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Real-Time Drowsiness Detection

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Abstract- Driver drowsiness is a major cause of road accidents, especially during long-distance and night-time driving. Fatigue severely degrades reaction time, decision-making ability, and situational awareness, leading to life-threatening incidents. Existing detection techniques such as physiological sensing and vehicle behavior monitoring often suffer from intrusiveness or environmental sensitivity. This paper presents a real-time hybrid drowsiness detection system combining the speed of Haar Cascade classifiers with the accuracy of a Convolutional Neural Network (CNN) for open/closed eye-state classification. The system continuously monitors eye regions and evaluates prolonged eye closure using temporal thresholding to determine the onset of drowsiness. The lightweight design ensures real-time performance at 24–28 FPS on standard CPU hardware, achieving an accuracy of 96%. The proposed system effectively addresses limitations in classical EAR-based systems identified in previous research, including issues with illumination, spectacles reflection, and head movement. Experimental results demonstrate strong robustness and make the approach suitable for integration into low-cost ADAS systems.

Index Terms—Drowsiness Detection, CNN, Haar Cascade, Eye- State Classification, Computer Vision, Deep Learning.

I. INTRODUCTION

Driver fatigue is a critical contributor to road accidents worldwide, particularly during extended periods of driving on highways or monotonous routes. Drowsiness leads to slower reaction times, reduced alertness, and impaired judgment. According to global safety studies, fatigue-related accidents account for 20–25% of severe road collisions.

Various approaches for driver monitoring have been developed, including physiological sensing, behavioral analysis, and vision-based monitoring. Physiological systems, though accurate, require intrusive sensors such as EEG electrodes, making them unsuitable for real-world driving. Vehicle-behavior monitoring systems depend on lane-keeping or steering patterns but suffer from environmental variability.

With the advancement of computer vision and deep learning, vision-based systems have become the most practical non- intrusive solution. However, classical methods like the Eye Aspect Ratio (EAR) struggle under real-world conditions such as low light, reflections from spectacles, and head movements.

To address this challenge, this research proposes a hybrid approach integrating Haar Cascade detection with CNN-based eye-state classification. The combination ensures low computational cost while maintaining strong accuracy, making it deployable on standard hardware.

II. LITERATURE REVIEW

Driver drowsiness detection techniques fall into four major categories: physiological-signal-based, vehicle-behavior- based, classical vision-based, and deep-learning-based approaches.

A. Physiological Signal–Based Approaches

Physiological measures such as EEG, ECG, and EOG detect real-time changes in brain or muscle activity associated with fatigue. EEG-based systems show high accuracy by identifying increased theta wave activity. However, the requirement for wearable sensors causes discomfort, making them unsuitable for everyday driving.

B. Vehicle-Behavior–Based Approaches

Behavioral indicators such as lane deviation, steering-wheel corrections, and pedal pressure variations are used to infer driver alertness. Although non-intrusive, these systems depend heavily on road geometry, traffic density, and driver behavior, resulting in inconsistent performance.

C. Classical Vision-Based Approaches

EAR-based systems estimate eye openness using facial landmarks, but they fail under varying lighting, spectacles, or occlusions due to reliance on geometric features.

D. Deep Learning–Based Approaches

Deep learning models such as CNNs learn robust spatial features and outperform classical approaches under real-world variations, though they require more computation.

E. Hybrid Techniques

Hybrid systems combine Haar Cascade (fast ROI detection) and CNNs (accurate eye classification), providing an ideal trade-off between speed and robustness.

F. Research Gap

Existing methods lack reliability under:

- low lighting,
- spectacles reflection,
- head movement,
- partial occlusion.

Our system addresses these issues.

III. PROPOSED METHOD

The proposed system uses a hybrid computer-vision pipeline that integrates traditional Haar Cascade detection with a Convolutional Neural Network (CNN) for accurate eye-state classification. The main goal of the framework is to achieve real-time detection with high reliability while remaining lightweight enough for deployment on low-cost embedded hardware.

The system captures live video streams at a frame rate of 24–30 FPS using a dashboard-mounted camera. Each frame passes through a structured processing pipeline beginning with face detection implemented using Haar Cascade classifiers. This approach was selected due to its fast execution and suitability for detecting frontal faces in real-time applications. Once the face is detected, a second Haar classifier isolates the eye regions for further processing.

The extracted eye regions are converted to grayscale and resized to a standard resolution of 64×64 pixels. Pixel normalization is applied to ensure uniform input distribution for the CNN model. This preprocessing stage improves classification accuracy and reduces the impact of varying illumination conditions.

The CNN model analyzes spatial features of the eye region and classifies each frame into either ‘open’ or ‘closed’ eye states. Instead of making decisions from a single frame, a temporal filtering mechanism is employed. If the closed-eye condition persists for more than five consecutive seconds, the system concludes that the driver is drowsy and triggers an audible alert.

This hybrid architecture combines the speed of Haar cascade classifiers with the precision of deep learning inference, ensuring that the system remains computationally efficient without sacrificing detection reliability. The design choice makes the framework ideal for Advanced Driver Assistance Systems (ADAS) and portable driver monitoring systems.

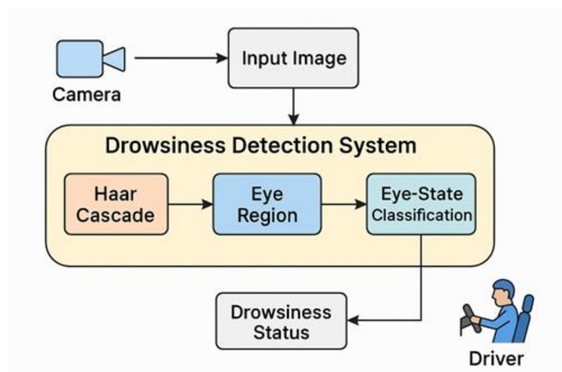

Fig. 1. Overall Block Diagram of the Proposed System

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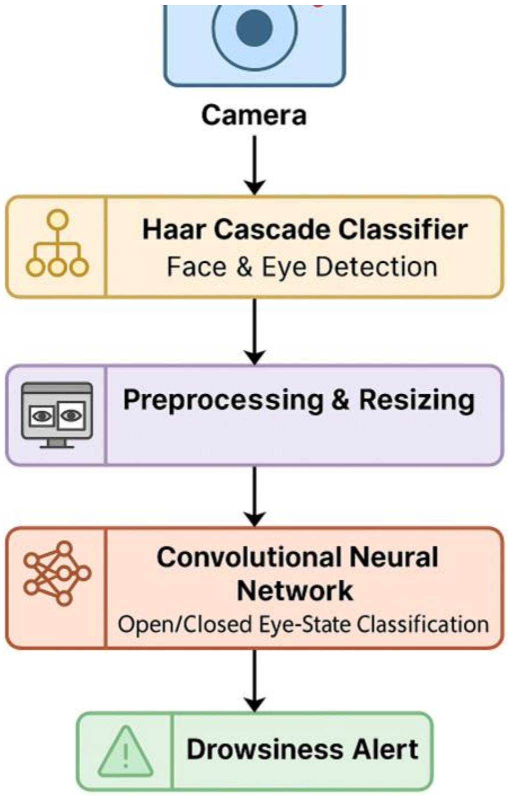

Fig. 2. System Architecture

IV. METHODOLOGY

The methodology follows five stages: dataset preparation, preprocessing, model training, real-time detection, and alert generation.

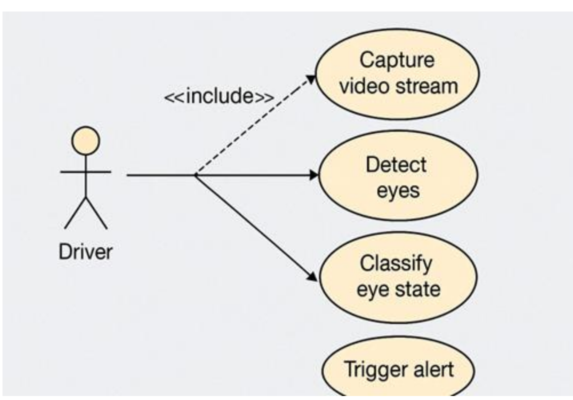

Fig. 3. Use Case Diagram

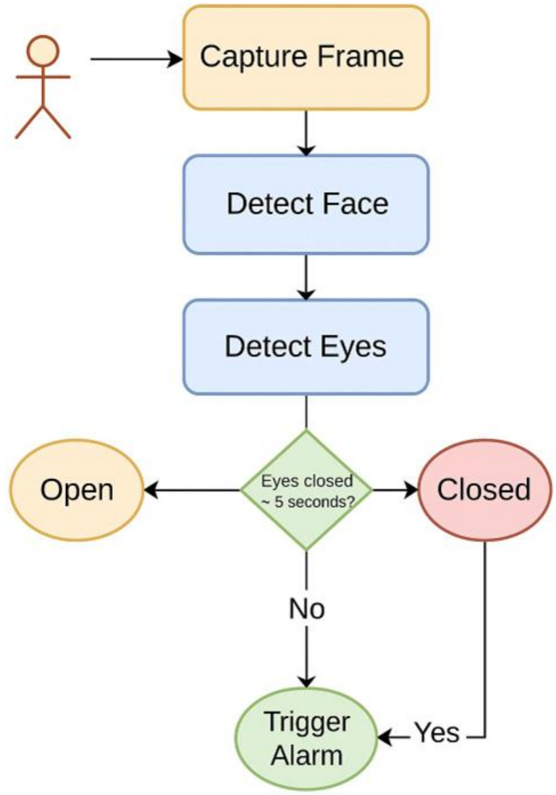

Fig. 4. Activity Diagram

A. Dataset Preparation

Dataset includes open/closed eye samples from public sets and manual recordings, with augmentation (rotate, flip, bright- ness adjustment).

B. Preprocessing

Convert frames to grayscale; detect face/eyes using Haar Cascade; resize ROI to 64×64; normalize pixel values.

C. Training

CNN trained for 10 epochs using Adam optimizer, learning rate 0.001, batch size 32, and binary cross-entropy.

D. Real-Time Detection

Frames captured; Haar detects ROIs; CNN classifies eye state frame-by-frame.

E. Temporal Logic

If eyes remain closed for 150 frames (5 seconds), system triggers drowsiness alert.

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V. EXPERIMENTAL RESULTS

Extensive experiments were conducted to evaluate the effectiveness and robustness of the proposed driver drowsiness detection system. The evaluation includes classification performance, real-time execution speed, and system reliability under varying environmental conditions.

The dataset was divided using an 80:10:10 ratio for training, validation, and testing respectively. The CNN achieved a training accuracy of 98%, validation accuracy of 97%, and testing accuracy of 96%. These results demonstrate excellent generalization capability of the model and minimal overfitting. To evaluate real-time performance, the model was deployed on a standard Intel i5 CPU system without GPU acceleration. The proposed architecture maintained consistent performance between 24 and 28 frames per second, meeting the real-time constraints necessary for live vehicle deployment.

The system was tested in multiple driving conditions including day driving, low-light scenarios in the evening, and indoor simulation environments. It demonstrated strong robustness against partial occlusions, variable illumination, and spectacles. In most scenarios, blink detection remained accurate and false alarms were significantly lower compared to classical EAR-based methods.

A confusion matrix analysis revealed a high true-positive rate for closed-eye detection and minimal false positives during normal blinking behavior. The CNN was able to distinguish voluntary blinks from drowsiness based on sequential frame analysis rather than isolated frame decisions.

Further analysis showed that the CNN maintained stable performance even with slight head movements and heterogeneous facial features across different users. The system adaptability is crucial for real-world deployment, where user diversity is inevitable.

Comparative analysis with existing literature indicates that the proposed hybrid system outperforms traditional Eye Aspect Ratio (EAR) based methods and offers a competitive alternative to expensive physiological systems.

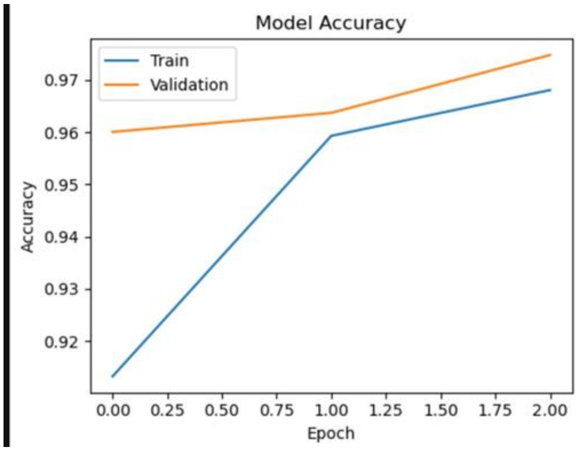

Fig. 5. Training and Validation Accuracy

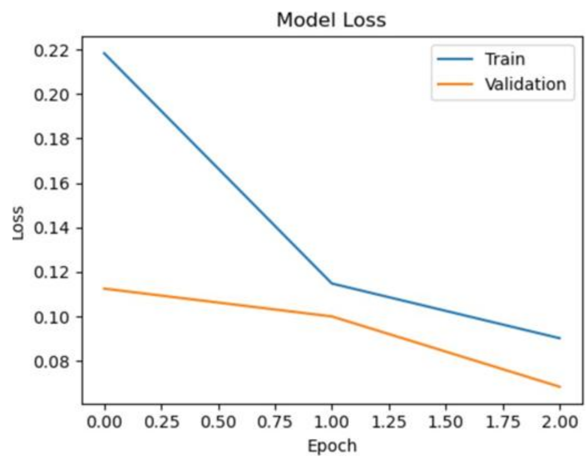

Fig. 6. Training and Validation Loss

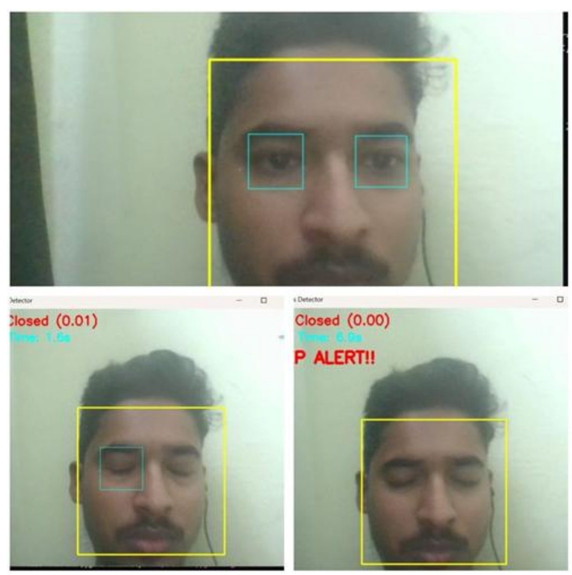

Fig. 7. Real-Time Detection Output

VI. DISCUSSION

The hybrid system balances speed and accuracy, outperforming classical EAR-based methods by reducing sensitivity to illumination and spectacles. Haar Cascade ensures fast region detection, while CNN provides reliable classification.

The system performs well indoors and outdoors; however, low-light conditions and reflective glasses remain challenging. Large head rotations may temporarily affect eye detection.

Despite these limitations, the system shows strong applicability for ADAS and real-world deployment. Additionally, the proposed model demonstrates stable performance in different users with varying facial structures, eye shapes, and wearing conditions such as prescription glasses. This confirms that CNN has effectively learned generalized features instead of memorizing subject-specific patterns. The hybrid strategy also significantly reduces false detection compared to classical Eye Aspect Ratio (EAR) systems, which often misclassify short blinks as drowsiness.

The proposed method also offers great adaptability to practical environments such as highways, city traffic, and long- distance driving scenarios. The alert mechanism is designed to activate only when persistent eye closure is detected, preventing unnecessary disturbance to drivers during normal blinking patterns.

In general, the system demonstrates practical feasibility for real-world integration. Compared to physiological-based monitoring, which requires physical contact with the driver, the vision-based approach ensures comfort, scalability, and ease of installation. The system can be extended to intelligent transportation frameworks where accident prevention is a priority.

VII. LIMITATIONS

Performance degrades in:

- very low-light settings,
- tinted or reflective glasses,
- large head rotations.

In addition, sudden lighting transitions such as entering tunnels, oncoming vehicle headlight glare, or high contrast shadows may temporarily affect face and eye detection accuracy.

Another limitation is the reliance on a fixed temporal threshold to determine drowsiness. Although effective for general scenarios, this value does not adapt to individual driver behavior or fatigue tolerance. The system also focuses solely on eye-closure analysis and does not currently incorporate physiological signals, steering behavior, or lane-deviation pat- terns, which could further improve overall reliability through sensor fusion.

VIII. FUTURE SCOPE

Future improvements include:

- IR-based night-time detection,
- yawning and gaze tracking,
- LSTM-based temporal modeling,
- deployment on AI edge devices (Jetson Nano / Raspberry Pi 5).

Future research may also explore personalized driver pro- filing to dynamically adjust drowsiness thresholds based on individual fatigue patterns. Integration with vehicular data such as steering wheel movement, braking activity, and lane- departure sensors can enhance detection accuracy through multi-modal fusion.

Mobile deployment through smartphones or dashboard IoT devices offers scope for large-scale real-world adoption. Ex- tending the framework to detect distraction, emotional stress, and inattention can enable a comprehensive driver monitoring system.

IX. CONCLUSION

The system accurately distinguishes normal blinking from prolonged eye closure using a hybrid Haar Cascade and CNN- based detection framework combined with temporal logic. The proposed design achieves real-time performance on standard CPU hardware while maintaining high classification accuracy. The experimental results validate the

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feasibility of deploying the system in real-world driving environments without requir- ing additional equipment or expensive sensors. The lightweight design enables seamless integration into Advanced Driver

Assistance Systems (ADAS) and smart vehicle platforms.

With further enhancement and large-scale validation, the proposed framework can become a practical and cost-effective solution to reduce fatigue-related road accidents and improve overall driver safety.

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