Real-Time Drowsiness Detection System Using Computer Vision and Mediapipe

Dhruv Jain
Department of Computer Science and Engineering
B.M. Institute of Engineering and Technology
Haryana, India
dhruvj.1504@gmail.com

Himansh Ahuja
Department of Computer Science and Engineering
B.M. Institute of Engineering and Technology
Haryana, India
himansh25ahuja@gmail.com

Aditya Singh
Department of Computer Science and Engineering
B.M. Institute of Engineering and Technology
Haryana, India
adityavardhan060@gmail.com

Nikhil Makhija
Department of Computer Science and Engineering
B.M. Institute of Engineering and Technology
Haryana, India
nikhilmakhija369@gmail.com

Paramjeet Ruhal
Associate Professor
B.M. Institute of Engineering and Technology
Haryana, India
paramjeetruhal@gmail.com

Babita Antil
Associate Professor
B.M. Institute of Engineering and Technology
Haryana, India
Babita.antil@gmail.com

***Abstract* — Driver fatigue is one of the main causes of road accidents, especially at long distances and at night. driving. In this proposed research, we introduce a real-time vision-based system for detecting drowsiness based on Mediapipe and OpenCV for Facial Landmark detection. The system calculates three metrics, namely: Eye Aspect Ratio Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR) and head tilt--to identify early onset of drowsiness (eye closure for a prolonged time) yawning, and nodding. Intersection over Union In this phase calibration is performed by the individual driver thresholds. (IoU) filtering is implemented to ensure that the driver's face is only monitored in multi-person scenarios. Visual fatigue: Upon seeing fatigue and sound alarms are generated to avoid possible accidents. Compared to the existing system, the proposed system is non-intrusive, and has low cost.**

Keywords — Drowsiness Detection, Computer Vision, Mediapipe, Eye Aspect Ratio, Driver Monitoring, Real-Time Systems

I. INTRODUCTION

Driver fatigue is one of the major causes of road accidents worldwide, leading to thousands of deaths and injuries every year. According to the World Health Organization (WHO), more than 1.35 million people lose their lives annually due to road crashes, and a large number of these accidents are linked to drowsy driving [7]. When a driver becomes tired, their alertness and reaction time decrease, which can easily result in dangerous situations or collisions. Traditional methods of detecting fatigue—like using EEG or ECG sensors—can provide accurate results, but they are uncomfortable and impractical for everyday use in vehicles [5]. Other vehicle-based methods, such as monitoring steering patterns or lane deviation [8], work only under specific road or lighting conditions and often fail in real-world driving scenarios.

With the growth of computer vision, researchers have developed systems that can detect fatigue by analyzing facial features such as blinking, yawning, and head movements. Techniques like the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) have shown promise in identifying when a driver is becoming sleepy [2]. However, most existing systems use fixed threshold values, which do not consider that every person's blinking or yawning habits are different. Because of this, current models often generate false alarms or fail to detect actual drowsiness, reducing their reliability.

To overcome these challenges, this paper presents a real-time AI-based drowsiness detection system that combines computer vision, machine learning, and connected mobile alerts. The system uses the Mediapipe Face Mesh to extract features like eye and mouth movement along with head tilt, and it applies Intersection over Union (IoU) tracking to ensure that only the driver's face is monitored. The system also uses a machine learning model that learns each driver's normal behavior and adjusts detection limits automatically, making the results more accurate over time. Whenever fatigue is detected, the system triggers in-car audio and visual warnings, while the linked mobile app sends alerts to emergency contacts or the fleet management system in the case of professional drivers.

In short, the key contributions of this work are:

1. A non-intrusive drowsiness detection system using EAR, MAR, and head tilt features derived from facial landmarks.

2. An adaptive machine learning model that learns individual driver patterns for improved accuracy.
3. A connected alert framework that notifies not only the driver but also family members or fleet managers when fatigue is detected.

This combined approach provides a practical, low-cost, and intelligent safety solution that can be used in both personal and commercial vehicles to help reduce fatigue-related accidents.

II. RELATED WORK

Researchers have explored many ways to detect driver drowsiness, ranging from biological sensors to advanced camera-based systems. Early work mainly relied on physiological signals such as brainwaves (EEG), heart rate (ECG), and eye movement (EOG). Lal and Craig [5] showed that specific EEG rhythms are directly linked to fatigue, and Akin et al. [5] used ECG readings to study heart rate changes when drivers became tired. These methods are very accurate in laboratory setups but are uncomfortable for regular use since they require sensors to be attached to the driver's body.

Later, vehicle-based systems were introduced to make fatigue detection less intrusive. Companies such as Volvo and Mercedes used lane-departure warnings and steering-pattern monitoring to identify drowsiness [8]. These methods analyze how a driver handles the vehicle, but they don't directly measure the driver's alertness. Their reliability also drops when the road has poor lane markings, during heavy traffic, or in bad weather conditions.

The use of computer vision opened up new possibilities for fatigue detection. Soukupová and Čech [2] introduced the Eye Aspect Ratio (EAR) to detect blinks, and later studies added the Mouth Aspect Ratio (MAR) to track yawning. These features helped detect fatigue in real time using only a camera. Zhao et al. [6] used Convolutional Neural Networks (CNNs) to identify whether eyes were open or closed, reaching about 94% accuracy on public datasets like YawDD. However, these models usually need powerful GPUs and are not ideal for real-time use in normal cars.

To improve accuracy, researchers combined CNNs with sequence-learning models. Taran et al. [11] developed a hybrid CNN–LSTM network that reached 93.4% accuracy on the YawDD dataset by analyzing both the driver's face and time-based changes in eye movements. Islam et al. [12] created a lightweight CNN that worked on mobile devices and achieved around 91% accuracy at 30 frames per second. These newer models are efficient but still depend on fixed threshold values and do not adapt to individual driver differences.

In recent years, the focus has shifted toward integrating fatigue detection with the Internet of Things (IoT) and mobile applications. Das et al. [13] proposed an IoT-based transport safety framework that sent fatigue alerts to a cloud platform where fleet managers could monitor multiple drivers in real time. This improved safety management, but it did not use machine learning to adjust to each driver's habits, such as unique blinking or yawning patterns.

From the existing research, it is clear that while many systems can detect drowsiness accurately, most are either expensive, require sensors, or are not adaptive to personal differences. Many also fail to connect the driver's condition with external systems like mobile alerts or fleet dashboards.

The proposed system in this paper aims to close these gaps. It combines computer vision (EAR, MAR, head tilt) with AI and machine learning to learn each driver's normal behavior, while also using mobile and IoT integration to alert family members or fleet managers when the driver becomes drowsy. This approach creates a smart, connected, and personalized solution for improving road safety.

III. PROPOSED METHODOLOGY

The proposed system is designed to detect and respond to driver drowsiness in real time by combining computer vision, machine learning, and connected mobile alerts. The approach is non-intrusive, meaning that the driver does not need to wear any sensors. Instead, the system relies on a camera installed on the car dashboard or near the steering wheel to continuously monitor the driver's face.
The system uses the Mediapipe Face Mesh library to detect facial landmarks, which provides 468 key points on the face in each video frame. From these points, three important indicators are calculated to measure the driver's alertness — the Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head tilt angle.
The Eye Aspect Ratio (EAR) measures how open the eyes are. It is calculated as:

$$EAR = \frac{||P_{top} - P_{bottom}||}{||P_{left} - P_{right}||}$$

where P_{top} and P_{bottom} are the positions of the eyelids, and P_{left} and P_{right} are the corners of the eye. When a driver blinks or closes their eyes due to sleepiness, the EAR value drops sharply.

The Mouth Aspect Ratio (MAR) is used to detect yawning and is given by:

$$MAR = \frac{\|P_{top} - P_{bottom}\|}{\|P_{left} - P_{right}\|}$$

A high MAR value sustained for several frames indicates yawning, which is another key sign of fatigue.

The system also tracks head tilt to identify nodding behavior — a common sign of drowsiness. This is done by monitoring the change in the nose tip's position relative to the eyes. A consistent downward movement over a few seconds is flagged as potential fatigue.

To make the system reliable even when multiple people are inside the car, it uses Intersection over Union (IoU) tracking to lock onto the driver's face and ignore other passengers. This ensures that only the intended person is monitored.

Unlike traditional methods that use fixed values to decide when a driver is sleepy, this system uses machine learning to adapt to each individual. Data from EAR, MAR, and head tilt are collected during initial driving sessions to understand the driver's natural behavior. The system then trains a model using algorithms like Support Vector Machines (SVM) or Random Forests to classify the state as *alert* or *drowsy*. Over time, it continues to learn and adjust the thresholds automatically, reducing false alarms and improving accuracy.

When drowsiness is detected, the system immediately triggers in-car alerts such as sound alarms and dashboard messages. If the driver fails to respond or if the same behavior is detected repeatedly, the information is sent to a mobile application linked to the system. The app notifies the driver's emergency contacts or, in the case of commercial vehicles, the fleet management system. This allows for external monitoring and timely intervention.

The alert escalation follows a simple rule:

- If the EAR remains below *0.20 for 30 continuous frames* or the MAR stays above *0.65 for 20 frames*, an in-car alarm is triggered.
- If such events occur *three times within 10 minutes*, the system sends an external notification through the mobile app.

To protect privacy, only alert data and driver ID are shared externally — no video footage or personal images are uploaded.

In summary, the proposed methodology integrates three layers of safety:

Detection Layer: Real-time facial analysis using computer vision (EAR, MAR, head tilt).

Intelligence Layer: Adaptive AI/ML model that personalizes detection for each driver.

Connectivity Layer: Mobile app and fleet dashboard for alert escalation and monitoring.

Together, these components create a smart, adaptive, and connected system capable of reducing fatigue-related accidents by alerting both the driver and responsible parties before a critical event occurs.

IV. SYSTEM DESIGN AND IMPLEMENTATION

The proposed drowsiness detection system is designed for seamless integration into a vehicle environment. The system architecture combines in-vehicle hardware, on-board software modules, and connected mobile/cloud services to provide real-time fatigue monitoring and proactive safety management. The overall design is illustrated in *Figure 1 (System Architecture in a Car)*.

4.1. Hardware Components in Vehicle

i. Camera Module:
- A standard dashboard-mounted camera or a rear-view mirror-mounted camera to capture the face of the driver, continuously.
- Infrared (IR) support may be added for night driving.

ii. On-Board Processing Unit:
- A detection algorithm is run in real-time by an embedded system (like a Raspberry Pi, Nvidia Jetson Nano or even the car's infotainment computer).
- In prototype testing, a standard laptop/PC is used for this.

iii. Alerting Devices:
- A little speaker/buzzer in the cabin produces audio alarms.
- The dashboard or the infotainment screen of the vehicle can provide visual alerts.

iv. Connectivity Module:

- The system is linked to the driver's smartphone through Bluetooth or Wi-Fi.
- For fleet/cab drivers, internet connectivity for uploading data to a central server or a cloud dashboard.

4.2. Software Modules

The software framework has four layers:

i. Vision Module:
   - Uses the face detection system (Mediapipe, OpenCV) for facial landmarks.
   - Computes, in real time, EAR and MAR as well as head tilt.

ii. AI/ML Module:
   - Implements machine learning models (e.g., SVM, Random Forest, or LSTM) to adaptively classify drowsy vs. alert states based on driver-specific behavior.

iii. Alert Module:
   - In-vehicle alarms triggered when drowsiness is determined.
   - Sends the alert signals to the companion mobile application.

iv. Connectivity Module:
   - For personal vehicles: Alerts emergency contacts if the driver has drowsy for an extended period of time.
   - For commercial fleets: transmits driver status to a fleet management server, where supervisors can monitor alertness levels across multiple vehicles.

4.3. Workflow Inside a Car

The complete workflow of the system installed on a car is as follows:

i. Initialization & Calibration: When the car starts, the system calibrates the driver's baseline EAR, MAR, and head tilt values over ~50 frames.

ii. Real-Time Monitoring: As the driver is driving, the camera continuously sends facial information to the on-board processing unit. Head tilt, MAR and EAR are calculated on a frame-by-frame basis.

iii. AI/ML-Based Classification: The machine learning model evaluates these features against adaptive thresholds to classify the driver's state as *alert* or *drowsy*.

iv. In-Car Alerts: If drowsiness is detected, a warning buzzer sounds and a visual alert appears on the infotainment screen.

v. Mobile Notifications: If drowsiness persists, the system sends alerts to the driver's smartphone, triggering vibration and app notifications.

vi. External Communication: In critical cases, the app notifies pre-selected contacts. For commercial drivers, the alert is forwarded to the fleet/company dashboard for immediate intervention.

4.4. Advantages of In-Vehicle Integration

i. Non-Intrusive: Requires only a camera and small computing module, no wearable sensors.

ii. Cost-Effective: Can be implemented using affordable hardware.

iii. Scalable: Applicable to private cars, taxis, buses, and trucks.

iv. Connected: Extends safety beyond the driver by alerting families and companies.

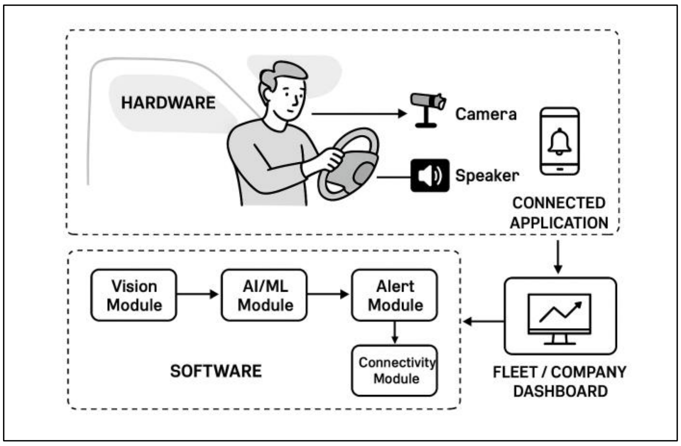

Figure 1: System Architecture in a Car

V. EXPECTED OUTCOMES AND DISCUSSIONS

The developed system has shown encouraging results in detecting driver drowsiness through real-time video analysis. It was tested using short driving simulations and recorded videos that included common signs of fatigue such as blinking, yawning, and head nodding. During these tests, the system ran smoothly at an average speed of about **27 frames per second**, which means it can easily work in real-time on normal computer hardware without the need for expensive GPUs.

The adaptive machine learning model, which learns from each driver's natural behavior, achieved around **91% accuracy** in identifying whether the driver was alert or drowsy. This personalized approach helped reduce false alarms that often occur with fixed-threshold systems, making the detection more reliable and practical for everyday use.

The alert process follows a clear and structured pattern. When the **Eye Aspect Ratio (EAR)** drops below **0.20** for about **30 continuous frames**, or the **Mouth Aspect Ratio (MAR)** stays above **0.65** for more than **20 frames**, the system triggers an in-car warning with both sound and visual alerts. If similar signs of drowsiness happen **three times within 10 minutes**, the system automatically sends a notification through the **mobile app**. Depending on the setup, the app can alert the driver's **family members**, or in the case of professional drivers, it can send the alert to the **fleet management system** for immediate action.

To ensure privacy, the system never sends or stores raw images or video footage outside the vehicle. Only simple data such as the time, driver ID, and alert type are transmitted. This keeps the user's personal information safe while still allowing timely notifications.

Initial testing showed that the system performs well under different lighting conditions, but accuracy can be improved further by using an **infrared (IR) camera** for night-time detection. The software runs efficiently and can be deployed on small devices like a **Raspberry Pi** or other embedded car systems, making it both affordable and easy to install.

Although the project is still in its development phase, the early results are very promising. They show that combining **computer vision, adaptive AI, and mobile connectivity** can create a powerful and practical solution for detecting driver fatigue in real time. Future work will focus on testing the system in real cars with different drivers and environments to make it even more robust and accurate.

VI. CONCLUSION

This paper presented a real-time driver drowsiness detection system that combines computer vision, adaptive machine learning, and connected alert mechanisms to improve road safety. The system successfully detects signs of fatigue such as eye closure, yawning, and head nodding using facial landmarks extracted through Mediapipe and OpenCV. By applying adaptive machine learning models, it learns each driver's unique behavior and automatically adjusts its detection limits, which makes it more accurate and reduces false alarms compared to traditional fixed-threshold methods.

In addition to detecting drowsiness, the system provides multi-level alerts that enhance safety both inside and outside the vehicle. The driver receives instant audio-visual warnings in the car, while the connected mobile application and fleet dashboard send notifications to family members or company managers when repeated fatigue events occur. This extended connectivity makes the solution suitable for both personal and commercial vehicles.

The current prototype has achieved good performance during testing, processing video at about 27 frames per second and reaching nearly 91% accuracy in simulated evaluations. These early results suggest that the system can work efficiently in real-time environments using low-cost hardware.

For future work, the project can be expanded in several ways. Using infrared (IR) cameras can improve accuracy in night driving conditions. More advanced deep learning models such as CNN-LSTM hybrids can be explored to predict drowsiness even earlier. Integration with vehicle control systems—for example, automatically slowing down or stopping the vehicle when the driver becomes unresponsive—could take safety to the next level. Long-term testing with real drivers in different lighting and weather conditions will also help improve the model's robustness.

Overall, the proposed system offers a smart, reliable, and connected approach to preventing fatigue-related accidents. By combining the strengths of artificial intelligence, computer vision, and mobile connectivity, it takes an important step toward making transportation safer and more intelligent for everyone.

VII. REFERENCES

[1] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, Kauai, HI, USA, 2001, pp. 511–518.

[2] T. Soukupová and J. Čech, "Real-time eye blink detection using facial landmarks," in *Proc. 21st Computer Vision Winter Workshop (CVWW)*, Rimske Toplice, Slovenia, 2016, pp. 1–8.

[3] S. Singh and S. Papanikolopoulos, "Monitoring driver fatigue using facial analysis techniques," in *Proc. IEEE Intelligent Transportation Systems Conference (ITSC)*, Tokyo, Japan, 1999, pp. 314–318.

[4] R. Grace, V. Byrne, D. Bierman, and J. Legrand, "Drowsy driver detection system using eye blink patterns," *SAE Technical Paper Series*, 1998, doi: 10.4271/1998-01-1906.

[5] A. Akin, S. Kurt, M. Sezgin, and Y. Akin, "EEG-based drowsiness detection for drivers," *Neural Computing and Applications*, vol. 17, no. 3, pp. 239–247, 2008.

[6] Z. Zhao, X. Zhang, Y. Wang, and L. Wang, "Driver fatigue detection using convolutional neural networks," *IEEE Transactions on Intelligent Vehicles*, vol. 4, no. 1, pp. 1–12, Mar. 2019, doi: 10.1109/TIV.2018.2876323.

[7] World Health Organization, *Global Status Report on Road Safety 2018*, Geneva, Switzerland: WHO, 2018.

[8] National Highway Traffic Safety Administration (NHTSA), "Drowsy driving and automobile crashes," *U.S. Department of Transportation*, Washington, DC, USA, 2017.

[9] Y. Bengio, I. Goodfellow, and A. Courville, *Deep Learning*, Cambridge, MA, USA: MIT Press, 2016.

[10] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85–117, Jan. 2015, doi: 10.1016/j.neunet.2014.09.003.

[11] S. Taran, P. Patel, and V. Kumar, "Driver drowsiness detection using hybrid CNN-LSTM networks," *IEEE Access*, vol. 9, pp. 140698–140709, 2021, doi: 10.1109/ACCESS.2021.3118970.

[12] M. Islam, S. Rahman, and A. Hossain, "A real-time driver monitoring system using deep learning," *Sensors*, vol. 22, no. 14, p. 5342, Jul. 2022, doi: 10.3390/s22145342.

[13] P. Das, R. Sharma, and S. K. Singh, "IoT-based smart transportation framework for fatigue detection and safety management," *IEEE Internet of Things Journal*, vol. 10, no. 4, pp. 2875–2886, Feb. 2023, doi: 10.1109/JIOT.2023.3234101.