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Development of a Driver's Activity Monitoring System Using Facial and Heartbeat Parameters

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Abstract
Driver fatigue and distraction significantly contributes to road accidents worldwide, as such monitoring drivers' physical and mental states could mitigate these risks of fatigue and natural distraction. The existing driver monitoring systems are often complex, and inaccessible to drivers. The real-time driver monitoring device presented in this study is intended to improve road safety by identifying indicators of driver weariness and drowsiness. An ESP32-CAM module is integrated into the system to record live video, which is then processed using computer vision algorithms to identify signs of exhaustion, such as yawning and eye closing. More so, a MAX30102 heart rate sensor was incorporated with an Arduino Nano to monitor the driver's pulse rate, providing a complementary method for identifying signs of drowsiness. The system was able to process the data from both video and sensor inputs to issue alerts whenever any fatigue scenarios were detected. The system was tested successfully in a simulated scenario, demonstrating its effectiveness in detecting signs of drowsiness and alerting the driver accordingly. The system accurately detected driver fatigue to be 87% accurate and drowsiness to be 79% accurate through facial expression analysis and the designed web app effectively alerted drivers of any of these options. The heart rate of the driver was also measured, and the monitoring results shows a strong correlation with driver stress levels to about 66%. This driver monitoring system demonstrated feasibility and effectiveness in detecting driver fatigue and distraction. Its simplicity, and high accuracy makes it suitable for widespread adoption while further research prospect should consider artificial intelligent approach for optimization.

Keywords: *Monitoring, driver drowsiness, fatigue, eye closure, yawn detection, road safety.*

1.0 Introduction

The rapid increase in vehicle ownership and developments in transportation infrastructure has considerably improved mobility worldwide. However, these advancements have also contributed to an increase in traffic accidents, many of which are brought on by driver-related problems like fatigue, drowsiness, and distraction. The World Health Organization (WHO) reports that a significant portion of traffic accidents worldwide are caused by inattentive drivers, underscoring the need for practical ways to improve road safety (Li *et al.*, 2021).

Driver fatigue has been identified as a significant contributor to traffic accidents, garnering increasing global attention (Zhang et al., 2016). Examples of human factors in auto accidents or collisions include drivers, other road users, and objects by the side of the road that could cause an accident. Driving behavior, auditory and visual clarity, making decisions quickly, and responding quickly are a few examples. 93% of incidents are caused by human factors, including driver error, drowsiness, and alcohol use, according to a study based on collision data from the US and the UK (Rolison, 2020). Therefore, the primary cause of a large number of traffic accidents is human factors. Human error is largely to blame for these incidents, with driver weariness and inattention being the main offenders.

Driver monitoring systems (DMS) have emerged as important technology to address these difficulties. These technologies are designed to detect and assess a driver's physical and cognitive status, delivering real-time feedback and interventions to limit potential risks. Identifying symptoms of exhaustion, sleepiness, and distraction (Ren *et al.*, 2021).

1.1 Drivers Monitoring Measures

Driver Monitoring Systems (DMS) are advanced technical systems that monitor and analyze a driver's behavior and condition while driving a vehicle. These systems use a combination of sensors, cameras, and algorithms to monitor indicators such as eye movement, head posture, and physiological signals to determine the driver's level of alertness, attentiveness, and health. The relevance of DMS in terms of traffic safety cannot be too emphasized. According to global data, human factors such as exhaustion and distraction contribute significantly to traffic accidents (Nelesen *et al.*, 2008).

DMS can help to prevent such accidents by giving real-time alerts and solutions, resulting in fewer injuries and lives lost. Additionally, incorporating DMS into contemporary cars is a significant step toward fully autonomous driving, where the system may make corrections to maintain safety even in the event that a human driver fails.

To assess drivers' levels of drowsiness, researchers have used behavioral and physiological signs in addition to vehicle-based examinations (Albadawi *et al.*, 2022).

Steering wheel movement, speed, acceleration, and vehicle deviation and location are examples of vehicle-based measurements. Along with eye movement, the camera captures a range of face emotions, such as yawning, blinking, and head orientations. Finally, electrocardiograms (ECG), electromyography (EMG), and electroencephalograms (EEG) are examples of physiological measurements (Doudou *et al.*, 2020).

Road accidents resulting from inability to monitored drivers' activities can be considered disasters because of their wide-ranging impacts on human life, the economy, and infrastructure. Every year, millions of people are killed or seriously injured in road crashes, leading to immense human suffering. This loss of life and the long-term injuries caused are similar to the devastation seen in natural disasters. The economic toll is also massive, as the cost of emergency services, medical care, vehicle repairs, and loss of productivity due to injuries or deaths places a heavy burden on societies, especially in developing countries.

Additionally, serious accidents can cause extensive damage to roads, bridges, and surrounding infrastructure, disrupting transportation and daily life. As toxic compounds contaminate land and water, incidents involving hazardous materials can cause environmental harm akin to industrial or ecological disasters.

The public health impact is another reason road accidents are viewed as disasters. Hospitals and medical services often struggle to cope with the number of accident victims, which strains healthcare resources. Socially, communities suffer as families lose loved ones, breadwinners, or face the challenges of long-term care for injured members (Borza *et al.*, 2012).

1.2 Driver Monitoring Systems

Steering wheel movement (SWM) was first introduced by Fairclough *et al.* (1999) and Feng *et al.* (2009), with these development vehicles were made to measure to diagnose fatigue using an angle sensor. Considering the geometric elements of the route is not always possible. Roads in poor countries are often overly narrow and prone to potholes. The steering wheel's movement varies according to the condition of the road. This system won't be able to determine whether drivers are sufficiently tired on streets with cracked pavement.

Furthermore, Alshaqaqi et al. (2013) employed symmetry in their automatic tiredness detection system for facial recognition and eye localization. They used direct face expression and eye position to teach data symmetry. After defining the interest zone using facial zone identification, this work used eye localization to assess the current status of the eyes.

Alioua et al. suggested a method for localized edge detection of needed zones from the face. The rounded edge of localizing zones is used to pinpoint the mouth and eye. Drowsiness is detected using both open-mouth and closed-eye methods. Therefore, face capture is used to extract the zones of interest. They then built the facial detection procedure using the support vector machine technique, also known as the SVM technique. Eyes and lips were included in the lowered interest zones that developed within the facial zone. By recognizing micro sleep intervals—brief sleep intervals of two to six seconds—the suggested method ascertains the current condition (Alioua and colleagues, 2011).

1.3 Heat beat information

The number of heartbeats in a minute is known as heart rate, or heartbeat per minute (BPM). The heartbeat often surpasses a threshold value when fully awake and involved. The sort of activity frequently determines a healthy person's heart rate. A person's heart rate is lower when they are sleepy or fatigued than when they are awake or active. The MAX30102 measures the amount of reflected light using a photodetector after shining both lights onto the finger or earlobe—or really anywhere where the skin isn't too thick to allow both lights to easily penetrate the tissue. This method of utilizing light to identify pulses is called a photoplethysmogram. The MAX30102's two primary uses are heart rate measurement and pulse oximetry, which is a method which gauges blood oxygen levels.

A red LED and an infrared (IR) LED are the two light sources that the sensor uses to function. These LEDs emit light into the skin, and the amount of light that is absorbed or reflected varies according to blood flow (Sagonas et al., 2013).

1.4 Facial expression information

An indicator of how near or open the eyes are is the eye aspect ratio, or EAR. The eye aspect ratio is used in the suggested method to differentiate between the active, fatigued, and sleeping stages. The Euclidean vertical and horizontal distances between the upper and lower eyelids are used to calculate the EAR. An open eye has a greater EAR value than a closed one, claim Dalal *et al.* (2005). The metric data for the percentage of eye closure (PERCLOS) is used by the system to gauge drivers' alertness. PERCLOS is a real-time fatigue detection technique that measures the eye closure rate across the pupil. Slow eyelid closures or drips, as opposed to numerous eye blinks, are used to establish it.

Another kind of weariness indication is yawning, which is classified using the lip distance. "Lip landmark points," which are helpful in determining lip distance, are shown in the figure below. The average top lip weight is subtracted from the average lower lip weight to determine the distance. The numerous points of the upper and lower lips are represented in Figure 10. Notably, the upper and lower lips each possess eight unique points (Ito *et al.*, 2012).

2.0 Research Methodology

2.1 System Description

The developed system receives frames(pictures), evaluates the information and sends the feedback. The system uses the camera module to identify frames when the driver is either wearing spectacles or not looking at the camera. The system obtains the necessary frames to identify 68 spots on the driver's face. From the designated eyes and lip points, the system computes the lip distance and eye aspect ratio (EAR). The eye ratio, or EAR, is a metric used to measure how close or open the eyes are.

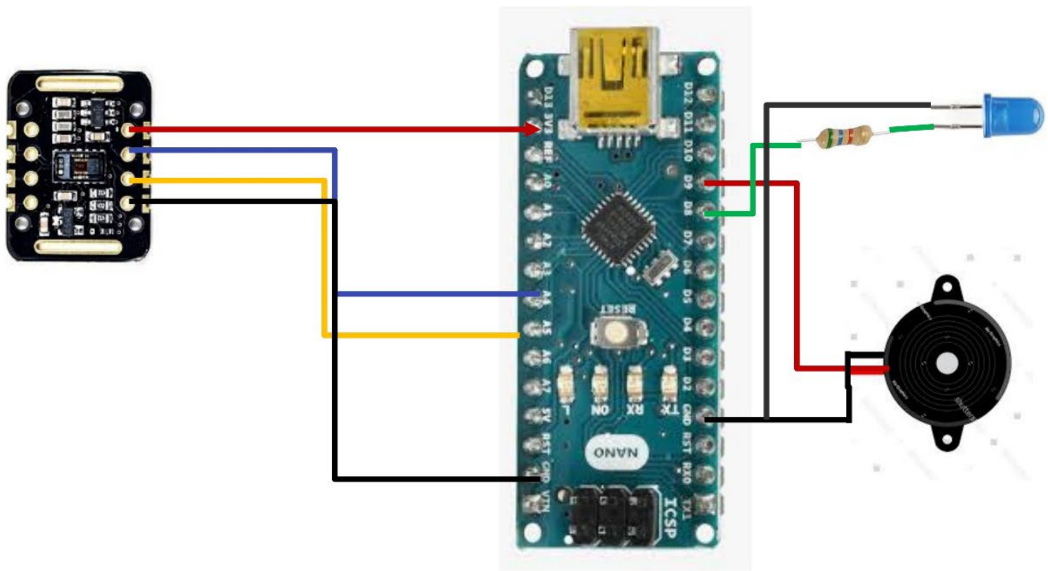

Figure 1: Circuit diagram of heart rate module

The developed technique distinguishes between the active and weary stages using the ocular aspect ratio. Furthermore, the lip distance is used to categorize yawns, another sign of fatigue. The Lip landmark locations can be used to calculate Lip distance. The distance is calculated by subtracting the average weight of the top lip from the average weight of the bottom lip. The Euclidean vertical and horizontal distances between the upper and lower eyelids are used to calculate the EAR. After the initial boot-up, the system uses its ESP32 camera module to record real-time frames and loads the model. The face detection procedure starts as soon as the system gets the first frame from the live video being recorded. After receiving frames, the system analyzes the data and provides feedback. On the other hand, the heart rate module immediately begins recording BPM values. The heart rate module then evaluates the driver's condition using the detected heart BPM and provides feedback if necessary. The heart rate module determines the tiredness states on its own. Figure 1 displays the flow chat for the driver's activity tracking.

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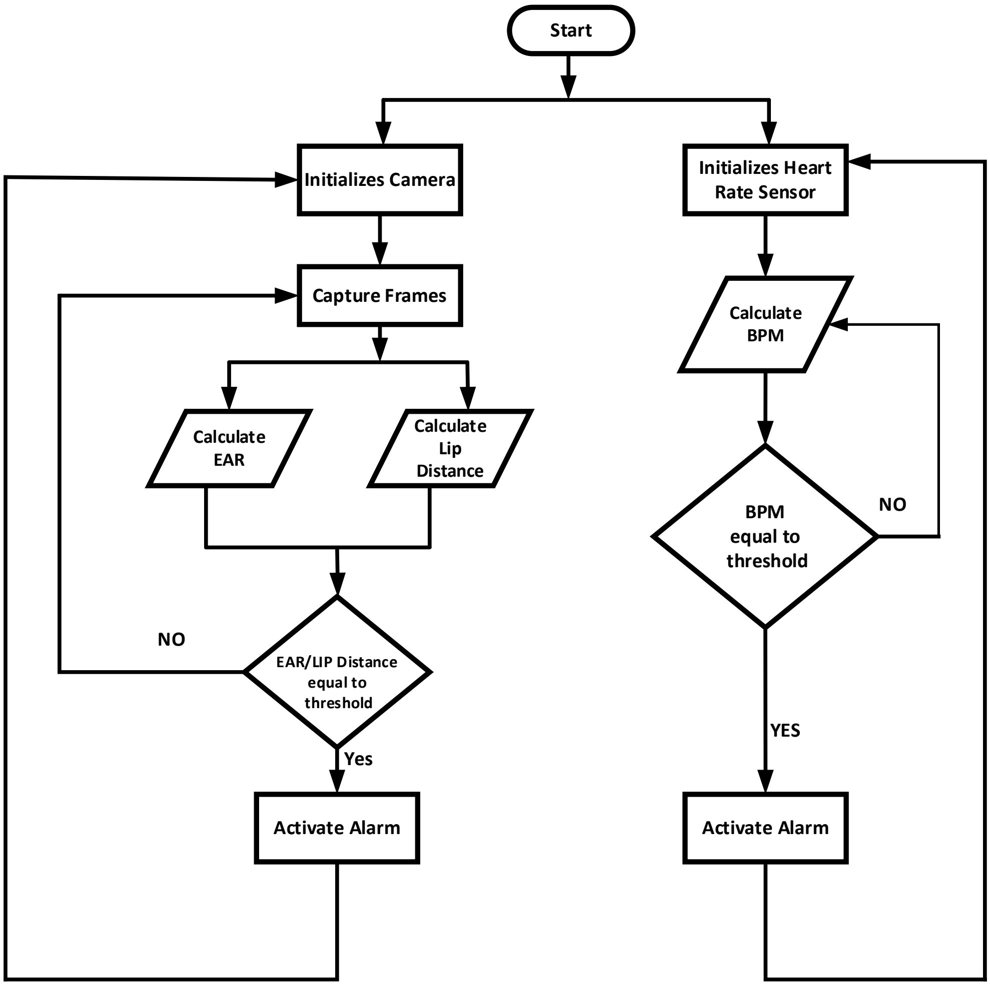

Figure 2: Flowchart of the driver's activity monitoring system

An open eye has a higher EAR value than a closed eye. By comparing the lip distance and eye ratio to predetermined threshold values, the device assesses the driver's state. Lastly, when the driver exhibits signs of fatigue, the system turns on the warning module. It is challenging to fall asleep because the driver rapidly returns to an engaged state. However, the heart rate module starts recording BPM values right once. Using the measured heart BPM, the heart rate module then assesses the driver's condition and, if required, gives feedback. The fatigue states are automatically determined by the heart rate module.

2.2 Testing Setup

The eye aspect ratio is used by the developed system's computer vision module to differentiate between the active and fatigued periods. Additionally, yawns—another form of weariness indication—are classified using the lip distance. Lip distance can be calculated with the help of the Lip landmark locations. The average top lip weight is subtracted from the average lower lip weight to determine the distance. The EAR is computed using the Euclidean vertical and horizontal distance between the upper and lower eyelids. Following the initial boot-up, the system loads the model and records real-time frames using its ESP32 camera module. For each test scenario, the system was evaluated at various distances from the camera sensor and in both bright and poor lighting. The drivers who tested the system were sited in motion scenarios. The face detection process is started by the system as soon as it receives the first frame from the live video that is being recorded.

2.3 System Metric Justification

The EAR value of an open eye is higher than that of a closed eye. 45 was the YAWN threshold and 0.15 was the EAR level. When the driver shows signs of exhaustion, the system activates the alarm module. The eye ratio and lip distance are compared to these preset threshold values to assess the driver's condition. The driver quickly switches back to an engaged state, which makes it difficult to fall asleep. On the other hand, the heart rate module immediately begins monitoring heart rate, uses the measured heart rate to determine the driver's condition, and provides feedback if necessary. The heart rate module determines the tiredness states on its own. The system receives frames, evaluates the information and sends the feedback. The system is designed to only prioritize frames associated with fatigue and drowsiness. The algorithm filters unnecessary frames from the camera sensor, so as to maximize efficiency and to improve accuracy of the system. Conversely, the heart rate module starts tracking BPM numbers right away. The heart rate module then uses the detected heart BPM to assess the driver's state and sends feedback if need be. The exhaustion states are determined independently by the heart rate module. The flow chat for the driver’s activity monitoring is presented in figure 2.

3.0 Data Presentation and Discussion for The Driver’s Activity Monitoring System

The findings of the Driver Monitoring System (DMS), which was created in this study and combined video feed analysis with heart rate monitoring to evaluate driver weariness, are shown in this section. When these two methods are combined, a complete system that can recognize weariness using both physiological and visual signs is guaranteed.

3.1 System Testing Analysis

To get real-time BPM data, a few participants had the heart rate monitoring device fastened around their wrists. To replicate a driving situation, the participants were instructed to stay seated comfortably while having their pulse rates continually recorded. The disparity in different states exhibited by one of the volunteers is represented by Figure 3.

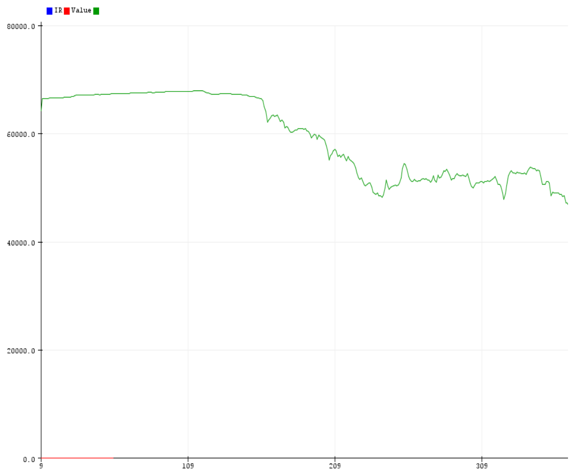

Figure 3: Decrease in heart rate from active state to drowsy state

The ESP32-CAM was set up to capture clear footage of the subject's face. The video feed was transmitted to the web application via a Wi-Fi connection, where it was analysed using the EAR and YAWN algorithms. Although the system was not tested inside a vehicle, it simulated a scenario where the subject mimicked driver behaviour, including normal facial expressions, eye closure, and yawning, to evaluate the system perform.

The system evaluated the subject from different angles. The video feed received by the web application filtered the frames and processed the frames associated with fatigue. Figure 4 presents the rear angle drowsiness result of one of the processed frames. This frame has an EAR of 0.13 and a lip distance value of 25.83. Figure 5 presents the oblique angle yawn result of the system. This frame has an EAR of 0.38 and a lip distance value of 45.33. Figure 6 presents the rear angle yawn result of one of the frames processed by the web application. This frame has an EAR of 0.22 and a lip distance value of 46.33. The system also evaluated the subject from different angles and distances, under a brighter lighting condition. Figure 7 presents the rear angle drowsiness result of the system. This frame has an EAR of 0.12 and a lip distance value of 16.33. Figure 8 presents the oblique angle drowsiness result of one of the frames processed by the web application. This frame has an EAR of 0.14 and a lip distance value of 16.00. The system also evaluated the subject from different angles. Figure 9 presents the oblique angle drowsiness result of the system. This frame has an EAR of 0.13 and a lip distance value of 22.33. Figure 10 presents the oblique angle yawn result of one of the frames analysed by the web application. This frame has an EAR of 0.41 and a lip distance value of 47.67. Figure 11 presents the oblique angle yawn result of one of the frames analysed by the web application. This frame has an EAR of 0.13 and a lip distance value of 22.33. Figure 12 presents the oblique angle yawn result of one of the frames analysed by the web application. This frame has an EAR of 0.09 and a lip distance value of 26.50. Figure 13 presents the oblique angle yawn result of one of the frames analysed by the web application. This frame has an EAR of 0.32 and a lip distance value of 45.67.

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Figure 4: Rear angle drowsiness detection

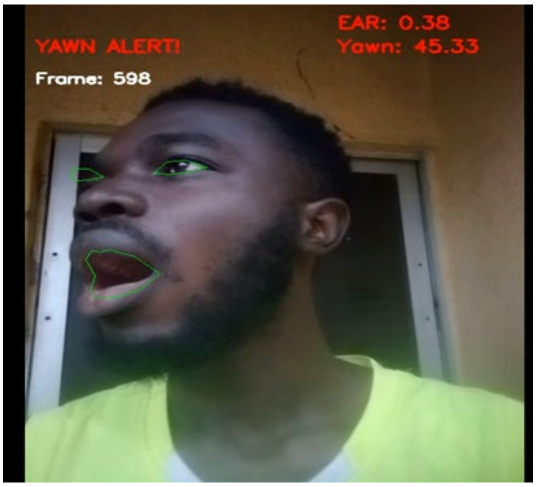

Figure 5: Oblique angle yawn detection

The system also evaluated the subject from different angles. Figure 6 presents the rear angle yawn results of the system. The system also evaluated the subject from different angles. Figure 7 presents the rear angle drowsiness result of the system.

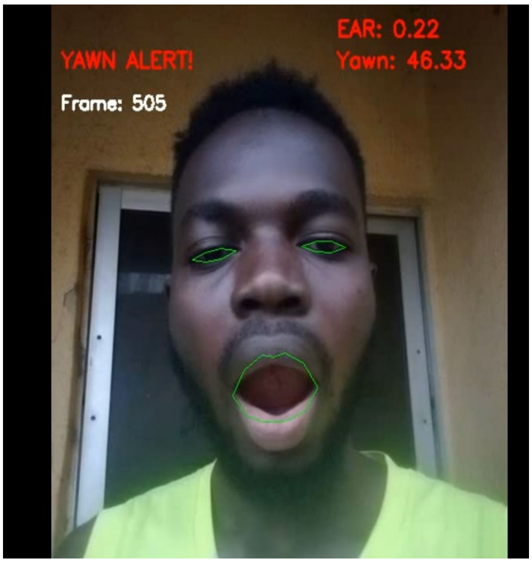

Figure 6: Rear angle yawn detection

Figure 7: Rear angle drowsiness detection

The system also evaluated the subject from different angles. Figure 8 presents the oblique angle drowsiness result of the system.The system also evaluated the subject from different angles. Figure 9 presents the oblique angle drowsiness result of the system.

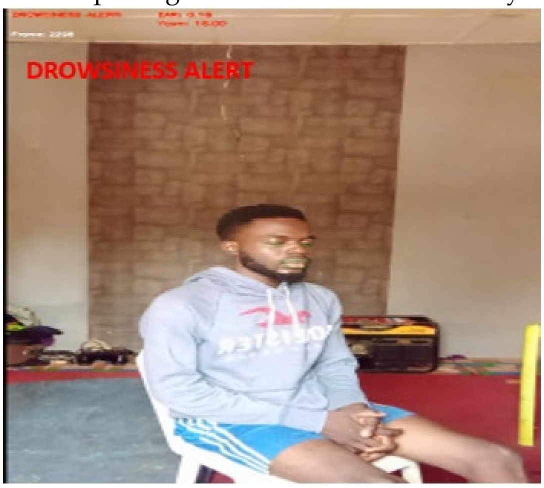

Figure 8: Oblique angle drowsiness detection

Figure 9: Oblique angle drowsiness detection

The system also evaluated the subject from different angles. Figure 10 presents the oblique angle yawn result of the system. The system also evaluated the subject from different angles. Figure 11 presents the oblique angle drowsiness result of the system.

Figure 10: Oblique angle yawn detection

Figure 11: Oblique angle drowsiness detection

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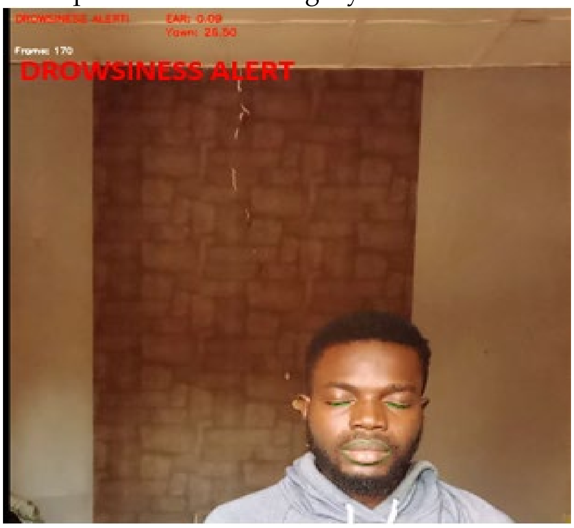

Figure 12: Oblique angle drowsiness detection

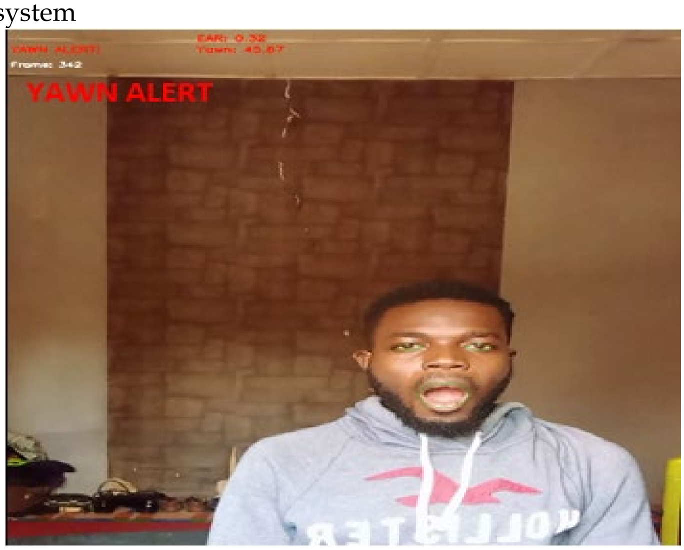

Figure 13: Oblique angle yawn detection

The EAR threshold used was 0.13 and the YAWN threshold used was 50. The web app processed the video feed in real-time using pre-trained algorithms designed for eye and yawn detection, which are key indicators of driver fatigue. The system was also tested on video streams where the subject tested different oblique views to test the computer vision module. The system provided about a 70% accuracy when it was tested with different positions. The system was also tested using video streams that had the subject at a distance from the camera in order to test the efficiency of the system. The web app successfully processed the live video feed, and both the eye closure and yawn detection algorithms worked as expected.

The margin of error was about 5% and the accuracy was calculated using the following metrics: True Positives – 153, False Positives – 51, True Negatives – 109, False Negatives – 37. The web app successfully processed the live video feed, and both the eye closure and yawn detection algorithms worked as expected.

The web app processed the video feed in real-time using pre-trained algorithms designed for eye and yawn detection, which are key indicators of driver fatigue in this research. The system was also tested on video streams where the subject tested different oblique views to test the computer vision module. The system achieved an accuracy of 70% (85% confidence level: 65% - 75%) when tested with different positions, indicating a moderate level of reliability in detecting driver behaviour. The 85% confidence interval for the accuracy was calculated using the binomial proportion confidence interval formula.

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4.0 Conclusion and Recommendations

4.1 Conclusion

This research developed an innovative driver monitoring system leveraging on the available affordable technologies. By combining computer vision, pulse sensing, and web app developed, a comprehensive solution for enhancing road safety among drivers were created with this model. Facial expression analysis using ESP32 CAM accurately detected driver fatigue and drowsiness. MAX30102 pulse sensor and Arduino Nano effectively monitored heart rate, correlating with the driver's stress levels. The system addressed limitations of existing solutions by providing miniaturized hardware (ESP32 Cam, MAX30102, Arduino Nano), simplicity and easy installation and maintenance, and high detection rates for fatigue and drowsiness. This driver monitoring system has significant potential to reduce road accidents caused by fatigue and distraction and enhance roads safety. The developed prototype is a substitute for other suggested methods of tiredness detection, and the system as a whole is readily integral into a range of automobiles. The device's low cost and portability make it a potential game changer in lowering the number of road accidents caused by human error in poor nations.

4.2 Recommendations

In light of the results obtained from this driver monitoring system, the system can be further optimized for real-time performance by improving the efficiency of the algorithms used in the computer vision module, re-evaluating the heart rate sensor's placement on the driver's wrist for comfort and accuracy and by integrating additional biometric sensors, such as temperature or electroencephalogram (EEG) sensors, to enhance the system's accuracy in detecting drowsiness.

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Author Contributions: I, Tambari William Mainasara carried out the conceptualization and design of the study. Data collection, analysis, interpretation of results, review and approval of the final version of the manuscript were carried out by Engr. Dr. Kufre Esenowo Jack, Engr. Dr. Babawuya Alkali, Engr. Justice C. Anunuso, Mr. Thomas A. Mamman while Mr. Paul Abraham Attah supervised the process.

Availability of Data and Materials: The authors confirm that the data supporting the findings of this study titled "Design and Construction of a Low-Cost Driver's Activity Monitoring System". are available within the article [and/or] its supplementary materials.

Conflicts of Interest: I, Tambari William Mainasara, solely declare that there is no conflict of interest regarding the present study titled "Development of a Driver's Activity Monitoring System Using Facial and Heartbeat Parameters".

References

Albadawi Y., Takruri M., Awad M. A review of recent developments in driver drowsiness detection systemsdeception. *J. Imaging.* 2018; 4:1–20.

Alioua N., Amine A., Rziza M., Aboutajdine D. *Computer Analysis of Images and Patterns.* 2011. Driver's fatigue and drowsiness detection to reduce traffic accidents on road; pp. 397–404.

Alshaqaqi B., Baquhaizel A., Amine Ouis M., Boumehed M., Ouamri A., Keche M. *International Workshop on Systems, Signal Processing and Their Applications (WoSSPA)* 2013. Driver drowsiness detection system; pp. 585–596.

Avram R., et al. Real-world heart rate norms in the Health eHeart study. *Nat. Dig. Med.* 2019; 2:1–10.

Bezerra G., Gomes R. 2018. Recognition of occluded and lateral faces using mtcnn, dlib and homographies; pp. 1–4.

Biswal A., Singh D., Pattanayak B., Samanta D., Yang M. IoT-based smart alert system for drowsy driver detection. *Wirel. Commun. Mob. Comput.* 2021; 2021:1–13.

Borza D., Itu R., Danescu R. In the eye of the deceiver: analyzing eye movements as a cue to F. *International Conference on Pattern Recognition.* 2012. Detection of eyes by circular Hough transform and histogram of gradient; pp. 1795–1798.

Dalal N., Triggs B. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 1.* 2005.

Histograms of oriented gradients for human detection; pp. 886–893.

Doudou M., Bouabdallah A., Berge-Cherfaoui V. Driver drowsiness measurement technologies: current research, market solutions, and challenges. *Int. J. Intell. Transp. Syst. Res.* 2020;18:297–319.

Fairclough S.H., Graham R. Impairment of driving performance caused by sleep deprivation or alcohol: a comparative study. *Hum. Factors.* 1999;41:118–128.

Feng R., Zhang G., Cheng B. *International Conference on Networking, Sensing and Control.* 2009. An on-board system for detecting driver drowsiness based on multi-sensor data fusion using Dempster-Shafer theory; pp. 897–902.

Harrington M.E. Neurobiological studies of fatigue. *Prog. Neurobiol.* 2012;99:93–105.

Ingre M., ÅKerstedt T., Peters B., Anund A., Kecklund G. Subjective sleepiness, simulated driving performance and blink duration: examining individual differences. *Sleep Res.* 2006;15:47–53.

Ito Y., Ohyama W., Wakabayashi T., Kimura F. *International Conference on Pattern Recognition.* 2012. Detection of eyes by circular Hough transform and histogram of gradient; pp. 1795–1798.

Kocalevent R.D., Hinz A., Brähler E., Klapp B.F. Determinants of fatigue and stress. *BMC Res. Notes.* 2011; 4:238–242.

Li X., Xia J., Cao L., Zhang G., Feng X. Driver fatigue detection based on convolutional neural network and face alignment for edge computing device. *Proc. Inst. Mech. Eng., Part D, J. Automob. Eng.* 2021; 235:2699–2711.

Mandal B., Li L., Wang G.S., Lin J. Towards detection of bus driver fatigue based on robust visual analysis of eye state. *IEEE Trans. Intell. Transp. Syst.* 2017; 18:545–557.

Nelesen R., Dar Y., Thomas K., Dimsdale J.E. The relationship between fatigue and cardiac functioning. *JAMA Intern. Med.* 2008;168:1–15.

Petridou E., Moustaki M. Human factors in the causation of road traffic crashes. *Eur. J. Epidemiol.* 2000; 16: 819–826.

Reddy B., Kim Y., Yun S., Seo C., Jang J. *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)* 2017. Real-time driver drowsiness detection for embedded system using model compression of deep neural networks; pp. 438–445.

Reimers A.K., Knapp G., Reimers C.D. Effects of exercise on the resting heart rate: a systematic review and meta-analysis of interventional studies. *J. Clin. Med.* 2018;7; 1–30.

Ren Z., Li, R., Chen, B., Zhang, H., Ma, Y., Wang, C., Lin, Y., Zhang, Y., Methodist, H. EEG-based driving fatigue detection using a two-level learning hierarchy radial basis function. *Front. Neurorobot.* 2021;15; 1–12.

Rolison J.J. Identifying the causes of road traffic collisions: using police officers' expertise to improve the reporting of contributory factors data. *Accid. Anal. Prev.* 2020; 135:1–8.

Sagonas C., Tzimiropoulos G., Zafeiriou S., Pantic M. *International Conference on Computer Vision Workshops.* 2013. 300 faces in-the-wild challenge: the first facial landmark localization challenge; pp. 397–403.

Warwick B., Symons N., Chen X., Xiong K. *International Conference on Mobile Ad Hoc and Sensor Systems.* 2015. Detecting driver drowsiness using wireless wearables; pp. 585–588.

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