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Facial Landmark-based Real-Time Driver Drowsiness Detection.

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Abstract - *Driver drowsiness is a significant contributor to road traffic accidents worldwide, accounting for an estimated 20–30% of severe crashes. This paper presents a non-intrusive, real-time driver drowsiness detection system based on facial landmark analysis using computer vision techniques. The proposed method computes the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to detect prolonged eye closure and yawning, which are well-established visual indicators of fatigue. The system is designed for real-time operation on consumer-grade hardware using a standard RGB camera. Experimental evaluation conducted on a custom dataset demonstrates a drowsiness detection sensitivity of 91% while maintaining a processing speed of 24–28 frames per second. The results indicate that the proposed approach provides a practical and cost-effective solution for real-time driver monitoring under controlled lighting conditions.*

Keywords— Computer Vision, Drowsiness Detection, Eye Aspect Ratio, Facial Landmarks, Mouth Aspect Ratio

I. INTRODUCTION

Driver drowsiness is a major factor contributing to road traffic accidents, particularly during long-distance driving and nighttime travel. Fatigue impairs reaction time, attention, and decision-making ability, often without the driver being consciously aware of the degradation in performance. As a result, drowsy driving remains difficult to detect and prevent using conventional safety mechanisms.

In recent years, vision-based driver monitoring systems have gained attention due to their non-intrusive nature and relatively low cost compared to physiological sensing approaches. However, many existing systems rely on indirect vehicle-based indicators or rigid thresholding mechanisms that do not generalize well across different drivers and operating conditions. Vehicle-behavior-based methods often detect fatigue only after driving performance has already deteriorated, limiting their effectiveness for early intervention.

This paper presents a real-time driver drowsiness detection system based on facial landmark analysis using computer vision techniques. The system employs Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to identify prolonged eye closure and yawning, respectively. To prioritize computational efficiency and real-time deployability on consumer-grade hardware, fixed threshold values are used rather than personalized adaptive models. Although individual adaptation is not addressed, this design choice enables stable performance and reproducibility under controlled conditions.

The primary objective of this study is to demonstrate that a rule-based, facial landmark-driven approach can achieve reliable drowsiness detection while maintaining real-time performance without the need for specialized sensors. The focus of this work is on practical implementation, performance evaluation, and deployment feasibility rather than the development of new visual features or learning-based models.

II. LITERATURE REVIEW

Driver drowsiness detection methods can be broadly classified into three categories: physiological monitoring, vision-based analysis, and vehicle behavior assessment.

Physiological approaches, such as electroencephalography (EEG) and electrocardiography (ECG), provide high detection accuracy by directly measuring brain and cardiovascular activity. However, the requirement for invasive sensor placement limits their practicality in real-world driving scenarios [2]. The use of electrodes reduces driver comfort and restricts widespread adoption in everyday driving environments

Vision-based systems analyze observable facial cues such as eye closure duration, blink frequency, and yawning behaviour. The PERCLOS measure has received extensive confirmation as an effective measure of driver alertness [3]. Soukupová and Čech [1] introduced the Eye Aspect Ratio (EAR) for real-time blink detection using facial landmarks, demonstrating its effectiveness in identifying prolonged eye closure. On the same note, the yawning behaviour is also identifiable in terms of Mouth Aspect Ratio (MAR) and as such, the features can be effectively used in real-time fatigue detection. These metrics provide

enough computational capabilities on real-time implementation that can be used with standard cameras.

Vehicle-based decision-making systems analyze steering behavior, lane departure patterns, and vehicle dynamics to infer driver fatigue. Although non-invasive, these methods typically detect fatigue only after driving performance has degraded, limiting their usefulness for early intervention.

Premium automotive manufacturers have incorporated proprietary driver sensors and closed system architectures, often relying on specialized vehicles, which are based on closed architectures and special video sensors and are thus more difficult to access and replicate. Although open-source vision-based solutions offer improved accessibility and scalability, many rely on fixed threshold values that do not generalize well across diverse drivers and operating conditions, leading to higher false-positive rates [4].

The gap in the literature lies in the lack of affordable and non-invasive systems capable of real-time operation while maintaining cross-user generalizability with a low false-positive rate. This study addresses this gap by proposing a vision-based system optimized for consumer-grade hardware.

III. METHODOLOGIES

System Architecture. The proposed system follows a sequential processing pipeline consisting of video capture, face detection, facial landmark localization, feature extraction, temporal smoothing, and fatigue detection. A standard RGB camera operating at 24–30 frames per second is used for video acquisition. Frames are converted to grayscale to reduce computational load while preserving the structural facial information required for reliable landmark detection.

A. Facial Landmark Detection. A pre-trained Dlib 68-point facial landmark model is used to localize key facial features. The model is capable of handling moderate head rotations, facial expressions, and inter-individual anatomical variations. The extracted landmarks are subsequently used to compute fatigue-related visual features.

B. Feature Extraction. Eye Aspect Ratio (EAR): EAR measures the degree of eye-opening resulting in Euclidean distances among eye landmarks:

$$EAR = (||p_2 - p_6|| + ||p_3 - p_5||) / (2 \times ||p_1 - p_4||) \quad (1)$$

p1 to p6 are eye landmark coordinates. Typical EAR values range between 0.25 and 0.35 for open eyes, while sustained values below this range indicate prolonged eye closure associated with drowsiness.

Mouth Aspect Ratio (MAR): MAR is a measure of mouth opening done by:

$$MAR = (||p_{63} - p_{67}|| + ||p_{62} - p_{66}|| + ||p_{61} - p_{65}||) / (3 \times ||p_{60} - p_{64}||) \quad (2)$$

Elevated MAR values (greater than 0.75) correspond to sustained mouth opening, which is commonly associated with yawning behaviour.

C. Rule-Based Decision Logic

Drowsiness is detected when the EAR value remains below 0.25 for 48 consecutive frames, corresponding to approximately two seconds at 24 FPS. This duration exceeds normal blink intervals and indicates prolonged eye closure. Yawning is detected when elevated MAR values persist for more than 15 consecutive frames, allowing differentiation between yawning and short-duration mouth movements such as speech to reduce frame-level noise, both EAR and MAR signals are smoothed using an exponential moving average (EMA):

$$EMA(t) = \alpha x(t) + (1 - \alpha)\, EMA(t - 1) \quad (3)$$

where a = 0.3. This reduces the noise at frame-level and enhances stability. Hysteresis-based logic is applied to further reduce false positives caused by normal blinking, facial expressions, or speech-related movements

IV. IMPLEMENTATION

A. Development Environment

Software: Python 3.9, OpenCV 4.5.3, Dlib 19.22, and NumPy 1.21.2, running on Windows 10. Hardware: Intel Core i5 processor, 8 GB RAM, standard RGB webcam 640x480 pixels, 24-30 FPS.

B. Processing Pipeline

The average frame processing latency was 38–45 milliseconds, enabling real-time operation. Temporal stabilization of the EAR and MAR signals is achieved using an exponential moving average filter with α = 0.3 Upon fatigue detection, the system generates both visual (on-screen) and audible alerts to warn the driver in real time.

V. RESULTS AND DISCUSSION

A. Experimental Setup

The custom dataset consisted of 18 subjects (14 male and 4 female), each recorded for 10–15 minutes under two lighting conditions daylight (500-1000 lux) and indoor (300-500 lux). The amount of total footage was 4.5 hours of video. Ground truth labels for drowsiness and yawning

events were obtained through manual frame-level annotation.

B. Performance Results

Table I. Performance Metrics of the Proposed System

Metric	Drowsiness	Yawning
Sensitivity	91%	82%
Accuracy	82%	89%
Precision	89%	--
False Positive Rate	13%	15%
Processing Speed	24-28 FPS	24-28 FPS

Table II: Work Results in varying lighting conditions. Lighting Condition Sensitivity to drowsiness Yawning Accuracy of yawning

Lighting Condition	Sensitivity to Drowsiness	Yawning Accuracy
Daylight (>500 lux)	97%	82%
Indoor (300-500 lux)	88%	78%
Low-light (<200 lux)	65%	58%

The system maintained high detection performance under adequate lighting conditions, while performance degraded significantly in low-light environments due to reduced landmark visibility.

C. Comparative Analysis

The combined EAR and MAR approach demonstrated higher sensitivity compared to a PERCLOS-only baseline, achieving sensitivities of 91% and 78%, respectively. The rule-based method provides the best compromise between accuracy, efficiency and ability to deploy on resource constrained platforms.

D. Limitations

Principal limitations include: (1) performance degradation in low-light conditions (2) reduced accuracy under extreme head rotations (greater than ±20°) (3) non-adaptive threshold values and (4) sensitivity to occlusions (sunglasses, masks).

VI. CONCLUSION AND FUTURE WORK

This study presents a real-time and cost-effective driver drowsiness detection system based on facial landmark analysis. The system uses Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to detect prolonged eye closure and yawning, achieving a drowsiness detection sensitivity of 91% while operating in real time on consumer-grade hardware. The rule-based approach offers computational efficiency and ease of deployment compared to more complex methods.

Future work

(1)Future work will focus on incorporating infrared imaging to improve performance under low-light conditions, introducing adaptive thresholding for personalized detection, evaluating CNN-based landmark detection models for improved robustness, and conducting long-term validation in real-world driving environments., (2) introducing adaptive thresholding to personalize detection across drivers, (3) evaluating CNN-based landmark detection models for improved robustness, and (4) conducting long-term validation in naturalistic driving environments with larger and more diverse participant groups.

The proposed system demonstrates practical viability for real-world driver monitoring without requiring specialized hardware

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