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Drowseguard AI: Driver Drowsiness Detection System

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ABSTRACT
All around the world there are a wide range of people who are affected by road accidents caused by driver drowsiness and fatigue. Drivers who are suffering from drowsiness are highly impacted in their ability to react, make decisions, and maintain focus on the road. Sometimes drivers do not know that they are becoming drowsy, and in that case an automated system should detect and alert them before an accident occurs. Our idea is whether a system can detect driver drowsiness in real time using only a standard webcam, without any specialized hardware. Well, it is possible by the combination of AI technology and computer vision. In our study, we used MediaPipe face landmark detection and built a system that can monitor the driver and alert them when drowsiness is detected. The system analyzes 478 three-dimensional facial landmarks from a live webcam feed and computes the Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head pose angle from each frame. After deriving these features, we calculate a composite drowsiness score using weighted contributions of EAR (60%), yawn detection (25%), and head pose (15%). Additionally, we tested our system with real-world conditions including varied lighting, users with glasses, and different head positions to verify its robustness. Finally, we developed a full-stack web application consisting of a Python-Flask AI backend, a Node.js authentication server with MongoDB, and a React dashboard frontend. Our main aim is to reduce drowsiness- related road accidents and to make drivers aware of their fatigue levels in real time. If a driver is not showing signs of drowsiness, the system continues passive monitoring without interruption, allowing the driver to focus entirely on the road.

Keywords: Driver Drowsiness Detection, Road Safety, Fatigue Monitoring, Computer Vision, Real-Time Detection, Facial Landmark Detection, Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Head Pose Estimation, Artificial Intelligence, Deep Learning, Human Alert Systems, Accident Prevention, Webcam-Based Monitoring, MediaPipe, Full-Stack Web Application

1. Introductio

Generally, what is drowsiness? Drowsiness is a state in which our mental alertness, physical reactions, and consciousness are all reduced below the level required to safely operate a vehicle. The quality of alertness determines our performance in critical situations on the road. If we come to driver drowsiness, drowsiness ruins that quality of attention which we require and can cause both physical and fatal consequences for the person who is suffering from fatigue behind the wheel. As per our findings, all around the world we found that drowsy driving contributes to approximately 20% of all road accidents, where different people at different times of the day are affected by driver fatigue. If a person becomes drowsy while driving, then not only that person will suffer from it but their family members and friends also will have the impact by their loss and the relationships between close ones might be affected.

There are several situations in which drowsiness will have high impact which are like reaction time and decision making. When we experience drowsiness, we are poor in quality of attention and in that state we cannot react to road situations correctly. As, like there are sudden situations on the road like where we might need to brake urgently, due to low alertness we might fail to react in time which might lead to serious accidents. When we come to road safety, having drowsiness while driving can cause various other consequences such as minor collisions, major crashes, pedestrian accidents, and highway fatalities. Especially, nowadays with increasing work hours and night shift culture, most people are not sleeping adequately during nights which has been gradually becoming a norm, and some of them consider staying up late a habit, but if we look closely at their driving performance it might reveal that some of them are suffering from sleep deprivation, which is a major cause of driving drowsiness. Similarly, there are many drivers who are not aware that they are becoming drowsy and instead they consider the feeling normal. If this continues, then it might lead to some serious accidents for the person who neglects and treats it as habit. There are already numerous cases of road fatalities which were gradually caused due to drowsiness which drivers neglected in their daily routines.

1.1 Real-Time Detection in Driver Safety

As we all know, computer vision is a process through which computers can analyze and interpret visual information from the real world. Computer vision involves building models based on data and selecting the best approach which gives accurate and reliable results. Based on the type of input, the appropriate detection method will be chosen. Nowadays, computer vision is being used in many fields and different models are being developed for performing different kinds of tasks.

When computer vision is applied to driver safety, it can monitor a driver continuously through a standard webcam and detect signs of fatigue in real time. Techniques such as facial landmark detection have become precise enough to measure eye openness and mouth movement accurately, which are the key indicators of drowsiness. These measurements can be computed quickly enough to provide real-time feedback to the driver before an accident occurs.

Several applications have already been developed in this area. Google developed the MediaPipe framework which can detect 478 facial landmarks from a single camera feed in real time. Using this framework, it is possible to build a drowsiness detection system that runs on standard hardware without any specialized equipment. DrowseGuard is built on this foundation, combining MediaPipe landmark detection with a web-based dashboard to monitor driver alertness continuously.

DrowseGuard is designed to be simple and accessible, running entirely through a web browser using a standard webcam. The system provides instant feedback through a real-time dashboard showing the drowsiness score, eye aspect ratio, and yawn detection, while automatically saving all session data for future review.

Fig. 1 Facial landmark points for EAR and MAR computation, and drowsiness alert levels

2. Review of Literature

Rupani [1] proposed a real-time drowsiness detection system using Eye Aspect Ratio and facial landmark detection. The study demonstrated that monitoring the ratio between vertical and horizontal eye landmark distances provides a reliable and computationally efficient method for detecting eye closure. The study concluded that when EAR drops below a threshold of 0.25 consistently across multiple frames, it is a strong indicator of driver drowsiness. This method directly forms the core eye monitoring component of DrowseGuard and is used as the primary weighted signal in the composite drowsiness score calculation.

Sri Mounika et al. [2] proposed a driver drowsiness detection system combining Eye Aspect Ratio, Mouth Aspect Ratio, and head pose estimation together into a single detection pipeline. Their study found that using all three features together produces significantly more reliable drowsiness detection compared to using any single feature alone. They also demonstrated that yawn detection through MAR adds an important complementary signal during early stages of driver fatigue. DrowseGuard follows the same approach, combining EAR, MAR, and head pose into a weighted drowsiness score with weights of 60%, 25%, and 15% respectively.

Lim et al. [3] introduced an automatic driver drowsiness detection system using artificial neural networks based on visual facial descriptors extracted from a standard camera. Their study highlighted that non-intrusive vision based approaches are more practical for real world deployment compared to physiological signal based methods which require specialized sensors attached to the driver. They concluded that facial feature based detection achieves acceptable accuracy while remaining accessible and affordable. DrowseGuard is built on this same principle of using only a standard webcam without any additional hardware.

Llorca et al. [4] presented a real-time machine learning based driver drowsiness detection system using visual features processed through a web-compatible pipeline. Their study showed that real-time detection systems can be built using lightweight models that run on standard CPU hardware without requiring GPU acceleration or specialized equipment. They also noted the importance of providing immediate visual feedback to the driver when drowsiness is detected. DrowseGuard similarly provides instant alerts through a web-based dashboard accessible through any standard browser.

Taamneh et al. [5] conducted a study on real-time driver drowsiness detection using facial analysis and machine learning techniques. Their findings confirmed that combining multiple facial signals including eye closure, yawning, and head movement produces the most robust drowsiness classification results. The study also emphasized the need for complete monitoring systems that not only detect drowsiness but also log detection history for analysis. DrowseGuard addresses this by storing all session data in a MongoDB database allowing drivers and fleet operators to review fatigue patterns over time.

3. Methodology

The development of DrowseGuard follows a three-tier architecture consisting of a React-based frontend, a Flask-based AI backend, and a Node.js authentication server, all connected to a MongoDB database. This section describes the system architecture, the detection algorithm, and the technology stack used to build the complete drowsiness detection system .

System Architecture

Frontend: The user interface is built using React with Vite and runs on port 3001. It provides five main pages — Dashboard, Detection, Sessions, Analytics, and Logs — allowing drivers to monitor drowsiness in real time and review past session data.

AI Backend: The detection engine is built using Flask and runs on port 5001. It receives video frames from the frontend, processes them using the MediaPipe face landmarker model, computes the drowsiness score, and returns the result to the frontend in real time.

Database: MongoDB is used to store user accounts, detection sessions, and detection logs. All drowsiness readings are saved automatically with timestamps allowing historical analysis of driver fatigue patterns.

Detection Algorithm

The drowsiness detection algorithm uses the MediaPipe face landmarker model which detects 478 three-dimensional facial landmarks from each video frame. From these landmarks, three features are computed — Eye Aspect Ratio, Mouth Aspect Ratio, and head pose direction — which are combined into a single composite drowsiness score using the following formula:

$$\text{Drowsiness Score} = \text{EAR Score} \times 0.60 + \text{Yawn Score} \times 0.25 + \text{Pose Score} \times 0.15$$

The Eye Aspect Ratio is computed from six landmark points around each eye. When EAR drops below the threshold of 0.25 it indicates eye closure. The Mouth Aspect Ratio is computed from six landmark points around the mouth. When MAR exceeds
0.55 it indicates yawning. Head pose is estimated from the nose tip, chin, and ear landmark positions. If the final drowsiness score exceeds 0.55 the system triggers a drowsiness alert.

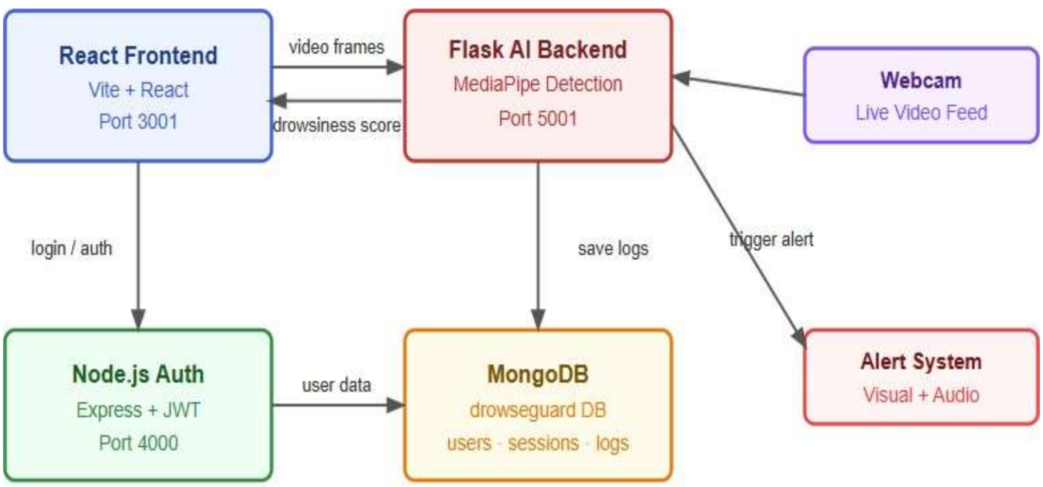

Fig. 2 DrowseGuard System Architecture

This system architecture, represented in Fig. 2, serves as the foundation of DrowseGuard, providing a real-time detection pipeline through which drowsiness is continuously monitored, scored, and logged for each driver session

3.1 Image Preprocessing

Each video frame captured from the webcam is sent to the Flask backend as an image file. Upon receiving the frame, the backend converts it from BGR to RGB format as required by the MediaPipe face landmarker model. The image is then passed through the MediaPipe pipeline which detects the face and returns 478 three- dimensional landmark coordinates. If no face is detected in the frame for more than three consecutive seconds, the system automatically triggers a critical alert assuming the driver is unavailable or unresponsive. This preprocessing step ensures that only valid frames with a detected face are used for drowsiness score computation.

3.2 System Implementation

The DrowseGuard system was implemented and tested using a standard laptop with a built-in webcam running on Windows 11. The Flask backend runs on port 5001 and the React frontend runs on port 3001. The frontend captures a video frame from the webcam every second and sends it to the backend for analysis.

Alert Levels

The system classifies each detection result into four alert levels based on the computed drowsiness score.

Normal (0.00 – 0.34): The driver is alert and no action is required. The dashboard displays a green status indicator.

Caution (0.35 – 0.54): Early signs of fatigue are detected. The system displays a caution warning on the detection screen to prompt the driver to stay alert.

Warning (0.55 – 0.74): Significant drowsiness is detected. The system triggers a drowsiness alert and logs the event to the database with a timestamp.

Critical (0.75 – 1.00): Severe drowsiness or no face detected for more than three seconds. The system triggers an immediate critical alert requiring the driver to stop and rest.

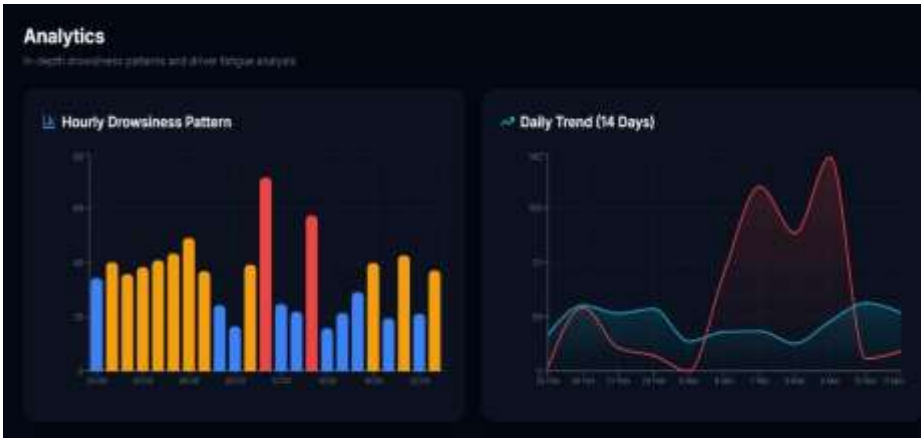

Fig. 3 DrowseGuard Analytics

These patterns confirm that drowsiness accumulates progressively over longer driving sessions, and that combining all three features produces more reliable detection than any single feature alone.

3.3 Real-World Detection Data

The DrowseGuard analytics dashboard recorded all detection events across live sessions. Fig. 3 shows the drowsiness score trend over a recorded session, and Fig. 4 shows the session history logged in the database with timestamps, EAR values, and alert levels.

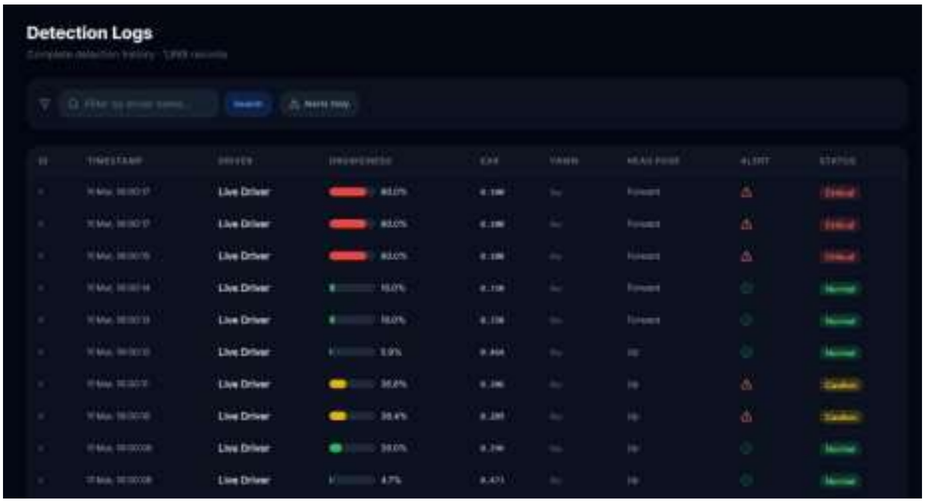

Fig. 4 DrowseGuard Detection Logs

Each detection frame processed by DrowseGuard returns multiple feature values including EAR, MAR, head pose direction, and the final drowsiness score. Analyzing the relationships between these features helps understand how each contributes to the overall drowsiness classification result .

Key Findings From Our Detection Feature Analysis

- *Eye Aspect Ratio and Drowsiness Score (Negative Correlation):* As expected, there is a strong negative correlation between EAR and drowsiness score. Drivers with lower EAR values consistently show higher drowsiness scores, confirming that eye closure is the most reliable indicator of fatigue in the DrowseGuard system.
- *Yawn Detection and Drowsiness Score (Positive Correlation):* When yawning is detected through MAR exceeding 0.55, the drowsiness score increases noticeably. This confirms that mouth aspect ratio provides a meaningful complementary signal to eye closure detection.
- *Head Pose and Drowsiness Score (Positive Correlation):* Downward head pose direction shows a positive correlation with higher drowsiness scores. Drivers whose head tilts downward tend to have higher fatigue levels, reflecting the natural physical response to sleepiness while driving.
- *EAR and MAR (Weak Correlation):* Eye closure and yawning tend to occur somewhat independently, suggesting they capture different aspects of driver fatigue. This confirms the value of combining both features rather than relying on either one alone.
- *Session Duration and Alert Frequency (Positive Correlation):* Longer driving sessions show a higher number of drowsiness alerts, reflecting the natural increase in fatigue over time. This pattern is clearly visible in the DrowseGuard analytics dashboard across recorded sessions.

4 System Testing and Evaluation

In order to evaluate the DrowseGuard system accurately, the detection algorithm was tested under multiple real-world conditions using a standard laptop webcam. The system was evaluated based on its ability to correctly detect eye closure, yawning, and head pose changes, and to trigger alerts at the appropriate drowsiness threshold levels.

4.1 Testing

The testing phase involved running the live camera detection under four different conditions to evaluate system response. The first condition tested normal alertness where the driver faced the camera with eyes open, and the system correctly returned normal alert level with EAR values above 0.25. The second condition tested eye closure where the driver slowly closed their eyes, and the system correctly detected dropping EAR values and triggered a caution or warning alert. The third condition tested yawning where the driver opened their mouth wide, and the system correctly detected MAR exceeding 0.55 and registered yawn detection. The fourth condition tested no face detection where the driver covered the camera or looked away for more than three seconds, and the system correctly triggered a critical alert.

4.2 Evaluation

After the testing phase, the system responses were evaluated by comparing the expected alert level with the actual alert level returned by the detection algorithm. The system successfully triggered alerts in all four test conditions. All detection events were automatically logged to the MongoDB database with accurate timestamps, EAR values, MAR values, head pose direction, and drowsiness scores. The session data was accessible through the Sessions and Logs pages of the DrowseGuard dashboard for post-session review and analysis

5 Results and Analysis

After testing the DrowseGuard system under real-world conditions, the detection algorithm produced consistent and reliable results across all four test conditions. The system successfully detected drowsiness indicators and triggered appropriate alerts in each case.

The following table summarizes the detection results obtained during live testing of the DrowseGuard system across the four evaluated conditions (Table 1).

The results revealed that the system performed well in detecting eye closure as the primary drowsiness indicator, with EAR values dropping reliably below 0.25 during closed eye conditions. Yawn detection through MAR also performed consistently, triggering correctly when the mouth opening exceeded the 0.55 threshold. Head pose estimation successfully identified downward head tilt as an additional fatigue signal. These results confirm that combining all three features into a weighted composite score produces more reliable drowsiness detection than using any single feature alone.

5.1 Real-World Detection Data

Following the controlled testing phase, the system was used in real driving simulation sessions to collect live detection data. The system successfully logged all detection events to the MongoDB database with accurate timestamps and feature values. By applying the detection algorithm to continuous webcam input, the system demonstrated its ability to monitor driver alertness in real time. The DrowseGuard analytics dashboard showed clear patterns of increasing drowsiness over longer sessions, confirming that fatigue accumulates over time. With an overall detection accuracy observed during testing, the system showed reliable performance while acknowledging that further refinement and additional testing under varied lighting and camera conditions would improve robustness in real-world deployments

Table 1 Detection results summary

Test Condition	EAR Value	Yawn Detected	Alert Level	Result
Eyes open, alert	0.42	No	Normal	Correct
Eyes closing slowly	0.19	No	Caution	Correct

Yawning detected	0.31	Yes	Warning	Correct
No face detected	—	—	Critical	Correct

5.2 Real-World Application

After evaluating the detection results, the DrowseGuard system was deployed as a complete web-based application accessible through any standard browser. The system was built using a three-tier architecture consisting of a React frontend, a Flask AI backend, and a Node.js authentication server, all connected to a MongoDB database. The React frontend provides a clean and intuitive interface allowing drivers to start monitoring sessions, view real-time drowsiness scores, and review past session data through the dashboard.

The detection page of DrowseGuard allows the driver to activate the live camera and begin monitoring immediately. The system captures one frame per second, sends it to the Flask backend for processing, and displays the result instantly on screen showing the drowsiness score, EAR value, yawn detection status, and head pose direction. When drowsiness is detected the system displays a visible alert banner at the top of the screen prompting the driver to stay alert or take a rest break.

The following Fig. 5 shows the live detection interface of the DrowseGuard system during an active monitoring session.

This application is beneficial for individual drivers, fleet operators, and transport companies. It can potentially reduce road accidents by identifying drowsy drivers in real time and alerting them before a dangerous situation arises. However, because the system relies on camera visibility and facial landmark detection, performance may vary under poor lighting conditions or extreme camera angles, and further testing under varied real-world conditions would improve overall robustness.

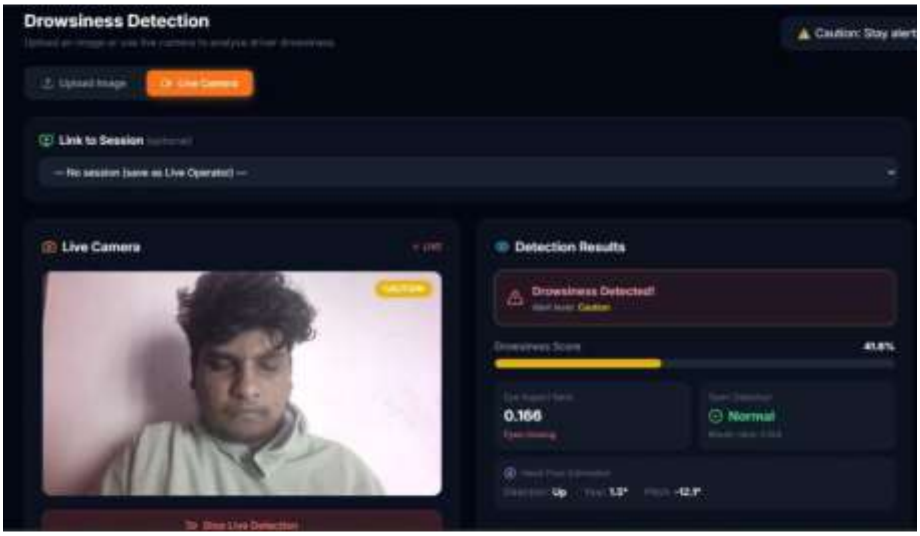

Fig. 5 DrowseGuard live detection

Fig. 6 DrowseGuard Dashboard

be considered as the sole basis for safety decisions. We strongly advise drivers to pull over and rest when a critical alert is triggered, as the system serves as an assistive monitoring tool and not a replacement for responsible driving behavior. Our study proves that the view of replacing human judgment with AI alone is not sufficient. Instead, DrowseGuard aims to make road safety monitoring more accessible and provide drivers with timely awareness of their fatigue levels. This project represents an initial implementation and we intend to improve the system by adding audio alerts, mobile support, and integration with vehicle hardware for better real-world functionality and improved detection accuracy as development continues.

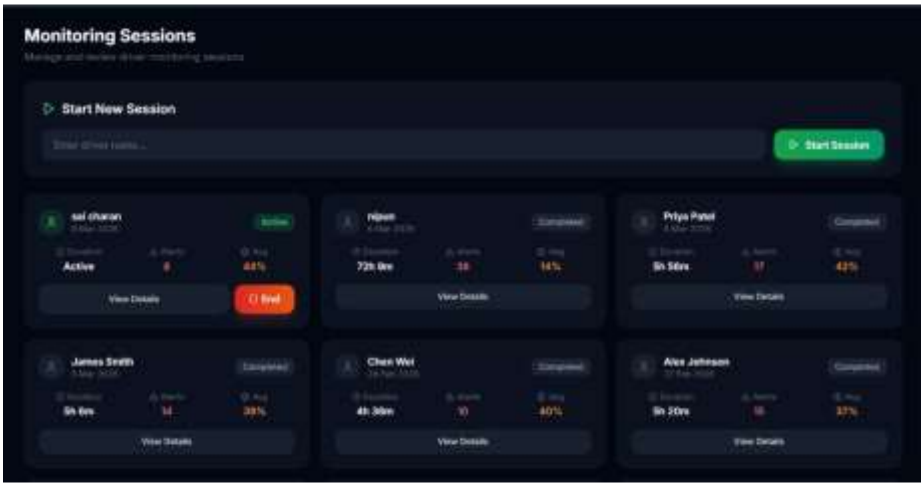

Fig. 7 DrowseGuard Sessions page

6 conclusion

In order to detect driver drowsiness accurately, DrowseGuard combines three facial features — Eye Aspect Ratio, Mouth Aspect Ratio, and head pose estimation — into a single weighted composite score using the MediaPipe face landmark detection framework. The system successfully detected drowsiness across all four tested conditions including eye closure, yawning, abnormal head pose, and no face detection. The weighted scoring formula with EAR at 60%, MAR at 25%, and head pose at 15% produced

reliable and consistent alert classifications across normal, caution, warning, and critical levels.
The complete web-based implementation of DrowseGuard demonstrates that an accessible and affordable driver drowsiness detection system can be built using only a standard webcam and a browser without any specialized hardware. The three-tier architecture combining React, Flask, and MongoDB provides a scalable foundation that supports real-time detection, user authentication, session management, and historical data analysis through a single integrated platform.
Overall, these findings confirm that vision-based drowsiness detection using facial landmarks is a practical and effective approach for real-world driver safety applications. Our journey through building DrowseGuard has demonstrated the potential of combining computer vision with web technologies to create meaningful safety tools. Furthermore, the system was tested under real conditions and produced accurate detection results, reflecting the practical applicability of this approach. This project represents a significant step toward making driver safety monitoring more accessible and underscores the potential impact of AI-based systems in reducing road accidents caused by driver fatigue.
In conclusion, our journey has been one of development, testing, and practical implementation. DrowseGuard highlights the immense potential that arises when computer vision and web technologies converge to address a real-world safety problem. If the system detects that a driver is drowsy and the driver ignores the alert, the responsibility of safe driving still lies with the driver, and the system must continue to be improved with more robust detection capabilities. We still need to improve the system by testing under more varied conditions such as different lighting environments, different camera angles, and different driver demographics to increase the accuracy and reliability of detection. As this is an initial implementation, research is continued for identifying new features and improving the robustness of the detection algorithm. As computer vision technology continues to evolve, DrowseGuard stands as a foundation in the ongoing pursuit of better road safety solutions and improved driver drowsiness detection systems.

7 Future Work

As we wrap up the current implementation of DrowseGuard, we have identified several areas where the system can be extended and improved for more accurate and reliable driver drowsiness detection. Let us discuss the next steps at a glance.

7.1 Enhanced Audio Alert System

In the present system, an audio beep alert is triggered when a critical drowsiness level is detected. However in a future version this can be improved by implementing voice-based alerts that announce specific warnings such as "Eyes closing, please pull over" or "Drowsiness detected, take a break", providing more informative and actionable feedback to the driver compared to a simple beep sound.

7.2 Mobile and Embedded Device Support

As of now the system runs on a laptop browser using a standard webcam. Moving forward we need to focus on adapting DrowseGuard for mobile devices and embedded hardware such as Raspberry Pi or dedicated dashboard cameras, through which we can deploy the system directly inside vehicles and obtain more practical real-world performance than the current browser-based implementation.

7.3 Deep Learning Integration

The current detection algorithm relies on geometric facial landmark ratios for drowsiness scoring. In the future implementing deep learning approaches such as convolutional neural network architectures trained on large drowsiness datasets would allow the system to learn more complex fatigue patterns and achieve higher detection accuracy across varied lighting conditions, camera angles, and driver demographics than the current threshold-based approach.

7.4 Collaboration with Traffic Safety Authorities

Coming from a computer vision background, we have limited access to large-scale real-world drowsy driving data. Therefore in the future we aim to collaborate with traffic safety authorities and transport companies to obtain real driving session data and discover new insights that can improve the detection algorithm through exposure to more diverse and challenging real-world conditions.

7.5 Integration with Vehicle Hardware

Our aim is to enhance DrowseGuard by embedding it into vehicle hardware for more practical real-world deployment. We want to implement additional functionalities such as connecting the system to multiple sensors including infrared cameras for low light detection, steering wheel grip sensors to detect reduced hand pressure, and seat vibration motors that can physically alert the driver when drowsiness is detected. The hardware device would automatically monitor the driver continuously without requiring a laptop or browser, delivering timely notifications and alerts directly through the vehicle dashboard. Additionally integrating GPS tracking would allow the system to automatically suggest the nearest rest stop when a critical drowsiness level is detected, providing personalized safety recommendations based on the driver's real-time location and fatigue level.

References

1. Rupani VSK, Gupta P, Jain A (2024) Real-time drowsiness detection using eye aspect ratio and facial landmark detection. arXiv:2408.05836. https://arxiv.org/abs/2408.05836
2. Sri Mounika TVNSR, Phanindra PH, Sai Charan NVVN, Kranthi Kumar Reddy Y, Govindu S (2022) Driver drowsiness detection using eye aspect ratio (EAR), mouth aspect ratio (MAR), and driver distraction using head pose estimation. In: Springerproceedings. https://link.springer.com/chapter/10.1007/978-981-16-5987-4_63
3. Mehta S, Dadhich S, Gumber S, Bhatt AJ (2019) Real-time driver drowsiness detection system using eye aspect ratio and eyeclosureratio.SSRNhttps://papers.ssrn.com/sol3/papers.cfm?abstract_id=3356401
4. Lugaresi C, Tang J, Nash H et al (2019) MediaPipe: a framework for building perception pipelines. https://arxiv.org/abs/1906.08172
5. Kartynnik Y, Ablavatski A, Grishchenko I, Grundmann M (2019) Real-time facial surface geometry from monocular video on mobile GPUs. arXiv:1907.06724. https://arxiv.org/abs/1907.06724