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Real-Time Driver Drowsiness And Fatigue Detection Using Facial Landmarks And Deep Learning: A Review And Webcam-Based System Design

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Abstract—Driver fatigue is one of the most common and preventable causes of road accidents. Long hours, monotonous highways and lack of rest reduce alertness, often without the driver noticing. Many existing solutions depend on wearable physiological sensors or expensive vehicle hardware that most drivers do not have. This paper reviews driver drowsiness detection approaches and presents the design of a real-time system that needs only an ordinary webcam. Behavioural, physiological and vehicle-based methods are compared, and vision-based techniques are examined in detail, including face detection, dense facial landmark extraction with MediaPipe Face Mesh, eye aspect ratio and mouth aspect ratio measures, PERCLOS and convolutional neural networks that verify eye closure and yawning. Public datasets for drowsiness and yawning are discussed. In the proposed design, OpenCV captures video, Face Mesh locates 468 landmarks, ratios are computed in every frame, and a CNN confirms closed eyes and yawns to reduce false alarms; if signs persist across consecutive frames, an audible alarm is raised. Research gaps, objectives, a comparison of methods and challenges such as night-time lighting, spectacles, head pose and individual variation are discussed.

Index Terms—Driver drowsiness detection, fatigue, eye aspect ratio, mouth aspect ratio, MediaPipe Face Mesh, CNN, PERCLOS, road safety

I. INTRODUCTION

Road safety reports [1], [2] show that India records a very large number of road deaths each year, and fatigue contributes to many crashes, especially among truck and long-distance drivers who drive at night. A drowsy driver may experience microsleeps lasting a few seconds, during which a vehicle at highway speed travels a long distance uncontrolled.

Fatigue develops gradually, and drivers often underestimate their own sleepiness. An automatic system that watches for signs of drowsiness and warns the driver can prevent crashes. Sikander and Anwar [3] reviewed driver fatigue detection systems and grouped them into subjective, vehicle-based, physiological and behavioural approaches.

This paper reviews these approaches with emphasis on low-cost vision methods and presents a webcam-based system design.

II. RELATED WORK

Viola and Jones [4] introduced boosted cascades of simple features for fast face detection, used in many early drowsiness systems. Kazemi and Sullivan [5] proposed regression-tree face alignment that estimates landmarks in about a millisecond, and Soukupová and Čech [6] used these landmarks to compute EAR and detect blinks robustly.

Kartynnik *et al.* [7] presented the model behind MediaPipe Face Mesh, which estimates 468 three-dimensional facial landmarks in real time on mobile GPUs, giving dense coverage of eyes and lips. Lin *et al.* [8] showed that a wearable EEG system can track vigilance accurately, but wearing electrodes is impractical for everyday drivers.

For learning-based detection, Weng *et al.* [9] introduced the NTHU drowsy driver dataset and a hierarchical temporal deep belief network. Ghoddoosian *et al.* [10] released a realistic dataset of drowsiness recorded in natural conditions and argued for temporal models. Abtahi *et al.* [11] provided the YawDD dataset of drivers yawning, talking and singing, useful for distinguishing yawns from speech. Ramzan *et al.* [12] surveyed techniques and concluded that combining measures improves reliability. Table I summarizes these works.

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Sr. No.	Ref.	Year	Methodology	Findings	Research Gap
1	[13]	1998	PERCLOS measure	Validated eye-closure alertness metric	Needs reliable eye tracking
2	[4]	2001	Boosted cascade face detection	Fast face localization	Sensitive to pose and lighting
3	[8]	2014	Wearable EEG vigilance	Accurate fatigue tracking	Intrusive
4	[11]	2014	YawDD yawning dataset	Yawns vs. talking and singing	Limited drivers
5	[6]	2016	Eye aspect ratio from landmarks	Simple robust blink detection	Fixed threshold issues
6	[9]	2016	Hierarchical temporal DBN; NTHU dataset	Temporal drowsiness modelling	Acted scenarios
7	[7]	2019	Face Mesh (468 landmarks)	Dense real-time facial geometry	Occlusion by sunglasses
8	[10]	2019	Realistic drowsiness dataset	Natural early drowsiness	Not in vehicles

TABLE I Summary of Literature Survey

III. PRELIMINARIES

3.1 Approaches To Drowsiness Detection

Fig. 1 summarizes the main categories. Physiological methods such as EEG are accurate but intrusive; vehicle-based methods analyse steering and lane position but react late; behavioural vision methods observe the eyes, mouth and head non-intrusively.

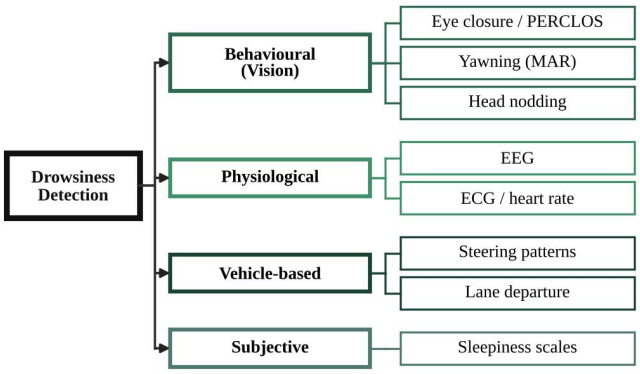


Fig. 1. Approaches to driver drowsiness detection.

3.2 Eye And Mouth Measures

PERCLOS, the percentage of time the eyes are mostly closed over a window, was validated by Dinges and Grace [13] as a reliable measure of reduced alertness. The eye aspect ratio (EAR) of Soukupová and Čech [6] provides a frame-by-frame measure of eye opening from facial landmarks, and a mouth aspect ratio (MAR) similarly measures mouth opening for yawn detection.

IV. PROBLEM STATEMENT AND OBJECTIVES

4.1 Identified Research Gaps

Single-threshold EAR systems produce false alarms when drivers glance down or squint in sunlight.

Performance at night and with spectacles or sunglasses is rarely evaluated.

Many datasets are recorded in simulators rather than real vehicles.

Individual differences in eye shape require calibration that many systems lack.

Low-cost systems for Indian commercial drivers are scarce.

4.2 Objectives Of The Review

- **O1:** To review drowsiness detection approaches and their trade-offs.
- **O2:** To study facial landmark-based measures and CNN verification.
- **O3:** To design a real-time webcam-based drowsiness and fatigue alert system.
- **O4:** To compare methods in accuracy, cost and intrusiveness.

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- **O5:** To identify challenges and future improvements.

4.3 Proposed Framework

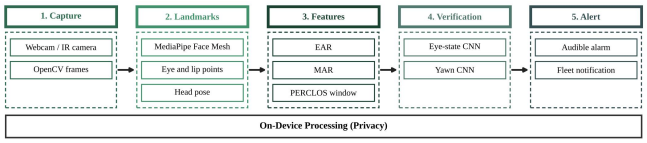


Fig. 2 shows the proposed system.

Fig. 2. Proposed webcam-based drowsiness and fatigue alert system.

4.4 Capture Layer

A dashboard webcam (preferably with infrared illumination for night use) captures the driver's face at 20–30 frames per second through OpenCV.

4.5 Landmark Layer

MediaPipe Face Mesh locates 468 landmarks; eye and mouth points are selected and head pose is estimated.

C. Feature Layer

EAR, MAR and PERCLOS over a sliding window are computed; blink rate and yawn frequency are tracked.

4.6 Verification Layer

A small CNN classifies cropped eye and mouth regions as open or closed and yawning or not, confirming the ratio-based signals.

4.7 Alert Layer

If closed eyes or yawns persist beyond a set number of frames, an audible alarm sounds and, optionally, a message is sent to a fleet manager.

V. WORKING METHODOLOGY

Fig. 3 shows the per-frame processing. The eye aspect ratio is

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

and the mouth aspect ratio (MAR) is defined analogously from lip landmarks. An alert is raised when EAR stays below a threshold τ_E for N_E consecutive frames, or MAR stays above τ_M for N_M frames, where thresholds are calibrated for each driver during the first minute of driving. Combining ratio checks with CNN verification reduces false alarms.

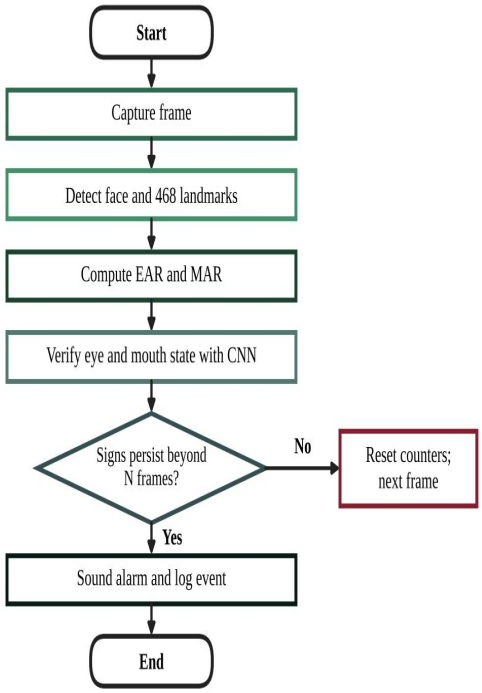


Fig. 3. Per-frame drowsiness detection workflow.

VI. DISCUSSION

6.1 Comparison Of Approaches

Table II compares drowsiness detection methods. Vision methods offer the best balance of cost and non-intrusiveness, physiological methods are most accurate but intrusive, and vehicle-based methods are passive but react late.

Method	Accuracy	Cost	Intrusiveness
EAR threshold only	Medium	Very low	None
EAR + MAR + CNN	High	Low	None
EEG headset	Very high	High	High
Steering analysis	Medium	Medium	None

TABLE II Comparison of Drowsiness Detection Methods

6.2 Open Challenges And Future Work

Table III summarizes challenges. Future work includes infrared cameras for night driving, temporal deep models trained on real-road data, integration with vehicle systems

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to slow the vehicle safely, and smartphone-based versions for two-wheeler and truck drivers.

Challenge	Mitigation
Night driving	Infrared camera and illumination
Spectacles / sunglasses	CNN verification; IR imaging
Head pose changes	Pose-aware landmark selection
Individual differences	Per-driver calibration
Alarm fatigue	Escalating alerts; rest suggestions

TABLE III Challenges and Mitigation

VII. CONCLUSION AND FUTURE WORK

Driver drowsiness detection can prevent a significant share of fatigue-related crashes. The reviewed literature shows that dense facial landmarks, EAR and MAR measures and CNN verification together enable accurate, real-time detection with only a webcam. Calibration, night-time capability and real-road validation are the main steps needed before such systems can be widely deployed.

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