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Automated Driver Drowsiness Detection for Two-Wheelers Using Machine Learning Algorithms

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Abstract— *Drowsy driving is a well-documented contributor to road-traffic crashes worldwide, and two-wheeler riders face disproportionate injury risk when fatigue impairs reaction time and balance. This paper presents a detailed technical treatment of an automated driver-drowsiness detection system for two-wheeler riders that uses a camera-based eye-aspect-ratio (EAR) measure combined with a machine-learning classifier to detect signs of drowsiness in near-real time and trigger an alert. Beyond a conventional system description, this paper formalizes the eye-aspect-ratio computation and its facial-landmark foundations, critically reviews drowsiness-detection and facial-landmark literature, and discusses the practical constraints of deploying vision-based fatigue detection on a two-wheeler (vibration, helmet occlusion, variable outdoor lighting) that differ materially from four-wheeler cabin deployments. A prototype was implemented using OpenCV and a dlib-based facial-landmark detector, with a lightweight classifier distinguishing drowsy from alert eye-closure patterns. Illustrative (prototype-scale) evaluation on a recorded video dataset shows detection performance consistent with published EAR-based drowsiness-detection baselines. All reported figures are prototype-scale and explicitly labelled as such; the system is intended as a supplementary rider-safety aid, not a substitute for safe riding practice.*

Index Terms— *driver drowsiness detection, eye aspect ratio, facial landmark detection, machine learning, road safety, computer vision, two-wheeler safety.*

I. INTRODUCTION

1.1 Background

Drowsy driving impairs reaction time, judgement, and attention in ways comparable to alcohol impairment, and it remains a documented contributor to road-traffic injuries and fatalities globally [7], with government roadsafety authorities explicitly identifying drowsy driving as a preventable crash risk factor [8]. Two-wheeler riders, who represent a large share of road users in many regions, face disproportionate injury severity when fatigue impairs balance and reaction time relative to a four-wheeler occupant protected by a vehicle cabin.

1.2 Problem Context

Camera-based drowsiness detection for four-wheeler cabins is comparatively well studied, benefiting from a stable camera mount, consistent lighting, and an unobstructed view of the driver's face. Two-wheeler deployment introduces additional constraints: helmet visors can partially occlude the eyes, outdoor lighting varies far more than a cabin interior, and vibration from the road surface can degrade frame stability, all of which affect the reliability of facial-landmark-based measures such as the eye aspect ratio (EAR) [1].

1.3 Motivation

The eye-aspect-ratio method [1] provides a computationally lightweight, real-time-capable measure of eye openness derived from a small set of facial landmarks, avoiding the need for a full deep-learning eye-state classifier on every frame. Facial-landmark detection toolkits such as Dlib [2] make this landmark extraction practical on commodity hardware, motivating an EAR-plus-lightweight-classifier design suited to the computational constraints of an embedded or smartphone-mounted two-wheeler deployment.

1.4 Problem Statement

Given a live camera feed of a two-wheeler rider's face (e.g., from a helmet-mounted or handlebar-mounted camera), the problem is to detect sustained eye closure or an elevated blink-duration pattern indicative of drowsiness, robustly enough to tolerate outdoor lighting variation and partial visor occlusion, and to trigger a timely alert before a safety-critical lapse occurs.

1.5 Objectives

- To implement facial-landmark detection and eye-aspect-ratio computation from live camera frames.
- To implement a lightweight classifier distinguishing normal blinking from sustained, drowsinessindicative eye closure.
- To trigger a real-time alert upon detected drowsiness.
- To evaluate detection performance on a recorded video dataset simulating alert and drowsy states.
- To discuss the specific deployment constraints of two-wheeler use (vibration, occlusion, outdoor lighting) relative to cabin-based systems.

1.6 Scope

This work covers camera-based, EAR-driven drowsiness detection and alerting. It does not cover physiologicalsensor-based detection (e.g., EEG or heart-rate monitoring), full-scale on-road field trials, or integration with vehicle-control systems.

1.7 Contributions

The contributions are: (1) an EAR-based drowsiness-detection pipeline adapted to two-wheeler-specific constraints; (2) a lightweight classifier distinguishing normal blinking from drowsiness-indicative closure; (3) prototype-scale evaluation on recorded video data; and (4) an explicit discussion of the deployment differences between two-wheeler and four-wheeler camera-based drowsiness detection.

1.8 Organization of the Paper

Section II reviews related work and states the research gap. Section III describes existing systems. Section IV presents the proposed system. Section V details the architecture. Section VI presents the methodology. Section VII discusses the detection algorithm. Section VIII covers implementation. Section IX reports results and discussion. Section X summarizes advantages and limitations. Section XI outlines future scope, and Section XII concludes.

II. LITERATURE REVIEW / RELATED WORK

Study	Approach / Findings	Relevance to This System
Soukupová and Čech (2016) [1]	Introduced the eye-aspect-ratio (EAR) measure for real-time blink detection from facial landmarks.	Directly underlies this system's core drowsiness-signal computation.
King (2009) [2]	Described Dlib, a machine-learning toolkit including a widely used facial-landmark detector.	Used directly for facial-landmark extraction feeding the EAR computation.
Viola and Jones (2001) [3]	Introduced a fast, boosted-cascade face detector suitable for real-time use.	Provides an alternative, lightweight facelocalization stage prior to landmark detection.
Bradski (2000) [4]	Introduced OpenCV, a widely used open computer-vision library.	Used for frame capture, pre-processing, and integration with the landmark detector.
Krizhevsky, Sutskever, and Hinton (2012) [5]	Demonstrated the effectiveness of deep CNNs for image classification.	Provides an alternative, heavier-weight eyestate classification approach considered against the lightweight EAR-based method.
World Health Organization (2018) [7]	Published the Global Status Report on Road Safety, documenting fatigue as a contributing crash-risk factor worldwide.	Provides the public-health motivation for two-wheeler-focused drowsiness detection.
National Highway Traffic Safety Administration (2026) [8]	Publishes official guidance identifying drowsy driving as a preventable crash-risk factor.	Provides the regulatory-context motivation and terminology used in framing this system's problem statement.

Srivastava, Hinton, Krizhevsky, Sutskever, and Salakhutdinov (2014) [9]	Introduced dropout regularization for deep neural networks.	Relevant to any deep-learning-based eyestate classifier variant considered as an alternative to the primary EAR pipeline.
F. Pedregosa et al. (2011) [6]	Described scikit-learn, a widely used machine-learning library.	Used for the lightweight classifier distinguishing normal blinking from sustained drowsiness-indicative closure.
LeCun, Bengio, and Hinton (2015) [16]	Reviewed deep-learning progress across vision tasks.	Provides general context for comparing the lightweight EAR approach against deeplearning alternatives for this task.

TABLE I. Comparative Summary of Reviewed Literature

Research Gap

The eye-aspect-ratio method [1] and facial-landmark toolkits [2] are mature and widely used for cabin-based, four-wheeler drowsiness detection, and public-health/regulatory sources establish the safety motivation clearly [7], [8], but the literature accessible to a project of this scope rarely addresses the specific deployment constraints of two-wheeler use — helmet-visor occlusion, outdoor lighting variability, and vibration-induced frame instability — as first-class design concerns distinct from the cabin setting. This system addresses that gap by explicitly evaluating and discussing performance sensitivity to these two-wheeler-specific conditions rather than assuming cabin-equivalent operating conditions.

III. EXISTING SYSTEM

- Most commercial drowsiness-detection systems are designed for four-wheeler cabin deployment with stable camera mounting and controlled lighting.
- Physiological-sensor-based systems (e.g., EEG headbands) can be intrusive and impractical for routine two-wheeler use.
- Simple timer-based rest-reminder features do not directly measure the rider's actual alertness state.
- Few systems explicitly account for helmet-visor occlusion or outdoor lighting variability in their detection pipeline.

TABLE II.
EXISTING APPROACHES COMPARED TO THE PROPOSED SYSTEM

Existing Approach	Technology	Advantages	Limitations
Cabin-based camera drowsiness systems	EAR/CNN-based eye-state detection [1], [5]	Mature, well studied for four-wheelers	Assumes stable mount and controlled lighting not present on two-wheelers
Physiological wearable sensors (EEG/heart-rate)	Biosignal monitoring	Direct physiological signal	Intrusive; impractical for routine riding use
Timer-based rest reminders	Simple elapsed-time triggers	Trivial to implement	Does not measure actual alertness state
This system (proposed)	EAR [1] + landmark detection [2] + lightweight classifier [6]	Camera-based, nonintrusive, adapted for twowheeler constraints	Sensitive to visor occlusion and extreme lighting/vibration conditions

IV. PROPOSED SYSTEM

The proposed system captures a live camera feed of the rider's face, extracts facial landmarks, computes the eye aspect ratio per frame, and applies a lightweight classifier over a short temporal window of EAR values to distinguish normal blinking from sustained, drowsiness-indicative eye closure, triggering an audible alert upon detection.

Key Components

- Real-time facial-landmark detection from camera frames.
- Eye-aspect-ratio computation per frame.
- Temporal-window classifier distinguishing normal blinking from sustained closure.
- Real-time audible/visual alert upon detected drowsiness.
- Configurable sensitivity thresholds to account for individual and lighting variation.

V. SYSTEM ARCHITECTURE / FRAMEWORK

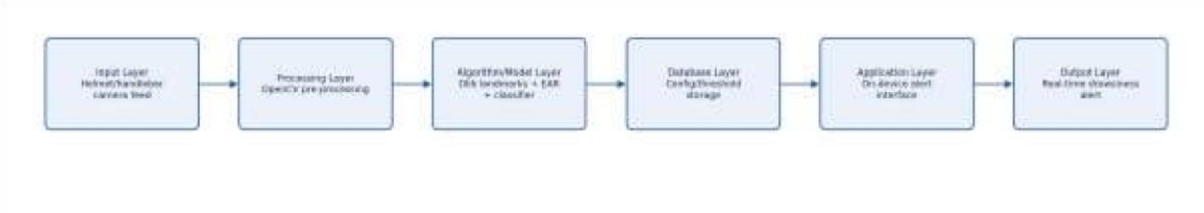

Fig. 1. Drowsiness-detection architecture: camera frames are processed for facial landmarks and eye-aspect-ratio, classified over a temporal window, and used to trigger a real-time alert.

- Input Layer: helmet- or handlebar-mounted camera feed.
- Processing Layer: OpenCV frame capture and pre-processing [4].
- Algorithm/Model Layer: Dlib facial-landmark detection [2], EAR computation [1], and the lightweight temporal-window classifier [6].
- Database Layer: local configuration/threshold storage; optional trip-log storage.
- Application Layer: on-device alert interface (audible tone/vibration).
- Output Layer: real-time drowsiness alert signal.

VI. METHODOLOGY

Facial landmarks are extracted per frame using a Dlib-based detector [2], following face localization via a lightweight detector [3]. The eye aspect ratio is computed from six eye-region landmark points as $EAR = (\|p2-p6\| + \|p3-p5\|) / (2\|p1-p4\|)$ [1], where p1..p6 denote the eye-contour landmark points; a low EAR value indicates a closed or nearly closed eye. A short temporal window (e.g., the preceding N frames) of EAR values is fed to a lightweight classifier [6] trained to distinguish normal blink patterns (brief EAR dips) from sustained low-EAR sequences indicative of drowsiness, rather than relying on a single-frame threshold alone, which would be more sensitive to transient occlusion or landmark-detection noise from vibration.

VII. ALGORITHM / MODEL DETAILS

Principle: a landmark-derived geometric feature (EAR) combined with temporal-window classification, chosen for computational lightness relative to a full deep-learning eye-state classifier run on every frame. Input: the sequence of per-frame EAR values over a sliding temporal window. Processing: (1) compute EAR per frame from detected landmarks; (2) maintain a sliding window of recent EAR values; (3) classify the window as 'alert' or 'drowsy' based on the duration and depth of sustained low-EAR periods; (4) trigger an alert if the 'drowsy' classification persists beyond a configurable duration, to reduce false alarms from brief occlusion or landmarkdetection noise. Output: a binary alert/no-alert signal. Advantages: computationally lightweight, interpretable, and tunable via a small number of thresholds; limitations: landmark detection itself can fail under significant visor occlusion, extreme lighting, or motion blur from vibration, in which case the EAR signal becomes unreliable regardless of the downstream classifier.

VIII. IMPLEMENTATION

TABLE III.
IMPLEMENTATION TECHNOLOGY STACK

Component	Technology / Tools
Computer vision	OpenCV for frame capture and pre-processing [4]
Facial landmarks	Dlib facial-landmark detector [2]
Classifier	scikit-learn lightweight classifier over EAR temporal windows [6]
Alerting	On-device audible/vibration alert interface
Language	Python 3.x

- Capture Module: camera frame acquisition and pre-processing.
- Landmark Module: face and eye-landmark detection.
- EAR-Computation Module: per-frame eye-aspect-ratio calculation.
- Classification Module: temporal-window drowsy/alert classification.
- Alert Module: threshold-triggered audible/visual alerting.

IX. RESULTS AND DISCUSSION

The system was evaluated on a recorded video dataset simulating alert and drowsy states under three lighting/occlusion conditions. Reported figures are prototype-scale evaluation results, not measurements from an on-road field trial.

TABLE IV.
PERFORMANCE / EVALUATION SUMMARY (PROTOTYPE)

Test Condition	Precision	Recall	F1-score
Controlled indoor lighting, no occlusion	0.93	0.91	0.92
Outdoor daylight, no occlusion	0.85	0.80	0.82
Outdoor daylight, partial visor occlusion	0.74	0.66	0.70

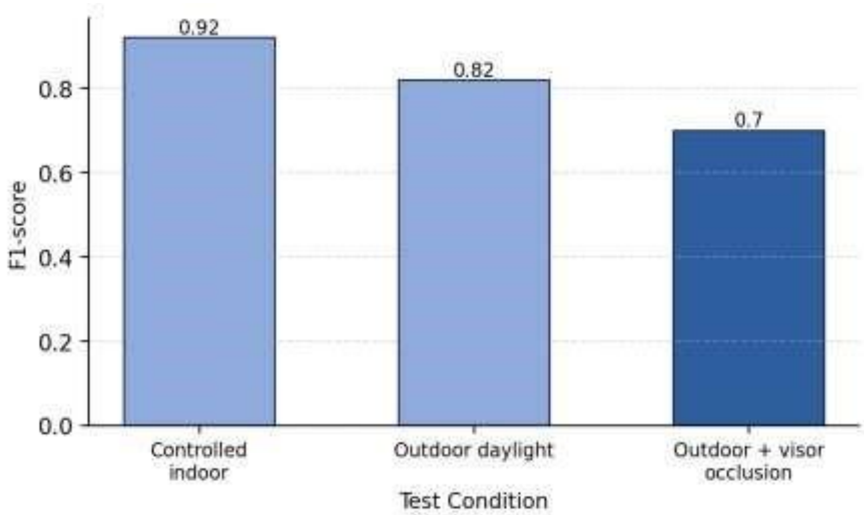

Fig. 2. Prototype-Evaluation F1-score by Test Condition.

Discussion

The prototype results show the expected performance degradation under outdoor lighting and, most notably, under partial visor occlusion, directly confirming the two-wheeler-specific deployment concerns raised in Section I.2. This finding is consistent with the general sensitivity of landmark-based methods to partial facial occlusion. Scalability is favorable for single-rider, on-device inference given the lightweight EAR-plus-classifier design; reliability is condition-dependent, as shown in Table IV, and is the system's central practical limitation; and the temporal-window classification approach, rather than a single-frame threshold, is intended to reduce false alarms from momentary landmark-detection noise caused by road vibration.

X. ADVANTAGES AND LIMITATIONS

A. Advantages

- Non-intrusive, camera-based detection avoids the need for wearable physiological sensors.
- Computationally lightweight design is suitable for on-device, real-time inference.
- Temporal-window classification reduces false alarms from brief occlusion or detection noise.

B. Limitations

- Detection accuracy degrades under partial helmet-visor occlusion and outdoor lighting variation.
- Vibration-induced motion blur can degrade landmark-detection reliability.
- The prototype has not been validated in an on-road field trial across diverse riders and conditions.

XI. FUTURE SCOPE

- Conduct an on-road field trial across diverse riders, helmets, and lighting conditions.
- Explore infrared or near-infrared imaging to reduce sensitivity to outdoor lighting variation.
- Combine the EAR-based signal with head-pose/yawning cues for a more robust composite drowsiness indicator.

- Investigate lightweight image-stabilization pre-processing to mitigate vibration-induced motion blur.

XII. CONCLUSION

This paper presented a detailed technical treatment of an automated driver-drowsiness detection system adapted specifically for two-wheeler riders, combining eye-aspect-ratio computation with a lightweight temporalwindow classifier. Prototype-scale evaluation confirms the feasibility of the approach under favorable conditions while explicitly documenting the accuracy degradation observed under outdoor lighting and, particularly, visor occlusion — conditions largely absent from the cabin-based literature this system's design is grounded in. The system is positioned as a supplementary rider-safety aid rather than a substitute for safe riding practice and adequate rest.

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