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AI – BASED DRIVER DROWSINESS DETECTION SYSTEM

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Abstract: Driver fatigue and distraction are among the leading causes of road accidents worldwide. Early detection of these conditions can significantly improve road safety and reduce accident risks. However, many existing driver monitoring systems rely on expensive hardware such as infrared cameras and physiological sensors, limiting their practical use. This project presents an AI-Based Driver Drowsiness Detection System that use computer vision and deep learning techniques to monitor driver alertness in real time using only a standard webcam. The proposed system combines multiple methods to achieve both accuracy and efficiency. Facial landmarks are detected using MediaPipe, and the Eye Aspect Ratio (EAR) is calculated to identify prolonged eye closure, a common indicator of drowsiness. To improve reliability, a lightweight Convolutional Neural Network (CNN) is used to classify eye states when EAR-based prediction is uncertain. This hybrid approach minimizes unnecessary computation while maintaining real-time performance. The system also incorporates head pose estimate to detect driver distraction and a dynamic alertness score to continuously evaluate the driver`s attention level. Developed using Python, OpenCV, MediaPipe, PyTorch, and Streamlit, the solution is lightweight, scalable, and easy to deploy. Experimental results demonstrate that the system effectively reduces false alarms while achieving real-time performance of over 20 frames per second on a standard CPU. Overall, the proposed approach provides a practical, non-intrusive, and cost-effective solution for enhancing road safety and supporting intelligent transportation systems.

Keywords: *Driver Drowsiness Detection, Driver Monitoring System, Artificial Intelligence, Computer Vision, Convolutional Neural Network, MediaPipe, Eye Aspect Ratio, Streamlit.*

1. INTRODUCTION

Road safety has become one of the most important challenges in modern transportation systems, as a large number of accidents are caused by driver fatigue, distraction, and loss of attention [14]. Factors such as long driving hours, lack of sleep, mobile phone usage, and mental stress further increase the risk of accidents. Traditional driver monitoring systems usually depend on physiological sensors like Electroencephalography (EEG), Electrocardiography (ECG), and other wearable devices. While these methods can be accurate, they are often expensive, uncomfortable for drivers, intrusive, and difficult to deploy on large scale [10][11]. In recent years, advancements in Artificial Intelligence (AI), Computer Vision, and Deep Learning have made it possible to develop non-intrusive Driver Monitoring Systems (DMS) that use standard cameras for real-time analysis of driver behavior [1][6]. These systems observe facial expressions, eye movement, blinking patterns, yawning frequency, and head orientation to detect signs of fatigue and distraction [5][7][10]. Such approaches are more cost-effective, scalable, and easier to integrate into modern vehicles and intelligent transportation systems [1][10]. This research proposes and AI-Based Driver Drowsiness Detection System that combines traditional computer vision techniques with deep learning models to enable real-time driver safety monitoring [1][5]. In the first stage, the system uses MediaPipe Face Mesh to detect facial landmarks and calculate the Eye Aspect Ratio (EAR), which helps identify eye closure and drowsiness [2][3]. When the EAR value stays below a defined threshold for several consecutive frames, the system triggers and alert. This rule-based approach is fast and computationally efficient [12][13]. To improve accuracy and reduce false alarms caused by lighting changes, camera angles, or natural blinking, a second stage is added using a Convolutional Neural Network (CNN) trained on eye-state datasets [6][8][15]. The third stage introduces a hybrid strategy where the CNN is activated only when EAR-based system detects uncertain or suspicious conditions. This helps reduce unnecessary computation while maintaining high accuracy [1][5]. In the final stage, head pose estimation and a dynamic alertness scoring system are incorporated using 3D facial landmarks and the cv2.solvePnP algorithm [2][7]. This allows the system to detect distraction behaviors such as looking away from the road or using a mobile phone[7][10]. The complete system is deployed through a Streamlit dashboard that enables live monitoring, visual alerts, and performance tracking. Furthermore, the increasing adoption of intelligent transportation technologies has created a strong demand for reliable and real-time driver monitoring solutions. Recent studies have demonstrated that combining computer vision techniques with deep learning models can significantly improve the detection of drowsiness, distraction, and unsafe driving behavior while maintaining computational efficiency [1][6][11]. The proposed solution works on standard webcam hardware without requiring wearable sensors and delivers real-time performance on CPU-based system. Its hybrid design achieves a balance between efficiency and accuracy, making it suitable for smart vehicles, fleet management, public transport systems, and Advanced Driver Assistance System (ADAS) [5][7][10].

1.1 OBJECTIVES

The specific objectives are:

1. To develop a real-time, non-intrusive driver monitoring system that uses a webcam to continuously track driver behavior and alertness without requiring specialized hardware.
2. To accurately detect driver drowsiness and distraction by combining Eye Aspect Ratio (EAR), CNN-based eye-state classification, head pose estimation, and gaze tracking, while maintaining efficient real-time performance.
3. To enhance road safety through continuous monitoring and timely alerts by maintaining a dynamic alertness score, providing visual and audio warnings, and offering a scalable, low-cost solution for smart vehicles, fleet management, public transportation, and ADAS applications.

2. LITERATURE REVIEW

Srivastava et al. (2026) proposed an AI-Based Driver Drowsiness Detection System that combined computer vision and deep learning techniques to detect driver drowsiness and distraction in real time. The study demonstrates the effectiveness of non-intrusive monitoring using facial features and behavioral analysis. Similar approaches have been explored by several researchers using facial landmark detection, gaze tracking, deep learning models, and hybrid AI techniques for real-time driver monitoring. The following studies discuss various approaches to driver monitoring and fatigue detection.

Albadawi et al. (2023) develop a machine-learning-based driver drowsiness detection system using Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head pose features, achieving high accuracy in real-time fatigue detection.

Badri et al. (2025) utilize MediaPipe Face Mesh for facial landmark extraction and EAR calculation, demonstrating an efficient and lightweight approach for real-time monitoring.

An et al. (2025) combine MediaPipe with gaze-tracking techniques to improve driver attention monitoring and enhance detection robustness under varying conditions.

Sawant et al. (2025) propose a real-time drowsiness detection system using OpenCV, MediaPipe, and EAR, achieving approximately 92% accuracy with low computational cost.

Florez et al. (2024) employ CNN-based eye and mouth analysis to achieve highly accurate driver drowsiness detection.

Zaman et al. (2024) develops a Deep Convolution Neural Network (DCNN)-based approach for detecting fatigue through facial cues such as eye closure and yawning.

Kose et al. (2019) introduce a spatio-temporal CNN framework for detecting multiple driver distraction behaviors.

Zhao et al. (2024) presents a head-pose estimation model for distraction.

Kin et al. (2023) develop an infrared-based monitoring system for low-light conditions.

Akhmedov et al. (2025) proposes a hybrid CNN and facial landmark-based framework that improves reliability and reduces false alarms, highlighting the effectiveness of combining deep learning with traditional computer vision techniques.

2.2 Research Gap

Existing driver monitoring systems are mainly based on either geometric facial features or deep leaning models. Geometric methods are computationally efficient but often suffer from reduced accuracy under varying lighting and real-world conditions. In contrast, deep learning approaches provide higher accuracy but require greater computational resources. To address these limitations, this research proposes a hybrid system combining MediaPipe-based facial landmarks, CNN-based eye-state classification, head pose estimation, and dynamic alertness scoring for efficient real-time monitoring. The proposed system aims to provide:

- Improved detection accuracy with reduced false alarms.
- Real-time performance on standard hardware.
- A low-cost and scalable solution using only a standard webcam.

3. METHODOLOGY

The proposed AI-Based Driver Drowsiness Detection System uses computer vision, deep learning, and geometric analysis in a multi-phase approach. It processes live video to extract facial features, compute Eye Aspect Ratio (EAR), apply CNN classification, estimate head pose, and assess driver alertness, providing real-time monitoring with alerts through a dashboard.

Overall System Workflow:

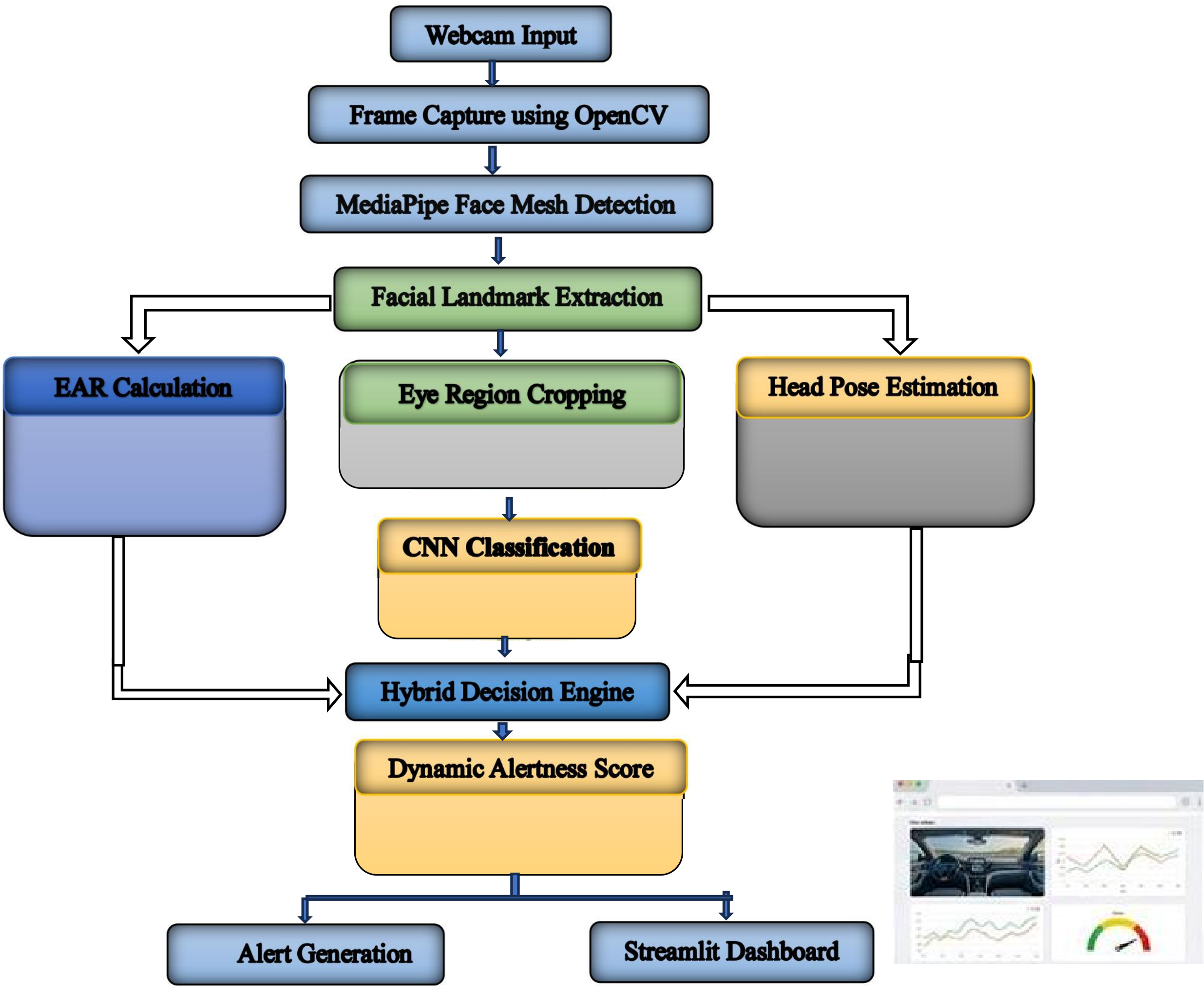

Figure 1: Methodology Flowchart

Phase 1 – EAR-Based Geometric Detection

The first focuses on building a simple and lightweight rule-based system for detecting drowsiness using facial landmark geometry. In this stage, Eye Aspect Ratio (EAR) is used to monitor eye movements and identify signs of fatigue such as prolonged eye closure or reduced blinking activity. This phase is designed to provide fast and efficient detection with minimal computational load.

Facial Landmark Detection

The system uses the MediaPipe Face Mesh framework to detect 468 facial landmarks from each frame captured by the webcam in real time. MediaPipe was selected because it provides fast processing, a lightweight structure, smooth performance on CPU-based systems, and highly accurate facial landmark detection.

This facial landmark detection module is implemented in the file: phase1/detection.py

Eye Aspect Ratio (EAR)

To detect whether the driver's eyes are open or closed, the system calculates the Eye Aspect Ratio (EAR) using the distances between specific eye landmarks. These distances are computed using the Euclidean distance method, comparing vertical and horizontal eye points.

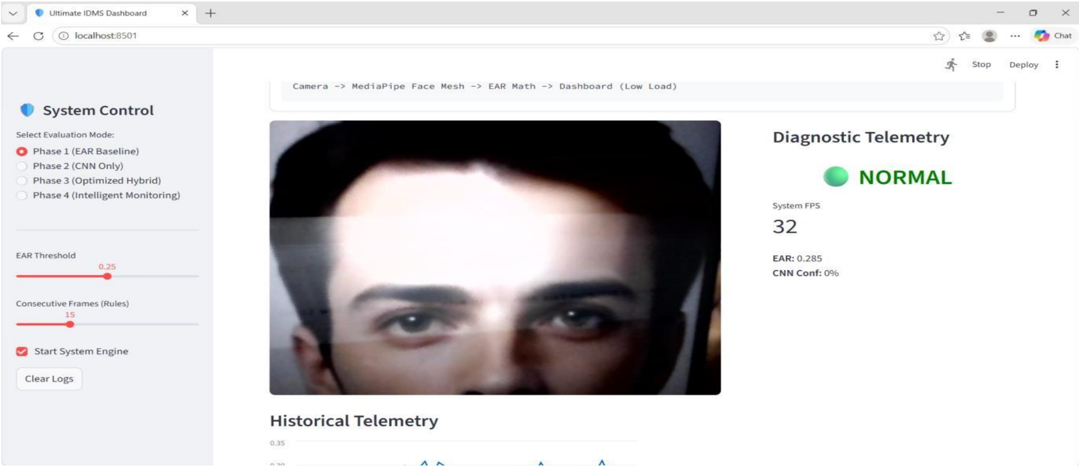

Figure 2: Shows a real-time driver monitoring system using EAR with live video, FPS, and driver status

Alert Generation

In Phase 1, the system continuously monitors Eye Aspect Ratio (EAR) using a webcam. If the eyes stay closed beyond a set limit, it detects drowsiness and immediately triggers a warning message, an alarm sound (via winsound), and a visual alert on the screen.

The full logic is implemented in phase1/main.py.

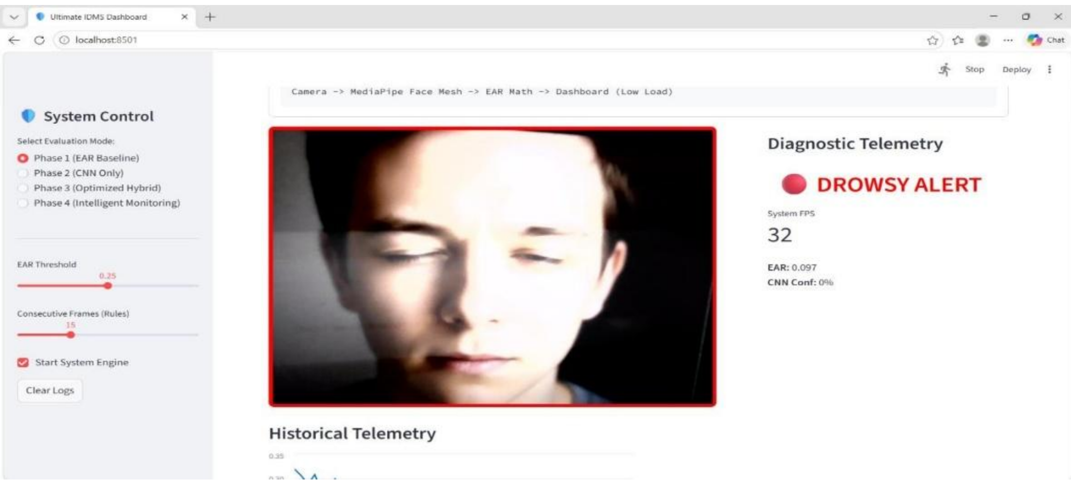

Figure 3: Shows the system detecting drowsiness and giving a warning alert to the user

Phase 2 – CNN-Based Deep Learning Detection

While EAR-based methods are fast and lightweight, they can sometimes give incorrect alerts due to normal blinking, changes in lighting, or differences in facial structure. To overcome these limitations, Phase 2 uses a CNN- based deep learning model to more accurately classify the eye state and improve the reliability of drowsiness detection.

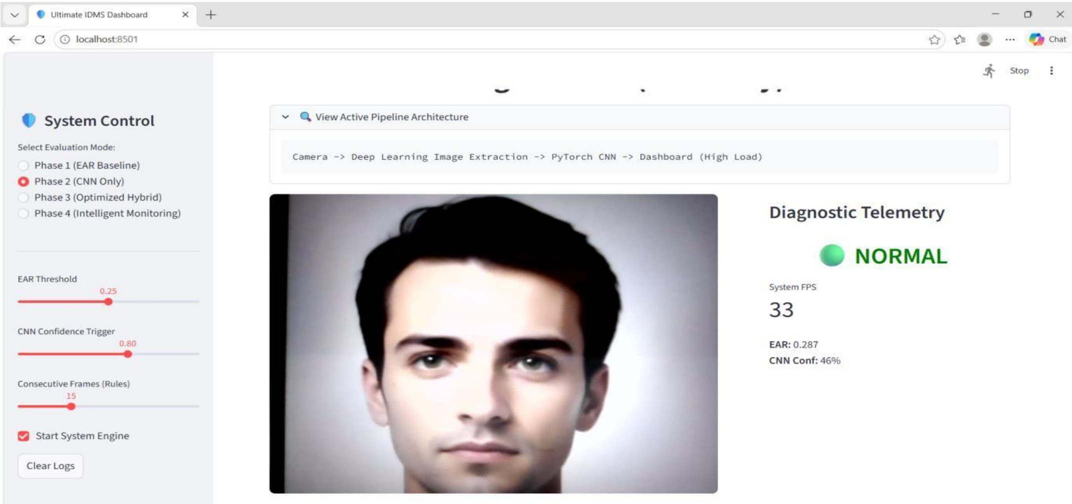

Figure 4: Shows CNN-based eye state detection (open or closed) using a PyTorch model

Dataset Preparation

To build a reliable training dataset, balanced data was collected from the-

- Driver Drowsiness Dataset (DDD)
- Driver Inattention Detection Dataset
- And MRL Eye Dataset

The entire dataset preparation process was implemented in phase2/prepare_dataset.py.

Dataset Processing Steps

1. Images were first extracted from the dataset archives,
2. The eye region was then cropped using MediaPipe,
3. All images were resized to 64 x 64 pixels for consistency,
4. The dataset was balanced to ensure equal numbers of open-eye and closed-eye samples,
5. Finally, the data was split into training and validation sets.

After processing, the final dataset consisted of around 6000 eye images with an equal distribution of open and closed eye classes.

Model Training

The CNN training pipeline was implemented in: phase2/train_cnn.py

Training Configuration

- Optimizer: Adam
- Learning Rate: 0.001
- Loss Function: CrossEntropyLoss
- Epochs: 15
- Input Size: 64 x 64 x 3

The model weights were saved in: phase2/drowsiness_cnn.py

Phase 3 – Hybrid AI Optimization

In Phase 3, the system was enhanced for better real-time performance by combining traditional geometric EAR-based detection with CNN-based eye state classification. This hybrid approach improves both accuracy and efficiency by leveraging the strengths of both methods.

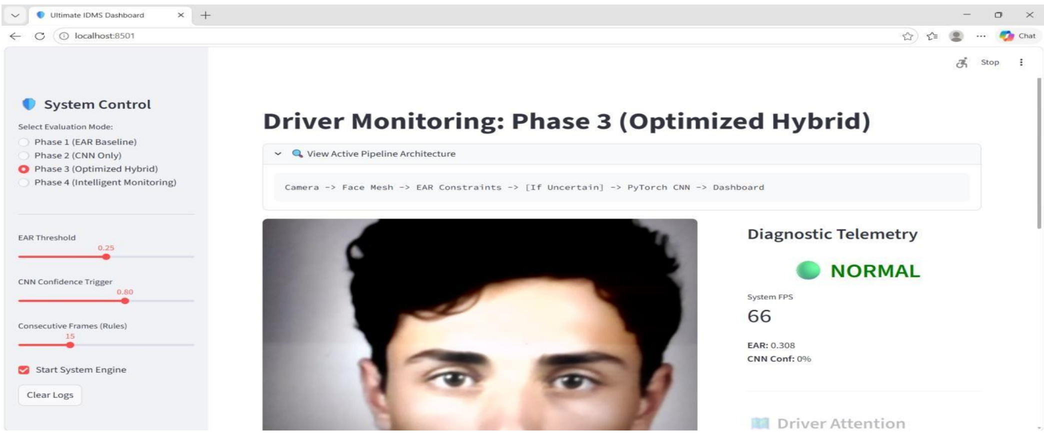

Figure 5: Shows a hybrid approach using EAR first and CNN only when needed for better efficiency

Hybrid Routing Strategy

Instead of running the CNN on every frame, the system uses a smarter approach to improve efficiency.

IF EAR > 0.03 →Skip CNN Execution

ELSE → Run CNN Verification

This optimization significantly reduces: CPU usage, Deep learning inference overhead, Real-time latency. At the same time, it improves: FPS performance, Battery efficiency, System scalability.

Streamlit Dashboard

To improve usability and make the system easier to understand, a real-time Streamlit dashboard was developed. It provides live webcam visualization along with key metrics such as: EAR values, CNN confidence scores, driver state monitoring, and FPS tracking.

The dashboard was implemented in: phase3/app.py

Phase 4 - Intelligent Driver Monitoring

The final phase enhanced the system with distraction analysis and behavioral monitoring.

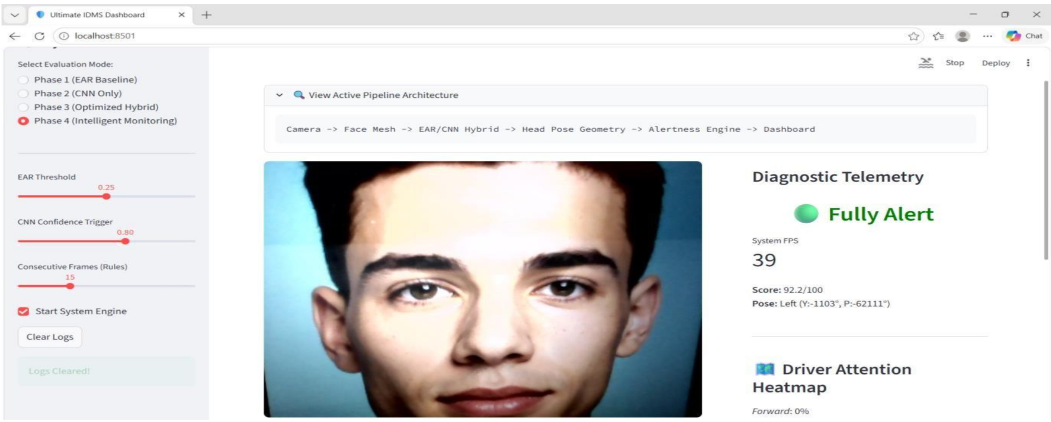

Figure 6: Advanced driver monitoring interface with head-pose estimation and dynamic alertness analytics

Head Pose Estimation

Driver distraction was detected using head pose estimation.

The system utilized: Nose tip, Chin, Left check, Right cheek landmarks.

Head Pose States

Forward, Left, Right, Downward.

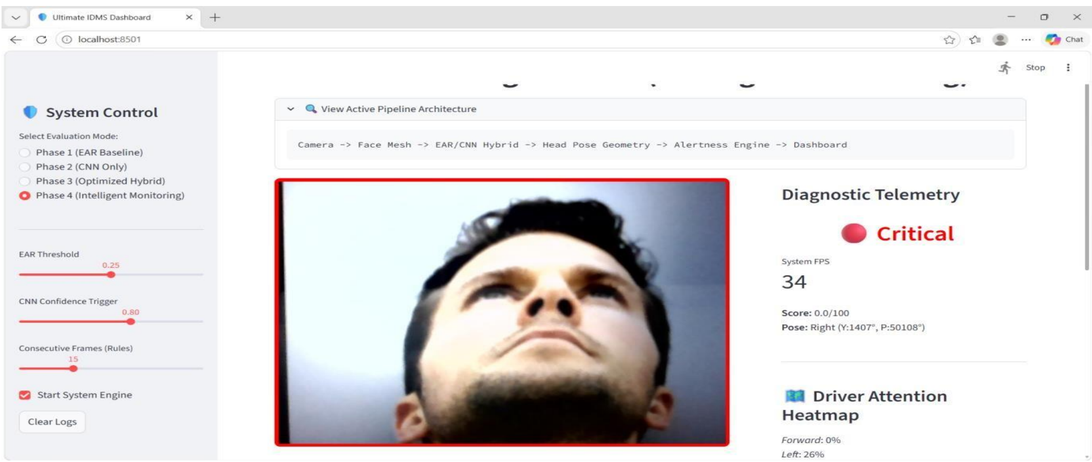

Figure 7: Head Pose Estimation

Dynamic Alertness Engine

Instead of using only binary states such as "Awake" or "Drowsy" the project implemented a continuous alertness scoring mechanism.

The alertness system was implemented in: phase4/alertness_score.py

Alertness Logic

- EAR below threshold →score decreases,
- Distracted head pose →score decreases,
- CNN drowsiness confirmation →heavy penalty,
- Normal attentive behavior →gradual recovery.

Performance Optimization

Several optimizations were applied to improve system efficiency:

- CNN inference skipping during normal eye states,
- Reduced graph refresh frequency,
- Lightweight CNN architecture,
- Efficient MediaPipe landmark extraction,
- CPU-based inference optimization.

These optimizations enabled the system to maintain:

- Real-time execution,
- Smooth webcam rendering,
- Approximate performance of 20-25 FPS on standard laptops.

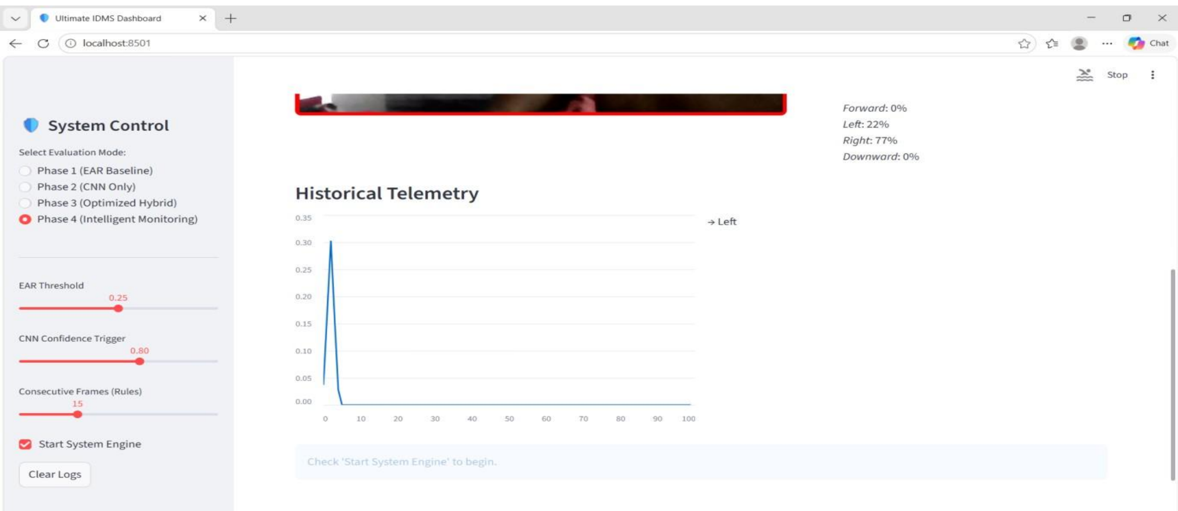

Figure 8: Performance Optimization

4. RESULTS AND DISCUSSION

The proposed AI-Based Intelligent Driver Monitoring System was experimentally evaluated across all four-development phase to analyze its real-time performance, detection accuracy, computational efficiency, and robustness under different driving conditions. The evaluation was conducted using live webcam testing, balanced eye-state datasets, and hybrid AI-based monitoring techniques. The system was tested on standard laptop hardware without GPU acceleration to ensure practical real-world deployment capability.

Experimental Setup

The experimental environment used for testing the system is summarized below

TABLE 1: Experimental Setup

Component	Specification
Processor	Intel Core i5
RAM	8 GB
Camera	720p Webcam
GPU	Not Required
Storage	256 GB SSD
Software	Python, OpenCV, MediaPipe, PyTorch, Streamlit

Phase-Wise Evaluation

The proposed system was implemented and tested progressively across four phases.

Phase 1: EAR-Based Detection

Phase 1 utilized Eye Aspect Ratio (EAR) for detecting prolonged eye closure. The system provided very fast real-time performance with minimal computational load and smooth webcam processing.

Observations:

- Real-time performance was extremely fast.
- Low CPU usages during execution.
- System detection prolonged eye closure effectively.
- Natural blinking occasionally caused false alarms.

Phase 1 Performance:

Metric	Result
FPS	25-30
Speed	Very Fast
False Positive	High
Computation	Very Low

Phase 2- CNN-Based Detection

A lightweight CNN model was trained using balanced eye-state datasets for classification of open and closed eyes.

Observations:

- Accuracy improved significantly.
- Performance improved under lighting variations.
- False alerts reduced compared to EAR method.
- CPU load increased due to continuous inference.

Phase 2 performance:

Metric	Result
Accuracy	~95%
FPS	10-15
False Positive	Low
Computation	High

Phase 3: Hybrid AI System

Phase 3 integrated EAR-based filtering with CNN verification to improve efficiency and reduce unnecessary computation.

Hybrid Routing Logic

IF EAR > 0.30 => Skip CNN

ELSE => Execute CNN

Observations:

- FPS improved compared to CNN-only system.
- Reduced computational overhead.
- Better real-time stability.
- False positive reduced significantly.

Phase 3 Performance:

Metric	Result
FPS	20-25
Accuracy	High
False Positives	Very Low
Computation	Medium

Phase 4: Intelligent Monitoring System

Phase 4 introduced head pose estimation and dynamic alertness scoring.

Detected behaviors

- Looking left
- Looking right
- Looking downward
- Eye closure detection

The alertness score changed dynamically based on driver behaviour, providing continuous monitoring.

Driver State Simulation:

Scenario EAR/Pose	Alertness	Score	State
Normal Driving	0.35 Forward	100	Alert
Looking Down	0.34 Down	72	Distracted
Eye Closure	0.15 Forward	48	Critical
Sleep Simulations	0.12 Down	35	Critical

Overall Performance Comparison:

Phase	Technique	Accuracy	FPS	Cost	False Positive
Phase 1	EAR	Moderate	25-30	Low	High
Phase 2	CNN	High	10-15	High	Low
Phase 3	Hybrid	Very High	20-25	Medium	Very Low
Phase 4	Intelligent	Very High	18-22	Medium	Very Low

Analyze of Results:

- EAR Method is fast but sensitive to blinking and lighting changes.
- CNN improves accuracy by learning deep visual features.
- Hybrid system balances speed and accuracy effectively.
- Head pose estimation improves distraction detection capability.
- Alertness scoring provides continuous behavioral monitoring

5. CONCLUSION

Road accidents caused by driver fatigue and distraction remain a major concern worldwide, highlighting the need for intelligent and real-time monitoring systems. This research presented an AI-Based Driver Drowsiness Detection System that combines computer vision and deep learning to detect both drowsiness and distraction in a non-intrusive and cost-effective manner. The system uses a standard webcam and requires no specialized hardware. The first phase used Eye Aspect Ratio (EAR) and MediaPipe Face Mesh for real-time eye closure detection. This approach was fast and lightweight but sometimes produced false alerts due to natural blinking and environmental changes. In the second phase, a CNN-based model improved eye state detection accuracy under varying conditions. To improve efficiency, the third phase used a hybrid approach combining EAR-based filtering with CNN verification. The reduced unnecessary processing while maintaining high accuracy and smooth real-team performance. The final phase added head pose estimation and dynamic alertness scoring for distraction detection and continuous monitoring. Experimental results showed stable real-time performance around 20-25 FPS with fewer false positives.

6. FUTURE SCOPE

Although the system works well in real-time and gives reliable results, and make it more suitable for large-scale real-world use.

- Advanced deep learning models can be used in future to improve accuracy and handle difficult real-world driving conditions better.
- Cloud-based and mobile platforms can enable real-time monitoring, instant alerts, and management of multiple drivers and vehicle simultaneously.
- GPS and vehicle integration can improve location tracking and support faster response during emergency situations.
- Large-scale deployment with driver behavior analysis can help detect risky driving patterns and support public transportation, smart city projects and improve overall road safety.

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