# International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 15 Issue 2 (2026) | Pages: 221-226


# Automated Driver Drowsiness Detection System Using Artificial Intelligence


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**Peer Review Information**

***Type***: *Article*
***Received***: *23 May 2026*
***Revised***: *18 June 2026*
***Accepted***: *11 July 2026*
***Published***: *07 Aug 2026*



**Abstract**

This paper presents an AI-based driver drowsiness detection system that monitors driver fatigue in real time using a low-cost webcam. The system detects facial features with OpenCV and classifies eye state using a Convolutional Neural Network (CNN). It also analyses yawning and ocular redness to estimate a weighted drowsiness score. An adaptive calibration process personalises detection for each driver, while graded audible alerts provide timely warnings. To improve energy efficiency, the system supports Manual, Continuous, and Auto operating modes. The proposed approach is low-cost, non-intrusive, and suitable for various vehicles, helping reduce fatigue-related accidents and improve road safety.



**Keywords:** Driver Drowsiness Detection; Artificial Intelligence; Convolutional Neural Network; OpenCV; Multi-Cue Fusion; Red-Eye Detection; Adaptive Threshold; Power-Aware Monitoring; Road Safety Technology



**How to Cite This Article**

Rubisha, V., Adria, O., Rajisha, C., & Aysha Shabnam, I. (2026). Automated driver drowsiness detection system using artificial intelligence. *International Journal on Advanced Computer Engineering and Communication Technology,* 15(2), 221–226.



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## Introduction

Road traffic accidents are one of the foremost causes of injury and fatality worldwide, and driver fatigue is consistently ranked among their most significant contributing factors. Prolonged driving, monotonous highway conditions, night-time travel, and underlying sleep disorders such as narcolepsy and obstructive sleep apnea substantially reduce a driver's alertness. Fatigue impairs cognitive processing, slows reaction time, narrows attention span, and can ultimately lead to momentary lapses of consciousness known as "microsleeps," during which a vehicle may travel a considerable distance uncontrolled.

Unlike alcohol- or distraction-related accidents, drowsiness-related incidents are notoriously difficult to detect through conventional means because they build up gradually and are often unnoticed by the driver until it is too late. This has motivated significant research interest in automated, non-intrusive systems capable of continuously monitoring driver alertness and providing timely warnings. Advances in computer vision and deep learning have made it feasible to build low-cost, camera-based monitoring systems that analyse visual cues — eye closure, yawning, and ocular redness — to infer a driver's state of alertness in real time.

This paper proposes a hybrid early-warning system that combines multiple visual fatigue indicators, an adaptive per-driver threshold, a graded alert mechanism, and a power-aware operating scheme, described in the following sections.

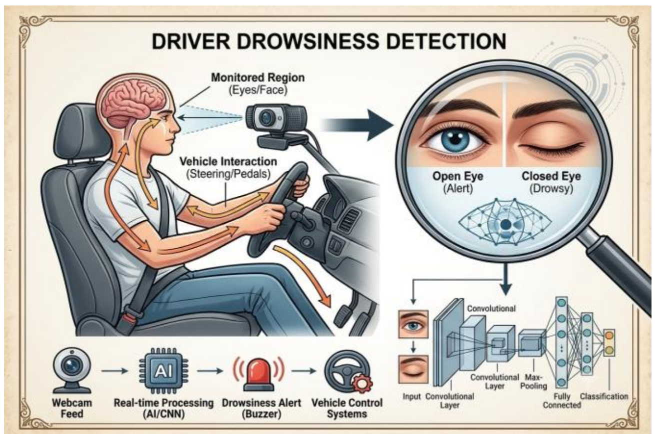


***Fig. 1.*** *Overview of driver drowsiness detection: monitored regions, eye-state classification, and the AI processing pipeline.*

### Literature Survey

Driver drowsiness detection using visual and physiological data has been the subject of numerous research investigations. Physiological methods measure signals such as EEG, ECG, and EOG, and while accurate, they require sensors worn directly on the body, making them intrusive for everyday driving. Vehicle-based methods infer fatigue indirectly from steering and lane-position patterns; these are non-intrusive but less reliable, since driving style and road geometry can produce similar patterns independent of fatigue.

Vision-based approaches analyse facial features captured through a camera. Early work relied on handcrafted features such as the Eye Aspect Ratio (EAR) combined with facial landmark detectors, and on PERCLOS (percentage of eyelid closure over time) as a fatigue metric, while the Viola-Jones boosted-cascade detector and, later, Histogram of Oriented Gradients (HOG) descriptors were widely used for robust face localization. Deep Convolutional Neural Networks have since become the dominant approach for automatically learning discriminative visual features rather than relying on these handcrafted descriptors. Open-source libraries such as OpenCV and deep learning frameworks such as Keras have made such systems practical to build and deploy. Prior work has also explored yawning specifically as a fatigue indicator using instrumentation-based measurement. However, the majority of current systems concentrate on a single cue — usually eye closure alone — apply a fixed detection threshold regardless of the individual driver, and run continuous full-frame-rate video processing regardless of actual risk level or time of day. A straightforward, low-cost approach that fuses multiple visual cues, adapts to the individual driver, and manages power consumption intelligently is still required. This study proposes such a hybrid strategy.

### Problem Statement

Existing driver-assistance systems in most conventional vehicles do not actively monitor a driver's physiological or behavioural state of alertness. Physiological monitoring is accurate but intrusive; vehicle-behaviour monitoring is indirect and prone to false detections; and existing vision-based systems typically rely on a single cue, a fixed global threshold that does not account for individual eye shape or eyewear, and continuous processing that unnecessarily drains battery during low-risk daytime driving. This project proposes a hybrid early-warning system that uses eye closure, yawning, and red-eye detection together with a Convolutional Neural Network to assess driver alertness. In addition to visual cues, the system applies an adaptive, driver-specific calibration and a power-aware Manual/Continuous/Auto operating scheme. The algorithm computes a weighted drowsiness score and issues a graded, escalating alert once the score exceeds the calibrated threshold. This system's primary benefit is that it offers a fast, affordable, non-intrusive, and power-efficient early-warning approach suitable for private, public, and commercial vehicles, even though it cannot replace attentive driving or professional vehicle safety systems.

## Objectives

- To develop a real-time drowsiness detection system using Artificial Intelligence.
- To detect driver fatigue by monitoring eye state, yawning, and ocular redness (red-eye) through a standard webcam.
- To fuse these cues into a single, adaptively-calibrated drowsiness score personalized to each driver.
- To alert the driver through a graded, escalating alarm before an accident occurs.
- To minimize unnecessary power/battery consumption via Manual, Continuous, and Auto operating modes.

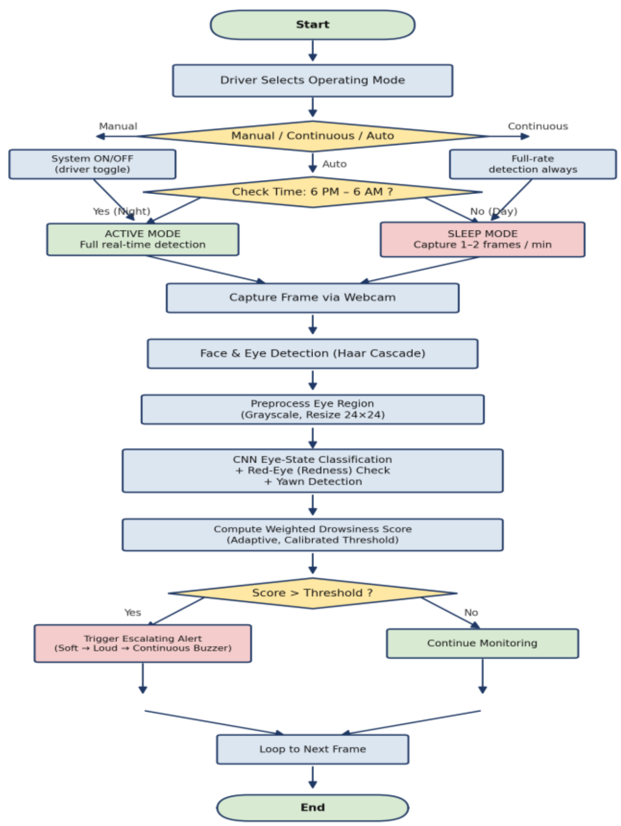


***Fig. 2.*** *Flowchart of the system's operating logic.*

## Proposed Methodology

A hybrid approach incorporating eye-state classification, yawning detection, red-eye analysis, and power-aware scheduling is used in the proposed system. First, live video is captured from a webcam; the face and eye regions are localized using Haar Cascade classifiers. Each detected eye region is converted to grayscale, resized to 24×24 pixels, and passed to a trained CNN that classifies it as open or closed. The same eye region is separately analysed in HSV colour space for redness, and the mouth region is analysed for yawning. To increase accuracy, a brief 10–15 second calibration phase at trip start records the driver's baseline blink rate and eye openness, and subsequent thresholds are set relative to this baseline. The three cues are combined into a single weighted drowsiness score. The system's frame-sampling rate is itself governed by a Power Mode Controller: in Auto mode, full-rate detection runs at night (6 PM–6 AM) while daytime hours use a low-power sleep mode sampling only 1–2 frames per minute, escalating immediately to full-rate detection if a suspicious frame is caught. Python and open-source machine learning libraries (OpenCV, Keras, TensorFlow) are used throughout the implementation, making the system quick, easy, and economical to deploy.

## Working Principle

The proposed method relies on a CNN-based classifier combined with rule-based colour and geometry analysis to assess driver alertness. The system first captures webcam frames at a rate set by the current power mode. Detected eye regions are preprocessed and passed to the trained CNN, which predicts open or closed state; in parallel, redness in the sclera and mouth-aspect-ratio for yawning are computed. These three signals are combined into a weighted drowsiness score using the driver's calibrated baseline. If the score exceeds the adaptive threshold, the system escalates through a graded alert sequence — a soft cue first, then a louder alarm, then a continuous alarm if no response is detected — and remains in an active, high-frequency monitoring state until the driver's alertness is confirmed, at which point it can return to a lower-power sampling state if operating in Auto mode. This closed loop of capture, classify, fuse, decide, and alert repeats continuously while the vehicle is in motion.

**System Design**

The system is composed of the following functional modules, operating in sequence for every processed video frame:

- Video Acquisition Module — captures continuous live video from a webcam mounted to face the driver.
- Face and Eye Detection Module — uses Haar Cascade classifiers to localize the face and isolate the left and right eye regions within each frame.
- Preprocessing Module — converts detected eye regions to grayscale and resizes them to 24×24 pixels for input into the CNN.
- Classification Module — the trained CNN predicts whether each eye is open or closed.
- Yawning and Red-Eye Analysis Module — evaluates mouth-aspect-ratio for yawning and sclera redness as supplementary fatigue signals.
- Adaptive Calibration Module — records each driver's baseline blink rate and eye openness during a brief trip-start calibration and sets subsequent thresholds relative to this baseline.
- Power Mode Controller — manages Manual, Continuous, and Auto operation, including the night-time active window and daytime sleep-sampling cycle.
- Decision and Alert Module — combines the three cues into the weighted drowsiness score and triggers the graded, escalating alert once the calibrated threshold is crossed.

Conceptually, data flows linearly through these modules under the supervision of the Power Mode Controller: Webcam → Face/Eye Detection → Preprocessing → CNN Classification + Yawning/Red-Eye Check → Weighted Drowsiness Decision Logic → Graded Alert, forming a continuous, power-aware, real-time monitoring loop that re-evaluates the driver's state on every active frame.

**Implementation**

Tools and technologies: Python as the programming language; Keras with a TensorFlow backend as the deep learning framework; OpenCV for Haar Cascade-based face and eye detection; a Convolutional Neural Network as the classification model; Python's datetime and time.sleep()-based scheduling for the Power Mode Controller; and a software-triggered buzzer/alarm as the alert mechanism. The webcam feed is processed frame-by-frame using OpenCV; each detected eye image is converted to grayscale, resized to 24×24 pixels, and normalized before being passed to the trained CNN, while the mouth region and sclera are analysed in parallel for yawning and redness. A running weighted score is incremented as cues indicating drowsiness are detected and decremented as the driver is confirmed alert; once the score crosses the calibrated threshold, the graded alert sequence is triggered and continues until the driver responds.

**Applications**

The proposed hybrid drowsiness detection system is intended for private vehicles, public transport, and commercial fleets, particularly for long-distance and night-shift drivers who face the highest statistical risk of fatigue-related accidents. Because it relies on a standard webcam and open-source AI libraries rather than specialized or wearable hardware, it can be deployed as an affordable add-on device or software module without modifying the vehicle itself. Fleet operators could use the escalating-alert and power-mode logic to reduce both accident risk and device power draw across large vehicle fleets. The system can also serve as a decision-support layer feeding into more advanced Advanced Driver-Assistance Systems (ADAS), or as a standalone safety accessory for individual drivers, including ride-share and delivery drivers who frequently work irregular or night-time hours.

**Performance Analysis**

The effectiveness of the proposed approach is assessed by how well it classifies eye state and detects sustained drowsiness using the fused multi-cue score. The trained CNN is evaluated using standard metrics — accuracy, precision, recall, and F1-score — with a confusion matrix used to examine true positives, true negatives, false positives, and false negatives. High recall is particularly important in this application, to ensure that genuine drowsiness episodes are not missed. In real-time testing, the multi-cue fusion approach reduced missed detections compared to eye-closure-only testing, since yawning and red-eye cues occasionally flagged early fatigue before sustained eye closure occurred, and the adaptive calibration step improved consistency across test subjects with differing eye shapes. The power-aware

Auto mode substantially reduced average processing duty-cycle during simulated daytime driving while still escalating promptly whenever a Sleep Mode check flagged a possible fatigue cue.

## Advantages

The proposed drowsiness detection system has several benefits that make it a practical, efficient safety solution. Combining eye closure with yawning and red-eye detection makes the system more robust than single-cue detectors, since it can flag early fatigue signs before sustained eye closure occurs. Because the approach depends on a standard, widely available webcam rather than costly diagnostic or wearable hardware, it is inexpensive and easy to deploy in private, public, or commercial vehicles. The adaptive calibration phase personalizes accuracy to each driver, reducing false alarms or missed detections caused by differing eye shapes or eyewear. The power-aware Auto mode conserves battery during low-risk daytime driving while remaining fully active at night, when accident risk is statistically highest, and the graded alert escalation avoids startling the driver unnecessarily while still ensuring a strong response to sustained drowsiness. Overall, the system blends effectiveness, affordability, and accessibility, making it a useful tool for improving road safety.

## Limitations

- Detection accuracy can degrade under extreme lighting conditions, such as very low light or strong glare.
- Drivers wearing sunglasses, or in some cases prescription eyewear, may reduce the reliability of eye detection.
- Redness-based analysis can be affected by naturally bloodshot eyes, allergies, or coloured ambient lighting, which may cause occasional false positives.
- Yawning detection can be confounded by talking, singing, coughing, or partial occlusion of the mouth (e.g., a hand or mask).
- Performance may vary with camera placement, angle, and distance from the driver's face.
- The system depends on continuous, unobstructed visibility of the driver's face, which may be affected by sudden head turns or occlusion.
- The Sleep Mode's 1–2 frame-per-minute sampling in Auto mode means a very sudden onset of drowsiness during daytime hours could, in rare cases, be detected slightly later than in Continuous mode.
- The 10–15 second adaptive calibration phase at trip start means detection is not yet fully personalized during the very first moments of a trip.

## Future Scope

Future advancements to the proposed drowsiness detection system are promising. Accuracy can be improved by training on larger and more diverse driver datasets covering a wider range of eye shapes, lighting conditions, and ethnicities. Incorporating head-pose and head-nod detection would capture additional fatigue cues beyond eye, mouth, and redness analysis. A CNN-LSTM temporal model could be added to capture blink-pattern trends over time rather than relying on per-frame classification alone, and Grad-CAM-based explainability could be introduced to visualize which eye regions influenced each prediction, increasing driver and reviewer trust in the system. Integrating the system with a vehicle's ADAS would allow automated corrective action beyond alerting, and deploying the model on embedded/edge hardware would enable a dedicated, lower-power in-vehicle device. In conclusion, this system has a broad and promising future, with clear opportunities to expand functionality, improve accuracy, and incorporate more advanced AI techniques.

## Conclusion

In conclusion, by fusing artificial intelligence with multiple visual fatigue indicators — eye closure, yawning, and red-eye detection — the proposed approach for driver drowsiness detection offers a practical and efficient safety solution. This approach aids in early fatigue detection, which is essential for preventing accidents caused by microsleep and reduced alertness. The system remains fast and effective thanks to CNN-based classification and multi-cue fusion, adaptive per-driver calibration, and a graded escalating alert. It stays affordable and non-intrusive by relying on a standard webcam and open-source AI libraries rather than specialized hardware, and it manages power consumption intelligently through its Manual, Continuous, and Auto operating modes. The system is a useful real-time safety and decision-support tool for drivers and fleet operators, but it does not replace attentive driving. All things considered, this research shows how combining AI with basic visual monitoring can address a practical road-safety issue, improve alertness outcomes, and reduce fatigue-related accidents.

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