwide, particularly during long-distance travel and night-time driving [1], [13]. Fatigue reduces alertness, slows reaction time, and impairs decision-making, leading to a high risk of lane departure and collision [13]. Therefore, developing an accurate and real-time driver drowsiness detection system has become an important research focus in intelligent transportation and advanced driver assistance systems (ADAS) [6], [11]. Advances in computer vision and deep learning have enabled non-intrusive monitoring of driver behavior using facial cues [3], [7]. Indicators such as frequent eye closure, prolonged blinking, yawning, and head nodding are widely recognized as strong symptoms of drowsiness [6], [11]. However, practical deployment of such systems remains challenging due to variations in lighting conditions, facial pose changes, and the need for low-latency processing in real-time environments [3], [7]. To address these issues, the system proposes a robust driver drowsiness detection framework that combines facial landmark-based feature extraction with deep learning classification. MediaPipe is employed for fast and reliable facial landmark detection, allowing efficient computation of critical parameters such as the Eye Aspect Ratio (EAR) for eye closure, Mouth Aspect Ratio (MAR) for yawning detection, and head pose estimation for nodding or tilting behavior [6], [11]. These temporal facial features are then processed using a hybrid deep learning model integrating Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU), enabling effective learning of both spatial and time-dependent patterns associated with fatigue [7], [9]. To improve system reliability in low-light environments, Retinex-based image enhancement is incorporated to increase visibility and maintain detection performance. The proposed approach aims to provide accurate and real-time drowsiness detection, contributing to accident prevention and improved road safety [1], [13].

II. NEED OF THE STUDY

Driver drowsiness is a major factor in road accidents and is responsible for a significant percentage of fatal crashes worldwide. Drowsiness reduces driver alertness, impairs judgement, and increases reaction time, which can lead to dangerous driving behaviour and accidents.

Existing drowsiness detection methods have several limitations. Self-reporting approaches are unreliable, while physiological sensor-based methods (EEG, ECG, EOG) are intrusive and expensive. Vehicle-based measures are often inaccurate because they depend heavily on driving conditions and the environment. In addition, vision-based monitoring systems can be affected by poor lighting, occlusions, and other external factors, reducing detection reliability.

III. LITERATURE REVIEW

Driver drowsiness detection has gained significant research attention due to its strong correlation with road accidents and fatalities. With the increasing demand for intelligent transportation systems and advanced driver assistance systems (ADAS), detecting fatigue-related impairment in real time has become an important safety requirement. Over the years, researchers have proposed various approaches to identify drowsiness by analyzing physiological signals, vehicle dynamics, and driver facial/behavioral cues.

A. Real-Time Driver Drowsiness Detection using Hybrid CNN-LSTM Model with Facial Feature and Behavioral Analysis

The existing driver drowsiness detection system continuously captures video of the driver using a camera installed inside the vehicle and processes the video frame by frame. The system detects the driver's face and extracts facial landmarks such as the eyes, mouth, and head position using MediaPipe FaceMesh. From these landmarks, important behavioural features like Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) are calculated to detect eye closure and yawning, while head pose estimation identifies head tilting or nodding. These extracted features are then provided to a hybrid CNN-LSTM deep learning model, where CNN analyzes spatial features like facial structure and expressions, and LSTM analyzes temporal patterns across frames to detect continuous eye closure, repeated yawning, and gradual head movements. Based on this combined analysis, the system classifies the driver as drowsy or non-drowsy and performs real-time monitoring throughout the journey [1], [3], [11], [12].

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B. An Improved Driver Drowsiness Detection using Haar Cascade Classifier

Several early studies on driver drowsiness detection employed classical computer vision techniques due to their low computational requirements and ease of implementation [1], [12]. One commonly used approach is based on the Haar Cascade classifier, which detects facial regions such as eyes from real-time video frames [1]. In this method, the system first performs eye detection using Haar-like features and cascade-based classification, and then determines driver drowsiness by monitoring eye closure duration. The decision logic is generally threshold-based, where eye closure over consecutive frames is treated as an indicator of fatigue [11]. If the eyes remain closed beyond a predefined time threshold, the driver is classified as drowsy. Such systems report moderate performance, achieving approximately 80% accuracy in eye detection and around 78% accuracy in drowsiness recognition [4]. However, Haar Cascade based techniques have notable limitations, including reduced robustness under varying illumination conditions such as low light, glare, and sudden brightness changes [12]. In addition, the absence of deep learning-based feature extraction limits the system's ability to generalize across different drivers and complex real-world scenarios, resulting in comparatively lower accuracy.

C. Real-Time Driver Drowsiness Detection using YOLOv5

Recent research has increasingly adopted deep learning-based object detection frameworks for real-time driver monitoring due to their high detection speed and strong feature extraction capability [3], [6]. A notable approach uses YOLOv5 to identify and localize the driver's face and key facial regions such as the eyes and mouth in each video frame [3]. The detected regions are further analyzed to classify eye state (open/closed) and mouth activity (yawning), which are commonly used indicators of driver fatigue [6]. The key advantage of YOLOv5-based systems lies in their ability to perform fast frame-by-frame processing, making them suitable for real-time applications where timely alerts can be issued to the driver upon detecting signs of drowsiness [7]. However, such methods primarily rely on instantaneous frame-level detection and often lack temporal analysis, which is essential for modeling fatigue patterns over time. In addition, the absence of low-light enhancement techniques can reduce performance under night driving or poor illumination conditions [11]. Furthermore, these systems may not incorporate behavioral metrics and memory-based prediction models, limiting their ability to robustly distinguish between short-term facial actions and sustained drowsiness behavior.

IV. METHODOLOGY

The proposed system detects driver drowsiness in real time using a hybrid CNN–GRU deep learning model [7], [9]. Facial images captured from a front-facing camera are preprocessed using Retinex-based enhancement to correct lighting variations and improve landmark visibility. The CNN extracts spatial features such as eye closure, yawning, and head tilts, while the GRU models temporal patterns across consecutive frames to detect gradual fatigue [7]. Behavioral features like Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head pose are analyzed sequentially to classify the driver as alert, slightly drowsy, or drowsy [6], [11]. Upon detecting fatigue, the Alert Generation module provides immediate feedback through audible alarms or visual warnings. All results are logged for analysis, and the modular design ensures reliable, real-world operation across different vehicles and lighting conditions, enabling accurate and timely detection of driver fatigue [6], [9].

V. PROPOSED SYSTEM

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The proposed Driver Drowsiness Detection System is designed to monitor the driver's behavior in real time and identify early signs of fatigue or drowsiness. The system integrates computer vision techniques and deep learning models to analyze facial features and behavioral patterns associated with driver fatigue. It utilizes image enhancement, facial landmark detection, and behavioral feature extraction to obtain relevant information from the driver's facial expressions. A hybrid CNN–GRU architecture is employed to capture both spatial and temporal patterns in the driver's behavior, enabling accurate detection of drowsiness-related actions such as eye closure and yawning. Additionally, the BLIP model is incorporated to generate semantic descriptions of the driver's visual behavior, enhancing the system's ability to identify abnormal patterns. The overall system operates in two main stages: the training phase, where the model learns from labeled datasets, and the testing phase, where the trained model performs real-time monitoring and alert generation.

A. Image Acquisition and Preprocessing

The Image Acquisition module captures real-time video from a front-facing camera positioned to monitor the driver's face. The camera is designed to operate under various environmental conditions, including daylight and night driving. Captured frames are forwarded to the preprocessing module for enhancement and normalization. In the Image Preprocessing stage, Retinex-based image enhancement is applied to address challenges such as uneven lighting, shadows, and glare. Retinex theory enhances image contrast and clarity, mimicking human visual perception to improve visibility of facial features. This ensures that facial landmarks can be accurately detected even in challenging conditions like nighttime driving or tunnels. Additionally, preprocessing reduces noise and corrects color inconsistencies, providing cleaner inputs for the CNN-GRU model. It also standardizes frame dimensions and intensity values, improving model stability and inference speed. These enhancements collectively increase the reliability and accuracy of drowsiness detection across diverse driving environments.

B. Facial Landmark Detection

The Facial Landmark Detection module uses MediaPipe Face Mesh, a lightweight and efficient framework, to locate critical points on the driver's face, including the eyes, mouth, and head. From these landmarks, the system calculates behavioral indicators such as:

- Eye Aspect Ratio (EAR): Measures the ratio of eye height to width to determine eye closure. A consistently low EAR signals prolonged closure, indicating fatigue.
- Mouth Aspect Ratio (MAR): Measures mouth opening to detect yawning.
- Head Pose Estimation: Evaluates head orientation and tilt to detect nodding or downward movements associated with drowsiness.

C. Feature Extraction and CNN-GRU Analysis

The CNN-GRU hybrid model is the core analytical component of the system. The CNN extracts spatial features from enhanced facial images, detecting subtle visual cues such as eye closure, yawning, and head tilts. Multiple convolutional and pooling layers allow the network to learn hierarchical representations of these features. Extracted spatial features are passed to the GRU, which captures temporal dependencies across consecutive frames. The GRU models patterns of eye movement, yawning, and head motion over time, allowing the system to identify gradual transitions from alertness to fatigue. By combining spatial and temporal learning, the CNN-GRU model ensures reliable detection even in dynamic driving environments. This hybrid approach enables the system to differentiate between normal facial movements and fatigue-related behavior, reducing false positives. It also allows real-time analysis without significant computational delay, making it suitable for in-vehicle deployment. Additionally, the model continuously adapts to the driver's unique behavioral patterns, improving detection accuracy over prolonged usage.

D. BLIP

BLIP (Bootstrapping Language–Image Pre-training) is a vision–language model that jointly learns from images and text to understand visual scenes at a semantic level. It can generate natural language descriptions from images (image captioning) and answer questions based on visual content (visual question answering). In this driver drowsiness detection project, BLIP can be incorporated as an auxiliary module to provide high-level interpretation of driver facial states such as eye closure, yawning, or head drooping. This semantic output can support automatic annotation of training data, improve explainability by generating human-readable descriptions of detected fatigue cues, and assist in validation by comparing model predictions with text-based visual interpretations. Although the primary drowsiness classification is performed using landmark-based features (EAR, MAR, and head pose) and deep learning models such as CNN–GRU, BLIP enhances the system by enabling interpretable, text-based reasoning and facilitating dataset preparation for robust model training.

E. System Alert

The System Alert component is responsible for providing an immediate warning to the driver when the proposed model classifies the state as drowsy. Once fatigue indicators such as prolonged eye closure (low EAR), frequent yawning (high MAR), or abnormal head pose patterns are detected, the system triggers an alert to prevent accidents caused by delayed driver reaction. The alert mechanism can be implemented as an audible alarm (buzzer), ensuring that the driver is instantly notified and encouraged to regain attention.

VI. PROPOSED SYSTEM DESIGN

The proposed system is designed to detect driver drowsiness in real time using facial feature analysis and a hybrid deep learning model. The system integrates computer vision techniques with a CNN–GRU based architecture to analyze spatial and temporal behavioral patterns of the driver. Facial features such as eye movement, mouth opening, head pose, and blink rate are extracted from live video input and processed to classify the driver's alertness state. The system operates continuously and generates timely alerts when signs of drowsiness are detected, thereby enhancing road safety.

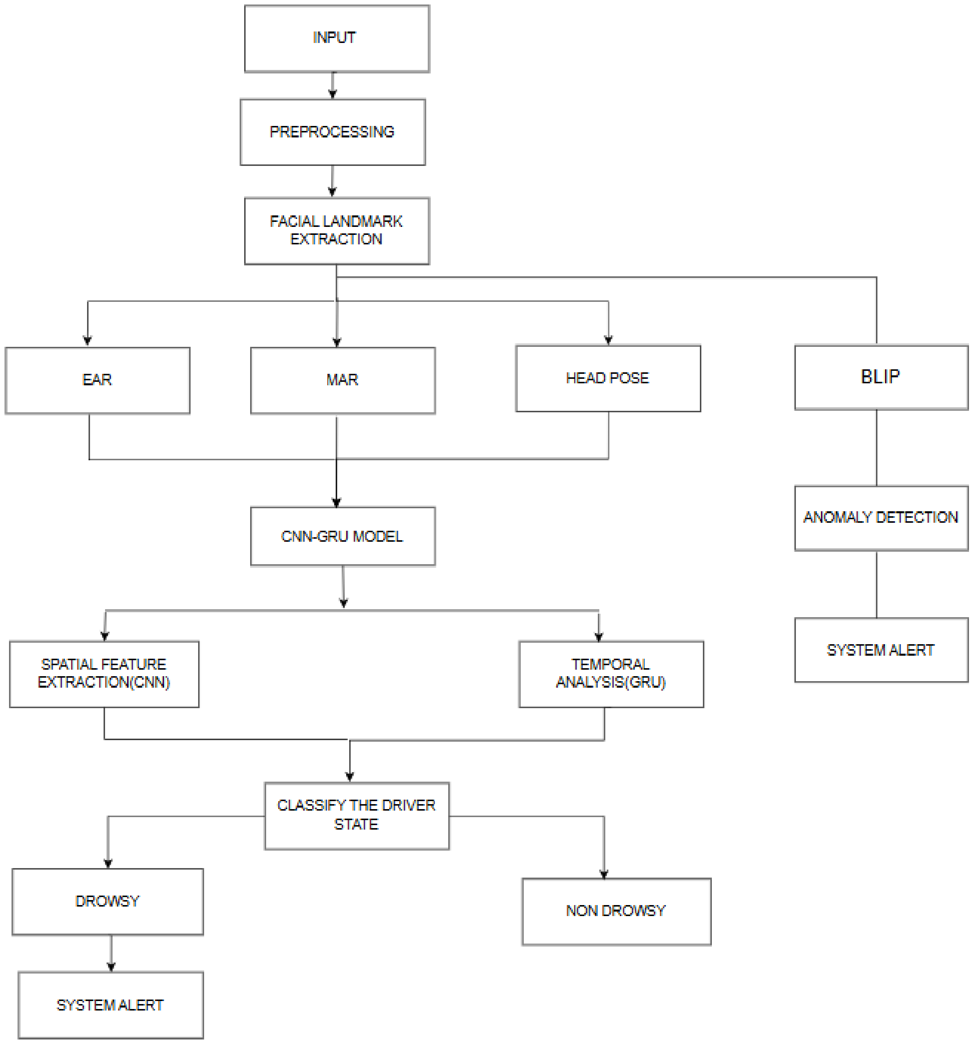

Figure 1.Architecture Diagram

E. Training Phase

- Dataset: A labeled dataset consisting of facial images and video sequences representing drowsy and non-drowsy driver states is prepared.
- Augmentation: Data augmentation techniques such as horizontal flipping, scaling, rotation, and brightness adjustment are applied to improve model robustness and generalization.
- Data Splitting: The dataset is divided into training and testing sets to evaluate model performance.
- CNN–GRU Architecture: An architecture diagram visually represents the structure and interactions of components within the driver drowsiness detection system, providing a high-level overview of how the system functions. It illustrates the flow of data from video input through preprocessing, facial landmark extraction, feature computation, and deep learning-based classification. The diagram also shows how spatial and temporal features are combined to determine the driver's state.

The Figure 1, Architecture Diagram, illustrates the complete driver drowsiness detection system integrating computer vision modules with a CNN–GRU deep learning model.

a) CNN (Spatial Feature Extraction): The CNN extracts spatial features from facial regions such as eyes, mouth, and head orientation. These features capture visual patterns related to eye closure, yawning, and head movement.

b) GRU (Temporal Analysis): The GRU analyzes sequences of extracted features over time to capture temporal dependencies such as prolonged eye closure, repeated yawning, and continuous head nodding.

c) Classification Layer: The final layer classifies the driver's state as Drowsy or Non-Drowsy based on learned spatial and temporal features.

F. Testing Phase

- Input: Real-time video frames captured using an in-vehicle camera serve as the input during system operation.
- Image Preprocessing: Each frame is resized, normalized, and enhanced using Retinex-based image preprocessing to improve visibility under poor lighting conditions.

- Facial Landmark Extraction: Facial landmarks are extracted using MediaPipe Face Mesh to identify key regions such as eyes, mouth, and head position.
- Feature Extraction: Behavioral features such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Head Pose, and Blink Rate are computed from the extracted landmarks.
- CNN–GRU Model: The trained CNN–GRU model processes the extracted features and predicts the driver's alertness level.
- BLIP: Bootstrapping Language–Image Pre-training is a vision–language model used to analyze images and generate semantic descriptions, helping identify unusual or anomalous behaviors in visual data.
- Classification: The driver's condition is classified as Drowsy or Non-Drowsy, along with a confidence score for each prediction.

G. System Alert Architecture

Feature Monitoring Module

- Continuously monitors EAR, MAR, head pose, and blink frequency.
- Detects abnormal behavioral patterns associated with driver fatigue.

Anomaly Detection

- Identifies prolonged eye closure, frequent yawning, or repeated head nodding.
- Differentiates normal behavior from fatigue-induced patterns.

Alert Generation System

- Audio Alert: Generates a buzzer or warning sound when drowsiness is detected.
- Visual Alert: Displays warning messages on the dashboard or screen.
- System Logging: Records drowsiness events for further analysis.

When the driver is classified as drowsy, the alert system is activated immediately to regain driver attention. If the driver is classified as non-drowsy, the system continues monitoring without interruption.

VII. RESULT

The Real-Time Driver Drowsiness Detection System monitors the driver's facial features and behavior to identify signs of fatigue such as prolonged eye closure, yawning, and sleeping. The system analyzes these indicators in real time and immediately triggers an alert sound when drowsiness is detected, while also sending a notification message to a registered companion to ensure external awareness. Retinex-based image enhancement improves performance under low-light and uneven illumination conditions by enhancing facial feature visibility, enabling reliable computation of Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head pose estimation. The integration of BLIP (Bootstrapping Language–Image Pre-training) provides semantic interpretation of the driver's visual state by generating descriptive captions for detected behaviors, which improves the detection of abnormal actions and enhances system reliability. Experimental results show that the eye-closure detection module achieved 100% accuracy, the BLIP-based behavior interpretation module achieved 97% accuracy, and the overall system reached an accuracy of 98.25%, demonstrating its effectiveness in detecting and describing driver fatigue.

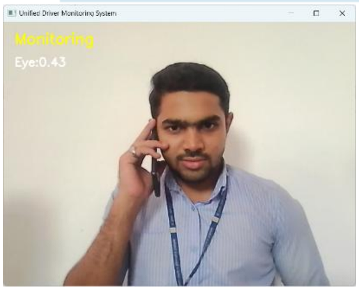

Figure 2. Monitoring

Figure 2 shows the real-time monitoring stage of the proposed driver drowsiness detection system. In this stage, the camera continuously captures the driver's facial images and tracks important facial landmarks such as the eyes, mouth, and head position.

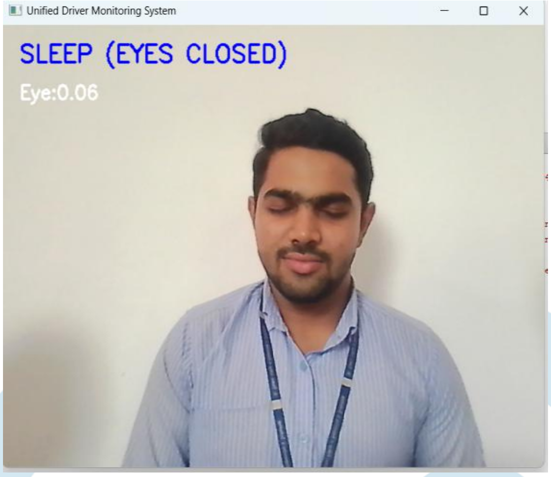

Figure 3. Sleeping Detection

Figure 3 illustrates the system detecting a sleeping or drowsy state based on prolonged eye closure. The facial landmark detection module continuously monitors the driver’s eye region and calculates the eye closure duration. When the eyes remain closed beyond a predefined threshold, the system classifies the driver’s condition as sleeping. Once detected, the system triggers an alert mechanism to warn the driver and prevent potential accidents caused by fatigue.

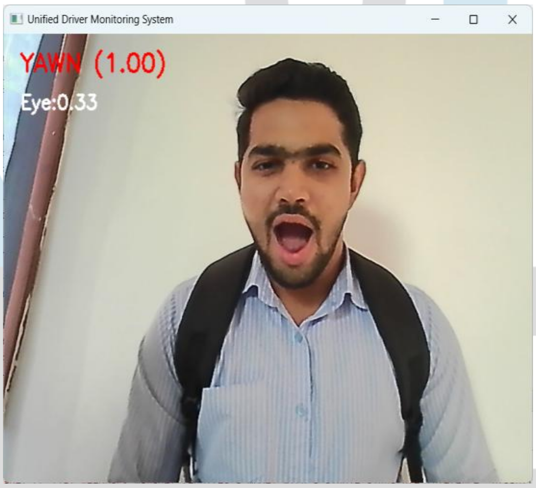

Figure 4. Yawning Detection

Figure 4 shows the detection of yawning behavior, which is another key indicator of driver fatigue. The system tracks the mouth region using facial landmark detection and analyzes the degree of mouth opening over consecutive frames. When a wide and sustained mouth opening pattern characteristic of yawning is identified, the system classifies it as a fatiguerelated behavior. This detection helps the system identify early signs of drowsiness and initiate appropriate alerts.

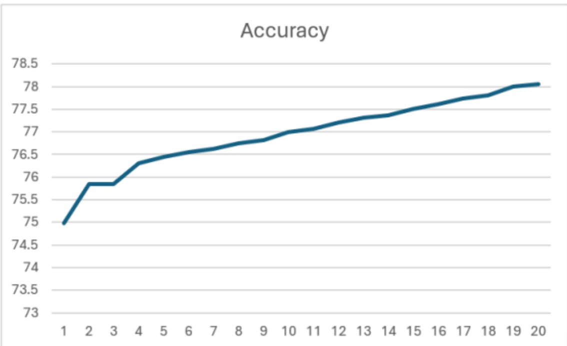

Figure 5. GRU Training:Epoch-Accuracy

In Figure 5 horizontal axis represents the number of training epochs, while the vertical axis indicates the classification accuracy achieved by the model. At the initial stage of training, the accuracy is relatively low because the model parameters are randomly initialized and the network has not yet learned meaningful patterns from the input data. As training progresses over multiple epochs, the model gradually learns significant visual and temporal features associated with driver drowsiness, including eye closure, blinking patterns, yawning, and head movements. Consequently, the classification accuracy steadily improves with each epoch, indicating that the model is effectively learning to distinguish between alert and drowsy driver states.

Figure 6. GRU-Training:Epoch-Loss

Figure 6 illustrates the variation of training loss during the learning process. The horizontal axis represents the number of epochs, while the vertical axis indicates the loss value, which reflects the difference between predicted outputs and actual labels. Initially, the loss is high due to inaccurate predictions. As training progresses, the loss gradually decreases, indicating that the model is effectively minimizing prediction errors and improving its performance.

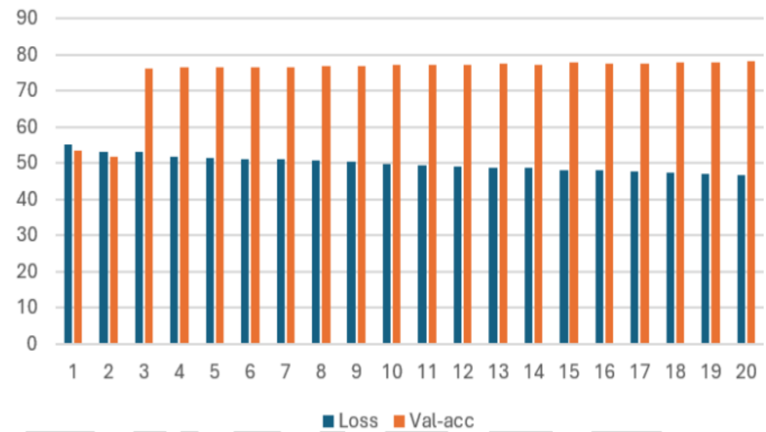

Figure 7: GRU Training : Loss-Validation Accuracy

Figure 7 illustrates the relationship between training loss and accuracy of the proposed driver drowsiness detection model over 20 training epochs. The horizontal axis represents the number of epochs, while the vertical axis indicates the corresponding loss and accuracy values. As training progresses, the loss gradually decreases while the accuracy steadily increases

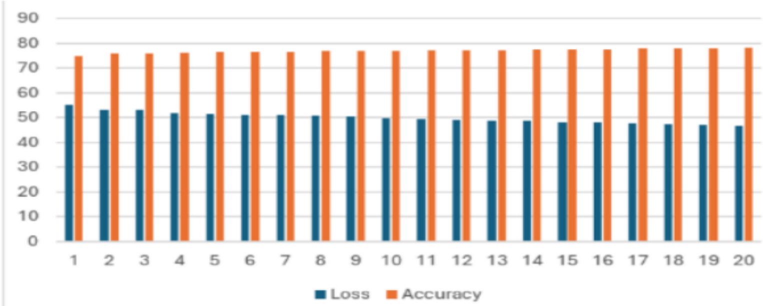

Figure 8. GRU Training :Loss Accuracy

Figure 7 illustrates the relationship between training loss and accuracy of the proposed driver drowsiness detection model over 20 training epochs. The horizontal axis represents the number of epochs, while the vertical axis indicates the corresponding loss and accuracy values. As training progresses, the loss gradually decreases while the accuracy steadily increases. This trend indicates that the model is effectively learning from the data and improving its ability to correctly classify the driver's state. The figure 8 compares the loss values and validation accuracy across different training epochs. The orange bars represent the validation accuracy, while the blue bars indicate the corresponding loss values. As the number of epochs increases, the validation accuracy gradually improves, while the loss values decrease. This trend demonstrates that the model is effectively learning from the training data and enhancing its capability to accurately detect driver drowsiness.

VIII. CONCLUSION

The Real-Time Driver Drowsiness Detection System presents a reliable and effective method for detecting driver fatigue by employing a hybrid CNN–GRU deep learning architecture combined with facial feature extraction and behavioral analysis. By continuously evaluating key indicators such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head pose movements, the system achieves accurate and real-time identification of drowsiness. The incorporation of Retinex-based image enhancement enhances system performance in challenging conditions such as low illumination and partial facial occlusion, thereby improving overall robustness and reliability. This AI-driven approach offers a non-intrusive, intelligent, and cost-effective solution for monitoring driver alertness without disrupting normal driving behavior. The system plays a significant role in reducing fatigue-related accidents, improving road safety, and supporting timely driver alerts through vehicle warning mechanisms. Additionally, the framework allows for future enhancements, including automatic vehicle control and seamless integration with Advanced Driver Assistance Systems (ADAS) for proactive safety intervention.

Furthermore, the system can be adapted to different vehicle types and driving environments, increasing its practical applicability in real-world scenarios. The use of deep learning enables continuous improvement in detection accuracy as more driving data becomes available. The solution also supports scalability for large-scale deployment in commercial and public transportation systems. By enabling early detection of fatigue, the system contributes to enhanced driver well-being and safer long-distance travel. Overall, this project highlights the potential of intelligent monitoring systems to transform road safety and advance the development of smart transportation infrastructures.

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