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Integrative Mobile Sensor Framework for Driver Behavior Analysis: Real-Time Monitoring of Facial and Physiological Parameters to Enhance Road Safety

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***Abstract*:**

Everywhere in the world, the behavior of drivers has been the various reasons for horrible accidents, which are causing deaths, fatalities, and injuries. Every Day, the number of accidents is increasing globally. Many scientists have concluded drivers have less sleep and more workload, which causes drivers' mood changes. In this paper, an experimental model is used to detect the drivers' behavior to decrease the possibility of accidents caused by this problem, which increases driver safety. During this work, two methods effectively detect a person's behavior. The Driver's face is captured, eye retina detection and facial feature extraction are completed, blinking values are calculated, and threshold values are set. Secondly, an Aurdino module is used, which is integrated with elastomeric sensors for real-time calculation of driver hand pressure on the wheel, and the threshold value is prepared. A result from both methods is taken as input for making a judicial decision and alerting the driver.

Keywords: *Driving Strategies, IoT, Driver fatigue, Driver Behaviour.*

1. INTRODUCTION

In day-to-day life, transportation systems play an important role in human activities. Anyone can be the victim of a road accident at any time for various reasons, but abnormal behavior by drivers cause most accidents. The main reasons for this behavior are lack of rest and sleep, which causes tiredness on long journeys. Due to these factors, driver vigilance will be reduced, which will cause serious situations and increase the chances of accidents. Because of this, most accidents happen all over the world yearly. In this technologically advanced era, new technologies can play an important role in solving this problem [1].

Considering the data analysis done by the National Sleep Foundation USA, 100000 accidents are caused by driver drowsiness problems. Indeed, analysis report shows that if a person is awake for 18 hours, it causes drowsiness. Therefore, the period of observation of the motive force standing and important feedback (e.g., alarms or safety automatic procedures) have to be integrated to improve the security of automotive systems. Luckily, various technologies will answer these problems these days, like distributed pressure sensors, eye cameras, or wearable devices for important parameter detection [2].

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Even though existing wearable technologies will give data related to the driving force posture, the correct natural process of the person or his pulse, the selection of different parameters of vehicle sensors is the most important and safe, particularly in automobile environments wherever the vehicles enforced are additional dangerous than low-security cars. On the other hand, 2 main options, driver comfort and redundancy, should be taken into consideration in-vehicle systems [3].

The sensing equipment should represent a virtually clear layer for the driving force to permit a traditional behavior throughout driving and avoid discomfort or impairing the tasks performed just in case of emergency [4]. Multiple watching systems and data sensing merging must be integrated to avoid single failures or false device results. In the vehicle automation system, the various device platforms represent how the automobile interacts with the surroundings and driving force to ensure a high level of safety and boost overall comfort throughout the trip. These technologies typically communicate with one another through customary automotive bus protocols [5]. The one used for this method is that the controller space network (CAN), a famed customary serial bus communication protocol with a period management and high knowledge irresponsibleness, unfolds all told kinds of vehicles [6].

This paper proposes a unique method for detecting a person's behavior based on two factors. The first one is to capture facial and eye features from the camera and detect blinking of eyes, and the threshold value is set for a minimum value of eye closing. Secondly, Aurdino module is used, which is integrated with elastomeric sensors for real-time calculation of driver hand pressure on the car steering wheel, and the threshold value is set. The result from both methods is input for making the final decision and alerting the driver. The paper discusses designing and implementing an improved algorithm to extract facial and eye features and hardware integration with Arduino and pressure sensors to detect driver situations.

2. RELATED WORK

Previous works are reportable within the literature survey for reducing road accidents due to behavior detection and monitoring drowsiness systems based on real-time data.

Real-time identification of driver fatigue [7] represents an application of computer vision. The system notifies the driver with a Raspberry Pi, a webcam, and a signaling mechanism. The technologies capable of analyzing the collected data and identifying the driver's face include hyperspectral imaging, convolutional neural networks, Bayesian filtering, and Gaussian processors. We utilize the Viola-Jones face recognition algorithm to accomplish this swiftly and accurately. This methodology is employed in AdaBoost and cascade classifiers and feature selection approaches such as Haar. This technique for monitoring faces and evaluating eye states has consistently yielded precise results regardless of lighting, backdrop, or facial orientation. Jeon S. et al. [8] introduced an innovative method for evaluating a driver's condition: the Distracted Driving Decision Algorithm. It employs eye blink detection and gaze estimation. DDDA differentiates itself from others using computational methodologies instead of machine learning models. This system achieves an average accuracy rate of 83.5% and processes data at a pace of 42 ms per frame. The utilization of the DDDA enhances the accuracy and accessibility of the Driver Monitoring System (DMS). An analysis of intelligent transportation systems to reduce traffic accidents [9] investigated driver overtaking behaviors. This system's light-emitting diode (LED) illumination and displays are designed to enhance mobility, reduce risk, and facilitate intelligent traffic management. The report identifies passing ranks as the primary cause of road accidents and fatalities. The paper's authors propose a driving assistance system utilizing real-time traffic data to enhance overtaking decisions for drivers.

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Ghandour et al. [10] identified inattentive drivers utilizing various machine learning techniques, including decision trees, naive Bayes, support vector machines, and EEG data. Prolonged driving or inadequate sleep may induce drowsiness. Timely recognition of fatigue indications may potentially preserve lives. Multiple novel methodologies have been developed for fatigue prediction utilizing sensors and physiological indicators, including an electrocardiogram (ECG). The device is engineered to detect variations in heart rate and using advanced logistic regression, a machine learning technique, to generate predictions. Eliminating extraneous signals enhances the quality of ECG data. Driver assistance systems facilitate the detection and rectification of potentially hazardous driving behaviors. It suggests analyzing driving operations across various time intervals and distances with a model of anticipated driver behavior to identify inefficient driving and maneuvering and draw conclusions. The outcomes of this comparison might inform or alert the driver accordingly. The foundation of the behavior model may derive from data collected from numerous drivers or from data specific to individual drivers. Operators of several vehicle types— including automobiles, school buses, and large trucks—may utilize the procedures outlined above. Operating a vehicle while fatigued is a primary contributor to traffic accidents. The two principal components of the sleep cycle are non-REM sleep and REM sleep, or rapid eye movement. Drowsiness constitutes the initial stage of the non-REM sleep cycle. Lethargy includes various suggested detection methods, including image processing and physiological signal analysis [11].

Lin et al. [12] utilized image processing techniques on camera-captured images to identify and assess a range of physical changes that drivers can perceive. Such changes may manifest as prolonged gazing, eyelid movement, fatigue, and lethargy. Methods for detecting bio-signals have been established to assess the physiological alterations of drivers, taking into account the intricate relationship between their sleep cycles and the electrical activity of the brain and heart. These bio-signals provide accurate predictions of lethargy. The current study on in-vehicle Decision Support Systems (DSSs) offers alerts and techniques to recognize accident-prone zones. The authors concur that additional high-resolution vehicle data testing is necessary to validate the functionality of in-car DSSs across diverse real-world settings; nevertheless, they also acknowledge significant advancements in their real-time field investigations. In addition to discussing the influence of personality types and age on driving behavior, the author underscores the importance of friendliness in reducing the probability of hazardous braking incidents. The authors introduce an extensive in-vehicle DSS that alerts drivers of potential accident hotspots utilizing location analytics derived from a national database of accident records.

A camera in front of the driver captures visual data for the fatigue detection system developed by Sabet et al. [13]. This data is subsequently processed to discover indicators of fatigue. The device utilizes a video camera and software to record duration and monitor the driver's eyelid movements at predetermined intervals. Commencing with the Viola-Jones face detector within the OpenCV package, which facilitates face identification and the detection process, the STASM library subsequently locates the pupils with an eye detector based on a neural network. The STASM library facilitates the creation of dynamic shape models for real-time eye localization [14]. The face alignment is evaluated based on the eyes' vertical positions after identification. The angle between the two pupils can be ascertained by aligning the frame with their positions. Normalization is accomplished by removing and resizing a rectangular section of the pupil region. Their identification is contingent upon their location where eyes are absent relative to recognized areas. Research demonstrates that the system can rapidly and reliably identify indicators of fatigue. The experimental data suggest that significant fluctuations in light and the presence of glasses predominantly influence the system's operation.

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Abtahi et al. [15] presented an approach to reduce accidents caused by fatigued drivers. This method continuously captures and observes the driver's facial expressions with a camera positioned behind the side mirror. Identifying the face region is crucial; subsequently, one can utilize the coordinates of the eyes and mouth to detect yawning. The geometric characteristics of the oral cavity facilitate the identification of yawning episodes. Upon detecting a yawn, the device promptly notifies the user, indicating fatigue and potentially hazardous driving conditions. Choi et al. [16] examine the application of head position estimation and gaze direction tracking to detect driver fatigue. Examining head posture facilitates determining facial characteristics' optic flow, allowing for a corner detection method. The primary objective of this study is to examine the driver's head movements, including nodding, shaking, and tilting, among others. The pupil's center is monitored, and the frequency of ocular movements is determined by CDF analysis based on the driver's gaze direction.

The prevalence of significant vehicular collisions underscores the serious consequences of texting while driving. This study examines the prediction of cell phone usage with driving factors. The data employed in this research originated from Yannis et al. [17]. The researchers utilized smartphone sensors to collect realtime statistics on driving behavior. This study provides concrete evidence that utilizing a mobile device while driving markedly alters driving behavior and increases the likelihood of vehicular accidents. A comprehensive statistical and economic analysis of the collected data facilitates assessing how cell consumption affects the driving risk parameters.

3.PROPOSED SYSTEM DESIGN

The overall design idea of Driver behavior detection is to capture an image from the camera and accurately calculate the state of drivers with data processing. The required hardware and software material must be collected to realize these requirements. Python machine learning and Arduino are used for this project, along with a camera and load cell sensor. For face and eye detection, the OpenCV and HOG algorithms and OpenCV libraries are used. Driver Behaviour Detection requires hardware and software components, including sensors to detect hand pressure and send values to Arduino and a camera to detect the face and eyes and process the eye blinking rate. Figure 1 demonstrates the proposed architecture of the model.

Algorithm: Driver Behavior Detection

Input: Hand wheel Pressure and Face detection from the camera

Output: Detect Driver Behaviour

Begin

1. Initialize dlib's face detector (HOG-based) and then create the Facial landmark predictor
2. Grab the indexes of the facial landmarks for the left and right eye, respectively
3. Start the video stream thread
4. Loop over frames from the video stream
5. Detect faces in the gray scale frame
6. Convert the facial landmark (x, y)-coordinates
7. Extract the left and right eye coordinates
8. Compute the convex hull for the left and right eye
9. Check to see if the eye aspect ratio is below the blink
10. Threshold, and if so, increment the blink frame counter

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11. If the eyes were closed for a sufficient number send data to Arduino
12. Take pressure readings from hand wheel and send to Arduino 13. Check if both values are above threshold then start alarm.
13. End

The HOG algorithm is employed to preprocess the image, which includes image resizing and color normalization. During this project, HOG is employed to detect efficient features for eye detection, extract HOG features from the image patterns, and offer the exact region of eyes from the captured image of the driver. After capturing the driver's image and preprocessing, the next process is to calculate the behavior of the driver-supported blinking rate. Values are calculated for each frame, and changes within the blink rate are verified with a threshold value. HOG is employed to detect the eye blinking rate effectively, which is helpful for face detection and supplies an accurate eye detection rate.

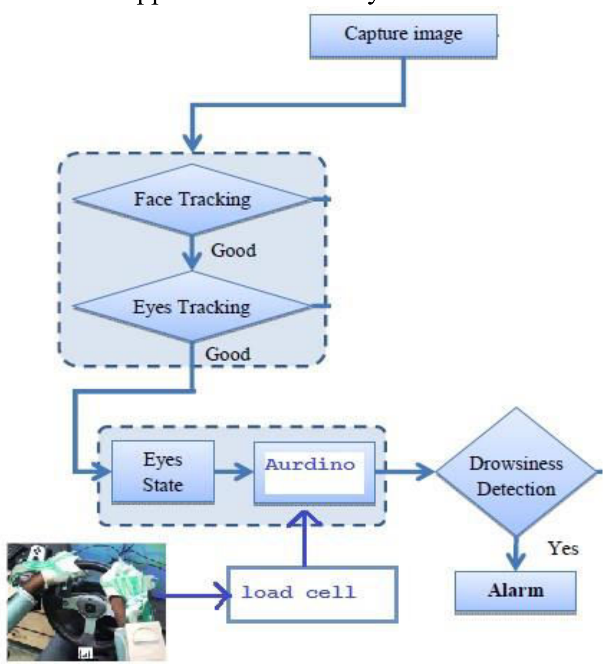

Figure 1: Architecture of Proposed Model

For this project, an Arduino microcontroller is employed, which could be a user-friendly open-source input and output system. A load cell sensor gives input to the controller whenever hand pressure increases the available wheel values. Other input to Arduino is eye brink ratio received from camera and software application which is connected to Arduino using system cable.

4. EXPERIMENTAL RESULT

The data set is collected from a live video file of a person driving a car. Features of the user are captured using a live camera, and live eye movement tracking is captured and used as input data for making decisions. Shape predictor marks are used for verifying user data.

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Table 1: Performance evaluation

Dataset	Eyeblink values	Sensor value	Correctly detection	False detection
Live video with eye blink	48	-10	30%	70%
Live video while driving without eye blink	<48	-10	0%	100%
Live video without person	0	0	0%	100%
Live video without pressure sensor data	<48	0	50%	50%
Live video with pressure sensor and eyeblink data	>48	>20	96%	4%

The performance of this application is tested under different scenarios like when the user is not driving. Still, eyes are closed and opened along with pressure sensor values are calculated, and if a user is driving on the go, values are tested with both eye blinking and the pressure sensor. If pressure sensor values and eye blink values are above the threshold value, then only the alarm is set to on state. Else the alarm is off state. False rate and positive rates are detected, and values are calculated. False rates are chances when the alarm is not set to on state. Positive rates are chances when the alarm is set to on state when both sensor and eye blink threshold are matched.

Table 1 shows different tested values with input videos and sensor and eye blinking values. Here, we have tested with various persons with live video tracking. We have also tested without any person on video but getting pressure sensor values. From these results false and positive test results are generated.

This dataset demonstrates the effectiveness of a system that uses video and sensor data to detect eye blinks in a variety of environments, as shown in Figure 2. The system can detect 48 eye blinks in real-time video, but it has accuracy issues, correctly detecting blinks only 30% of the time and misidentifying them 70% of the time. The negative sensor value (-10), which means that the results are affected by faulty or extraneous sensor data, may be the reason for this poor performance. In the absence of anticipated eye blinks during live video driving, the system fails completely, resulting in 100% false detections and 0% accurate detections, exacerbated by a negative sensor value. The system has a critical flaw in processing empty inputs, consistently misinterpreting blinks in live video with no people, despite the absence of both blinks and sensor data. The system effectively processes live video with no pressure sensor input, achieving 50% accuracy and 50% false positive rate. This indicates that while the system can sporadically

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detect blinks, its accuracy is compromised by insufficient sensor data. Finally, the system's best performance is shown in a live video scenario that includes both pressure sensor and blink data. The system achieves a 96% correct identification rate and only 4% inaccurate detection rate, particularly at high eyeblink values (>48) and sensor values (>20), underscoring the essential need for accurate sensor data to improve detection accuracy. The dataset underscores the importance of sensor data in augmenting blink detection and identifies opportunities for improvement, particularly in scenarios with missing or faulty sensor inputs.

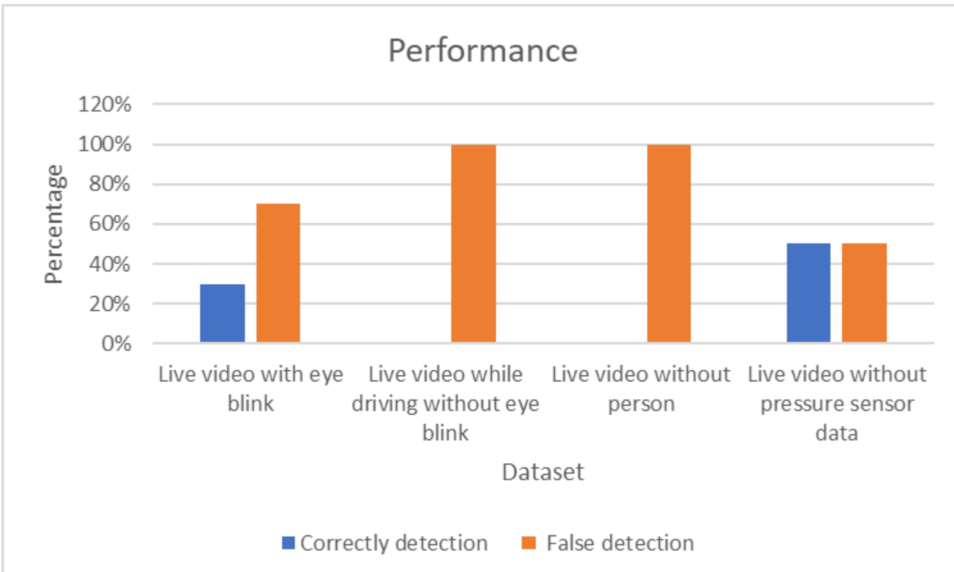

Figure 2: Performance analysis

5. CONCLUSION

This study presents a novel approach to enhancing driver safety by integrating real-time hand pressure monitoring on the steering wheel with facial and ocular feature detection. The system monitors driver behavior by analyzing facial features, eye blinking patterns, and pressure data from elastomeric sensors connected to an Arduino module. The twin-method approach ensures comprehensive assessment and facilitates prompt notifications to avert any issues. The experimental model demonstrates the practicality and effectiveness of this integrated system, highlighting its ability to reduce accident risks and enhance overall driver safety significantly. Future research may improve algorithms and augment the system's capabilities to handle various driving circumstances and diverse driver actions.

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