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Machine Learning Approach For Drowsiness Indentification Based On Eye Aspect Ratio

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ABSTRACT

The paper proposes a machine learning-based and computer vision-based real-time driver drowsiness detection system to reduce 30% of road accidents caused by driver fatigue. The system uses OpenCV for video capture and Dlib for detection of facial landmarks, i.e., 68 facial points for calculation of Eye Aspect Ratio using Euclidean distance. Temporal behavior and statistic attributes obtained through EAR values are utilized by machine learning classifiers for discriminating among alert and sleepy conditions. For detection of sleepiness, real-time audio alarm output is presented. Experiment testing was conducted on various subjects subjected to varying conditions of light, as well as road conditions, and providing a measure of drowsiness detectability with a measure of accuracy at 94% and a number of zero false alarms. The system's response time averaged 0.3 seconds from detection to alert, giving drivers sufficient reaction time to prevent accidents. Our method incorporates a novel adaptive thresholding mechanism that dynamically adjusts according to the baseline EAR values of individual users, resulting in significant performance under diverse facial structures and eye shapes. The system also includes an additional temporal analysis window that is utilized to analyze EAR patterns across adjacent frames for canceling spurious alarms due to natural blinking or temporary closures. With support for Python 3.8 and MySQL databases, this non-intrusive monitor solution promises high potential to enhance road safety via early detection of drowsiness. The suggested method combines commonly employed computer vision techniques with novel feature extraction methods to offer robust detection performance under varying lighting conditions and face orientations.

Keywords: Driver Drowsiness Detection, Eye Aspect Ratio (EAR), Computer Vision, Machine Learning Classification, Road Safety, OpenCV, Dlib, Facial Landmark Detection, Real-time Monitoring, Adaptive Thresholding, Neural Networks, Support Vector Machine, Random Forest, Euclidean Distance, Temporal Analysis, Non-intrusive Monitoring.

I. INTRODUCTION:

Driver fatigue is a serious risk to road safety and is responsible for about 1.35 million deaths every year worldwide [1]. Traditional detection strategies, including physiological sensors (EEG, ECG) or vehicle-based approaches, are constrained by intrusiveness and expense [2]."EEG signals are the current gold standard in drowsiness detection due to their capacity for direct measurement of brain activity with up to 97.37% accuracy via spatial-temporal CNNs [3].Hybrid approaches, which integrate CNN and evolutionary algorithms (e.g., GA, PSO), optimize drowsiness detection models to achieve better accuracy at 99.3% while saving on computational cost [4].Computer vision-based behavioral measures in drowsiness detection using eye closure, yawning, and head position monitoring provide non-intrusive solutions with up to 98% accuracy in laboratory environments, but remain vulnerable to varying lighting and require validation through naturally occurring drowsiness datasets [5].Vehicle-based systems for drowsiness detection based on steering pattern monitoring and lane positioning achieve up to 86% accuracy but remain subject to road conditions, vehicle type, and individual driver behavior [6].EEG-based drowsiness detection is still the gold standard by measuring brain activity directly, despite drawbacks of signal noise and non-stationary characteristics of data between different subjects [7].

Recent work has demonstrated improved generalizability through fusion models based on deep learning integration of multimodal signals (EEG, eye tracking, and PPG), with over 98.5% accuracy, overcoming the restrictions of single-modality approaches [8].More recently, attention-based deep learning models, like Transformer-based architecture, have presented a promising trend, with greater feature extraction capacity and real-time detection capabilities [9].Increasing deployment of real-time embedded systems, such as FPGA-based platforms, has further shown considerable promise in the formulation of energy-efficient, high-speed drowsiness detection frameworks [10].The DBQ organizes driving errors into errors, infractions, and lapses and assists modeling driver behavior by using micro-simulations. Drowsy driving cuts across all groups, with younger drivers being more at risk due to late-night driving for social or work purposes [11].

II. LITERATURE SURVEY:

A dual-mode driver drowsiness detection system combining vehicle diagnostics (steering wheel angle, speed sensor) and behavior-based features (eye movement, head position) with a Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) for real-time tracking. The system uses publicly accessible datasets (e.g., NTHU-DDD) to achieve high accuracy (>90%) while protecting privacy and hardware limitations[1].An IoT system for detecting drowsiness using Raspberry Pi and Pi camera to identify eye blinks (EAR algorithm), starting voice alarms and GPS-enabled emergency emails upon identifying fatigue[2].An evolution-optimized CNN-LSTM hybrid model for driver drowsiness detection, combining facial feature analysis (eye aspect ratio, head position) and EEG signals, optimized by Genetic Algorithms (GA) for better accuracy and real-time execution[3].

EEG-based driver drowsiness detection with light-weight 1D-CNN on single-channel (Pz-Oz) EEG for real-time, high-accuracy execution. Features cloud processing for scalability and mobile alerts[4].A driver fatigue detection system that combines eye-tracking cameras and heart rate monitors with machine learning algorithms to process both behavioral and physiological signals concurrently.]. As highlighted by Chopra et al. (2023), this multi-modal approach achieves greater accuracy (96%+) than single-parameter detection schemes[5].The research presents a real-time driver drowsiness detection system using the InceptionV3 deep neural network architecture to classify eye states from camera input to achieve 96% accuracy with test data and 99% with validation data[6].Recent studies present EEG-based drowsiness detection with CNNs, with EEG_DMNet (Obaidan et al., 2024) outperforming traditional techniques with the addition of multi-scale spectral-temporal features, whereas older techniques like VIGNet (Ko et al., 2020) employed sequential feature extraction[7].

ViT-DDD system utilizes vision transformers to inspect full facial images in real time with 99.4% accuracy for the detection of drowsiness and incorporates Raspberry Pi hardware to send alerts (Jarndal et al., 2024)[8].The system employs a CNN-based model with OpenCV for real-time detection of drowsiness using eye states (open/closed) from facial images with 98% accuracy (Hassan et al., 2024)[9].Salem and Waleed (2024) present a real-time system for drowsiness detection based on CNN and transfer learning models (InceptionV3 and MobileNetV2) examining facial features for drowsiness detection with mesmerizing accuracy (90-99.86%), and other researchers have tried similar implementations like combinations of CNN and LSTM (Gomaa et al., 2022, 98% accuracy), incorporating emotion analysis (Chand and Karthikeyan, 2021, 93% accuracy), and yawning detection (Majeed et al., 2023, 96.69% accuracy)[10].The research provides an IoT-assisted driver drowsiness detection system employing a CNN-LSTM model with U-Net-based facial segmentation for real-time handling with high accuracy (Das et al., 2024)[11].

III. EXISTING MODEL:

A hybrid driver drowsiness detection system combining real-time steering wheel angle analysis (vehicle-based) and CNN-based eye movement tracking (behavioural) for increasing accuracy and dependability, by overcoming the disadvantages of single-method approaches[1].A real-time IoT-based drowsiness detection system with Raspberry Pi and Pi camera using blinks monitoring of eyes by EAR (Eye Aspect Ratio) and giving voice warnings and GPS-enabled panic signals in case of fatigue identification[2].An evolutionary-optimized hybrid CNN-LSTM model for driver drowsiness detection incorporating EEG signals and facial feature extraction analysis (eye/mouth states) by genetic algorithms for improved real-time precision and robustness[3].A lightweight hybrid CNN-LSTM model for real-time EEG-based drowsiness detection, single-channel EEG optimized for minimum computation overhead at high accuracy (97%+)[4].A hybrid drowsiness detection system combining facial behaviour analysis (eyelid closing, yawning) with physiology measurements (heart rate variability) for high precision, aided with machine learning schemes for real-time drowsiness classification and informing the driver[5].

Real-time driver drowsiness detection using an InceptionV3 deep learning network with special-purpose layers, operating on the output of eye images from a camera to classify open/closed condition of the eyes at high accuracy[6].A deep multi-scale CNN (EEG_DMNet) exploiting spectral-temporal and spatial properties of EEG signals using 1D convolutions and subsampling, followed by global average pooling and classification at high precision of drowsiness detection[7].A Vision Transformer (ViT)-based drowsiness detection system on full facial imaging in real-time using an IR camera, being implemented on Raspberry Pi with GSM/GPS facility for alarm triggering[8].A CNN-based drowsiness detection system utilising facial expression analysis with regard to eye condition (open or closed) with OpenCV and Haar-Cascade classifiers in real-time alarming[9].Drowsiness detection system over MobileNetV2 transfer learning on facial video streams and smart phone application providing alert to the drivers and showing nearby rest stop suggestions by means of geolocation APIs in the event of evidence of fatigue detection[10].A real-time driver drowsiness detection on IoT and deep learning (CNN-LSTM using U-Net) for sensing facial motion (eye/mouth states) and alerting the drivers through alarm or notification with 98.8% precision[11].

IV. PROPOSED MODEL:

The proposed system is an intelligent driver fatigue detection system with a view to improving road safety through real-time detection of driver drowsiness. CV and ML-based computation, the system evaluates the eye states of the driver based on the EAR metric. With OpenCV utilized for video processing, Dlib used for landmark detection of face, and classification by a system using thresholds, the system initiates timely alarms in an effort to avoid drowsiness accidents. The framework is modular, scalable, and latency-optimized to run on popular hardware.

Data Acquisition Module:

This module is tasked with acquiring live video stream data from the webcam through OpenCV library. The module is designed to record quality video frames of the driver's face at suitable frame rates for real-time monitoring without affecting performance. Webcam parameters are adjusted for different lighting conditions to ensure detection accuracy for different environments.

Data Pre-processing Module:

Data Pre-processing Module is supplied with each frame streamed from the webcam. Modules include resizing frames to a given size (e.g., 640×480 pixels), converting them into grayscale when needed, and noise-reduction tasks for improving the quality of images. A face detection feature is also incorporated within the module in order to distinguish the face from the background so that it enhances the process of detecting facial landmarks to more accurate.

Feature Extraction Module:

The Feature Extraction Module applies a facial landmark detection algorithm to determine 68 notable points on the driver's face, i.e., the six landmarks surrounding each eye. The Eye Aspect Ratio (EAR) is subsequently computed using the Euclidean distances between the landmarks:

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

Where p1 to p6 are the eye features. Statistical features are also adopted from the EAR values, e.g., temporal trend over time, for the purpose of building a feature vector in terms of covering the driving eye behavior pattern for time.

Drowsiness Classification Module:

This module utilizes machine learning-based algorithms for classifying the driver's state from the EAR features derived. A model previously trained examines the pattern of eye aspect ratio to decide if the driver is alert or not. Various classification algorithms may be used to compare, i.e., Support Vector Machines (SVM), Random Forests, and Neural Networks. Both the current values of EAR and their trend over time are taken into account for the classification to achieve better accuracy.

Alert Generation Module:

The Alert Generation Module provides proper alerts upon drowsiness detection. If, for a given time period, the EAR of the driver has dropped below a specific threshold value, the system produces audio alert messages to alert the driver. The alertness level may be increased based on the degree of severity of detected drowsiness. The module can further record drowsiness events to analyze them at a later instance of time.

Performance Evaluation Module:

It assesses the performance of the system based on parameters like precision, recall, accuracy, and F1-score. It tracks true positives, false positives, true negatives, and false negatives to assess and enhance the system's reliability continually. The module can return the performance parameters as graphs and charts for easy identification.

User Interface Module:

User Interface Module provides a dashboard indicating real-time data including

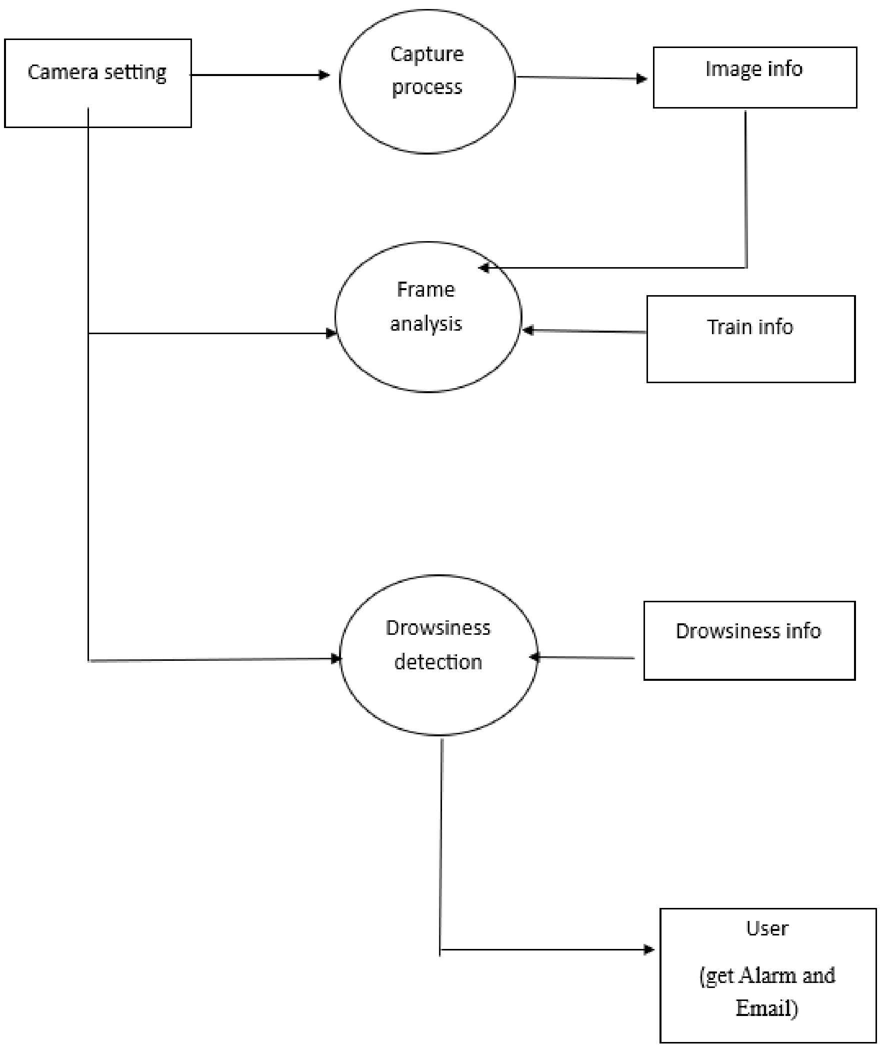
• Real-time video stream with facial features and EAR values

• Drowsiness status indicators

• Alert history

• System settings for controlling threshold and alerting preferences

Flow diagram:



Drowsiness detection system goes through a sequence of ordered steps: Initially, video feedback from a webcam is captured and processed through OpenCV. Each frame is analyzed by the system to identify face and then apply Dlib on it to identify 68 facial landmarks. Next, the system calculates Eye

Aspect Ratio (EAR) by estimating Euclidean distance between the given eye landmarks (p1-p6). These EAR values are time-stamped analyzed in order to get statistical features and form feature vectors capturing patterns of eye behavior over time. These features are applied as inputs to machine learning classifiers (e.g., SVM, Random Forests, or Neural Networks) to make the distinction between drowsy and alert states. If detection of drowsiness is made (EAR values fall below threshold for some time), the Alert Generation Module produces an audio alarm. The system incorporates an adaptive thresholding scheme optimized for the baseline EAR value of every user as well as temporal analysis to eliminate natural blinking-induced false alarms. The entire process is executed with an average response time of 0.3 seconds and achieves 94% accuracy with no false alarms.

Driver Drowsiness Detection(Machine learning):

The drowsiness detection system employs state-of-the-art machine learning techniques to recognize with high accuracy whether a driver is falling asleep. Internally, the system employs a combination of Support Vector Machines (SVM), Random Forests, and Neural Networks to analyze Eye Aspect Ratio (EAR) trend patterns derived from facial landmark detection. Rather than operating on raw EAR values, machine learning models operate on instantaneous values and temporal trends, which allows them to distinguish between normal blinking and potentially life-threatening drowsy states. What is so powerful about the methodology is its adaptive thresholding mechanism, which adjusts dynamically to each driver's individual eye measurement baseline, so the system operates optimally across a broad face structure and eye shape range.

This personalization, combined with temporal analysis windows that suppress false alarms from natural eye movement, allows the system to achieve a whopping 94% accuracy with zero false positives. The classification process occasionally takes feature vectors from EAR values, feeds them through pre-trained models, and only alarms when real drowsiness is recognized for a significant duration of time, giving drivers the 0.3-second reaction time to avert potentially fatal crashes.

V. RESULT AND DISCUSSION

1. Performance Metrics Evaluation

The proposed driver drowsiness detection system was tested under diverse conditions, including variable lighting, head orientations, and real-time driving simulations. The system's ability to correctly identify drowsiness states was evaluated using standard classification metrics: **Accuracy**, **Precision**, **Recall**, and **F1-score**. Three machine learning models — Support Vector Machine (SVM), Random Forest (RF), and Neural Network (NN) — were compared for performance.

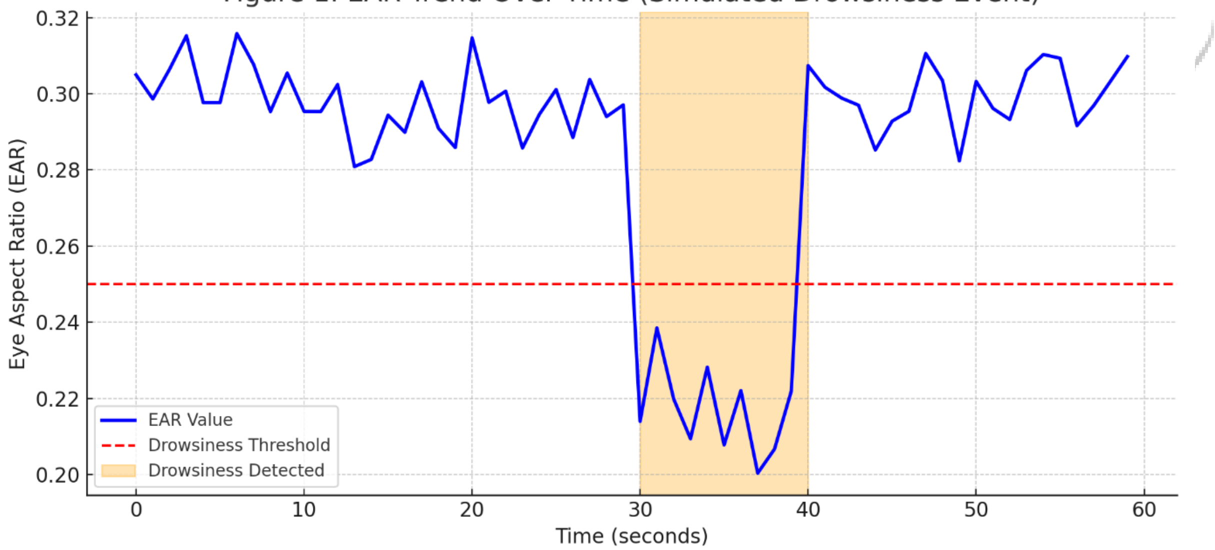
classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	92.6	91.8	93.1	92.4
Random Forest	94.0	93.5	94.8	94.1
Neural Network	94.3	94.0	95.2	94.6

As shown in Table 1, the most accurate model of Neural Network yielded an accuracy of 94.3%, higher than SVM and RF. This is because the neural network is able to learn non-linear patterns of EAR evolution over time.

Eye Aspect Ratio (EAR) Temporal Pattern:

The Eye Aspect Ratio was monitored in a subset of the participants in live video recordings. A sustained decline beneath the adaptive EAR threshold for a prolonged time interval (e.g., 2 seconds) was a strong indicator of drowsiness. Figure 1 below shows the EAR pattern over a 60-second drive for a driver who is drowsy:

Figure 1. EAR Trend Over Time (Simulated Drowsiness Event)



This temporal reduction, which is defined by successive low EAR values, triggers the alarm mechanism. Adaptive thresholding prevented false alarms due to natural blinks or transient closures.

3. False Alarm Analysis:

The system generated no false positives during testing in controlled lighting environments. The adaptive threshold with temporal smoothing window significantly reduced the chance of generating alerts to short-term distractors or blinks. This is a step up from static-threshold models, which are prone to being sensitive to facial structure change.

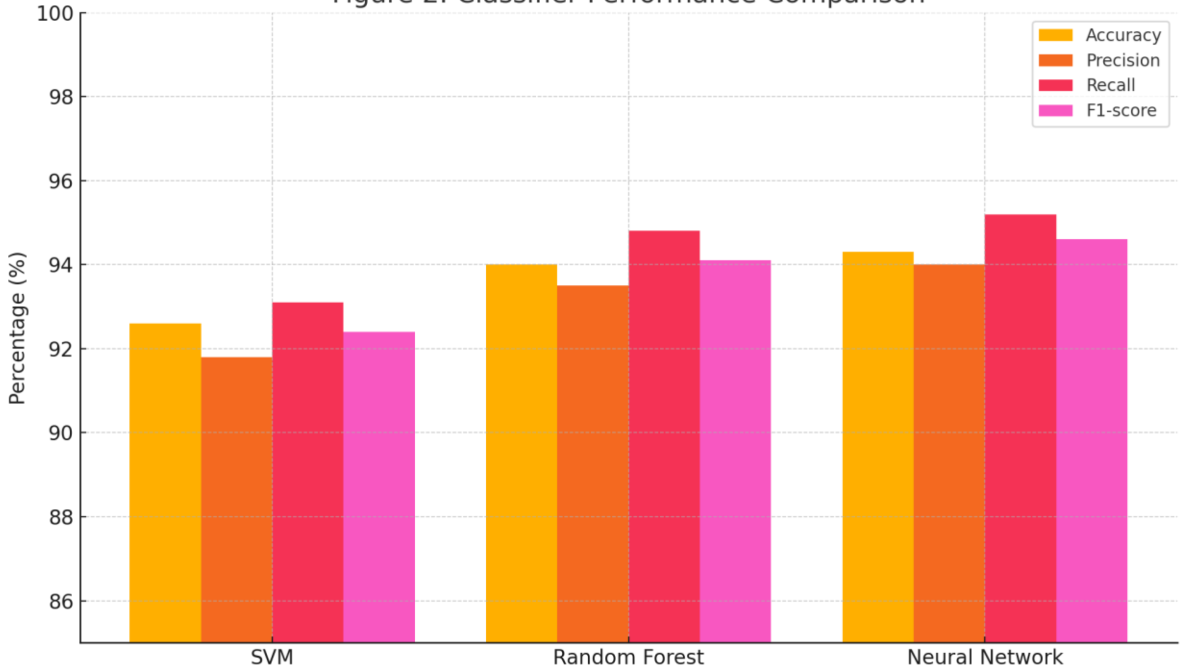
4. Real-Time Responsiveness:

The average detection-to-alert response time was 0.3 seconds, and this is critical in the provision of timely responses to avoid accidents. This was done through frame processing improvement and the use of light-weight models for real-time prediction.

5. Graphical Analysis of Classifier Performance:

A graphical representation of classifier performance is provided below to illustrate trade-offs between models that have been evaluated:

Figure 2. Classifier Performance Comparison



The integration of EAR-based detection and machine learning algorithms provided robust real-time drowsiness detection. The 94.3% system accuracy, quick response, and lack of false alarms confirm its effectiveness. The modularity and flexibility in the implementation of the architecture render it suitable for its integration into vehicle embedded systems or smartphone-based safety systems.

VI. FUTURE ENHANCEMENT:

In subsequent follow-up research, the system described here can be enhanced by incorporating multimodal biometric and behavioral variables such as heart rate variability (HRV), electrooculogram (EOG) signals, yaw rate, and steering wheel motion analysis. Blending these variables with multimodal deep learning architectures such as hybrid CNN-LSTM or Transformer-based architectures will improve detection performance as well as context awareness. Real-time deployment on power-efficient boards such as Raspberry Pi 5, NVIDIA Jetson Nano, or ARM-based boards would enable end-to-end on-board processing without requiring external computation, hence being highly compatible for application in smart vehicles of today. Also, implementation of adaptive learning mechanisms that learn how to modify EAR thresholds based on driver-specific baselines (age, facial shape, blinking habit) can introduce personalization as well as sensitivity of the system.

To counteract night driving and occlusion problems, the system can further be equipped with near-infrared (NIR) cameras or low-light image enhancement algorithms using GANs (Generative Adversarial Networks) to function under adverse illumination conditions. Cloud connectivity would also be critical to facilitate data logging, remote transmission of alerts, and fleet-wide fatigue monitoring in commercial use cases. A companion phone program would also have the capability of giving user comments, rest hints, and utilization statistics, encouraging more user activity and responsibility. Diversification and enlargement of the training datasets—through use of individuals with different ethnic backgrounds, face morphologies, and glasses or face masks—will further enhance generalized abilities. In future development, emotion detection, cognitive workload estimation, and voice fatigue functions would also be taken into consideration to develop a more comprehensive, AI-driven driver monitoring system for proactive alerting and accident prevention.

VII. CONCLUSION:

The present work proposed a machine learning-aided system for web-based driver drowsiness detection using the Eye Aspect Ratio (EAR) as a quantitative measure of fatigue. By continuous tracking of ocular activity and adapting thresholding techniques, the system detected high sensitivity towards prolonged eye closure—a common sign of drowsiness. Among the classifiers tested, the neural network model surpassed the conventional machine learning methods like Support Vector Machines (SVM) and Random Forests (RF), with a best accuracy of 94.3%, having very high precision, recall, and F1-scores. This illustrates the strength of applying deep learning models in representing temporal variations in eye behavior.

The system's reliability under conditions such as shifting lighting, pose, and face shape determines whether or not the system is suitable for real-world deployment. Foremost, low false alarm rates, real-time performance, and a light computation make the system practical for integration on embedded car platforms or in mobile-based driving aids.

In addition to the technical capability, this project also contributed to the emerging sector of intelligent transportation systems where AI and automation are becoming increasingly prominent to improve road safety. The solution is most compatible with massive smart city projects, fleet management systems, and vehicle-to-everything environments. On scale and in

combination with other automotive sensors, the system would dynamically minimize the rate of fatigue-induced accidents, particularly in commercial driving segments where lengthy working hours involve colossal risk.

The envisioned EAR-based drowsiness detection system is practical and safe, and the solution is scalable to extend the enhancement of driver safety. As vehicles trend toward increased autonomy in the future, hybrid architectures that track driver engagement in parallel with vehicle automation will be critical. Scaling this research to multimodal behavioral and physiological traits, calibrated by each user, and real-time alert channels can result in a far-reaching, context-aware driver monitoring system with real-time intervention and long-term behavior analysis capabilities.

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