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Drowsiness Detection System for Safe Driving

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***Abstract:*-Driver drowsiness is a major contributor to road accidents, demanding continuous monitoring systems for enhanced road safety. This paper presents a real-time, camera-based drowsiness detection system using computer vision and machine learning techniques. The model extracts facial landmarks to compute Eye Aspect Ratio (EAR) for eye closure detection and Mouth Aspect Ratio (MAR) for yawn identification. EAR and MAR thresholds are analyzed with head pose estimation to determine the severity of driver fatigue. A Convolution Neural Network (CNN) further improves classification accuracy under varying illumination and driving conditions. When abnormal EAR and MAR values are detected, the system issues an instant alert to prevent accidents. Experimental results show high accuracy and low latency, making the proposed method suitable for integration into intelligent transportation systems.**

KEYWORDS— Drowsiness detection, Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Computer vision, Facial landmark detection, Intelligent transportation systems.

1. INTRODUCTION

Human-driven vehicles continue to dominate modern transportation due to their flexibility, accessibility, and widespread use. However, this heavy reliance on manual driving has also increased the vulnerability of road users to human errors—especially those caused by driver fatigue. Driver drowsiness has emerged as one of the most prevalent causes of road accidents in recent years. Studies indicate a consistent rise in fatigue-related crashes, resulting in significant loss of life and long-term injuries across the globe.

According to the Ministry of Road Transport & Highways (MoRTH), India alone reports over 4500 accidents every year caused specifically by sleepy or exhausted drivers, taking hundreds of lives. This problem is intensified during night-time driving, particularly among operators of heavyloaded vehicles who travel long distances for extended hours without adequate rest. Fatigue impairs reaction time, reduces attention span, and increases the likelihood of microsleep episodes, making drowsiness a silent but extremely dangerous threat on highways.

The World Health Organization (WHO) has classified road traffic accidents as a major global public health challenge. As highlighted in the World Road Safety Status Report 2015, more than 1.25 million people die annually due to road accidents, while millions more suffer life-altering disabilities. Given this alarming scenario, the development of intelligent, real-time accident-avoidance systems is crucial. Detecting and preventing driver drowsiness is a key component of such systems, offering effective early intervention before a hazardous situation escalates into a fatal accident.

This paper focuses on designing a robust, vision-based drowsiness detection system using Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and machine learning techniques to reduce the risks associated with driver fatigue and enhance overall road safety.

2. RELEVANT WORK

Several researchers have explored diverse machine learning and vision-based strategies to detect driver drowsiness. Prasath N *et al.* [12] proposed an image processing-based technique that focuses on locating the driver's eyes in real time and monitoring eye closure patterns to determine fatigue. Their system captures facial images, detects eye regions, and updates driver status based on continuous eye-state analysis, issuing alerts when prolonged closure is identified.

Priyanka Basavaraj Murdeshwar*et al.* [13] introduced a machine-learning approach using facial landmarks and multiple classifiers to distinguish between open and closed eye states. Their lightweight model demonstrates efficiency and suitability for embedded, real-time driving environments.

Shreyans Mittal *et al.* [14] presented a hybrid method combining image processing with machine learning to improve the reliability of drowsiness detection. By employing Haar Cascade for face detection and classification algorithms for fatigue recognition, their system achieves greater robustness under varying illumination and moderate driver movement. Aneesa Al Redhaei *et al.* [15] developed a real-time monitoring system optimized for low-latency video processing, enabling continuous assessment of driver alertness with rapid response times suitable for practical deployment in vehicular safety systems.

Ayman Altameem *et al.* [16] proposed an early-stage drowsiness detection framework that leverages hybrid machine-learning techniques to analyze behavioural indicators such as blink duration and yawning frequency. Their study emphasizes proactive detection, aiming to identify fatigue symptoms before the driver reaches a critical level of drowsiness.
Collectively, these studies highlight the importance of integrating facial feature analysis, real-time monitoring, and machine learning to improve detection accuracy. However, challenges remain in handling illumination changes, yawning detection, and false positives. Motivated by these gaps, the present work adopts a combined EAR–MAR approach with CNN-based classification to enhance robustness and reliability in real-time drowsiness detection.

3. System Architecture

The driver drowsiness system is designed to detect signs of drowsiness or fatigue in the driver and alert them to take a break or rest. The system uses machine learning algorithms to analyse the driver's behaviour and identify patterns that indicate drowsiness, such as drooping eyelids, yawning etc.

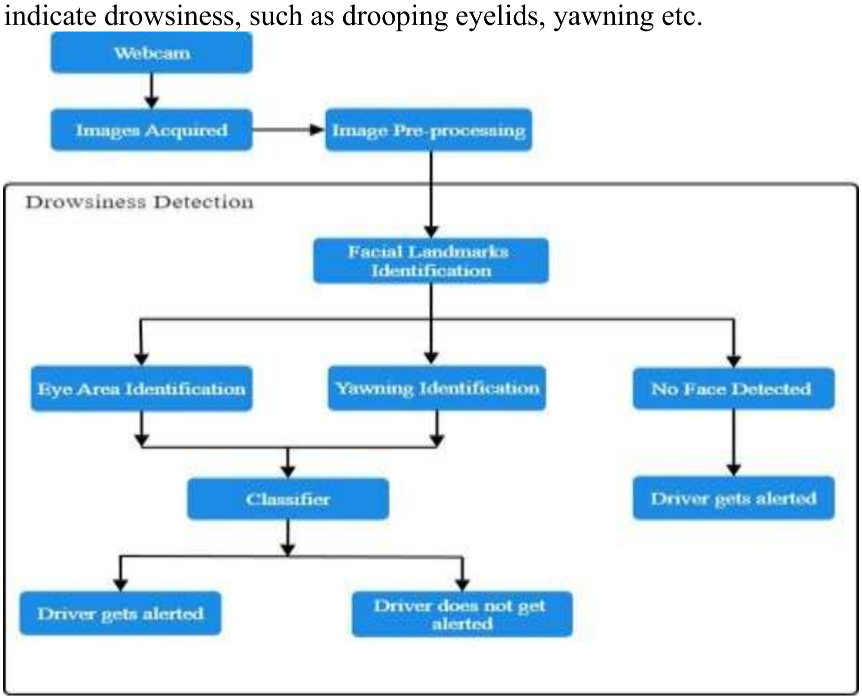

Fig 1. system architecture of drowsiness detection system

The flowchart represents the complete working pipeline of the Driver Drowsiness Detection System, demonstrating how input from the camera is processed step-by-step to determine whether the driver is in a drowsy state. Each block in the flowchart corresponds to a functional module that performs a specific task, ultimately contributing to an intelligent alert mechanism.

The provided flowchart illustrates the operational architecture of a Drowsiness Detection System designed to monitor a driver's state and provide timely alerts. The process begins with data collection via a Webcam, which captures live footage to ensure Images are Acquired in real-time. These raw images then undergo an Image Pre-processing stage, which likely involves noise reduction, grayscale conversion, or resizing to prepare the data for more complex analysis.

The Drowsiness Detection Core

Once the images are cleaned, they enter the main detection phase, which relies on Facial Landmarks Identification. This step maps specific points on the driver's face to track movements. From here, the system branches into three primary logic paths:

Eye and Mouth Monitoring: The system simultaneously performs Eye Area Identification (to check for drooping lids or prolonged closure) and Yawning Identification. These two data points are fed into a Classifier, a machine learning model that determines if the driver is fatigued.

Safety Outcomes: Based on the Classifier's analysis, the system reaches a decision: if drowsiness is detected, the Driver gets alerted; otherwise, the Driver does not get alerted.

Fail-safe Mechanism: A separate branch handles the event where No Face is Detected (perhaps if the driver has slumped over or looked away). In this scenario, the system bypasses the classifier and immediately ensures the Driver gets alerted for safety.

4. Methodology

The proposed **Drowsiness Detection System for Safe Driving** is constructed as a comprehensive computer vision–based monitoring architecture that continuously evaluates the driver's alertness level using facial behavioral indicators. As shown in Figure 1.1, the framework operates through a set of structured stages that ensure robust, uninterrupted, and real-time fatigue detection. The system integrates classical machine learning concepts, temporal geometric feature extraction, and image processing techniques to identify conditions such as prolonged eye closure, decreased blink rate, and yawning, all of which are stronglycorrelated with the onset of drowsiness. The design of the model emphasizes minimal computational load, real- time responsiveness, and adaptability to varying driving environments.The framework is engineered to function effectivelyin real- world automotive settings, where factors such asinconsistent lighting, partial occlusions, head rotation, and dynamic Cameraanglesmaydegrade detection performance. Thus, the system incorporates preprocessing and adaptive detection mechanisms that help stabilize the captured data before feature extraction. The modular design of the framework ensures that each stage—from imageacquisition to alert triggering—operates independently yet synchronously, enabling high scalability, easy integration into Advanced Driver Assistance Systems (ADAS), andlow- latencyprocessing.

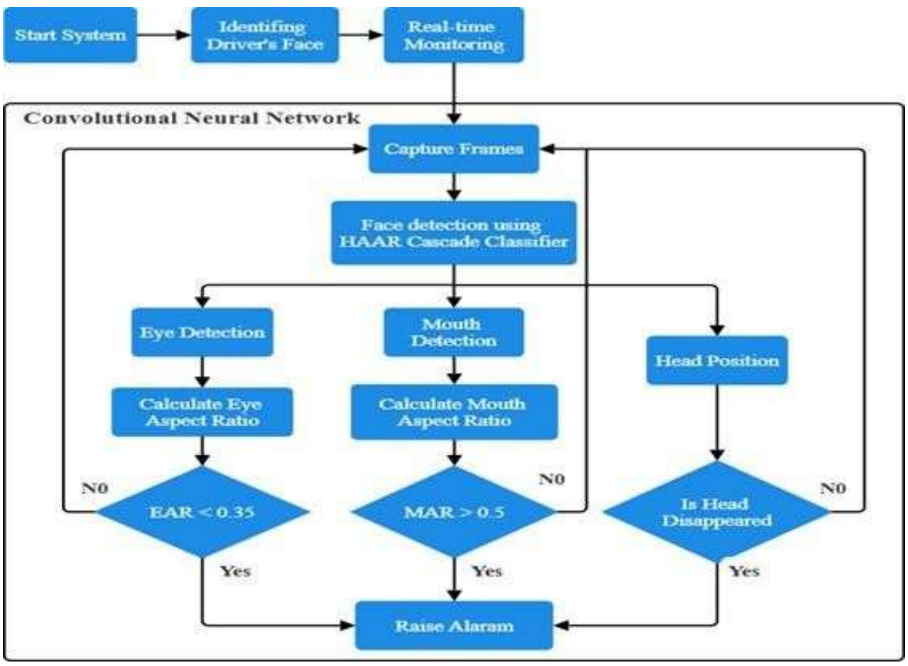

Fig 2. Proposed Framework

The flow chart illustrates the comprehensive methodological framework formulated for the real-time detection and assessment of driver drowsiness using a vision-based monitoring architecture. The process commences with the initialization of the imaging hardware and computational modules, which serve as the primary interface for acquiring continuous facial video streams from the driver during vehicle operation. To ensure the stability and integrity of the captured frames, the system employs a dedicated preprocessing pipeline consisting of grayscale conversion, illumination normalization, denoising, and spatial enhancement operations. These procedures effectively counteract variations in ambient lighting, sensor noise, and motion artifacts, there by producing are fined and consistent data stream suitable for subsequent analytical tasks Following preprocessing, the system performs hierarchical face localization using the HAAR Cascade Classifier, a computationally efficient and real-time- optimized algorithm for robust detection of frontal facial structures. This stage isolates the Region of Interest (ROI), enabling the system to focus exclusively on relevant facial components while discarding irrelevant background information. Once the face region is identified, the framework bifurcates into two specialized analytical subsystems dedicated to the extraction of key physiological indicators of drowsiness: ocular feature extraction and oral feature extraction.

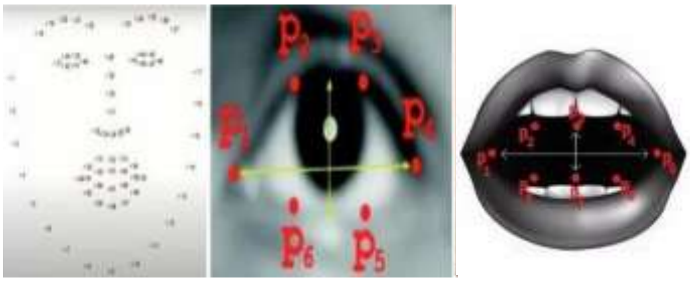

Fig 3. Facial Features Landmarks

The methodology adopted in this project focuses on building a real-time vision-based system capable of detecting driver drowsiness and yawning using facial landmark analysis. The implementation utilizes Python, OpenCV, Dlib, and HAAR Cascade classifiers to extract facial features and compute fatigue-related metrics, ensuring reliable and computationally efficient performance. The system is structured into several sequential stages: system initialization, frame acquisition, face detection, landmark extraction, EAR/MAR computation, drowsiness inference, and audio alert generation.

The first stage involves system initialization, where the camera module is activated and all required models— including HAAR Cascade classifiers for face, eye, and mouth detection and Dlib's landmark predictor are loaded. This ensures that the system is prepared to capture live video feed and process each frame in real time. In the ocular analysis branch, the Eye Aspect Ratio (EAR) is computed using landmark-based geometric relationships around the eyelids. EAR provides a temporally sensitive descriptor of eyelid dynamics, enabling reliable identification of prolonged eye closure, slow blinking, and micro-sleep episodes. A sustained depression in EAR across consecutive frames is regarded as a critical indicator of declining alertness. In parallel, the oral analysis branch computes the Mouth Aspect Ratio (MAR), derived from lip landmarks, to quantify the extent of mouth opening. MAR effectively captures yawning behavior—another strong physiological correlate of fatigue—and complements the ocular indicators to enhance detection reliability.

The EAR and MAR values are then integrated within a threshold-driven decision inference module. This module incorporates temporal smoothing mechanisms and multi- frame verification to avoid misclassifications caused by normal blinking, speech-related mouth movements, or transient facial variations. Only when the EAR falls below its threshold or the MAR exceeds its yawning threshold for a sustained duration does the system conclusively classify the driver as drowsy.

Eye Detection and EAR Computation:-

Following face detection, the system identifies the eye regions. This is performed using either:

- Embedded HAAR eye detectors, or
- Facial landmark detectors (more accurate under variations)

Once the eyes are localized, the Eye Aspect Ratio (EAR) is computed. EAR is a stable, geometry-based metric representing the openness of the eyes

EAR Formula

$$EAR = \frac{\| p_2 - p_6 \| + \| p_3 - p_5 \|}{2 \times \| p_1 - p_4 \|}$$

Where:

- p_1, p_4 are horizontal eye landmarks
- p_2, p_3, p_5, p_6 are vertical eye landmarks

Why EAR is Effective

- It does not require training data.
- It is in variant to head tilted a rtial rotation.
- It is stable across different face shapes.
- It is computationally very light.

EAR-Based Drowsiness Indicators

- **EAR drop**→ eyelids closing
- **EAR=0**→ eyes fully closed
- **EAR consistently low for > 15 frames** → micro- sleep

The system measures EAR across time to detect fatigue- related behavior like:

- Slow blinking
- Increased blink duration
- Reduced blinking frequency
- Prolonged eye closure(most reliable indicator)

Mouth Detection and MAR Computation

In parallel with eye detection, the system performs Mouth Detection. The mouth region is extracted using:

- HAAR mouth detector
- Lower-face landmark region

Using the extracted boundary points, the Mouth Aspect Ratio (MAR) is computed.

MAR Formula

$$MAR = \frac{\| p_{14} - p_{18} \| + \| p_{15} - p_{17} \| + \| p_{13} - p_{19} \|}{3 \times \| p_{12} - p_{16} \|}$$

Where:

- Vertical mouth distances represent mouth opening
- Horizontal distance normalizes mouth size variation

Why MAR is Essential

Yawning is a natural behavior associated with fatigue. MAR increases sharply when yawning occurs.

High MAR for several frames indicates:

- Yawning
- Reduced alertness
- Onset of sleepiness

Unlike EAR, which captures rapid eyelid changes, MAR captures slower fatigue cues. This combination improves reliability, reducing false positives. Finally, upon confirming drowsiness, the system activates the audio alert module, which triggers aloud alarm sound to immediately re-engage the driver's attention. In this project, the audio alert is the only warning mechanism, chosen for its simplicity, effectiveness, and ease of real-time implementation. This methodology ensures a structured , efficient, and real time drowsiness detection system that leverages light weight computer vision techniques, geometric feature computation ,and audio based warning mechanisms to enhance driver safety and reduce fatigue-related accidents.

5. Result and Analysis

Fig 4. No Face Detected

face absence detection is used to identify situations where the driver's face is not visible in the camera frame. When the system fails to detect the driver's face continuously, it displays a warning message indicating "No Face Detected – Check Driver." This condition may occur due to the driver looking away, excessive head movement, or nodding off, and it is treated as a potential safety risk. The system immediately alerts the driver to regain proper attention and positioning, ensuring continuous monitoring and enhanced driving safety.

Fig 5. Real time Monitoring

when the driver starts the car, the camera turns on and detects the eyes using Haar Cascade. As soon as the eyes are open, the system starts continuous monitoring. The CNN model then checks every frame to see if the eyes remain open or turn closed. If the eyes stay closed for several frames, the system immediately triggers a drowsiness alert to ensure safe driving.

Fig 6. Yawning Detection

Yawning detection is a technique used to identify fatigue by analyzing the driver's mouth movements in real time. When the driver opens their mouth widely for a longer-than- normal duration, the system recognizes this as a yawn. Using facial detection methods, the mouth region is tracked continuously, and features such as mouth opening width, height, and shape are measured. If these values cross a certainthreshold, the system confirms a yawn. Frequent yawning within a short period indicates early signs of tiredness or reduced alertness. By detecting yawns accurately, the system can warn the driver with alert message and beep sound before drowsiness becomes more serious, improving overall safety.

Fig 7.Prolong Eye Closure Detection

Prolonged eye closure detection is used to identify critical levels of driver drowsiness by continuously monitoring the driver's eye movements in real time. When the driver's eyes remain closed for a duration longer than normal blinking, the system interprets this as a dangerous sign of fatigue. Using facial landmark detection, the eye region is tracked frame by frame, and the Eye Aspect Ratio (EAR) is calculated to measure eye openness.

If the EAR value falls below a predefined threshold and remains low for a continuous period, the system confirms prolonged eye closure. This condition indicates reduced alertness or microsleep, and the system immediately triggers a high-priority warning to alert the driver and prevent potential accidents.

Fig 8. Prolong Yawning and Eye Closure Detection

Prolonged yawning detection is used to identify extreme levels of driver fatigue by continuously analyzing mouth movements along with eye closure in real time. When the driver's mouth remains widely open for a longer-than-normal duration, the system detects this condition as prolonged yawning using the Mouth Aspect Ratio (MAR). Simultaneously, the Eye Aspect Ratio (EAR) is monitored to track eye closure. If both MAR exceeds its threshold and EAR remains below its threshold for a sustained period, the system classifies the condition as extreme fatigue. This combined detection of prolonged yawning and eye closure indicates a high risk of microsleep, and the system immediately generates a high-priority warning to alert the driver and prevent potential accidents.

Fig 9. Low Light Yawning Detection

It illustrates the system detecting prolonged yawning even in low-light conditions. Although the driver's eyes are open, the system identifies extreme mouth opening using the Mouth Aspect Ratio (MAR), which exceeds the predefined threshold, confirming prolonged yawning. The facial mesh overlay shows accurate facial landmark tracking, while the low-light enhancement module ensures reliable detection despite poor illumination. This condition indicates early or increasing fatigue, and the system generates a warning to alert the driver and prevent potential drowsiness-related risks.

Overall, the results of our evaluation indicate that our real-time driver drowsiness detection system based on image processing techniques is highly accurate, effective, and user friendly. The system can be integrated into vehicles to provide real-time monitoring of driver drowsiness, thereby enhancing road safety.

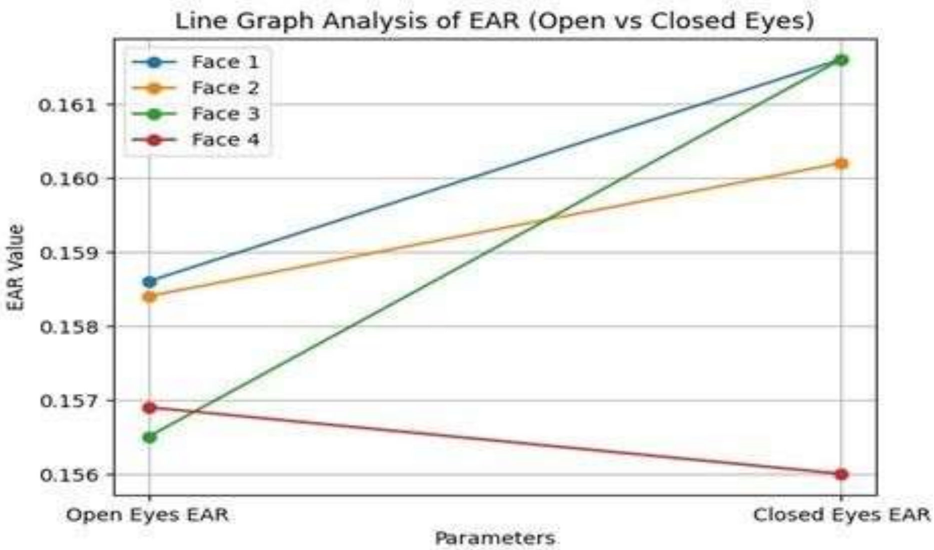

Fig 10. EAR variation during eye closure

Line graph illustrates the comparison of Eye Aspect Ratio (EAR) values for four different faces under two conditions: open eyes and closed eyes. Each line represents an individual face (Face 1 to Face 4), showing how EAR changes between the two parameters.

Faces 1, 2, and 3 show an increase in EAR when eyes are closed, with Face 3 having the highest change. Face 4 shows a slight decrease, indicating individual variation. Overall, the graph shows that EAR varies between open and closed eye states, supporting its use for eye-state analysis

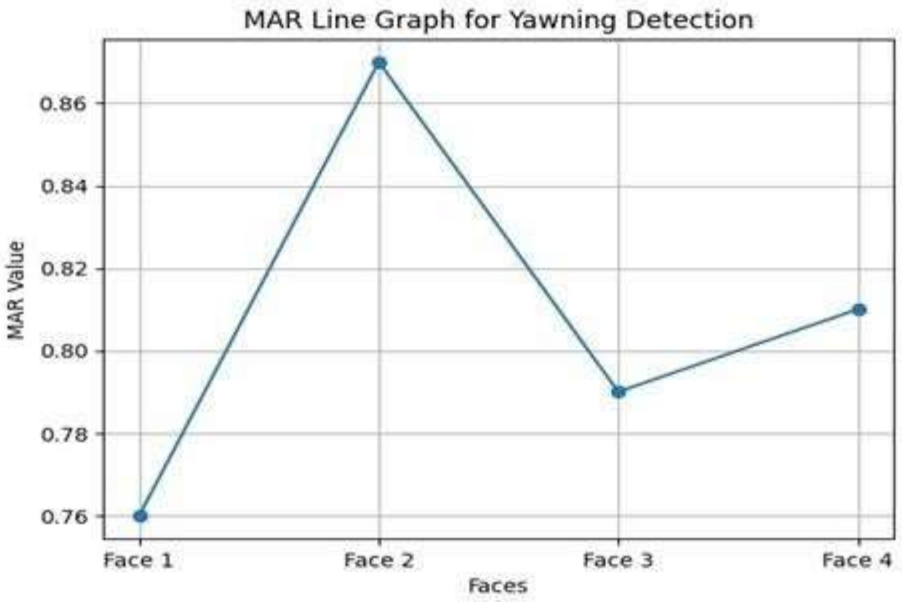

Fig 11. MAR variation during prolonged yawning

Line graph shows MAR values for four faces used in yawning detection. Face 2 has the highest MAR value, indicating a stronger mouth opening and higher likelihood of yawning. Face 1 shows the lowest MAR value, suggesting minimal mouth opening. Faces 3 and 4 have moderate MAR values. Overall, higher MAR values correspond to increased yawning activity, validating MAR as an effective parameter for yawning detection.

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