International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Guarding Vigilance: A Smart System to Detect and Defeat Drowsiness in Real-Time

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Abstract – Driver drowsiness is a leading cause of road accidents, often resulting in severe consequences. This research paper presents a real-time, non-intrusive driver drowsiness detection system that leverages the Eye Aspect Ratio (EAR) derived from eye movement tracking to evaluate fatigue levels. By analyzing facial landmarks using advanced computer vision techniques via a webcam or vehicle-mounted camera, the system detects when the EAR drops below a customizable threshold and triggers an alert to warn the driver. The non-invasive design ensures comfort and ease of integration into vehicles, while the model's training on a large dataset ensures accurate detection across diverse drivers. Real-time testing demonstrates the system's effectiveness in improving road safety, and future enhancements, including adaptive thresholding, multi-modal data fusion, and real-time calibration, are proposed to further optimize performance and reliability under varying conditions.

***Key Words*:** computer vision, drowsiness detection, EAR, real-time testing.

1.INTRODUCTION

Drowsy driving is a major global road safety concern, responsible for a significant share of traffic accidents, injuries, and fatalities each year. Fatigue and sleep deprivation impair cognitive functions, slow reaction times, and diminish focus, making drivers unable to respond promptly to hazards [12]. In India alone, drowsy driving accounts for approximately 100,000 accidents annually, resulting in over 1,500 deaths, 71,000 injuries, and economic losses exceeding $12.5 billion, according to the National Highway Traffic Safety Administration (NHTSA). Globally, driver fatigue contributes to 10-15% of fatal road accidents, often occurring at high speeds due to delayed reactions [17]. Subtle symptoms like prolonged eye closure, yawning, and reduced attention frequently go unnoticed, leading drivers to underestimate their condition and continue driving in a compromised state [20][21]. This highlights the urgent need for effective prevention systems to detect and mitigate drowsy driving, ultimately enhancing road safety and reducing the social and economic burden of fatigue-related accidents.

Advancements in computer vision and machine learning have opened new possibilities for monitoring driver behaviour in real time, enabling the development of intelligent driver assistance systems to address this issue [13][14]. Among these, driver drowsiness detection systems are gaining prominence for their ability to identify fatigue through visual indicators like eye and mouth movements [6][7]. A widely used measure is the Eye Aspect Ratio (EAR), which quantifies eye openness by analysing facial landmarks, where a significant drop in EAR indicates potential drowsiness [34]. This research work proposes a real-time, non-intrusive driver drowsiness detection system leveraging OpenCV to monitor facial features captured by standard or vehicle-mounted cameras. The system detects prolonged eye closure, triggering visual alerts to warn the driver and prevent accidents. This work demonstrated reliability, achieving an accuracy of 97.7%, precision of 91.3%, and recall of 87.5% in identifying drowsy behaviour. While its non-invasive design ensures driver comfort and easy integration into vehicles, challenges such as poor lighting and accessories like sunglasses can affect performance [24]. Future enhancements, including infrared cameras for nighttime detection, wearable sensors, and adaptive machine learning models, are proposed to improve robustness and reliability under varying conditions [19]. By leveraging advanced computer vision techniques, this system offers a promising solution to reduce accidents, enhance road safety, and mitigate the economic and human losses caused by drowsy driving.

The remainder of this research paper has been organized as follows. Section 3 briefly explained about the proposed methodology of this proposed work. Section 4 provides the experimental results and analysis part of this work followed by conclusion in Section 5.

2. LITERATURE SURVEY

In recent years, researchers have explored various methods for driver drowsiness detection, utilizing techniques ranging from traditional computer vision to deep learning approaches.

Key Insights: Advancements in driver drowsiness detection systems have introduced modern algorithms that significantly enhance accuracy and real-time performance. These strengths stem from the integration of machine learning, deep learning, and computer vision technologies [13][14], which enable robust detection of fatigue indicators such as eye closures [34], yawning [27], and facial expressions [26]. However, despite their impressive progress, these systems still face notable challenges that limit their reliability and widespread adoption.

Strengths: Modern algorithms, especially those based on deep learning, excel in analyzing complex patterns in facial features [36], making them highly accurate in detecting drowsiness. Real-time processing capabilities have also improved significantly, thanks to the use of optimized frameworks such as OpenCV and edge computing devices [40]. These developments enable faster detection and alert systems, which are critical for preventing accidents. Furthermore, the integration of these algorithms into compact, cost-effective systems has made them increasingly practical for commercial deployment in vehicles [4][40].

Challenges: Despite these strengths, several challenges remain unresolved. One of the most critical issues is the poor performance of these systems in low-light conditions, such as nighttime driving or dimly lit environments [1][4]. Facial detection becomes unreliable when visibility is compromised, impacting the accuracy of drowsiness detection [5][21]. Additionally, deep learning models, while effective, are computationally intensive and require significant hardware resources, making them less suitable for vehicles with limited processing power [40]. Another major limitation arises when drivers wear glasses, masks, or other facial obstructions, which can hinder the detection of key fatigue indicators[24]. Sunglasses, for example, obscure the eyes, while masks conceal facial expressions, reducing the system's ability to analyze critical features like yawning or eye closure [27]. Environmental factors, such as glare from oncoming headlights or weather conditions, can also interfere with system performance [19][20]. Addressing these challenges requires innovative solutions, such as incorporating infrared cameras for better low-light detection [1], optimizing deep learning models for efficiency [40], and integrating multimodal systems that combine facial analysis with other physiological data, like heart rate or blink frequency [8].

Research Gap: Despite advancements in driver drowsiness detection, several gaps remain. Many existing systems rely on deep learning models that, while accurate, are computationally intensive and require high-performance hardware [40], making them unsuitable for real-time deployment in vehicles with limited processing power. Additionally, current solutions often struggle with poor lighting [1], high-speed driving, and obstructions like sunglasses or masks [23][24], impacting their real-time performance and accuracy. There is a pressing need for a cost-effective, lightweight, and accurate system that can be deployed on edge devices in vehicles [40]. Moreover, many systems fail to adapt to diverse drivers and varying environmental conditions, such as glare or weather. Future research should focus on developing efficient, scalable algorithms for real-time, on-device monitoring, ensuring reliability under various real-world conditions [37][38].

3.METHODOLOGY

The development of the eye state detection and drowsiness monitoring system was carried out through a structured and multi-phase approach. The proposed work integrates traditional computer vision methods (Haar Cascade for face and eye detection) with deep learning-based classification (CNN for eye state prediction) to achieve accurate and efficient drowsiness monitoring. The system operates in the following stages.

Data Collection and Preprocessing

The first step involved gathering a dataset of images of human eyes labeled as "Open" and "Closed" from public repositories, real-time captures, or other relevant sources. To prepare the data for model training, preprocessing steps were applied, including resizing all images to a uniform dimension of 84x84 pixels to standardize input for the deep learning model, converting them to grayscale to reduce computational overhead while retaining essential features, and normalizing pixel values to a [0, 1] range by dividing by 255.0 for faster and more stable training. The processed dataset was then split into training and validation sets to ensure effective model training and evaluation on unseen data.

Model Development

A Convolutional Neural Network (CNN) was designed as the core model for eye state classification, leveraging CNNs' suitability for image-based tasks due to their ability to learn spatial hierarchies of features. The architecture included two convolutional layers with ReLU activation to extract spatial features like edges and textures, followed by MaxPooling layers to reduce spatial dimensions and computational complexity. The output was then flattened into a one-dimensional array and passed through a fully connected dense layer with 128 nodes to learn high-level patterns. The model was trained for 50 epochs with a batch size of 32 using the pre-processed training data, and its performance was monitored using validation data to ensure good generalization to unseen inputs.

Real-Time Eye Detection and Prediction

The trained CNN model was integrated into a real-time video processing pipeline using OpenCV, where face detection was first performed using the Haar Cascade Classifier (haarcascade_frontalface_default.xml) to identify regions of interest within video frames. Within each detected face, the Haar Cascade Eye Detector (haarcascade_eye.xml) was used to locate and extract the eye regions. These extracted eye images were then resized to 84x84 pixels, converted to grayscale, normalized, and reshaped to match the CNN model's input format. The pre-processed eye images were fed into the pre-trained CNN model, which predicted the eye state using the Eye Aspect Ratio (EAR)—a mathematical formula that calculates vertical and horizontal distances between specific eye landmarks to determine if the eyes are open or closed based on changes in these distances.

The formula is:

$$EAR = \frac{||P2 - P6|| + ||P3 - P5||}{2 \times ||P1 - P4||}$$

Where:

1. P1, P2, P3, P4, P5, P6 are key landmarks detected around the eyes. P1 and P4 represent the horizontal distance between the eye's outer and inner corners. P2 and P6, P3 and P5 represent vertical distances between points along the eye's vertical axis.

2. ||P2 - P6|| and ||P3 - P5|| represent the vertical distances, while ||P1 - P4|| represents the horizontal distance.

The Eye Aspect Ratio (EAR) formula calculates eye closure by adding two vertical distances between specific eye landmarks in the numerator and normalizing the result by multiplying the horizontal distance by 2 in the denominator. A low EAR value, typically below a threshold of 0.5 maintained for 20 consecutive frames, indicates that the eyes are likely closed, making this formula crucial for real-time monitoring of driver drowsiness or fatigue. The CNN model outputs a probability value for each eye image, where predictions greater than 0.5 are classified as "Open" and predictions of 0.5 or less as "Closed." The real-time video feed is annotated with bounding boxes around detected eyes along with labels indicating their state, and if the eyes are classified as "Closed," a warning message such as "Closed. Drowsiness Detected" is displayed on the screen to alert the user.

Flowchart

The work flow diagram (flowchart) of this proposed work is shown in the below which depicts a graphical representation of the classification results for a driver drowsiness detection system as discussed so far.

Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

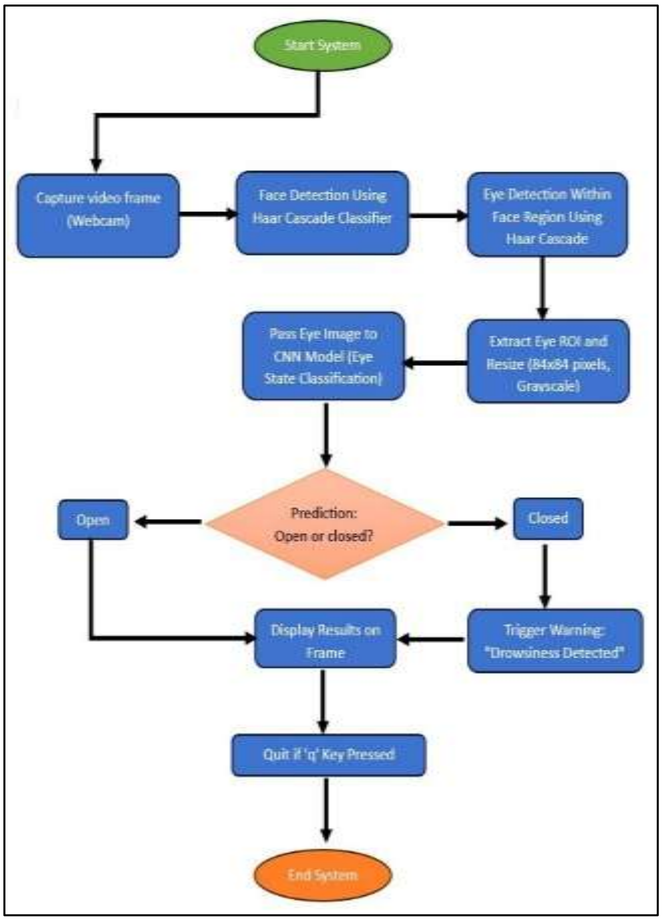

Fig -1 Flowchart of the model

4.RESULTS & ANALYSIS

This section presents an in-depth analysis of the performance and outcomes of the proposed real-time drowsiness detection system. The results are discussed through model evaluation metrics, graphical representations, and system outputs, highlighting the effectiveness of the approach in detecting drowsiness under real-world conditions.

Model Performance Evaluation

To ensure accurate classification of eye states, the Convolutional Neural Network (CNN) model was trained and validated on a labelled dataset of eye images. The performance of the model was evaluated using accuracy and loss as key metrics, which provide insights into the model's ability to learn and generalize.

Model Accuracy Analysis

The accuracy curves for both training and validation phases are shown in the graph below:

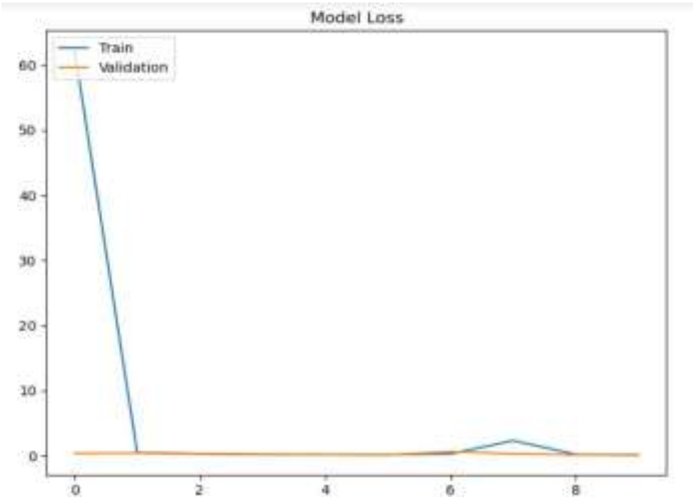

Fig- 2. Accuracy graph of the model

The graph illustrates a steady improvement in accuracy over successive epochs. The training accuracy consistently increased as the model learned the underlying features of the eye states. Similarly, the validation accuracy followed a comparable trend, indicating that the model was able to generalize effectively to unseen data.

Model Loss Analysis

The corresponding loss curves for the training and validation phases are depicted below:

Fig. 3. Loss graph of the model

The loss graph shows a continuous decline in both training and validation loss values, demonstrating the model's ability to minimize classification errors as the training progressed. The near-convergence of the training and validation losses indicates that the model achieved a good balance between learning and generalization, ensuring reliable performance during real-time detection.

Model Performance Evaluation

The proposed system was tested on live video input captured through a webcam to assess its real-time performance. The system successfully detected faces, localized eye regions, and classified the eye states as either "Open" or "Closed." Prolonged detection of closed eyes triggered drowsiness warnings. The examples is shown in the below figures.

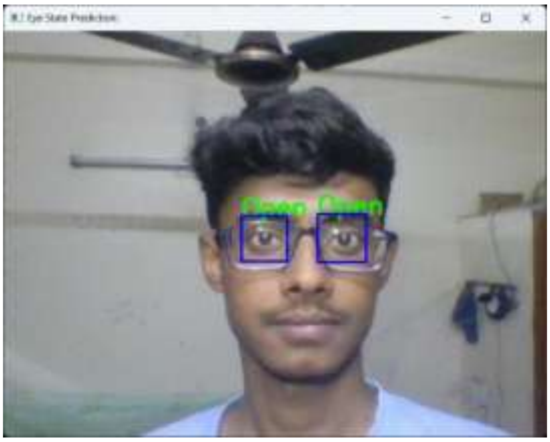

Fig- 4. Detected 'Open'

Fig- 5. Closed. Drowsiness Detected

The system's real-time output is displayed on the video feed with annotated regions and warning messages to enhance usability and clarity. When the system is detected that the eyes are beyond the EAR value, the system highlights a red "Closed Drowsiness Detected" alert message, providing a clear visual warning to the driver. Additionally, the system classifies the eye state as either "Open" or "Closed," with the output visually marked using labeled bounding boxes around the eyes. This intuitive design ensures that detection results are easy to interpret, effectively communicating the driver's alertness status in real time.

The results confirm that the proposed system is a reliable and efficient solution for real-time drowsiness detection. By combining traditional computer vision techniques with deep learning, the system can effectively monitor eye states and identify early signs of fatigue. This makes it particularly suitable for applications in driver safety monitoring, workplace vigilance, and other safety-critical environments

5. CONCLUSION & FUTURE WORK

The proposed driver drowsiness detection system offers a timely and effective response to the global challenge of fatigue-related road accidents. By combining the Eye Aspect Ratio (EAR) with advanced computer vision techniques, the system is capable of continuously monitoring a driver's eye state in real-time and issuing alerts when signs of drowsiness are detected. Its contactless, non-intrusive design ensures user comfort and practicality, making it suitable for integration into a wide range of vehicle types. The system's high accuracy and responsiveness highlight its potential as a valuable safety enhancement, particularly in long-distance travel and commercial transport sectors where driver fatigue is a common risk.

Looking ahead, several enhancements can be pursued to further improve the system's robustness and adaptability. Introducing adaptive thresholding would allow the system to personalize drowsiness detection based on individual eye behavior, reducing false alarms and improving reliability. Incorporating multi-modal data sources—such as steering patterns, lane deviations, heart rate, and yawning detection—can enrich the model's context awareness and decision-making accuracy. Additionally, implementing real-time calibration mechanisms to adjust for varying environmental conditions (e.g., lighting changes, eyewear, head position) would ensure consistent performance across diverse scenarios. Integration with cloud-based analytics and vehicle communication systems (V2X) could also enable fleet-level monitoring and predictive safety measures. With continued refinement and integration, this technology holds the promise of becoming a standard, intelligent driver assistance system that not only saves lives but also supports the broader vision of safer, smarter, and more autonomous transportation ecosystems.

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