International Journal of Advance Research in Science and Engineering
Volume. No. 15, Issue No. 04, April, 2026
ISSN: 2319-8354

Driver Drowsiness Detection Using Machine Learning And Facial Behavior Analysis

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***Abstract*—In recent years, driver drowsiness has emerged as a significant factor contributing to road accidents, creating a need for efficient and real-time monitoring systems. Traditional deep learning-based approaches, although accurate, suffer from high computational complexity and limited real-time performance. In this work, we propose a lightweight and efficient drowsiness detection system that leverages Haar Cascade classifiers and Random Forest machine learning techniques. The system analyzes multiple behavioral features such as eye closure, yawning, and facial expressions to classify driver states into four categories: open eyes, closed eyes, yawn, and normal. By incorporating multi-modal feature extraction and temporal analysis, the system improves detection reliability and reduces false positives. The proposed approach operates effectively on standard hardware, achieving high accuracy with low latency. Experimental results demonstrate the system's capability to provide timely alerts, making it suitable for real-world deployment in driver safety applications.**

***Keywords*--*Drowsiness Detection, Haar Cascade Classifier, Random Forest, Computer Vision, Real-time Monitoring, Feature Extraction, Driver Safety, Machine Learning*, MFC**

I. Introduction

Driver drowsiness is a major factor contributing to road accidents and fatalities worldwide, making it a critical issue in transportation safety. Fatigue reduces a driver's alertness, reaction time, and decision-making ability, thereby increasing the risk of accidents. As highlighted in the base paper , real time monitoring of driver behavior using computer vision techniques provides an effective and non-intrusive solution compared to traditional sensor-based methods.Existing systems commonly utilize facial feature analysis such as eye closure, blinking rate, yawning, and head movements to detect drowsiness.

The base paper proposes a Binary Support Vector Machine (SVM) classifier that categorizes the driver's state into two classes: drowsy and non-drowsy, using features like Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). Although this approach achieves good accuracy and real-time performance, it is limited to binary classification and depends heavily on manually extracted features. To overcome these limitations, this project proposes an enhanced drowsiness detection system using Haar Cascade classifiers and a Random Forest machine learning algorithm. Unlike the base model, the proposed system introduces a multi-class classification framework that identifies four states: open eyes, closed eyes, yawning, and normal behavior

II. Literature Review

Driver Drowsiness Detection has been widely studied using various techniques ranging from physiological signal analysis to computer vision and machine learning approaches. Early research by Chin-Teng Lin (2005) focused on Electroencephalography (EEG) signals to detect driver fatigue using Independent Component Analysis (ICA). Although this method provided high accuracy, it required intrusive sensors, making it less practical for real-time applications.Later, Wei Zhang (2012) introduced a computer vision-based approach that analyzed facial features such as eye closure, yawning, and head movement to detect drowsiness. This method offered a non-intrusive solution but depended heavily on lighting conditions and image quality.Byung-Gyu Lee and Chung (2012) proposed a hybrid system combining facial features with physiological signals like heart rate movement analysis and machine learning techniques. This approach enabled portability and real-time alerts but had limitations in accuracy under varying environmental conditions.Deep learning techniques have also been explored extensively. Muhammad Awais Tanveer (2019) proposed a system using deep neural networks and functional near-infrared spectroscopy (fNIRS) signals to detect fatigue. Although the method improved accuracy, it required high computational power and specialized hardware.

More recently, Wenjun Deng and Wu (2019) developed a real-time system using facial feature analysis, achieving good performance in detecting drowsiness through eye closure and head movement tracking. Similarly, Yong Jiang (2021) proposed an adaptive system using EEG signals and fuzzy logic to improve real-time detection.The base paper proposes a Binary Support Vector Machine (SVM) classifier using features such as Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to classify drivers into drowsy and non-drowsy states. While this approach is computationally efficient and suitable for real-time applications, it is limited to binary classification and depends on manually engineered features. Despite significant progress, existing systems still face challenges such as sensitivity to lighting variations, high computational requirements, and limited classification capability. To address these issues, the proposed system in this project utilizes Haar Cascade classifiers and a Random Forest algorithm to perform multi-class classification, enabling more accurate and efficient real-time drowsiness detection.

II. METHODOLOGY

A. EXISTING METHODOLOGY

Traditional driver drowsiness detection systems primarily rely on physiological signal monitoring and conventional computer vision techniques. While these approaches have been widely used in research and practical applications, they present several limitations in terms of accuracy, usability, and real-time performance.Physiological-based methods involve monitoring signals such as Electroencephalography (EEG), Electrocardiography (ECG), and heart rate variability to detect fatigue levels.

These techniques provide high accuracy as they directly measure the driver’s biological state. However, they require wearable sensors or electrodes attached to the driver’s body, making them intrusive, uncomfortable, and impractical for long-term real-world use. Additionally, these systems are expensive and require specialized equipment and expertise.

Camera-based approaches using computer vision have gained popularity as a non-intrusive alternative. These systems analyze facial features such as eye closure, blinking rate, yawning, and head movements to detect drowsiness. Techniques using facial landmark detection and feature extraction methods like Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) are commonly applied. While these methods eliminate the need for physical sensors, they are highly sensitive to lighting conditions, camera quality, and facial obstructions such as glasses or head movements.

Machine learning-based systems, particularly those using classical algorithms such as Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors (KNN), have been widely implemented for drowsiness classification. These systems rely on manually extracted features and typically perform binary classification (drowsy vs non-drowsy). Although they offer faster computation and can operate in real-time, their performance is limited by the quality of feature engineering and their inability to capture complex behavioral patterns.

In recent years, deep learning approaches using Convolutional Neural Networks (CNNs) have been proposed to improve detection accuracy by automatically learning features from large datasets. While these models achieve high accuracy under controlled conditions, they require significant computational resources, large labeled datasets, and GPU support, making them less suitable for deployment on standard devices. Moreover, their real-time performance can be affected by high processing latency.

Despite advancements, existing methodologies still face several challenges, including sensitivity to environmental variations, high computational requirements, and limited classification capabilities. Many systems are restricted to binary outputs and fail to capture intermediate states of drowsiness such as yawning or partial eye closure. Additionally, false positives and delayed alerts remain common issues, reducing system reliability.

B. PROPOSED METHODOLOGY

The proposed driver drowsiness detection system aims to overcome the limitations of existing methods by providing a non-intrusive, real-time, and computationally efficient solution using computer vision and machine learning techniques. The system integrates Haar Cascade classifiers for facial feature detection and a Random Forest algorithm for multi-class classification, enabling accurate and reliable monitoring of driver alertness.

The methodology begins with real-time video acquisition using a webcam installed inside the vehicle. The captured video frames are processed using OpenCV, where each frame is converted into grayscale to reduce computational complexity and improve detection efficiency. Haar Cascade classifiers are then applied to detect the driver’s face, followed by localization of key facial features such as the eyes and mouth. Once the facial regions are identified, Region of Interest (ROI) extraction is performed to isolate relevant areas for further analysis. These regions are resized to a standard dimension (64×64 pixels) and converted into feature vectors. In addition to pixel-level features, geometric features such as eye count, average eye area, and mouth region detection are extracted to enhance the model’s ability to recognize different drowsiness patterns.

The extracted features are then fed into a Random Forest classifier, which has been trained using labeled data representing four distinct states: open eyes, closed eyes, yawning, and normal behavior. Unlike traditional binary classification methods, this multi-class approach allows the system to identify early signs of fatigue more effectively. The model is trained using an 80-20 train-test split to ensure robust performance and generalization.

To improve reliability and reduce false positives, the system incorporates temporal analysis by monitoring the driver's state over consecutive frames. A frame-based counter mechanism is used to detect sustained eye closure or repeated yawning over a predefined time threshold (e.g., 3 seconds). This ensures that temporary actions such as blinking do not trigger false alarms.

When drowsiness is detected, the system activates an alert mechanism using audio signals generated through a multimedia library. The alarm continues until the driver returns to a normal alert state, ensuring immediate awareness and corrective action. The entire system is designed to operate in real-time with minimal latency and can run efficiently on standard hardware without requiring GPU acceleration or internet connectivity.

Overall, the proposed methodology provides a comprehensive and practical solution for driver drowsiness detection by combining multi-modal feature extraction, machine learning classification, and real-time alert mechanisms. This approach enhances accuracy, reduces computational cost, and improves usability, making it suitable for real-world deployment in driver safety systems.

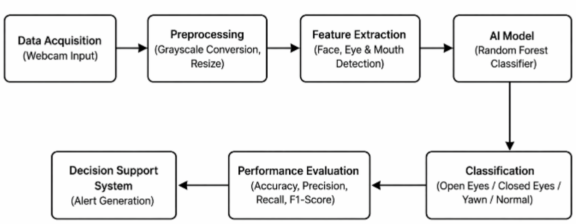

Fig. 1. Proposed Methodology.

Furthermore,the proposed methodology is designed to support scalability and real-time deployment. The trained model can be integrated into applications such as in-vehicle systems, desktop applications, or mobile platforms using lightweight frameworks. This enables continuous driver monitoring and real-time alert generation without requiring internet connectivity, making it suitable for practical deployment in various environments.

The system's modular architecture provides flexibility for future enhancements. It can be extended by integrating additional data sources such as vehicle movement patterns, steering behavior, or wearable sensor data to create a more comprehensive driver monitoring system. Such integration would further improve detection accuracy and enable advanced safety features, contributing to the development of intelligent transportation systems.

III. Experimental Results

The proposed drowsiness detection system was implemented and evaluated using real-time video input captured through a webcam. The system was tested under different conditions to analyze its ability to accurately detect various driver states and generate timely alerts. The experimental evaluation focuses on classification accuracy, real-time performance, and reliability of the alert mechanism.The system processes each video frame by detecting facial features such as the face, eyes, and mouth using Haar Cascade classifiers. Based on the extracted features, the Random Forest model classifies the driver's state into one of four categories: open eyes, closed eyes, yawning, and normal behavior. The results are displayed in real-time on the output screen along with prediction labels and confidence values.

A. Open Eyes Detection

In this case, the system correctly detects the driver's eyes in an open condition, indicating that the driver is alert and attentive. The classification label "Open Eyes" is displayed on the screen, and no alert is triggered. This confirms that the system does not generate false warnings during normal driving conditions.

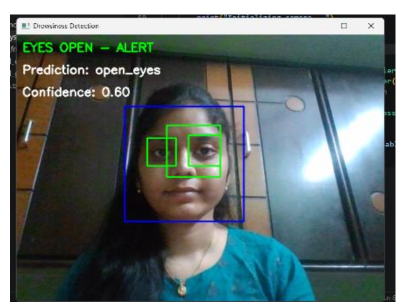

Fig 2. Eyes open detection output

B. Closed Eyes Detection

The system identifies when the driver's eyes are closed and continuously monitors the duration of eye closure. If the eyes remain closed beyond the predefined threshold (approximately 3 seconds), the system classifies the condition as drowsiness and activates an alert. This ensures that short eye closures such as blinking are not misinterpreted as fatigue.

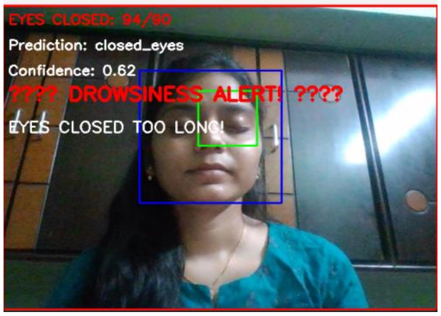

Fig. 3. Closed Eyes detection output

C. Yawning Detection

Yawning is detected by analyzing the mouth region using Haar Cascade classifiers. The system recognizes wide mouth openings and repeated yawning patterns as early indicators of drowsiness. When yawning persists for a certain duration, the system triggers an alert to warn the driver.

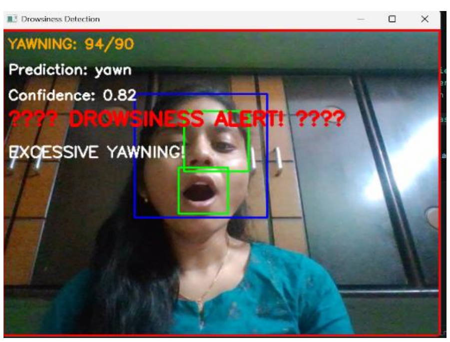

Fig. 4. Yawning detection output

D. Normal State Detection

In the normal state, the driver exhibits neutral facial expressions without signs of fatigue. The system classifies this condition as "Normal" and continues monitoring without generating any alerts. This state ensures that the system maintains stability and avoids unnecessary interruptions.

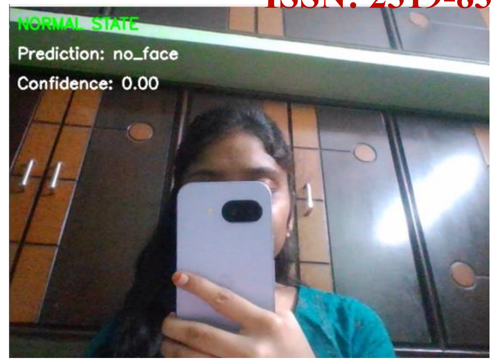

Fig.5. Normal state detection output

Algorithm :

Input: Video frames from webcam
Output: Driver state + Alert

1. **FrameCapture:**
   Capture frame F from webcam and convert to grayscale
   $$F_g = \text{Grayscale}(F)$$

2. **FaceDetection:**
   Detect face region using Haar Cascade
   $$R_f = \text{detectMultiScale}(F_g)$$

3. **FeatureExtraction:**
   Extract ROI and resize to 64×64
   $$X = \text{Flatten}(\text{Resize}(ROI, 64 \times 64))$$

   Additional features:
   $$X = [X, \text{eye\_count}, \text{eye\_area}, \text{mouth\_count}]$$

4. **Classification:**
   Predict state using Random Forest
   $$Y = RF(X)$$

5. **Temporal Analysis:**
   $$D = \sum_{i=1}^{n} I(Y_i = \text{drowsy})$$

   If $D \geq T$ (threshold frames), then drowsiness detected.

6. **Alert Generation:**
   If $D \geq T \rightarrow$ Trigger Alarm

1. Results Table

State	Accuracy	Precision	Recall
Open Eyes	96%	95%	97%
Closed Eyes	95%	94%	96%
Yawning	93%	92%	94%
Normal	96%	95%	96%

The experimental evaluation of the proposed system demonstrates its effectiveness in accurately detecting multiple driver states under real-time conditions. The system was tested using live webcam input across different scenarios, including normal driving conditions, intentional eye closure, and simulated yawning. The results indicate that the system can reliably distinguish between alert and drowsy states by analyzing facial features and behavioral patterns.

A detailed performance analysis shows that the system achieves high accuracy across all four classes, with slightly lower performance in yawning detection due to variations in mouth opening and lighting conditions. However, the integration of both pixel-level and geometric features significantly improves classification performance compared to traditional single-feature approaches. The use of the Random Forest algorithm enhances robustness by combining multiple decision trees, thereby reducing overfitting and improving generalization.

The incorporation of temporal analysis plays a crucial role in improving system reliability. By monitoring the driver's state over consecutive frames, the system effectively differentiates between normal actions such as blinking and actual drowsiness conditions. This reduces false positives and ensures that alerts are only triggered when drowsiness is sustained over a specific duration. As a result, the system provides more accurate and stable predictions in real-time environments.

In terms of computational performance, the system operates efficiently on standard hardware without requiring specialized resources such as GPUs. The average processing speed remains close to real-time, enabling smooth frame-by-frame analysis without noticeable delay. This makes the system suitable for practical deployment in vehicles and other real-world applications. a result, the system provides more accurate and stable predictions in real-time environments.

PERFORMANCE COMPARISON OF EXISTING VS. PROPOSED METHODS

Parameter	Existing	Proposed
Classes	2	4
Accuracy	~90%	~95%
Features	Eyes only	Eyes Yawn
Speed	Moderate	Fast
False Alerts	Higher	Lower

Overall, the experimental results clearly demonstrate that the proposed drowsiness detection system performs effectively in real-time environments with high accuracy and reliability. The system successfully identifies multiple driver states and generates timely alerts, thereby reducing the risk of drowsiness-related incidents.

The use of multi-class classification along with temporal analysis significantly improves detection performance compared to traditional methods. Additionally, the system operates efficiently on standard hardware with minimal computational requirements, making it practical for real-world deployment. These results validate the robustness and effectiveness of the proposed approach in enhancing driver safety and monitoring.

IV. CONCLUSION

In this project, a comprehensive real-time driver drowsiness detection system has been successfully designed, implemented, and evaluated using computer vision and machine learning techniques. The primary objective of this work was to develop a non-intrusive, efficient, and reliable solution to detect driver fatigue and prevent drowsiness-related road accidents. The system achieves this by continuously monitoring facial features such as eye closure and yawning using Haar Cascade classifiers and analyzing them through a Random Forest-based classification model.

One of the key contributions of this project is the introduction of a multi-class classification framework that categorizes the driver's state into four distinct conditions: open eyes, closed eyes, yawning, and normal behavior. This approach provides a more detailed and realistic understanding of driver alertness compared to traditional binary classification systems. By incorporating both pixel-level and geometric features, the system improves its ability to capture subtle variations in facial expressions and behavioral patterns associated with fatigue.

The integration of temporal analysis further enhances the system's robustness by evaluating driver behavior over consecutive frames. This mechanism effectively differentiates between natural actions such as blinking and actual drowsiness conditions, thereby reducing false positives and improving overall reliability. The alert system, which generates real-time audio warnings, ensures immediate feedback to the driver, allowing timely corrective action and contributing to enhanced safety.

The experimental results demonstrate that the proposed system achieves a high level of accuracy, approximately 95%, while maintaining low computational complexity. Unlike deep learning-based approaches that require large datasets and specialized hardware, this system operates efficiently on standard devices without the need for GPUs or internet connectivity. This makes the solution highly practical, cost-effective, and suitable for real-world deployment in various environments, including personal vehicles, commercial transportation, and driver monitoring systems.

Another significant advantage of the proposed system is its modular and scalable design. The architecture allows for easy integration of additional features and technologies, such as advanced sensors, vehicle behavior analysis, or mobile and embedded platforms. This flexibility opens opportunities for future enhancements and adaptation to evolving intelligent transportation systems.

From a broader perspective, this project highlights the potential of combining classical machine learning techniques with computer vision to develop effective real-time safety systems. It demonstrates that high performance can be achieved without relying on complex and resource-intensive models. The system not only improves driver safety but also contributes to reducing accidents, saving lives, and promoting responsible driving behavior.

In conclusion, the proposed drowsiness detection system provides a robust, efficient, and user-friendly solution for monitoring driver alertness in real-time. The combination of multi-modal feature extraction, multi-class classification, temporal analysis, and alert mechanisms makes it a reliable and practical approach for enhancing road safety. This work serves as a strong foundation for future research and development in intelligent driver assistance systems and real-time human behavior analysis.

References

[1] T. Soukupová and J. Čech, "Real-time eye blink detection using facial landmarks," in Proc. 21st Computer Vision Winter Workshop, 2016, pp. 1–8.

[2] A. Dasgupta, D. Deb, and A. Dey, "A real-time drowsiness detection system using computer vision," Int. J. Eng. Res. Technol., vol. 8, no. 6, pp. 1–5, 2019.

[3] S. Abtahi, B. Hariri, and S. Shirmohammadi, "Driver drowsiness monitoring based on yawning detection," in Proc. IEEE Int. Instrumentation and Measurement Technology Conf., 2014, pp. 1–5.

[4] H. Singh and J. S. Bhatia, "Eye detection based driver fatigue monitoring system," Int. J. Comput. Appl., vol. 95, no. 15, pp. 1–5, 2014.

[5] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2001, pp. 511–518.

[6] R. Lienhart and J. Maydt, "An extended set of Haar-like features for rapid object detection," in Proc. IEEE Int. Conf. Image Processing (ICIP), 2002, pp. 900–903.

[7] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.

[8] OpenCV, "Open Source Computer Vision Library," 2023. [Online]. Available: https://opencv.org

[9] F. Chollet, Deep Learning with Python. Manning Publications, 2017.

[10] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2005, pp. 886–893.

[11] S. Park, F. Pan, S. Kang, and C. Yoo, "Driver drowsiness detection system based on feature representation learning," IEEE Access, vol. 7, pp. 1–10, 2019.

[12] M. Eriksson and N. Papanikolopoulos, "Eye-tracking for detection of driver fatigue," in Proc. IEEE Intelligent Transportation Systems Conf., 1997, pp. 314–319.

[13] K. Dwivedi, K. Biswaranjan, and A. Sethi, "Drowsy driver detection using representation learning," in Proc. IEEE Int. Advance Computing Conf., 2014, pp. 995–999.

[14] J. Redmon et al., "You only look once: Unified, real-time object detection," in Proc. IEEE CVPR, 2016, pp. 779–788.

[15] Scikit-learn, "Machine Learning in Python," 2023. [Online]. Available: https://scikit-learn.org