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(IJIREV)**www.gaexcellence.com/ijirev**A SOLAR-POWERED CONTEXT-AWARE WEARABLE IOT
SYSTEM FOR REAL-TIME MICROSLEEP DETECTION**Wan Suhaifiza W Ibrahim^{1*}, Zahari Abu Bakar², Zakariah Yusuf³, Nur Iqtiyani Ilham⁴¹Faculty of Electrical Engineering, Universiti Teknologi MARA, Johor Branch, Pasir Gudang Campus wsuhaifiza@uitm.edu.my <https://orcid.org/0009-0003-7971-9498>²Faculty of Electrical Engineering, Universiti Teknologi MARA, Johor Branch, Pasir Gudang Campus zahar311@uitm.edu.my <https://orcid.org/0009-0008-9301-0078>³Faculty of Electrical Engineering, Universiti Teknologi MARA, Johor Branch, Pasir Gudang Campus zakariah Yusuf@uitm.edu.my <https://orcid.org/0000-0001-5647-8474>⁴Faculty of Electrical Engineering, Universiti Teknologi MARA, Johor Branch, Pasir Gudang Campus iqtiyani9089@uitm.edu.my <https://orcid.org/0000-0003-2539-5080>

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Abstract:

Microsleep episodes, characterised by brief involuntary lapses in consciousness, pose significant risks in safety-critical activities such as driving and industrial operations. Existing microsleep detection systems primarily rely on camera-based vision techniques or electroencephalography (EEG), which often require computationally intensive processing, continuous and unobstructed visual monitoring, or cumbersome electrode placement, thereby limiting their practicality for continuous, long-term wearable applications. This study proposes a solar-powered, context-aware wearable microsleep detection system that integrates lightweight sensor fusion and IoT connectivity for real-time monitoring and multimodal alerting. The proposed system combines infrared-based eye-closure detection, accelerometer-based head-motion analysis, and ambient-light sensing through a brightness-adaptive decision algorithm executed on an ESP32 microcontroller. Sensor data are processed locally to trigger visual, auditory, and vibration alerts and transmit notifications to the Blynk IoT platform. The prototype was evaluated through 40 controlled experimental trials involving predetermined combinations of eye-closure and head-nodding movements performed by one researcher, comprising 20 trials under bright lighting and 20 trials under dark lighting. The system correctly classified 38 of the 40 trials, achieving an overall detection accuracy of 95% and an average response time of 1.68 seconds. The adaptive decision algorithm achieved an overall sensitivity of 95% and specificity of 95%, with no false positives under bright lighting conditions and no false negatives under dark lighting conditions. These findings demonstrate the feasibility of combining context-aware, on-

device sensor fusion, real-time IoT alerting, and solar energy harvesting within a wearable microsleep detection prototype.

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Keyword:

Context-Aware Systems, Drowsiness Detection, Microsleep Detection, Sensor Fusion, Solar Energy Harvesting, Wearable Iot



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Introduction

Microsleep refers to brief, involuntary episodes of sleep that typically last between one and five seconds and often occur without the individual's awareness. While brief, microsleep episodes present serious threats to safety in critical settings like driving, flying, and industrial settings. Even brief inattention has been shown to be strongly linked to transportation crashes and decreased safety (Helmy Ilhamsyah et al., 2025), (Nurul'aini et al., 2025). Therefore, it is essential to diagnose and treat microsleep timely manner to prevent its consequences.

Most of the current approaches to microsleep detection are based on electroencephalography (EEG), computer vision, or sensor-based methods. EEG-based method has been proven quite reliable in monitoring brainwave activity and identifying cases of microsleep (Hasan et al., 2024), (Shah et al., 2023). However, these gadgets have invasive sensors, advanced signal processing and are not convenient to apply in practice (Minhas et al., 2025). Deep learning and image processing methods in computer vision have also proved to be an effective detection method of drowsiness and eye closure (Rusli et al., 2025), (Aditya Madane et al., 2025). Nevertheless, they are computationally intensive, illumination-sensitive and lack privacy in a real-world environment (Fu et al., 2024).

An alternative is wearable sensor-based systems. Head-nodding is sensed by inertial sensors and accelerometers, and physiological and behavioural signals, such as eye blink and heart rate variability, are also employed to identify drowsiness states (Fujiwara et al., 2024), (Saleem et al., 2023). Additionally, wearable devices can also be connected to Internet of Things (IoT) technologies to offer real-time monitoring and alerts (Biswal et al., 2021). However, single-mode systems are weaker and can lead to the creation of false alarms or inability to detect in unpredictable environmental and user conditions (Fu et al., 2024).

Besides, the wearable IoT systems can offer continuous monitoring and wireless connectivity, making them prone to consuming more power, thereby shortening the life of the system. To facilitate sustainability, autonomous, energy-efficient systems are required. Current studies demonstrate that it is possible to combine small and energy efficient and wearable sensing systems, which may operate continuously (Pham et al., 2023).

However, there is still a lack of research into hybrid sensor fusion, brightness-adaptive logic, and renewable energy support in an integrated, affordable wearable platform for microsleep detection. Consequently, in this research, we develop a solar-powered context-aware wearable IoT-based microsleep detection system. The system features infrared and accelerometer sensors, brightness-adaptive decision-making rules, and IoT-driven real-time feedback. The system is experimentally validated in terms of detection accuracy, reliability and detection speed.

Literature Review

Microsleep and driver drowsiness detection have gained significant attention in the research community for their significant implication in safety. Technological advances in sensing and intelligent systems have led to the emergence of detection methodologies that can be classified into physiological, visual and wearable sensor-based types.

Physiological Signal-Based Detection

Physiological signal methods, especially electroencephalography (EEG), are considered to be very effective in the detection of microsleep and driver drowsiness. EEG can be used to measure the activity of the brain, which makes it possible to monitor the phenomena associated with fatigue in real-time. The recent research indicates a high level of prediction accuracy of microsleep detection based on machine learning approaches on EEG signals (Hasan et al., 2024),(Shah et al., 2023).

Additionally, wearable devices have also been studied in other physiological parameters, including heart rate variability (HRV), where they achieved high success in real-world detection (AlArnaout et al., 2025). Although they are correct, they usually entail invasive sensors, and they might need sophisticated signal processing methods, which limit their application in our lives (Perkins et al., 2023).

Vision-Based Detection Approaches

Visual techniques employ computer vision and deep learning to monitor facial expressions such as eye closing, blinking, and yawning. These methods have demonstrated a high detection rate in recent studies, and some systems achieve accuracy rates of more than 95% when using convolutional neural networks and transfer learning models (Rusli et al., 2025),(Essel et al., 2025).

More recent research has used deep learning and edge computing to be more accurate and reduce time delay (Lamaazi et al., 2023). Nevertheless, they are weather sensitive, and camera location and computing capabilities. In addition, their practical use is influenced by privacy concerns and different environmental influences (Fu et al., 2024).

Wearable Sensor-Based Detection

Wearable sensor technologies have attracted considerable interest for their potential to be continuous, cheap and wearable. Such approaches generally employ inertial, infrared and physiological sensors to track behavioural and physiological signs of sleepiness.

Most studies rely on accelerometers and motion sensors for detecting drowsiness-induced head movements or nodding patterns, and infrared sensors for non-contact eye tracking. Multimodal wearable devices are also created and have proven to be more accurate in comparison to single-sensor systems (Pham et al., 2023).

Nonetheless, studies have shown that wearable systems that use one type of sensor are more likely to be less robust and prone to false detections in other environmental factors (Saleem et al., 2023). These constraints propose a possibility of integration of multimodal sensing modalities.

IoT-Based and Smart Monitoring Systems

Remotely monitoring and alerting have been made possible using wearable devices with IoT platforms. The drowsiness monitoring based on an IoT platform can send real-time alerts to the mobile apps and the cloud-based servers, which will improve the responsiveness and safety features (Biswal et al., 2021), (G Sudha Rani, 2024).

Improvements have also occurred in recent times when it comes to using edge computing and distributed systems to enhance real-time responsiveness and latency. (Lamaazi et al., 2023). Nonetheless, energy efficiency, durability and resilience in dynamic settings are still problematic.

Research Gaps and Motivation

Despite significant advances in microsleep detection, existing approaches remain difficult to implement as continuous, long-term wearable solutions because of limitations related to sensor placement, computational requirements, detection robustness, and energy consumption:

- EEG-based systems offer high detection accuracy but require cumbersome electrode placement, which limits user comfort and practicality during continuous monitoring.
- Vision-based systems require computationally intensive processing and are sensitive to lighting conditions and unobstructed camera views.
- Single-sensor wearable systems may have limited robustness because their performance can be affected by variations in environmental and user conditions.
- IoT-based systems require continuous sensing and wireless communication, resulting in higher energy consumption and reduced suitability for long-term operation.

Therefore, there remains a lack of an integrated, low-cost wearable system that combines multimodal sensing, context-adaptive detection, real-time IoT alerting, and energy-efficient operation within a single platform. Addressing this gap is essential for developing a practical and reliable microsleep detection system suitable for continuous real-world use (Fu et al., 2024), (Albadawi et al., 2022), (Shankara Chari & Prashant, 2024).

Contributions To This Study

To overcome these challenges, this paper proposes a solar-powered, context-aware wearable IoT system that combines:

- Hybrid sensor fusion (infrared + accelerometer)
- Brightness-adaptive decision algorithm
- Real-time IoT-based alerting
- Energy sustainability through solar power

The main goal is to develop a cost-effective, non-invasive, energy-efficient microsleep monitoring system with high performance in real-time implementation.

Methodology

System Architecture

The proposed solar-powered wearable system integrates infrared-based eye-closure detection, accelerometer-based head-motion analysis, ambient-light sensing, on-board data processing, multimodal alerting, and IoT communication. The system uses the ESP32 microcontroller, which is commonly used in IoT devices because of its low power requirements, small size and on-board Wi-Fi connectivity, and is an ideal choice for real-time wearable applications (Biswal et al., 2021). The system design of the solar-powered microsleep detection system can be seen in Figure 1.

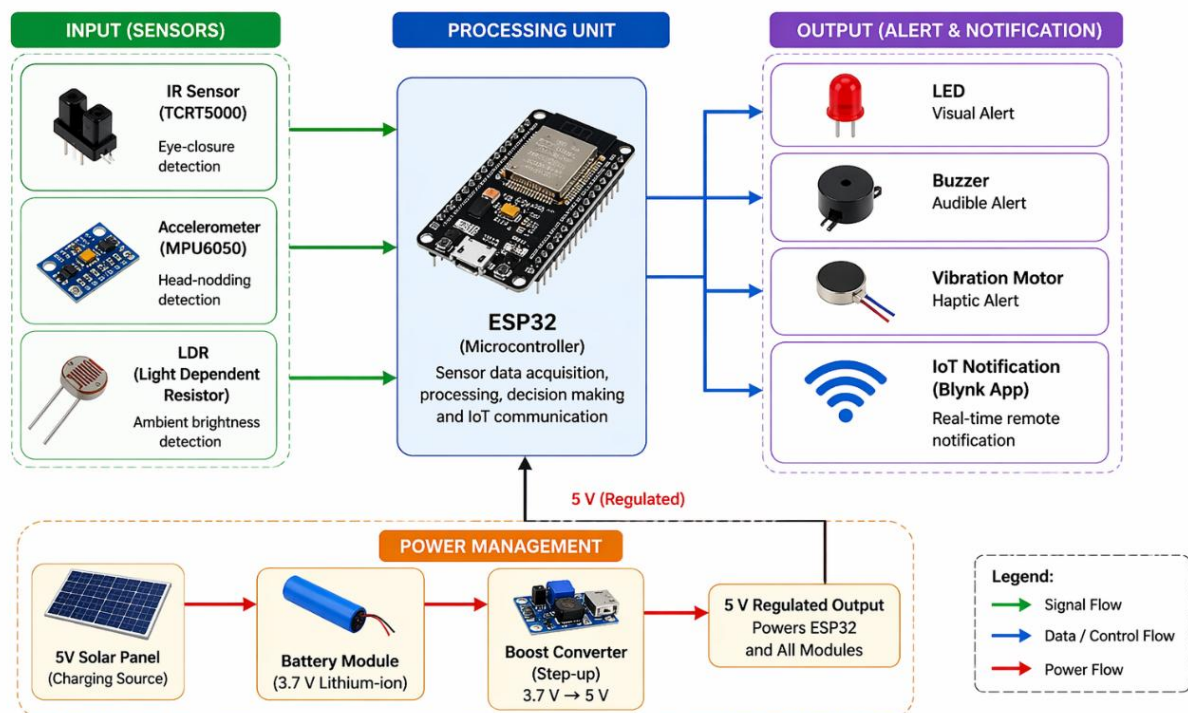


Figure 1: Block Diagram of the Solar-powered Context-aware Wearable Microsleep Detection System

The sensing module has three major parts:

1. Infrared (IR) Sensor (TCRT5000):
Checks on the closure of the eyes with infrared reflections. Infrared-based eyeblink detection is also commonly used in drowsiness detection systems since it is a non-invasive and valid technique in eye tracking monitoring of eyelid movement in various lighting conditions. (Rusli et al., 2025).
2. Accelerometer (MPU6050):
Monitors head movement due to fatigue and microsleep. Inertial sensor-based movement detection is often adopted in wearable drowsiness detection systems because it can meet the requirements of low computational cost and real-time (Fu et al., 2024).
3. Light-Dependent Resistor (LDR):
The intensity of light is detected to enable context-specific adaptive algorithms to be applied, enabling detection in varying lighting conditions. Infrared (IR) Sensor (TCRT5000): This detector reads the eyelid movement using an IR sensor.

The ESP32 will handle the processing of the data in real-time and will be used to implement the logic. In the case of a microsleep episode, it triggers multimodal alerts (visual, auditory and vibration). It also transmits notifications to a smart device via the Blynk IoT platform to provide remote monitoring and feedback (Biswal et al., 2021). A small solar panel with a rechargeable battery provides a renewable energy source, enhancing the autonomy of the device and making it more appropriate for a wearable device that can be worn on a long-term basis.

Context-Aware Adaptive Decision Algorithm

The system employs a brightness-adaptive decision algorithm to maintain detection performance under varying lighting conditions. Based on the ambient-light level measured by the LDR, the algorithm switches between AND and OR decision rules.

- Bright Environment Mode:
It is based on the logic of AND, where both the head nodding and eye closure need to be detected to prompt an alert. This will avoid false alarms caused by normal blinks or head movements.
- Dark Environment Mode:
It operates on OR logic, where eye closure or head nodding will activate an alarm. This improves sensitivity in low-light situations, where the accuracy of the sensor may be affected.

This dynamically adaptable methodology increases the reliability of the detection system by ensuring the detection sensitivity and specificity under different environmental conditions, which addresses some limitations of the single-sensor-based detection systems (Fu et al., 2024) reported.

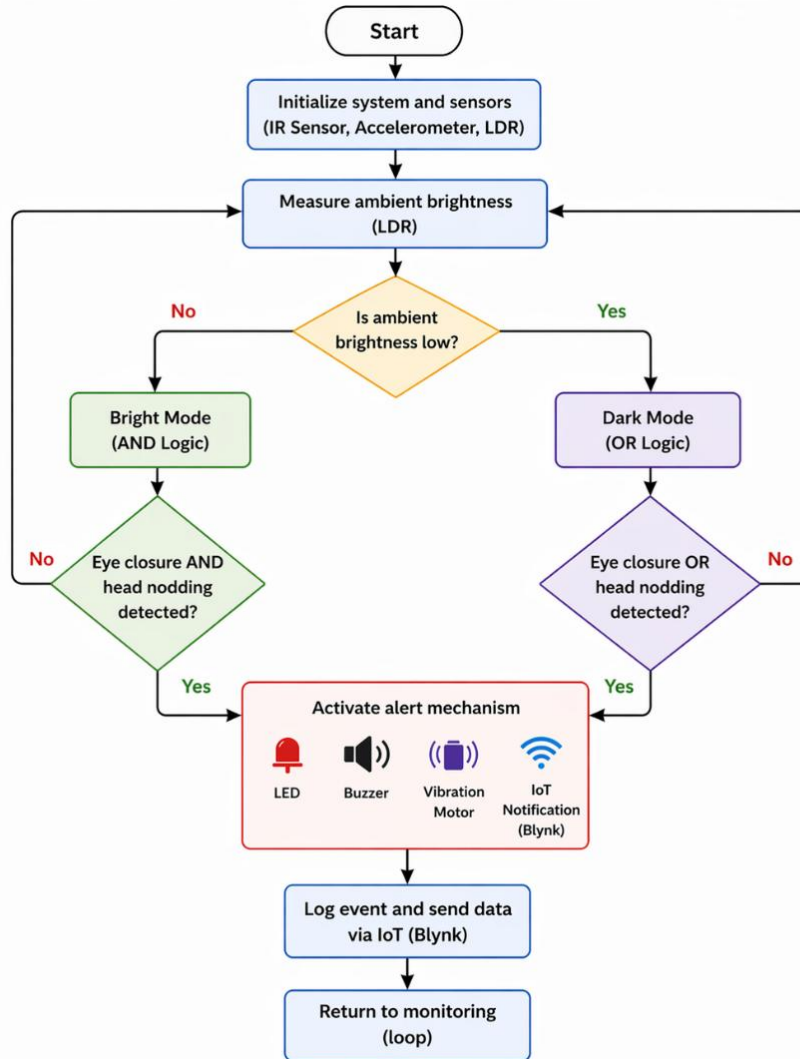


Figure 2: Flowchart of the Solar-powered Context-aware Wearable Microsleep Detection System

Prototype Development and Integration

The sensor was initially tested on a breadboard to ensure that the system was working and the logic was sound. After the verification, a printed circuit board (PCB) was created to improve the stability of the device and make it easier to wear.

The infrared sensor was placed in the vicinity of the eyes to accurately detect the eyelids, and the accelerometer was firmly attached to enable accurate assessment of head movements. A buzzer, LED and vibration motor were also included to offer multimodal user alerts. The prototype exhibits the real-time integration of the sensing, processing, alerting and IoT communication subsystems in a wearable form factor.

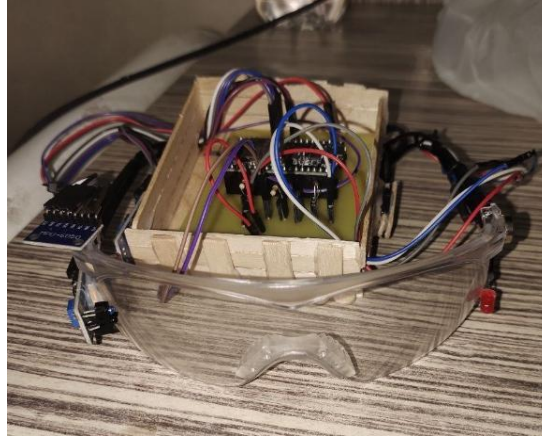


Figure 3: Final Assembled Solar-powered Microsleep Detection Glasses Prototype

Experimental Validation Procedure

The prototype was evaluated through 40 controlled experimental trials involving predetermined combinations of eye closure and head-nodding movements performed by one researcher. The same researcher completed all 40 trials, comprising 20 trials under bright lighting conditions and 20 trials under dark lighting conditions.

In each trial, we tested the system response based on various combinations of eye closure and head-nodding movements represented in the adaptive detection model. Positive cases were those conditions where an alert must occur (defined by microsleep conditions), and the negative cases referred to conditions where an alert must not occur when normal conditions exist.

The system response time was evaluated using a stopwatch approach, by measuring the time taken from the onset of simulated microsleep (simultaneous eye closure and head nodding) to the alert. The responses were measured five times to obtain the average response time.

Performance Evaluation Metrics

To validate system accuracy, detection accuracy, false positive rate (FPR) and false negative rate (FNR) were calculated.

Detection reliability is defined as:

$$\text{Detection Reliability} = \frac{\text{Number of Correct Detections}}{\text{Total Trials}} \times 100$$

The false positive rate (FPR) is defined as:

$$\text{FPR} = \frac{\text{False Positive}}{\text{Total Negative Cases}}$$

The false negative rate (FNR) is defined as:

$$\text{FNR} = \frac{\text{False Negatives}}{\text{Total Positive Cases}}$$

These measures assess system performance in terms of accuracy, sensitivity and resilience in various environmental settings.

Result and Discussion

Prototype Output Validation via IoT Interface

To ensure real-time system functionality, the output behaviour of the system prototype was observed on the Blynk IoT platform user interface. In the normal mode, the system continually monitors and presents the ambient brightness intensity, eye movement, and head positions. In the absence of microsleep, the alert system is disabled and continuous monitoring is maintained.

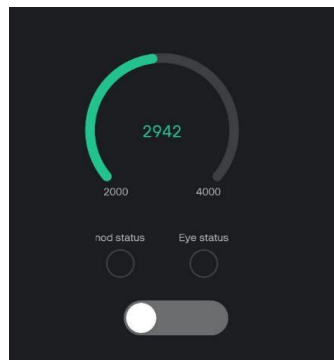


Figure 4: Blynk Interface under Normal Conditions (No Microsleep Detected)

When simulated microsleep conditions were applied, the system activated the LED, buzzer, vibration motor, and mobile notification. The Blynk interface was updated in real time, confirming the coordinated operation of the sensing, on-device processing, alerting, and IoT communication modules. This points to the possibility of wearable sensors and remote monitoring using IoT, as demonstrated in earlier IoT-based drowsiness early detection in drivers (Biswal et al., 2021).

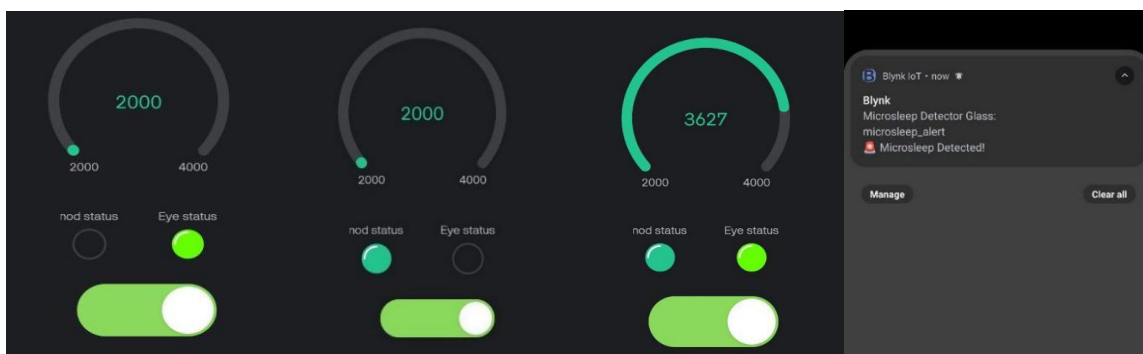


Figure 5: Blynk Interface During Microsleep Detection and Alert Activation

Detection Reliability Under Adaptive Logic Conditions

The proposed system correctly classified 38 of the 40 controlled experimental trials, resulting in an overall detection accuracy of 95%. The combined confusion matrix comprised 19 true

positives, 19 true negatives, one false positive, and one false negative. Consequently, the system achieved a precision of 95%, recall of 95%, specificity of 95%, and an F1-score of 95%. The overall false positive and false negative rates were both 5%.

Table 1: Detection Performance under Different Lighting Conditions

Lighting Condition	TP	TN	FP	FN	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Bright	4	15	0	1	95.00	100.00	80.00	88.89
Dark	15	4	1	0	95.00	93.75	100.00	96.77
Overall	19	19	1	1	95.00	95.00	95.00	95.00

Note: TP = true positive; TN = true negative; FP = false positive; FN = false negative.

Pham et al. (2023) reported precision and recall values of 76% and 85%, respectively, for a behind-the-ear wearable system. However, direct comparison is limited because the studies employed different participants, experimental protocols, and validation conditions. Therefore, the present results should be interpreted as controlled proof-of-concept performance.

The high detection rate of the system is attributed to the fact that the sensor fusion (IR + accelerometer) was combined with the context-sensitive adaptive logic to enhance the system's performance during different lighting environments. This follows other studies that found that single sensors may be vulnerable to poor performance and instability (Fu et al., 2024), hence the implementation of multiple sensors in the intended system.

Bright Environment Performance (AND Logic)

Under bright lighting conditions, the AND-based decision algorithm eliminated false positives but produced one false negative. This indicates higher specificity at the expense of reduced sensitivity.

The finding indicates that the logic of AND is effective in removing the influence of noise, including blinking and small head movements. This offers the same sensitivity as conventional threshold- or single-signal-based methods, but with specificity. The finding is consistent with studies that show the use of multiple indicators of multiple physical elements can enhance the accuracy of drowsiness detection systems (Saleem et al., 2023).

Dark Environment Performance (OR Logic)

Under dark lighting conditions, the OR-based decision algorithm eliminated false negatives but produced one false positive. This indicates higher sensitivity at the expense of reduced specificity.

The OR-based decision algorithm maintained 100% recall under dark lighting conditions but produced one false positive. This result reflects the intended trade-off of prioritising sensitivity under low-light conditions while accepting a moderate reduction in specificity.

False Detection Rate Analysis

Across all 40 trials, one false positive occurred among 20 negative cases and one false negative occurred among 20 positive cases, resulting in an overall false positive rate of 5% and a false negative rate of 5%.

These results indicate a stable detection, and they are in agreement with the expectations of wearable sensor-based systems. The proposed rule-based adaptive logic is more consistent in performance than purely machine learning-based systems that can be affected by overfitting or data dependency without the need to train using large amounts of data (Fu et al., 2024).

Response Time Performance

The system achieved an average response time of 1.68 seconds, enabling alert activation within the typical 1-5-second duration of a microsleep episode. This helps to intervene at the right time before a critical lapse is experienced.

The rapid reaction time is achieved mostly due to the light decision-making logic that is executed directly on the microcontroller by circumventing the delays that would be involved in processing an image or computing in the cloud. Conversely, frame processing and model inference latency commonly characterise vision-based and deep learning systems (Aditya Madane et al., 2025). This highlights the advantage of the proposed system for real-time safety-critical applications.

Overall System Implications

The experimental results validate the effectiveness of the proposed context-aware adaptive detection strategy. The dynamic mode of interaction between the system with AND and OR logic in changing the ambient brightness is an original contribution that enhances the strength of the detection when environmental conditions change.

Compared to existing approaches:

- EEG-based systems offer high accuracy but are intrusive and complex (Hasan et al., 2024). Vision-based systems are accurate but computationally expensive and sensitive to lighting (Rusli et al., 2025)
- Single-sensor wearable systems lack robustness (Fu et al., 2024)

In contrast, the proposed system:

- Combines multi-sensor fusion
- Introduces context-aware adaptive logic
- Uses rule-based, on-device processing
- Supports energy sustainability via solar power

Together, these features demonstrate the feasibility of the proposed system as a wearable microsleep detection prototype.

Limitations and Future Works

The performance of the system is also encouraging, but the experimental validation was done in controlled single-user conditions. To further improve system reliability and generalisability, multi-user testing, actual deployment (e.g., car driving), and adaptive threshold maximisation should be part of future work.

Conclusion

This study presented the design and controlled experimental validation of a solar-powered, context-aware wearable microsleep detection system with IoT connectivity. The prototype integrated infrared-based eye-closure detection, accelerometer-based head-motion analysis, ambient-light sensing, and a brightness-adaptive decision algorithm. Across 40 controlled trials, the system achieved 95% accuracy, precision, recall, specificity, and F1-score, with an average response time of 1.68 seconds. The AND-based decision rule eliminated false positives under bright lighting, whereas the OR-based decision rule eliminated false negatives under dark lighting.

The findings demonstrate the feasibility of integrating context-aware sensor fusion, a brightness-adaptive decision algorithm, real-time IoT alerting, and solar energy harvesting within a wearable microsleep detection prototype. The system provides a non-invasive and rule-based, on-device approach for controlled real-time monitoring; however, its scalability and real-world performance require further validation through multi-user testing and field deployment.

Future work will involve multi-user validation, real-world use in dynamic conditions and the use of adaptive thresholding or intelligent learning methods to further improve detection accuracy and system adaptability.

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- Ethics Statement:** The prototype validation involved one of the researchers, who performed simulated eye-closure and head-nodding movements. No external participants were recruited, and no personal or sensitive data were collected or stored.
- Author Contribution Statement:** Wan Suhaifiza W Ibrahim developed the research framework, system architecture and spearheaded the entire project implementation and supervision. Zahari Abu Bakar worked on hardware development and the integration of prototypes. Zakariah Yusuf conducted experimental validation, data collection, and performance analysis. Nur Iqtiyani Ilham contributed to literature review development, manuscript drafting, and critical revision of the manuscript. All authors reviewed, revised, and approved the final version of the manuscript prior to submission.
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