An Affordable Driver Fatigue Detection System in Real Time

Nipuni H. Wijesinghe, and M. D. R. Perera

Abstract Fatigue and drowsiness in drivers are substantial factors contributing to fatal road accidents. This research presents an affordable and real-time driver drowsiness detection system designed to mitigate accidents resulting from driver drowsiness. Within the spectrum of approaches for detecting driver drowsiness, this study advocates for a computer vision-based methodology. This embedded system includes a processor board that runs drowsiness detection algorithms, an infrared (IR) camera that monitors the driver's condition in different lighting conditions and triggers alerts upon detecting signs of drowsiness. The proposed approach integrates two distinct drowsiness detection mechanisms, namely eye closure detection and yawning detection. In video frames, the system identifies facial regions using the Haar cascade classifier. To precisely locate the facial landmarks of the eyes and mouth, support vector machines (SVM) and histogram of oriented gradients (HOG) are utilized. Eye closure is evaluated by computing the eye aspect ratio (EAR), and yawning is detected by measuring the distance between the driver's upper and lower lips. Based on the empirical findings obtained during field testing, this research has demonstrated a noteworthy accuracy of 96% in effectively detecting driver drowsiness across diverse scenarios, including daytime, nighttime, low-light conditions, with or without eyeglasses, even during eating and while talking. The project aims to expand its scope by incorporating computer vision and physiological feature detection through the implementation of a machine learning (ML) model utilizing the TinyML technique, thereby elevating its performance accuracy in real-world situations.

Index Terms— **Detection of Driver Drowsiness, Eye Monitoring, Yawn Detection, Eye Aspect Ratio, Infrared Technology, Haar Cascade Algorithm**

I. Introduction

APPROXIMATELY 1.35 million individuals lose their lives annually due to traffic accidents [Margie, 2004]. In 2017, drowsy drivers were responsible for 91,000 documented incidents, resulting in nearly 800 fatalities and about 50,000 injuries, according to data from the National Highway Traffic Safety Administration. However, experts in fields such as traffic safety, sleep research, and public health believe that this figure may underestimate the true impact of drowsy driving [Adamos et al., 2013).

The National Sleep Foundation in the United States (US) has noted a disturbing trend of increasing mortality rates over the years. Alarming statistics reveal that approximately half of adult drivers in the US admit to regularly driving while feeling drowsy, and nearly 20% confess to having dozed off at the wheel within the past year. Shockingly, more than 40% of drivers admit to experiencing this perilous situation at least once in their driving career. The underlying causes of driver "drowsiness" can vary. To prevent drowsiness behind the wheel, it's crucial to detect changes in driver alertness accurately and alert the driver appropriately. Several indicators of drowsiness have been identified, including fluctuations in eye blink ratios, heavy eyelids, head tilting, yawning, alterations in heart rate, changes in driving patterns, and fluctuations in blood pressure. These factors have been leveraged to create systems for detecting driver drowsiness. Techniques for drowsiness detection encompass computer vision-based approaches, physiological signal analysis, and vehicle motion analysis, aiming to create effective systems to alert and mitigate risks associated with driver fatigue Studies conducted aim to minimize the occurrences of accidents attributed to driving while drowsy. Although achieving a zero-death rate due to drowsiness may remain a challenging goal, a substantial reduction in fatalities would be a commendable achievement.

The suggested system presents an affordable real-time detection system for driver drowsiness, employing a night vision camera integrated with Haar Cascade and dlib libraries to monitor eye closure and yawning.

II. Literature Review

Researchers have explored various methodologies to improve driver drowsiness detection systems. These investigations primarily center on identifying key indicators of drowsiness, such as eye activity, yawning occurrences, monitoring head tilts, tracking heart rate, observing shifts in driving patterns, changes in steering wheel behavior, and even alterations in vehicle motion. Depending on the

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chosen technique or methodology for identifying driver drowsiness, these systems can be categorized into three main groups, as follows,

-- Computer vision-based systems
-- Physiological signal-based systems
-- Vehicle motion analysis-based system.

A. Computer Vision Based-Systems

Driver drowsiness is detected in computer vision-based systems by analyzing one or a combination of physical characteristics, including metrics like eye blink ratios, eye closure durations, yawning, head tilts, and heavy eyelids.

Certain researchers have concentrated their efforts on eye detection as a means to monitor drowsiness. For instance, A. A. Miah et al. [2020] examined the patterns of eye blinks and the distance between eye landmarks of drivers, providing warnings with a remarkable 93% accuracy when drowsiness was detected. But, as this experiment was conducted on a dataset, it may not encompass all the diverse scenarios encountered in real-world situations. Similarly, A. K. Biswal et al. [2021] also employed eye closure detection for drowsiness detection. T. J. Lim et al. (2021) conducted a study utilizing a blend of techniques to accurately assess the driver's eye condition. A limitation of this research was the continuous camera monitoring used to detect the driver's eye condition, which could be inconvenient for the driver in practical terms. In a separate study conducted by Lisheng Jin et al. [2021], they utilized an SVM approach based on eye movements to identify drowsiness, achieving an accuracy to identify drowsiness, achieving an accuracy rate of 72.23%.

Additionally, specific research has focused exclusively on yawning detection as a means to monitor drowsiness. For instance, N. Alioua et al. [2014] concentrated on analyzing mouth features to identify instances of driver yawning in video footage.

Conversely, a handful of research studies have taken a more comprehensive approach, incorporating both eye and yawning detection. N. C. Barwar and N. Kuamr [2020], for instance, aimed to detect driver drowsiness using eye blinking and yawning. Similarly, C. M. S. Rani and B. Mohana employed a face extraction method based on SVM and isolated mouth regions to accurately identify yawning, achieving 98% accuracy. In their study, P. Shi and T. Wang [2005] implemented a Kalman filter to track the facial region, which resulted in an 86% accuracy rate. M. Manasa and collaborators (2019) developed an algorithm based on eye blink and yawn frequency, utilizing parameters like EAR, eye closure percentage, and yawn threshold, achieving an impressive accuracy range of 91-96%.

In certain research investigations, drowsiness is gauged through head tilt detection. For instance, Kusuma Kumari B.M. and Ramakanth Kumar. P [2020] employed Haar-like classifiers for eye and mouth identification and implemented skin segmentation to detect head tilts, achieving an accuracy rate of about 92%. I. H. Choi and Y. G. Kim [2014] executed a system in which the driver's head pose was estimated. Their findings suggested that the drowsiness level of a well-rested driver typically remains below 50%, while that of a drowsy driver exceeds 90%.

In response to the limitations of standard cameras in low-light conditions and when drivers wear glasses, some studies have turned to infrared (IR) cameras as a solution. In a study conducted by B. Bhowmick and K. S. C. Kumar [2020], drowsiness detection was accomplished using infrared (IR) cameras. In another research study by H. Bakhoda et al. [2020] it was noted that the identification of the decrease in respiration rate was made possible using an IR camera, offering a potential method for future researchers to detect drowsiness. W. Tipprasert et al. [2019] used IR images and achieved an impressive 98% accuracy in detecting eye closure and 92.5% accuracy in detecting yawning. Meanwhile, R. Li et al. [2020] employed ML models to integrate facial landmarks and recognition models, and they incorporated pose orientation as a method for detecting drowsiness in their research.

B. Physiological Signal Based-Systems

Physiological features encompass readings and measurements stemming from the physiological processes of the human body. In the context of driver drowsiness detection, certain studies have explored the possibility of detecting drowsiness by closely monitoring these signals, such as changes in pulse rate, electrooculography (EOG), electroencephalogram (EEG), and electrocardiogram (ECG or EKG) [Anon, 2021].

In their research, T. Xing et al. [2020] presented a drowsiness detection system operating on mobile devices. This system computes heart rate data and detects yawning movements, achieving an impressive 97.1% accuracy, denoted as "dWatch."

Another approach proposed by Li and Chung [2015] involves a drowsiness detection system that employs wavelet analysis of HRV in combination with SVM classifiers, resulting in a high accuracy rate of 95%.

In their investigation, H. A. Rahim et al. [2015] utilized infrared heart rate or pulse sensors affixed to the driver's finger or hand to identify drowsy drivers.

Meanwhile, L. B. Leng et al. [2015] introduced a custom-designed wristband equipped with a photoplethysmography (PPG) sensor and a galvanic skin response sensor, achieving an impressive accuracy of 98.02%. However, in the aforementioned studies, drivers were required to wear specific wristbands, helmets, or other equipment to enable drowsiness detection, leading to practical challenges and discomfort for drivers.

Efforts have been made to develop non-intrusive methods for drowsiness detection, but achieving high levels of accuracy has proven challenging. In a study by Manasa et al. [2019] they utilized heart rate variability (HRV) as a non-intrusive method. While the system successfully detected drowsiness, implementing it in real time posed

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significant challenges due to the high complexity of the algorithm.

C. Vehicle Motion Based-Systems

Vehicle-based measures involve the analysis of a driver's abilities and control over a vehicle to evaluate driving performance. In motion-based systems that examine driving characteristics, aspects such as the driver's capabilities, steering wheel movements (including gas pedal pressure), lane deviation, and speed fluctuations are considered.

In their research, Z. Li et al. [26] utilized data from sensors affixed to the steering lever, capturing steering wheel angle (SWA) information. This approach yielded an accuracy level of 78.01%.

Drowsiness detection through lane position deviation relies on tracking the vehicle's position relative to a specified lane and assessing any deviations. These methods are heavily reliant on the driver's driving behavior. Nevertheless, changes in steering wheel behavior or deviations in lateral position tend to become apparent in the later stages of drowsiness, potentially when it is

already too late to avert an accident. They tend to perform less reliably in real-world scenarios with significant variations.

III. Design and Methodology

This study focused on two primary approaches for detecting drowsiness within the system. Specifically, eye closure detection and yawning detection. To enable this system to operate effectively, an infrared (IR) sensing camera with IR-emitting diodes was utilized under various conditions, including:

-- Daytime driving.
-- Nighttime driving when lighting conditions are poor.
-- Scenarios where the driver wears glasses.
-- Scenarios where the driver does not wear glasses.

The experimental setup was designed to track the driver's facial features discreetly, ensuring their comfort during the monitoring process.

In a survey involving 66 participants, 53 of whom were drivers, it was found that despite the initial discomfort, over 96% of drivers were willing to be monitored if it helped prevent them from falling asleep at the wheel. Consequently, the camera was strategically positioned to minimize distraction for the drivers, and the system was integrated with an alarm mechanism that would alert the driver in the event of detected drowsiness.

This research was structured into four distinct sections:

Eye Closure Detection:
-- Utilized the Eye Aspect Ratio (EAR) to calculate and identify instances of eye closure.

Yawning Detection:
-- Observed variations in the distance between the

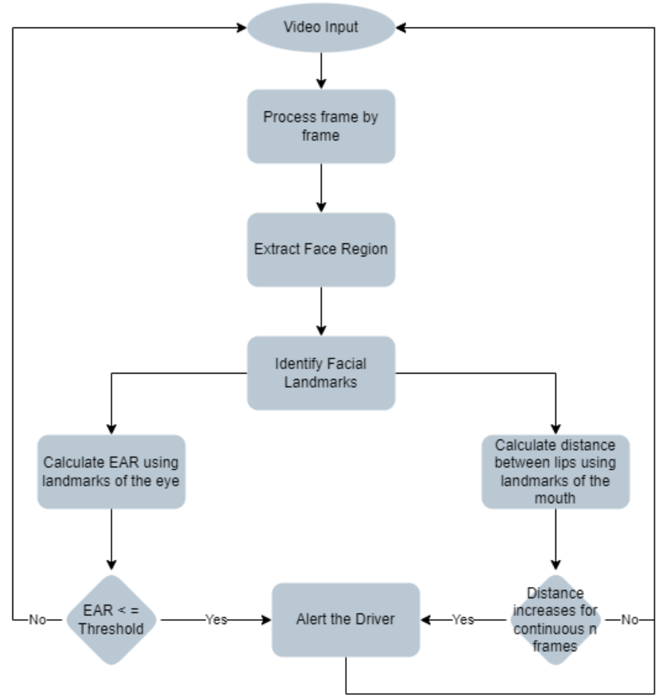

Fig. 1. Methodology Flowchart

upper and lower lip to detect yawning.

Alerting System:
-- Following the successful detection of drowsiness through eye closure, yawning, or a combination of both, an alerting system was activated to notify the driver.

System Implementation:
-- The system was integrated into the vehicle in a manner that minimized distraction for the driver. All hardware components were neatly organized within a box, ensuring that only the camera remained visible at the front end.

A. Face Detection

One of the initial and primary signs of drowsiness is the gradual closing of a person's eyes.

To enhance facial features, the frames were resized and converted to grayscale. The Haar cascade classifier was employed to identify faces within the images. This classifier evaluates image patches on a cascade of scales, categorizing them as positive or negative concerning the object being sought within each frame. The Haar cascade classifier was chosen due to its swift execution and lower computational demands.

To detect facial landmarks, a combination of SVM and Histogram of Oriented Gradients (HOG) was employed. HOG is known for its high accuracy in terms of its true positive detection rate. Figure 2 illustrates the identified facial landmarks in a video frame.

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Fig. 2. Landmarks of the face

Fig. 3. Landmarks of an eye (P1, P2, P3, P4, P5, P6)

B. *Eye Closure Detection*

In the context of eye closure detection, once the facial landmarks within the face region are identified, the focus shifts to the specific landmarks within the eye regions. Figure 3 provides a visual representation of the facial landmarks within an eye, which are denoted as P1, P2, P3, P4, P5, and P6.

After the facial landmarks in each frame have been extracted, the eye aspect ratio (EAR) is calculated to determine the extent of eye closure exhibited by the driver. EAR, as defined in Eq. (1) represents the ratio of eye height to eye width and serves as an estimate of the degree to which the eye is open.

$$EAR = \frac{|Eye\ Height|}{|Eye\ Width|} \tag{1}$$

$$EAR = \frac{\| p2 - p6 \| + \| p3 - p5 \|}{2 \| p1 - p4 \|} \tag{2}$$

Equation (2) illustrates the method by which the eye landmarks were employed to compute the Eye Aspect Ratio (EAR).

To determine the appropriate threshold value for EAR indicative of a drowsy individual, a test was conducted involving 5 subjects, of which the results are presented in Table I below:

TABLE I
AVERAGE EYE ASPECT RATIO DURING EYE CLOSURE AND EYE OPEN

Person	Eye Closure EAR (Drowsy)	Eye Open EAR
1	0.13	0.31
2	0.17	0.35
3	0.12	0.31
4	0.11	0.36
5	0.17	0.33
Average	*0.14*	*0.33*

Hence, the EAR of a drowsy person (eye closed) was averaged to be 0.14, while the average EAR of an awake person (eye open) was 0.33.

$$EAR = \begin{cases} x \geq 0.3, eyes\ open \\ x < 0.3, eyes\ close \end{cases} \tag{3}$$

As evident from Equation (3), the Eye Aspect Ratio (EAR) for an awake person with open eyes is typically a consistent value of approximately 0.3, and when closed, it approaches nearly 0. If the EAR remains consistently below 0.3 for a consecutive series of n frames (e.g., 30 frames), it indicates that the driver's eyes have been closed for a duration longer than the norm, suggesting drowsiness or dozing off. In such cases, the system triggers an alarm to alert the driver. Figure 4 illustrates an instance of eye closure detection as detected by the system.

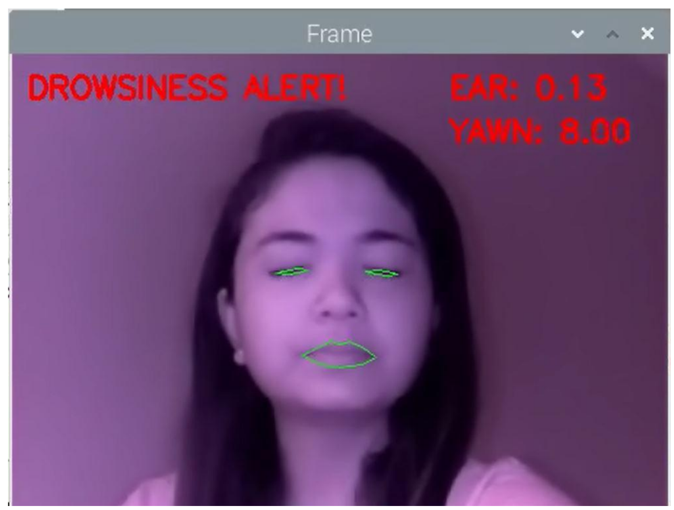

Fig. 4. Successful detection of eye closure

C. *Yawning Detection*

An essential characteristic of a drowsy individual is the frequent occurrence of yawning. When a person is drowsy, they tend to yawn repeatedly, resulting in a notably wide opening of the mouth, surpassing the typical range for yawning.

To quantify this, the system utilized facial landmarks associated with the mouth (Figure 5) to measure the upper and lower lips' distance of the driver's mouth.

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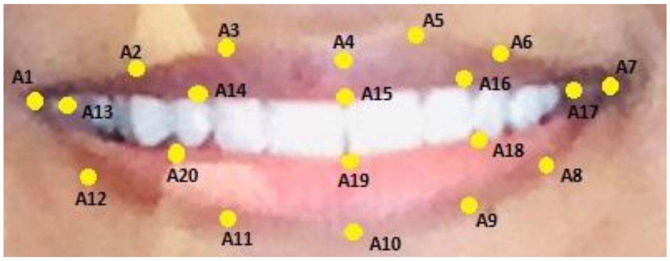


Fig. 5. Facial landmarks associated with the mouth

In order to determine the number of frames to be considered for yawning detection, it was tested on 5 subjects. Below Table II shows the results of the same:

TABLE II
AVERAGE DISTANCE BETWEEN THE LIPS

Person	Distance Between the Lips	Frames
1	31.17	19
2	31.40	20
3	31.26	20
4	31.09	21
5	31.14	21
Average	*31.21*	*20.2*

Consequently, if the distance between the upper and lower lips consistently increases over a continuous sequence of n frames (20), it signifies a potential yawning episode by the driver. In response to this, the system activates an alarm to notify the driver. Figure 6 provides an illustration of a yawning detection event as detected by this proposed system.

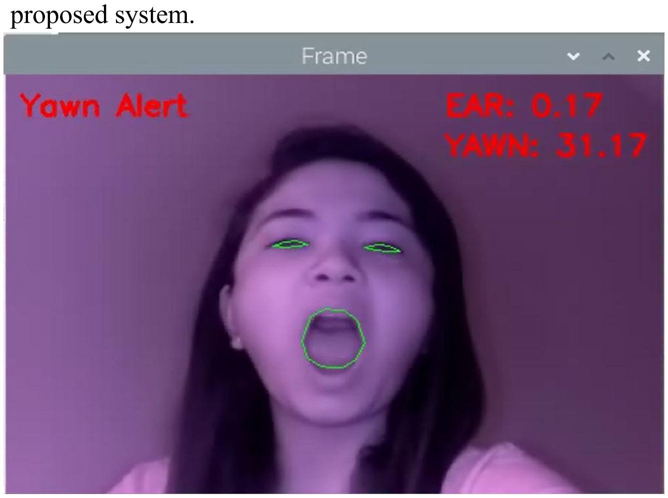


Fig. 6. Effective identification of yawning

IV. IMPLEMENTATION DETAILS

A. *Hardware Implementation*

The system incorporated several hardware components, including a buzzer, a RAM 4G Raspberry Pi 4 processor board, a Night Vision camera - Raspberry Pi, and a battery pack. The processor board was powered by a battery pack, and the camera and buzzer were connected to it. The entire setup was thoughtfully enclosed within a container, and the system was positioned in front of the driver to minimize distraction. It's worth noting that the camera's positioning needed to be adjusted in accordance with the driver's eye level.

The system incorporated several hardware components, including a buzzer, a RAM 4G Raspberry Pi 4 processor board, a Night Vision camera - Raspberry Pi, and a battery pack. The processor board was powered by a battery pack, and the camera and buzzer were connected to it. The entire setup was thoughtfully enclosed within a container, and the system was positioned in front of the driver to minimize distraction. It's worth noting that the camera's positioning needed to be adjusted in accordance with the driver's eye level.

For reference, Figure 7 provides an overview of the hardware components and their respective ports used for connection to the Raspberry Pi. Figure 8 offers a visual representation of the experimental setup of the system.

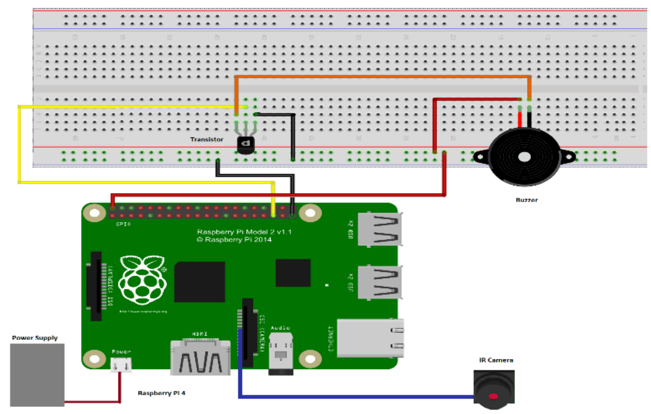
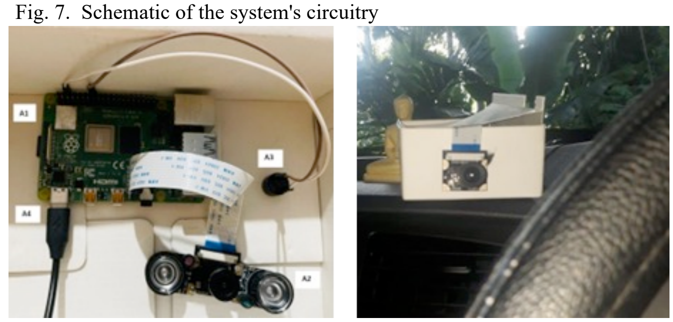


Fig. 7. Schematic of the system's circuitry



a) Setup - Experimental b) Setup - Vehicle

Fig. 8. Drowsiness detection system
(a) (A1) Raspberry Pi 4 Model B, (A2) Raspberry Pi Night Vision Camera, (A3) Buzzer, (A4) Power supply

B. *Costing*

Table III displays the overall hardware costs necessary for implementing the proposed system (in US dollars).

TABLE III
OVERALL COST

Components	Price (US $)
Processor - Raspberry Pi 4 (Model: B)	55
Camera - Raspberry Pi Camera (IR – Night Vision)	22
Alarm Buzzer	0.15
Power Battery Pack	4.03
Bread board	0.9
Memory Card (Storage: 32GB)	4.9
Jumper Wires	0.8
Total	87.78

ISSN: 2961-5992

V. Results and Discussion

A. Questionnaire Results

Before implementing the system, a survey was conducted to gauge public perspectives. A questionnaire aimed at gathering feedback from individuals about drowsy driving and their receptiveness to a cost-effective system was distributed among 66 respondents, 53 of whom were drivers.

TABLE VIII
FIELD TEST RESULTS FOR YAWNING DETECTION DURING NIGHTTIME

Yawning Detection Status	%
Success (TP)	100%
Failure (FN)	0%

The results revealed that a significant 88.7% of all drivers acknowledged experiencing drowsiness while driving, with nearly 40% encountering drowsiness daily, highlighting a potentially perilous situation.

Furthermore, among all the participants who were drivers, over 98% expressed a positive interest when presented with the concept of an affordable real-time drowsiness detection system.

B. Field Test Results

The drowsy driving detection system that was developed was subjected to testing using a group of 25 participants. These participants fell within the age range of 23 to 65, and among them, 15 individuals wore glasses. During the testing, the participants engaged in real-life activities while driving, such as talking and eating.

In the subsequent results, "success" refers to instances where the system accurately detected eye closure or yawning (tp - true positives). Conversely, "failure" corresponds to situations where the system did not detect eye closure or yawning even when these actions occurred (fn -false negatives).

Drowsiness Detection at Daytime

To evaluate drowsiness detection during the daytime, two methods, "Eye Closure Detection" and "Yawning Detection," were employed. All 25 participants were subjected to testing with both approaches in daytime conditions. Table IV displays the success rate for the eye detection results among the 25 participants during the daytime. This success rate serves as one of the factors used to assess the accuracy of the drowsiness detection system.

TABLE IV
FIELD TEST RESULTS FOR EYE CLOSURE DETECTION AT DAYTIME

Eye Closure Detection Status	%
Success (TP)	92%
Failure (FN)	8%

The success rate of eye closure detection significantly outperforms the error rate, demonstrating the favorable outcomes of this study.

Table V presents the results of yawning detection among the sample participants during the daytime, serving as an additional factor to evaluate the system's accuracy in detecting drowsiness under daytime conditions.

TABLE V
FIELD TEST RESULTS FOR YAWNING DETECTION AT DAYTIME

Yawning Detection Status	%
Success (TP)	92%
Failure (FN)	8%

The success rate for eye detection during the daytime is again quite high at 92%, with an error rate of only 8%. Notably, the success rate for yawning detection is also 92%, which is 11 times higher than the error rate. The 8% error rate in both cases can be attributed to the interference of the bright sun, which caused unwanted reflections on the camera and hindered accurate mouth detection. This issue was most pronounced around noon, when the sun's rays were strongest. These errors could potentially be mitigated by introducing a visible light-cut filter to the system.

In summary, the drowsiness detection system's accuracy during daytime is 92%, with an 8% error rate. These errors are primarily due to natural factors like direct sunlight affecting the camera and sun rays hitting the glasses of drivers wearing them.

To assess the system's performance with drivers wearing glasses, data analysis was conducted on the results from 25 participants, 15 of whom wore glasses. Table VI illustrates the eye closure detection results for participants with glasses. Notably, there is an 86.7% success rate for eye closure detection with glasses, and although there is a 13.3% error rate, the system's success rate remains significantly higher. Furthermore, the system achieved a 100% success rate when participants were not wearing glasses.

TABLE VI
RESULTS OF DROWSINESS DETECTION FOR PARTICIPANTS WEARING GLASSES DURING DAYTIME

Drowsiness Detection Status	%
Success (TP)	86.7%
Failure (FN)	13.3%

Drowsiness Detection at Nighttime

Both "Eye Closure" and "Yawning" detection approaches were employed to evaluate drowsiness detection during the nighttime. The same 25 participants were subjected to testing with both methods at nighttime.

Table VII presents the results of eye closure detection among the sample participants during the nighttime. It is noteworthy that the success rate for eye detection at nighttime was 100%, as it was successfully detected for all participants. Consequently, the error rate is 0%.

TABLE VII
EYE CLOSURE DETECTION STATUS

Eye Closure Detection Status	%
Success (TP)	100%
Failure (FN)	0%

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Table VIII presents the results of yawning detection among the participants during nighttime, particularly in poor light conditions. It is evident that the success rate for yawning detection achieved a perfect score of 100% at the nighttime.

In conclusion, the drowsiness detection system exhibited exceptional accuracy at nighttime, achieving a perfect 100% success rate for both eye closure detection and yawning detection.

To assess the system's performance with drivers wearing glasses during the nighttime, 15 participants who wore glasses were used. Table IX illustrates the eye closure detection success rate with glasses.

It's evident that there is a remarkable 100% success rate for drowsiness detection even when participants were wearing glasses.

Overall Results

As shown in Table X, the overall accuracy rate for drowsiness detection during the daytime is 93%, whereas during the nighttime, it reaches 100%. When considering the combined results of drowsiness detection, including both eye closure detection and yawning detection, for both daytime and nighttime conditions, the proposed cost-effective driver drowsiness detection system achieves a commendable 96% accuracy rate.

TABLE IX
RESULTS OF DROWSINESS DETECTION FOR PARTICIPANTS WEARING GLASSES DURING NIGHTTIME

Drowsiness Detection Status	%
Success (TP)	100%
Failure (FN)	0%

Figure 9 and Figure 10 below depict successful instances of eye closure detection and yawning detection during a field test conducted with a university student.

It's worth noting that using the timer function of the Raspberry Pi, it was determined that the algorithm runs within a maximum of 3 seconds.

VI. CONCLUSIONS AND FUTURE WORKS

A. Conclusion

In conclusion, our research presents a robust driver drowsiness detection system utilizing eye closure and yawning detection, achieving an impressive overall success rate of 96%. This system effectively addresses various challenging conditions, including daytime and low-light nighttime scenarios, as well as drivers wearing or not wearing glasses. The successful outcomes affirm the viability of our approach in enhancing road safety by providing timely alerts to drowsy drivers, potentially preventing accidents and saving lives across a range of driving conditions. The achieved success rate underscores the potential for widespread implementation and integration of such technologies into modern vehicles, contributing to safer roadways for all.

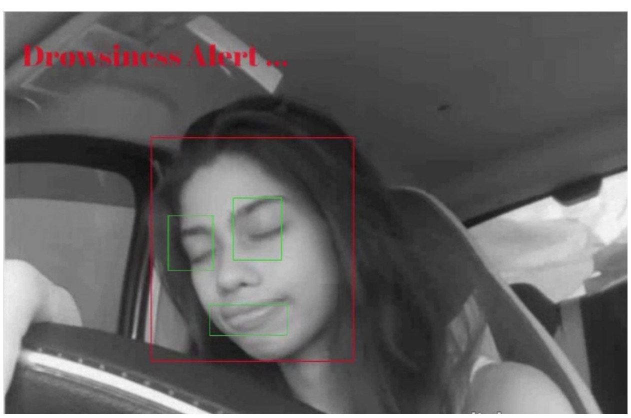

Fig. 9. Eye Closure Detection - A Successful Instance

Fig. 10. Yawning Detection - A Successful Instance

TABLE X
OVERALL RESULTS OF DROWSINESS DETECTION

Drowsiness Detection Condition	Success Rate
Daytime – No Glasses	100%
Daytime – With Glasses	87%
Nighttime – No Glasses	100%
Nighttime – With Glasses	100%
Overall Day Time	*93%*
Overall Nighttime	*100%*

B. Challenges and Future Works

While conducting this research study, quite a few challenges were faced.

Initially, a Raspberry Pi 3 board was considered the processor for the system, but its processing power was not efficient enough; hence, a Raspberry Pi 4 board was used instead. In the Raspberry Pi 4 board, the algorithm runs within 3 seconds, and this efficiency can be increased if a more efficient processor could be used for the study.

Additionally, the system's performance could be further improved by replacing the night vision Pi camera with a Quark2 640 IR camera, which offers a higher frame rate of 60 fps, doubling the frames per second, and potentially delivering faster results.

To address distractions (glare from sunlight) caused by daylight effects, an enhancement could involve integrating a visible light-cut filter into the system.

Additionally, since there are more features that can be

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captured to detect drowsiness, like heart rate, and blood pressure, it would be better if this system could incorporate some more features to ensure its efficiency. Given that physiological features have demonstrated superior accuracy in performance, incorporating a non-intrusive module based on physiological signals into the existing system could enhance its overall reliability.

Furthermore, in the proposed system, the placement of the camera necessitates manual adjustments to align with the individual driver's position. It is anticipated that in future enhancements, automated adjustments will be implemented by ensuring that the identified facial landmarks of the user aptly align within the camera frame. In the future, an ML model encompassing computer vision and physiological features could detect driver drowsiness, enhancing system viability for multiple users. TinyML streamlines ML applications for efficient on-device analytics, particularly beneficial for low-energy systems such as sensors and microcontrollers [Ribeiro, 2021]. Consequently, our objective is to enhance system accuracy by integrating a machine learning model using TinyML.

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