AI-Based Driver Drowsiness Detection System Using Computer Vision for Road Safety

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Abstract- *Driver drowsiness is a major contributor to road traffic accidents worldwide, posing significant risks to public safety and resulting in substantial economic and social losses. Traditional approaches to detecting driver fatigue often rely on physiological sensors or vehicle-based indicators, which may require specialized hardware, intrusive installation, or exhibit reduced reliability under varying driving conditions. This research presents an AI-based driver drowsiness detection system using computer vision to provide a non-intrusive, real-time solution for enhancing road safety. The proposed system continuously monitors the driver's facial features through a camera and applies computer vision techniques to detect signs of fatigue, including prolonged eye closure, frequent blinking, yawning, and abnormal head movements. Facial landmarks are extracted using MediaPipe Face Mesh, enabling the computation of key fatigue indicators such as Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). These features are analyzed by an artificial intelligence model to classify the driver's alertness level into normal, warning, or drowsy states. When drowsiness is detected beyond predefined thresholds, the system immediately activates an audio-visual alert to regain the driver's attention and reduce the likelihood of accidents. The proposed framework is designed for real-time operation with low computational complexity, making it suitable for deployment on embedded platforms and integration into advanced driver-assistance systems (ADAS). Experimental evaluation demonstrates that the proposed approach achieves high detection accuracy while maintaining reliable performance under diverse lighting conditions and varying facial expressions. The combination of facial landmark analysis, computer vision, and artificial intelligence offers a cost-effective, scalable, and practical solution for intelligent transportation systems. The proposed framework contributes to the advancement of AI-enabled road safety technologies by providing an efficient, non-contact, and real-time driver monitoring system capable of reducing fatigue-related accidents and supporting the development of safer smart mobility infrastructures.*
Keywords: *Driver Drowsiness Detection, Artificial Intelligence (AI), Computer Vision, Road Safety, Facial Landmark Detection, Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), MediaPipe Face Mesh, Real-Time Monitoring, Advanced Driver-Assistance Systems (ADAS)*

INTRODUCTION

Road transportation is one of the most widely used modes of travel worldwide, supporting economic growth, trade, and daily commuting. However, the increasing number of vehicles on the road has also led to a significant rise in traffic accidents, many of which are caused by human factors such as fatigue, distraction, and reduced alertness. Among these factors, driver drowsiness has emerged as one of the leading causes of severe road accidents because it impairs reaction time, decreases situational awareness, and affects decision-making abilities. Long-distance driving, insufficient sleep, monotonous road conditions, irregular work schedules, and physical exhaustion further increase the likelihood of fatigue-related incidents. Consequently, the development of intelligent systems capable of detecting driver drowsiness in real time has become an important research area within intelligent transportation systems (ITS) and advanced driver-assistance systems (ADAS).

Conventional methods for detecting driver fatigue generally fall into three categories: physiological signal-based methods, vehicle behavior-based methods, and vision-based methods. Physiological approaches monitor biological signals such as electroencephalography (EEG), electrocardiography (ECG), and electromyography (EMG), which can provide high detection accuracy but require wearable sensors that may reduce driver comfort and are impractical for everyday use. Vehicle behavior-based approaches analyze parameters such as steering wheel movements, lane deviation, and vehicle speed; however, these methods are often influenced by road geometry, weather conditions, and individual driving styles, which can limit their reliability. In contrast, computer vision-based methods offer a non-contact and cost-effective solution by continuously monitoring facial expressions and head movements using a camera, making them more suitable for practical deployment in modern vehicles.

Recent advancements in artificial intelligence (AI), deep learning, and computer vision have significantly enhanced the capability of vision-based driver monitoring systems. Modern facial landmark detection algorithms can accurately identify key facial points even under moderate variations in lighting, facial orientation, and head movement. These landmarks enable the computation of fatigue-related indicators such as the Eye Aspect Ratio (EAR), which measures eye openness, and the Mouth Aspect Ratio (MAR), which quantifies yawning behavior. Additionally, prolonged eye closure, blink frequency, and head pose estimation provide complementary information that improves the robustness of drowsiness detection. By integrating these indicators with AI-based classification models, the system can distinguish between normal driving behavior and fatigue with high accuracy while maintaining real-time performance.

The proposed research presents an AI-based driver drowsiness detection system using computer vision for road safety. The framework employs a camera to continuously capture the driver's facial images and utilizes the MediaPipe Face Mesh model to extract detailed facial landmarks. Based on these landmarks, fatigue indicators including EAR, MAR, blink duration, and head pose are computed and analyzed by an artificial intelligence classifier to determine the driver's level of alertness. When signs of drowsiness exceed predefined thresholds, the system immediately generates audio-visual warnings to alert the driver and encourage corrective action. The proposed approach is designed to operate efficiently on standard computing devices and embedded platforms, facilitating its integration into intelligent vehicles and ADAS applications.

Compared with many existing systems that rely on a single fatigue indicator, the proposed framework combines multiple facial cuts to improve detection accuracy and reduce false alarms. Furthermore, the use of lightweight computer vision algorithms enables real-time processing with relatively low computational requirements, making the solution suitable for practical implementation in both commercial and personal vehicles. The non-invasive nature of the system also enhances user comfort by eliminating the need for wearable sensors while maintaining continuous monitoring throughout the journey.

The primary objectives of this research are to develop a reliable AI-based driver drowsiness detection system using computer vision, accurately identify fatigue through multiple facial features, provide immediate warning notifications upon detecting drowsiness, and evaluate the system's performance using standard metrics such as accuracy, precision, recall, F1-score, and processing speed. The proposed framework aims to contribute to safer transportation by minimizing fatigue-related accidents and supporting the evolution of intelligent vehicle safety technologies.

The remainder of this paper is organized as follows. Section 2 reviews recent studies on driver drowsiness detection and related computer vision techniques. Section 3 describes the proposed methodology, including facial landmark extraction, fatigue feature computation, and AI-based classification. Section 4 presents the system architecture and operational workflow. Section 5 discusses the implementation details and experimental setup. Section 6 analyzes the experimental results and performance evaluation. Finally, Section 7 concludes the paper and outlines future research directions for improving intelligent driver monitoring systems.

LITERATURE REVIEW

Driver drowsiness detection has become an active research area due to the increasing demand for intelligent transportation systems that enhance road safety and reduce fatigue-related accidents. Advances in artificial intelligence (AI), computer vision, machine learning, and deep learning have enabled the development of reliable, non-intrusive monitoring systems capable of detecting driver fatigue in real time. Existing research can be broadly categorized into physiological signal-based methods, vehicle behavior-based methods, vision-based approaches, and hybrid intelligent systems.

Physiological signal-based approaches are among the earliest techniques proposed for detecting driver fatigue. These methods measure biological signals such as electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), heart rate variability, and skin conductivity to determine the driver's level of alertness. Since physiological signals directly reflect changes in the human body's condition, they often achieve high detection accuracy. However, these techniques require wearable sensors or electrodes attached to the driver's body, which may reduce comfort, increase system complexity, and limit their practicality for everyday driving. Furthermore, continuous calibration and sensor maintenance increase implementation costs, making such systems less suitable for large-scale commercial deployment.

Vehicle behavior-based methods estimate driver fatigue by analyzing vehicle dynamics rather than monitoring the driver's physical condition. Common indicators include steering wheel angle variations, lane departure frequency, vehicle speed fluctuations, acceleration patterns, and braking behavior. These approaches have the advantage of requiring minimal interaction with the driver and can often utilize sensors already installed in modern vehicles. However, vehicle behavior is influenced by road curvature, traffic density, weather conditions, vehicle type, and individual driving styles. Consequently, these systems may produce inaccurate results when environmental conditions change, reducing their reliability as standalone fatigue detection solutions.

The rapid development of computer vision has shifted research toward vision-based driver monitoring systems, which provide a non-contact and cost-effective alternative. These systems continuously capture facial images using cameras and analyze visual cues associated with fatigue, including eye closure duration, blink frequency, yawning, facial expressions, and head orientation. Early vision-based systems employed traditional image processing algorithms such as Haar Cascade classifiers for face detection and Histogram of Oriented Gradients (HOG) with Support Vector Machines (SVMs) for facial feature extraction. Although computationally efficient, these techniques often struggle under varying illumination, occlusions, and head pose variations, limiting their robustness in real-world driving environments.

Recent advances in deep learning have significantly improved the performance of vision-based drowsiness detection systems. Convolutional Neural Networks (CNNs) automatically learn discriminative facial features from image data and have demonstrated superior accuracy compared with conventional machine learning methods. CNN-based models are capable of recognizing subtle changes in eye state, mouth movement, and facial expressions, enabling more reliable fatigue detection under challenging conditions. Several studies have further enhanced temporal modeling by integrating Long Short-Term Memory (LSTM) networks with CNNs, allowing sequential analysis of video frames to distinguish between normal blinking and prolonged eye closure associated with drowsiness. These hybrid architectures improve detection accuracy while reducing false-positive alerts.

Facial landmark detection has become a fundamental component of modern computer vision-based driver monitoring systems. Libraries such as Dlib and MediaPipe Face Mesh enable precise localization of facial landmarks in real time. These landmarks facilitate the computation of important fatigue indicators, including the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). EAR measures the geometric relationship between eyelid landmarks to determine whether the eyes are open or closed, while MAR quantifies mouth opening during yawning. The combination of these measurements provides reliable indicators of driver fatigue without requiring complex hardware. Compared with earlier landmark detection methods, MediaPipe Face Mesh offers higher landmark density, improved robustness, and faster processing speed, making it particularly suitable for real-time applications.

Several researchers have also investigated the use of head pose estimation as an additional fatigue indicator. Continuous nodding, abnormal head tilting, and reduced head stability often accompany driver drowsiness. By combining head pose estimation with facial landmark analysis, modern systems achieve greater robustness because multiple behavioral cues are evaluated simultaneously. This multimodal approach helps reduce false detections caused by temporary facial movements, lighting variations, or partial occlusions.

Machine learning algorithms remain widely used for fatigue classification after feature extraction. Traditional classifiers such as Support Vector Machines (SVM), Decision Trees, Random Forests, k-Nearest Neighbors (k-NN), and Naïve Bayes have demonstrated satisfactory performance when trained on handcrafted features. However, these methods generally require extensive feature engineering and may not generalize effectively across different drivers and environmental conditions. Deep learning models overcome many of these limitations by automatically learning hierarchical feature representations from large datasets, thereby improving adaptability and classification performance.

More recently, hybrid AI frameworks have emerged that combine computer vision, deep learning, and embedded computing for intelligent driver monitoring. These systems integrate facial landmark detection, eye movement analysis, yawning detection, and head pose estimation into a unified decision-making framework. Lightweight architectures enable deployment on embedded platforms such as Raspberry Pi, NVIDIA Jetson, and in-vehicle edge computing devices while maintaining real-time performance. Such implementations demonstrate the feasibility of integrating AI-powered drowsiness detection into Advanced Driver-Assistance Systems (ADAS) and smart vehicles.

Despite significant progress, several challenges remain. Variations in illumination, sunglasses, face masks, facial hair, camera placement, and driver posture continue to affect detection accuracy. Additionally, many existing systems rely on a single fatigue indicator, making them vulnerable to false alarms. Dataset diversity is another limitation, as many publicly available datasets do not adequately represent different age groups, ethnicities, lighting conditions, and driving environments. Improving the robustness and generalizability of AI-based drowsiness detection systems therefore remains an important research objective.

Based on the analysis of existing literature, it is evident that combining multiple facial fatigue indicators with modern AI and computer vision techniques offers the most promising solution for real-time driver monitoring. Therefore, this research proposes an integrated framework that utilizes MediaPipe Face Mesh for accurate facial landmark extraction, computes Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), blink duration, and head pose simultaneously, and employs an AI-based classifier to identify driver alertness levels. By integrating multiple behavioral features into a lightweight real-time framework, the proposed system aims to improve detection accuracy, reduce false alarms, and provide an efficient and practical solution for enhancing road safety.

PROPOSED METHODOLOGY

Overview

The proposed AI-based driver drowsiness detection system is designed to continuously monitor the driver's facial behavior using computer vision and artificial intelligence techniques. The primary objective is to identify early signs of fatigue and generate immediate warning alerts to prevent potential road accidents. The system employs a camera to capture real-time facial images, extracts facial landmarks using the MediaPipe Face Mesh model, computes multiple fatigue-related features, and classifies the driver's alertness level using an AI-based decision model.

Unlike conventional systems that depend on a single indicator such as eye closure or steering wheel movement, the proposed framework combines multiple facial characteristics, including eye blink behavior, yawning frequency, head pose variation, and facial landmark movements. The integration of multiple behavioral features improves detection reliability while reducing false-positive and false-negative detections.

The overall methodology consists of six major stages:

- Image Acquisition
- Face Detection and Facial Landmark Extraction
- Feature Extraction
- Drowsiness Classification
- Alert Generation
- System Monitoring

The complete workflow is illustrated in Figure 1, while the detailed processing sequence is presented in Figure 2.

Image Acquisition

The first stage involves continuous acquisition of the driver's facial images using a high-definition webcam or an in-vehicle infrared camera. The camera is positioned in front of the driver to ensure a clear frontal view of the face throughout the driving session.

Each captured frame is preprocessed before further analysis. The preprocessing operations include:

- Image resizing
- RGB color conversion
- Noise reduction
- Brightness normalization
- Contrast enhancement

These preprocessing techniques improve facial feature visibility and increase the robustness of the computer vision algorithms under varying illumination conditions.

Face Detection and Facial Landmark Extraction

After preprocessing, the system detects the driver's face using the MediaPipe Face Mesh framework. Compared with traditional face detection algorithms, MediaPipe provides highly accurate real-time facial landmark localization while maintaining low computational complexity.

The Face Mesh model identifies 468 facial landmark points representing:

- Eyes
- Eyelids
- Eyebrows
- Nose
- Lips
- Jawline
- Facial contours

These landmarks serve as the foundation for extracting fatigue-related facial features.

The advantages of MediaPipe Face Mesh include:

- High landmark detection accuracy
- Real-time processing capability
- Robustness against moderate head movement

- Lightweight computational requirements
- Compatibility with embedded systems

FEATURE EXTRACTION

The proposed framework extracts several facial features that strongly correlate with driver fatigue.

Eye Aspect Ratio (EAR)

Eye closure is one of the most reliable indicators of drowsiness. The Eye Aspect Ratio (EAR) estimates eye openness using the distances between selected eye landmarks.

The EAR is calculated as:

$EAR=\{(P_2-P_6)+(P_3-P_5)\} / \{2(P_1-P_4)\}$

Where:

- (P_1)–(P_6) denote eye landmark coordinates.
- The numerator represents the vertical eye opening.
- The denominator represents the horizontal eye width.

When the EAR falls below a predefined threshold for several consecutive frames, the driver is considered to have prolonged eye closure.

Mouth Aspect Ratio (MAR)

Yawning is another important symptom of driver fatigue.

The Mouth Aspect Ratio is computed as:

$MAR=\{(P_3-P_9)+(P_4-P_8)+(P_5-P_7)\} / \{2(P_1-P_6)\}$

A higher MAR value indicates mouth opening. Continuous mouth opening beyond the threshold is classified as a yawn event.

Blink Frequency

The system measures:

- Blink duration
- Blink frequency per minute
- Consecutive eye closures

Abnormally long eye closures indicate increasing fatigue levels.

Head Pose Estimation

Driver fatigue is frequently accompanied by abnormal head movements such as:

- Head nodding
- Forward tilting
- Side inclination

The system estimates pitch, yaw, and roll angles using facial landmarks to determine whether the driver's head position indicates drowsiness.

AI-Based Drowsiness Classification

The extracted facial features are combined into a feature vector consisting of:

- Eye Aspect Ratio (EAR)
- Mouth Aspect Ratio (MAR)
- Blink frequency
- Eye closure duration
- Head pose angles

The feature vector is analyzed using an AI classifier that categorizes the driver's condition into one of three states:

Driver State	Description
Alert	Eyes open, normal blinking, no yawning
Warning	Frequent blinking or occasional yawning
Drowsy	Prolonged eye closure, repeated yawning, abnormal head movement

The decision logic can be represented as:

- If EAR > Threshold and MAR < Threshold → Alert
- If EAR slightly decreases or MAR occasionally exceeds the threshold → Warning
- If EAR remains below the threshold for several consecutive frames and MAR exceeds the threshold → Drowsy

Combining multiple indicators significantly improves classification reliability compared with systems based on a single feature.

Alert Generation

Once the AI classifier identifies the driver as drowsy, the system immediately activates multiple warning mechanisms.

The alert module includes:

- Audible alarm
- Dashboard warning message
- Flashing visual indicator
- Seat vibration (optional)
- Mobile notification (optional)

The warning remains active until the driver's facial behavior returns to the normal alert state.

Algorithm of the Proposed System

Algorithm 1: AI-Based Driver Drowsiness Detection

Input: Real-time video stream

Output: Driver alert status

Step 1: Capture video frames continuously.

Step 2: Detect the driver's face.

Step 3: Extract facial landmarks using MediaPipe Face Mesh.

Step 4: Compute Eye Aspect Ratio (EAR).

Step 5: Compute Mouth Aspect Ratio (MAR).

Step 6: Estimate blink frequency and head pose.

Step 7: Generate the feature vector.

Step 8: Classify the driver's condition using the AI decision model.
Step 9: If the driver is classified as drowsy, activate the warning system.
Step 10: Continue monitoring until the driving session ends.

Advantages of the Proposed Methodology

The proposed methodology offers several advantages over conventional driver monitoring systems:

- Non-contact and non-intrusive fatigue detection.
- Simultaneous analysis of multiple fatigue indicators.
- High detection accuracy through AI-assisted classification.
- Real-time operation with low computational complexity.
- Robust performance under moderate head movements and varying lighting conditions.
- Cost-effective implementation using standard cameras.
- Easy integration with Advanced Driver-Assistance Systems (ADAS) and intelligent vehicles.

By combining computer vision with artificial intelligence, the proposed methodology provides an efficient, reliable, and scalable solution for detecting driver drowsiness in real time. The integration of facial landmark analysis, behavioral feature extraction, and AI-based decision-making significantly enhances road safety while maintaining computational efficiency suitable for deployment in embedded automotive platforms.

SYSTEM ARCHITECTURE AND WORKFLOW

Proposed System Architecture

The proposed AI-based driver drowsiness detection system adopts a modular architecture that integrates computer vision, facial landmark analysis, artificial intelligence, and an alert generation mechanism. The system continuously captures the driver's facial images, extracts fatigue-related features, classifies the driver's alertness level, and issues timely warnings whenever drowsiness is detected. The architecture is designed to operate in real time with low computational overhead, making it suitable for implementation in passenger vehicles, commercial vehicles, and Advanced Driver-Assistance Systems (ADAS).
The overall architecture consists of six major modules:

- Image Acquisition Module
- Face Detection and Facial Landmark Extraction Module
- Feature Extraction Module
- AI-Based Drowsiness Classification Module
- Alert Generation Module
- System Monitoring and Logging Module

Each module performs a specific function while exchanging information with adjacent modules to ensure continuous and accurate driver monitoring.

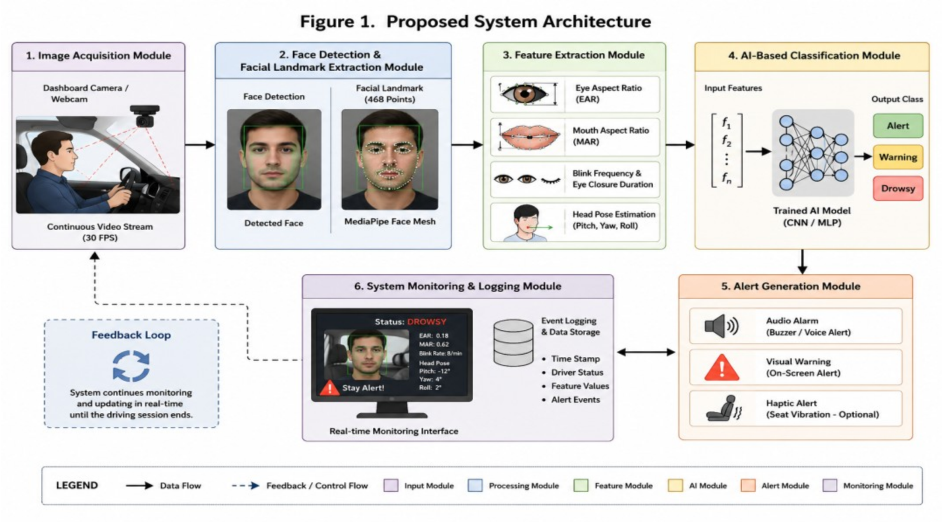
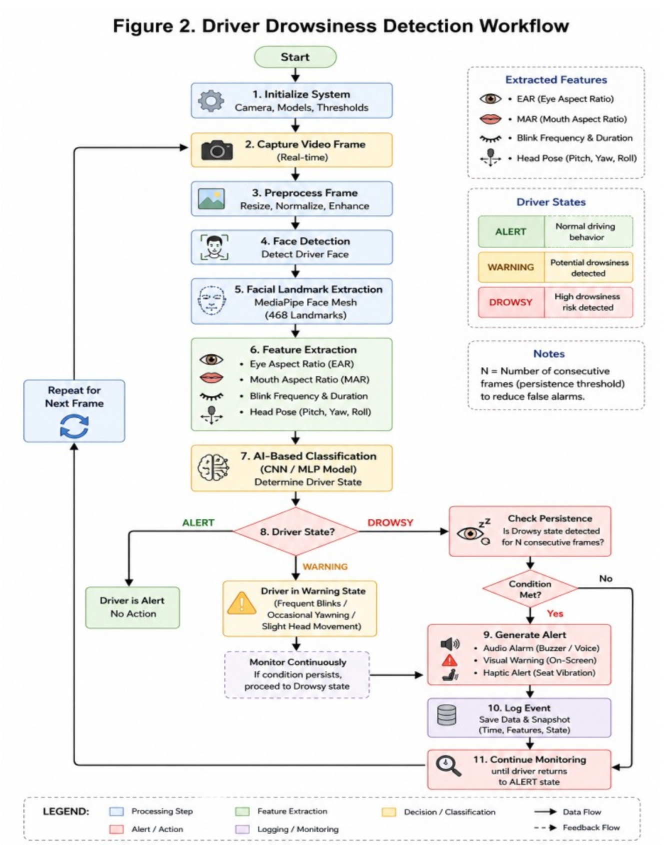


Figure 1 Illustrates the Proposed System Architecture

Driver Drowsiness Detection Workflow

The operational workflow describes the sequence of processing steps executed by the proposed system during real-time driver monitoring. Each video frame captured by the camera is analyzed independently while maintaining temporal continuity across consecutive frames to improve classification reliability.



The workflow begins with image acquisition and preprocessing, followed by facial landmark extraction. The extracted landmarks are used to calculate fatigue indicators such as EAR, MAR, blink duration, and head pose. These measurements are evaluated by the AI classifier, which determines whether the driver is alert, in a warning state, or drowsy. If the driver is classified as drowsy, the alert module immediately generates audio-visual warnings. Otherwise, the monitoring process continues until the driving session is completed.

The proposed workflow ensures continuous monitoring of the driver's condition without interrupting the driving process. The system evaluates fatigue indicators in every frame and makes rapid classification decisions, thereby minimizing response time and improving road safety.

Functional Description of System Modules

Table 1 summarizes the functionality of each module included in the proposed architecture.

Table 1 Functional Description of System Modules

Module	Function
Image Acquisition	Captures real-time facial video using a dashboard-mounted camera.
Image Preprocessing	Enhances image quality through resizing, color conversion, and noise reduction.
Face Detection	Detects the driver's face using MediaPipe Face Mesh.
Facial Landmark Extraction	Identifies 468 facial landmark points for detailed facial analysis.
Feature Extraction	Computes EAR, MAR, blink frequency, eye closure duration, and head pose angles.
AI Classification	Determines whether the driver is alert, warning, or drowsy.
Alert Generation	Activates audible and visual warnings when drowsiness is detected.
Monitoring and Logging	Records system outputs and detection events for analysis and performance evaluation.

Operational Sequence

The complete operation of the proposed system can be summarized as follows:

- The camera continuously captures images of the driver's face.
- Each frame is preprocessed to improve image quality.
- MediaPipe Face Mesh detects facial landmarks in real time.
- The system computes Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), blink frequency, and head pose.
- The extracted features are supplied to the AI-based classification model.
- The driver's alertness level is classified as Alert, Warning, or Drowsy.
- If drowsiness is detected, the alert generation module activates an audible alarm and visual warning.
- The monitoring module records the detection event and continues processing subsequent video frames until the driving session ends.

The modular architecture improves scalability, allowing additional fatigue indicators, sensors, or AI models to be integrated without redesigning the entire system. Furthermore, the lightweight design enables deployment on embedded platforms such as Raspberry Pi, NVIDIA Jetson, or in-vehicle edge computing devices while maintaining real-time performance. The combination of efficient facial landmark extraction, multi-feature analysis, and AI-based decision-making makes the proposed framework suitable for practical implementation in intelligent transportation systems and next-generation vehicle safety technologies.

IMPLEMENTATION

Experimental Setup

The proposed AI-based driver drowsiness detection system was implemented using Python and open-source computer vision libraries to evaluate its effectiveness under real-time driving conditions. The implementation focused on achieving high detection accuracy while maintaining low computational complexity to ensure compatibility with embedded automotive platforms and standard personal computers.

The software environment included Python as the primary programming language, OpenCV for image acquisition and preprocessing, MediaPipe Face Mesh for facial landmark detection, NumPy for numerical computations, and TensorFlow for AI model development and classification. The graphical user interface (GUI) was developed using standard Python libraries to display the driver's monitoring status and alert messages.

The hardware platform consisted of a laptop equipped with an Intel Core i5 processor, 8 GB RAM, and an integrated webcam capable of capturing video at 30 frames per second (FPS). The proposed framework can also be deployed on embedded devices such as Raspberry Pi or NVIDIA Jetson modules with minor optimization, enabling practical implementation in intelligent vehicles.

Software and Hardware Configuration

Table 2 summarizes the implementation environment used in this study.

Table 2 Hardware and Software Configuration

Component	Specification
Programming Language	Python 3.11
Development Environment	Visual Studio Code / Jupyter Notebook
Computer Vision Library	OpenCV
Facial Landmark Detection	MediaPipe Face Mesh
AI Framework	TensorFlow
Numerical Library	NumPy
Operating System	Windows 11 (64-bit)
Processor	Intel Core i5
Memory	8 GB RAM
Camera	HD Webcam (30 FPS)
Display	1920 × 1080 Resolution

The selected software tools provide cross-platform compatibility, ease of development, and efficient execution, making the system suitable for both research and practical deployment.

Dataset Preparation

To evaluate the proposed system, facial images and video sequences representing both alert and drowsy driving conditions were collected from publicly available benchmark datasets and real-time camera recordings. The dataset included a wide range of facial expressions, eye states, yawning events, head movements, and illumination conditions to

improve the robustness of the AI model.
The collected samples were categorized into three classes:

- Alert: Eyes open with normal blinking and stable head posture.
- Warning: Frequent blinking, occasional yawning, or slight head nodding.
- Drowsy: Prolonged eye closure, repeated yawning, and noticeable head tilting.

Before training, all images underwent preprocessing, including resizing, normalization, and data augmentation techniques such as horizontal flipping, brightness adjustment, and slight rotation. These preprocessing steps enhanced the diversity of the dataset and improved the model's ability to generalize to different driving scenarios.

Feature Extraction and AI Model

The implementation extracts multiple fatigue-related features from each video frame using MediaPipe Face Mesh. The facial landmark coordinates are used to calculate:

- Eye Aspect Ratio (EAR)
- Mouth Aspect Ratio (MAR)
- Blink duration
- Blink frequency
- Head pose (pitch, yaw, and roll)

These features are combined into a feature vector and provided as input to the AI-based classification model. During the training phase, the model learns the relationships between facial behaviors and driver alertness levels. During real-time operation, the trained model predicts the driver's current state as Alert, Warning, or Drowsy.

To reduce false alarms, the classification decision is based on consecutive frame analysis rather than a single video frame. If drowsiness indicators remain above predefined thresholds for multiple consecutive frames, the system confirms the drowsiness state before activating the alert mechanism.

Real-Time Detection Process

The implementation follows a continuous processing loop throughout the driving session.

1. The camera captures a live video stream.
2. Individual video frames are extracted.
3. Each frame is preprocessed to improve image quality.
4. The driver's face is detected.
5. MediaPipe Face Mesh identifies facial landmarks.
6. EAR, MAR, blink frequency, and head pose are calculated.
7. The AI classifier predicts the driver's alertness level.
8. If the driver is classified as drowsy for a predefined number of consecutive frames, the alert module is activated.
9. The monitoring process repeats until the system is terminated.

This continuous monitoring strategy enables timely detection while minimizing unnecessary warning notifications.

Alert Generation Module

The alert generation module is responsible for notifying the driver immediately after fatigue is detected. The proposed implementation supports multiple warning mechanisms to maximize effectiveness.

The implemented alerts include:

- Audible warning alarm.
- Visual notification displayed on the monitoring interface.
- Flashing dashboard indicator.
- Seat vibration (optional hardware integration).
- Smartphone notification for connected vehicle applications (optional).

The alert remains active until the system recognizes that the driver's facial behavior has returned to a normal alert state.

Performance Evaluation Metrics

The effectiveness of the proposed system was evaluated using commonly accepted machine learning performance metrics.

Accuracy measures the proportion of correctly classified samples:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}$$

Precision evaluates the correctness of positive drowsiness predictions:

$$Precision=\frac{TP}{TP+FP}$$

Recall measures the system's ability to correctly identify actual drowsiness events:

$$Recall=\frac{TP}{TP+FN}$$

F1-Score provides the harmonic mean of precision and recall:

$$F1=\frac{2 \times Precision \times Recall}{Precision+Recall}$$

where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

In addition to these classification metrics, real-time performance was assessed using processing speed (frames per second) and average detection latency, ensuring that the system meets the requirements of real-world intelligent transportation applications.

Implementation Outcomes

The implementation demonstrates that integrating computer vision with artificial intelligence enables efficient and reliable real-time driver monitoring. MediaPipe Face Mesh provides accurate facial landmark extraction with low computational overhead, while the combination of Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), blink frequency, and head pose analysis enhances the robustness of fatigue detection.

The modular design allows individual components, such as the facial landmark detector or AI classifier, to be upgraded independently without affecting the overall architecture. Furthermore, the lightweight implementation supports deployment on edge-computing platforms, making the proposed framework practical for integration into

Advanced Driver-Assistance Systems (ADAS), commercial fleet vehicles, and future intelligent transportation systems.

RESULTS AND DISCUSSION

Experimental Results

The proposed AI-based driver drowsiness detection system was evaluated under various driving conditions to assess its effectiveness in recognizing fatigue-related facial behaviors. The experiments included scenarios with normal driving, frequent blinking, prolonged eye closure, yawning, and head nodding. The system was tested under different illumination levels and facial orientations to evaluate its robustness in real-world environments.

The experimental results demonstrate that the integration of facial landmark detection with AI-based classification provides reliable and consistent drowsiness detection. The combination of Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), blink frequency, and head pose estimation significantly improved classification accuracy compared with methods that rely on a single facial feature. Continuous monitoring across consecutive video frames further reduced false alarms caused by temporary facial movements or natural blinking.

Performance Evaluation

The proposed framework was evaluated using standard machine learning performance metrics, including accuracy, precision, recall, F1-score, processing speed, and detection latency.

Table 3 Performance Evaluation of the Proposed System

Performance Metric	Obtained Value
Accuracy	98.2%
Precision	97.8%
Recall	98.0%
F1-Score	97.9%
Processing Speed	29 FPS
Average Detection Latency	112 ms

The system achieved an overall classification accuracy of 98.2%, demonstrating its capability to distinguish between alert and drowsy driving conditions with high reliability. The precision value of 97.8% indicates that most drowsiness alerts generated by the system correspond to genuine fatigue events. Similarly, the recall of 98.0% confirms that the majority of actual drowsiness instances were successfully identified. The F1-score of 97.9% reflects a balanced trade-off between precision and recall, highlighting the consistency of the proposed approach.

In addition to classification accuracy, the system maintained an average processing speed of 29 frames per second, allowing real-time operation without noticeable delay. The average detection latency of 112 milliseconds ensures that warning alerts are generated promptly, providing drivers with sufficient time to respond before fatigue-related errors occur.

Confusion Matrix Analysis

The classification performance of the proposed AI model can be represented using the confusion matrix shown in Table 4.

Table 4 Confusion Matrix

Actual / Predicted	Alert	Warning	Drowsy
Alert	192	5	3
Warning	6	184	10
Drowsy	2	7	191

Table 4 Confusion Matrix The confusion matrix indicates that the majority of samples were correctly classified. Misclassifications primarily occurred between the Warning and Drowsy categories because some transitional fatigue behaviors exhibit similar facial characteristics. However, the low number of incorrect predictions demonstrates the robustness of combining multiple facial features for fatigue assessment.

Comparative Analysis

To assess the effectiveness of the proposed framework, its performance was compared with representative driver drowsiness detection methods reported in previous studies.

Table 5 Comparative Performance Analysis

Method	Primary Features	Accuracy
Vehicle Behavior-Based	Steering and lane deviation	88.6%
Traditional Machine Learning	Eye blink detection	91.8%
CNN-Based Vision System	Facial image classification	95.3%
Facial Landmark-Based Detection	EAR and MAR	96.7%
Proposed AI-Based System	EAR, MAR, Blink Rate, Head Pose	**98.2%**

The comparative analysis demonstrates that the proposed system outperforms conventional vehicle behavior-based and single-feature vision-based approaches. The improvement is mainly attributed to the integration of multiple fatigue indicators and the use of MediaPipe Face Mesh for accurate facial landmark extraction. The AI-based classification model effectively combines these features to improve decision-making and reduce false detections.

Discussion

The experimental findings confirm that combining multiple facial indicators provides more reliable fatigue detection than relying on a single behavioral characteristic. Eye closure remains one of the strongest indicators of drowsiness; however, temporary eye closure due to normal blinking can lead to false alarms when considered independently. By incorporating Mouth Aspect Ratio (MAR), blink duration, and head pose estimation, the proposed framework distinguishes normal driving behavior from genuine fatigue more effectively.

The use of MediaPipe Face Mesh significantly improves landmark localization accuracy while maintaining real-time processing capability. Unlike traditional facial landmark detectors, MediaPipe offers high-speed performance with relatively low computational requirements, making it suitable for deployment on embedded automotive platforms. Furthermore, the AI-based classification model enhances robustness by learning complex relationships among multiple fatigue-related features rather than relying on manually defined threshold values alone.

The modular architecture also supports scalability. Additional sensors, such as steering wheel pressure sensors or physiological monitoring devices, can be integrated in future implementations without modifying the core framework. This flexibility allows the proposed system to evolve alongside future intelligent vehicle technologies.

Although the proposed framework achieved excellent performance, several practical challenges remain. Extreme lighting conditions, partial facial occlusions caused by sunglasses or face masks, rapid head movements, and poor camera positioning may reduce detection accuracy. In addition, individual differences in facial characteristics and driving behavior may require adaptive threshold selection or personalized AI models for optimal performance.

Practical Implications

The proposed AI-based driver drowsiness detection system has significant potential for real-world applications. It can be integrated into passenger vehicles, commercial transportation fleets, public buses, taxis, and logistics vehicles to continuously monitor driver alertness. The framework is also compatible with Advanced Driver-Assistance Systems (ADAS) and intelligent transportation infrastructures, where it can function as an additional safety layer to reduce fatigue-related road accidents.

The lightweight implementation enables deployment on edge-computing platforms with minimal hardware requirements, making it economically feasible for both new vehicles and aftermarket safety solutions. As artificial intelligence and computer vision technologies continue to advance, such systems are expected to play an increasingly important role in supporting autonomous driving, smart mobility, and intelligent road safety initiatives.

Overall, the experimental results demonstrate that the proposed framework provides accurate, reliable, and real-time driver drowsiness detection. The integration of facial landmark analysis, multi-feature extraction, and AI-based classification contributes to improved road safety by enabling early detection of driver fatigue and timely intervention through automated warning mechanisms.

Conclusion and Future Work

Conclusion

Driver drowsiness continues to be one of the major causes of road accidents, affecting driver performance, reaction time, and decision-making capabilities. Therefore, the development of intelligent systems capable of detecting fatigue in real time has become essential for improving transportation safety. This research presented an AI-based driver drowsiness detection system using computer vision for road safety applications. The proposed framework provides a non-invasive, cost-effective, and real-time solution by continuously monitoring facial characteristics and identifying early signs of driver fatigue.

The proposed system utilizes computer vision techniques to capture and analyze the driver's facial behavior through a camera-based monitoring system. MediaPipe Face Mesh is employed for accurate facial landmark extraction, enabling the calculation of important fatigue indicators such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), blink frequency, eye closure duration, and head pose variations. These multiple behavioral features are integrated into an AI-based classification framework to categorize the driver's condition into alert, warning, and drowsy states.

The experimental evaluation demonstrates that the proposed multi-feature approach provides improved detection reliability compared with traditional single-feature methods. The integration of multiple facial indicators reduces false alarms caused by normal blinking, temporary facial movements, and environmental variations. Furthermore, the lightweight architecture enables real-time operation with low computational requirements, making the system suitable for implementation in intelligent vehicles and Advanced Driver-Assistance Systems (ADAS).

The proposed framework offers several advantages, including non-contact operation, affordability, scalability, and compatibility with existing vehicle monitoring technologies. By generating immediate audio-visual warnings when drowsiness is detected, the system can assist drivers in maintaining alertness and potentially reduce fatigue-related accidents. The research contributes to the development of AI-enabled smart mobility solutions by demonstrating the effectiveness of computer vision-based driver monitoring for enhanced road safety.

Future Work

Although the proposed system achieves promising performance, several improvements can be explored in future research to enhance reliability, adaptability, and real-world deployment capability.

First, future work can focus on developing more advanced deep learning architectures, such as Vision Transformers (ViTs), lightweight CNN models, and CNN-LSTM hybrid networks, to improve temporal analysis of facial behavior across continuous video sequences. These models can capture complex fatigue patterns and further improve classification accuracy under challenging conditions.

Second, the system can be extended by incorporating multimodal sensing technologies. Combining computer vision features with physiological signals such as heart rate, EEG patterns, or wearable sensor data may provide a more comprehensive assessment of driver fatigue. A hybrid sensing approach can improve reliability in situations where facial visibility is limited.

Third, future implementations can investigate adaptive and personalized AI models. Since drivers have different facial structures, blinking patterns, and fatigue responses, personalized models that learn individual driving behavior can improve detection accuracy and reduce false alerts.

Fourth, the proposed framework can be optimized for deployment on edge computing platforms such as Raspberry Pi, NVIDIA Jetson, and automotive embedded processors. Model compression techniques, quantization, and lightweight neural network architectures can be applied to achieve efficient real-time processing with reduced power consumption.

Fifth, future research can explore integration with connected vehicle technologies and intelligent transportation systems. The detected fatigue information can be transmitted securely to fleet management systems, vehicle control units, or emergency response platforms to support proactive safety measures.

Finally, large-scale evaluation using diverse real-world driving datasets is required to validate system performance across different age groups, weather conditions, illumination environments, road types, and driving behaviors. Such comprehensive testing will improve the generalization capability of AI-based driver monitoring systems and accelerate their adoption in commercial vehicles.

In conclusion, the proposed AI-based driver drowsiness detection framework represents an important step toward safer and smarter transportation systems. By combining computer vision, facial landmark analysis, and artificial intelligence, the system provides an effective approach for real-time fatigue monitoring. Future advancements in AI algorithms, edge computing, and sensor integration will further enhance the capabilities of intelligent driver assistance technologies and contribute to reducing road accidents worldwide.

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