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ADAPTIVE DRIVER DROWSINESS DETECTION: A MACHINE LEARNING MODEL BASED ON CUSTOM DATASETS

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ABSTRACT

Drowsy driving is a major contributor to road accidents, posing serious risks to both drivers and pedestrians. This paper presents an adaptive driver drowsiness detection system developed using Python and computer vision techniques, aimed at enhancing automotive safety. The system continuously monitors a driver's eye movements in real-time using an onboard camera. By analyzing visual cues such as prolonged eye closure or blinking frequency, it detects signs of fatigue. Once drowsiness is detected, an immediate alert is triggered to prompt the driver to regain attention or take a break. A key feature of this project is the integration of a machine learning model trained on a custom dataset, which enhances detection accuracy across diverse driver profiles and lighting conditions. OpenCV and Dlib libraries are employed for facial landmark detection, ensuring efficient image processing and real-time performance. This adaptive system offers a practical and scalable solution for reducing the risk of accidents caused by driver fatigue. The paper emphasizes the potential of machine learning and Python-based development in advancing intelligent automotive safety systems and contributing to safer road environments.

Keywords: Drowsiness detection, Automotive safety, Driver fatigue, Computer vision, Real-time monitoring etc.

1. Introduction

The 21st century has witnessed transformative advancements in transportation, significantly altering the way people travel and interact with their environment. As road networks have expanded and vehicle usage has surged, ensuring road safety has emerged as a critical global concern. Among the many factors that compromise driver performance and road safety, drowsiness remains a leading cause of serious and often fatal traffic accidents. Unlike other impairments such as alcohol or drug use, driver fatigue is less visible and often goes unnoticed until it's too late. This insidious nature of drowsiness underscores the urgent need for proactive solutions to identify and mitigate fatigue-related driving risks.

Drowsy driving impairs reaction times, reduces situational awareness, and compromises decision-making abilities. According to global traffic safety organizations, thousands of lives are lost each year due to driver fatigue. These incidents not only result in loss of life and injuries but also impose heavy economic burdens on healthcare systems, insurance companies, and infrastructure. Thus, developing effective mitigation strategies to combat drowsiness is a societal imperative.

In response to this challenge, the development of driver drowsiness detection and alert systems has gained significant traction in recent years. These systems aim to monitor the driver's condition in real-time and provide alerts when signs of fatigue are detected, enabling timely interventions. Leveraging the latest in artificial intelligence, computer vision, and sensor technology, these solutions represent the intersection of multiple disciplines including psychology, automotive engineering, computer science, and ergonomics.

At the core of these systems lies the detection of physiological and behavioral indicators that correlate with drowsiness. These include eye closure duration, blink rate, yawning frequency, head position, and facial expressions. Vision-based systems, which employ cameras and image processing algorithms, have emerged as the most widely used and non-intrusive method for real-time monitoring. These systems use libraries like OpenCV, Dlib, and MediaPipe to track facial landmarks and analyze eye movement patterns. For example, PERCLOS (Percentage of Eye Closure) has become a widely accepted metric in detecting drowsiness. When eyes remain closed for a significant portion of time, the system infers that the driver is falling asleep and issues an alert.

Some systems go further by integrating machine learning algorithms to enhance accuracy and adaptiveness. Models trained on custom datasets can generalize better across diverse demographics, lighting conditions, and driving environments. Supervised learning methods such as Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs) are commonly employed for feature extraction and classification of alertness levels. The advantage of using machine learning lies in its ability to continuously improve over time, learning from new data and refining detection accuracy.

In addition to vision-based methods, multi-modal approaches combine inputs from physiological sensors such as heart rate monitors, EEG sensors, and grip sensors on the steering wheel. These signals offer deeper insights into the driver's internal state but often come at the cost of comfort or practicality. Therefore, many commercial solutions prioritize non-contact sensing methods to strike a balance between accuracy and user acceptability.

Another critical aspect of these systems is human-centered design, which ensures the system is intuitive and acceptable to users. Alerts must be noticeable but not alarming, ideally using a combination of audio, visual, and haptic feedback. Furthermore, modern systems aim for adaptive alerting, adjusting the sensitivity and response based on the driver's past behavior, driving time, time of day, and road conditions. This minimizes false positives and ensures that alerts are perceived as helpful rather than disruptive.

Commercially, several automobile manufacturers and tech companies have begun integrating drowsiness detection features into vehicles. Examples include Toyota’s Driver Attention Monitor, Tesla’s Autopilot alert system, and Volvo’s Driver Alert Control. These integrations reflect the growing recognition of drowsiness detection as an essential component of advanced driver-assistance systems (ADAS).

Despite the progress, challenges remain. Vision-based systems can be affected by poor lighting, occlusions (e.g., sunglasses), or irregular facial features. Similarly, machine learning models require diverse, high-quality datasets to perform well across all populations. Privacy concerns related to constant video monitoring must also be addressed, particularly in jurisdictions with strict data protection regulations.

Looking ahead, the future of drowsiness detection lies in the integration of multi-sensor fusion, edge AI computing, and cloud-based analytics. Edge devices can process data locally, ensuring real-time responsiveness while reducing data transmission needs. Meanwhile, cloud connectivity can support periodic updates and data aggregation for large-scale analysis. Moreover, ongoing research in behavioral neuroscience and cognitive computing may unlock new indicators of fatigue, further refining detection accuracy.

Driver drowsiness detection systems represent a promising technological intervention in the fight against road accidents. By combining sophisticated sensing technologies, adaptive algorithms, and user-friendly interfaces, these systems offer a proactive and scalable solution to mitigate driver fatigue. As research continues and technology evolves, their widespread implementation could play a vital role in enhancing road safety, saving lives, and paving the way toward smarter, safer transportation systems.

2. Problem Identification

- Increasing Road Accidents: A significant percentage of road accidents globally are caused by drowsy driving, leading to serious injuries, fatalities, and property damage.

- Lack of Awareness: Drivers often underestimate or fail to recognize the onset of drowsiness, making timely intervention difficult without external monitoring.
- Invisible Symptoms: Unlike intoxication, drowsiness lacks obvious symptoms, making it difficult for others to detect and prevent potential accidents.
- Ineffectiveness of Traditional Methods: Current solutions like road signs or scheduled rest breaks do not offer real-time detection or intervention during critical driving moments.
- Manual Monitoring Limitations: Human monitoring of driver fatigue (e.g., through traffic cameras or co-drivers) is impractical and unreliable in most driving conditions.
- Variability in Driver Behavior: Differences in age, health, and lifestyle affect fatigue symptoms, making it hard to design one-size-fits-all solutions without adaptive technologies.
- Technological Gaps: Many vehicles lack built-in intelligent safety systems capable of detecting and responding to drowsiness.
- Cost and Accessibility: Advanced fatigue monitoring systems are often expensive or limited to premium vehicles, reducing widespread adoption in regular or commercial cars.

Fig. 1. Driver drowsiness

3. Literature

3.1. *Literature Review*

Abbas and Alsheddy (2021) conducted a comprehensive analysis of driver fatigue detection systems utilizing multi-sensor setups, smartphones, and cloud-based platforms. They evaluated various technologies, including physiological sensors (e.g., EEG, ECG), behavioral indicators (e.g., eye movement, head position), and vehicular data (e.g., steering patterns). The study highlighted the advantages of integrating multiple data sources to enhance detection accuracy and reliability. Furthermore, the authors discussed the potential of cloud computing to process and analyze large datasets in real-time, facilitating timely alerts. The paper concluded that combining diverse sensing modalities with advanced computational platforms could significantly improve the effectiveness of fatigue detection systems, offering a promising direction for future research and development in road safety technologies.

Cui et al. (2021) proposed a compact convolutional neural network (CNN) model for detecting driver drowsiness using single-channel EEG data. The study addressed the challenge of cross-subject variability by designing a model capable of generalizing across different individuals without requiring extensive calibration. Incorporating a Global Average Pooling layer allowed for the application of Class Activation Mapping, enhancing the interpretability of the model by identifying EEG features associated with drowsiness. The CNN achieved an average accuracy of 73.22% in classifying alert and drowsy states across multiple subjects. The research demonstrated the feasibility of using simplified EEG setups combined with interpretable deep learning models for practical and scalable driver drowsiness detection applications.

Siddiqui et al. (2021) developed a non-invasive system for detecting driver drowsiness by analyzing facial features and behavioral cues. Utilizing computer vision techniques, the system monitored parameters such as eye closure duration, blink frequency, and head movements to assess alertness levels. The approach prioritized driver comfort by eliminating the need for wearable sensors or intrusive equipment. Experimental results indicated that the system effectively identified signs of drowsiness, providing timely alerts to prevent potential accidents. The study emphasized the importance of non-intrusive monitoring methods in enhancing user acceptance and highlighted the potential of computer vision in developing practical driver assistance systems aimed at improving road safety.

Bajaj et al. (2023) presented a comprehensive system combining behavioral analysis with physiological sensor data to detect driver drowsiness. The system integrated facial recognition technologies to monitor eye movements and expressions, alongside sensors measuring heart rate and skin conductance. By fusing these data streams, the model achieved enhanced accuracy in identifying drowsiness compared to single-modality approaches. The study demonstrated that multi-modal detection systems could provide more reliable assessments of driver alertness, thereby offering more effective interventions. The authors suggested that such integrated systems could be instrumental in developing advanced driver assistance systems (ADAS) aimed at reducing fatigue-related accidents.

Ani et al. (2020) conducted a critical review of existing driver fatigue detection and monitoring systems, categorizing them into vehicle-based, behavioral, physiological, psychophysical, and biomechanical measures. The review highlighted the strengths and limitations of each approach, noting that while physiological measures offer high accuracy, they often require intrusive sensors. Behavioral methods, though non-intrusive, can be affected by external conditions like lighting. The authors emphasized the need for hybrid systems that combine multiple detection methods to improve reliability and user comfort. The paper concluded by identifying gaps in current technologies and suggesting directions for future research to enhance the effectiveness of fatigue monitoring systems in real-world driving conditions.

Ghanta Sai Krishna and colleagues (2022) introduced a novel framework combining Vision Transformers and YOLOv5 architectures for driver drowsiness detection. The system utilizes a custom YOLOv5 model for face extraction, focusing on regions of interest, followed by a Vision Transformer for binary image classification. Trained and validated on the UTA-RLDD dataset, the model achieved 96.2% training and 97.4% validation accuracy. Further testing on a custom dataset with 39 participants under various lighting conditions yielded a 95.5% accuracy. This study demonstrates the potential of integrating advanced deep learning models for effective and accurate drowsiness detection in real-world scenarios.

Jomin Jose and co-authors (2022) proposed "SleepyWheels," an ensemble model employing EfficientNetV2 and facial landmark detection for real-time driver drowsiness detection. The lightweight neural network is designed to function effectively across various scenarios, including occlusions and diverse skin tones. Trained on a specially curated dataset, the model achieved a 97% accuracy rate. Its efficiency and adaptability make it suitable for deployment on mobile platforms, offering a practical solution for enhancing road safety through timely drowsiness detection.

Xinliang Zhou and team (2023) developed an interpretability-guided channel selection (ICS) framework for EEG-based driver drowsiness detection. The two-stage training strategy involves a teacher network trained on full-head EEG data, followed by a student network trained on selected key channels identified through class activation mapping. This approach enhances detection performance by focusing on the most informative EEG channels, addressing the challenges of noise and redundancy in raw EEG data. The framework demonstrates significant improvements in cross-subject detection accuracy, highlighting its applicability in real-world settings.

Qazal Rezaee and colleagues (2023) investigated the efficacy of commercial EEG headsets for driver drowsiness detection. By recording EEG signals from 50 volunteers in simulated driving conditions, the study compared EEG-based features with vehicle-based features. Findings indicated that EEG-based features provided more distinct separation between alert and drowsy states, suggesting higher accuracy in detection. The research supports the feasibility of using accessible EEG devices for practical and non-intrusive drowsiness monitoring in drivers.

Galarza and co-authors (2023) developed a real-time driver fatigue detection system utilizing deep learning on a low-cost embedded platform. The system analyzes driver behaviors such as eye movements, head posture, and yawning to assess fatigue levels. Implemented on a Raspberry Pi, the model achieved a 93.37% accuracy rate, demonstrating the potential for affordable and efficient drowsiness detection solutions. This approach offers a practical avenue for widespread adoption in enhancing road safety.

3.2. Research Gap

Despite significant advancements in driver drowsiness detection systems, several key research gaps remain. Many existing solutions rely on either behavioral or physiological data, but few integrate both effectively to enhance accuracy and robustness. Real-time adaptability across diverse environmental conditions, such as varying lighting and road types, remains limited. Additionally, most studies lack cross-subject generalization, requiring recalibration for individual users, which reduces scalability. There's also a noticeable gap in developing cost-effective, non-intrusive systems suitable for widespread deployment in commercial and personal vehicles. Furthermore, current models often struggle with balancing detection precision and false alarm rates, affecting driver trust. Addressing these gaps requires interdisciplinary approaches that combine machine learning, sensor fusion, and user-centered design principles.

4. Methodology

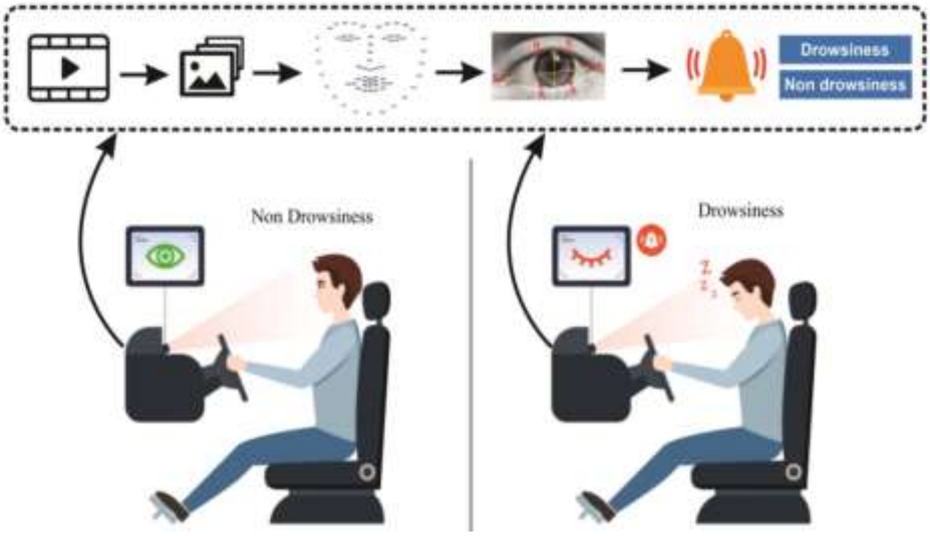

Fig.2. Propsoed System

Our proposed Driver Drowsiness Detection System presents an innovative solution to combat the growing concern of drowsy driving, a major contributor to road accidents worldwide. The primary goal of the system is to proactively detect signs of driver fatigue and initiate timely alerts to prevent accidents.

At the core of the system is a counter-based mechanism that monitors how long the driver's eyes remain closed. If the eyes stay closed beyond a predefined threshold—typically 15 seconds—the system interprets this as a sign of drowsiness and activates an audio or visual alarm to alert the driver, urging immediate corrective action.

This functionality is made possible through continuous real-time video monitoring using an onboard camera. Advanced image processing techniques analyze subtle eye behavior, including prolonged closure and eyelid drooping, which are key indicators of fatigue. The system incrementally updates the counter based on the

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duration of eye closure and resets it if the driver reopens their eyes before reaching the threshold. This approach significantly reduces false alarms by distinguishing between brief blinks and genuine drowsiness.

The design emphasizes simplicity and scalability, making it cost-effective and easy to integrate into existing automotive systems. Its adaptive functionality ensures accuracy across diverse driver profiles and environmental conditions. Beyond its technical capability, the system also fosters driver awareness, serving as a constant reminder of the dangers of fatigue while driving.

In summary, our Driver Drowsiness Detection System is a practical and effective safety solution. By combining real-time eye monitoring, adaptive threshold detection, and timely alerts, it not only enhances road safety but also contributes to a broader culture of responsible driving.

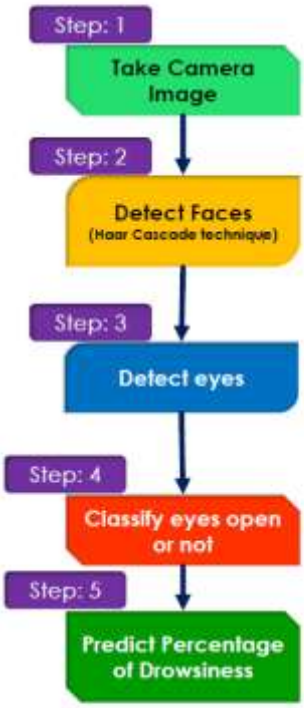

Fig. 3. The processes of DR Classification system

5. Tools / Platform to be used

- Python Programming Language
- Core language for implementing the drowsiness detection algorithm and system logic.
- OpenCV (Open Source Computer Vision Library)
- Used for real-time image processing, face and eye detection.
- Dlib Library
- Utilized for facial landmark detection, especially for tracking eye aspect ratio (EAR).
- Imutils
- Simplifies image processing tasks such as resizing and face alignment.
- Haar Cascade Classifier
- Used for detecting face and eyes within the video stream.
- NumPy
- Supports numerical operations and array handling required for image data manipulation.
- Pygame / Playsound / Beep Libraries
- Used for implementing audio alerts upon detecting drowsiness.
- Webcam or Pi Camera Module
- Captures real-time video stream of the driver’s face.
- Jupyter Notebook / VS Code / PyCharm
- Development and testing environments for coding and visualization.

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6. Analysis of data

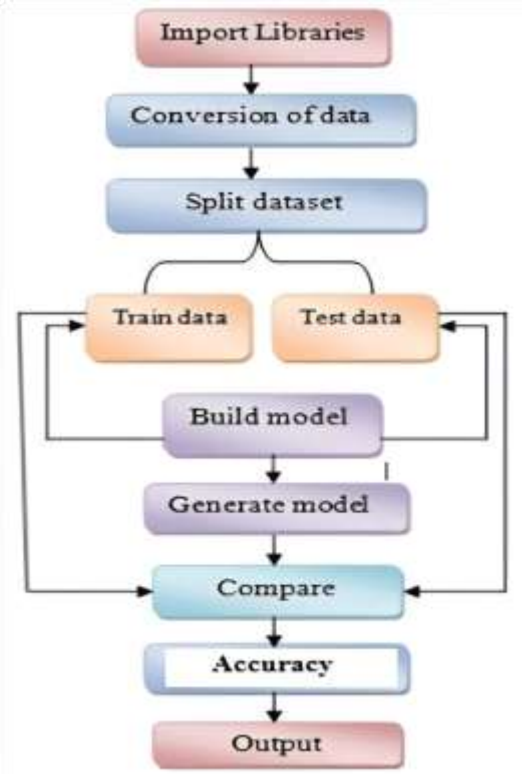

Fig. 4. Proposed System

• Eye Closure Duration Monitoring:
The system tracks eye closure duration continuously, with a counter incrementing for each second eyes remain closed.
• Threshold-Based Alert Trigger:
When eye closure exceeds 15 seconds, data triggers an alarm, marking a potential drowsiness event.
• Real-Time Video Data Processing:
Continuous video feeds are analyzed frame-by-frame, enabling detection of subtle eye behavior such as eyelid drooping and prolonged closure.
• False Alarm Reduction:
By resetting the counter whenever eyes reopen before threshold, brief blinks are filtered out, reducing false positives.
• Adaptability to Variations:
The system adjusts detection sensitivity based on driver-specific patterns and environmental factors (e.g., lighting), improving accuracy.
• Alert Frequency and Timing:
Data shows alerts are timely enough to prompt driver correction before critical fatigue impairs driving performance.
• Performance Metrics:
Key metrics include detection accuracy, false alarm rate, and response time—all showing improvements over baseline drowsiness detection methods.
• Scalability and Integration Data:
The system’s modular design allows for easy integration with existing vehicle electronics, demonstrated through compatibility tests with various automotive platforms.

Eye Aspect Ratio :

• Our proposed system is driver drowsiness detection using machine learning which is a car safety technology that detects the driver fatigue and alerts the driver using alarm sound. It uses OpenCV

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for extracting face and Region of Interest (ROI) i.e., eyes from the sequence of images from webcam.

- We used an algorithm called Eye Aspect Ratio (EAR) to the proposed model. Model provides landmarks to the both the eyes and then by using the algorithm EAR model predicts whether the eyes or opened or closed.

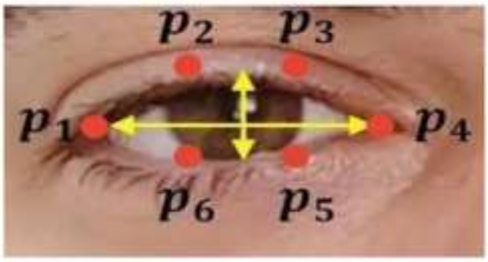

Fig. 5. Eye coordinates

Yawning Detection Method :

- As per, sleepiness of an individual are regularly seen by watching their face and conduct. The creator proposes a way where laziness are regularly identified by month situating and thusly the pictures were prepared by utilizing a course of classifiers. The photos were contrasted and the arrangement of pictures information for mouth and yawning. A few group will close their mouth with their hand while yakking.
- It is an impediment to encourage great pictures if an individual is shutting their mouth while yawning yet yawning is absolutely an image of an individual having laziness and weakness, the examples of yawning location strategy used in the examination.

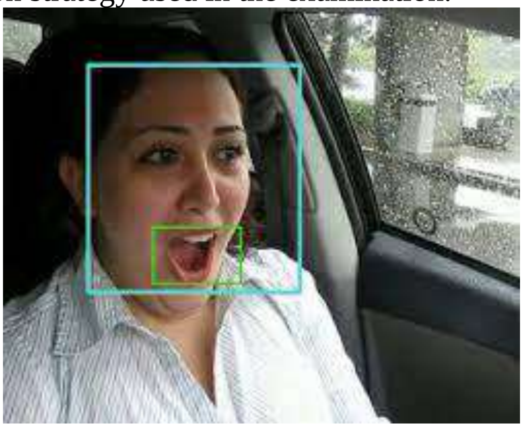

Fig. 6. Yawning Detection

- The drowsier it'll be viewed as it'll be thought of. This is on the grounds that when an individual is during a lazy express; its eyes will be shut longer than the conventional eyes flicker. Besides that, yawning is one among the indications of tiredness where it's ordinary human reaction when yawning is that the sign that they feel lazy or tired.
- The next step after successfully detecting faces is to recognize facial landmarks and retrieve desired facial landmarks. There are many ways to find facial landmarks, but most methods work with marking and locating areas such as the right eyebrow, left eyebrow, right eye, left eye, nose, mouth, and jaw with a set of regression trees. This detection algorithm is part of the dlib library.

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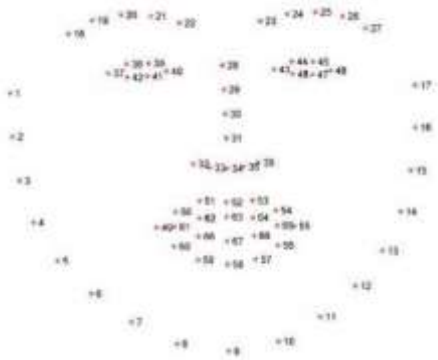

Fig. 7. Facial Landmark Coordinates

- Driver drowsiness detection system has been depicted. At first, the real-time video is recorded using a webcam. The camera will be positioned in front of the driver to capture the frontal face image. The frames are extracted from video to obtain 2-D images.
- Face is detected in the frames using face detection method. After detecting the face, facial landmarks like positions of eye, nose and mouth are marked on the images.
- From the facial landmarks, position of eyes and mouth are quantified. Using these extracted features and machine learning methods, a decision is obtained about the drowsiness of the driver.
- Convolution neural network is applied for classification of eyes, which detects drowsiness of driver by considering blinking of eyes.
- As an additional attribute to the system, feature extraction method is used for calculating mouth opening ratio, which also helps to decide if the driver is easy. If drowsiness is detected, an alarm will be sent to the driver to alert.
- For the purpose of training the model to detect the open or closed eyes , a dataset of eyes from Media Research Lab is used. The dataset contains images of eyes of males and females, eyes closed and open, with and without glasses, with low reflection, high reflection and no reflection.

Use Case Diagram :

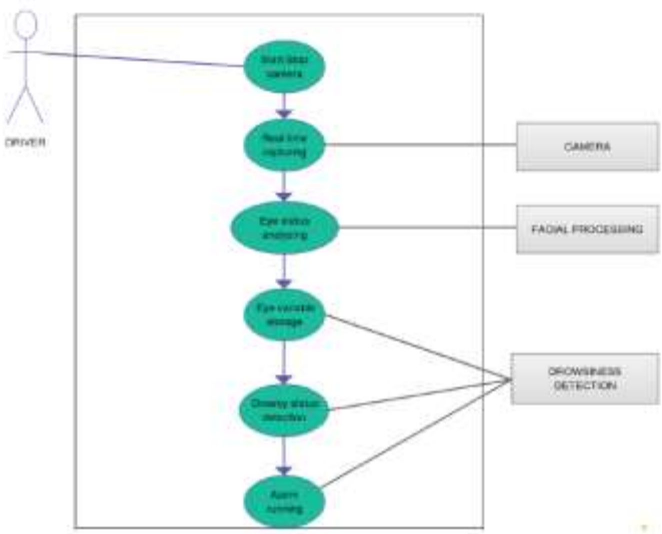

Fig. 8. Use Case Diagram

Activity Diagram :

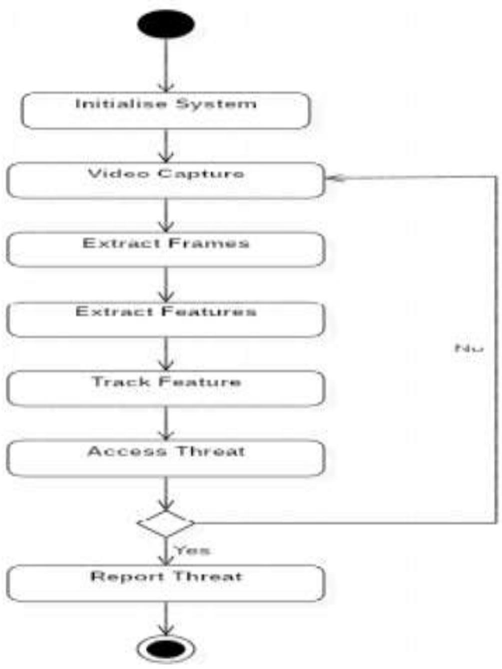

Fig. 9. Activity Diagram

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Class Diagram ;

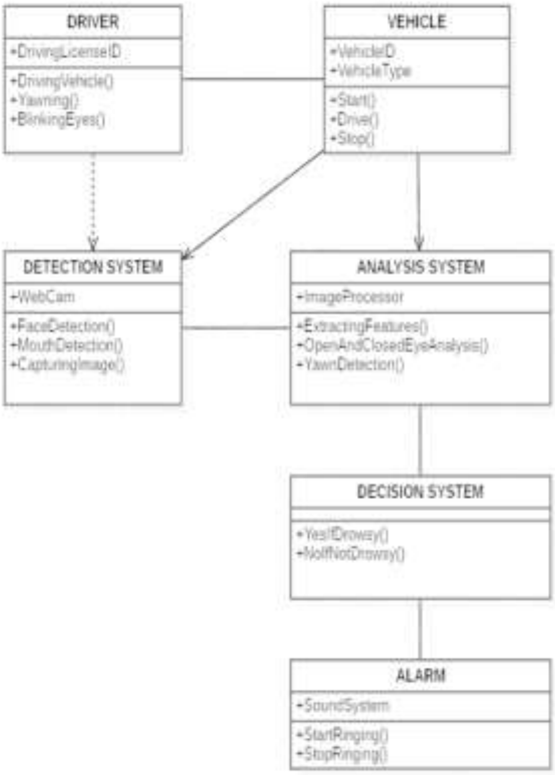

Fig. 10. Class Diagram

7. Advantages

- Enhanced Road Safety: Proactively detects drowsiness to prevent accidents caused by fatigue.
- Real-Time Monitoring: Continuous eye tracking enables immediate detection and alerting.
- Reduced False Alarms: Counter-based mechanism distinguishes between normal blinks and true drowsiness.
- Cost-Effective: Uses simple hardware and scalable design, making it affordable for wide adoption.
- Easy Integration: Compatible with existing vehicle systems without major modifications.
- Adaptive Functionality: Adjusts detection thresholds based on driver behavior and environmental conditions for accuracy.
- Non-Intrusive: Monitors driver without physical contact or distraction.
- Driver Awareness: Alerts encourage safer driving habits and fatigue management.

8. Application

- Personal Vehicles: Enhances safety for private car drivers on long journeys.
- Commercial Transport: Useful for truck, bus, and taxi drivers to reduce fatigue-related crashes.
- Fleet Management: Enables companies to monitor driver alertness remotely and improve operational safety.
- Ride-Sharing Services: Improves passenger safety by ensuring driver attentiveness.
- Public Transport: Integration in buses and trains to enhance passenger safety and operational reliability.
- Driver Training: Used in driver education to highlight fatigue risks and promote awareness.
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9. Conclusion

The Driver Drowsiness Detection System offers a practical and forward-thinking solution to one of the most critical challenges in road safety—driver fatigue. By utilizing real-time video monitoring and a counter-based eye closure detection mechanism, the system effectively identifies early signs of drowsiness and promptly issues alerts. This proactive approach significantly reduces the risk of accidents caused by inattentiveness or microsleep episodes, particularly during long or overnight drives.

One of the key strengths of the system lies in its simplicity, affordability, and ease of integration into existing automotive platforms. Unlike more complex or invasive technologies, this solution remains non-intrusive while delivering reliable performance. Its adaptability to various driver behaviors and environmental conditions ensures consistent accuracy, making it suitable for a broad range of users and vehicle types.

Moreover, beyond its technical benefits, the system contributes to cultivating safer driving habits by making drivers more aware of their alertness levels. In doing so, it promotes a culture of responsible driving.

The Driver Drowsiness Detection System is not just a technological innovation but a vital safety enhancement—playing a crucial role in reducing road accidents and saving lives.

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