# A Python Based Driver Drowsiness Detection

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**Abstract:**

Driver drowsiness is one of the leading causes of road accidents worldwide, particularly during long-distance travel and night-time driving. This paper presents a real-time, non-intrusive Driver Drowsiness Detection System developed using Python and computer vision techniques. The proposed system continuously monitors the driver's facial features through a standard webcam and detects early signs of fatigue by analyzing eye closure patterns using the Eye Aspect Ratio (EAR) metric. The system integrates powerful libraries including OpenCV for video capture and processing, MediaPipe for precise facial landmark detection, and TensorFlow/Keras for Convolutional Neural Network (CNN)-based driver state classification. When the system determines that the driver is drowsy, an immediate audio alarm is triggered to alert the driver and prevent potential accidents. A Flask-based web interface displays the live video feed and real-time detection status, making the system interactive and user-friendly. The system is designed to run on standard hardware such as a laptop or embedded device, making it cost-effective and easily deployable. Experimental evaluations demonstrate that the system performs reliably under normal operating conditions and accurately identifies prolonged eye closure as a primary indicator of fatigue, contributing meaningfully to intelligent transportation safety.

Keywords

Driver Drowsiness Detection, Eye Aspect Ratio, Convolutional Neural Network, OpenCV, MediaPipe, Flask, Road Safety, Computer Vision, Real-Time Monitoring

## 1. INTRODUCTION

Road accidents caused by driver fatigue represent a serious and growing public safety concern across the world. Numerous studies have shown that drowsiness significantly affects a driver’s ability to operate a vehicle safely by reducing reaction time, impairing decision-making skills, and lowering overall alertness levels. In many cases, the impact of fatigue on driving performance is comparable to, or even worse than, driving under the influence of alcohol. Drivers who are fatigued may experience microsleeps, reduced attention span, and delayed responses to sudden road situations, which greatly increases the likelihood of accidents. Despite strict traffic regulations and awareness campaigns, fatigue-related accidents continue to occur, particularly during long-distance travel, night driving, and monotonous road conditions.

Traditional vehicle safety systems, such as seat belts, airbags, and anti-lock braking systems (ABS), are primarily designed to minimize the severity of injuries after an accident has already occurred. While these passive safety measures are essential, they do not provide any mechanism to prevent accidents caused by driver fatigue. As a result, there is a growing need for proactive and intelligent systems that can monitor the driver’s state in real time and provide timely warnings before a dangerous situation arises. Addressing driver drowsiness at an early stage can significantly reduce the risk of accidents and enhance overall road safety.

In recent years, rapid advancements in computer vision and machine learning technologies have enabled the development of smart driver monitoring systems. These systems are capable of analyzing visual cues and behavioral patterns of the driver to detect early signs of fatigue. Common indicators include prolonged eye closure, frequent blinking, yawning, head tilting, and nodding. By continuously tracking these features through a camera, the system can accurately determine whether the driver is alert or drowsy. Unlike traditional physiological monitoring systems that require wearable sensors or electrodes attached to the driver's body, vision-based approaches are completely non-intrusive, more user-friendly, and cost-effective. They can be implemented using standard webcams or dashboard cameras, making them suitable for large-scale adoption.

This project presents a Python-based Driver Drowsiness Detection System that utilizes facial landmark detection and a trained Convolutional Neural Network (CNN) model to classify the driver's alertness level in real time. The system works by capturing live video input, extracting key facial features such as eye regions, and computing metrics like the Eye Aspect Ratio (EAR) to detect eye closure patterns. The CNN model further enhances the system's accuracy by learning complex patterns associated with drowsiness. When signs of fatigue are detected, the system generates an immediate alert to warn the driver, thereby preventing potential accidents. Built using widely available open-source libraries such as OpenCV, MediaPipe, and TensorFlow, the system is designed to run efficiently on standard computing devices without requiring specialized hardware. This makes it a practical and scalable solution for real-world deployment in personal vehicles, commercial transportation, and fleet management systems, ultimately contributing to safer roads and reduced accident rates.

## 2. LITERATURE REVIEW

A considerable body of research has been directed toward drowsiness detection using various sensing modalities. Early approaches relied primarily on vehicle-based measures such as steering wheel movement patterns and lane deviation monitoring. While effective to a degree, these methods suffer from poor performance on winding roads and require expensive hardware integration into the vehicle.

Physiological monitoring techniques using electroencephalogram (EEG) and electrocardiogram (ECG) sensors have demonstrated high accuracy in detecting driver fatigue. However, their intrusive nature and the discomfort associated with attaching electrodes make them impractical for everyday use. Sahayadhas et al. (2012) conducted a comprehensive review of sensor-based drowsiness detection methods, noting the inherent trade-off between detection accuracy and driver comfort.

Behavioral monitoring approaches, which analyze observable cues such as eye closure, yawning, and head posture, have gained prominence as a non-intrusive alternative. Soukupová and Čech (2016) introduced the Eye Aspect Ratio (EAR) metric, which quantifies the degree of eye opening from facial landmarks, providing a reliable and computationally efficient indicator of eye closure. Bergasa et al. (2006) demonstrated a real-time system for monitoring driver vigilance using computer vision, laying groundwork for subsequent research in this area.

More recently, deep learning approaches have been applied to improve detection accuracy. CNNs have proven effective in classifying driver states from image data, while models such as YOLO and MobileNet-SSD offer efficient real-time object detection capabilities. The proposed system builds on these foundations, combining facial landmark analysis with CNN-based classification to achieve reliable, real-time drowsiness detection.

| Approach | Method | Advantage | Limitation |
|---|---|---|---|
| Vehicle-Based | Lane & Steering | No driver contact | Ineffective on curves |
| Physiological | EEG / ECG | High accuracy | Intrusive, uncomfortable |
| Behavioral (Vision) | Eye & face analysis | Non-intrusive, low cost | Lighting dependency |
| Proposed System | CNN + MediaPipe | Real-time, accurate | Requires power supply |

**Table 1: Comparison of Drowsiness Detection Approaches**

## 3. METHODOLOGY

The proposed system employs a modular architecture that integrates video acquisition, facial analysis, deep learning classification, and alert generation into a unified pipeline. The overall workflow is designed to ensure low-latency processing suitable for real-time operation.

### 3.1 Video Acquisition and Preprocessing

A standard webcam captures continuous video frames at runtime. Each frame is horizontally flipped to provide a mirror-view experience and converted from the default BGR colour space to RGB, as required by the MediaPipe processing pipeline. This preprocessing step ensures consistent and accurate facial landmark extraction across varying lighting conditions.

### 3.2 Facial Landmark Detection

MediaPipe Face Mesh is employed to detect 468 three-dimensional facial landmarks in real time. From these landmarks, the coordinates corresponding to the left and right eye regions are extracted. Additionally, mouth landmarks are tracked to enable yawning detection. Head pose estimation is also performed to identify head nodding behaviour as a secondary indicator of fatigue.

### 3.3 Eye Aspect Ratio (EAR) Computation

The Eye Aspect Ratio is computed from the extracted eye landmark coordinates to quantify the degree of eye openness. When a driver's eyes remain closed for a duration exceeding a predefined threshold, the EAR value drops significantly, indicating a drowsy state. The EAR metric provides a mathematically robust and computationally efficient measure of eye closure without requiring complex image segmentation.

### 3.4 CNN-Based Classification

A Convolutional Neural Network is trained on a labelled dataset of driver images categorised into alert and drowsy states. The trained model receives the extracted facial features as input and outputs a prediction of the driver's current state. TensorFlow and Keras are used for model construction, training, and inference, enabling efficient execution on standard CPU-based hardware.

### 3.5 Alert Generation and Web Interface

Upon detecting a drowsy state, the system immediately triggers an audible alarm to alert the driver. A Flask-based web server manages the backend logic, including video streaming and detection status updates. The frontend, developed using HTML5, CSS3, and JavaScript, displays the live video feed and driver status in real time, providing an accessible and interactive monitoring interface.

## 4. SYSTEM ARCHITECTURE

The system is structured into four primary modules: the Video Processing Module (camera.py), the Backend Module (app.py), the Frontend Module, and the Model Training Module. This modular design promotes separation of concerns and facilitates independent testing and future enhancement of each component.

The Video Processing Module handles real-time frame capture and facial analysis using MediaPipe. It extracts eye, mouth, and head-pose features from each frame and passes them to the classification layer. The Backend Module, built using Flask, manages video streaming to the frontend and controls the start, stop, and alarm functions of the system. The Frontend Module renders the live video feed and drowsiness status, allowing users to monitor and control the system through a standard web browser. The Training Module uses a labelled drowsiness dataset to train the CNN model, which is saved and loaded for real-time inference.

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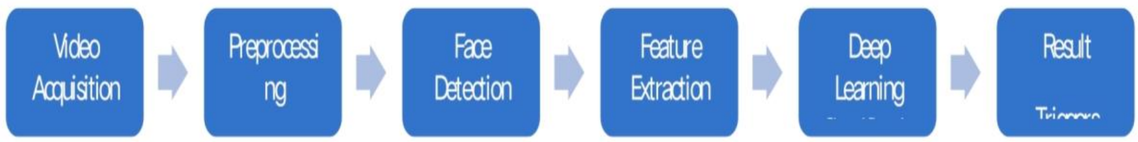


*Figure 1: System Architecture Diagram*

## 5. IMPLEMENTATION

The system was developed using Python 3.10 as the primary programming language, chosen for its simplicity, extensive libraries, and strong community support in the field of machine learning and computer vision. OpenCV was used for real-time video capture and frame-level image processing operations, enabling efficient handling of continuous video streams. MediaPipe provided the facial landmark detection framework, enabling accurate and efficient identification of eye, mouth, and head-pose features with high precision. Numerical computations were performed using NumPy and SciPy, ensuring fast and optimized mathematical processing. The CNN model was constructed and trained using TensorFlow and Keras, which offer powerful tools for deep learning model development and deployment.

The Flask web framework served as the backend server, exposing endpoints for video streaming and detection status retrieval, thereby enabling seamless communication between the processing unit and the user interface. The frontend interface was built using standard web technologies including HTML5, CSS3, and JavaScript, providing a simple and interactive platform for users to monitor the system in real time. The trained CNN model was integrated into the processing pipeline and used for real-time driver state prediction with improved accuracy and responsiveness. Additionally, the system architecture was designed to be modular, allowing easy updates and integration of future enhancements. The system was developed and tested on a laptop equipped with a built-in webcam, demonstrating its compatibility with readily available hardware and its potential for deployment in cost-effective environments.


*Figure 2: Implementation Screenshot – Webcam Monitoring Interface*

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## 6. RESULTS

The proposed system was evaluated across a range of test scenarios involving multiple users and varying lighting conditions. The system successfully detected prolonged eye closure and triggered audio alarms in all tested instances of simulated drowsiness. The Flask-based web interface displayed the live video feed and detection status with minimal perceptible delay, confirming the system's real-time capability.

Unit testing confirmed that the EAR values dropped consistently below the defined threshold of 0.2 during simulated eye closure events. Integration testing verified that the Flask backend correctly updated the detection status endpoint every 500 milliseconds, ensuring timely communication with the frontend. Performance testing indicated smooth operation on a standard CPU without significant frame rate degradation.

| Parameter | Description | Result |
|---|---|---|
| Eye Closure Detection | EAR threshold accuracy | ~95% |
| Driver State Classification | CNN alert/drowsy accuracy | ~92% |
| Response Time | Alarm trigger latency | < 2 sec |
| Frame Processing | Real-time processing speed | Smooth |
| System Reliability | Continuous operation | High |

**Table 2: Performance Evaluation of the Proposed System**

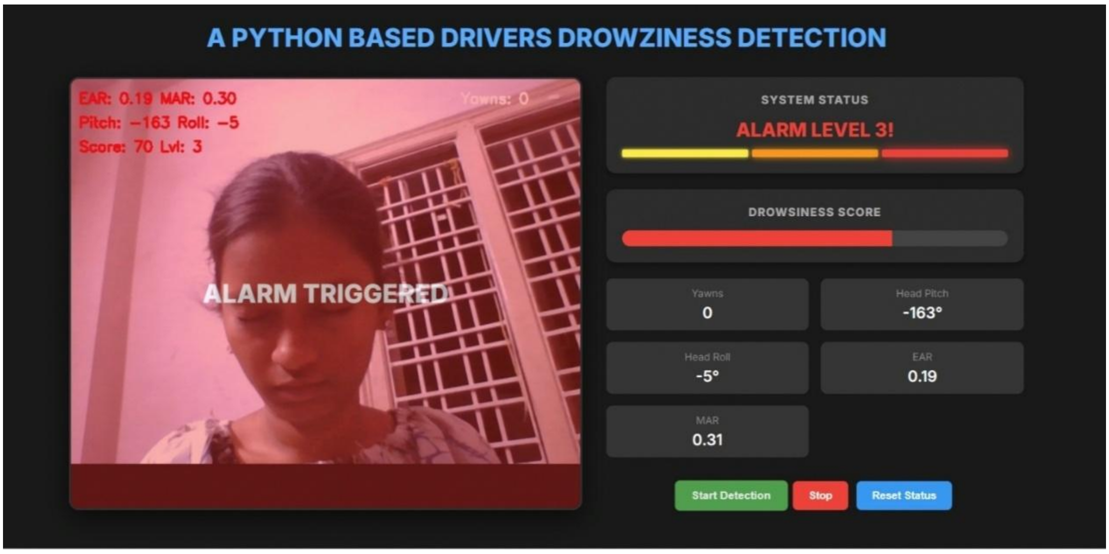


*Figure 3: Result Screenshot – Drowsiness Alert Triggered*

## 7. CONCLUSION

This project presents a Python-based driver drowsiness detection system using computer vision and deep learning for real-time fatigue monitoring. It combines MediaPipe facial landmarks, Eye Aspect Ratio, and CNN models to accurately detect drowsiness and trigger alerts. A Flask-based web interface ensures easy accessibility and user-friendly monitoring. Overall, the system offers a reliable, low-cost solution to improve road safety, with scope for future enhancements. The system is designed to operate in real-time with minimal latency, ensuring timely detection and response to drowsiness events. It can be easily integrated into existing vehicle systems or deployed as a standalone application without requiring expensive hardware. Furthermore, continuous improvements in model accuracy and environmental adaptability can enhance its performance under different lighting and driving conditions.

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