

Vision –Based Real-Time Driver Drowsiness , Crash Detection and Alert System

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Abstract— Road accidents caused by fatigue and delayed emergency response continue to be global safety problems. In order to increase road safety, this study presents a real-time driver drowsiness and accident warning system that makes use of computer vision and sensor-based monitoring. The driver's face is captured by a dashboard-mounted camera, and yawning and blinking are signs of fatigue. A pretrained algorithm collects facial landmark points and calculates the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to identify prolonged eye closure and excessive yawning. Instant auditory indications for fatigue are sent to drivers. Additionally, an accelerometer-based module monitors sudden crashes or unusual vehicle motions to identify collisions. Following an accident, the system instantly notifies emergency contacts via IoT of the vehicle's location. The proposed technology is feasible in intelligent transportation systems because to its affordable, non-invasive, real-time preventative drowsiness detection and prompt post-accident response.

Keywords— Driver Drowsiness Detection, Computer Vision, Facial Landmark Detection, Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Accident Detection, Accelerometer Sensor, Internet of Things (IoT), Real-Time Monitoring, Intelligent Transportation Systems

I. INTRODUCTION

Road safety is a global concern as human factors, such as driver fatigue and drowsiness, are responsible for a large number of traffic accidents. Long driving hours, little sleep, and dull driving conditions reduce driver awareness, which slows reaction times and decision-making, according to studies. Conventional safety approaches place more emphasis on post-accident response than early prevention, highlighting the need for intelligent technologies to continuously monitor driver behavior.

Early studies looked at technical approaches to increase security and avoid mishaps. The application of embedded systems and machine learning models for safety-critical real-time monitoring and predictive analysis was demonstrated by Kharade et al. [1] and [2]. These studies highlight the

growing importance of intelligent systems in identifying abnormal patterns and reacting on their own, which is the foundation of modern driver monitoring technology.

Methods for detecting driver tiredness have been extensively studied in surveys and research. Ngxande et al. [3] conducted a thorough evaluation of machine learning-based drowsiness detection techniques and discovered that facial behavior analysis is more non-invasive and practical than physiological approaches. In a cutting-edge study, Ramzan et al. [4] discovered that vision-based methods integrating eye closure, yawning detection, and facial cues may detect driver fatigue in real time.

Thanks to mobile and embedded computers, real-world vision-based drowsiness detection systems are now feasible. Galarza et al. [5] demonstrated the practicality of camera-based monitoring by creating a smartphone-based real-time driver drowsy detection system that uses facial image behavior. These findings support the development of a real-time system that combines sensor-based accident detection with computer vision-based tiredness detection to enhance emergency response and preventative safety.

II. LITERATURE SURVEY

A Raspberry Pi-based IoT-based driver sleepiness detection and traffic collision prevention system is described in [6]. The technology improves road safety with camera-based facial monitoring and sensors. Drowsiness alarms and collision prevention are implemented in real time. Basic threshold-based detection may degrade accuracy under different illumination and driving situations. This constraint encourages stronger face feature analysis methods.

A computer vision-based sleepiness monitoring system for motorized vehicles with online push alerts is proposed in

[7]. Eye closure patterns indicate weariness, and the system delivers network-based alarms. Controlled experiments demonstrate real-time performance. The need for consistent internet access might restrict its reliability in rural or low-network areas. This emphasizes the necessity for targeted alerts and internet notifications.

A real-time driver sleepiness monitoring framework employing 3D neural networks on mobile devices is presented in [8]. The algorithm detects temporal face traits accurately using deep learning. The computational complexity of 3D neural networks increases processing overhead for embedded devices, notwithstanding their efficacy. This limits low-power system applicability, increasing the necessity for lightweight and efficient models.

Eye movement and head posture are used to identify tiredness in a driver monitoring system [9]. The technology improves detection reliability in simulated driving scenarios with real-time monitoring. The method does not integrate accident detection or emergency response. Preventive and post-accident safety solutions are needed due to this constraint.

A computer vision-based driver sleepiness detection system employing face feature analysis is proposed in [10]. The technology employs eye closure and yawning recognition to measure weariness in real time and shows promise. Accelerometers for collision detection are not used in the system. This gap illustrates the necessity for multi-modal systems that combine vision-based sleepiness detection and sensor-based accident detection.

[11] describes a computer vision-based eye closure and yawning detection method for tiredness. The device detects weariness using real-time facial movement tracking. Experiments show reliable detection under regulated illumination. Facial occlusions and poor light decrease performance. This shortcoming emphasizes the necessity for powerful real-time facial landmark-based methods.

The Driver Alert Control (DAC) technology in commercial vehicles detects driver drowsiness based on steering behavior and vehicle dynamics [12]. It increases driving safety with timely notifications. It depends mainly on vehicle-based metrics, not driver monitoring. The downside encourages camera-based behavioral analysis for more accurate tiredness detection.

An EEG-based driver drowsiness detection system combining chaotic characteristics and statistical analysis is proposed in [13]. The approach accurately identifies early weariness. The accurate system requires wearing EEG sensors, making it obtrusive and unsuitable for daily driving. This constraint highlights the need for non-invasive vision-based detection.

Eye blink patterns are used to identify sleepy drivers in [14]. Normal blinking is distinguished from fatigue-induced

ocular closure by the system. It ignores yawning and head movement. This gap implies multi-feature face analysis to increase detection reliability.

In [15], mouth movement analysis is used to monitor driver tiredness via yawning. The method accurately detects yawning and matches tiredness levels. Yawning does not indicate sleepiness alone. Eye and mouth-based characteristics are needed for strong detection because of this constraint.

The dual-camera yawning detection system in [16] monitors driver tiredness. The device captures various facial angles to better detection. Multiple cameras increase system complexity and expense. This limitation spurs single-camera, low-cost alternatives.

Driver sleepiness monitoring employing real-time yawning detection is examined in [17]. The technology performs well in controlled conditions. However, warning and accident detection modules are not integrated. This flaw highlights the necessity for robust safety frameworks with detection and response.

The [18] study uses traditional image processing to identify yawning for driver tiredness monitoring. System shows real-time deployment potential. When drivers' facial expressions fluctuate greatly, its accuracy is restricted. Due to this constraint, adaptive and landmark-based facial analysis algorithms are needed.

SqueezeNet, a lightweight deep learning architecture in [19], achieves good accuracy with little model size. The concept works for embedded and real-time applications. It needs careful tuning for face feature extraction. This encourages efficient, task-specific driver monitoring models.

Face detection and alignment using a multitask cascaded convolutional neural network (MTCNN) is proposed in [20]. The model localizes face landmarks accurately. However, computational expense may restrict low-power embedded device performance. This constraint encourages real-time landmark detection frameworks to be lightweight.

The classic [21] introduces iterative picture registration, utilized in computer vision. The approach established face alignment and motion analysis. It's too computationally demanding for real-time embedded systems. This encourages speedier landmark-based methods.

According to [22], adaptive correlation filters for visual object tracking are more robust. It tracks face characteristics in video streams well. It difficulties with abrupt lighting changes. Tracking with landmark-based detection may improve performance due to this constraint.

Kerneled correlation filters for tracking-by-detection are studied in [23]. The technology boosts tracking accuracy and efficiency. Real-time use demands careful parameter tweaking despite its merits. This encourages easier and more reliable integrated driver monitoring detection.

A scale-adaptive correlation filter tracker with feature integration is proposed in [24]. The tracker accommodates object size and enhances robustness. It increases computing complexity. This constraint emphasizes the need for accuracy-efficiency balance in real-time driver monitoring systems.

In [25], discriminative scale-space tracking improves object tracking accuracy. The approach handles scale differences nicely. However, computational needs restrict its use in low-power devices. This emphasizes embedded system vision model lightweightness.

The [26] study suggests a deep compact picture representation for visual tracking. The method tracks well with a small model. GPU acceleration is still needed for best performance. This limitation encourages real-time deployment using simpler landmark-based approaches.

The [27] study shows an intelligent video-based sleepy driver detection system under different lighting situations. The system resists illumination changes. Accident detection and emergency notification are missing. Integrated safety measures are needed due to this constraint.

Driver tiredness detection utilizing eye tracking and dynamic template matching is proposed in [28]. It properly detects tiredness patterns. Template matching is susceptible to noise and face changes. This constraint proposes ratio-based measures like EAR for improved generalization.

Facial analysis is used to evaluate driver tiredness in [29]. The technology recognizes weariness visually. However, sensor-based accident validation is missing. This gap allows accelerometer-based accident detection.

The computer vision-based driver sleepiness detection system in [30] is thorough. The technology detects reliably in controlled situations. It does not cover post-accident emergency response. This constraint inspired the suggested solution, which combines sleepiness detection with accelerometer-based accident detection and IoT-enabled emergency warnings.

III. METHODOLOGY

Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) generated from real-time video feeds are used to continually analyze the driver's facial behavior to identify tiredness. The Dlib library's pretrained facial landmark identification algorithm properly identifies the eyes and mouth in each video frame. $EAR = (A + B) / (2C)$, where A

and B are the vertical distances between eyelid landmarks and C is the horizontal eye width. Similarly, the MAR is calculated as the ratio of the upper and lower lip landmarks' vertical distance to the mouth's horizontal breadth, enabling accurate yawning detection. Experimental calibration determines EAR and MAR threshold values to account for typical blinking and speaking. The system tracks ratio changes in subsequent video frames in real time. The algorithm assesses the driver as tired when the EAR stays below the threshold for a set length or when the MAR exceeds it, suggesting frequent yawning. An alarm mechanism alerts the motorist promptly upon detection, improving preventative safety.

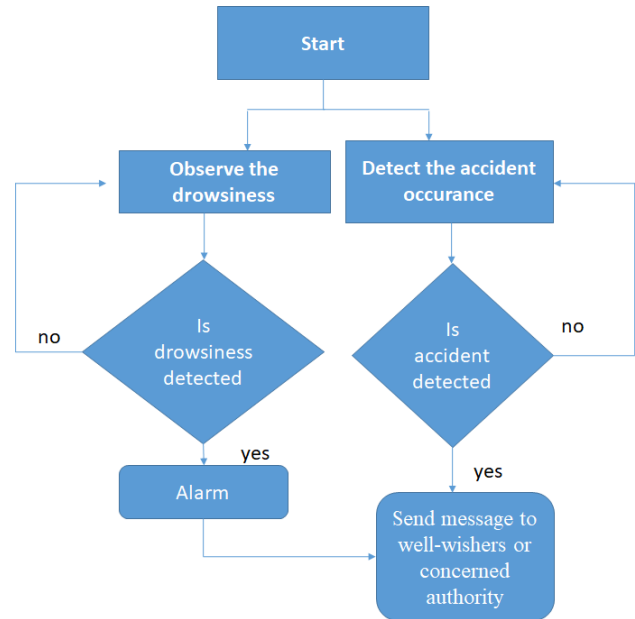


Fig1 Methodology Flow chart

A. Proposed Undertaking:

The project's goal is to develop a non-invasive, real-time driving safety system that can identify fatigue and react to collisions. Unlike vehicle-based or physiological methods, computer vision-based behavioral analysis tracks the driver's facial features. Using facial landmark points, the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) are computed from live dashboard-mounted camera video frames. These measurements use yawning and prolonged eye closure to identify fatigue. In order to prevent accidents, the driver is alerted audibly when they are sleepy.

The proposed system uses an accelerometer-based accident detection module to reduce drowsiness and enhance post-accident safety. By identifying sudden hits or unusual acceleration patterns, the accelerometer continuously tracks the motion of the vehicle and identifies collisions. By using the Internet of Things to transmit the vehicle's GPS position to specified contacts or authorities, accident detection initiates an emergency response process. Combining sensor-driven accident identification with real-time vision-based tiredness detection offers a comprehensive and affordable driver safety solution for embedded deployment in intelligent transportation systems.

B. System Architecture:

The suggested system architecture combines sensor-based accident detection modules with vision-based sleepy detection modules via an integrated processing unit. The Raspberry Pi receives footage of the driver's face from a dashboard camera for processing. To extract the features of the lips and eyes, the Raspberry Pi manages facial landmark detection. To evaluate driver attentiveness, EAR and MAR are computed in real time. The Raspberry Pi promptly triggers an alert mechanism to notify the driver when calculated data indicates drowsiness, reducing fatigue-related collisions.

Simultaneously, an accelerometer and a microcontroller module with Wi-Fi capabilities are employed to detect accidents. The accelerometer tracks the motion of the vehicle continuously and detects collision indicators such sudden impacts or erratic acceleration patterns. Accident data is transmitted by the Wi-Fi module to a cloud platform, which notifies authorities or selected emergency contacts of the location. The system is reliable, scalable, and perfect for real-time deployment in intelligent transportation contexts because to its dual-layer architecture, which uses IoT-based communication to identify tiredness and react swiftly to incidents.

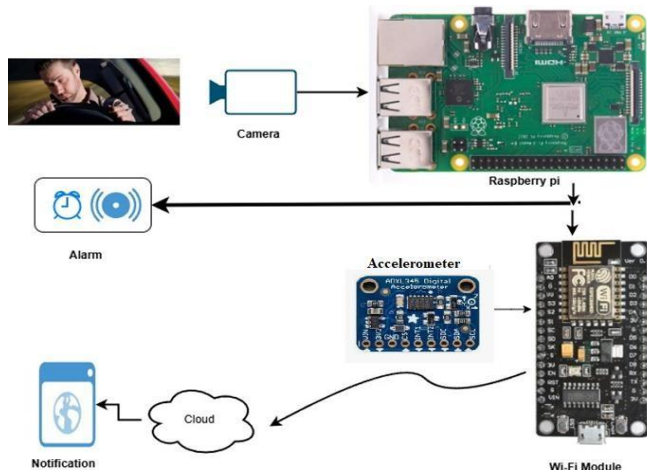


Fig.2. Proposed architecture

IV. IMPLEMENTATION

1. MODULES:

a) Video Acquisition Module

This module uses a camera installed on the dashboard to continuously record the driver's face. The primary input for the study of sleepiness is the gathered frames. Drivers are continuously observed by the camera.

b) Facial Landmark Detection Module

This module recognizes facial landmarks in Raspberry Pi video frames using a pretrained landmark recognition model. Drowsiness-related behaviors can be extracted by identifying important areas around the mouth and eyes.

c) Drowsiness Detection Module (EAR & MAR Analysis)

Face landmarks are used to compute the aspect ratios of the mouth and eyes. While MAR detects yawning, EAR

detects prolonged eye closure. Drowsiness in drivers is detected using threshold-based evaluation.

$$EAR = \frac{||P2-P6|| + ||P3-P5||}{2||P1-P4||}$$



$$MAR = \frac{|EF|}{|AB|}$$

d) Alert Generation Module

This module alerts the driver with a buzzer or alarm if it detects drowsiness. The alert system aids in maintaining focus and preventing collisions.

e) Accelerometer-Based Accident Detection Module

This module uses an accelerometer to track the motion of the vehicle. For real-time accident detection, abrupt impacts or unusual acceleration patterns are looked at.

f) IoT Communication Module

The IoT module's Wi-Fi-capable microcontroller transmits accident data to a cloud platform. When a vehicle is detected, alerts and its position are given to authorities or emergency contacts.

g) Cloud and Notification Module

This module manages message forwarding and cloud storage. For prompt response, it consistently sends emergency alerts to web platforms or mobile devices.

2. ALGORITHMS

a) Bayesian Classifier

The Bayesian classifier makes probabilistic classifications using Bayes' Theorem. The proposed approach determines the driver's level of attentiveness or sleepiness based on facial features such as Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). The classifier computes posterior probabilities assuming feature independence using feature likelihoods and prior class probabilities. Because of its ease of use and low computational complexity, the Bayesian classifier is perfect for real-time binary classification tasks like driver drowsiness detection.

b) Fisher's Linear Discriminant Analysis (FLDA)

Fisher's Linear Discriminant Analysis uses supervised dimensionality reduction and classification to maximize class separation. To optimize the drowsy-alert distinction, FLDA projects face feature vectors from EAR and MAR values onto a lower-dimensional space. This projection enhances classification by reducing noise and improving class separability. FLDA is computationally effective and helpful for embedded real-time applications when the data is linearly separable.

c) Support Vector Machine (SVM)

A dependable machine learning classification method that determines the optimal class boundary is the Support Vector Machine. In the suggested method, labeled facial feature vectors that reflect alert and drowsy states are used to train an SVM. SVM can handle non-linear and high-dimensional data distributions with the use of kernels. It is perfect for real-time driver tiredness detection using facial behavioral indicators because of its wide generalization and high classification accuracy.

V. EXPERIMENTAL RESULTS

The driver fatigue and accident detection system was constructed on an embedded platform using a camera and accelerometer sensor located on the dashboard. By continuously calculating Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) values from real-time video frames, eye closure and yawning behavior were identified. According to experimental findings, the system recognizes fatigue when MAR values exceed yawning limits or EAR levels drop below thresholds. The alarm system was triggered in these circumstances, promptly alerting the driver. The system is perfect for continuous driving monitoring since it uses threshold-based decision logic and lightweight feature extraction to provide real-time performance with minimal latency.

Unexpected crashes and unusual vehicle motion were simulated in order to evaluate the accelerometer-based accident detection module. By surpassing acceleration thresholds, the sensor identified impact occurrences and used the IoT communication module to send emergency alerts. By addressing both preventative and post-incident safety, vision-based drowsiness detection and sensor-based accident identification improved system reliability. The integrated system performs effectively under normal driving conditions and reacts quickly in an emergency, according to experimental testing. These findings demonstrate the viability and efficacy of the proposed real-time driver safety monitoring technique in intelligent transportation systems.

Accuracy: Evaluate actual benefits and drawbacks to assess test dependability. Then comes mathematics.:

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Accuracy in classification or positive instances is measured by precision. Accuracy is determined by applying the following:

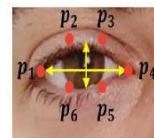
$$Precision = \frac{TP}{(TP + FP)}$$

Recall: The ratio of accurately predicted positive observations to total positives reveals how well a model can identify all machine learning class instances.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: An accurate machine learning model has a high F1 score. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$



Eye aspect ratio will be larger and relatively constant over time when eye is open

Eye aspect ratio will be almost equal to zero when a blink occurs

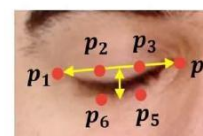
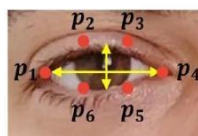


Fig 3 EYE Analysis

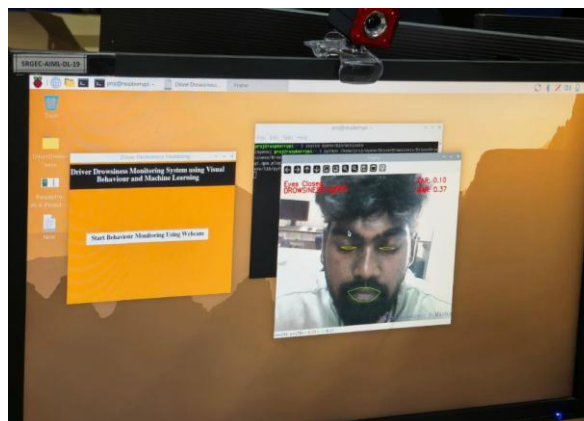


Fig 4 results

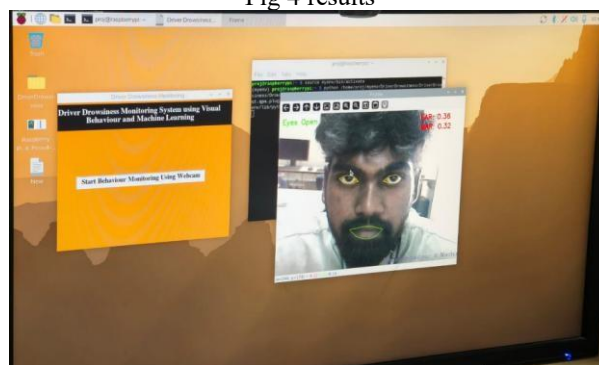


Fig 5 results

VI. CONCLUSION

This study detailed a real-time driver tiredness and accident warning system that enhances road safety through sensor-based monitoring and behavioral analysis based on computer vision. In order to prevent fatigue-related accidents, drowsiness is identified by analyzing facial landmarks and calculating Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) in real time. In addition to promptly detecting crashes, the accelerometer-based accident detection module uses the Internet of Things to

transmit emergency messages. Experiments show that the proposed approach is computationally efficient, non-invasive, and appropriate for real-time embedded deployment. The technology is a practical and affordable intelligent transportation safety solution since it detects preventive tiredness and responds quickly after an accident.

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