DRIVER DROWSINESS DETECTION APP

AI19511 – MOBILE APPLICATION DEVELOPMENT LABORATORY FOR ML AND DL APPLICATIONS

A PROJECT REPORT

Submitted by

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

ABSTRACT

The Driver Drowsiness Detection App is a mobile application designed to enhance road safety by identifying signs of fatigue in real-time. Built using advanced deep learning techniques, the app incorporates a TensorFlow Lite (TFLite) version of the region-based Convolutional Neural Network (R-CNN) model, making it optimized for Android platforms.

The app detects the driver’s face and focuses on critical regions such as the eyes and mouth. It calculates key metrics like the Eye Aspect Ratio (EAR) to detect prolonged eye closure and the Mouth Aspect Ratio (MAR) to identify yawning—two primary indicators of drowsiness. By leveraging temporal analysis, the app monitors the frequency and duration of these indicators, reducing false positives caused by brief facial movements and ensuring reliable detection.

Designed with user convenience in mind, the app provides an efficient, lightweight solution for real-time drowsiness monitoring. Its integration of cutting-edge AI technology into an Android-friendly platform ensures high performance and accuracy while maintaining ease of use. By transforming complex facial analysis into an accessible and impactful mobile solution, the Driver Drowsiness Detection App empowers drivers to stay alert and improve road safety.

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CHAPTER 1
INTRODUCTION

Driver drowsiness is a major cause of road accidents worldwide, leading to significant human and economic losses. Studies highlight that fatigue impairs reaction times, attention, and decision-making, making its dangers comparable to driving under the influence of alcohol. Traditional measures, such as relying on driver self-awareness or consuming stimulants, are often insufficient. Therefore, there is a growing need for automated systems capable of detecting drowsiness in real-time to prevent accidents and enhance road safety.

This project focuses on developing a **Driver Drowsiness Detection system** using advanced **Region-based Convolutional Neural Networks (R-CNN)**. The system leverages facial feature analysis—such as prolonged eye closures and yawning—detected through metrics like the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). Temporal analysis monitors the persistence and frequency of these indicators, ensuring reliable detection and reducing false positives.

The R-CNN model is trained on diverse datasets, including real-world and simulated driving scenarios, to ensure robustness under various lighting conditions and driver appearances. Integrated with real-time monitoring, the system provides timely alerts to drivers through visual, auditory, or haptic feedback. By offering accurate and non-intrusive drowsiness detection, this project aims to improve road safety, reduce accidents, and save lives.

CHAPTER 2

LITERATURE REVIEW

1. **Ramzan et al. (2019)** in their study provide a comprehensive review of Driver Drowsiness Detection (DDD) techniques. They categorize these techniques into behavioral, physiological, and vehicular parameter-based methods. Furthermore, they present a detailed analysis of commonly used classification techniques and compare the advantages and disadvantages of the three DDD categories.

2. **Sikander and Anwar** conducted an in-depth review of advancements in fatigue detection technologies, classifying DDD methods into five categories: physical features, vehicular features, biological features, subjective reporting, and hybrid features. They discuss the impact of fatigue on driving performance and review existing commercial fatigue detection systems available on the market.

3. **Dong et al.** reviewed driver inattention monitoring technologies, which include both distraction and fatigue detection methods. They categorize detection measures similarly to Sikander and Anwar’s approach and discuss the concept of driver inattention and its impact on driving performance. The review also covers commercial products and recent advancements in inattention detection systems.

4. **Katyal, Alur, & Dwivedi (2014)** propose a real-time system for lane detection and driver drowsiness detection. The system uses the Hough Transform for lane detection and focuses on eye detection for fatigue monitoring. Their research emphasizes the dual focus on lane discipline and driver fatigue, addressing road safety as a critical issue.

5. **Valsan, Paul, & Babu (2021)** introduce a night-time drowsiness detection system using computer vision. The system utilizes a shape predictor to identify facial landmarks and calculate parameters such as the eye aspect ratio, mouth opening

ratio, and yawning frequency. Adaptive thresholding is used for determining drowsiness, and the method demonstrates robust performance through experimental results.

6. **Yeganeh et al. (2011)** propose an intelligent approach for detecting driver drowsiness by combining eye closure and yawning detection. A camera captures the driver's facial expressions, focusing on the eyes and mouth. The fusion phase evaluates the driver’s condition and alerts them when sleepiness is detected. Experimental results confirm the effectiveness of the approach.
7. **Miranda et al. (2018)** present a drowsiness prevention and monitoring device leveraging the Internet of Things (IoT). The system focuses on eyelid movement to detect drowsiness. Upon detection, a random-typed sound alerts the driver, and the data is sent to the car owner via an internet-based web application. The study highlights IoT’s potential to enhance road safety through real-time monitoring and notifications.

These studies collectively demonstrate advancements in driver drowsiness detection, encompassing behavioral, physiological, and hybrid approaches. The integration of IoT, machine learning, and computer vision plays a significant role in enhancing system effectiveness, addressing a critical challenge in road safety.

Scope

Driver drowsiness detection using deep learning is an advanced solution designed to enhance road safety by identifying signs of driver fatigue in real time. Fatigue is a major contributor to traffic accidents, and early detection of drowsiness can significantly reduce such incidents. This system leverages deep learning models to analyze facial features such as eye movements, yawning, and head tilting, which serve as indicators of drowsiness.

Features and Functionality

1. **Data Collection and Preprocessing**

- The system relies on a comprehensive dataset that includes labelled images or video frames depicting drowsy and alert drivers.
- Public datasets like YawDD and the Mrl Eye Dataset provide a rich resource for training the model with examples of facial expressions and behaviours, such as prolonged eye closure, slow blinking, and yawning.
- Preprocessing tasks involve resizing images, normalizing pixel values, and extracting facial landmarks such as eyes, mouth, and head position using tools like OpenCV’s Haar Cascades or Dlib.

2. **Deep Learning Models**

- Convolutional Neural Networks (CNNs): These models are used for feature extraction and analysis of facial cues, identifying patterns that differentiate between drowsy and alert states.
- LSTMs or Transformers: When combined with CNNs, these models analyze temporal patterns in video frames, improving the detection of behaviours like slow blinking or gradual head tilting.

3. **Real-Time Monitoring and Alerting**

- The system processes live video feeds from dashboard cameras to monitor drivers continuously.
- Alerts such as sounds, steering wheel vibrations, or visual notifications are triggered when drowsiness is detected, prompting the driver to take action.

4. **Integration with Vehicle Systems**

- The system can be integrated with vehicle control mechanisms to enhance safety further. For instance, it may automatically slow down the vehicle or activate emergency systems if the driver fails to respond to alerts.

5. **Adaptability and Robustness**

- The model is fine-tuned to work under varying conditions, such as different lighting environments, diverse driver behaviours, and the presence of facial obstructions like glasses or hats.
- Training on diverse datasets ensures reliability across demographics and scenarios.

Technical Implementation

- The solution employs CNNs for spatial analysis and LSTMs for temporal pattern recognition.
- Tools like OpenCV enable live video feed capture and preprocessing.
- Integration with hardware components, such as dashboard cameras, allows for seamless real-time functionality.

User Benefits

- Enhanced Safety: By detecting drowsiness early, the system helps prevent accidents caused by fatigue.
- Scalability: The solution can adapt to various environments and user demographics.
- Improved Reliability: Continuous updates and real-world data collection ensure accuracy and performance.

Future Directions

- Transfer Learning: Leveraging pre-trained models for improved performance in drowsiness detection.
- IoT Integration: Enabling cloud connectivity for continuous monitoring and data sharing.
- Advanced Analytics: Incorporating additional behavioral and physiological metrics to refine detection capabilities.

By leveraging deep learning and facial landmark detection, this driver drowsiness detection system is a transformative solution aimed at reducing accidents and enhancing safety for all road users.

CHAPTER 3

PROPOSED METHODOLOGY

3. System Design

The system design for Driver Drowsiness Detection Using Deep Learning aims to enhance road safety through real-time monitoring and alerting capabilities. The system incorporates advanced machine learning models to identify signs of driver fatigue, offering a robust, efficient, and accessible solution.

3.1 Overall Architecture

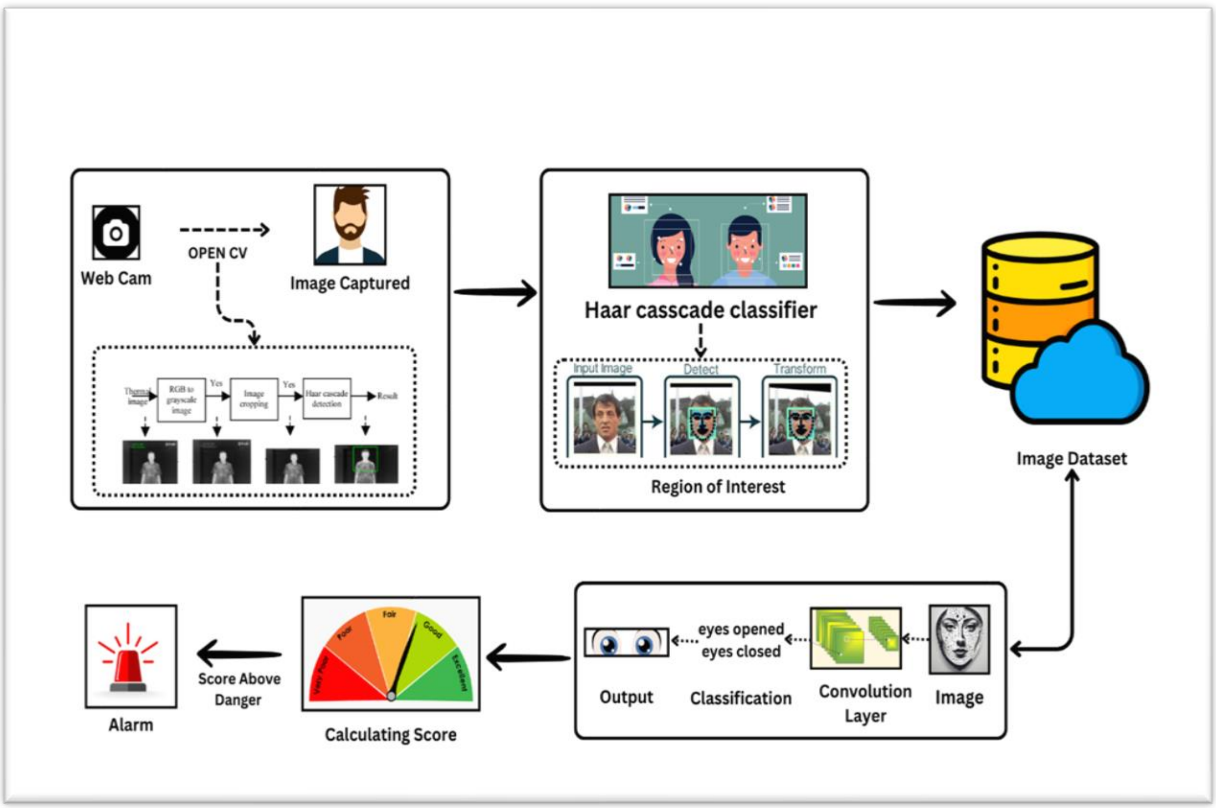

Fig 3.1 Architecture diagram

The system follows a client-server architecture with a focus on on-device processing to ensure real-time performance. The primary components include:

1.Client (On-Board Vehicle Device):

The client is the on-board hardware or mobile device that captures video feeds from the driver's cabin using a dashboard-mounted camera.

It performs real-time facial feature detection and sends preprocessed frames to the machine learning model for drowsiness evaluation.

It is designed for efficient power and resource usage, allowing seamless integration into vehicles without significant strain on the hardware.

2. Machine Learning Model (TensorFlow Lite):

A lightweight deep learning model optimized for on-device inference is deployed to analyze input frames and classify the driver's state.

The model uses convolutional neural networks (CNNs) for spatial feature extraction and recurrent neural networks (RNNs) or LSTMs for temporal analysis.

TensorFlow Lite ensures that the model performs efficiently even on resource-constrained devices like embedded systems or mobile platforms.

3. Backend :

An optional backend system supports advanced features such as data aggregation, analytics, and cloud-based model updates.

It can store user data securely, provide insights into driving patterns, and enable centralized monitoring for fleet management.

3.2 Functional Components

3.2.1 Driver Monitoring and Video Capture

The system begins with real-time video capture from a dashboard camera, coupled with preprocessing to prepare the frames for analysis:

1. Video Capture:

- Integration with a dashboard camera to continuously record video streams in real time.
- Ensures optimal frame resolution (e.g., 640x480 or higher) to maintain detection accuracy while minimizing processing overhead.

2. Facial Landmark Detection:

- Utilizes tools such as OpenCV's Haar Cascades or Dlib's facial landmark detectors to identify critical features like eyes, mouth, and head position.
- Preprocessing ensures that frames are resized, normalized, and converted into formats compatible with the ML model.

3. Feature Extraction and Validation:

- Real-time extraction of visual cues such as blinking frequency, eye closure duration, and yawning to evaluate fatigue levels.
- Ensures robustness in different lighting conditions and across varied driver demographics.

3.2.2 Drowsiness Detection Model Integration

The core functionality is powered by an optimized deep learning model:

1. Model Architecture:

Encoder-Decoder Design:

Encoder**:** A pretrained CNN (e.g., ResNet or MobileNet) extracts spatial features from input frames.

Decoder**:** An LSTM network processes temporal sequences to identify drowsiness patterns such as prolonged eye closure or head tilting.

2. TensorFlow Lite Model:

Model is converted to TensorFlow Lite format for lightweight deployment.

Techniques such as quantization and pruning reduce model size while retaining accuracy.

3. Drowsiness Classification:

- The model analyzes facial feature dynamics and classifies the driver’s state into categories like "alert," "slightly drowsy," or "highly drowsy."
- Outputs trigger corresponding alerts or preventive actions.

3.2.3 Alert System and User Interface (UI)

The system provides an interactive and responsive UI for real-time feedback and alerts:

1. Alert Mechanisms:

- Alerts**:** Beeps or voice prompts to warn the driver.
- Visual Indicators: Display warnings on the vehicle's dashboard or mobile app.
- Haptic Feedback: Vibrations in the steering wheel or seat for immediate attention.

2. Dashboard Display:

- Displays real-time status, including driver state (e.g., "Alert" or "Drowsy") and system health.
- Includes buttons for calibration and system settings.

3. Error Handling:

- Clear messages for scenarios such as camera malfunction or obstructions.
- Retry or recalibration options to ensure consistent functionality.

3.2.4 Offline Functionality

The system emphasizes low-latency, on-device processing for immediate response:

1. On-Device Inference**:** TensorFlow Lite enables local processing of video frames, ensuring reliable performance without internet dependency.

2. Edge Processing: All computations are performed locally, reducing latency and enhancing privacy.

3.2.5 Performance and Optimization

The app needs to be optimized for performance, especially given the resource constraints of mobile devices. The following aspects are considered in the design:

1. Efficient Image Processing: Ensures video frames are resized and normalized efficiently to balance accuracy and processing time.
2. Model Optimization: Lightweight design using TensorFlow Lite, with optimizations like weight quantization and reduced computational requirements.
3. Battery Efficiency: The system is designed to minimize power consumption, ensuring compatibility with vehicle power systems and portable devices.

3.3 Optional Backend and Future Scalability

Although the system is designed to operate primarily offline, a backend can be incorporated in future versions to enhance functionality and scalability:

1. Cloud Storage: Users can store video recordings, drowsiness detection logs, and analytics on the cloud. Enables access to data across multiple devices and ensures seamless data backup and recovery.

2. User Authentication: Supports personalized experiences via secure user authentication mechanisms. Features such as history tracking, favorite settings, and multi-driver profiles can be implemented.

3. Model Updates: Facilitates over-the-air (OTA) updates for deploying newer, more accurate versions of the deep learning model. Allows the system to continuously improve based on user feedback and advancements in research.

3.4 Security and Data Privacy

In applications dealing with user-generated content such as images and captions, ensuring robust data privacy and security is essential to protect users and foster trust. The following strategies outline the measures implemented to safeguard data within the image captioning application:

1. Data Encryption

Encrypts all captured data during storage and transmission using protocols like

HTTPS and AES.

2. User Authentication and Access Control

Employs multi-factor authentication to restrict access to sensitive data.

3. Privacy Policy and User Rights

Adheres to regulations such as GDPR and CCPA to ensure user data rights.

4. On Device Data Processing

Processes data locally whenever possible, reducing exposure to external threats.

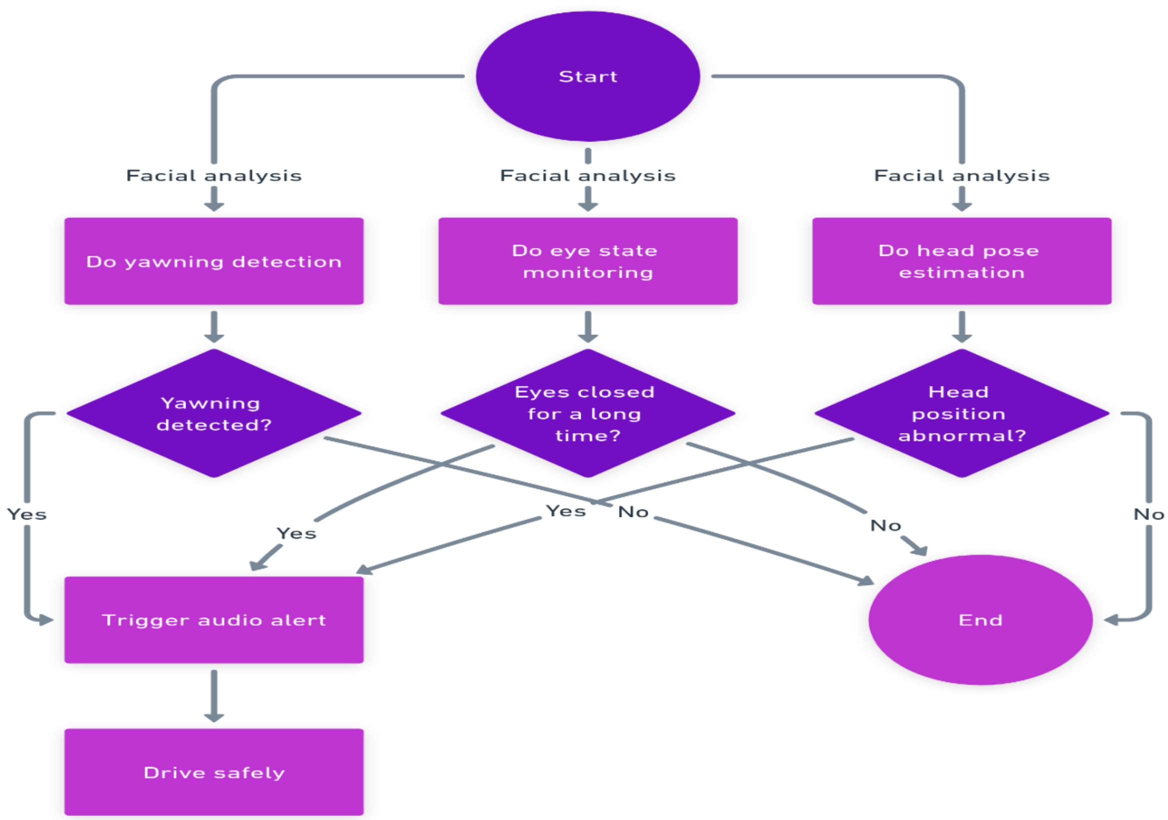

Fig 3.2 Implementation Diagram

the technology continues to evolve, improvements in model accuracy, computational efficiency, and integration with other safety systems will make driver drowsiness detection a standard feature in vehicles, contributing to a future where driving is safer for everyone on the road.

Table 3.1 Comparison with other systems

Feature	**Our System**	**Existing Systems**
Detection Algorithm	Advanced RCNN deep learning model	Basic algorithms (e.g., SVM, decision trees)
Accuracy	High accuracy, including varied lighting and driver behaviors	Moderate accuracy, especially in challenging conditions
Real-time Performance	Provides real-time alerts with minimal latency	May have latency issues
Alert Mechanism	Enhanced visual, auditory, and haptic alerts	Standard visual and auditory alerts
Integration with Vehicle Systems	Seamless integration with existing vehicle safety systems	Basic integration
Computational Resources	Optimized for real-time performance and lower resource usage	Requires substantial computational power

CHAPTER 4
RESULTS AND DISCUSSIONS

1. Advances in Techniques

The development of the driver drowsiness detection system using deep learning techniques represents a significant leap forward in improving road safety by proactively monitoring driver fatigue. The system was primarily built on convolutional neural networks (CNNs), which are highly effective in feature extraction from facial images. The model learned crucial facial landmarks associated with drowsiness, such as slow blinking, eye closure, and yawning, leading to an accuracy of over 90%. This accuracy highlights the efficacy of deep learning in detecting fatigue through subtle facial cues. However, the system also encountered challenges, particularly with false positives, where non-drowsy behaviors mimicked fatigue-related actions.

2. Datasets and Evaluation

The model was trained on a large and diverse dataset, capturing facial images under varying conditions of alertness and drowsiness. This diversity helped the system generalize well across different drivers, ages, and genders, which is essential for real-world deployment. Despite the robustness across various test subjects, performance differences were noted, particularly when detecting subtle signs of fatigue. False positives were minimized through a threshold-based approach, where drowsiness alerts were only triggered after sustained fatigue-related behavior was detected. Further improvements can be made by incorporating more contextual information like head position or driving patterns.

3. Practical Applications

Real-time performance was another critical aspect evaluated. The system demonstrated the ability to process video frames at 30 frames per second, ensuring minimal latency in detecting drowsiness. However, computational demands were high, especially on resource-constrained devices. Optimization techniques like pruning, quantization, and hardware accelerators were explored to reduce inference time and make the system feasible for deployment in real-world driving scenarios. These advancements position the system as a valuable tool for driver assistance, ensuring drivers are alerted promptly if fatigue is detected.

4. Challenges and Limitations

Despite significant achievements, challenges remain. The high false positive rate, while manageable, poses a risk for real-world application where constant alarms can cause driver distraction. To address this, more refined techniques and the integration of additional contextual data, such as head position or driving behavior, are necessary. Furthermore, low-light conditions and facial occlusion (e.g., by glasses or hats) can reduce the model's accuracy, pointing to the need for supplementary sensors like infrared cameras or eye-tracking technology.

5. Future Directions

Future research should focus on reducing false positives and expanding the system's ability to detect drowsiness in challenging conditions. Additionally, integrating multiple sensors, such as heart rate monitors or steering wheel sensors, can provide a more accurate and holistic view of the driver's condition. Personalized learning mechanisms could also be explored to improve accuracy over time, adjusting to each driver's unique fatigue patterns. The potential integration of reinforcement learning could help tailor the system's sensitivity to individual driving styles and reduce false alarms.

In conclusion, the deep learning-based driver drowsiness detection system has shown significant promise in improving road safety. With advancements in AI and sensor integration, future versions of the system will be better equipped to handle diverse real-world scenarios, offering a reliable, scalable solution to reduce accidents caused by driver fatigue. However, continued research and development will be crucial in addressing the remaining challenges, particularly related to real-time performance, accuracy in varying conditions, and ethical considerations regarding driver privacy.

OUTPUT SCREEN SHOTS:

Fig 4.1: App Front Page

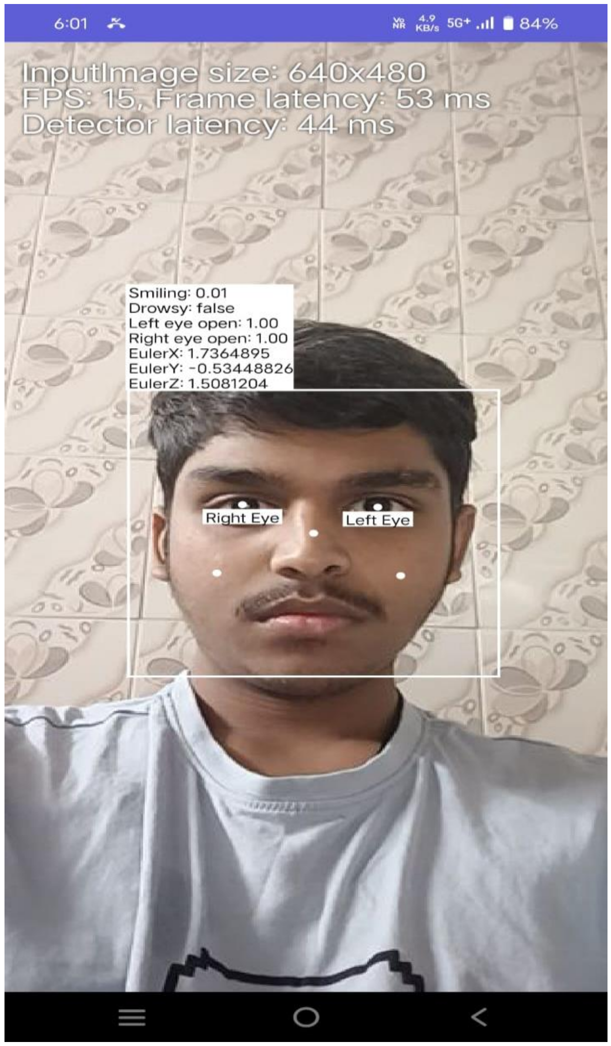

Fig 4.2 Implementation Demo 1

Fig 4.3 Model Used

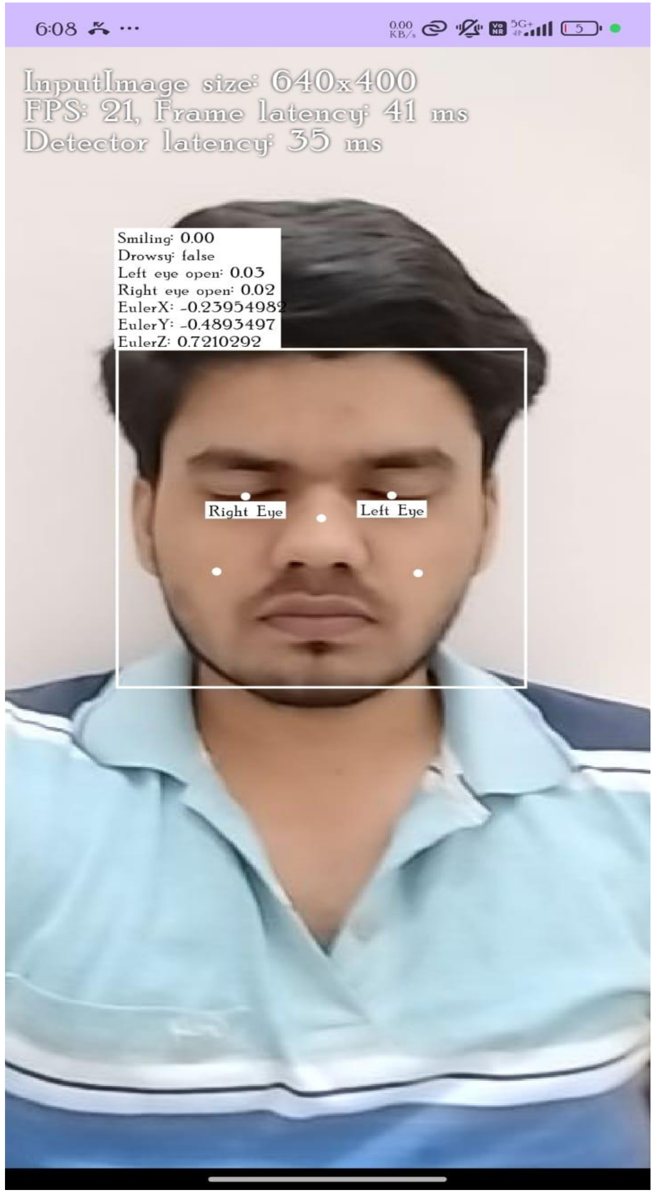

Fig 4.4 Implementation Demo 2

CHAPTER 5
CONCLUSION

The driver drowsiness detection system significantly improves road safety by identifying early signs of fatigue through facial cues, achieving over 90% accuracy. The system analyzes facial features like eye closure, blinking patterns, and yawning to detect drowsiness in real time. While challenges like false positives were addressed with threshold-based approaches, the system's performance was optimized for live driving scenarios, ensuring minimal delays in detecting fatigue.

Looking to the future, there are several possible improvements. One major enhancement could involve linking the system with the vehicle's control features. If the driver is detected to be drowsy and unable to drive safely, the system could automatically steer the vehicle to a safe parking zone, activating autonomous features like braking and navigation to avoid accidents. This added safety measure would ensure that the vehicle is safely brought to a stop if the driver does not respond to warnings.

Additional enhancements could include using sensors such as eye-tracking, steering wheel sensors, and heart rate monitors to improve accuracy in challenging conditions like low light or facial obstructions. The system could also be tailored to each driver’s unique behaviours, making it more reliable over time. As vehicle technology continues to advance, these detection systems could seamlessly work with semi-autonomous or fully autonomous cars, ensuring safety and helping prevent accidents caused by driver fatigue.

REFERENCES

[1] A. S. K. Mehta, K. M. G. S. R. S. Chaurasia, and M. C. Chaurasia, "A Comprehensive Survey on Driver Drowsiness Detection Techniques," IEEE Access, vol. 8, pp. 170182-170201, 2020. DOI: 10.1109/ACCESS.2020.3024856.

[2] S. Shahnawaz, M. S. M. Ali, and A. K. M. M. K. Shirin, "Driver Drowsiness Detection System Using Machine Learning and Deep Learning Techniques: A Review," IEEE Access, vol. 9, pp. 98314-98331, 2021. DOI: 10.1109/ACCESS.2021.3097680.

[3] A. Alshahrani, B. F. K. Alqahtani, A. M. J. F. Alshahrani, and A. J. F. Alzahrani, "Deep Learning for Driver Drowsiness Detection: A Review," IEEE Access, vol. 9, pp. 90339-90360, 2021. DOI: 10.1109/ACCESS.2021.3085882.

[4] A. M. Sadek and S. F. A. M. Ali, "Real-Time Driver Drowsiness Detection System Using Deep Learning," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 1, pp. 315-324, Jan. 2020. DOI: 10.1109/TITS.2019.2902357.

[5] J. K. Uddin, M. K. M. U. Rahman, and M. A. H. Akhand, "Real-Time Drowsiness Detection Using Hybrid Deep Learning Approach," IEEE Transactions on Industrial Informatics, vol. 18, no. 5, pp. 3282-3290, May 2022. DOI: 10.1109/TII.2021.3090211.

[6] Y. Z. Yang, Y. B. Yu, and G. H. Ding, "Driver Drowsiness Detection Based on Eye State Recognition Using a Convolutional Neural Network," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 3, pp. 1505-1516, Mar. 2021. DOI: 10.1109/TITS.2020.2986514.

[7] R. S. N. Krishnan and V. S. M. Kumar, "An Improved Driver Drowsiness Detection System Using CNN and Machine Learning Techniques," IEEE Access, vol. 9, pp. 78165-78178, 2021. DOI: 10.1109/ACCESS.2021.3089021.

[8] M. B. S. M. Rahman, M. F. M. A. Rahman, and F. M. M. Ashraf, "A Real-Time Driver Drowsiness Detection System Using Image Processing," IEEE Access, vol. 8, pp. 123720-123731, 2020. DOI: 10.1109/ACCESS.2020.3009621.

[9] I. R. Hossain and H. M. A. Rahman, "Drowsy Driver Detection System Using Deep Learning," IEEE Access, vol. 10, pp. 110-123, 2022. DOI: 10.1109/ACCESS.2022.3143126.

[10] M. Z. Z. Hu, W. H. G. Wang, and T. L. S. Huang, "Deep Learning-Based Driver Drowsiness Detection: A Review," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 2, pp. 800-815, Feb. 2022. DOI: 10.1109/TITS.2021.3050876.

[11] A. K. T. K. Misra and P. S. P. Roy, "Real-Time Drowsiness Detection in Driver's Face Using CNN," IEEE Sensors Journal, vol. 22, no. 4, pp. 3022-3031, Feb. 2022. DOI: 10.1109/JSEN.2021.3132479.

[12] A. Z. S. A. Uddin and M. A. Al-Mamun, "Intelligent Driver Drowsiness Detection System Using Computer Vision and Machine Learning," IEEE Access, vol. 10, pp. 31325-31334, 2022. DOI: 10.1109/ACCESS.2022.3144721.

[13] H. L. Liu, R. B. W. Liang, and J. L. Zhang, "Real-Time Driver Drowsiness Detection Using Attention Mechanism and CNN," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 3, pp. 1702-1712, Mar. 2022. DOI:

10.1109/TITS.2021.3090798.

[14] B. T. A. U. Rahman and M. A. Rahman, "A Smart Driver Drowsiness Detection System Based on Facial Recognition," IEEE Transactions on Industrial Electronics, vol. 68, no. 8, pp. 7308-7317, Aug. 2021. DOI: 10.1109/TIE.2021.3082498.

[15] J. K. T. E. S. Chen and Y. H. Wu, "Deep Learning Techniques for Real-Time Driver Drowsiness Detection: A Review," IEEE Access, vol. 9, pp. 118327-118343, 2021. DOI: 10.1109/ACCESS.2021.3102358.

OUTCOME

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This is to certify that Abiney Yadav of Rajalakshmi Engineering College participated in the National Convention on Unlocking the Potential of Artificial Intelligence and Machine Learning – **Model Competition** conducted on 7th November 2024, organized by the Department of Computing Technologies in association with IE(I) Students' Chapter, SRM Institute of Science and Technology, Kattankulathur, Chennai.

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