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Development of a Driver Drowsiness Detection System Using Infrared, Tilt and Heart Rate Sensors

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Abstract

Driver drowsiness is a major contributor to road accidents, making early detection systems essential for enhancing vehicle safety. This paper presents the design and evaluation of a wearable drowsiness detection prototype integrating an infrared (IR) sensor for eye blink monitoring, an MPU6050 accelerometer for head tilt detection, and a MAX30100 sensor for heart rate and oxygen saturation measurement. Laboratory validation was first carried out using servo motors and oscilloscope readings to simulate eyelid movement and head tilts. The system was then tested in-vehicle under real driving conditions, where real-time monitoring of eye status, head posture, and heart rate was displayed on an LCD with buzzer and LED alerts. Results demonstrated reliable detection of prolonged eye closure, abnormal head tilts, and reduced heart rate, with an estimated overall accuracy of approximately 85%. These findings confirm that combining behavioral and physiological indicators enhances detection robustness compared to single-parameter systems. The prototype demonstrates a low-cost, portable, and non-intrusive solution for drowsiness detection, making it suitable for vehicles lacking advanced driver-assistance systems. Furthermore, the use of easily available components allows for wide applicability and integration into various vehicle types. Future research will focus on refining adaptive thresholds, conducting long-term driving trials, and applying machine learning techniques to further improve detection reliability.

1. Introduction

Driver drowsiness is widely recognized as a major contributor to road accidents worldwide, especially during extended driving and nighttime travel. Fatigue impairs situational awareness, slows reaction time, and reduces decision-making capacity, making drivers more vulnerable to accidents. In Malaysia, fatigue has been identified as a significant factor in highway accidents, highlighting the urgent need for effective detection systems to enhance road safety [1,6]. According to the National Safety Council, drowsy driving can be as dangerous as alcohol-impaired driving, with accident risks increasing significantly after prolonged hours behind the wheel [6].

Modern vehicles increasingly incorporate Advanced Driver Assistance Systems (ADAS), including lane departure warning, adaptive cruise control, and automatic emergency braking [2,4,5]. While these features improve safety, they do not specifically address drowsiness. Higher-end vehicles may integrate eye-tracking and head-position sensors to detect fatigue, but such technologies remain costly and inaccessible in lower-priced cars [3,7–9]. Furthermore, even commercial drowsiness detection systems often face limitations such as false alarms, user discomfort, and poor adaptability to different driver profiles [9].

Recent research demonstrates growing interest in physiological and AI-based drowsiness detection approaches. A systematic review of deep learning techniques revealed that models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can achieve median accuracies and F1-scores exceeding 0.95 under both simulated and real-world driving conditions [10]. Similarly, studies exploiting heart rate variability (HRV) features from wearable sensors have achieved detection accuracies of around 86% with machine learning classifiers. Eye-blink monitoring has also proven effective, with detection accuracies above 90% reported under controlled lighting environments [11]. Broader reviews further highlight that combining physiological and behavioral measures strengthens robustness while maintaining affordability [12,13]. These insights suggest that hybrid systems, which combine affordable physiological sensors with intelligent algorithms, may offer the most practical pathway for widespread adoption in future vehicles.

Motivated by these findings, this research develops a prototype-level driver drowsiness detection system that integrates low-cost sensors for monitoring blink duration, head movement, and heart rate. The objective is to design a practical, accessible solution for everyday vehicles, evaluated under simulated driving conditions as proof-of-concept for future real-world applications.

2. Methodology

This part explains the methodology used to design and implement the driver drowsiness detection system. The development process includes system design, sensor integration, and algorithm development for real-time monitoring. Key components include sensors for heart rate, eye blink detection, and head position, all of which provide input data to the microcontroller for processing. The methodology also covers the testing procedures used to evaluate system performance under various simulated drowsiness conditions.

The algorithm continuously monitors three physiological parameters, which are heart rate, eye blink patterns, and head position, to detect early signs of driver drowsiness. Heart rate serves as a vital indicator, with normal resting values ranging between 60 and 100 beats per minute. During driving, heart rate tends to rise due to physical and cognitive engagement. However, a noticeable drop, such as from 89.8 to 81.5 beats per minute, can signal declining alertness and the onset of fatigue. These measurable variations provide a reliable basis for assessing drowsiness and triggering appropriate warnings to alert the driver.

In addition to heart rate, the system monitors eye blink activity by evaluating both blink duration and frequency. Blinks lasting longer than 500 milliseconds or occurring at a rate below 10 blinks per minute are considered signs of microsleep, which can significantly impair driving performance. Head position is another critical factor, with tilts exceeding 15 degrees forward or sideways for more than 3 seconds flagged as abnormal behavior. These combined indicators enable the system to detect drowsiness with greater accuracy and issue timely alerts to prevent potential accidents.

Table 1 summarizing the thresholds for each sensor used in the drowsiness detection system. These values are typically set based on initial calibration, experimentation, and literature review related to physiological norms.

Table 1 *Thresholds for each sensor*

Sensor	Parameter Measured	Threshold Value	Description
IR Sensor (Eye Blink)	Eye Close Duration	> 2 seconds	If the driver's eyes are closed for more than 2 seconds, it indicates drowsiness.
MPU6050 (Tilt Sensor)	Head Tilt Angle	> ±15 degree from vertical	If the driver's head tilts beyond 15°, it may suggest nodding off
MAX30100 (Heart Rate Monitor)	Heart Rate	< 75.9 BPM	A heart rate below 75.9 BPM could suggest drowsiness or fatigue.

Fig. 1 shows the block diagram of a drowsiness detection system powered by a 3.7V LiPo battery. The battery is connected to a charging module and a switch, which then supplies power through a boost converter to the Arduino Nano. Arduino Nano acts as the main controller and receives input from three sensors which are the IR sensor, MPU6050, and MAX30100. It controls the output components such as a buzzer, LED, and LCD to respond based on the sensor input.

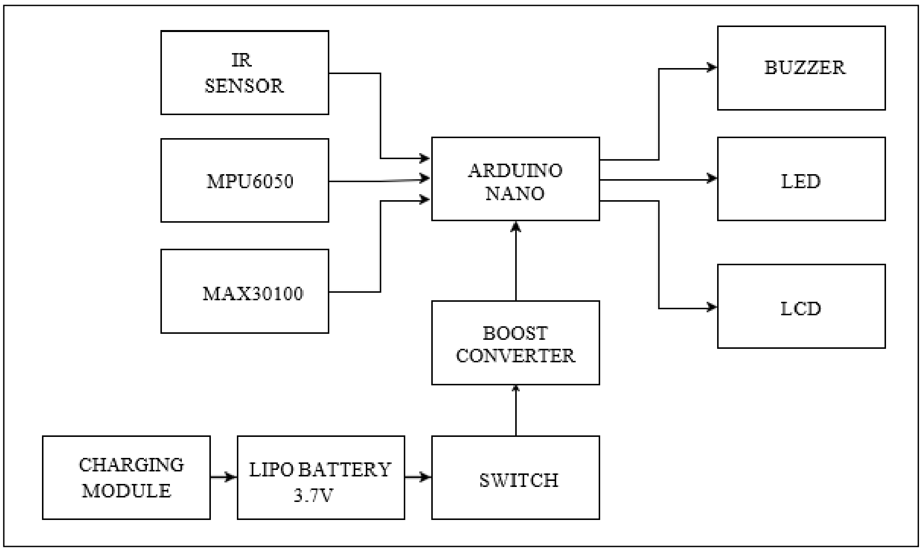

Fig. 1 *Block diagram for the system*

Fig. 2 illustrates the flowchart of the driver drowsiness detection system. The process starts with the initialization of sensors including the infrared, tilt, and heart rate sensors. The system continuously reads input from each sensor and checks for signs of drowsiness. It evaluates whether the eye remains closed for too long, the head is tilted beyond a normal angle, or the heart rate drops below a set threshold. If any of these conditions are met, the system triggers an alert to notify the driver. The process then repeats in a loop to ensure real-time monitoring.

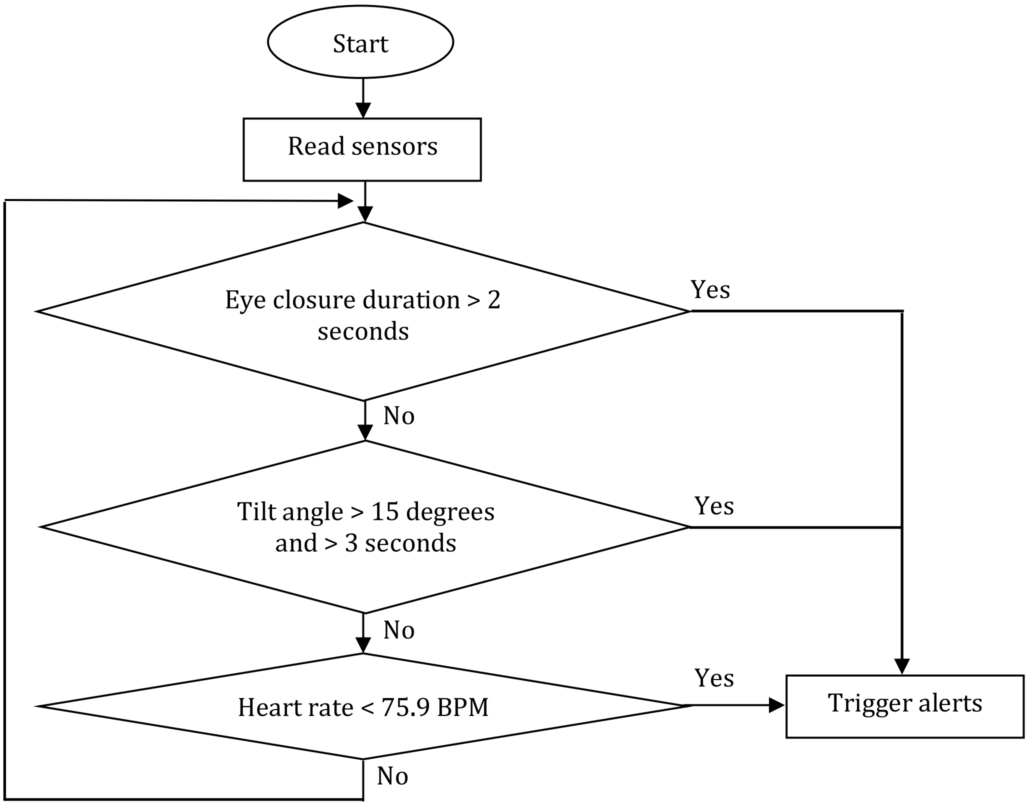

Fig. 2 *Flowchart for all sensors in looping*

Fig. 3 illustrates the flowchart of the driver drowsiness detection system, highlighting the process of monitoring and responding to signs of fatigue. The system collects data from sensors measuring eye blink frequency, head position, and heart rate. This data is analyzed to detect drowsiness, and if identified, the system activates visual and audio alerts to warn the driver. In vehicles like the Perodua Myvi, which feature lane-keeping assist, the system may also engage safety functions to slow down the vehicle or guide it to a safer position, enhancing road safety and preventing fatigue-related accidents.

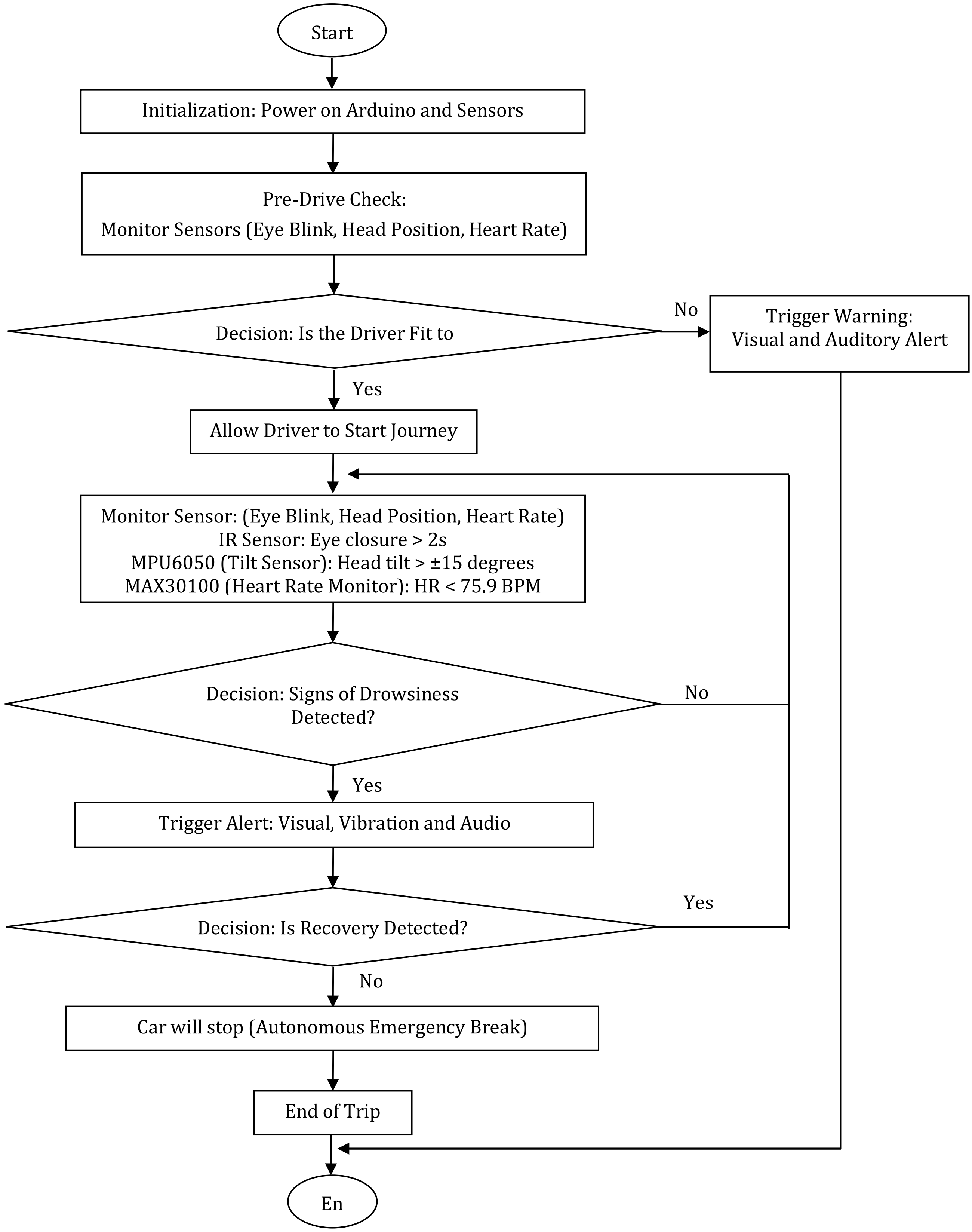

Fig. 3 *Algorithm for the system*

2.1 System Design

The proposed driver drowsiness detection system integrates three types of sensors (infrared (IR), MPU6050 tilt, and MAX30100 heart rate) connected to an Arduino Nano microcontroller. A rechargeable 3.7V Li-Po battery powers the system through a charging module and boost converter. The Arduino processes real-time sensor inputs and activates alert mechanisms, including a buzzer, LED indicator, and LCD display, when drowsiness symptoms are detected.

Fig. 1 presents the block diagram of the system, while Fig. 2 illustrates the overall process flow. The workflow begins with sensor initialization and continuous monitoring of eye blink duration, head tilt angle, and heart rate. Once a parameter exceeds its threshold value, an alert is triggered to warn the driver. The loop then repeats for continuous real-time monitoring.

2.2 Eye Blink Sensor

Fig. 4 illustrates the infrared (IR) sensor mounted on modified sunglasses, which functions as a proximity detector to monitor eyelid movement. By placing the sensor at eye level, the device can track blink duration and frequency without obstructing the user's view. When prolonged eye closure is detected, the IR sensor outputs a signal to the Arduino Nano, which subsequently activates alerts such as a buzzer or LED. This configuration enables non-intrusive monitoring of the driver's visual attention and provides early detection of potential drowsiness.

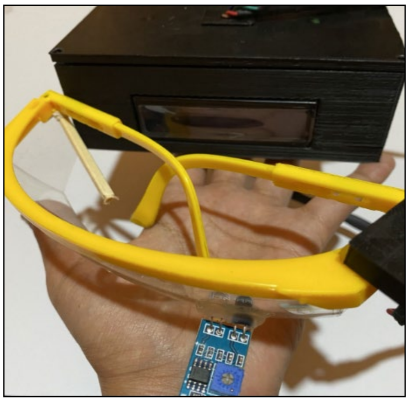

Fig. 4 *IR sensor mounted on sunglasses for proximity detection*

2.3 Tilt Sensor

Fig. 5 shows the tilt detection module, implemented using the MPU6050 accelerometer, attached to laboratory glasses. The sensor measures head movement by detecting changes in acceleration along multiple axes. Head tilts exceeding normal posture may indicate drowsiness, particularly when the driver begins to nod. Data from the MPU6050 are transmitted to the Arduino Nano, which evaluates whether the tilt exceeds the calibrated threshold. If so, alerts such as a buzzer or LED are activated to warn the driver. This design provides lightweight, comfortable, and real-time monitoring of head posture, suitable for extended use.

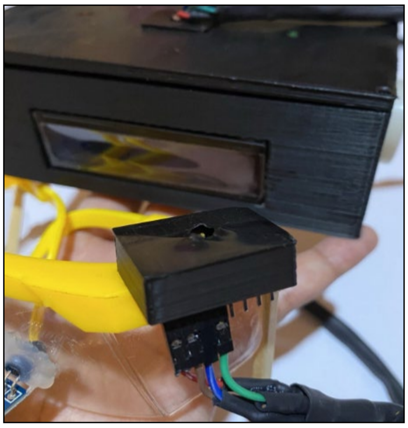

Fig. 5 *Wearable tilt detection module using mpu6050 sensor*

2.4 Heart Rate Monitor

Fig. 6 depicts the MAX30100 heart rate sensor module, which employs infrared and red LEDs along with a photodetector to measure heart rate and blood oxygen levels. In this project, the sensor was placed on the user's fingertip to capture blood volume pulse variations, allowing accurate measurement of heart rate. Within the proposed system, the MAX30100 works in conjunction with the IR and tilt sensors to enhance the overall reliability of drowsiness detection. When the system identifies a reduction in heart rate together with extended eye closure or abnormal head tilt, a stronger warning is issued to alert the driver.

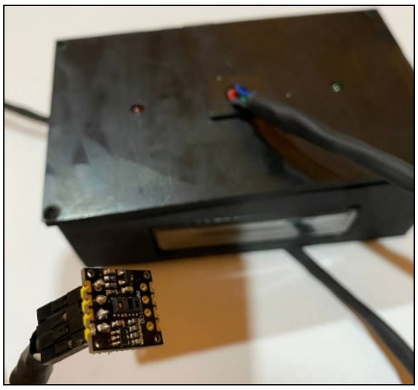

Fig. 6 *Heart rate sensor module using MAX30100*

2.5 Testing Procedure

System validation was conducted in two stages: laboratory testing and in-vehicle trials.

In the laboratory phase, servo motors were used to simulate eyelid movement and head tilts in a controlled setting. The infrared sensor was evaluated using a servo attached to glasses that periodically blocked and unblocked the sensor to replicate blinking. An oscilloscope was used to record voltage variations corresponding to eye open and closed states. For tilt detection, two servo motors were mounted on glasses to simulate forward and sideways head tilts, allowing evaluation of accelerometer sensitivity to abnormal postures.

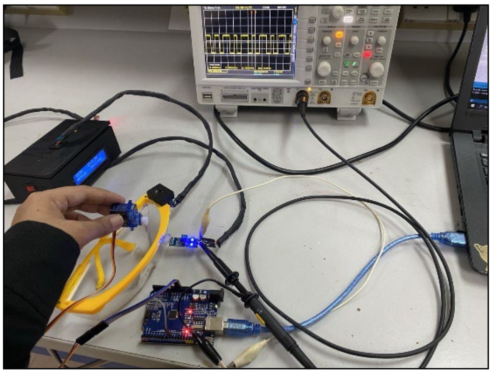

Fig. 7 *Laboratory setup for simulating eyelid movement using a servo motor and IR sensor*

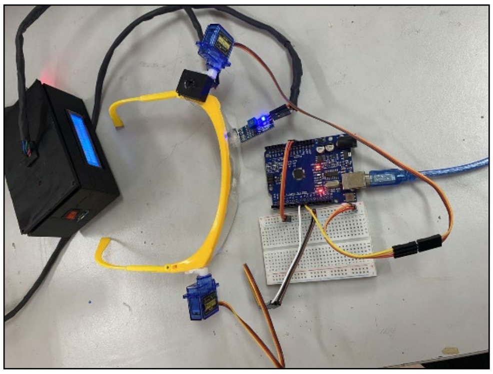

Fig. 8 *Laboratory setup for simulating head tilts using servo motors and MPU6050 sensor*

In the in-vehicle phase, the prototype was tested with a driver wearing modified glasses during short driving sessions. Real-time data from the IR sensor, tilt sensor, and heart rate sensor were monitored via the Arduino Nano and displayed on the LCD. Alerts were triggered when thresholds were exceeded, and both buzzer and LED indicators were observed for system response.

3. Calibration and Thresholds

To ensure reliable detection, the system was calibrated, and threshold values were determined with reference to existing literature as well as initial trials carried out during the project. For eye blink monitoring, an eye closure period longer than two seconds was considered an indicator of drowsiness, consistent with previous studies on blink-based fatigue detection [12]. Head tilt measurements were evaluated using the accelerometer, and tilts greater than ±15° from the vertical position sustained for more than three seconds were interpreted as abnormal posture related to drowsiness [13]. For heart rate monitoring, readings obtained from the fingertip using the MAX30100 sensor were analyzed, and values falling below 75 beats per minute (BPM) were associated with

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reduced alertness, as supported by prior research on HRV-based drowsiness detection [10]. These thresholds were carefully selected to balance sensitivity and specificity, ensuring that alerts were generated only when multiple symptoms of fatigue were observed simultaneously.

4. Results and Discussion

The prototype system was evaluated under simulated conditions to verify its ability to detect drowsiness through multiple behavioral and physiological indicators. The infrared sensor distinguished between normal blinking and prolonged eyelid closure, while the tilt sensor successfully detected abnormal head posture during simulated nodding movements. The heart rate module provided reliable readings when placed on the fingertip, with lower values associated with reduced alertness.

Fig. 9 illustrates the system in an active monitoring state, while Fig. 10 presents a warning condition where abnormal head tilt is detected. These results demonstrate that the system can capture early fatigue indicators before full drowsiness occurs.

Fig. 9 *Drowsiness detection system in an active monitoring state showing upright head posture, open eyes, normal heart rate (82 BPM), and oxygen saturation (95% SpO_2)*

Fig. 10 *System in a warning state, detecting abnormal head tilt while eyes remain open. The red LED indicates an alert for early fatigue symptoms*

4.1 In-Vehicle Results

The system was tested in a vehicle under real driving conditions. Fig. 11 shows the driver wearing the prototype, while Fig. 12 illustrates the LCD output during operation. The system displayed parameters such as eye status, head tilt, heart rate, and oxygen saturation in real time. In addition, the hardware module was positioned near the driver's hand for easy access and visibility during driving, as shown in Fig. 13.

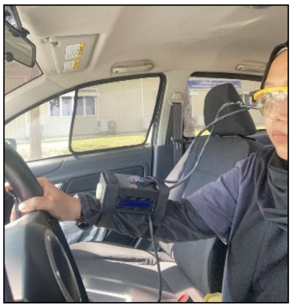

Fig. 11 *In-vehicle testing of the drowsiness detection system during driving*

Fig. 12 *Real-time display of head status, eye status, heart rate, and SpO_2 during in-vehicle testing*

Fig. 13 *Placement of the project hardware near the driver's hand to ensure accessibility and real-time monitoring during driving trials*

During testing, the system successfully distinguished between alert and fatigued states. Upright head posture, open eyes, and heart rates of ~82 BPM reflected alert conditions, while extended eye closure (>2 s), head tilts beyond ±15°, and reduced heart rate (<75 BPM) triggered LED and buzzer alerts. Occasional false alerts were noted during sudden, non-fatigue-related head movements, highlighting a need for adaptive thresholds.

By integrating physiological (heart rate, SpO_2) and behavioral (blink, head posture) measures, the system demonstrated higher robustness compared to single-parameter detection. Overall, the prototype achieved an estimated accuracy of ~85%, confirming its effectiveness as a low-cost driver assistance tool.

4.2 Laboratory Results

Blink duration and frequency analysis further confirmed the system's effectiveness. Short blink periods (100–300 ms) correlated with alert states, whereas longer periods (≥800 ms) indicated fatigue or microsleep onset. Fig.s 14–16 illustrate these patterns, while Table 2 summarizes the quantitative relationship between blink frequency and user condition.

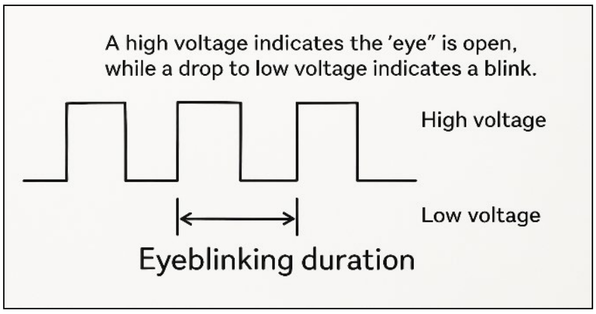

Fig. 14 *Measurement of blink duration, measuring the time for a full blink, including eyelid closing and reopening*

The laboratory experiments confirmed that the sensors responded accurately under controlled conditions. The infrared sensor reliably detected blink patterns, with oscilloscope readings distinguishing between open-eye (high voltage) and blink (low voltage) states. The tilt sensor successfully captured head orientation changes, validating its ability to detect posture shifts associated with drowsiness.

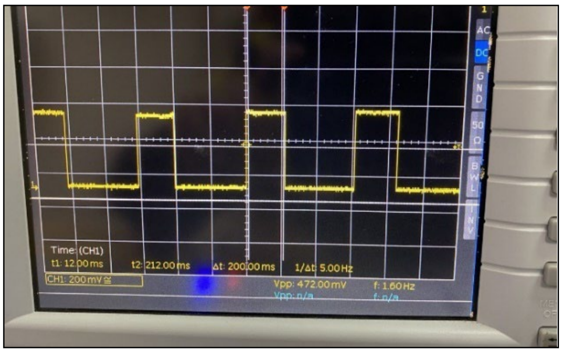

Fig. 15 *Osciloscope output for blinking signal at 200 ms (5.0 Hz), typical of an alert state*

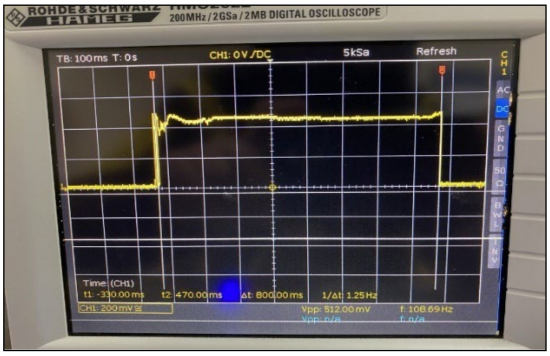

Fig. 16 *Osciloscope output for blinking signal at 800 ms (1.25 Hz), corresponding to fatigue or microsleep onset*

Table 2 presents the relationship between blink period, blink frequency, sensor voltage, and the user's alertness level. Blink frequency is calculated using the formula: Blink Frequency (Hz) = 1000 divided by Blink Period (ms). The infrared sensor outputs a high voltage when the eye is open and a low voltage during a blink. By monitoring these voltage changes and applying the formula, the system can estimate blink rate and eye closure duration to assess the user's level of alertness.

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$$\text{Blink Frequency (Hz)} = \frac{1000}{\text{Blink Period(ms)}}$$

At high blink frequencies, such as 10Hz at a 100ms blink period, the user is likely alert and active. When the blink period increases to 500ms, the frequency drops to 2Hz, suggesting early signs of drowsiness. A blink period of 1000ms results in a frequency of 1Hz, which may indicate microsleep or fatigue. These measured values allow the system to detect changes in driver alertness and issue early warnings to improve safety.

Table 2 *Relationship between blink period, frequency, and interpretation of alertness levels*

Test No.	Blink Period (ms)	Blink Frequency (Hz)	Voltage High (V)	Voltage Low (V)	Interpretation	Possible Condition
1	100	10.0	4.96	0	Very frequent blinking	Alert / Active
2	200	5.0	4.96	0	Normal blinking rate	Normal / Awake
3	300	3.3	4.96	0	Slightly reduced blink rate	Mild fatigue
4	400	2.5	4.96	0	Blinking slows down	Early drowsiness signs
5	500	2.0	4.96	0	Moderate blink delay	Drowsy
6	600	1.67	4.96	0	Long eye closure	Drowsy / Micro-sleep risk
7	700	1.43	4.96	0	Eyes closed longer	High drowsiness risk
8	800	1.25	4.96	0	Eyes mostly closed	Very drowsy
9	900	1.11	4.96	0	Micro-sleep detection range	Dangerously drowsy
10	1000	1.0	4.96	0	Prolonged eye closure	Micro-sleep / Sleep onset

The drowsiness detection system effectively integrates multiple physiological and behavioral indicators to assess driver alertness. By monitoring parameters such as head position, eye status, heart rate, and blood oxygen saturation, the system provides a comprehensive assessment of fatigue levels. When the user is alert, these parameters remain within normal thresholds, reflecting stable posture, regular blink activity, and consistent heart function. Early signs of fatigue are detected when irregularities such as head tilting, slower blinking, or reduced heart rate are observed, allowing the system to generate timely alerts.

The results demonstrated that the system is effectively distinguished between alert and fatigued states. Short blink durations (~200ms) and stable head posture corresponded to alert conditions, while extended eye closure (~800ms) and abnormal tilts were associated with drowsiness. Heart rate readings from the fingertip sensor further supported these findings, with reductions below 75 BPM correlating with lower alertness.

The system demonstrated high sensitivity in detecting prolonged eye closure and abnormal head tilts, successfully identifying early signs of drowsiness. However, occasional false alerts were observed, particularly during sudden head movements not related to fatigue. These findings highlight the balance between achieving high sensitivity while minimizing false positives to ensure reliable driver assistance.

5. Conclusion

This study developed and evaluated a wearable driver drowsiness detection system that integrates an IR sensor, MPU6050 accelerometer, and MAX30100 heart rate sensor. Laboratory testing confirmed accurate detection of blink patterns and head tilt simulation, while in-vehicle trials validated system performance under real driving conditions.

The results highlight the system's potential as a low-cost and accessible alternative to camera-based and deep learning approaches, which often require higher computational resources. Nonetheless, the study was limited by short-duration trials and controlled test environments. Future work will focus on extended real-world validation, improved calibration methods, and the application of machine learning algorithms for adaptive thresholding to enhance accuracy and reduce false detections. While the prototype achieved an estimated accuracy of 85% and demonstrated high sensitivity to drowsiness indicators, occasional false detections occurred, primarily due to abrupt driver movements. Addressing this limitation through improved adaptive algorithms and machine learning integration will be essential to further enhance reliability in future versions.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design****: Aida Farzana Mohd Faizal, Rahmat Talib;* ***data collection****: Aida Farzana Mohd Faizal;* ***analysis and interpretation of results****: Aida Farzana Mohd Faizal, Rahmat Talib;* ***draft manuscript preparation****: Aida Farzana Mohd Faizal. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Malaysian Road Safety Research Association. (2021). Road Traffic Accidents and Fatigue in Malaysia.

[2] Singh, J., Kanojia, R., Singh, R., Bansal, R., & Bansal, S. (2022). Driver drowsiness detection system – An approach by machine learning application. *PNR (Proceedings of National Conference on Research)*, 13(S10), 361.

[3] Perodua Myvi Official Website. (2022). Lane Departure Warning System.

[5] Advanced Driver Assistance Systems: Current Trends and Technologies. (2023). Journal of Automotive Engineering.

[6] National Safety Council. (2023). Advanced Driver Assistance Systems (ADAS) Impact on Road Safety.

[7] National Safety Council. (2023). Road Safety and Drowsy Driving: Causes and Solutions.

[8] The American Automobile Association. (2022). Vehicle Safety Technologies and Their Impact on Road Accidents.

[9] Carsten, O., & Fildes, B. (2021). Drowsiness Detection Systems: Current Commercial Systems and Future Directions. Road Safety Review Journal.

[10] Iskandar, A., et al. (2025). Drowsiness detection in drivers: A systematic review of deep learning-based approaches. *Applied Sciences*, 15(16), 9018.

[11] Patel, M., & Lal, S. K. L. (2016). Real-time drowsiness detection using eye blink monitoring. In *Proceedings of the International Conference on Communication and Signal Processing (ICCSP)*.

[12] Sahayadhas, A., Sundaraj, K., & Murugappan, M. (2022). A review of recent developments in driver drowsiness detection. *Frontiers in Neuroscience*, 16, 891489.

[13] Khan, S., et al. (2023). A systematic review of physiological signals-based driver drowsiness detection. *Sensors*, 23(5), 2457.