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Research Article

An Enhancement for Wireless Body Area Network Using Adaptive Algorithms

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Abstract:

Wireless Body Area Networks (WBANs) are one of the most critical technologies for maintaining constant monitoring of patient's health and diagnosing diseases. They consist of small, wearable wireless sensors transmitting signals. Within this vision, WBANs are not without unique difficulties, for instance, high energy consumption, heat from the sensor, and impaired data accuracy. This paper introduces adaptive algorithms combining Convolutional Neural Networks (CNNs) and dynamic threshold mechanisms to enhance the performance and energy efficiency of Wireless Body Area Networks. The study utilizes the MIB-BIH Arrhythmias dataset to improve the detection of arrhythmias. The results show a 10.53% improvement in battery life and a 5.62-fold enhancement in temperature management when sleep mode technology is applied. As a result, the model reached the average accuracy of ECG classification of 98% and a high level of selectivity and sensitivity to a normal type of heartbeat and quite satisfactory results in the classification of arrhythmia type of heartbeat.

1. Introduction

Wireless Body Area Networks (WBANs) have emerged as a critical technology for continuous health monitoring, providing real-time data to medical professionals. WBANs are diverse in application; they can be divided into four types of categories that perform technology modifications according to precise user requirements and environments. WBANs are essential in the medical field to continually monitor a patient's health and perform diagnostic checks on them; these must be highly reliable due to strict safety and privacy standards[1]. Fitness and Wellness WBANs are centered on lifestyle measurement, activity logging, and synchronous connectivity with the user's devices. Military WBANs feature highly reliable designs to work in harsh environments while keeping important data safe[2]. Lastly, in assistive technology, WBANs support the elderly and disabled and enhance their quality of life by connecting them with home systems for vitals and patients' safety. Every category shows how WBANs can be easily integrated and how they can revolutionize almost every sphere of personal, social, and business life, as well as perform vital functions[3].

Exploring the existing Works Related to WBAN It has been found that several refined techniques have been proposed and implemented for improving the system features of WBAN, where state-of-the-art advanced computing is used. Among them, Deep Learning (DL) algorithms, especially Convolutional Neural Networks (CNNs) can identify and extract features from raw sensor data to enhance health monitoring applications[4]. WBANs are part of modern healthcare improvement through monitoring technologies. These networks include motion sensors for gathering and forwarding physiological signs from the human body to medical practitioners to facilitate recovery and shorten treatment delays Wireless Body Area Networks (WBANs) have the potential to revolutionize healthcare by enabling the monitoring of patient's vital signs, like heart rate and temperature[5]. The primary challenge addressed in this work is the high energy consumption and overheating of the sensors in WBANs. Conventional techniques like static thresholding and simple averaging often fail to balance energy efficiency with accurate health monitoring. Static thresholding methods, for example, keep the sensors continuously active or inactive based on a fixed threshold, leading to unnecessary energy consumption during inactive periods. Simple averaging methods lack the responsiveness needed to adapt to rapid changes in physiological signals, resulting in inaccurate monitoring and increased heat generation. In contrast, our proposed method utilizes dynamic thresholds and CNNs to optimize sensor activity, thereby extending battery life and maintaining optimal sensor temperatures. The proposed method's advantages and results are detailed in Sections 4 and 5. Highlighting the drawbacks of existing solutions and the improvements offered by our approach. The. efficacy of the proposed method is demonstrated using the MIT-BIH Arrhythmia dataset.

2. Related Work

This section reviews the latest research efforts aimed at improving WBAN performance through innovative methodologies and technologies.

Fahad Masood et al. (2024) [6] proposed energy efficiency for SDWBANs via sophisticated routing techniques. They put into practice the fuzzy-based Dijkstra algorithm on routing decisions concerning the power source, link distance, and transmission power. This was tested against the IEEE 802.15 standard, which enhances network stability and lessens the routing load. Another important achievement is HUBsFlow, the interface protocol that optimizes the data flow by providing efficient management of data packet transmission and avoiding an excess of broadcast, which increases energy consumption. The study used simulations with a different area of operation of 300m×300m, and the total simulation time was 600 seconds. It also used different energy levels concerning nodes. The evaluation further showed that the fuzzy-based Dijkstra algorithm obtained a throughput of 3565.7 bps and an end-to-end delay of at least 0.007 seconds, while the throughput achieved by the HUBsFlow protocol was 16 packets/s, accompanied by a packet loss ratio of 0.014. These observations imply that SDWBANs have the potential to enhance patient monitoring systems immensely since they consume less energy as well as directing the data flow appropriately.

Razieh Mohammadi and Zahra Shirmohammadi (2023) [7] paper titled "DRDC: Deep Reinforcement Learning-Based Duty Cycle for Energy Harvesting Body Sensor Node is dedicated to enhancing the duty cycle of sensor nodes in energy-harvesting body area networks (EH-BAN), through the use of DRL. The considered algorithm, which is a Deep Q-network (DQN), targets optimizing the energy consumption and the operational cycle of these sensor nodes based on the variations in energy harvesting. Hence, their approach shows a drastic decrease in the duty cycle by a margin of 28% and a reduction in the data overhead by more than 50%, which implies an enhanced efficiency of the sensor nodes. This improvement in duty cycle management increases the battery life of the body's sensory network to support continuous health monitoring systems and applications.

Bassem Mokhtar et al. (2023) [8] “Nano-Enriched Self-Powered WBAN for Sustainable Health Monitoring Services” aims to develop state-of-the-art protocols and algorithms that enhance the performance of WBANs. Their suggestion entails a MAC Protocol based on Energy Harvesting which is focused on how effectively we can use energy from human movements through piezoelectric nano-biosensors. They also brought in the use of machine learning (ML) for its dynamic power management aimed at efficient distribution or consumption of energy based on certain statistics. Those techniques collectively improve self-sufficiency, reliability, and efficiency in WBANs that are necessary for long-term health monitoring applications.

Ashraf A. Taha et al. (2022) [9] have presented the Aquila Optimizer (AO) algorithm as a way of increasing the energy efficiency of WSN and extending its life. They compared AO with conventional approaches like LEACH protocol, Genetic Algorithm (GA), Coyote Optimization Algorithm (COY), and Harris Hawks Optimization (HHO). It was realized that AO could help retain more active nodes for an extended period using less power than other methods such as LEACH protocol, COY, and HHO which are very useful in sustainable wireless networks.

S. Ezhil Pradha et al. (2022) [10] proposed the design of the Scheduled Access MAC (SAMAC) protocol in their paper titled “Scheduled Access Strategy for Improving Sensor Node Battery Lifetime and Delay Analysis of Wireless Body Area Network.” The focus is to increase network lifetime while reducing latency in WBANs through improvements to the MAC layer. SAMAC is different from other wireless MAC protocols including IEEE 802.15.6 Baseline MAC and ZigBee MAC by avoiding wasting energy on unnecessary activities resulting in improved packet delivery ratios as well as end-to-end delays hence managing energy consumption and quality of service effectively within WBANs.

Omar Ahmed et al. (2020) [11]Energy Optimized a Congestion Control-Based Temperature Aware Routing Algorithm for Software Defined WBANs, proposed the EOCC-TARA algorithm, which prescribes the use of Enhanced Multi-Objective Spider Monkey Optimization (EMSMO). This algorithm enhances the network performance in terms of energy, congestion, and thermal impacts to achieve optimal efficiency in the case of SD-WBANs. The results of the simulation show its effectiveness and advantages over conventional methods by having a higher level of success rates in terms of accuracy and stressing the fact that it is very effective in enhancing some important network parameters.

Ch. Rajendra Prasad Polaiah Bojja (2020) [12]proposed a new multi-hop HEER protocol for WBA based on an ultra-low-power transceiver with an emphasis on the eHealth care system. The protocol follows an aggressive direct and indirect information exchange principle, which enhances a network’s energy consumption and lifespan. Also, it uses a novel synchronization schedule that assigns variable time slots to minimize colliding and energy waste ineffective protocol performance in comparison to initial work. These innovations play a central role in increasing the operational effectiveness and sustainability of eHealth systems.

3. Methodology

This paper has centered on upgrading the performance of sensors at Tier 1 in WBANs architecture. This section gives a detailed description of the design and the functioning of the proposed Wireless Body Area Network system (Figure 1). The system uses a Dynamic Threshold Algorithm alongside CNNs to minimize energy consumption and sensor overheating. The Dynamic Threshold Mechanism deactivates sensors during normal heart rates (60-100 BPM) and reactivates them when abnormalities are detected. The CNNs model processes ECG signals, reducing false positives and ensuring accurate monitoring. Data preprocessing involves noise reduction and normalization of ECG signals. The CNN model is trained on the MIT-BIH Arrhythmia dataset, achieving high classification accuracy. To design the proposed WBAN system, the following components were incorporated:

Figure 1. *Flowchart of the Dynamic Threshold Proposed System.*

3.1 Read Data

This section involves the process of dealing with and analyzing the collected data through WBANs. These stages are crucial in the development of applications utilizing raw data acquired through sensors for healthcare monitoring and others. As shown in Fig. 2, the typical stages include the following:

Data Pre-Processing

Data pre-processing This is the first step in processing the raw data gathered from WBAN sensors. Some of the most common pre-processing techniques include cleaning, normalizing, and segmenting the data to minimize the noise used in the data. This stage involves several key activities:

- **A. Data Cleaning:** This includes dealing with missing data whereby imputation or deletion is done on the missing values based on their number and significance. signals preprocessing to reduce the impact of sensor error on the results.
- **B. Data Integration:** Sensory data is consolidated into a single data representation; this may be the process of synchronizing the acquired data streams by time or other markers.
- **C. Dimensionality Reduction:** Linear methods, including Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA), are used to reduce noise and emphasize the most important features. Some pre-processing also involves data gathering over particular time durations (for instance, averaging over successive 1-minute intervals) to minimize the amount of data and highlight trends.
- **D. Normalization:** The sensor data is normalized to a certain scale, for instance, 0-1, which is crucial when handling different sensors and conditions.
- **E. Class Imbalance Handling:** There are some methods, like RandomOverSampler, that can help in handling the problem of class imbalance in the given set of data. This helps in making the model not inclined towards the major classes and able to identify the minority classes, which is vital in identifying rare forms of arrhythmias.

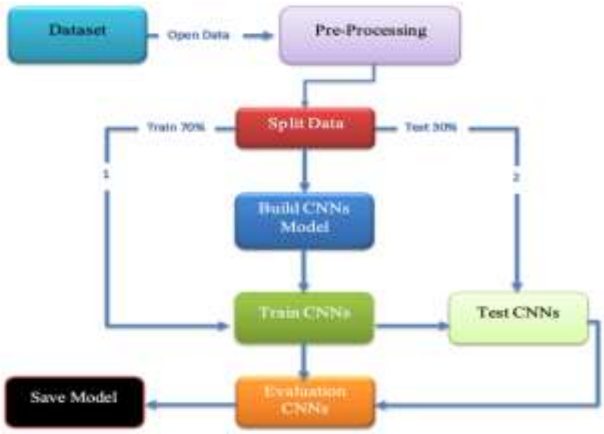


Figure 2. *Data Analysis Stages.*

3.2 Resampling and Splitting

To handle the issue of class imbalance in the dataset, the RandomOverSampler algorithm from the Imblearn package was implemented. This method creates new samples, thus applying a new distribution to the minority classes, which makes the model receive a balanced exposure to all classes during training. The data was then resampled and randomly divided into training 70%, validation 15%, and test sets 15%, respectively, to train as well as evaluate the results of the ML models.

3.3 Dynamic Threshold

The dynamic threshold mechanism is used to allow the sensor to sleep during the regular ECG measurements, thus conserving power.

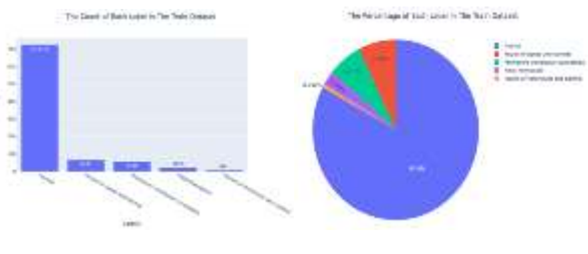


Figure 3. *Distribution of labels Train before balancing.*

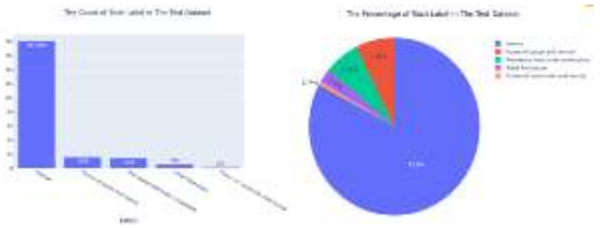


Figure 4. *Distribution of labels Test before balancing.*

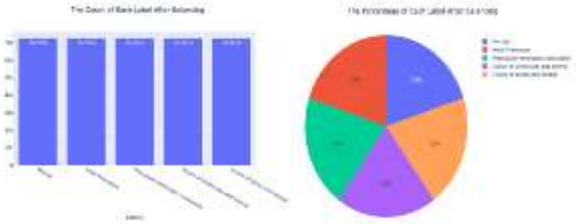


Figure 5. *Distribution of labels after balancing.*

Figure 3 shows distribution of labels Train before balancing while test one is shown in figure 4. In figure 5 the distribution of labels after balancing. It provides alarms to the medical staff when the ECG signals recorded are weighted out of a normal range. This mechanism changes input thresholds with previous heart rate values and utilizes a deep neural network to confirm abnormality, hence providing an accurate and power-efficient monitoring system.

The sensor utilizes a dynamic threshold mechanism to save power by going into sleep mode during ECG measurements. It alerts staff when recorded ECG signals deviate from the range. By adjusting input thresholds based on heart rate values and using a neural network to detect abnormalities this mechanism ensures precise monitoring while conserving energy. The detailed explanation sheds light on how the system saves power and ensures health monitoring. Fig. 6, offers an in-depth look at the decision-making process of the threshold mechanism starting with heart rate monitoring. The system checks if the heart rate falls below 60 BPM or exceeds 100 BPM. If within the range it then assesses whether the difference in heart rates is less, than 10 BPM. If not, the sensor remains active and records ECG data, if so, it enters sleep mode to conserve power. For abnormal heart rates, deep learning algorithms are employed to confirm the abnormality. Once confirmed, further checks are conducted. The system then assesses if the previous heart rate difference is less than 5 BPM. If it is not, the sensor remains in sleep mode, continuously detecting abnormal readings. If the previous heart rate difference is higher than 5 BPM, the sensor becomes active and records the ECG heart rate. The system finally returns to the simulation step to validate and adjust the dynamic threshold, ensuring efficient and accurate monitoring.

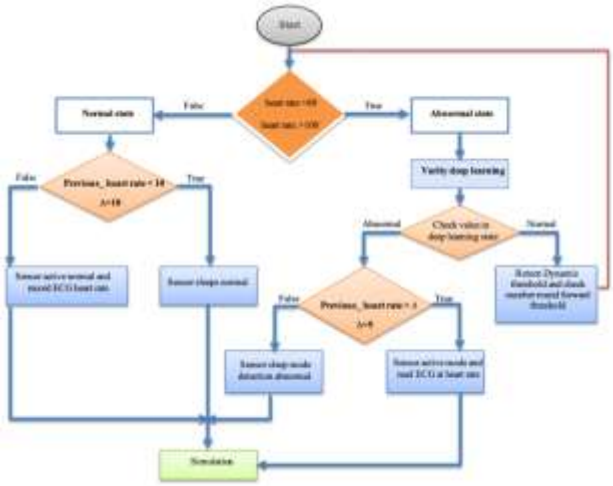


Figure 6. *Comparative Performance of sensors with and without sleep modes in terms of battery life and temperature management.*

3.4 Proposed CNN Model

CNNs are used in this work to analyze ECG signals. The CNN architecture provides an opportunity to train the model on the raw ECG data and extract the hierarchical features in a fully automatic approach that is suitable for the classification of different forms of arrhythmias. The CNN model architecture proposed is aimed at analyzing ECG signals and categorizing them into distinctive classes in this study. Here is a detailed explanation of the proposed CNN model:

A. **Input Layer:** The input layer accepts data of shape (187, 1), where 187 is the length of the ECG data, and 1 represents a single channel.
B. **First Convolutional Block:** The first block consists of a Conv1D layer with 64 filters and a kernel size of 6, followed by a ReLU activation function, BatchNormalization, and MaxPooling1D with a pool size of 3, strides of 2, and padding set to "same."
C. **Second Convolutional Block:** The second block has a Conv1D layer with 64 filters and a kernel size of 3, followed by ReLU activation, BatchNormalization, and MaxPooling1D with a pool size of 2, strides of 2, and padding set to "same."
D. **Third Convolutional Block:** The third block also features a Conv1D layer with 64 filters and a kernel size of 3, followed by ReLU activation, BatchNormalization, and MaxPooling1D with a pool size of 2, strides of 2, and padding set to "same."
E. **Flatten Layer:** The flattened layer prepares the data for the dense layers by converting the multi-dimensional output into a single-dimensional vector.
F. **First Dense Layer:** This layer contains 64 units and uses the ReLU activation function.
G. **Second Dense Layer:** This layer has 32 units and uses the ReLU activation function.

H. **Output Layer:** The output layer has a few units equal to the number of classes (e.g., 5) and uses the Softmax activation function for classification.

4. Training the Model and Evaluation

The performance of the proposed model was measured and assessed based on accuracy, precision, recall, and the F1 score. These metrics give a conclusive measurement of the model's functionality of correctly classifying the ECG recordings. The outcomes depict that the model differentiates heartbeats (Class 0) with accurate classification, recall, and F1 classification of 0. 99 each. However, its performance appeared to be slightly lower for the classification of types of arrhythmias; Class 1 and Class 3 have the F1 score of 0. 81 and 0. 78, respectively,

The MIT-BIH Arrhythmia Dataset was used for training and evaluation. The dataset consists of 87,554 samples, each with 188 features. Of these features, 187 represent ECG signal data. After balancing (Figure 5) the dataset using the RandomOverSampler, the data was split into training, validation, and test sets:

The model was trained using a dataset that included multiple subjects' ECG recordings. After preprocessing, the dataset was split into training, validation, and test sets with the following dimensions:

Training Set: 253,648 samples, each with 187 features. The labels were classified into 5 categories.

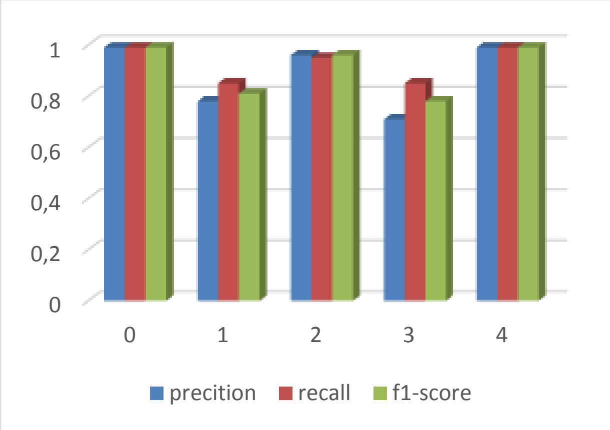
Validation Set: 108,707 samples, each with 187 features. The labels were classified into 5 categories.

Test Set: 21,892 samples, each with 187 features. The labels were classified into 5 categories.

To address class imbalance in the dataset, we employed the RandomOverSampler from the imblearn library. This method was applied before splitting the data into training, validation, and test sets. The oversampling helped balance the dataset, ensuring more reliable model training and evaluation.

The model was implemented and trained using Python, specifically utilizing the TensorFlow and Keras libraries for the deep learning components.

In the same regard, Anaconda comes bundled with Jupyter and Spyder, and Mesa contains efficient libraries and frameworks required for constructing, training as well as emulating DL models. Jupyter was used in the interactive development as well as visual analysis and simulation work was done in Spyder. As shown in Fig. 7, Performance Metrics for Each Class illustrate each class's precision, recall, and F1-score.



***Figures 7.** Performance Metrics for Each Class.*

This chart highlights the model's strengths in detecting normal heartbeats while pinpointing the need for improvements in arrhythmia classification.

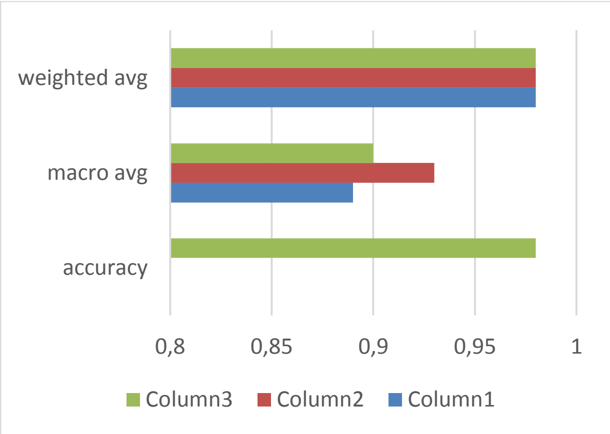


Figure 8. Aggregated Performance Metrics.

As shown in Fig. 8, Aggregated Performance Metrics provide an overall summary of the model's performance. This chart includes weighted and macro averages for precision, recall, and F1-score, as well as the overall accuracy. The weighted average, which considers the support of each class, demonstrates the model's robust performance with an accuracy of 0.98. Fig. 7, shows that while the model performs well overall, there are discrepancies in performance across different classes. Fig. 8, reinforces this by summarizing the model's general performance metrics.

5. Experimental Result and Discussion

. The main objectives are to improve the battery duration, monitor the temperature of the sensors suitably, and diagnose the improper signals suitably. According to the findings from this study, it is evident that the use of dynamic thresholds as well as sleep mode technology enhances battery life while regulating the sensor temperature without experiencing a predicted drop in the level of detection.

The proposed dynamic threshold mechanism was evaluated against static thresholding and simple averaging. Compared to these conventional methods, our approach showed significant improvements in energy efficiency and temperature management. In contrast, our dynamic threshold mechanism adapts in Visualization based on ECG data from the MIT-BIH Arrhythmia dataset, with CNN verification reducing false positives and ensuring accurate detection. This adaptive approach significantly conserves energy and maintains optimal sensor temperature, as demonstrated in our experimental results. Tables 1 and 2, illustrate the comparative performance of sensors with and without sleep modes. Specifically, the battery life increased by 10.53%, and temperature regulation improved 5.62-fold. These results highlight the efficacy of adaptive algorithms in enhancing WBAN performance.

The simulation was conducted for 7200 seconds. With a current step of 5001. During this time, the sensor's battery performance was analysed under two different modes: with and without sleep mode. As shown in Fig. (9) and (10):

1. **Sensor without Sleep Mode:** After approximately 120 minutes of operation, the battery began to decrease, and this decline continued steadily throughout the remaining simulation period. The battery's performance showed minimal conservation due to the absence of sleep mode.
2. **Sensor with Sleep Mode:** The battery life exhibited notable improvements. It maintained its charge for up to 180 minutes before beginning to decrease, demonstrating the impact of the sleep mode on energy conservation. The difference in battery depletion rates between the two modes is visualized in Tables (1) and (2), which compare the average battery percentages at different time intervals.

The data clearly shows that the sleep mode significantly extends the sensor's battery life during continuous operation, reducing the overall power consumption. These thresholds change dynamically with battery charge levels and reported temperature values to reduce energy consumption while at the same time minimizing false alarms in the case of detecting anomalous sub-categories of the data. The thresholds allow the sensors to sleep during regular measurements and wake up only during abnormal ones, thus saving the variance. The system accomplishes this through a Dynamic Threshold Algorithm in association with the CNN. In the same way, the system also involves a sleep mode of the sensor, and this working mode is managed depending on certain ECG threshold values (100-60). The sensor wakes up from sleep mode and notifies the medical staff only when there are variations in the patient's heart rate. As shown in Fig. 9, illustrates the comparative performance of sensors that utilize sleep

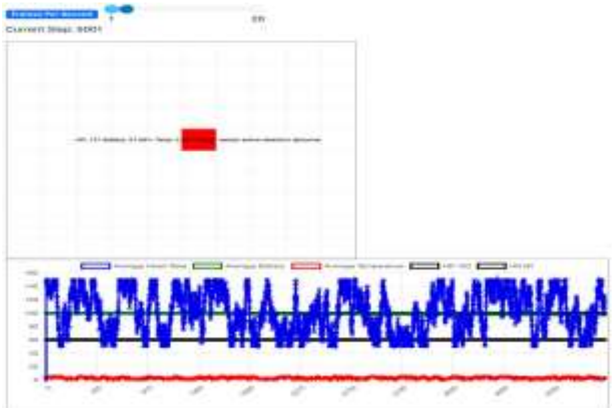


Figure 9. *Visualization of simulation results comparing the performance of sensors with sleep modes, demonstrating differences in battery life and temperature management.*

modes in terms of battery life and temperature management. The results show that sensors with sleep modes exhibit a more stable and extended battery life due to reduced power consumption during inactive periods. The graph also indicates better temperature management, as the sensors remain cooler by entering sleep mode when not actively monitoring. This enhanced performance underscores the effectiveness of incorporating sleep mode in WBAN sensors, providing. significant improvements in both energy efficiency and heat regulation.

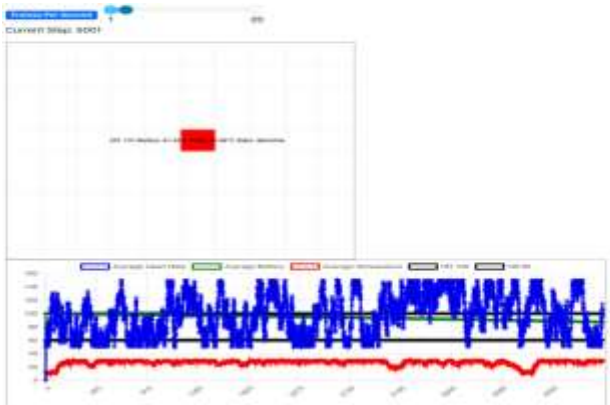


Figure 10. *Visualization of simulation results comparing the performance of sensors without sleep modes, demonstrating differences in battery life and temperature management.*

In contrast, Fig. 10, depicts the performance of sensors without sleep modes, highlighting the drawbacks of continuous operation. The data shows a rapid decline in battery life and higher temperature readings over time. These sensors consume more power and generate more heat as they continuously monitor without breaks. The comparison indicates that sensors without sleep modes are less efficient, leading to quicker battery depletion and higher temperatures, which can affect the reliability and longevity of the WBAN system.

***Table 1.** Simulation Result Sensor with Sleep Mode*

STEP Currently	Previous Heart Rate	Heart Rate	Average Battery	Average Temperature	ECG Recording
1	137 BPM	146 BPM	100.00%	5.00°C	sensor active detection of abnormal
2	146 BPM	150 BPM	100.00%	4.80°C	sensor sleep mode detection of abnormal
3	150 BPM	146 BPM	100.00%	4.34°C	sensor sleep mode detection of abnormal
4	146 BPM	141 BPM	100.00%	4.58°C	sensor active detection of abnormal
5	141 BPM	149 BPM	100.00%	4.42°C	sensor active detection of abnormal
6	149 BPM	150 BPM	100.00%	5.00°C	sensor sleep mode detection of abnormal
7	150 BPM	147 BPM	100.00%	4.58°C	sensor sleep mode detection of abnormal
8	147 BPM	150 BPM	100.00%	4.92°C	sensor sleep mode detection of abnormal
9	150 BPM	140 BPM	100.00%	4.09°C	sensor active detection of abnormal
10	140 BPM	148 BPM	100.00%	4.38°C	sensor active detection of abnormal
11	148 BPM	142 BPM	100.00%	4.60°C	sensor active detection of abnormal
12	142 BPM	150 BPM	100.00%	4.09°C	sensor active detection of abnormal
13	150 BPM	133 BPM	100.00%	4.54°C	sensor active detection of abnormal
109	95 BPM	85 BPM	100.00%	4.55°C	sensor active mode detection of abnormal
110	85 BPM	79 BPM	100.00%	4.27°C	sensor sleep mode normal
111	79 BPM	75 BPM	100.00%	5.00°C	sensor sleep mode normal
4999	121 BPM	115 BPM	97.69%	2.96°C	sensor active detection of abnormal
5000	115 BPM	107 BPM	97.69%	2.66°C	sensor active detection of abnormal
5001	107 BPM	127 BPM	97.69%	2.65°C	sensor active detection of abnormal

***Table 2.** Simulation Result Sensor without Sleep Mode*

STEP Currently	Previous Heart Rate	Heart Rate	Average Battery	Average Temperature	ECG Recording
1	50 BPM	52 BPM	100.00%	1.11°C	Abnormal
2	52 BPM	50 BPM	99.99%	12.66°C	Abnormal
3	50 BPM	56 BPM	99.98%	11.87°C	Abnormal
4	56 BPM	59 BPM	99.98%	10.63°C	Abnormal
5	59 BPM	50 BPM	99.98%	10.02°C	Abnormal
6	50 BPM	60 BPM	99.97%	10.82°C	Abnormal
7	60 BPM	68 BPM	99.97%	10.66°C	Normal
8	68 BPM	78 BPM	99.97%	11.49°C	Normal
9	78 BPM	71 BPM	99.96%	10.41°C	Normal
10	71 BPM	68 BPM	99.96%	11.31°C	Normal
11	68 BPM	72 BPM	99.96%	10.59°C	Normal
12	72 BPM	82 BPM	99.96%	10.48°C	Normal
13	82 BPM	78 BPM	99.96%	10.00°C	Normal
109	129 BPM	123 BPM	99.76%	16.97°C	Abnormal
110	123 BPM	113 BPM	99.76%	16.54°C	Abnormal
111	113 BPM	114 BPM	99.76%	17.11°C	Abnormal
4999	115 BPM	106 BPM	87.44%	28.70°C	Abnormal
5000	106 BPM	97 BPM	87.44%	27.96°C	Abnormal
5001	97 BPM	107 BPM	87.43%	28.08°C	Abnormal

5.1 Analysis of Simulation Results:

The results from the two simulations indicate significant differences in performance between sensors with and without sleep modes. General Ratio of the Optimization Process During the 2-houres simulation, the overall performance optimization can be summarized as follows**:**

A. Table (1): Results for Sensors with Sleep Mode

- Average Battery Level: Maintained close to 100% for most steps, slightly dropping to 97.69% at the last few steps.
- Overall Battery Conservation: The sensors with sleep mode show excellent battery conservation, with many readings indicating 100% battery life. This demonstrates that the sleep mode effectively reduces power consumption.

B. Table (2): Results for Sensors without Sleep Mode

- Average Battery Level: Ranges from 100% to 87.43%, with significant drops as the steps progress**.**
- Overall Battery Drain: The sensors without sleep mode experience a noticeable decrease in battery life, with the final readings showing 87.43% battery life. This indicates higher energy consumption compared to sensors in sleep mode.

C. Temperature Management Table (1): Results for Sensors with Sleep Mode

- Average Temperature: Remains consistently low, ranging from 2.65°C to 5.00°C**.**
- Temperature Stability: The sensors with sleep mode maintain a low and stable temperature, indicating effective management of heat generation.

D. Table (2): Results for Sensors without Sleep Mode

- Average Temperature: Ranges from 1.11°C to 28.08°C, significantly increasing as the steps progress **.**
- Temperature Increase: The sensors without sleep mode show a substantial rise in

temperature, particularly towards the later steps, reaching up to 28.08°C. This indicates poor heat management compared to sensors with sleep mode.

5.2 Equations

To quantify the improvement in sensor performance, we calculate the optimization ratio for both battery life and temperature management.

A. Battery Life Optimization Ratio

- Sensor with Sleep Mode:
  - initial Average Battery: 100%
  - Final Average Battery: 97.69%
- Sensor without Sleep Mode:
  - initial Average Battery: 100%
  - Final Average Battery: 87.43%

a. Optimization Ratio for Battery Life: The optimization ratio is calculated as the improvement in battery life preservation with sleep mode compared without sleep mode.

$$Optimization\ Ratio = \frac{Final\ Battery\ without\ Sleep\ Mode}{Final\ Battery\ with\ Sleep\ mode}$$

$$Optimization\ Ratio = \frac{87.43\%}{97.69\%} \approx 0.8947 \qquad (1)$$

This means that the battery life with sleep mode is approximately 10.53% better compared to without sleep mode.

B. Temperature Management Optimization Ratio

- Sensor with Sleep Mode:
  - Highest Average Temperature: 5.00°C
- Sensor without Sleep Mode:
  - Highest Average Temperature: 28.08°C

b. Optimization Ration for Temperature Management: The optimization ratio is calculated as the reduction in temperature with sleep mode compared to without sleep mode.

$$= \frac{Highest\ Temperature\ without\ Sleep\ Mode}{Highest\ Temperature\ with\ Sleep\ Mode}$$

$$Optimization\ Ratio = \frac{28.08\,℃}{5.00\,℃} \approx 5.616 \qquad (2)$$

This means that temperature management with sleep mode is approximately 5.62 times better compared to without sleep mode.

Battery Life Optimization Ratio: The battery life with sleep mode is approximately 10.53% better than without sleep mode. Temperature Management Optimization Ratio: Temperature management with sleep mode is approximately 5.62 times better than without sleep mode. These optimization ratios clearly illustrate the significant improvements in power consumption and heat management achieved by implementing the sleep mode in WBAN sensors.

6. Conclusions

The proposed method utilizes a dynamic threshold mechanism and CNNs to optimize sensor activity, thereby extending battery life and maintaining optimal sensor temperatures. This adaptive approach significantly conserves energy and ensures accurate health monitoring. The implementation of sleep mode technology significantly improves battery life and temperature regulation without compromising monitoring accuracy. Our experimental results demonstrated a 10.53% reduction in energy consumption and a 5.62-fold improvement in temperature control. The CNN model, trained on the MIT-BIH Arrhythmia dataset, achieved a 98% classification accuracy, further validating the effectiveness of the proposed method. In conclusion, our findings illustrate the potential for improved energy efficiency and thermal management in WBANs, making them viable for continuous health monitoring.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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