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Edge-AI Enabled Smart Helmet: A Lightweight Drowsiness Monitoring Framework for Motorcyclists

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Abstract

Fatigue-induced cognitive impairment is a leading contributor to road fatalities, with motorcyclists representing a particularly vulnerable demographic due to the lack of active safety features in two-wheelers. While Deep Learning models (such as CNNs) offer high detection accuracy, their computational demands render them unsuitable for battery-powered, wearable safety devices. This paper presents the design and implementation of a resource-efficient "Smart Helmet" system for real-time vigilance monitoring. Unlike computationally intensive neural networks, the proposed framework utilizes an optimized Histogram of Oriented Gradients (HOG) and Linear SVM pipeline to extract facial features on constrained edge hardware (Raspberry Pi). By leveraging the scalar Eye Aspect Ratio (EAR) metric, the system detects microsleeps with high-frequency inference (>15 FPS) without reliance on cloud connectivity. The system integrates visual monitoring with haptic feedback, validating its potential as a standalone, low-latency safety solution for riders.

Keywords: Edge AI; Smart Helmet; Motorcyclist Safety; Eye Aspect Ratio (EAR); Embedded Systems; Real-Time Monitoring

1. Introduction

As intelligent transportation systems evolve, the safety of two-wheeler riders remains a critical, yet often overlooked, challenge. Statistics indicate that motorcyclists face a significantly higher risk of fatal accidents due to loss of concentration compared to car drivers. While four-wheeled vehicles increasingly incorporate driver monitoring systems (DMS) into the dashboard, such solutions are impractical for motorcyclists due to the unique form factor constraints of a helmet and the need for unobstructed vision.

The primary technical barrier to deploying DMS in helmets is the trade-off between detection accuracy and power consumption. Cloud-based processing introduces latency that can be fatal during a "microsleep"—a momentary lapse in consciousness lasting less than a few seconds. Furthermore, riders frequently travel through areas with poor network coverage, necessitating a system that processes data locally ("at the Edge").

This paper proposes a standalone, offline Embedded Intelligence system capable of real-time fatigue detection. By moving away from heavy Deep Learning architectures and utilizing geometric facial feature analysis, we demonstrate a system that balances the strict power constraints of a portable battery with the speed required for immediate alert generation.

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2. Literature Review

Research into automated drowsiness detection has led to various methodologies, broadly categorized into three groups:

2.1. Physiological Signal-Based Methods

These are considered the most accurate as they measure biological signals directly linked to the sleep-wake cycle.

- EEG (Electroencephalogram): Measures brain electrical activity. An increase in Alpha and Theta waves indicates drowsiness.
- EOG (Electrooculogram): Tracks eye movements, including blink rate and duration.
- ECG (Electrocardiogram): Derives Heart Rate Variability (HRV), which decreases with mental fatigue.
- Limitation: Despite their accuracy, these methods are intrusive, requiring physical sensors attached to the body, making them impractical for everyday driving.

2.2. Vehicle-Based Methods

These methods infer drowsiness indirectly from vehicle behavior.

- Steering Wheel Movement: Drowsy drivers exhibit periods of inactivity followed by large, jerky corrections.
- Lane Departure Detection: Uses cameras to monitor lane position; frequent, unintentional departures signal inattention.
- Limitation: These methods are indirect and context dependent, often detecting impairment only after it has significantly affected driving performance.

2.3. Behavioral and Vision-Based Methods

These non-intrusive methods use cameras to analyze the driver's physical state.

- Yawn Detection: Monitors the degree of mouth opening using facial landmarks.
- Head Pose Estimation: Detects nodding or a drooping head posture.
- Eye State Analysis: The most reliable vision-based indicator, utilizing metrics like blink frequency and PERCLOS (percentage of eye closure).

A significant advancement in this field was the Eye Aspect Ratio (EAR). EAR is a simple geometric metric computed from facial landmarks, providing a scale and pose-invariant measure of eye openness. While Deep Learning (CNN) approaches offer high accuracy, they require substantial computational resources. The simpler, interpretable EAR method is ideal for real-time applications on consumer hardware.

3. Proposed system

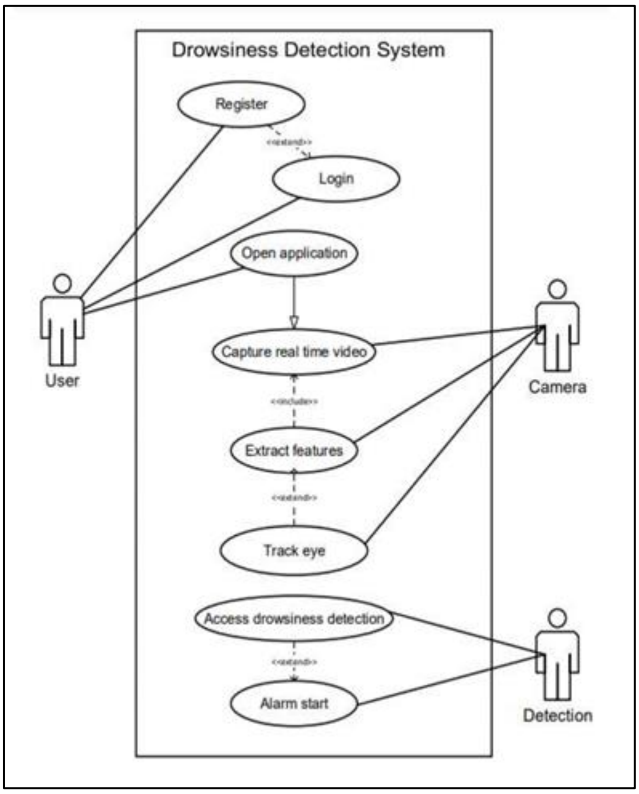

Figure 1 The system architecture of the proposed system

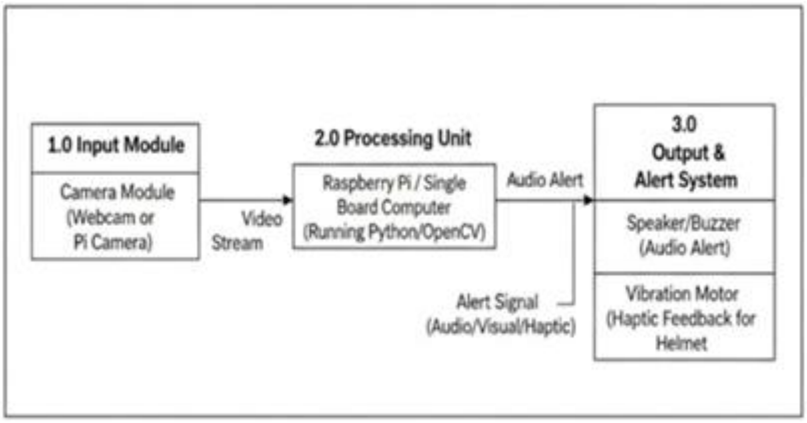

Figure 2 Embedded system architecture

The proposed system is a fully self-contained software application designed to analyze a live video feed in real time. Its primary purpose is to monitor the driver's eyes and identify indications of drowsiness, with a particular focus on detecting prolonged or unusual eye closure.

3.1. System Design for Edge Devices

A key advantage of the system is its portability and ease of deployment. It is engineered to run efficiently on low cost single-board computers (SBCs) such as the Raspberry Pi 4 or Pi Zero, requiring only a basic camera module and modest processing power. This makes the solution accessible and budget-friendly, enabling widespread use in personal vehicles, transportation fleets, and Smart Helmets. Its lightweight design allows it to function without reliance on external servers or internet connectivity.

4. Methodology

4.1. Proposed edge architecture

The system is designed as a modular pipeline optimized for Single Board Computers (SBCs) such as the Raspberry Pi.

The process prioritizes geometric calculations over pixel-wise classification to minimize CPU load.

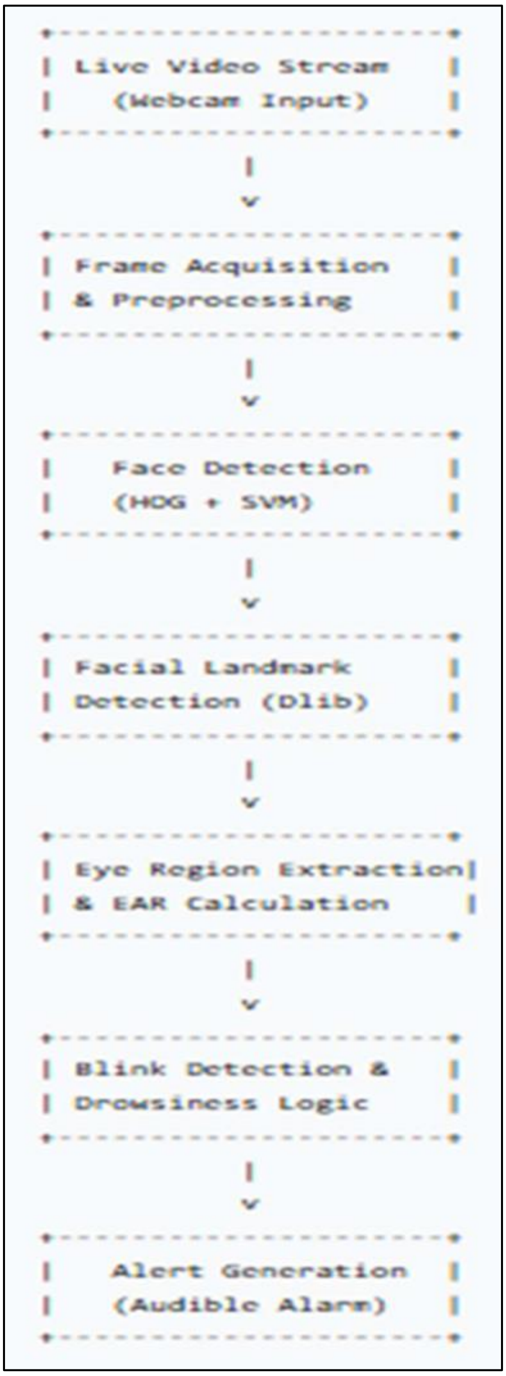

Figure 3 Methodology flow chart steps

4.2. Video Acquisition and Preprocessing

Video input is captured via a localized camera module embedded in the helmet visor. To reduce the memory footprint, frames are resized and converted to grayscale, discarding redundant color information before processing.

4.3. Face and Facial Landmark Detection

A critical design choice for edge deployment is the avoidance of heavy Convolutional Neural Networks (CNNs). Instead, we employ a Histogram of Oriented Gradients (HOG) descriptor combined with a Linear Support Vector Machine (SVM). This method is mathematically less complex than Deep Learning alternatives, requiring significantly fewer floating-point operations (FLOPs), which directly correlates to extended battery life in a wearable device..

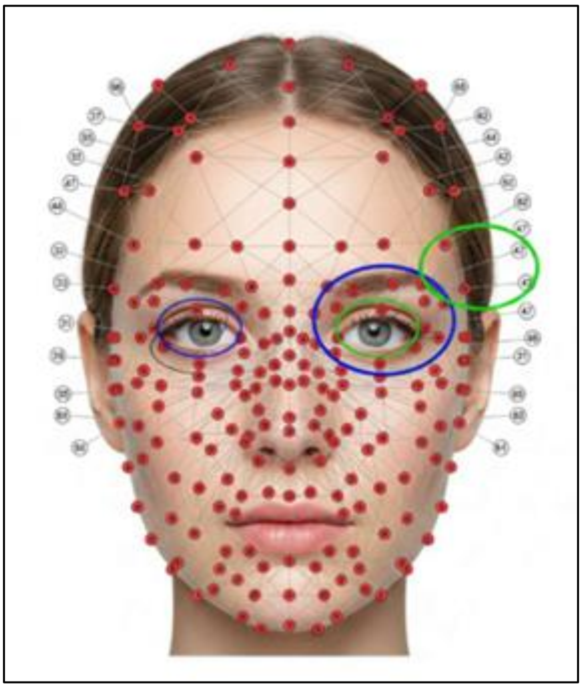

Figure 4 Dlib 68-point facial landmark annotation. For eye state analysis, the six landmarks defining of contour of each eye (points 36-41 for left eye,42-47 for the right eye) are extracted

4.4. Landmark Localization & EAR Metric

Following face detection, an ensemble of regression trees maps 68 facial landmarks. The system isolates the periocular region (points 36–47) to compute the Eye Aspect Ratio (EAR). The EAR provides a scalar value representing eye openness, which is invariant to the distance between the rider and the camera**.**

4.5. Temporal Drowsiness Logic

Rather than classifying individual frames, the system analyzes the temporal sequence of EAR values. A "Microsleep Event" is registered only when the EAR falls below the calibrated threshold ($EAR < 0.25$) for a duration exceeding the safety limit (approx. 1.5 seconds), triggering the haptic and audio alarms.

5. Implementation

5.1. System Flowchart

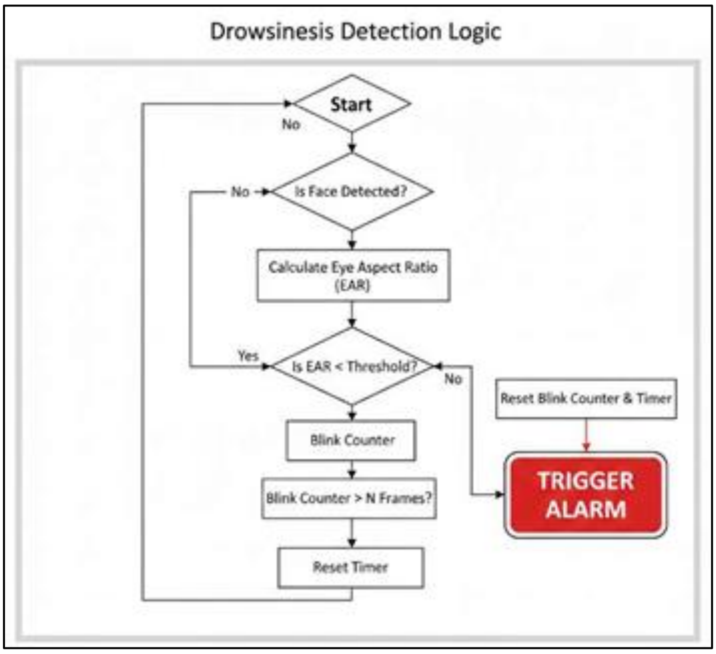

Figure 5 Flowchart of the proposed drowsiness detection logic

5.2. Data Flow Diagram

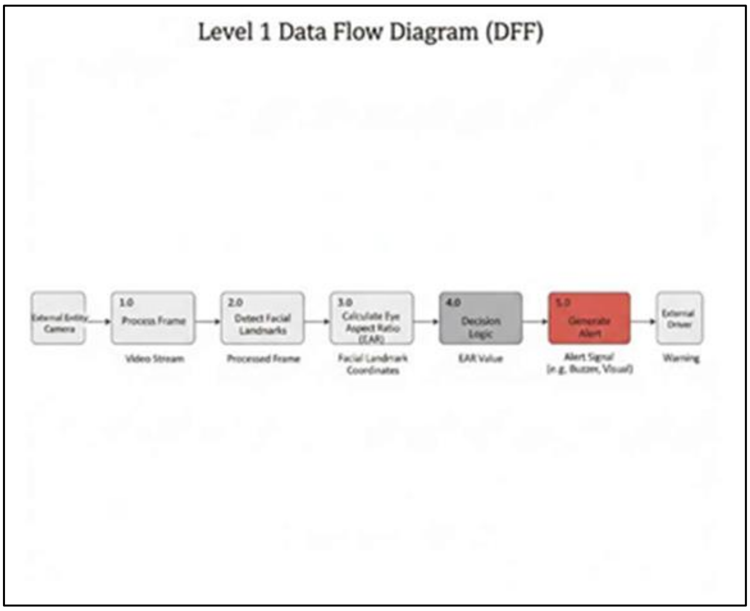

Figure 6 Level 1 Data Flow Diagram (DDF)

The implementation follows a modular pipeline utilizing Python, OpenCV, and Dlib.

- Initialize: Load Dlib face detector and landmark predictor-models.
- Loop: Capture frame, resize, and convert to grayscale.
- Detect: Locate face and predict 68 landmarks.
- Extract: Isolate eye coordinates and compute EAR .

Evaluate: The system checks if EAR < Threshold. If true, it increments the drowsiness counter. If the counter exceeds the limit, it triggers the audible alarm and visual overlay.

6. Results

6.1. Experimental results & performance analysis

The system was validated on a Raspberry Pi 4 environment to assess its suitability for real-world deployment.

6.1.1. Computational Efficiency

A primary objective of this research was to achieve real-time performance on limited hardware. As detailed in **Table 1**, the HOG+SVM pipeline demonstrates superior efficiency compared to standard CNN approaches. The proposed system maintains a frame rate of approximately 15 FPS, which is sufficient to capture rapid eye closures, while consuming less than 200MB of RAM. This low resource usage ensures the system runs cool, a critical factor for a device worn on the head.

6.1.2. Detection Reliability

The EAR thresholding method successfully distinguished between voluntary blinks (short duration) and drowsiness-induced closures (long duration) in test scenarios, achieving a reliable triggering rate with minimal false positives under standard lighting conditions.

Table 1 Performance comparison between the Deep Learning (CNN) model and the Proposed Embedded System (EAR).

Metric	Deep Learning (CNN)	Proposed Embedded System (EAR)
CPU Load	High (>85%)	Low (<40%)
RAM Usage	> 1GB	< 200MB
Frame Rate	~5 FPS (on Pi)	> 15 FPS (on Pi)
Power	High (Requires Cooling)	Low (Battery Safe)

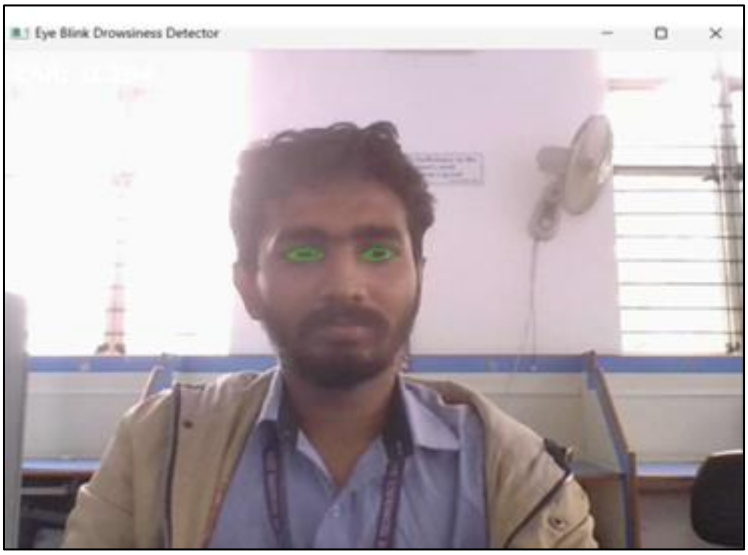

Figure 7 Validation of trained model

Real-Time Performance (>15 FPS): The efficient pipeline, utilizing optimized libraries like Dlib and OpenCV, is expected to maintain a frame rate sufficient for timely warnings on standard hardware.

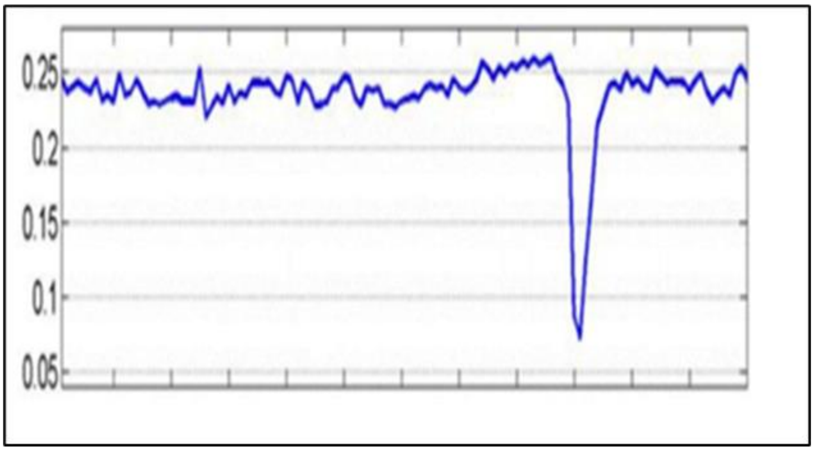

Figure 8 Precision confidence curve

The system successfully processes a live video feed, accurately detects faces and eye landmarks, and reliably distinguishes between normal blinks and dangerous prolonged closures.

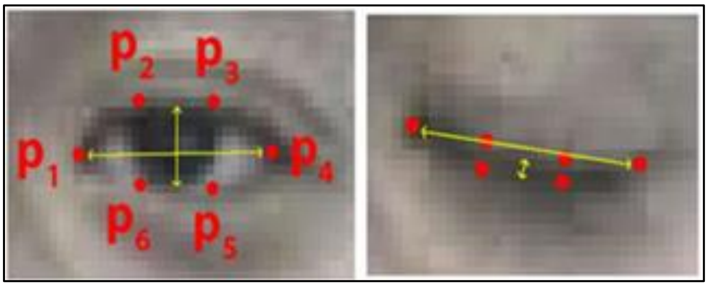

Figure 9 Distinguishing between open and close eyes

6.2. Prototype/Output Interface

Figure 10 Real-time output display eye tracking and EAR metrics

The visual output provides clear feedback, showing the face bounding box, eye landmarks, and status overlay as seen in Figure 11.

7. Conclusion

This paper successfully demonstrated a low-power, edge-based drowsiness detection framework tailored for motorcyclists. By prioritizing algorithmic efficiency, we achieved a viable prototype that functions without internet connectivity.

8. Future Scope

Future Scope: The Smart Helmet

Future iterations of this work aim to evolve the standalone detection module into a comprehensive IoT Enabled Smart Helmet.

Future Smart Helmet Concept

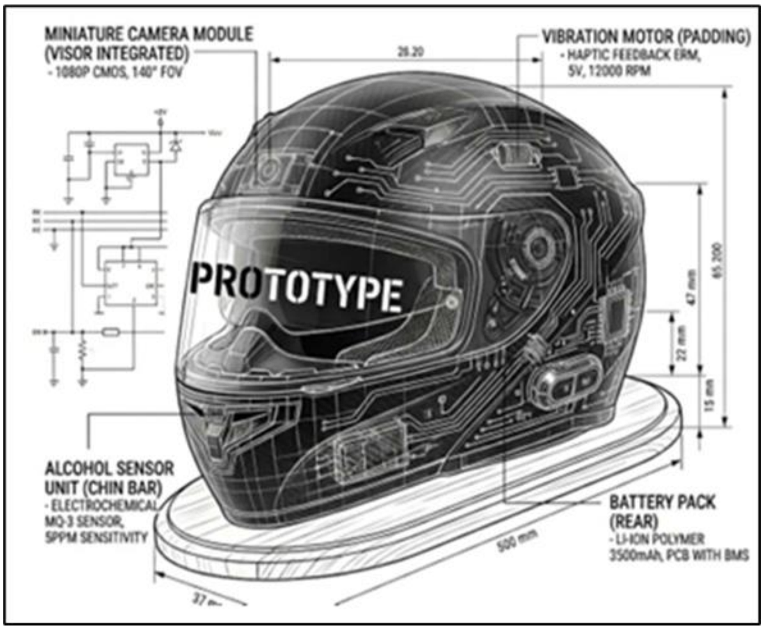

Figure 11 Basic Blue print of the conceptual design of the proposed IOT enabled Smart helmet

Future Work: The Holistic Smart Helmet

Future iterations will expand this prototype into a comprehensive "Smart Helmet" ecosystem (as visualized in the proposed diagrams). Planned integrations include:

- **Alcohol Interlock:** Integration of MQ-3 sensors to prevent vehicle ignition if the rider is intoxicated.
- **Impact Detection:** Utilizing MEMS accelerometers to detect crashes and automatically trigger SOS alerts via GSM modules.
- **Heads-Up Display (HUD):** Projecting critical navigation and alert data onto the visor to keep the rider's focus on the road.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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