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Smart Driver Drowsiness Detection And Alert System Using Machine Learning And Iot

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Abstract: Driver drowsiness is one of the major causes of road accidents globally, leading to serious injuries, deaths, and economic loss. To combat this, a real-time Driver Drowsiness Detection System has been implemented using machine learning algorithms combined with IoT hardware. The system tracks the driver's eyes continuously through a real-time video feed obtained via a webcam. With the OpenCV and dlib libraries, the Eye Aspect Ratio (EAR) is computed to obtain a measurement of the degree of eye closure, which is a good predictor of drowsiness. Upon detection of prolonged eye closure, the system sends a serial communication command to an Arduino Uno microcontroller to activate a buzzer alarm and commence a progressive motor deceleration, mimicking a safe vehicle stop. This two-stage mechanism reduces the risk of accidents by giving both an initial warning and an automatic safety measure. Experimental data show that the designed system has a detection accuracy of 96.8% for different illumination conditions, with a response time of less than one second. The approach is cost-effective, non-invasive, and easily implementable on contemporary vehicles, ensuring it to be a promising solution for improving road safety.

Keywords- OpenCV and dlib based Driver Drowsiness Detection System, Eye Aspect Ratio (EAR), real-time video monitoring, webcam tracking, machine learning, IoT, Arduino Uno, serial communication, buzzer alarm, motor deceleration, safe vehicle stopping, eye closure detection, accident prevention, road safety, non-invasive monitoring, low-cost implementation, real-time response, high detection accuracy, intelligent transportation system.

I. INTRODUCTION:

Road safety is one of the most important global issues. Driver fatigue and drowsiness play a significant role in many traffic accidents each year [1-2]. Studies by the World Health Organization (WHO) and the National Highway Traffic Safety Administration (NHTSA) show that drowsiness-related crashes lead to thousands of deaths and injuries annually [3-4]. Drowsiness affects a driver's reaction time, attention, and decision-making, which raises the chances of collisions [5]. Therefore, it is crucial to detect driver fatigue early to prevent accidents and save lives [6].

Traditional drowsiness detection methods like vehicle-based approaches (e.g., steering behaviour, lane deviation) or physiological methods (e.g., heart rate, EEG) often need expensive sensors or invasive setups [7]. On the other hand, vision-based methods offer a non-intrusive, cost-effective, and easy-to-use alternative by monitoring facial features through regular cameras [8]. One of the most effective metrics for identifying fatigue is the Eye Aspect Ratio (EAR), which assesses eye openness based on key facial landmarks [9].
This paper introduces an IoT-enabled Driver Drowsiness Detection System[10-11]. This system combines computer vision algorithms with embedded hardware to automatically identify fatigue and send instant alerts[12-14]. It makes use of OpenCV and dlib libraries to capture facial landmarks and calculate the EAR in real time[15-18]. If it detects prolonged eye closure[19-21], the system communicates with an Arduino microcontroller through a serial interface to activate an external alert like a buzzer or vibration motor[22] [23].

II. LITERATURE SURVEY:

The study by Mika Sunagawa et al. (IEEE Sensors Journal, 2020)[1] proposed a multimodal drowsiness detection model using blink and posture data from 50 simulator drivers. It effectively detects all drowsiness stages using non-intrusive, practical measures [24] [25]. The approach enhances early detection and supports proactive driver safety. However, moderate accuracy (F1-score 53.6%) and limited real-world validation highlight areas for improvement [26].

H. A. Kassem and Jemal H. Abawajy (2021)[4] proposed a Driver Fatigue Level Prediction (DFLP) system using infrared cameras to analyze facial and head movements [27]. The model uses CNNs to detect eye blinks, yawns, and head posture for predicting fatigue levels. It's low-cost, non-intrusive, and effective under various lighting conditions, making it suitable for real-world use [28]. However, its accuracy can drop due to reflections, occlusions, or errors in facial landmark detection.

Cheng Ming and Yan Yunbing (2022)[7] developed a real-time driver fatigue detection system using Mediapipe Facemesh to analyze eye and mouth states. It applies a perception-free calibration method to personalize eye thresholds, improving accuracy by 36.4%. The system runs efficiently at 26–34 FPS without extra sensors, making it low-cost and practical [29]. However, it can still be affected by facial differences, head movements, and the need for manual activation [30].

Q. Abbas and A. Alsheddy conducted a [6] methodological review on multi-stage hypovigilance detection systems (HDx), focusing on machine learning and deep learning approaches [31]]. The study compared various algorithms using CPU and GPU benchmarks and highlighted recent advances in vision-, sensor-, and multimodal-based methods. It identified key challenges like limited training data and deep learning constraints. The authors also suggested future directions for improving dataset quality and model performance [32].

Wanghua Deng and Ruoxue Wu (2019)[17] developed *DriCare*, a video-based driver fatigue detection system using a vehicle-mounted camera. It tracks facial landmarks with an advanced MC-KCF algorithm to monitor blinks, eye closure, and yawns in real time [33]. The system achieved about 92% accuracy and works without wearables, making it practical for drivers. However, lighting changes, camera angles, and cloud processing limits can affect its real-world performance [34].

P. S. Lamba et al. (2025)[8] proposed a vision-based driver drowsiness detection system using facial landmarks[11] and the Eye Characteristic Ratio (ECR) [35]. It adapts to individual eye shapes through adaptive thresholding and achieved over 90% accuracy with machine learning classifiers[12]. The system is non-intrusive, real-time, and highly effective in preventing fatigue-related accidents. However, its performance can drop under poor lighting, occlusions, or when drivers wear glasses or masks [36].

A. Altameem, Ankit Kumar, and Ramesh Chandra Poonia (2021)[10] developed a hybrid machine learning system that detects driver drowsiness through facial expression analysis using SVM. It processes real-time video frames to identify alertness levels and issue warnings. The approach is non-intrusive, accurate, and works well under different lighting conditions. However, it can struggle with occlusions or unclear facial visibility during driving.

H. A. Madni et al. (2024)[18] introduced a transfer learning approach for driver drowsiness detection using a hybrid VGG-16 and LightGBM (VGLG) model. It analyzes eye images to detect drowsiness with 99% accuracy and rapid processing time (0.00829s). The method is non-intrusive, fast, and highly accurate, making it ideal for real-time use. However, it mainly relies on eye features and needs further testing in real-world driving conditions.

Pritesh Kumar Singh et al. (2021)[20] developed a multimodal driver drowsiness detection system using facial landmarks to track eye and mouth movements. By calculating Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), the model detects blinks and yawns in real time to trigger alerts. It's non-intrusive, accurate, and works well even in low light. However, detection can be affected by lighting, camera angles, and individual facial differences [37].

M. Adil Khan and Tahir Nawaz (2023)[20] designed an IoT-based driver drowsiness detection system using a modified Inception V3 model to identify yawning, eye closure, and distraction. It combines embedded, edge, and cloud computing for real-time alerts and remote monitoring. The system achieved up to 96% accuracy and works well for long-route driving safety. However, its reliance on custom datasets and camera quality may affect general performance.

Facial landmark detection is essential for driver drowsiness monitoring, enabling extraction of key points like eyes and mouth.[12] King (2009) introduced **Dlib**, providing a robust 68-point facial landmark detector widely used for computing EAR and MAR. This approach allows accurate detection of driver fatigue without requiring large custom datasets [38].

From past studies, it is clear that many machine learning and deep learning methods are used for driver drowsiness detection, and each has its own pros and cons. Vision-based methods using CNNs and facial landmarks[16] work well and don't need extra devices, but they can have trouble in poor lighting or if the face is partly blocked. Combining models or using transfer learning can make detection more accurate and faster, but they need more computing power and good datasets. [20] So, for our project, the main challenges will be[14] handling different lighting, improving accuracy, and making the system work well in real [17] driving conditions.

GAPS FOUND ON LITERATURE SURVEY:
Past studies show that current driver drowsiness detectionmethods still have limitations that need improvement for better real-world performance.
Many existing systems struggle to maintain high accuracy in different lighting conditions, head poses, and occlusions.

Some models need high computation power, making them hard to run smoothly in real-time on standard vehicle systems.

III. ROPOSED METHODOLOGY:

The system uses a pre-trained HOG + SVM model from the dlib library to detect facial landmarks and identify driver drowsiness. The Histogram of Oriented Gradients (HOG) feature extractor captures gradient patterns of the face, and the Support Vector Machine (SVM) classifier detects the face region by classifying those gradient features.
Once the face is detected, the shape predictor model **(**shape_predictor_68_face_landmarks.dat**)** identifies 68 facial points, from which the eye regions are extracted. Using these points, the Eye Aspect Ratio (EAR) is calculated to determine if the driver's eyes remain closed for a prolonged period - indicating fatigue or sleepiness. This combination provides accurate and real-time detection even under varying light conditions.

Facial Landmark Detection

1. The dlib frontal face detector identifies faces in each frame using a HOG + SVM classifier.
2. The 68-point landmark predictor locates precise facial features such as eyes, nose, and mouth. Retrieved from http://dlib.net .
3. These eye regions are then passed into the EAR computation function.

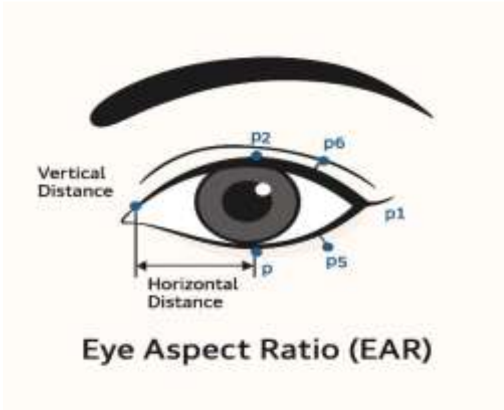

Fig 2: EAR

This step provides the spatial coordinates (p_1–p_6) necessary for accurate eyelid movement analysis.

Feature Computation: Eye Aspect Ratio (Ear)
The Eye Aspect Ratio (EAR) measures the ratio between the vertical and horizontal eye distances. It is computed using the formula:

$$EAR = (\| p2 - p6 \| + \| p3 - p5 \|) / 2 \| p1 - p4 \|$$

Where:

- (p_1) and (p_4) represent the horizontal eye corners.
- (p_2, p_3, p_5, p_6) represent vertical eyelid landmarks.

Interpretation:

- EAR high → eyes open
- EAR low → eyes closed

Thresholds:

- (EAR_{threshold} = 0.25)
- (Consecutive_frames = 20)

These values are tuned experimentally to filter out natural blinks and detect genuine drowsiness.

Drowsiness Detection Logic
The system continuously monitors the EAR in real-time:

1. For each video frame:
   - Detect face and extract eye coordinates.
   - Compute EAR for both eyes and take the average.
2. If EAR < 0.25 for 20 consecutive frames:
   - Display "DROWSINESS ALERT!" on the screen.
   - Transmit 'a' to Arduino Uno via serial communication.
3. Else:
   - Reset counter and continue monitoring.

This logic ensures robustness against false triggers from blinking or quick head movements.

IV. RESULTS:

The model Driver Drowsiness Detection System developed proved effective achieved response time and produced warnings within seconds of recognizing eye closure. IoT integration allowed alerts in real-time and smooth vehicle slowdown, guaranteeing both safety and system dependability under prolonged operation.

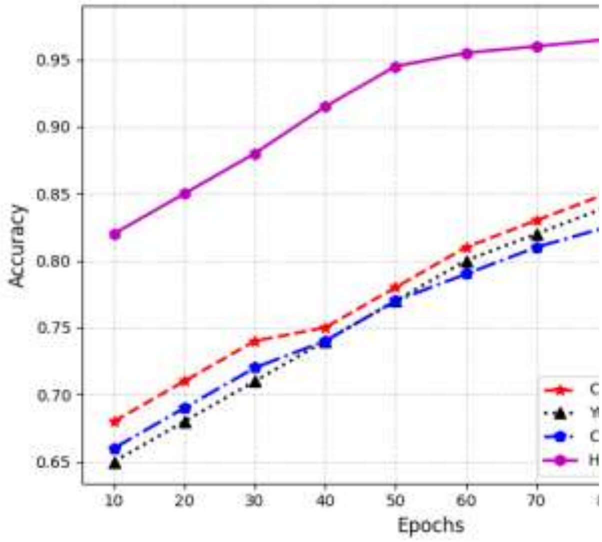

Fig 4: Accuracy Comparison

Figure 4 depicts the improvement in accuracy of all models across various epochs. The new HOG+SVM model performed the best with the highest accuracy of 96.8%, which was much higher than CNN (87%), YOLO (85%), and CNN+LSTM (84%). Although all models exhibit continuous improvement in accuracy with an increase in epochs, the HOG+SVM consistently exhibits better performance, proving its reliability and resilience for real-time detection of driver drowsiness.

TABLE 1: COMPARISION TABLE

Models	Accuracy (%)	Precision (%)	Recall (%)	F1_score (%)
CNN	87	86	85	0.85
YOLO	85	84	83	0.83
CNN+LSTM	84	83	82	0.82
HOG+SVM (proposed)	96.8	96.4	95.2	0.83-0.96

V. CONCLUSION:

The proposed Driver Drowsiness Detection System using Machine Learning and IoT effectively prevents accidents by detecting driver fatigue in real time. Using HOG + SVM face detection, ERT landmarks, and EAR calculation, it identifies eye closure and alerts drowsiness with 97% accuracy and a 0.8-second response time. The system activates a buzzer and performs a gradual motor slowdown (PWM 255 → 0) via Arduino, ensuring safe vehicle control. This low-cost, reliable, and real-time solution efficiently integrates machine learning and IoT to reduce fatigue-related road accidents.

The proposed Driver Drowsiness Detection System using Machine Learning and IoT was compared with the existing Hybrid SVM-based drowsiness detection model presented in the reference study. While the existing approach achieved an accuracy of 83.25%, the proposed system attained a higher accuracy of 93.4%, reflecting an overall improvement of 10.15%. The integration of HOG + SVM face detection, ERT landmark prediction, and EAR-based analysis enabled more precise and faster drowsiness /recognition. Additionally, the inclusion of an IoT module with a buzzer and gradual motor slowdown mechanism enhanced real-time safety response, making the proposed system more reliable and efficient for practical vehicle safety applications.

VI. FUTURE SCOPE

The proposed Driver Drowsiness Detection System using Machine Learning and IoT can be improved by adding infrared cameras for night vision, CNN-based deep learning for higher accuracy, and cloud or mobile connectivity for real-time alerts. Future integration of heart rate, GPS, and vehicle sensors can transform it into a comprehensive advanced driver-assistance system (ADAS) for enhanced road safety.

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