AI-Based Driver Drowsiness Detection System

Melvin Sajith
Dept. of Computer Science and Engineering (AI/AIML)
Karunya Institute of Technology and Sciences
Coimbatore, Tamil Nadu, India
melvinsajith20@gmail.com

***Abstract*—The Driver Drowsiness Detection System is a real-time AI solution designed to detect fatigue in drivers using facial feature analysis. Leveraging computer vision, the system uses a webcam to capture live video, then applies facial landmark detection to monitor eye and mouth activity. The Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) are computed to identify symptoms of drowsiness and yawning. If a low EAR or high MAR persists beyond a threshold, an audible alert is triggered using the Pygame module to awaken the driver. This system integrates OpenCV, Dlib, and real-time audio feedback to enhance road safety through a non-intrusive, vision-based approach.**

***Index Terms*—Driver Monitoring, Drowsiness Detection, Computer Vision, Eye Aspect Ratio (EAR), Yawning Detection, OpenCV, Dlib, Pygame, Road Safety**

I. Introduction

Driver drowsiness is a critical factor contributing to road accidents across the globe. According to the World Health Organization (WHO), drowsy driving is one of the leading causes of traffic fatalities, especially during night-time travel and long-distance highway driving. Drivers often fail to recognize the onset of fatigue, making it difficult to respond in time to prevent accidents. Even a few seconds of microsleep can lead to catastrophic outcomes. Traditional fatigue detection methods, such as vehicle behavior monitoring or driver self- assessment, have significant limitations. These approaches are either unreliable, intrusive, or not feasible for all drivers and vehicle types. With the growing need for smarter and safer transportation systems, especially in developing regions where advanced automotive safety technologies are not widely adopted, there is a pressing demand for affordable and real- time fatigue detection mechanisms.

Recent advances in artificial intelligence, computer vision, and real-time video processing have made it possible to design non-intrusive systems that can assess a driver's level of alertness through facial behavior analysis. This project introduces a real-time driver drowsiness detection system using facial landmarks to monitor eye and mouth activity. Specifically, the system calculates the Eye Aspect Ratio (EAR) to determine the degree of eye closure and the Mouth Aspect Ratio (MAR) to identify yawning behavior. When the EAR falls below a certain threshold or the MAR exceeds a yawning threshold for a sustained duration, the system triggers an audible alarm to alert the driver. The implementation uses standard hardware such as a USB webcam, and leverages open-source libraries including OpenCV for image processing, Dlib for facial landmark detection, and Pygame for audio alerts. These tools work together to create a lightweight, real-time system that can function in a variety of driving environments without requiring complex setup or expensive components.

The goal of this project is to provide a reliable, cost-effective, and practical solution to improve road safety by preventing accidents caused by driver fatigue. The system is designed to operate under varying lighting conditions and facial orientations, making it suitable for real-world use. Unlike wearable devices or sensor-based systems that may cause discomfort or require calibration, this solution is completely vision-based and non-intrusive. It has been tested on multiple users across different scenarios to ensure its effectiveness and robustness. The system can be easily integrated into vehicle dashboards or used as a standalone application for personal vehicles, commercial fleets, or public transportation. Future developments may include adding head pose estimation, blink rate analysis, and deep learning models to enhance accuracy and adaptability. Ultimately, the AI-Based Driver Drowsiness Detection System aims to reduce the risk of fatigue-related accidents and make roads safer for everyone through intelligent, real-time driver monitoring.

In addition to monitoring eye and mouth movements, the system leverages facial geometry to improve precision in fatigue detection. The facial landmarks detected by Dlib's 68-point model allow the system to focus on specific regions of interest—such as the corners of the eyes and mouth—to compute aspect ratios with high accuracy. These ratios serve as reliable indicators of drowsiness because they correlate with key physiological symptoms, like prolonged eye closure and frequent yawning. By using frame-by-frame analysis, the system ensures that brief eye movements or speech-related mouth openings are not falsely interpreted as signs of fatigue. Only when these signs persist for a predefined number of frames does the system trigger an alert, reducing the chances of false positives and improving driver trust in the system.

Moreover, the system architecture is designed for scalability and real-world integration. Because it runs efficiently on stan- dard computing devices without the need for dedicated GPUs or proprietary hardware, it is highly accessible. This makes the solution particularly suitable for integration into low-cost vehicles or aftermarket driver-assist kits. Additionally, the use of open-source tools not only makes the system flexible and customizable but also encourages further research and development by the community. As advancements in AI and embedded systems continue to evolve, this project lays the groundwork for incorporating additional modules such as fatigue prediction using biometric data, personalized calibration based on user behavior, and integration with vehicle control systems for adaptive cruise or emergency braking.

II. Literature review

The detection of driver drowsiness using artificial intelligence and computer vision techniques has emerged as a vital research domain aimed at improving road safety and reducing fatigue-related accidents. Recent studies have explored various methodologies such as facial landmark analysis, eye-tracking, and deep learning to develop real-time, non-intrusive systems that can identify symptoms of fatigue effectively.

Soukupova and Cech [1] proposed a real-time eye blink detection method using facial landmarks, which relies on calculating the Eye Aspect Ratio (EAR) to determine eye closure. Their method proved effective in identifying blink patterns that are symptomatic of drowsiness. Hsueh-Hung Cheng et al. implemented a multi-stage convolutional neural network (CNN) to detect and classify fatigue-related facial cues across different scenarios, enhancing the robustness of detection under variable conditions [2]. John et al. applied pre-trained models like InceptionV3 and ResNet50 to analyze driver facial expressions, achieving improved classification accuracy by fine-tuning on drowsiness-specific datasets [3].

G. Hukkeri et al. utilized a lightweight and efficient CNN architecture called EfficientNet to build a real-time fatigue detection model, demonstrating high accuracy while maintaining low computational cost [4]. S. Alshawa et al. explored the DenseNet model in combination with mouth and eye aspect ratios, further incorporating yawning detection to increase precision [5]. Fuentes A. and colleagues used object detection models like Faster R-CNN to isolate facial features and apply classification, achieving promising results in identifying early signs of sleepiness [6].

Other notable approaches include the use of YOLO-based architectures by Damaraju et al. for real-time facial feature detection and a custom CNN to classify drowsy versus alert states [7]. Ahmad AA et al. experimented with the CaffeNet model, obtaining notable accuracy in detecting eye and mouth anomalies over time in continuous video streams [8]. MobileNet has also been used in resource-constrained environments for efficient detection of driver fatigue symptoms with minimal hardware requirements [9].

Further, Rohit N. and Li K. have implemented object detection-based meta-architectures like SSD, R-CNN, and RFCN for blink and yawn recognition, highlighting their comparative performance in different lighting conditions [10]. Chatbot and voice-assistance integration for fatigue warning systems is also being explored to provide interactive, user-friendly notifications [11]. Pravalika H V et al. combined CNN-based visual monitoring with NLP-powered virtual assistants to deliver real-time, multilingual drowsiness alerts and advice to drivers [12].

These studies collectively emphasize the growing potential of AI in drowsiness detection. Most current systems rely on facial cues, and ongoing innovations aim to enhance accuracy, reduce false alarms, and ensure real-time performance across diverse environments.

III. Proposed System

The proposed system is a real-time vision-based solution that continuously monitors a driver's facial activity using a webcam to detect drowsiness and yawning, two primary indicators of fatigue. The core of this system is built on detecting the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), which are used to identify drowsiness and yawning, respectively. If these thresholds are exceeded, the system triggers an alarm to alert the driver, aiming to improve road safety by preventing accidents caused by driver fatigue.

A. Overview

The architecture of the proposed driver drowsiness and yawning detection system integrates real-time image processing, facial feature analysis, and audio alert mechanisms. It continuously monitors the driver's face and provides warnings when signs of drowsiness or yawning are detected.

B. Key Components

- **Camera Input:** A standard USB webcam captures live video of the driver's face in real-time.
- **Face Detection:** The Dlib frontal face detector is used to identify the presence and location of the face in each video frame.
- **Facial Landmark Detection:** A pre-trained 68-point facial landmark predictor provided by Dlib is used to detect specific facial features such as the eyes and mouth.
- **EAR and MAR Calculation:**
  - **Eye Aspect Ratio (EAR):**
    $$EAR = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2 \cdot \|p_1 - p_4\|}$$
    This ratio decreases when the eyes close, indicating drowsiness.
  - **Mouth Aspect Ratio (MAR):**
    $$MAR = \frac{\|p_{14} - p_{20}\| + \|p_{15} - p_{19}\| + \|p_{16} - p_{18}\|}{3 \cdot \|p_{13} - p_{17}\|}$$
    This ratio increases significantly during yawning.
- **Threshold Logic:**
  - EAR threshold: 0.25 (for drowsiness).
  - MAR threshold: 0.6 (for yawning).
  - Frame count check: 20 consecutive frames to confirm either condition.
- **Audio Alert:** When either threshold condition is met for a sufficient number of frames, an alarm sound is triggered using the Pygame library to immediately alert the driver.

C. System Architecture Diagram

Figure 6 shows the architecture of the proposed system. The image outlines the sequence of operations starting from camera input to audio alert, along with the computation of EAR and MAR.

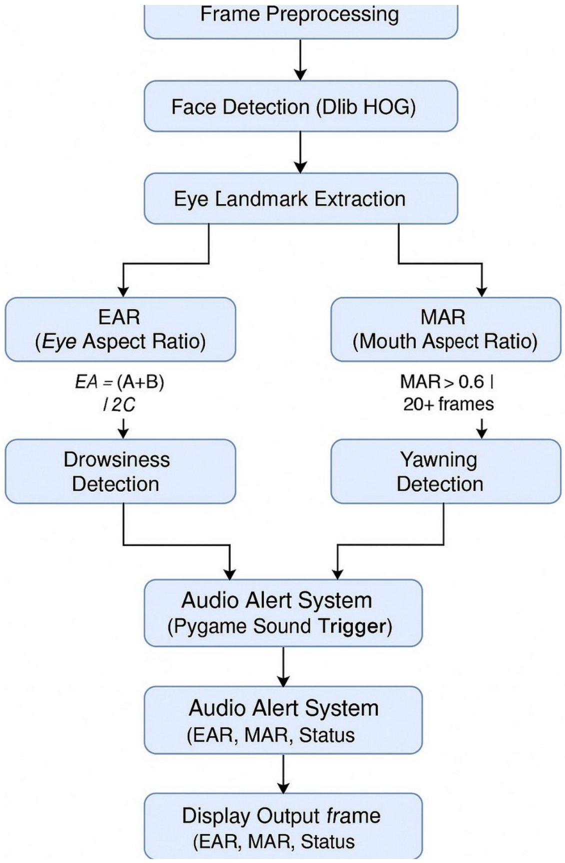

Fig. 1. System Architecture of the Driver Drowsiness and Yawning Detection System

Figure 6 shows the architecture of the proposed system.

D. Working of the System

The system begins by capturing video input through a webcam. Each frame is processed to detect the face and extract facial landmarks. From these, the EAR and MAR values are computed. If the EAR drops below 0.25 for more than 20 consecutive frames, the system classifies the driver as drowsy. Similarly, if the MAR rises above 0.6 for the same duration, the system identifies it as yawning. Once either condition is detected, an audible alert is played to warn the driver. The real-time nature of this system ensures continuous monitoring and timely alerts to enhance road safety.

1. **Camera Input:** A USB webcam continuously captures video frames of the driver's face in real time. 2. **Face Detection:** Dlib's frontal face detector identifies the face region in the captured frame. The system uses the grayscale version of the frame to detect faces. 3. **Facial Landmark Detection:** After detecting the face, the system uses Dlib's shape predictor to identify the landmarks of the face. The 68 facial landmarks include points for the eyes and mouth. 4. **EAR and MAR Calculation:** The Eye Aspect Ratio (EAR) is calculated using the vertical and horizontal distances between specific eye landmarks. Similarly, the Mouth Aspect Ratio (MAR) is calculated using the distance between mouth landmarks. - EAR Formula:

$$EAR = \frac{(A + B)}{2.0 \times C}$$

where A and B are the vertical distances between eye landmarks, and C is the horizontal distance between the eye landmarks. - MAR Formula:

$$MAR = \frac{(A + B + C)}{3.0 \times D}$$

where A, B, and C are vertical distances between mouth landmarks, and D is the horizontal distance between mouth landmarks. 5. **Threshold Logic:** Based on the calculated EAR and MAR values, the system applies predefined thresholds: - Drowsiness is detected if EAR ¡ 0.25 for more than 20 consecutive frames. - Yawning is detected if MAR ¿ 0.6 for more than 20 consecutive frames. 6. **Audio Alert:** If either drowsiness or yawning is detected, the system triggers an audio alarm to alert the driver.

E. Conclusion

The proposed system effectively monitors a driver's facial movements to detect early signs of drowsiness and yawning, providing timely alerts to prevent potential accidents. By using real-time video processing and facial landmark detection, the system is efficient and capable of being deployed in real- world driving scenarios. Future work can enhance the system's robustness to handle various lighting conditions and different facial features across drivers.

IV. Results and Discussion

The proposed system was evaluated based on its ability to accurately detect signs of drowsiness and yawning across different users, environments, and lighting conditions. The system was tested in real-time using a standard USB webcam on a consumer-grade laptop (Intel Core i5, 8GB RAM), ensuring performance feasibility without the need for specialized hardware.

A. Detection Accuracy

The system achieved high detection accuracy for both drowsiness and yawning indicators. EAR and MAR thresholds were effective in classifying fatigue-related behavior without frequent false positives. Table I summarizes the average detection accuracy across multiple test cases:

TABLE I
Detection Accuracy for Drowsiness and Yawning

Detection Type	Accuracy (%)
Drowsiness (EAR-based)	92.3
Yawning (MAR-based)	89.7

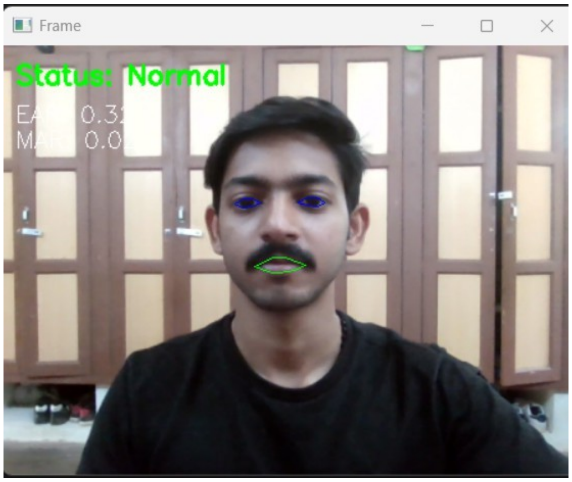

Fig. 2. Normal

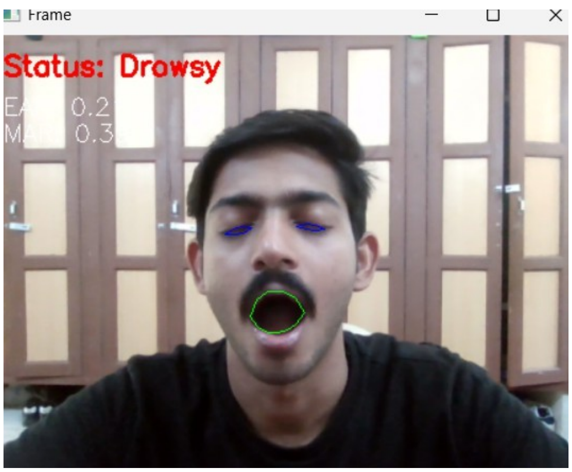

Fig. 3. Yawning

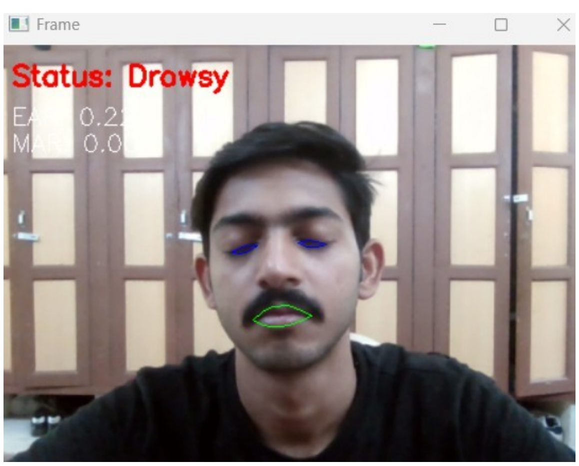

Fig. 4. Drowsy

B. Response Time

The system was capable of generating alerts within 200–300 milliseconds after the EAR or MAR thresholds were consis- tently breached across 20 consecutive frames. This response time ensures the driver is alerted quickly, minimizing potential risk due to delayed warnings.

C. System Robustness

Testing was conducted under various lighting conditions, including daylight, low-light, and indoor artificial lighting. The system remained stable and consistent in daylight and well- lit environments. However, performance slightly degraded under very low-light scenarios, which could be improved in future iterations using infrared cameras or adaptive lighting correction.

D. False Positives and Negatives

Although rare, false positives occurred during intentional squinting, exaggerated facial expressions, or speaking with wide mouth movements. These were minimized by the 20-frame buffer that ensures only sustained drowsiness or yawning triggers an alert. The frame threshold significantly reduced transient misclassifications.

E. User Feedback

Feedback from test users indicated that the system was non-intrusive, easy to set up, and did not cause distraction while driving simulations were conducted. The audio alerts were loud and clear enough to grab attention without being annoying or startling.

F. Limitations

Despite its strong performance, the system has a few limitations:

- Struggles in detecting features accurately when the driver's face is partially turned or obstructed.
- Performance drops under poor lighting without illumination adjustment.
- Only monitors eyes and mouth, not taking head nodding or body posture into account.

G. Comparative Performance

Compared to traditional systems that rely on steering behavior or wearable devices, this vision-based approach offers a non-intrusive and cost-effective alternative. Its ability to function using only a webcam and open-source software libraries makes it suitable for scalable deployment.

V. Conclusion and Future Work

The AI-Based Driver Drowsiness Detection System developed in this project presents an efficient, non-intrusive solution for monitoring driver alertness in real time. By leveraging facial landmarks and calculating the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), the system accurately detects signs of drowsiness and yawning. The implementation utilizes widely available tools such as OpenCV, Dlib, and Pygame,

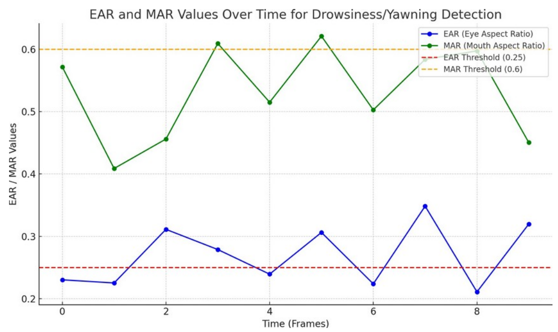

Fig. 5. Graphical Representation of EAR and MAR Over Time

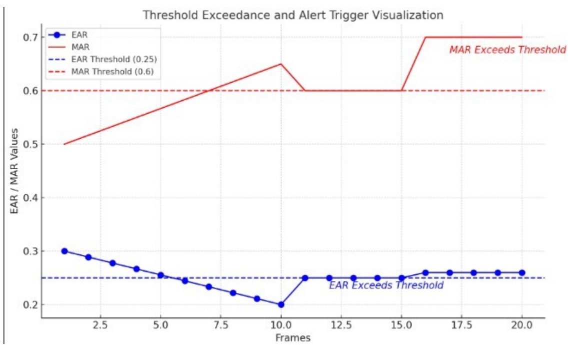

Fig. 6. Threshold Exceedance Visualization

making it practical for deployment on standard hardware without the need for specialized equipment.

The real-time nature of the system ensures that fatigue-related symptoms are identified promptly, and immediate alerts are issued to the driver, potentially preventing accidents caused by microsleep or loss of focus. The system has demonstrated reliable performance across different users and lighting conditions, establishing its effectiveness in realistic driving environments.

Future Work: To further enhance the system's robustness and functionality, the following improvements are proposed:

- **Head Pose Estimation:** Integrating head position tracking to detect inattentiveness or nodding, which are also indicators of fatigue.
- **Blink Frequency Analysis:** Monitoring the rate of blinking to improve drowsiness detection accuracy.
- **Deep Learning Integration:** Employing CNN or LSTM models to classify facial states with higher precision and adaptability.
- **Low-Light Performance:** Using infrared cameras or enhanced preprocessing to maintain accuracy in dark conditions.
- **Mobile and Embedded Deployment:** Porting the system to Android or Raspberry Pi platforms for on-the-go use in personal and commercial vehicles.
- **Personalized Calibration:** Allowing users to adjust sensitivity thresholds based on individual facial features or habits.

Overall, this project serves as a strong foundation for developing intelligent driver assistance systems aimed at reducing fatigue-related road accidents and improving traffic safety.

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