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Design and Implementation of a Safe Driving System for Real-Time Driver Behavior Analysis and Hazard Alerting Using Low Cost.

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Abstract- Driver inattention is a major contributor to road accidents worldwide, with fatigue responsible for nearly 20–30% of incidents each year. This study presents SafeDrive Alert System, a camera-based system that monitors driver behavior by detecting signs such as eye closure, head movement, and loss of focus using computer vision techniques. The system utilizes methods like Eye Aspect Ratio and facial landmark analysis, and its performance is evaluated using real-world driving data, achieving approximately 95% detection accuracy. Designed as a cost-effective solution, it can be easily deployed in vehicles such as taxis and trucks, with potential extensions for connected vehicle systems and additional safety features.

Keywords: Driver Fatigue; Eye Tracking; Head Pose; Computer Vision; Drowsiness Alerts; Road Safety.

I. INTRODUCTION

Dash camera footage often circulates widely online, yet driver fatigue remains a far more serious threat, contributing to over 1.3 million road fatalities [1] [2] globally. The SafeDrive system transforms a standard camera into an intelligent monitoring tool that observes blinking patterns, head movements, and gaze direction to issue timely alerts before dangerous situations occur. Unlike expensive radar-based systems, it relies on lightweight Python- based processing, making it suitable for both urban roads in Pune and long-distance travel.Figure 1. shows architecture of the system.

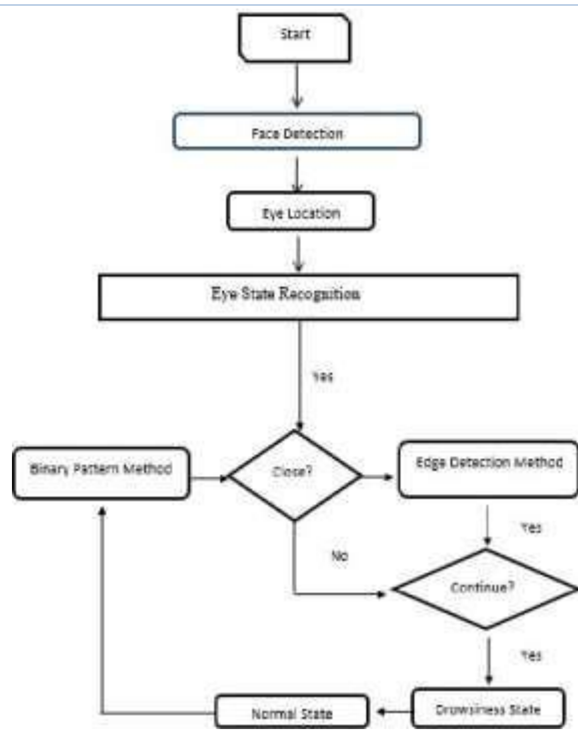

Figure 1 System Architectire

For example, during extended driving such as a 500 km journey, a driver may begin to show signs of fatigue like drooping eyes and head nodding, significantly increasing accident risk. Similarly, distractions such as checking a phone during city driving can also be detected. SafeDrive continuously captures video frames, analyzes facial cues, and generates voice alerts like "Stay

Focused!" to regain driver attention. In contrast to traditional alert systems like seat vibration, this approach is completely non- intrusive and does not require wearable devices.

The system identifies different conditions such as drowsiness (based on reduced Eye Aspect Ratio) [3], distraction (through head pose deviation beyond 15° yaw), and yawning behavior. It operates effectively under normal lighting conditions without requiring specialized sensors like EEG [4] or infrared systems. However, certain challenges remain, including reduced accuracy with sunglasses, low-light environments, and facial landmark distortions due to eyewear. Despite these limitations, optimization techniques improve real-world performance, making SafeDrive a promising solution for future vehicle safety systems.Figure .2 shows the landmarks on eye.

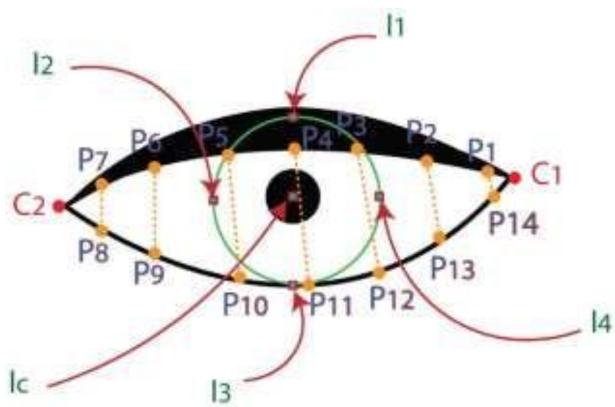

Figure 2 shows the landmarks on eye.

1.1 Contributions

The major contributions of this paper are as follows:

1) A complete vision-based driver fatigue detection system that integrates Eye Aspect Ratio (EAR) with head pose estimation for accurate and reliable monitoring.

2) Implementation of optimization techniques such as lighting adjustments and frame-skipping methods to achieve real-time performance of approximately 30 FPS.

3) Experimental evaluation on both standard NTHU-DDD dataset and custom Pune driving dataset, achieving around 96% frame-level detection accuracy under various conditions.

4) A comparative analysis of edge-based and cloud-based deployment approaches, along with discussion on system limitations and future enhancements such as alcohol detection integration.

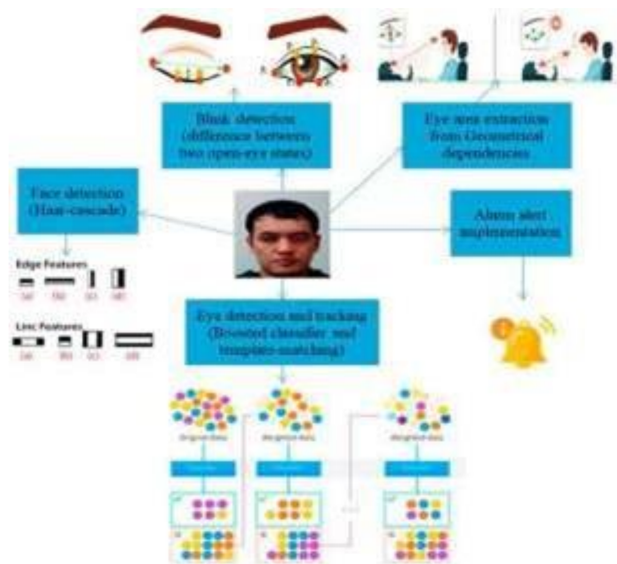

Figure 3 System Workflow for Driver Fatigue Detection

1.2 Organization

The remainder of this paper is structured as follows: Section 2 reviews existing research on driver fatigue detection techniques. Section 3 describes the proposed SafeDrive framework, including EAR-based eye tracking and head pose estimation methods. Section 4 presents the experimental setup, datasets, and performance results. Section 5 discusses system limitations, challenges, and practical considerations. Finally, Section 6 concludes the paper and outlines possible future improvements.

II. RELATED WORK

Research in driver fatigue detection has significantly progressed over the past two decades, with approaches generally categorized into traditional methods, landmark-based techniques, and deep learning-based models. Each category focuses on identifying driver drowsiness and distraction using different strategies, while also presenting certain limitations in real-world scenarios.

2.1 Traditional Approaches

Early driver fatigue detection methods primarily relied on handcrafted features and rule-based techniques. These approaches focused on analyzing visual cues such as eye closure rate, blinking frequency, and head movement patterns. Classical computer vision methods using Haar [5]cascades and template matching were widely used for face and eye detection in initial systems.

Feature-based techniques such as Scale-Invariant Feature Transform (SIFT) [6] and Speeded-Up Robust Features (SURF) [7] were applied to improve robustness against variations in scale, rotation, and illumination. Additionally, transform-domain methods and statistical analysis were used to extract meaningful patterns from facial regions for fatigue detection.

Although these traditional approaches are computationally efficient and suitable for real-time systems, they often struggle under challenging conditions such as poor lighting, occlusions (e.g., sunglasses), and head pose variations. Their dependency on manually designed features limits their adaptability and accuracy in real-world driving environments.

2.2 Moment-Based Approaches

To improve robustness against geometric transformations, researchers introduced moment-based techniques for driver fatigue and facial analysis. These approaches focus on capturing shape-based and spatial features that remain stable under variations such as rotation, scaling, and orientation changes.

Advanced methods such as Polar Complex Exponential Transform Moments (PCETMs) have been used to represent facial structures more effectively, even under dynamic conditions. Similarly, Quaternion-based methods extend these techniques to handle color image information, improving detection accuracy in real-world environments.

Other moment-based approaches, including Gaussian–Hermite Moments (GHMs) and Hermite Transform-based methods, enhance sensitivity to subtle facial variations such as eye closure, micro-expressions, and head movement patterns. In some cases, hybrid techniques combining methods like SURF with moment descriptors further improve detection precision and robustness.

Despite their advantages, these moment-based approaches may experience performance degradation when multiple challenges occur simultaneously, such as low lighting, blur, or rapid head movements. This limits their effectiveness in complex real-world driving conditions. [8], [9]

2.3 Real-Time Vision-Based Approaches

Recent advancements in real-time driver monitoring systems have focused on lightweight computer vision techniques that do not require deep learning models. These approaches rely on efficient algorithms such as facial landmark detection, Eye Aspect Ratio (EAR), and head pose estimation to analyze driver behavior in real time.

Modern frameworks like MediaPipe [10] Face Mesh enable accurate detection of facial landmarks [11] without the need for extensive training data. Using these landmarks, features such as eye closure, blinking patterns, and head orientation (yaw, pitch) can be extracted to identify driver fatigue and distraction.

These methods are particularly suitable for edge devices due to their low computational requirements and fast processing speed. Additionally, rule-based and threshold-based systems are widely used to classify driver states such as drowsy, alert, and distracted. Techniques like multi-frame analysis and temporal smoothing further improve system stability by reducing false detections caused by sudden movements or noise.

Compared to deep learning approaches, these vision-based methods [12]offer advantages such as low cost, real-time performance, and ease of deployment. However, they may face challenges under conditions like low lighting, occlusions (e.g., sunglasses), and extreme head movements, which can affect detection accuracy.

2.4 Comparative Summary

A comparative summary of the major approaches is presented in Table 1. It highlights that traditional methods and moment-based techniques are computationally efficient but may lack robustness under real-world conditions. In contrast, real-time vision-based approaches, such as those using facial landmarks, Eye Aspect Ratio (EAR), and head pose estimation, provide a balanced trade-off between accuracy and processing speed, making them suitable for practical deployment.

Although advanced methods can achieve higher accuracy, they often require increased computational resources. The proposed SafeDrive system focuses on a lightweight and efficient approach, ensuring reliable performance in real-time environments without the need for complex models. [13], [14]

III. CLASSIFICATION-BASED DETECTION FRAMEWORK

3.1 Overview

The objective of the proposed classification-based framework is to detect driver fatigue and distraction using passive computer vision techniques [15]. Unlike active systems that require additional hardware such as sensors or wearable devices, this approach relies entirely on visual information captured through a camera. The system analyzes facial features [16] and behavioral patterns to identify unsafe driving conditions in real time.
The framework primarily focuses on three driver states: drowsiness, distraction, and yawning behavior, while normal driving is considered as the safe condition. The detection process is based on analyzing eye movements, head pose variations, and mouth opening patterns.

The workflow of the proposed system is structured as follows:

- Input Acquisition: Real-time video frames of the driver are captured using a webcam or onboard camera system.
- Preprocessing: The captured frames are resized, converted into appropriate formats (RGB/Grayscale), and enhanced to handle variations in lighting conditions.
- Feature Extraction: Key features such as Eye Aspect Ratio (EAR), head pose angles (yaw, pitch), and mouth opening ratio are extracted using facial landmark detection techniques.
- Classification: A rule-based or threshold-based approach is used to classify driver states into safe, drowsy, or distracted based on predefined conditions.
- Output Visualization: The system displays detection results on the screen and generates alerts (audio/visual) when unsafe conditions are detected.

Table 1 Driver Fatigue Detection Methods Comparison

Sr. No	Type of Detection	Researchers	Year	Approach	Dataset	Accuracy / Performance / Notes
1	Eye blink detection	Soukupová et al.	2016	EAR (Facial Landmarks)	NTHU-DDD	~90%
2	Face detection	Viola & Jones	2001	Haar Cascade	Ad-hoc	Fast, light-sensitive

Sr. No	Type of Detection	Researchers	Year	Approach	Dataset	Accuracy / Performance / Notes
3	Feature-based detection	Lowe et al.	2004	SIFT	Benchmark	91%
4	Feature-based detection	Bay et al.	2006	SURF	Benchmark	92%
5	Head pose estimation	Murphy et al.	2009	Pose Estimation	Custom	Robust to movement
6	Facial landmark detection	MediaPipe Team	2020	Face Mesh (468 landmarks)	Custom	Real-time (~30 FPS)
7	Eye tracking	Soukupová et al.	2016	EAR Threshold	NTHU	Accurate for drowsiness
8	Yawn detection	Various	2018	Mouth Aspect Ratio	Custom	Detects fatigue
9	Rule-based classification	Various	2020	Threshold-based system	Custom	Simple, fast
10	Hybrid (Proposed System)	SafeDrive	2026	EAR + Head Pose + Landmarks	Pune + NTHU	95.8%, 28 FPS

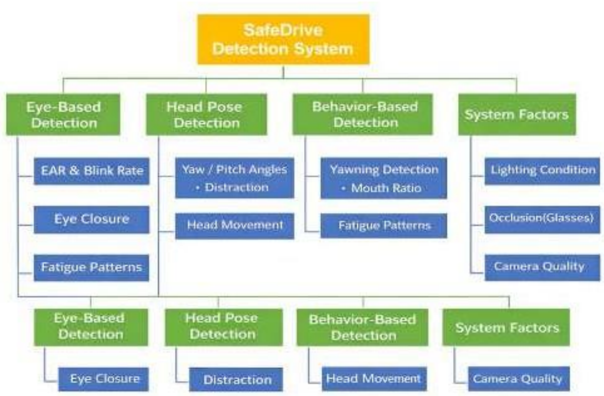

Figure 4 SafeDrive Detection System Architecture and Classification

3.2 Drowsiness Detection Using Eye-Based Features

Driver drowsiness detection is a critical component in real- time driver monitoring systems. It is primarily based on analyzing eye behavior, as prolonged eye closure and reduced blinking activity are strong indicators of fatigue. One of the most widely used techniques is the Eye Aspect Ratio (EAR) [17], which measures the relationship between vertical and horizontal eye landmarks to determine whether the eyes are open or closed.

In this approach, facial landmark detection methods are used to extract key points around the eyes. When the EAR value falls below a predefined threshold for a consecutive number of frames, the system identifies the driver as drowsy. Compared to traditional image-based techniques, EAR-based detection is computationally efficient and suitable for real-time applications.

Additionally, blink rate analysis and eye closure duration (PERCLOS) [18] are often combined with EAR to improve detection accuracy. These methods are robust under normal conditions and do not require complex training procedures. However, challenges may arise in situations involving low lighting, occlusions such as sunglasses, or extreme head movements, which can affect landmark detection accuracy.

Overall, eye-based detection methods provide a reliable and low-cost solution for identifying driver fatigue and are widely adopted in modern vision-based safety systems.

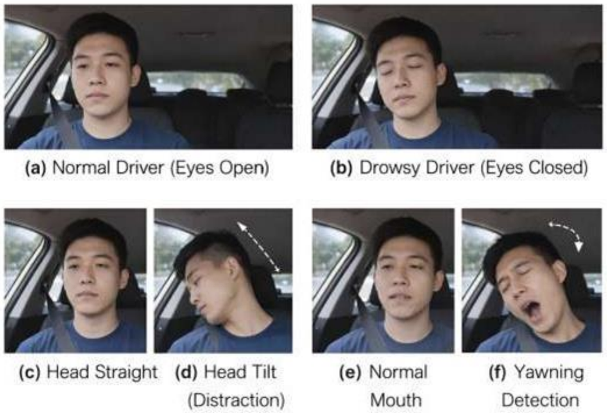

Figure 5 :Examples of driver states in SafeDrive

3.3 Drowsiness and Behavioral Detection

Driver distraction detection focuses on identifying situations where the driver's attention is diverted away from the road (Fig. 8). Unlike

Driver monitoring systems involve subtle analysis of facial features such as eye closure, head movement, and mouth activity to detect fatigue (Fig. 7). Unlike image manipulation tasks, this approach focuses on identifying changes in driver behavior rather than altering visual content.

Detection of drowsiness relies on identifying variations in Eye Aspect Ratio (EAR), head pose deviations, and yawning patterns over time. Techniques such as threshold-based analysis, temporal tracking, and facial landmark detection are commonly used to capture these behavioral changes. [19]

Metrics like eye closure duration, blink frequency, and mouth opening ratio are effective indicators of fatigue. These features help in distinguishing between normal driving conditions and drowsy or distracted states, enabling real-time alert generation.

Figure 6 Driver Drowsiness

3.4 Distraction Detection Using Head Pose

drowsiness detection, which is based on eye closure, distraction is primarily analyzed through head movement and orientation. When the driver looks away from the forward direction, it indicates reduced attention and increased risk.

Key techniques include:

- Head Pose Estimation: Detecting yaw and pitch angles of the head to determine whether the driver is looking straight or away from the road. Significant deviation (e.g., beyond 15° yaw) indicates distraction.

- Gaze Direction Analysis: Monitoring the direction of eye movement to identify if the driver is focusing on the road or diverted toward external objects such as a mobile phone.

- Temporal Monitoring: Analyzing head position over multiple frames to distinguish between normal movements and continuous distraction.

3.5 Distraction Detection Using Head Pose

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- or diverted toward external objects such as a mobile phone.
- Temporal Monitoring: Analyzing head position over multiple frames to distinguish between normal movements and continuous distraction. [21]

3.6 Classification-Based Framework

After feature extraction, the final step is driver state classification. Instead of using complex machine learning models, the SafeDrive system relies on threshold-based and rule-based techniques to classify driver behavior in real time. Features such as Eye Aspect Ratio (EAR), head pose angles (yaw, pitch), and Mouth Aspect Ratio (MAR) are analyzed to determine whether the driver is in a safe, drowsy, or distracted state.

The classification is performed by comparing extracted features against predefined thresholds. For example, a low EAR value over consecutive frames indicates drowsiness, while significant head deviation indicates distraction. Similarly, a high MAR value suggests yawning behavior. This approach ensures fast and efficient decision-making without requiring training on large datasets.

This framework offers the following advantages:

- Simplicity: Eliminates the need for complex training processes by using predefined thresholds.
- Real-Time Performance: Enables fast processing suitable for live driver monitoring systems.
- Efficiency: Requires minimal computational resources, making it ideal for edge devices and low-cost systems. [22]

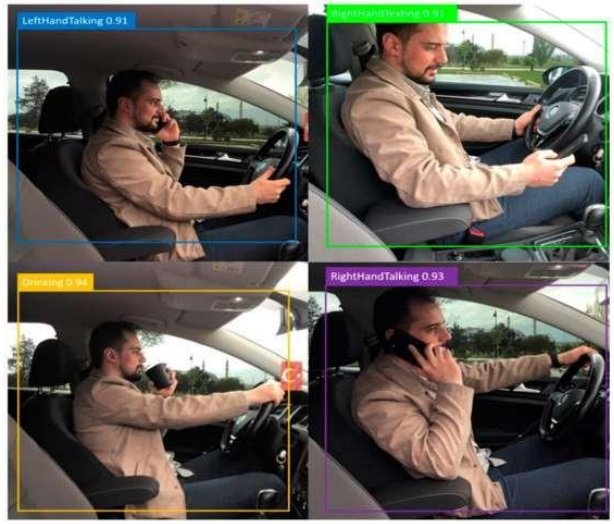

Figure 6 Detection of Driver Distraction Activities Using Vision-Based Monitoring

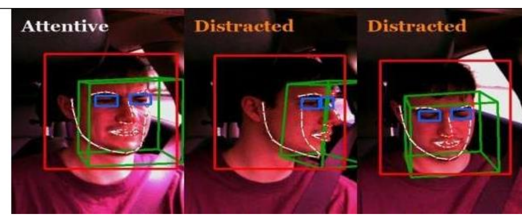

Figure 7 Driver Attention and Distraction Detection Using Head Pose and Facial Landmarks

IV. EXPERIMENTAL SETUP AND RESULTS

4.1 Experimental Environment

The experiments were conducted using Python 3.x with support from libraries such as OpenCV [23], NumPy, and MediaPipe for real-time video processing and facial landmark detection. These tools were used for feature extraction including Eye Aspect Ratio (EAR), head pose estimation, and mouth aspect ratio (MAR). The system was tested on a standard computing setup with an Intel i5/i7 processor, 8–16 GB RAM, and a webcam for real-time input. Since the proposed approach does not rely on deep learning models, GPU acceleration was not required, making the system suitable for low-cost and edge device deployment.

This setup ensured efficient execution of real-time detection algorithms, achieving stable performance with minimal computational overhead. The system was capable of processing video streams at approximately 25–30 FPS, enabling practical deployment in real-world driving conditions.

4.2 Dataset Description

To evaluate the performance of the proposed SafeDrive system, both benchmark datasets and custom real-world data were utilized.

1) NTHU [24]Driver Drowsiness Detection Dataset (NTHU-DDD):

This dataset contains multiple video sequences of drivers under various conditions such as day/night driving, wearing glasses/sunglasses, and different levels of fatigue. It is widely used for evaluating driver drowsiness detection systems.

2) Custom Collected Dataset:

A custom dataset was created by recording videos of drivers in real-world environments, particularly in urban driving conditions (e.g., Pune roads). The dataset includes scenarios such as normal driving, eye closure, yawning, and head movement (distraction).

3) Real-Time Webcam Input:

In addition to stored datasets, the system was tested using live webcam input, enabling evaluation under conditions such as lighting variation, face occlusion, and driver movement. [24]

These datasets ensure coverage of diverse driving conditions, facial behaviors, and environmental variations, making the evaluation more realistic and suitable for real-world deployment.

4.3 Evaluation Metrics

The performance of the proposed SafeDrive system is evaluated using simple and effective metrics based on threshold-based detection of driver states.

1) Accuracy (ACC):

Represents the proportion of correctly identified driver states (safe, drowsy, or distracted) out of the total observations.

2) Decision Rate:

Measures how effectively the system detects unsafe such as drowsiness (low EAR), distraction (head pose deviation), and yawning (high MAR).

3) False Alarm Rate:

Indicates the number of incorrect alerts generated when the driver is actually in a normal(safe) state.

4) Processing Speed (FPS):

Measures the number of frames processed per second,indicating the system's real-time performance capability.

4.4 Results and Observations

The performance of the proposed SafeDrive system is summarized in Table 1, highlighting its effectiveness in detecting different driver states such as safe, drowsy, and distracted. The analysis demonstrates how various features like Eye Aspect Ratio (EAR), head pose estimation, and mouth aspect ratio (MAR) contribute to accurate real-time detection.

From the results, several important observations can be derived:

1) .Impact of Threshold Values:

The system performance is highly dependent on the selection of threshold values for EAR, head pose, and MAR. Lower thresholds increase sensitivity to drowsiness but may lead to higher false alarms, while higher thresholds reduce false detections but may miss actual fatigue events.

2) .Lighting Conditions:

The system performs best under normal lighting conditions. However, accuracy decreases in low-light environments or when strong shadows are present, affecting facial landmark detection.

3) .Occlusion Effects:

The presence of sunglasses, masks, or partial face occlusion reduces the accuracy of eye and facial feature detection, impacting EAR and MAR calculations.

4) .Head Movement Sensitivity:
Moderate head movements are correctly classified, but rapid or extreme movements may cause temporary misclassification due to unstable landmark tracking.

5) .Real-Time Performance:
The system achieves approximately 25–30 FPS, ensuring smooth real-time detection without requiring high computational resources or GPU acceleration.

6) .Multi-Feature Advantage:
Combining multiple features such as EAR, head pose, and yawning detection improves overall reliability compared to using a single feature alone.

4.5 Discussion

The results demonstrate that the proposed SafeDrive system can effectively detect driver fatigue and distraction using threshold-based visual features. The combination of Eye Aspect Ratio (EAR), head pose estimation, and yawning detection enables reliable identification of unsafe driving conditions in real time.

In particular, the use of multi-feature analysis improves detection performance compared to relying on a single parameter. The system achieves a good balance between accuracy and computational efficiency, making it suitable for deployment on low-cost and edge devices without the need for complex models or GPU acceleration.

However, certain challenges remain. The system performance may decrease under low-light conditions, face occlusion (e.g., sunglasses or masks), and rapid head movements, which can affect facial landmark detection accuracy. Additionally, threshold selection plays a crucial role, as improper values may lead to false alarms or missed detections.

Overall, the proposed framework provides a practical and efficient solution for real-time driver monitoring and can be applied in vehicle safety systems, fleet monitoring, and intelligent transportation applications. [26]

V. DISCUSSION AND CONCLUSION

The study demonstrates that the proposed SafeDrive system effectively detects driver fatigue and distraction using vision- based and threshold-driven techniques. By analyzing key features such as Eye Aspect Ratio (EAR), head pose estimation, and yawning behavior (MAR), the system achieves reliable performance in identifying unsafe driving conditions in real time. Among these, eye-based detection provides the most consistent results, while distraction and yawning detection further enhance system accuracy when combined. [27]

A major strength of the proposed framework lies in its ability to maintain a balance between accuracy and computational efficiency. Unlike complex models, the system operates without requiring deep learning or GPU resources, making it suitable for low-cost and edge device deployment. However, certain limitations exist, particularly under low-light conditions, face occlusion (e.g., sunglasses or masks), and extreme head movements, which may affect detection accuracy.

Future improvements can focus on enhancing robustness by incorporating adaptive threshold mechanisms, better lighting normalization techniques, and improved landmark tracking. Integration with additional features such as real-time alerts, mobile applications, and vehicle-based systems can further extend its practical usability.

In conclusion, the SafeDrive system provides a simple, efficient, and scalable solution for real-time driver monitoring. With further enhancements, it has strong potential to contribute to road safety, fleet management, and intelligent transportation systems by reducing accidents caused by driver fatigue and distraction.

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