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DRIVER DROWSINSS DETECTION SYSTEM

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ABSTRACT :

Drowsy driving has joined the most serious threats to highway safety in the highly mobile and fast-paced world of the present day. Unlike alcohol impairment, which can readily be quantified and legally imposed, drowsiness builds unnoticed, usually before the driver is even aware of it, until his or her alertness is seriously impaired. This renders fatigued driving considerably more challenging to identify and control. Findings from the U.S. National Highway Traffic Safety Administration (NHTSA) outline the extent of the problem, as in 2017 alone there were over 91,000 road accidents and almost 800 fatalities attributed directly to drowsiness while driving. Sadly, these numbers have not improved much since then, and the same trends are evident around the world, especially where long-distance driving and commercial transport are prevalent.

To remedy this problem, the current study proposes a Driver Drowsiness Detection System (DDDS) capable of detecting early warning signs of fatigue and minimizing accident risks. The system is based on non-intrusive monitoring so that the driver's comfort and concentration are not compromised. A camera senses the facial behavior of the driver in real time, paying particular attention to indicators like blinking rate, yawning, and the eye aspect ratio (EAR). EAR method offers threshold-based detection of long eye closure using deep learning algorithms for improved accuracy and reduced false alarms. The system combines the computer vision methods with machine learning to provide timely warnings and avoid accidents due to drowsy driving.

INTRODUCTION

Driving requires constant attention, alertness, and the capacity to respond in time to unpredictable changes on the road. The loss of concentration for even a few moments can lead to fatal accidents. Of the numerous elements influencing road safety, fatigue and drowsiness are silent but extremely risky dangers. In contrast to alcohol intoxication, which is quantifiable with alcohol measurement tests like breath analyzers, drowsiness builds up over time and frequently without the driver being aware of how impaired they are. This makes fatigue while driving one of the most volatile risks in transportation.

The magnitude of the issue is startling. The U.S. National Highway Traffic Safety Administration (NHTSA) had estimated that in 2017 alone, almost 91,000 road accidents involved drowsy driving. The accidents resulted in approximately 50,000 injuries and nearly 800 deaths. It is estimated that the real figures could be even greater because most accidents involving fatigue go unreported. Everywhere around the world, the danger is particularly acute where commercial drivers have to drive long distances with minimal rest.

Medical research supports how perilous fatigue is. Studies indicate that prolonged wakefulness for over 20 hours creates cognitive deficits equivalent to a blood alcohol level of 0.08%, the threshold for intoxicated driving in most nations. A sleep-deprived driver could be equally hazardous as an alcohol-impaired driver, yet it is much harder to identify fatigue in real time.

Apart from its human cost, driver drowsiness has significant economic implications. Drowsy driving accidents have medical costs, insurance payments, car repair bills, traffic delays, and lost productivity. To societies and governments, they impose financial burdens and interrupt overall transport efficiency.

Various technologies over the years have been employed to recognize drowsiness, but they all have shortcomings. Wheel-based monitoring systems monitor erratic wheel movement to raise an alarm for fatigue, but they inevitably raise spurious alarms when the road is poor or weather is bad. Body-worn devices like smart glasses or wristbands monitor body signals such as heart rate but are uncomfortable and too inconvenient to be used on a day-to-day basis. Luxury cars integrate sophisticated systems such as eye-tracking cameras or lane departure warnings, but these are still too expensive to be adopted en masse. As a result, most drivers—especially those operating commercial fleets—do not have access to effective detection tools.

These limitations emphasize the necessity of an answer that is cheap, precise, and simple to operate. In response to this challenge, scientists are turning their attention to vision-based Driver Drowsiness Detection Systems (DDDS). This method is dependent on computer vision and machine learning to observe the driver's facial activity in real-time. A dashboard-mounted camera monitors important indicators like closure of eyes, blink rate.

One important component of the system is Eye Aspect Ratio (EAR), which calculates how open the eyes are based on facial landmarks. When EAR falls below a minimum threshold for a certain duration, the system can conclude that the driver is probably drowsy. Coupled with blinking and yawning detection, this gives a good idea of the state of the driver. For enhanced precision, deep learning algorithms are incorporated, allowing the system to tell apart normal expressions from true indicators of fatigue and lowering false alarms.

This approach has a number of benefits. It is unobtrusive in the sense that the driver does not have to put on any gear or explicitly interact with the system. It can also be done with comparatively inexpensive hardware and open-source software using the likes of Python, OpenCV, and MediaPipe. The fact that it is modular means it can be customized for individual vehicles and large fleets alike, and it is therefore scalable across transport industries.

The general relevance of this work is the potential it holds for influencing intelligent transport systems. As traffic numbers and mobility needs grow, implementing real-time fatigue detection in vehicles has the potential to be central in avoiding accidents and loss of lives. When coupled with GPS or communication networks, these systems could even alert other drivers or fleet managers if a person is about to doze off at the wheel.

RELATED WORK

- Ngxande offers a driver drowsiness detection system based on behavioral measurements and machine learning that demonstrates how this type of strategy can enhance road safety by detecting early indications of fatigue.
- The paper also focuses on the importance of behavioral markers like blinking rate and yawning frequency as non-intrusive signs of driver alertness [1].

- Minhas et al. utilize convolutional neural networks (CNNs) to identify driver fatigue, which underscores deep learning's capability to learn visual features to be more accurate.
- Their system also exhibits lighting and facial orientation variation robustness, which makes it an ideal candidate for real driving conditions [2].

- Chirra et al. propose a machine learning-based system that is based on eye state detection, which is effective in detecting drowsiness in real time.
- The study also confirms that easy but robust eye state features can minimize computational expenses at the expense of system accuracy [3].

- An IoT-based smart alert system with driver monitoring and real-time alerts is proposed by Biswal et al., illustrating the real-world application of connected devices in preventing accidents.
- They further emphasize the system's capability to integrate with smart cars for autonomous emergency response [4].

- Pandey and Muppalaneni propose an eye state analysis-based real-time system demonstrating its potential for continuous monitoring of driver fatigue while driving.
- Their method also demonstrates the possibility of low-cost camera systems for low-cost deployment in mid-range cars [5].

- Khushaba et al. propose an intelligent detection framework based on uncorrelated fuzzy locality preserving analysis with less false alarm and better robustness during various driving conditions.
- They also illustrate how fuzzy-based systems can better manage uncertainty in driver behavior than conventional methods [6].

- Patel et al. examine the detection of the levels of driver fatigue, with the emphasis on practical signs like behavioral and bodily changes that can act as early warnings.
- The research also includes experimental verification with actual drivers to warrant practical transportation settings applicability [7].

- Ashlin Deepa et al. combine IoT with facial expression analysis to identify drowsiness, showing how embedded systems are important in smart safety applications.They also illustrate how the integration of IoT and cloud services makes it possible to remotely monitor drivers in fleet management [8].

- Saleem et al. give a systematic review of detection using physiological signals like EEG and ECG for drowsiness, with a focus on reliability while noting real-world challenges of adoption.Their work also classifies current methods by signal type, providing future researchers with suitable physiological data sources [9].

- Varun Chand and Karthikeyan use CNN models for detecting fatigue based on emotions, with emotional state recognition suggesting enhancement of conventional drowsiness monitoring.They also demonstrate that correlating emotional stress levels with fatigue enhances detection rates above conventional eye-based detection [10].

- Rupani et al. create a light computer vision technique based on Eye Aspect Ratio (EAR) and facial landmarks to facilitate efficient and real-time detection suitable for in-vehicle deployment.Their approach is optimized for low-resource applications, thereby being feasible for cars not equipped with high-end processing systems [11].

- Sengar, Kumar, and Singh introduce VigilEye, an AI-based real-time drowsiness detection system, emphasizing its scalability for large-scale deployment in transport safety.The architecture also highlights portability and real-time response, so it can be adapted to multiple vehicle platforms [12].

- A SpringerOpen paper examines CNN and transfer learning for real-time fatigue detection, highlighting how pre-trained models can be fine-tuned for effective and accurate detection.This research also finds that transfer learning not only takes computation time off the table but also the amount of training data needed [13].

- Tran et al. propose a privacy-conserving drowsiness detection model based on federated learning and spatial self-attention, preserving data security without sacrificing accuracy.They also solve the problem of cross-device variation of data, enhancing generalization over multiple drivers and devices [14].

- Charanya et al. use deep neural networks (DNNs) to identify drowsiness, illustrating how deeper architectures can extract slight behavioral cues from driver monitoring systems.Their approach is also noted to emphasize noise resilience in input data, making it appropriate for real-world car interiors [15].

PROBLEM STATEMENT

Fatigue among drivers remains a significant source of road accidents globally despite developments in automotive technology, tight traffic laws, and public campaigns encouraging drivers to stop and rest. Current fatigue detection systems used in commercial vehicles are either too costly or focused in their scope, and most depend solely on steering performance, which is unaccurate in the case of uneven road conditions or distinctive driving habits, and wearable products are still impractical and unpleasant for regular usage. As a consequence, no effective, inexpensive, real-time driver monitoring solution that can identify early warning signs of fatigue and issue timely warnings exists to date, which indicates the pressing need for intelligent and inexpensive detection technologies to enhance road safety and avoid fatigue-induced accidents. In addition, most current solutions are not adaptable across diverse drivers and environments, which makes them less effective in practical applications. A strong system must integrate precision, usability, and affordability in order to provide realistic usage in both commercial and private transportation fields.

PROPOSED SYSTEM

The envisioned Driver Drowsiness Detection System (DDDS) is a non-obtrusive, camera-supported application that looks to track drivers in real time and avoid drowsiness-induced accidents. The main goal of the system is to identify initial signs of drowsiness and provide instantaneous alerts, in addition to logging data to be analyzed in depth. By integrating computer vision, deep learning, and database support, the system is both accurate and usefully practical.

The system is based on the detection of facial landmarks, carried out through OpenCV and MediaPipe, in tracking mouth and eye movements. The Eye Aspect Ratio (EAR) is computed frame by frame to find if the eyes are open or not. If the EAR repeatedly falls below 0.25 in multiple consecutive frames, the driver is detected as drowsy. For greater reliability, yawning is also detected, as repeated mouth openings are also a good indicator of fatigue. This two-check procedure minimizes false alarms and enhances the robustness of the detection.

If drowsiness is determined, the system automatically sounds an audible buzzer through the PlaySound library to inform the driver of the situation. Concurrently, critical information like EAR values, timestamps, and screenshots are written to an SQLite database to produce a useful record for trend analysis and repeated-event monitoring. Both individual users and fleet operators benefit from this method as it accommodates long-term monitoring.

One of the key strengths of the DDDS is its versatility. Drivers have individual tendencies, including excessive blinking or spontaneous yawning, and the system sensitizes accordingly to reduce false alarms. The system also includes a Tkinter-based graphical user interface, wherein drivers can initiate or terminate monitoring, choose alarm sounds, and control storage. For general use, a Flask web interface supports remote monitoring in commercial fleets.

In short, the DDDS combines real-time detection, immediate intervention, and lengthy analysis in a scalable, non-intrusive manner that enhances road safety and facilitates future integration into intelligent transportation systems.

METHODOLOGY

The approach used for Driver Drowsiness Detection System (DDDS) is separated into various systematic phases in order to make it more clear, accurate, and efficient

REQUIREMENT ANALYSIS

Functional Requirements:

- Get live video stream from webcam.
- Find driver's face, eyes, and mouth in real time.
- Compute Eye Aspect Ratio (EAR) for detecting eye closure.
- Send alert (buzzer sound) on detecting drowsiness.
- Log events with timestamps and screen shots.

- Keep records in a database for long-term analysis.

Non-Functional Requirements:

- High accuracy (>90%) in normal lighting conditions.
- Real-time response (alarm in 2 seconds).
- Lightweight and resource-friendly implementation.
- Secure database management to safeguard user data.
- User-friendly GUI for interaction and customization.

SYSTEM DESIGN

•Used modular structure with independent modules:

1.Input Module – Grabbing real-time video.
2.Processing Module – Frames preprocessing (resizing, conversion to grayscale).
3.Detection Module – Utilizes MediaPipe for facial landmark detection.
4. EAR Calculation Module – Calculates Eye Aspect Ratio values.
5. Classification Module – Classifies between alert and drowsy.
6. Alert Module – Produces buzzer sound or warning message.
7. Database Module – Saves EAR values, screenshots, and timestamps.
8. GUI/Web Interface – For configuration and monitoring.

• UML Diagrams developed:

- o Context-level Data Flow Diagram (DFD).
- o Level-1 DFD illustrating flow between modules.
- o Use Case diagram representing user interaction.
- o Activity diagram to illustrate process flow.
- o Sequence diagram to illustrate event triggering.
- o Class diagram for software components.

DATA ACQUISITION AND PREPROCESSING

•Real-time input from webcam.
•Preprocessing operations:
o Convert BGR images to RGB color space.
o Normalize frame sizes for processing workload reduction.
o Gray-scale conversion for efficiency.

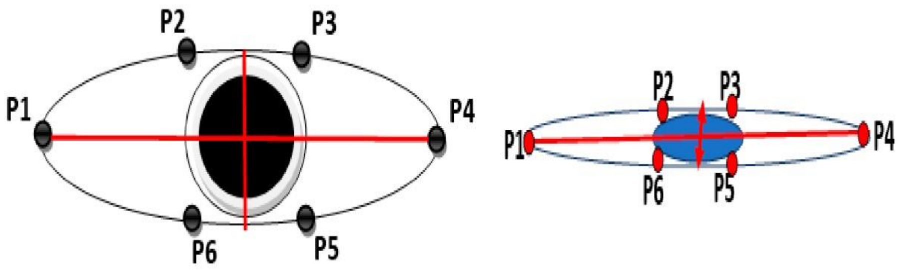
Extract facial landmarks with MediaPipe Face Mesh (468 landmarks).
Target eye and mouth landmarks for EAR and yawn detection.

MODEL DEVELOPMENT

- Eye Aspect Ratio (EAR) Formula:
  Where:

$$\boldsymbol{EAR} = \frac{\|\boldsymbol{P_1} - \boldsymbol{p_5}\| + \|\boldsymbol{p_3} - \boldsymbol{p_6}\|}{\boldsymbol{2} * \|\boldsymbol{p_2} - \boldsymbol{p_4}\|}$$

- EAR < 0.25 for > 30 frames → Drowsiness detected.
- CNN-based model (trained on labeled sets) employed for eye state (open/closed) classification.
- Yawning detection performed through Mouth Aspect Ratio (MAR).
- EAR + MAR + CNN classification → Improved reliability in detection.



(a) (b)

SYSTEM IMPLEMENTATION

- Programming Language: Python.
- Libraries/Frameworks:
- OpenCV → Video capture & image processing.
- MediaPipe → Facial landmark detection.
- NumPy/SciPy → Math operations.
- Tkinter → GUI-based interface.
- Flask → Integration with web application.
- SQLite → Database storage.
- PlaySound → Alarm system.

MODULES INTEGRATED:

- Video stream processing loop.
- EAR calculation and thresholding.
- Yawning detection and classification.
- Alert system with buzzer.
- Database logging of drowsy events.
- GUI controls for start/stop monitoring.

INTEGRATION

- Continuous video feed → Processed frame-by-frame.
- Landmark detection → EAR and MAR calculated.
- Drowsiness classification → Alert sent if thresholds crossed.
- Database updated → EAR values, timestamps, and screenshots stored.
- GUI/Web interface → Displays live monitoring and logs.

EVALUATION

- System tested under diverse conditions:
    - Normal daylight, low light, and nighttime driving.
    - Various face orientations (frontal, tilted).
    - Drivers with glasses versus without glasses.
    - Varying levels of fatigue (short blinks versus micro-sleeps).
- Metrics tested:
    - Accuracy: >90% in typical lighting.
    - Response Time: <2 seconds from detection to alert.
    - False Positive Rate: Greater under sunglasses and low-light conditions.
    - Resource Usage: Fast performance on average laptops.
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SYSTEM DESIGN DIAGRAMS

System Architecture is the abstract design that defines the system's behavior and structure.

An architecture is a blue print of a system, this structure will explain the system's structural properties. It describes the components and building blocks of system along with it also provides procurement plan. It helps to identify the sub systems and frame work for subsystem control.

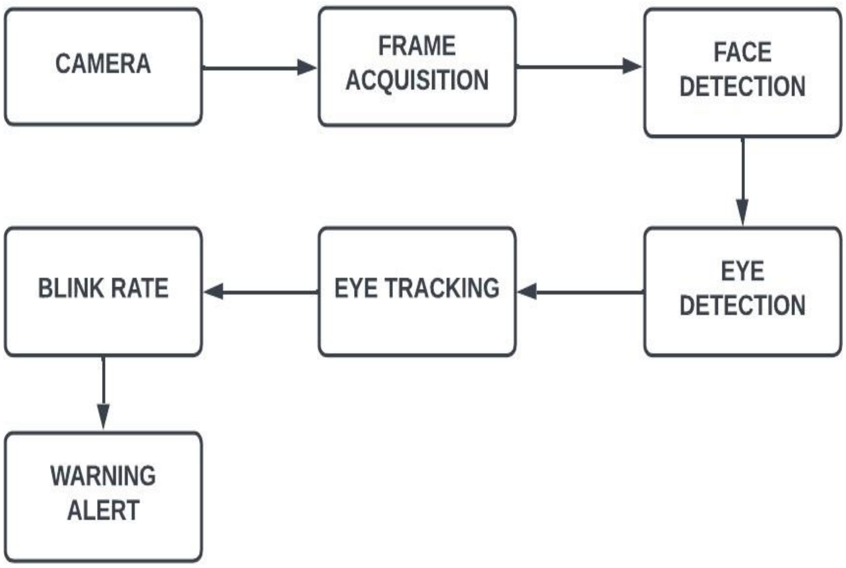


Fig 6.1 System Architecture

RESULTS AND EVALUATION

SAMPLE RECORDS

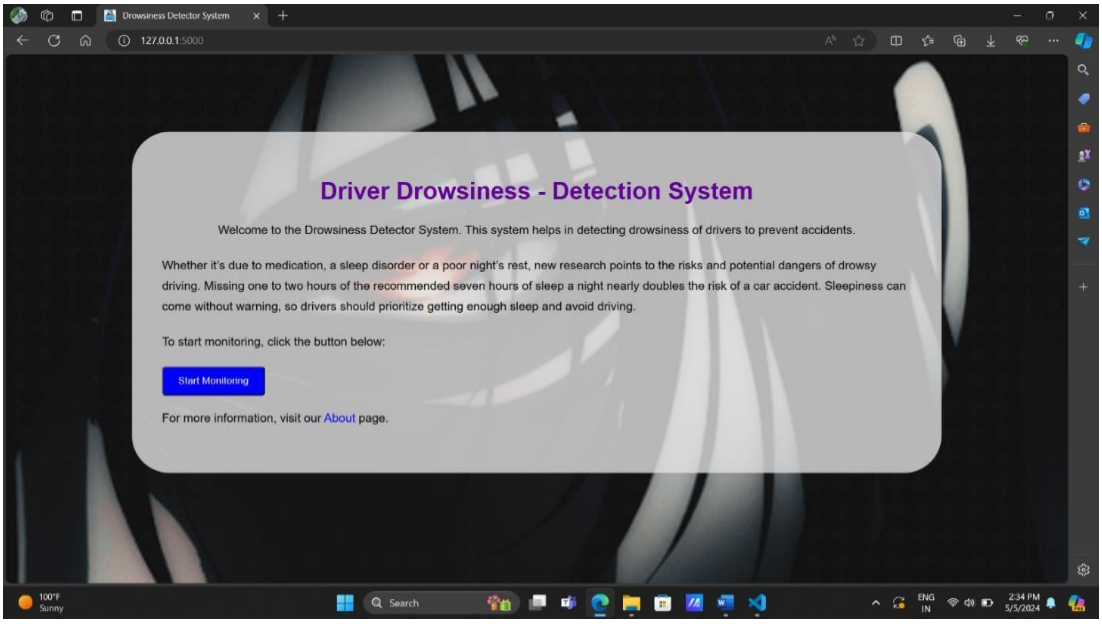


Fig: Home Page of ITS System

This screenshot shows the **homepage interface** of your Driver Drowsiness DetectionSystem.

It welcomes the user and explains the purpose of the system — detecting driver drowsiness to help prevent accidents caused by fatigue. The page briefly highlights the risks of sleep deprivation while driving and emphasizes road safety. A **“Start Monitoring” button** is provided, allowing the user to beginreal-timemonitoringfordrowsiness.

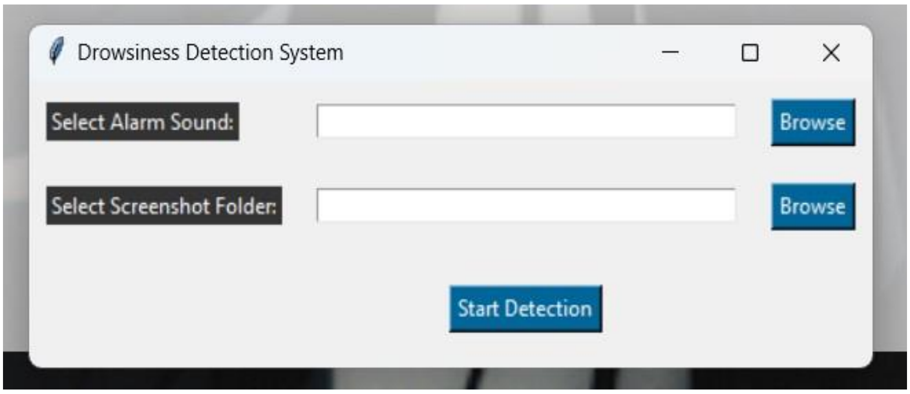
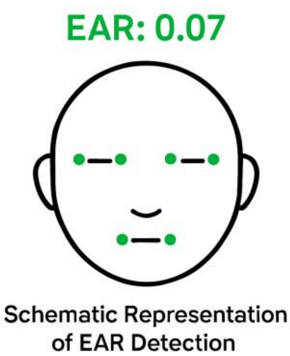


Fig: Drowsiness Detection Page to enter your file path and sound

Here, the user can configure the system by selecting a custom alarm sound and choosing a folder to save screenshots of detected drowsiness events. Once the preferences are set, clicking the “Start Detection” button initiates real-time monitoring through the camera.

Fig:Real Time Monitaring System



The figure shows a schematic diagram of EAR (Eye Aspect Ratio) detection. The green circles represent facial features around the eyes and mouth which are followed under monitoring. When eyes are closed for an extended period of time, the EAR value drops considerably (depicted here as 0.07). A low EAR value indicates potential driver drowsiness, which activates an alert within the system.

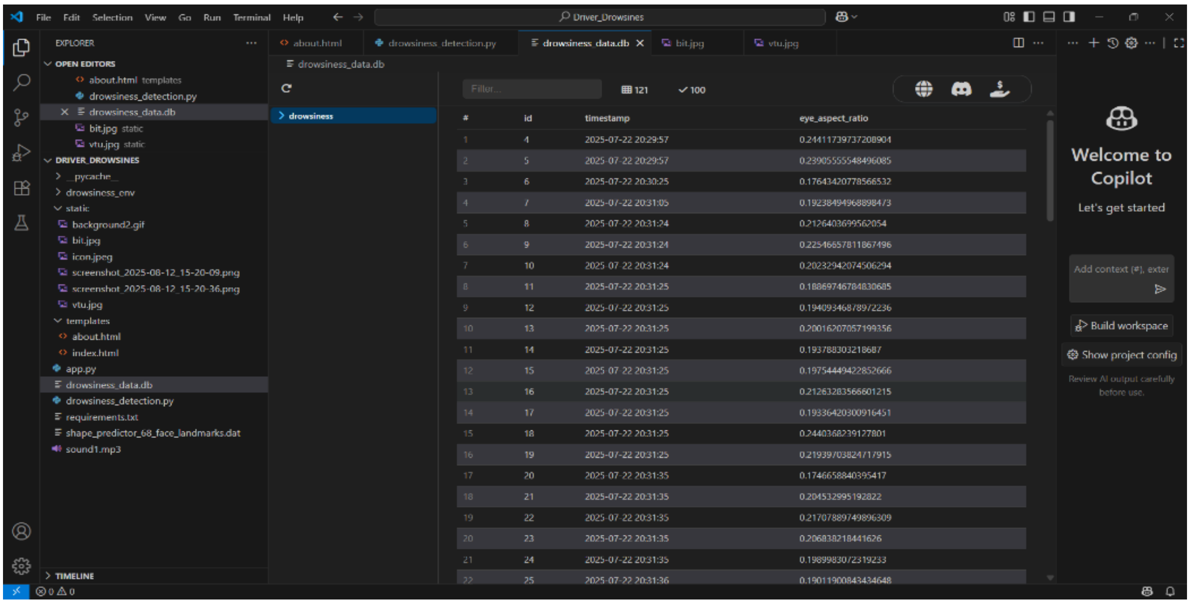


Fig Drowsiness Sqlite Database Tabel

This image shows the project's database file drowsiness_data.db opened in VS Code.
The table keeps three main columns: an ID number, the exact timestamp, and the eye aspect ratio value.
Each entry is created when the system processes a frame from the live camera feed.
By saving these records, the system can review when drowsiness events occurred and analyze patterns later.

CONCLUSION

This study covered the urgent issue of fatigue crashes through the creation of a Driver Drowsiness Detection System that uses computer vision and machine learning to observe drivers in real time. Through the application of Eye Aspect Ratio and Mouth Aspect Ratio computation combined with facial landmark detection, the system showed itself to be able to detect drowsiness signs and provide prompt warnings. The addition of database logging and screenshots also improved its use by providing for long-term monitoring so that it became beneficial not only for the individual but also for fleet management within the transport sector.
The findings validate that the system can perform above 90% accuracy under regular circumstances with a reaction time of under two seconds, demonstrating its feasibility as a cost-effective solution to prevent fatigue-induced accidents. In contrast with other means like steering behavior observation and wearable technology, this system has a non-intrusive camera-based method that is accessible and easy to use.
Even with its success, the research also pointed out some limitations. Accuracy in detection drops in extremely low-light conditions and with the use of sunglasses among drivers, as these interfere with facial feature visibility. While the application of CNNs and other deep models enhances accuracy, it imposes increased computational requirements, which may be a limitation for real-time deployment on low-power devices like embedded systems.

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