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A hybrid physiological-visual approach for real-time driver drowsiness detection: Design and experimental validation

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Abstract

Drowsy driving remains a significant contributor to traffic accidents in Indonesia, where most incidents are attributable to human error. With advances in vehicle technologies, opportunities arise to enhance road safety through real-time driver monitoring systems. This study proposes the development of a drowsiness detection device that uses a hybrid measurement method integrating physiological and visual indicators. The system incorporates the MAX30102 sensor for heart-rate monitoring and a camera-based visual analysis that employs Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to detect signs of drowsiness. The system is programmed using Python and C++. A series of experimental evaluations was conducted, including sensor performance testing; comparative analysis of the MAX30102 and a medical-grade oximeter; accuracy evaluation of EAR and MAR; impact of distance variation on detection latency; angular variation (yaw, pitch, roll); and the effect of light intensity on detection reliability. The experimental results demonstrate a detection success rate of 90%, indicating the system's potential for reliable real-time application. Future work will focus on improving system accuracy, such as nighttime driving and inclement weather, and validating the system's effectiveness in real-world driving scenarios.

Keywords

Driver drowsiness detection, Real-time, EAR-MAR, Hybrid, Physiological-visual

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Introduction

Research in drowsiness detection has been extensively studied using various methods. Previous studies have developed applications for motor vehicles that use heart rate sensors on smartwatches, achieving an accuracy of 86.3% [1]. Additionally, another study employed a drowsiness detection system using the Eye Aspect Ratio (EAR) method [2]. This drowsiness detection system uses a camera as its image sensor and facial-landmark technology based on the Eye Aspect Ratio (EAR) method [3]. The system uses a camera or webcam to monitor the eye area, and the Raspberry Pi processes the data. If the driver is detected to close their eyes with an EAR value <0.25 for 5 seconds, the Raspberry Pi will activate an alarm to indicate drowsiness [2].

Furthermore, in another study, a drowsiness detection system using the Mouth Aspect Ratio (MAR) method was employed [4]. The system operates by monitoring the mouth area via a camera. If the MAR value > 0.43 for 5 seconds, the system detects driver fatigue due to yawning [5]. Research on driver fatigue detection can be classified into two categories: Passive Driver Monitoring Systems and Active Driver Fatigue Control Systems [6]. Active systems are considered more effective for early detection [7]. One promising approach to detecting driver fatigue is the hybrid measurement method, which combines physiological and behavioral measures [8]. In this study, researchers developed a drowsiness detection device using a hybrid measurement method that combines heart-rate monitoring with visual analysis, such as Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) [2]. This wireless device is expected to enhance driver comfort without compromising effectiveness. The device will provide alerts via sound and Telegram notifications to inform drivers of detected drowsiness.

Method

This study employs a hybrid detection method combining physiological and visual parameters to monitor driver drowsiness. The system integrates heart-rate measurement via a biosensor with facial-feature analysis via camera-based EAR and MAR calculations. Hardware components are programmed in Python and C++. The methodology includes sensor validation, system responsiveness, and environmental testing to ensure accuracy and reliability in a real-time application.

Methods heart rate measurement

The first method the system employs to detect drowsiness is heart-rate measurement using the MAX30102 sensor. In this method, the normal heart rate threshold for adults is set at 80 BPM. If the threshold is below 80 BPM, the system will detect driver fatigue. This heart rate threshold is derived from data from the American Heart Association (AHA) [9].

Methods eye aspect ratio

Eye Aspect Ratio (EAR) is a scalar measure that quantifies changes in the opening and closing of the eyes, particularly during blinking [10]. During blinking, the EAR value can increase sharply or decrease drastically. The central system for detecting drowsiness requires the identification of eye blinks. Eye blinks captured by a computer webcam can be detected by computing the EAR using OpenCV and the Mediapipe Face Mesh prediction, which is based on a previously trained artificial neural network [2]. The EAR value can be determined by inputting six coordinates around the eyes, as illustrated in Figure 1, along with Equations (1) and (2) [11]:

$$EAR = \frac{|p2 - p6| + |p3 - p5|}{2|p1 - p4|} \quad (1)$$

$$Avg\ EAR = \frac{1}{2}(EAR\ Left + EAR\ Right)\ (2)$$

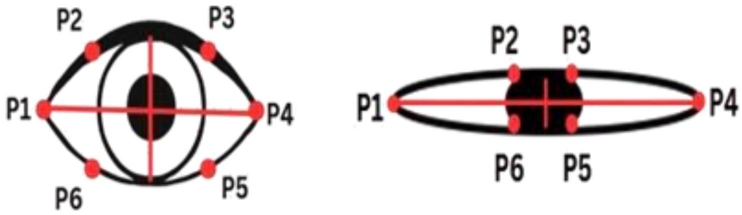

Figure 1. Illustration of opening and closing the eyes using facial landmarks [1]

The Eye Aspect Ratio (EAR) is formulated in Equation (1), where P1 through P6 denote the coordinates of two-dimensional landmarks around the eye region. Specifically, points P2, P3, P5, and P6 are employed to calculate the vertical eye height, while points P1 and P4 are utilized to determine the horizontal eye span. This configuration is illustrated in Figure 1. When the eyes are closed, the EAR value sharply decreases toward zero, whereas it remains relatively stable when the eyes are open.

Methods mouth aspect ratio

The Mouth Aspect Ratio (MAR) is calculated as the vertical mouth opening divided by the horizontal mouth width. Three vertical and one horizontal measurement are considered in this estimation. During a yawning event, the vertical distances tend to increase significantly, while the horizontal distance exhibits a slight decrease. A MAR value exceeding 0.43 indicates yawning behavior for accurate detection, whereas values below this threshold are disregarded [5].

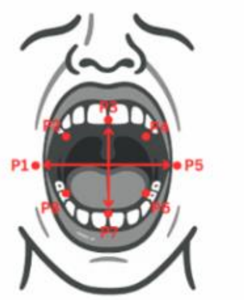

Figure 2. Landmark points in the mouth area [2]

From Figure 2, we can calculate the Mouth Aspect Ratio using the following formula.

$$CapMAR = \frac{|p2 - p8| + |p3 - p7| + |p4 - p6|}{3|p1 - p5|}\ (3)$$

This formula considers three points on the mouth for enhanced precision. As observed, when the mouth is open, the distances between the points (p2 and p8), (p3 and p7), and (p4 and p6) are considered. An increase in the distance between these points results in a higher MAR ratio. If this ratio exceeds the threshold of 0.43, the system will notify the driver and recommend taking a break.

Heart rate monitor device

The heart rate monitor circuit diagram for detecting driver fatigue, shown below, was created using Fritzing. Fritzing is open-source software for making electronic circuit diagrams, often used for circuit prototyping and design [12]. Here are the details of the components and their connections, including microcontrollers, sensors, and other electronic components shown in Figure 3.

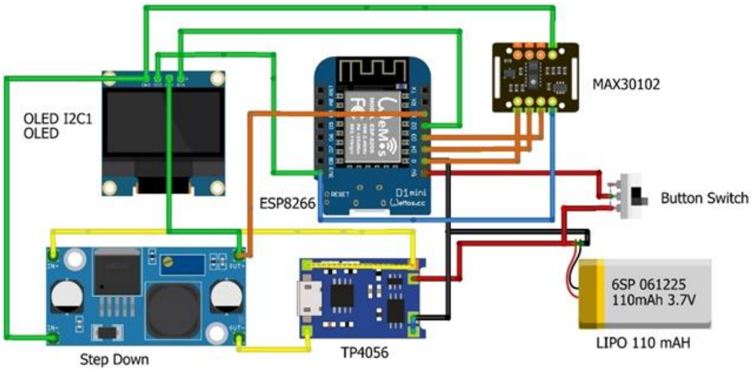

Figure 3. Schematic Design of Heartbeat [3]

The circuit diagram above illustrates the configuration of a heart-rate monitoring system using the ESP8266 (WeMos D1 Mini) microcontroller as the central unit. The system integrates multiple components, including the MAX30102 heart rate sensor, an I2C OLED display for visual feedback, a button switch for manual control, and a 110 mAh LiPo battery as the power source. Power management is handled by a TP4056 module for battery charging and protection, and a step-down voltage regulator is used to ensure a stable input voltage to the microcontroller and peripherals.

Eye and mouth ratio monitoring device

Figure 4 shows the circuit setup for a driver drowsiness detection system using Raspberry Pi. It connects the GPS BN-220 module, camera, and speaker to the Raspberry Pi 4 Model B, enabling location tracking, visual data capture, and real-time alerts.

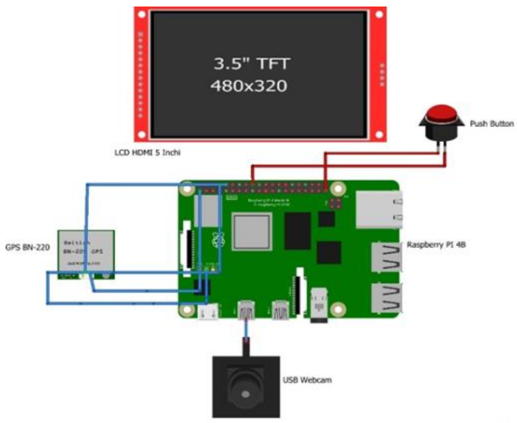

Figure 4. Schematic design of the detection of EAR and MAR [4]

Raspberry Pi 4 Model B. The GPS module is connected via the GPIO pins, and the dedicated camera interface connects to the camera. Additionally, a speaker is connected to provide audio feedback or alerts. This configuration allows the system to monitor the driver's location, capture visual data, and provide real-time alerts.

Block diagram

The developed fatigue and microsleep detection system integrates multiple hardware components into a cohesive architecture, as illustrated in the system block diagram presents in Figure 5. The MAX30102 heart rate sensor, powered by a 3.7V Li-Po battery and interfaced through a Wemos D1 Mini microcontroller, captures real-time heart rate data and displays it via an OLED module. This data is transmitted to a central processing unit, the Raspberry Pi, which also receives visual input from a USB camera for facial monitoring. When the heart rate drops below a predefined threshold (e.g., 60 BPM), an auditory alert is triggered, and facial analysis is activated to assess indicators of drowsiness, such as microsleep (via Eye Aspect Ratio, EAR) and yawning (via Mouth Aspect Ratio, MAR).

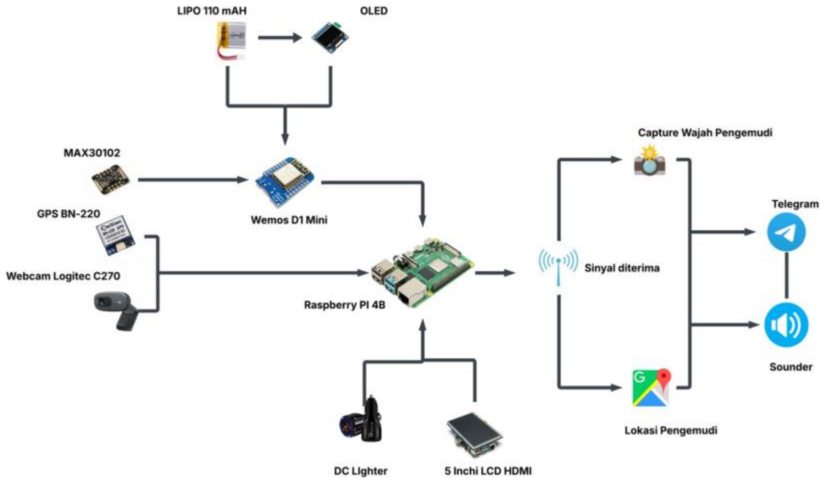

Figure 5. Block diagram of drowsiness detection [5]

Results and Discussion

Heart rate bracelet performance testing

The device was tested to verify its functionality, ensuring that all components were operating properly before conducting complete tests to minimize errors. Ten participants, four men and one woman, aged 21 to 25, were tested on various elements, including Sound and Telegram.

Table 1. HR monitor performance test result [6]

Age	Gender	Bpm	Equipment Perform Test	
			Sound	Telegram
22	Man	81	Yes	Yes
23	Man	93	Yes	Yes
25	Man	85	No	No
22	Man	79	Yes	Yes
21	Women	77	Yes	Yes

Based on the data in Table 1, male participants' heart rates ranged from 70to 75 bpm, whereas female participants ranged from 63 to 72 bpm, with men generally showing slightly higher heart rates. Most participants successfully passed all tests, indicating that the device works well for most users. However, one participant (a 7-year-old female) failed the Telegram test due to specific connectivity issues; the other participants completed all tests, demonstrating the device's overall effectiveness.

The device developed in this study offers several advantages over prior studies, particularly with respect to reliability and functionality. Unlike previous studies that focused primarily on heart rate monitoring without accounting for connectivity issues [14], this device integrates a Telegram-based warning system that provides real-time notifications when drowsiness is detected. Additionally, this study evaluates a broader range of components, including voice and connection, providing a more comprehensive performance assessment. Network instability issues often affect the accuracy of drowsiness detection. The device integrates a more reliable connectivity solution to address this issue, ensuring optimal functionality even under unstable network conditions and providing consistent alerts, unlike many previous studies that overlooked the importance of connectivity testing.

Comparison test of MAX30102 sensor with oximeter

Heart rate device testing at this stage is conducted to determine the accuracy of the heart rate threshold. First, the MAX30102 sensor's accuracy is assessed by comparing the results obtained with the oximeter. In the second test, the device's error value is determined. The error formula is as follows:

$$\%error = \left(\frac{max\,30102\ value - oxymeter\ value}{oxymeter\ value} \right) \times 100\% \quad (4)$$

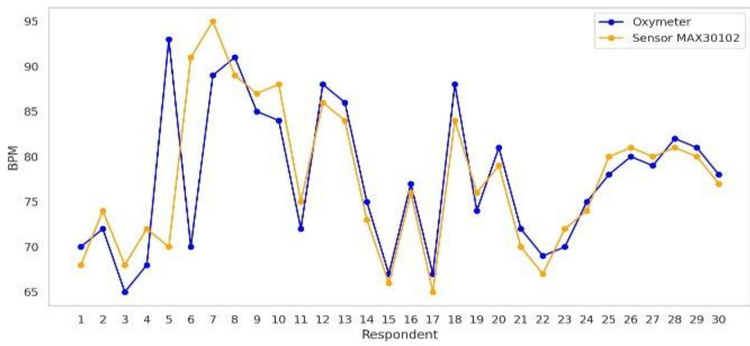

Figure 6. Test Result Comparison MAX30102 with Oximeter [7]

Based on Figure 6, a comparison of heart rate measurements between the Oximeter and the MAX30102 Sensor in 30 respondents, both devices exhibit similar trends. The BPM values from both devices tend to fluctuate in tandem, indicating that the MAX30102 sensor can track heart rate dynamics measured by the Oximeter. The fluctuations in the data may be attributed to several factors, including finger position during measurement, hand stability, ambient light, and device sensitivity. Overall, the graph indicates that the MAX30102 Sensor performs adequately in measuring heart rate, although further calibration and testing are still required to ensure data consistency and accuracy under field condition.

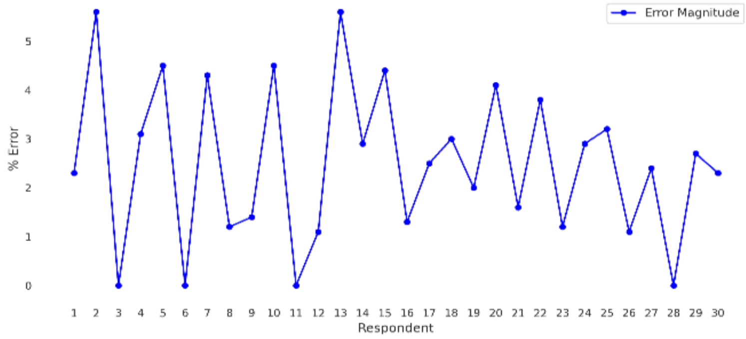

Figure 7. MAX30102 Sensor Test Error Value Graph [8]

Based on the test results shown in Figure 7, the MAX30102 sensor-based heart rate monitor demonstrated relatively high accuracy. This is evident in an average error of 2.40%, with a range of 0% to 5.74%. Most data show an error percentage below 4%, indicating good consistency in heart rate measurement. As a result, this device can be relied upon for heart rate monitoring, notably to support fatigue detection and the early signs of microsleep.

Performance testing of EAR and MAR devices

Testing was conducted to evaluate the device's performance using 10 subjects. This test was conducted to assess the performance of a driver drowsiness detection system based on the eye and mouth aspect ratios.

Table 2. Performance Test Result EAR and MAR [9]

No	Detection		Output	
	EAR	MAR	EAR	MAR
1.	Yes	Yes	Yes	Yes
2.	Yes	Yes	Yes	Yes
3.	Yes	Yes	Yes	Yes
4.	No	No	No	No
5.	Yes	Yes	Yes	Yes

Table 2 presents the performance of the drowsiness detection system using the EAR and MAR features. From 5 trials, the system successfully detected and produced outputs in 4 cases (90% accuracy). Only one test (No. 4) failed to detect and output results, likely due to poor visibility of facial landmarks or insufficient threshold sensitivity.

This result indicates the system's high reliability in identifying drowsiness through dual-parameter analysis. The consistent match between detection and output also reflects a well-integrated processing system. However, one failed case highlights the need for further refinement to improve performance under various real-world conditions.

Testing the effect of distance on the detection speed of the system

The effect of distance on the camera system's detection speed was evaluated to determine the optimal distance for effective detection of driver drowsiness. By varying the distance, the study aimed to assess how the camera's performance and detection speed change. This analysis is crucial for optimizing the system for real-time vehicle applications, ensuring timely alerts to drivers before fatigue leads to unsafe driving. The results could enhance the effectiveness of drowsiness detection systems in preventing fatigue-related accidents.

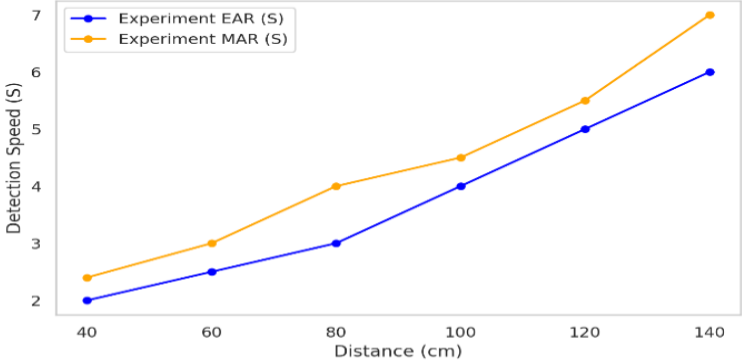

Figure 8. Test Result of the Effect of Distance on the Speed of the System [10]

Based on the test results in Figure 8, the drowsiness detection time (detection speed) increased with increasing distance between the sensor and the object, across both the EAR and MAR parameters. At 40 cm, the average detection time was approximately 2–2.4 seconds for EAR and 2.4–2.5 seconds for MAR, whereas at 140 cm it increased to 6–7 seconds. This indicates that distance significantly influences system performance, with slower detection at longer distances. Additionally, the experimental results shown in Figure 8 indicate that detection using MAR takes slightly longer than EAR at the same distance. The tested system is also equipped with a real-time warning mechanism that includes an audio alarm and notifications via a messaging app (e.g., Telegram), enabling prompt responses when drowsiness is detected and with relatively fast and consistent detection times.

Testing the effect of driver yaw, pitch, and roll angles on system detection capabilities and speed

In this subsection, tests were conducted to analyze the effect of the driver's yaw, pitch, and roll angles on the system's detection capability and speed. These rotation angles describe the driver's head motion, which can affect the system's ability to detect signs of drowsiness or fatigue. Yaw refers to the rotation of the head to the left or right, pitch describes the up-down movement of the head, while roll indicates the rotation of the head along the horizontal axis. By analyzing the effects of changes in these angles, this study aims to determine how head movements affect the system's detection response to the driver's condition.

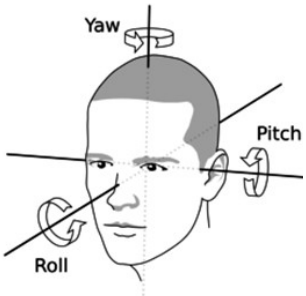

Figure 9. The yaw, pitch, and roll angles in the human head motion [14] [11]

However, large head angles introduce distortion and pose-related challenges in real-time face tracking, thereby reducing the effectiveness of the drowsiness detection camera system. Additionally, the optimal angle limits for yaw, pitch, and roll in a drowsiness-detection camera system are examined in this driving simulation study, where extreme head orientations can affect driver response time and the validity of drowsiness-detection data (Figure 9). Therefore, in developing this camera-based drowsiness detection system, tests were conducted to assess the effects of pitch, yaw, and roll angles on detection performance, to identify the optimal camera angles to improve detection speed.

Table 3. Test result of the effect of large yaw, pitch, and roll angles on system speed in detection [13]

No	Angle (°)	Yaw (S)	Pitch (S)	Roll (S)
1	0	1.5	1	1.25
	10	2.5	2	3
	20	3	3.5	-
	30	4	-	-
2	0	1.5	1.25	2
	10	2.25	1.5	3
	20	3.5	3	-
	30	4.5	-	-
3	0	1.25	1.5	1.75
	10	2.25	2.25	3.5
	20	3.5	3.25	-
	30	4.5	-	-
4	0	1.5	1	2
	10	2	2	3.5
	20	3	3.5	-
	30	4	-	-

As shown in Table 3, increases in yaw, pitch, and roll angles significantly increase the detection time of the drowsiness detection camera system. At small angles (0°–10°), detection time is relatively short, ranging from 1 to 2.5 seconds across all parameters. However, as the angle increases to 20° and 30°, the detection time rises sharply, and in some cases, the system fails to detect (indicated by a '-'). This pattern is consistent across all three experiments conducted.

This phenomenon indicates that extreme changes in the driver's head orientation (large angles) cause the camera system to struggle to accurately recognize facial features, slowing down or even failing the drowsiness detection process. This aligns with other studies that highlight the importance of accurate estimation of yaw, pitch, and roll angles in IMU- and camera-based systems. Thus, this Table confirms that large head orientation angles pose a significant challenge for drowsiness detection camera systems, both in terms of detection speed and reliability, necessitating the development of compensation methods or algorithm adaptations to improve system performance under extreme conditions.

Conclusion

In conclusion, this study successfully designed and validated a hybrid driver drowsiness detection system that integrates physiological (heart rate via MAX30102 sensor) and visual (EAR and MAR-based facial analysis) approaches. Experimental results demonstrated a high detection accuracy of 90%, with real- time alerts triggered by abnormal heart rates (<80 BPM), prolonged eye closure (EAR <0.25), or yawning (MAR >0.43). The system's robustness was confirmed through rigorous testing under variable conditions, including distance, head angles (yaw/pitch/roll), and light intensity (10–2000 Lux), although challenges were noted at extreme angles (>30°) and in low-light environments (<50 Lux).

These findings align with the research objectives by offering a practical solution to reduce drowsiness-related accidents, supported by quantitative validation. Future work should focus on: (1) optimizing performance in dynamic environments (e.g., nighttime or adverse weather), (2) integrating machine learning to reduce false alarms, and (3) large-scale real-world trials. This technology holds significant potential for deployment in commercial vehicles, thereby enhancing road safety.

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