International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Mathematical Modelling of Engineering Problems
Vol. 10, No. 6, December, 2023, pp. 2051-2062
Journal homepage: http://iieta.org/journals/mmep

Enhancing Cardiac Arrhythmia Detection in WBAN Sensors Through Supervised Machine Learning and Data Dimensionality Reduction Techniques

Safa Saad Hussein[1*], C. B. M. Rashidi[1], S. A. Aljunid[1], Muataz H. Salih[2], Mohammed Sabri Abuali[1], Arshad M. Khaleel[3,4]

[1] Centre of Excellence for Advanced Communication Engineering, Faculty of Electronic Engineering & Technology, Universiti Malaysia Perlis, Arau, Perlis 02600, Malaysia
[2] FLex, Universiti Malaysia Perlis, Arau, Perlis 02600, Malaysia
[3] Iraq Ministry of Education, Al-Anbar 31006, Iraq
[4] International Smart Card, Al-Anbar 31006, Iraq

Corresponding Author Email: eng.safa86@yahoo.com

https://doi.org/10.18280/mmep.100615

Received: 12 May 2023
Revised: 25 August 2023
Accepted: 15 September 2023
Available online: 21 December 2023

Keywords:
intelligent algorithms, anomalies detection, machine learning, heart pulses, supervised algorithms, numerical analysis, Python code

ABSTRACT

In recent years, the global medical community has endeavored to provide swift and efficient patient care by leveraging real-time patient databases. However, the efficacy of these systems, particularly wireless body area network (WBAN) sensors, has been undermined by inaccurate and low-performance readings, leading to unnecessary alarm triggers. This study scrutinizes the potential of data dimensionality reduction techniques and machine learning algorithms in augmenting the detection accuracy of cardiac abnormalities in WBAN sensors. Dimensionality reduction was performed using principal component analysis (PCA), independent component analysis (ICA), and spatial correlation methods. For arrhythmia prediction, Decision Tree and Multilayer Perceptron algorithms were implemented and their performance compared. Numerical simulations and Python code analysis revealed that the application of data reduction techniques significantly improved the reliability and effectiveness of WBAN sensors in handling voluminous datasets. Furthermore, the use of PCA, ICA, and spatial correlation strategies notably reduced WBAN sensor battery energy consumption, data storage needs, computational complexity, and processing time. These pragmatic solutions could potentially empower healthcare practitioners to intervene proactively before patients encounter life-threatening conditions. The results also demonstrated that feature selection effectively eliminated irrelevant attributes from noisy Electrocardiograms (ECGs), thereby enhancing the precision of the analyses.

1. INTRODUCTION

Arrhythmia, a condition causing irregular heart function and pulses, afflicts millions of individuals globally [1]. Traditional diagnostic approaches, such as ECG signal analysis, remain labor-intensive and susceptible to significant human error. However, with the advancement of artificial intelligence (AI) technology, there is a burgeoning interest in deploying machine learning (ML) algorithms for ECG signal analysis to facilitate arrhythmia detection.

Numerous promising studies have highlighted the potential of AI in arrhythmia detection. For instance, the use of Deep Neural Networks has been reported to accurately categorize 12 distinct types of arrhythmia [2]. Concurrently, the implementation of convolutional neural networks (CNNs) demonstrated reliable identification of various atrial fibrillation conditions, yielding an area under the receiver operating characteristic curve (AUROCC) of approximately 0.991 [3].

However, despite the promising potential of AI, several hurdles remain. The training and validation of AI models necessitates extensive and diverse ECG signal datasets. Additionally, the interpretation of AI model outputs may pose challenges for clinicians lacking appropriate training.

To address these challenges, the wireless body area network (WBAN) was developed as a functional network infrastructure for the collection of patient medical data and the detection of anomalous events. However, the data procured by sensor nodes are often marred by anomalies and irregularities due to hardware failures, inaccurate readings, unexpected events, and malicious attacks, compromising detection reliability [4-7].

The efficiency of a WBAN system is reflected in its detection metrics, such as true positives and false negatives, and operational efficiency, represented by power usage and data storage [8-10]. Therefore, the development of efficient and effective anomaly detection solutions for WBANs is a complex task, given the constraints of limited resources, large datasets (particularly in multivariate WBAN applications), and the real-time, streaming nature of sensor data.

This study aims to enhance the efficiency and adaptability of anomaly detection models for WBANs, specifically for dynamic streaming WBAN applications, by maximizing the utilization of limited sensor resources. The proposed methods are validated using multiple real-world medical datasets. WBANs, which enable constant patient monitoring and clinician notification from virtually any location, facilitate rapid biomedical data transfer from body-deployed sensors to a processing server.

WBANs are defined as networks of low-power, miniaturized, invasive or non-invasive, lightweight devices with wireless communication capabilities operating in close proximity to the human body [11, 12]. These wireless sensor nodes can remotely monitor and record a broad spectrum of human physiological parameters and are designed to be worn, carried, or implanted in the human body [13, 14]. Currently, WBANs find utility in a wide range of applications, including medical (wearable and implantable sensors), non-medical (entertainment, military and defense), and sports domains [15-18].

While wireless sensor networks (WSNs) have a plethora of non-medical applications, including home and industrial automation, the primary focus is given to the medical wireless sensor network (MWSN) due to its critical role in various domains - from sales tracking to industrial applications such as architecture and control, healthcare monitoring, and military applications for enemy target monitoring and tracking [19, 20].

Hence, priority should be given to the analysis of sensor data. As stated in [21], the primary purpose of WBAN extends beyond mere data collection from the deployment field; it also encompasses prompt data analysis, which forms the basis for critical decision-making. However, data quality, which reflects the true state of monitored surroundings, is of paramount concern. Regrettably, raw data procured from medical sensor nodes often suffer from inaccuracies and incompleteness, primarily due to incorrectly installed medical devices and ambient circumstances [22, 23].

There is an exigent need to develop and validate multiple detection methods for anomaly identification within WBANs. The efficacy of real-time anomaly detection techniques for local anomaly detection in multivariate data applications has been enhanced in recent WBAN applications [24-26]. Consequently, the detection of anomalies in multivariate data applications has a significant impact on the lifespan of WBANs. Furthermore, some real-time WBAN applications necessitate effective online detection methods without the burden of additional computational complexity or cost [27-29].

Given the dynamic nature of the collected sensory data, the regular information in WBAN becomes rigid. Detection methods tend to misclassify these variations, generating numerous false alarms, thereby diminishing the efficiency of the detection process [30-32]. These networks monitor these changes and update the regular databases as needed, eliminating unnecessary and faulty datasets. This is deemed beneficial in enhancing the performance of the detection process related to irregularities in heart pulses. Moreover, the adoption of the spatial correlation concept of sensor data in proximate neighborhoods could improve the detection effectiveness of heartbeat irregularities.

Practically, this study suggests an active approach to detecting anomalies in heart pulses. The objective is to enhance the accuracy, reliability, and performance of WBAN sensors and reduce erroneous signals and inaccurate anomaly detection in large heart pulse datasets.

The novelty of this work lies in the adoption of innovative approaches not extensively addressed in the existing literature. These include the elimination of unnecessary ECG signal datasets that may induce undue computational complexity, slower detection speed, increased energy consumption, and massive storage capacity. The innovation also extends to the implementation of four crucial data dimensionality reduction techniques (i.e., all features, spatial correlation, PCA, and ICA) and the application of multiple assessment metrics, including Accuracy, Precision, Recall, and F1-Score.

This research posits the following hypothesis: "The effectiveness of the anomaly detection solution for WBAN could be improved by multivariate data dimensionality reduction, efficient real-time adaptive learning and updating, and further considering spatial correlations of data measurements [33-35]".

The remainder of the paper is organized as follows:

Section 2 reviews recent publications discussing the benefits of ML principles and data dimensionality minimization techniques for WBAN sensors.

Section 3 outlines the adopted research methodology.

Section 4 presents the significant numerical results.

Section 5 concludes the study and discusses its main findings.

2. LITERATURE REVIEW

Anomaly detection algorithms for conventional networks have been the subject of a multitude of scholarly investigations. However, the implementation of these solutions is impeded by the processing, bandwidth, storage, and energy constraints inherent to Wireless Body Area Networks (WBANs) [36, 37]. Consequently, an imperative exists to either adapt existing methodologies to the unique requirements of WBANs or to formulate entirely novel approaches. Figure 1 elucidates the formidable challenges associated with anomaly detection in WBANs and underscores the limitations of currently available detection solutions.

The distinguishing trait of a viable solution for WBANs lies in its ability to detect abnormalities with both high accuracy and efficiency, while judiciously utilizing limited network resources. Moreover, Figure 2 delineates the specific challenges associated with Electrocardiogram (ECG) data within WBANs, which necessitates careful consideration during the development of anomaly detection technologies.

The effectiveness of anomaly detection is quantified through measures such as rate, false alarms, and accuracy, whereas efficiency is gauged through parameters such as memory utilization and energy consumption [38]. Thus, it is essential that any proposed solution strives to enhance detection effectiveness whilst mitigating the use of storage and energy resources in the detection process. With reference to Figure 2, two scenarios are presented, which epitomize the problems this research seeks to address, and underscore the pivotal considerations in the design of anomaly detection solutions.

The challenges depicted in Figure 1, including low detection accuracy, a high false alarm rate, and an inability to adapt adequately to dynamic data changes, can be addressed by reducing data dimensionality and curtailing unnecessary data volumes, such as those devoid of faults or irregularities in heartbeats. The constraints on resources in WBAN sensors can be alleviated by employing larger storage capacities for the recorded and collected datasets of heartbeats.

The primary contributors to the rapid depletion of sensor energy are the data transfers between sensor nodes and central sites, such as base stations or cluster heads. A substantial ratio (in the range of 103-104) has been reported between communication and calculation energy, highlighting the significance of this issue [39]. It is thus inferred that the conservation of energy, and consequently extension of sensor lifespan, can be achieved by minimizing the communication between cluster heads and sensors.

Typically, sensor readings exhibit consistency, with anomalies being a rarity [40]. Therefore, it is suggested that the transmission of only anomalous measurements could significantly curtail overall energy requirements. Additionally, the processing of multivariate data imposes an additional computational burden. As a result, the reduction of data dimensionality emerges as a critical strategy for enhancing efficiency and prolonging the operational lifetime of sensor networks.

The effectiveness of anomaly detection is influenced by both the size of the dataset and the complexity of the employed detection methods. The computational complexity of the 1-class support vector machine method equals O(max(n, d) min(n, d)^2), where n represents the total number of measurements/ points within a given time interval/ dimension, denoted by Kalpana et al. [41] and Ganaie et al. [42].

Such complexity precipitates rapid energy consumption, rendering the proposed solution infeasible for online detection, particularly in wireless sensor network (WSN) applications that necessitate real-time detection.

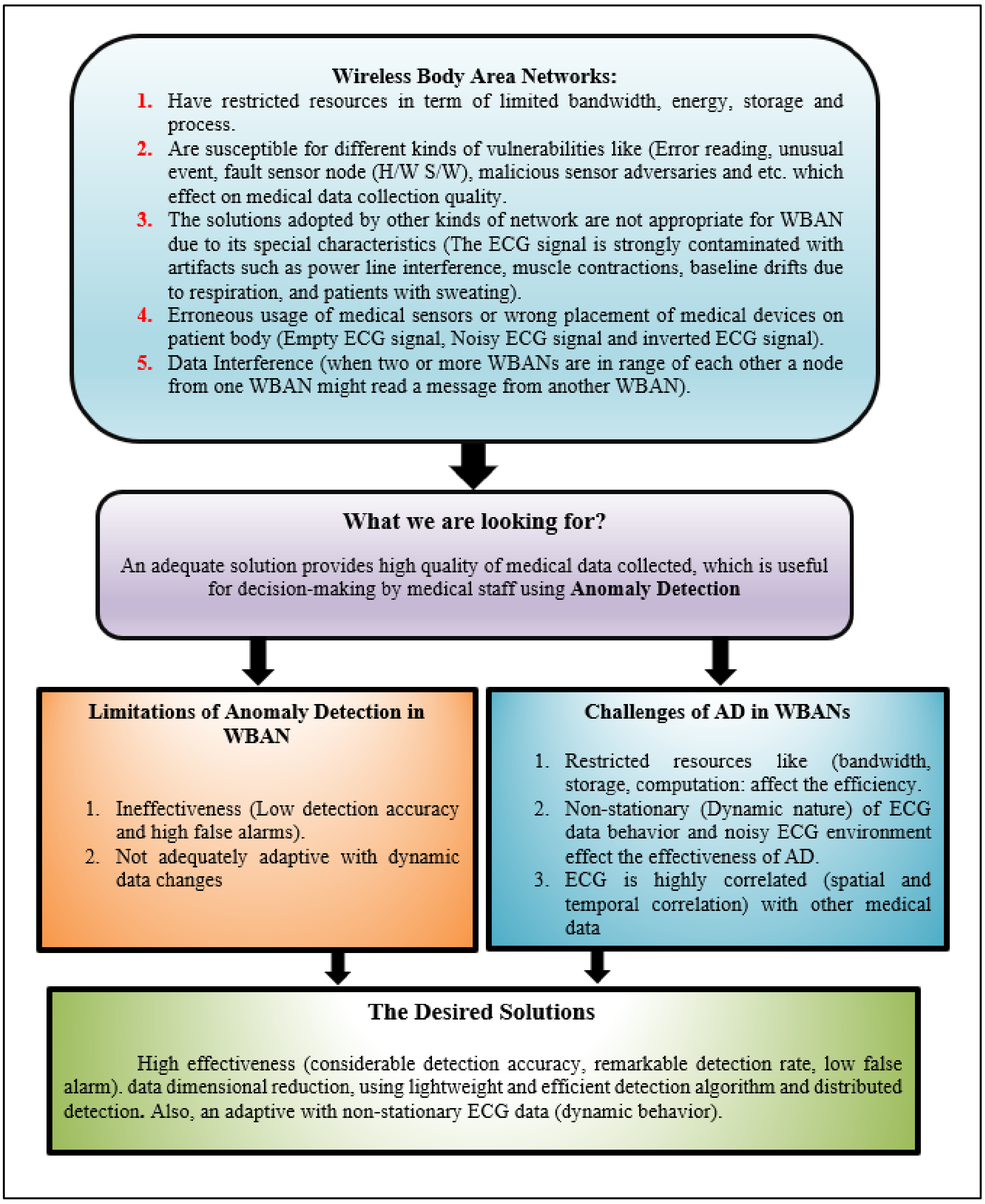

Figure 1. Critical limitations and major challenges associated with anomaly detection in WBANs

In response to the limitations and challenges associated with Electrocardiogram (ECG) data, as illustrated in Figure 2, several solutions have been proposed. These include: (A) the utilization of filtering techniques for noise elimination, (B) the application of clustering and organization methods for the differentiation of ECG signals from other data, (C) the remediation of the non-stationary behavior of ECG signals through skin preparation techniques, such as cleaning the sensor contact area, removing sweat, and hair, (D) the detection of hidden data (e.g., U-waves in patients) through advanced WBAN sensors, (E) the identification and removal of heartbeat irregularities through the analysis of regular datasets, (F) the management of large datasets through data dimensionality reduction methods, such as principal component analysis (PCA) and feature selection, and (G) the monitoring and remediation of changing frequency and amplitude variations in ECG signals through electrical power quality treatment techniques and transient disturbance removal.

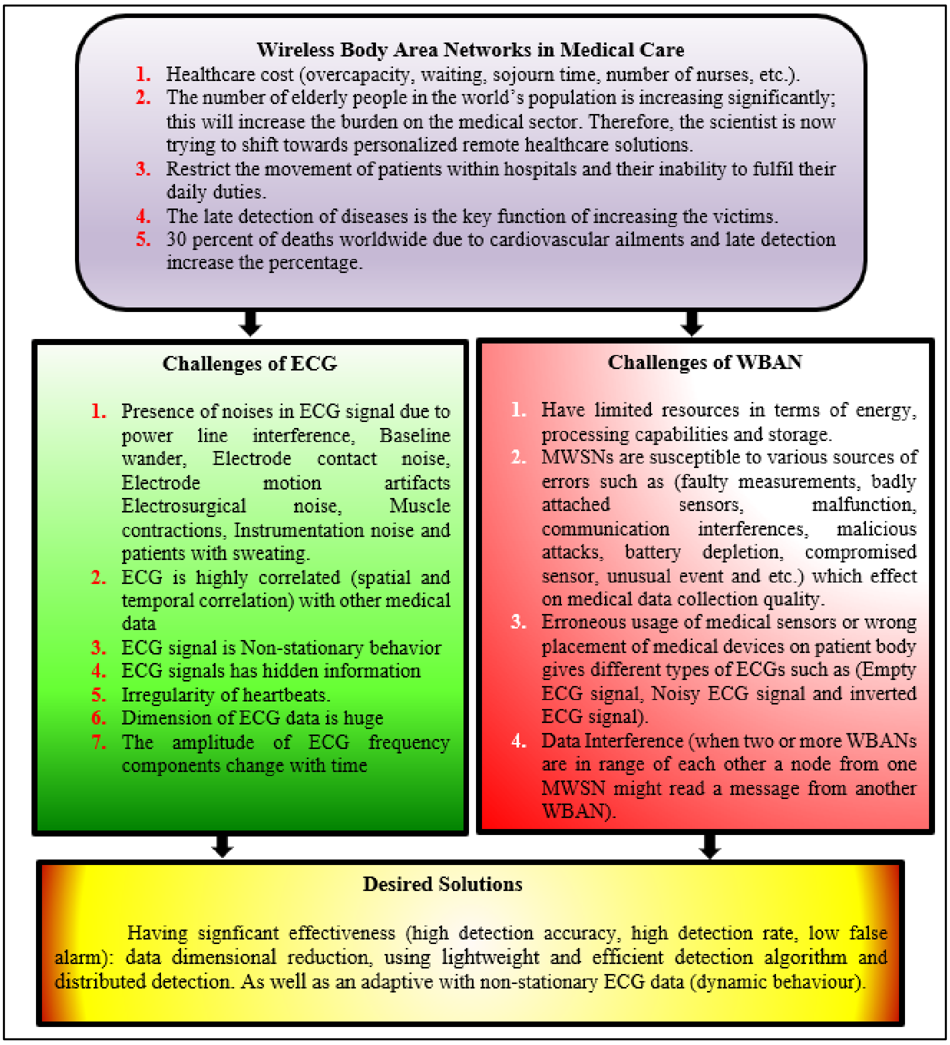

Figure 2. Major obstacles and challenges associated with anomaly detection in ECG

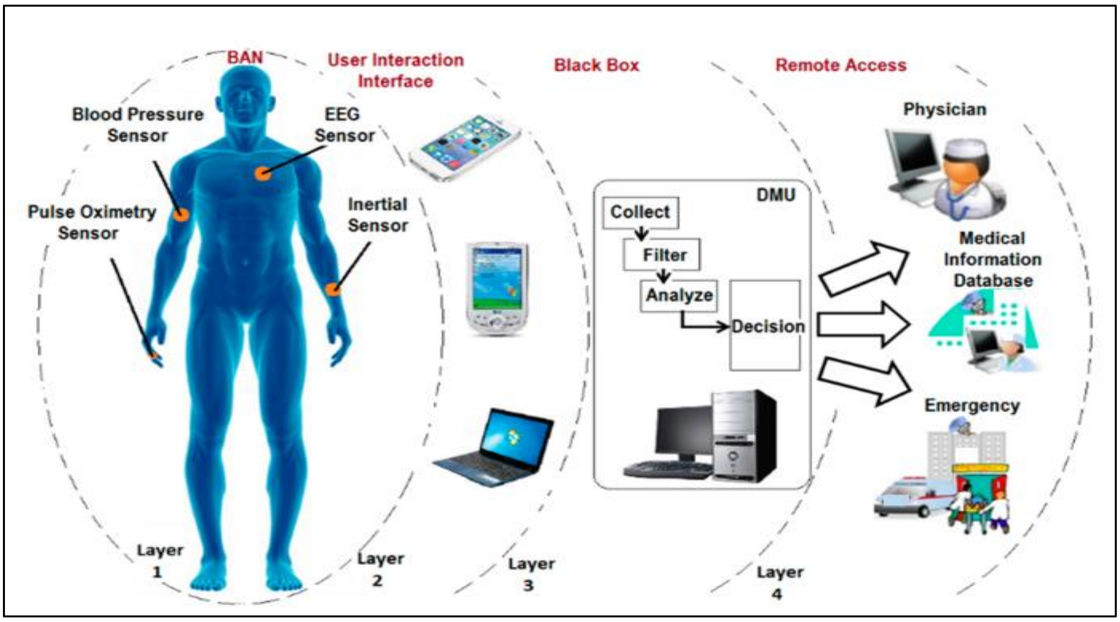

Figure 3. Wireless body area network in medical healthcare

The application of WBAN sensors is incredibly varied, spanning industries as disparate as universal health care, the military, sports, the entertainment business, and countless more that involve people in some way [43, 44]. Furthermore, it can be noted from the information illustrated in Figure 3 that WBAN Miniature sensors can be either invasive (intended for surgical implantation) or non-invasive (they can have inserted or affixed to the human skin). They don't interfere with people's activities, but they can record how the physical world changes while a person does things [45, 46].

3. RESEARCH METHODOLOGY

This paper is guided to investigate and assess the critical roles and substantial contributions of some intelligent algorithms, including:

[A] Decision Tree

[B] Multilayer Perceptron

Those algorithms are harnessed to detect and classify irregularities and anomaly data in the heartbeats and measure and register signals using ECG electrical devices integrated into the human body. The study relies on some critical research steps and analytical processes to achieve the primary goal of this work. Firstly, a simple review is carried out to address the critical rationale and key strengths of ML principles in enhancing the effectiveness of WBAN sensors to boost the reliability and precision of the real-time database of patients and offer more delicate alarms than conventional sensors and medical data recording devices that correspond to significant levels of errors and faults, resulting to disturbing faulty warnings and false alerts that make substantial losses in the effort and time of healthcare professionals as of inaccurate data. Hence, a case study of a patient facing heart problems is considered. This case study is representative of a realistic ECG dataset that comprises irregularities in heartbeats.

Using a WBAN sensor implanted in the patient, doctors may monitor vital signs in real-time. In this scenario, the datasets stand in for heartbeats or cardiac strokes that have been analyzed, and they have been shown to include flaws or anomalies. These two intelligent algorithms will improve the sensor's effectiveness and performance in a number of ways, including reliability, efficiency, competence, and accuracy in terms of precise alarms and trustful signals for doctors, nurses, physicians, and other healthcare providers, allowing them to save the patient's life in the midst of a potentially fatal heart attack. Figure 4 presents the research methodology implemented and adopted in this work.

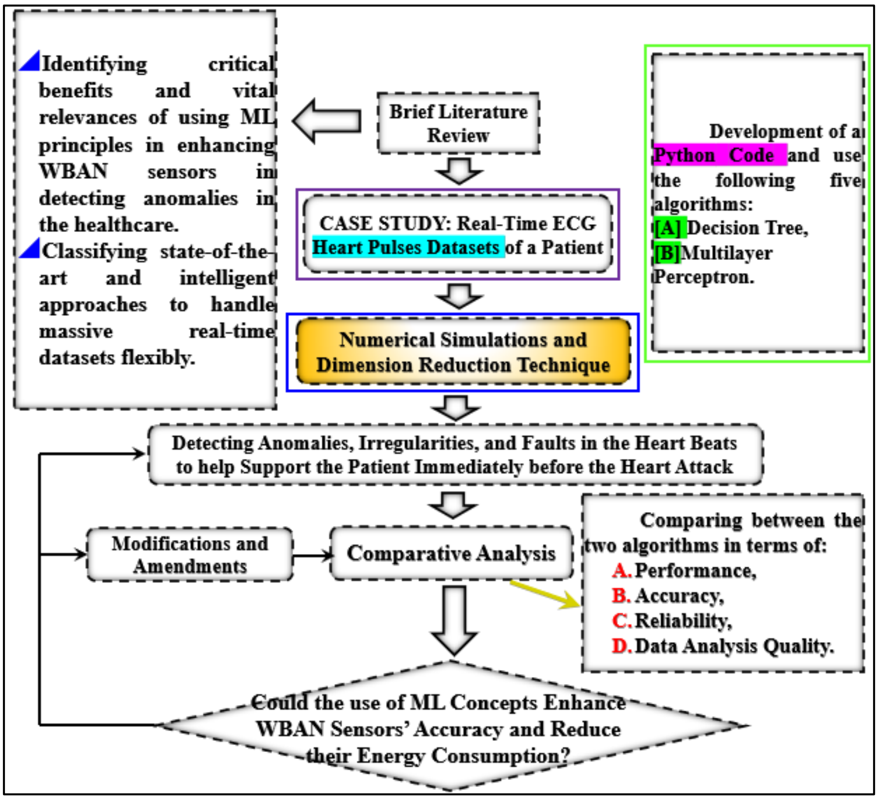

Figure 4. The research methodology adopted in this work

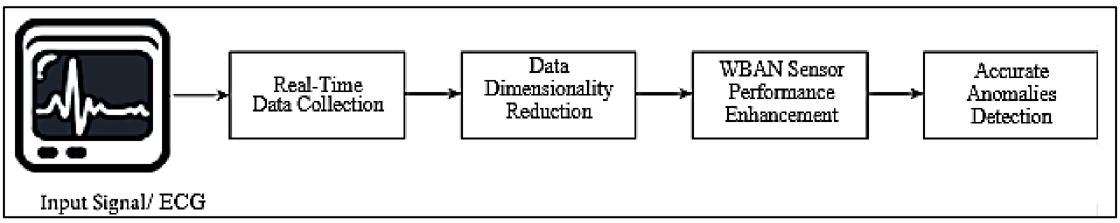

Figure 5. The ECG record and numerical dataset analysis procedure in this research

From the data described in Figure 4, it can be inferred that this article will follow a number of research phases and study steps to conduct the numerical analysis of anomalies in the heart pulses to detect them with significant rates of accuracy and effectiveness. Firstly, brief literature is represented to address the importance of novel methods and innovative techniques that were recently implemented by scholars to increase the efficiency and performance of the detection process in patients facing irregularities in heart function. Following this process, the research will analyze a case study in which ECG signals are investigated to identify abnormalities and anomalies. Numerical simulation procedures are carried out through numerical codes that are developed and run in Python software. Some criteria are taken into consideration, including recall, accuracy, F1-Score, and precision, to assess the effectiveness of intelligent algorithms and active AI models in conducting the detection process effectively. Then, modifications and adjustments are executed to validate the performance of intelligent ML schemes with the help of the comparative analysis that takes into account performance, accuracy, reliability, and data analysis quality in those numerical models.

Furthermore, because the size of the data collected would be considerable, some data will be discarded (which represent regular readings and comprise no anomalies). The importance of the data dimension reduction approach would help minimize the large size of this big data that may correspond to the more significant computational effort, energy consumption, and time required to treat all this data and predict the anomalies. In addition, the data dimension reduction technique will be implemented with intelligent ANN and DL algorithms.

One of the challenges faced by the researcher in offering the ECG data includes some limitations in taking permission from the patient who suffers from heart attacks to attack WBAN sensors. In addition, another rule of this work is reflected in the larger size of the dataset and the longer duration (24 hours and several days) required to record high-quality datasets.

For all these reasons, the ECG dataset was detected and taken from reference [47], in which authors provided and investigated multiple datasets associated with heartbeats of patients with real heart problems.

Following paragraphs represent the critical mathematical modeling of the algorithms considered in this study.

3.1 Description of the dataset

The dataset employed in this work includes the signals recorded with the help of the electro cardio gram (ECG) electric device, which measures the heart pulses and beats continuously (24 hours and several days) by virtue of WBAN sensors attached to the body of the patient, who suffers from arrhythmia. The category of this data is MIT-BIH Arrhythmia Database.

Hence, anomalies and irregularities of heartbeats can be flexibly detected and identified. Nonetheless, because this WBAN sensor records all those readings, it is predicted that the size of the MIT-BIH Arrhythmia dataset would be significantly large. Hence, more considerable computational complexity and processing time would be massive. Furthermore, because the MIT-BIH Arrhythmia dataset contains a record of several days and long durations, the energy consumption of the WBAN sensor, cost, and storage capacity would be enormous. To handle all these problems and treat these obstacles, scholars suggested the implementation of data dimensionality techniques, such as feature selection via spatial correlation (SC), independent component analysis (ICA), and principal component analysis (PCA).

Therefore, enhanced performance and better reliability of the detection process can be attained with the adoption of intelligent algorithms considered in this numerical analysis. The MIT-BIH Arrhythmia dataset processing and analysis will be conducted based on Figure 5.

It can be inferred from Figure 5 that the ECG's numerical analysis goes through four major phases, including (A) recording ECG signals via real-time data collection, (B) data dimensionality reduction (which is an effective method to increase the performance of the detection process), (C) WBAN sensor effectiveness enhancement by virtue of some improvements method and devices, and (D) the execution of anomalies detection with the support of ML concepts and numerical AI models.

3.2 Algorithms Implemented in this research

There are two major intelligent algorithms considered in this work to carry out high-performance detection of irregularities and anomalies in patients with heart problems. Those two algorithms are the decision tree and multilayer perceptron. Th e following paragraphs illustrate more details about decision tree theory and multilayer perceptron theory.

3.2.1 Decision tree theory

A decision tree (DT) algorithm can be defined as "A non-parametric intelligent supervised learning algorithm. It is employed to conduct various beneficial regression and classification tasks." And the results of that computation of entropy and data gain can be considered the DT. By performing a series of calculations until a class is assigned to all of the tree's characteristics, we can acquire this data [48].

The rules model can be considered an explanatory illustration, which presents the DT. Wang et al. [49] mentioned that the binary tree is recognized as a simple model of the DT algorithm. This tree has one branch, two leaf nodes, and one root node. This DT algorithm model, BDT, can be expressed using the relationship:

$$BDT = h(x, a_m) \tag{1}$$

where:
x: The continuous variable
a_m: The split characteristic parameter corresponds to m^{th} iteration

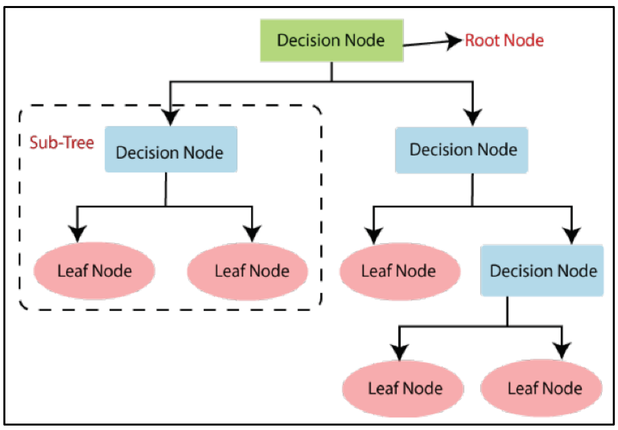

Figure 6. The DT algorithm's prominent architecture [50]

Figure 6 indicates the substantial principles and configuration of the DT algorithm.

It is concluded from Figure 6 that the DT architecture relies on various numerical methods, such as the decision node, which contains minor nodes known as leaf nodes, to help carry out the required numerical simulation and mathematical analysis procedure.

3.2.2 Multilayer perceptron theory

Multilayer perceptron (MLP) algorithm is depicted as "A supervised overall connected category of feedforward ANN principles." To give a further clear idea regarding the MLP algorithm, it is worth mentioning that a single-layer perception (SLP) is featured with only two output and input layers. Thus, it is recognized as the briefest shape of various ANN algorithms.

The disadvantage of SLP algorithms is reflected in the fact that they cannot handle and optimize the nonlinear and separable patterns with higher degrees of efficiency and flexibility. Hence, scholars and computer science researchers developed a modified type of this algorithm, known as MLP.

Saremi et al. [51] adopted mathematical modeling and analysis of some formulas and theoretical work related to the SLPs. They reported that the MLP algorithm is implemented in conjunction with grasshopper optimization principles to predict some critical outputs based on the simulation and analysis of the following relationship:

$$X_i = A_i + S_i + G_i \tag{2}$$

where, X_i denotes the location of i^{th} insect, A_i indicates the wind advection, S_i is social communication, and G_i presents the gravity strength related to the i^{th} insect. A modification of the previous formula can be applied to express the same function as:

$$X_i = r_3 A_i + r_1 S_i + r_2 G_i \tag{3}$$

where, r_1, r_2, and r_3 represent the random values related to the range [0,1]. The solution of the last equation using the MLP principles can be expressed as:

$$S_i = \sum_{j=1, j\neq i}^{N} s(d_{ij})\hat{d}_{ij}, d_{ij} = |x_j - x_i|, \hat{d}_{ij} = (x_j - x_i)/d_{ij} \tag{4}$$

where, d_{ij} indicates the the distance between the i^{th} and the j^{th} grasshopper. It is computed as $d_{ij} = |x_j - x_i|$, $s(d_{ij})$ is a function to be defined for the strength of social forces, $\hat{d}_{ij}$ is a unit vector related to the i^{th} grasshopper to the j^{th} grasshopper.

Figure 7 depicts the workflow and general structure of the multilayer perceptron algorithm, taking into consideration the cooling and heating load outputs of a facility [52].

It is inferred from Figure 7 that the workflow linked to the multilayer perceptron algorithm comprises an input layer in which the variables and dataset are defined, hidden layers in which the algorithm's simulation is conducted and an output layer by which the simulation findings are obtained.

Hussein et al. [53] mentioned that the critical benefits of those intelligent algorithms do not include only accurate and high-performance detection but also achieving active energy-savings and mitigation of massive energy consumption when real-time data are collected from patients.

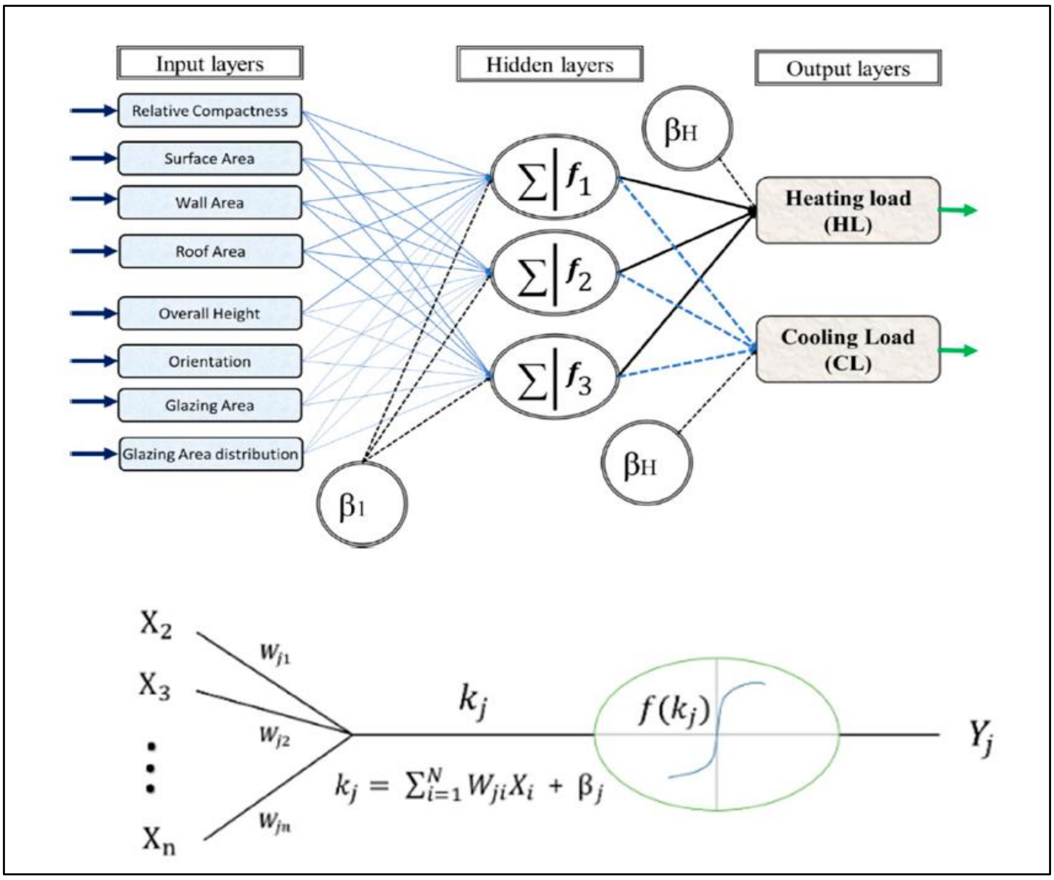

Figure 7. The workflow and general structure of the multilayer perceptron algorithm considering the cooling and heating load outputs of a facility [52]

4. NUMERICAL SIMULATION OUTCOMES

This section represents the critical results obtained from the Python code numerical analysis. A comparative analysis is conducted between the two ML algorithms based on the four data dimensionality reduction approaches, represented below:

(I) Selection, prediction, and optimization of **ALL** the **FEATURES** related to the ECG datasets;
(II) Selection, prediction, and optimization of the dataset depending on the **SPATIAL CORRELATION** (which can be employed for data dimensionality reduction and computational complexity mitigation);
(III) Features choice and identification depending on the **PCA** approach (as another technique for data dimensionality minimization);
(IV) Features identification and prediction depend on the **ICA** approach (as a third approach for data dimensionality reduction).

4.1 All-Feature approach results

The 'All-Features' selection and identification strategy was used in conjunction with ML algorithms to analyze the ECG dataset for abnormalities and identify anomalies. Based on the simulation and optimization procedures related to this approach, the critical findings can be represented in Table 1.

Table 1. ML assessment outputs using the all-features approach

Models	Accuracy	Precision	Recall	F1-Score
DT	93%	60%	50%	55%
MLP	95%	70%	52%	60%

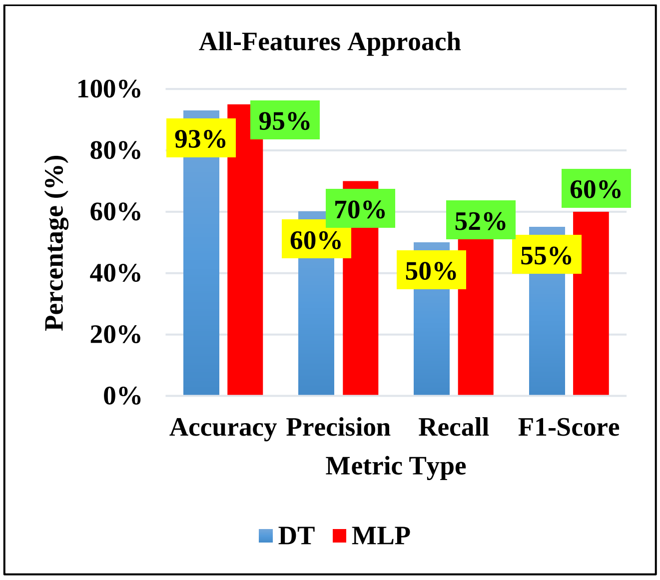

Figure 8. The four metrics' assessment findings for the first approach

It can be inferred from Table 1 that the accuracy of both algorithms used in this research ranges between 93% and 95%. Also, it is observed that the MLP algorithm gave the most significant accuracy compared with the DT algorithm, which has the lowest performance. Besides, Figure 8 indicates four fundamental assessment metrics and performance evaluation indices that could provide various ideas regarding the effectiveness, accuracy, and reliability of the two algorithms investigated in this work.

It is concluded from Figure 8 that (besides the accuracy) the precision of both algorithms ranges approximately between 60% and 70%, knowing that the MLP gave the highest precision rate compared with the DT. At the same time, the F1-Score ranges from roughly 55% and approximately 60%, considering that the MLP (as well) provided the most considerable F1-Score with a ratio of 60%. The recall range is between about 50% and 52%. The minimum recall rate was for the DT algorithm, contributing to a rate of 50%.

4.2 Spatial correlation approach results

Because of the large size of the patient's heart function dataset, the second data dimensionality reduction strategy was adopted to help the WBAN sensor provide more precise signals and reliable alarms. This could lead to significant improvements and reduced computational complexity and time efficiency. The results of the metrics and effectiveness evaluations based on the two algorithms investigated in this work are shown in Table 2.

Table 2. ML evaluation outputs via the spatial correlation approach

Models	Accuracy	Precision	Recall	F1-Score
DT	96%	66%	56%	61%
MLP	97%	76%	58%	66%

It can be noted from Table 2 that the accuracy ratios related to the two algorithms range from 96% and 97%. The MLP algorithm provided the most remarkable accuracy compared with the DT algorithm, corresponding to 97% compared to 96%, respectively. A graphical representation of accuracy, precision, recall, and F1-Score is described in Figure 9.

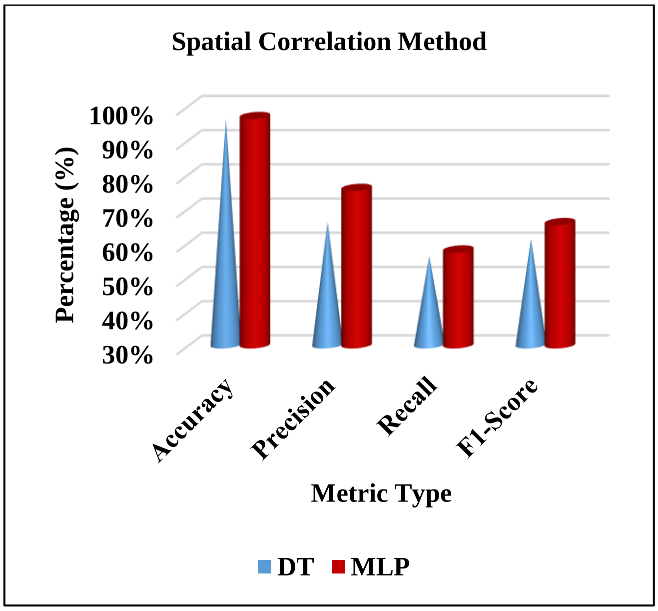

Figure 9. The four metrics' assessment findings for the second approach

It is depicted from Figure 9 that the precision of the two algorithms ranges between around 66% and 76%. The MLP again (as shown in the first approach [all features]) provided the highest precision ratio compared to the DT algorithm.

Meanwhile, the recall rate of both algorithms ranges between 56% and 58%. Nonetheless, the ML algorithm has the highest rate of recall than the DT. Also, it is inferred from this figure that the F1-Score portion ranges from 61% and 66%. Meantime, the MLP algorithm has only the most significant F1-Scare rate, contributing to 66%.

4.3 PCA approach outputs

The PCA approach is a third effective data dimensionality reduction tactic that helps optimize and alleviate the computational complexity and time consumption of the WBAN sensor used to alert healthcare professionals when a heart attack may occur in patients. Therefore, reliable and active assistance can be flexibly provided and given. Concerning the numerical results of this approach, Table 3 illustrates the primary evaluation metrics and effectiveness examination according to the two algorithms.

Table 3. ML evaluation outputs using the PCA approach

Models	Accuracy	Precision	Recall	F1-Score
DT	93%	61%	51%	56%
MLP	97%	71%	53%	61%

It can be observed from Table 3 that the accuracy ratios linked to the investigated algorithms correspond to very high values (like in MLP). Notwithstanding, the DT algorithm has the lowest accuracy (with an amount of 93%). Further illustrations of the four indices of performance evaluation are expressed in Figure 10.

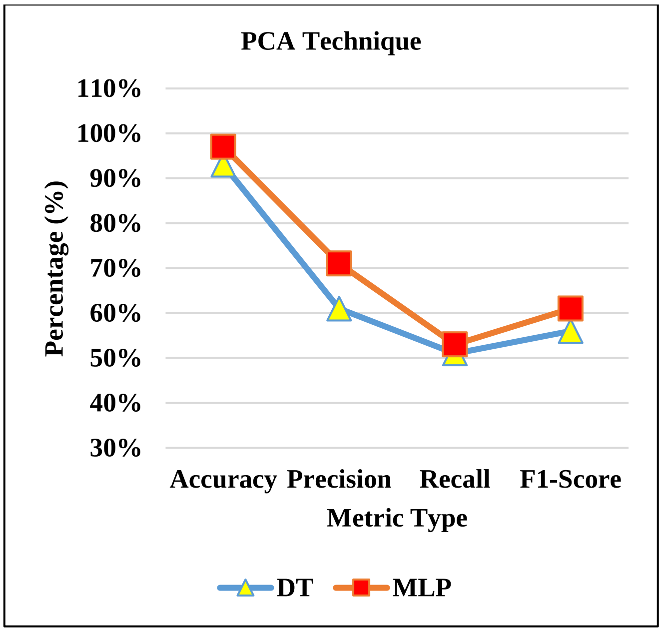

Figure 10. The four metrics' assessment findings for the third approach

It is indicated in Figure 10 that the two algorithm's precision has a range between approximately 61% and 71%. However, the two algorithms have a closer value (of 53% and 51%) related to the recall ratios. Moreover, the F1-Score range is between 56% and 61%. The MLP in this approach has the maximum F1-Score like the previous approaches compared with the DT algorithm.

4.4 ICA approach outputs

As the last functional data dimensionality reduction strategy, ICA can help optimize and mitigate the computational complexity and time consumption associated with the WBAN sensor used to alert healthcare professionals with a higher degree of accuracy and performance when a heart attack may occur in patients. So, it's simple to provide practical and trustworthy help. Table 4 displays the primary evaluation metrics and effectiveness examination related to the two algorithms used in this technique's numerical outcomes.

Table 4. ML evaluation outputs using the ICA approach

Models	Accuracy	Precision	Recall	F1-Score
DT	93%	63%	53%	58%
MLP	97%	73%	55%	63%

It is deduced from Table 4 that the two algorithms' accuracy ratios related to the investigated algorithms correspond to remarkably high quantities. Nevertheless, in this approach, only the MLP algorithm had the highest proportion (with a percentage of 97% than the DT, which has an accuracy of only 93%). In addition, Figure 11 offers a graphical representation pertaining to the four metrics and evaluation criteria considered to assess the performance and reliability of both algorithms in this work.

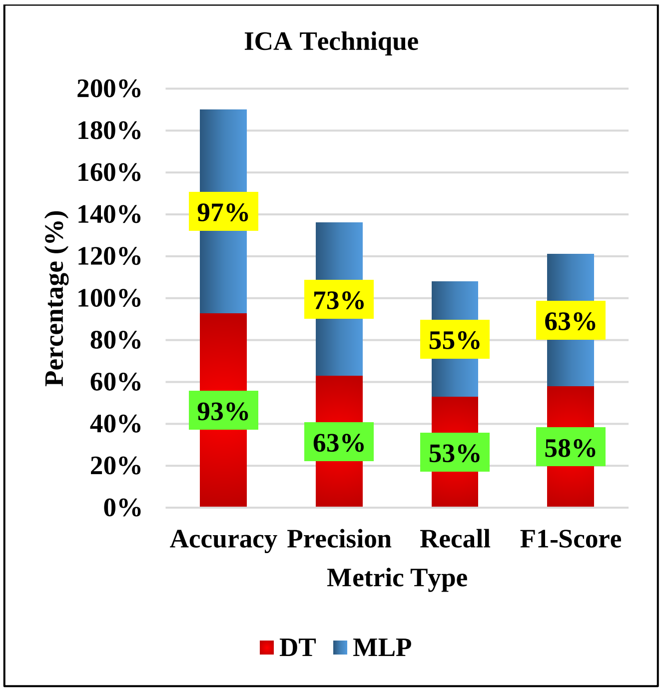

Figure 11. The four metrics' assessment findings for the fourth approach

According to the numerical outcomes presented in Figure 11, it can be inferred that the precision, F1-Score, and recall ranges contain the following ratios (63% to 73%, 53% to 55%, and 58% to 63%), respectively. Meanwhile, it is noted that the MLP algorithm has the most significant percentages of precision, recall, and F1-Score than the DT algorithm.

5. CONCLUSIONS

This research is guided to evaluate and examine the critical contributions and substantial impacts and benefits of implementing intelligent ML algorithms and data dimensionality reduction techniques in boosting the performance and efficiency of WBAN sensors in providing valid, accurate, and trustworthy alarming signals for the healthcare providers, like doctors, nurses, and physicians to help rescue the lives of patients suffering from heart arrhythmia. The study depended on PCA, ICA, and spatial correlation approaches for data dimensionality mitigation. Furthermore, Decision Tree and Multilayer Perceptron algorithms were employed to achieve accurate and high-performance detection of anomalies and irregularities. Based on the numerical simulation and Python code analysis, the work results can be summarized in the following paragraphs:

(I) Adopting active data dimensionality reduction techniques for the massive dataset would help improve WBAN sensors' trustworthiness and effectiveness.
(II) Employing PCA, ICA, and spatial correlation approaches helped alleviate WBAN sensor battery energy usage, data storage, computational complexity, and processing time.
(III) Utilizing data dimensionality strategies could support healthcare professionals in rescuing patients before severe death threats occur.
(IV) Employing feature selection removed irrelevant features from noisy ECGs.

6. RESEARCH LIMITATIONS

Despite the successful implementation of ML approaches and execution of this work, this research faced some challenges and critical obstacles that limited the overall achievement of this study. The most problematic barrier in this article was the ethical approval required for patients to permit the integration of WBAN sensors in their bodies to collect the necessary data associated with their heartbeats and predict anomalies and irregularities in the heart function based on the gathered database from those intelligent sensors. In addition, another barrier of this study is reflected in the long-term process of data collection to offer a sufficient amount of dataset that can be effectively analyzed by virtue of ML concepts. To overcome those two challenges, the researcher relied on the provision of the historical dataset available from other scholars who have already collected heart pulse information from other patients already and uploaded those datasets to the web.

7. FUTURE SUGGESTIONS AND OUTLOOK

Based on the research findings attained from the execution of this study, this study proposes a set of future suggestions and prospects that can be adopted and implemented to enhance the outputs and contributions of this work. Those future suggestions include the following aspects:

(I) To offer a real dataset from a patient suffering from arrhythmia and integrate WBAN sensors to measure his/her heartbeats to provide authentic datasets,
(II) To utilize other intelligent algorithms not used in this article, such as Particle Swarm Optimization (PSO).
(III) To measure other parameters and variables not assessed or examined in this manuscript.

REFERENCES

[1] Lippi, G., Sanchis-Gomar, F., Cervellin, G. (2020). Global epidemiology of atrial fibrillation: An increasing epidemic and public health challenge. International Journal of Stroke, 15(8): 819-821. https://doi.org/10.1177/1747493019897870
[2] Attia, Z.I., Kapa, S., Lopez-Jimenez, F., McKie, P.M., Ladewig, D.J., Satam, G., Pellikka, P.A., Enriquez-Sarano, M., Noseworthy, P.A., Munger, T.M., Asirvatham, S.J., Scott, C.G., Carter, R.G., Noseworthy, P.A. (2019). Screening for cardiac contractile dysfunction using an artificial intelligence–enabled electrocardiogram. Nature Medicine, 25(1): 70-74. https://doi.org/10.1038/s41591-018-0240-2
[3] Zhang, J., Gajjala, S., Agrawal, P., Tison, G.H., Hallock, L.A., Beussink-Nelson, L., Lassen, M.H., Fan, E., Aras, M.A., Jordan, C., Fleischmann, K.E., Melisko, M., Qasim, A., Shah, S.J., Bajcsy, R., Cheng, S. (2020). Fully automated echocardiogram interpretation in clinical practice using deep learning. Circulation, 142(21): 2028-2030. https://doi.org/10.1161/CIRCULATIONAHA.118.034338
[4] Abidi, B., Jilbab, A., Mohamed, E.H. (2018). An energy efficiency routing protocol for wireless body area networks. Journal of Medical Engineering & Technology, 42(4): 290-297. https://doi.org/10.1080/03091902.2018.1483440
[5] Pillai, R.R., Lohani, R.B. (2020). Abnormality detection and energy conservation in wireless body area networks using hidden Markov models: A review. In 2020 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, pp. 935-939. https://doi.org/10.1109/ICCSP48568.2020.9182131
[6] Salem, O., Serhrouchni, A., Mehaoua, A., Boutaba, R. (2018). Event detection in wireless body area networks using Kalman filter and power divergence. IEEE Transactions on Network and Service Management, 15(3): 1018-1034. https://doi.org/10.1109/TNSM.2018.2842195
[7] Salem, O., Alsubhi, K., Mehaoua, A., Boutaba, R. (2020). Markov models for anomaly detection in wireless body area networks for secure health monitoring. IEEE Journal on Selected Areas in Communications, 39(2): 526-540. https://doi.org/10.1109/JSAC.2020.3020602
[8] Tavera, C.A., Ortiz, J.H., Khalaf, O.I., Saavedra, D.F., Aldhyani, T.H. (2021). Wearable wireless body area networks for medical applications. Computational and Mathematical Methods in Medicine, 2021: 55774376. https://doi.org/10.1155/2021/5574376
[9] Liu, Q., Mkongwa, K.G., Zhang, C. (2021). Performance issues in wireless body area networks for the healthcare application: A survey and future prospects. SN Applied Sciences, 3: 1-19. https://doi.org/10.1007/s42452-020-04058-2
[10] Arfaoui, A., Kribeche, A., Senouci, S.M., Hamdi, M. (2019). Game-based adaptive anomaly detection in wireless body area networks. Computer Networks, 163:

106870. https://doi.org/10.1016/j.comnet.2019.106870
[11] Cicioğlu, M., Çalhan, A. (2019). SDN-based wireless body area network routing algorithm for healthcare architecture. Etri Journal, 41(4): 452-464. https://doi.org/10.4218/etrij.2018-0630
[12] Hasan, K., Biswas, K., Ahmed, K., Nafi, N.S., Islam, M.S. (2019). A comprehensive review of wireless body area network. Journal of Network and Computer Applications, 143: 178-198. https://doi.org/10.1016/j.jnca.2019.06.016
[13] Chavva, S.R., Sangam, R.S. (2019). An energy-efficient multi-hop routing protocol for health monitoring in wireless body area networks. Network Modeling Analysis in Health Informatics and Bioinformatics, 8: 1-10. https://doi.org/10.1007/s13721-019-0201-9
[14] Khan, R.A., Pathan, A.S.K. (2018). The state-of-the-art wireless body area sensor networks: A survey. International Journal of Distributed Sensor Networks, 14(4): 1550147718768994. https://doi.org/10.1177/1550147718768994
[15] Olatinwo, D.D., Abu-Mahfouz, A., Hancke, G. (2019). A survey on LPWAN technologies in WBAN for remote health-care monitoring. Sensors, 19(23): 5268. https://doi.org/10.3390/s19235268
[16] Soni, M., Singh, D.K. (2022). New directions for security attacks, privacy, and malware detection in WBAN. Evolutionary Intelligence, 16: 1917-1934. https://doi.org/10.1007/s12065-022-00759-2
[17] Bhatti, D.S., Saleem, S., Imran, A., Iqbal, Z., Alzahrani, A., Kim, H., Kim, K.I. (2022). A survey on wireless wearable body area networks: A perspective of technology and economy. Sensors, 22(20): 7722. https://doi.org/10.3390/s22207722
[18] Shokeen, S., Parkash, D. (2019). A systematic review of wireless body area network. In 2019 International Conference on Automation, Computational and Technology Management (ICACTM), London, UK, pp. 58-62. https://doi.org/10.1109/ICACTM.2019.8776847
[19] Abolhassani Khajeh, S., Saberikamarposhti, M., Rahmani, A.M. (2022). Real-time scheduling in IoT applications: A systematic review. Sensors, 23(1): 232. https://doi.org/10.3390/s23010232
[20] Zamini, M., Hasheminejad, S.M.H. (2019). A comprehensive survey of anomaly detection in banking, wireless sensor networks, social networks, and healthcare. Intelligent Decision Technologies, 13(2): 229-270. https://doi.org/10.3233/IDT-170155
[21] Safaei, M., Asadi, S., Driss, M., Boulila, W., Alsaeedi, A., Chizari, H., Abdullah, R., Safaei, M. (2020). A systematic literature review on outlier detection in wireless sensor networks. Symmetry, 12(3): 328. https://doi.org/10.3390/sym12030328
[22] Al Rasyid, M.U.H., Nadhori, I.U., Syarif, I., Winarno, I., Furoida, F., Amrullah, A. (2021). Anomaly detection in wireless body area network using Mahalanobis distance and sequential minimal optimization regression. In 2021 International Seminar on Application for Technology of Information and Communication (iSemantic), Semarangin, Indonesia, pp. 64-69. https://doi.org/10.1109/iSemantic52711.2021.9573193
[23] Newaz, A.I., Haque, N.I., Sikder, A.K., Rahman, M.A., Uluagac, A.S. (2020). Adversarial attacks to machine learning-based smart healthcare systems. In GLOBECOM 2020-2020 IEEE Global Communications Conference, Taipei, Taiwan, pp. 1-6. https://doi.org/10.1109/GLOBECOM42002.2020.9322472
[24] Liu, Y., Kumar, N., Xiong, Z., Lim, W.Y.B., Kang, J., Niyato, D. (2020). Communication-efficient federated learning for anomaly detection in industrial internet of things. In GLOBECOM 2020-2020 IEEE Global Communications Conference, Taipei, Taiwan, pp. 1-6. https://doi.org/10.1109/GLOBECOM42002.2020.9348249
[25] Ullah, W., Ullah, A., Haq, I.U., Muhammad, K., Sajjad, M., Baik, S.W. (2021). CNN features with bi-directional LSTM for real-time anomaly detection in surveillance networks. Multimedia Tools and Applications, 80: 16979-16995. https://doi.org/10.1007/s11042-020-09406-3
[26] Wu, W., He, L., Lin, W., Su, Y., Cui, Y., Maple, C., Jarvis, S. (2020). Developing an unsupervised real-time anomaly detection scheme for time series with multi-seasonality. IEEE Transactions on Knowledge and Data Engineering, 34(9): 4147-4160. https://doi.org/10.1109/TKDE.2020.3035685
[27] Xu, S., Qian, Y., Hu, R.Q. (2019). Data-driven network intelligence for anomaly detection. IEEE Network, 33(3): 88-95. https://doi.org/10.1109/MNET.2019.1800358
[28] Ding, N., Ma, H., Gao, H., Ma, Y., Tan, G. (2019). Real-time anomaly detection based on long short-Term memory and Gaussian Mixture Model. Computers & Electrical Engineering, 79: 106458. https://doi.org/10.1016/j.compeleceng.2019.106458
[29] Lee, H., Li, G., Rai, A., Chattopadhyay, A. (2020). Real-time anomaly detection framework using a support vector regression for the safety monitoring of commercial aircraft. Advanced Engineering Informatics, 44: 101071. https://doi.org/10.1016/j.aei.2020.101071
[30] Chen, J., Liao, X., Wu, Z., Umar, M., Yao, S. (2019). Data abnormal detection and classification in wireless body area networks using convolutional neural networks. In 2019 3rd International Conference on Electronic Information Technology and Computer Engineering (EITCE), Xiamen, China, pp. 1314-1318. https://doi.org/10.1109/EITCE47263.2019.9094855
[31] Yaghoubi, M., Ahmed, K., Miao, Y. (2022). Wireless body area network (WBAN): A survey on architecture, technologies, energy consumption, and security challenges. Journal of Sensor and Actuator Networks, 11(4): 67. https://doi.org/10.3390/jsan11040067
[32] Wu, J., Sun, J., Song, J., Xue, L. (2022). Health assessment method based on multi-sign information fusion of body area network. Information Sciences, 618: 136-149. https://doi.org/10.1016/j.ins.2022.10.033
[33] Wang, J., Jiang, C., Zhang, H., Ren, Y., Chen, K.C., Hanzo, L. (2020). Thirty years of machine learning: The road to Pareto-optimal wireless networks. IEEE Communications Surveys & Tutorials, 22(3): 1472-1514. https://doi.org/10.1109/COMST.2020.2965856
[34] Masdari, M., Khezri, H. (2021). Towards fuzzy anomaly detection-based security: A comprehensive review. Fuzzy Optimization and Decision Making, 20: 1-49. https://doi.org/10.1007/s10700-020-09332-x
[35] Rumbut, J., Fang, H., Carreiro, S., Smelson, D., Boyer, E. (2022). An overview of wearable biosensor systems for real-time substance use detection. IEEE Internet of Things Journal, 9(23): 23405-23415.

https://doi.org/10.1109/JIOT.2022.3207090
[36] Neghabi, A.A., Navimipour, N.J., Hosseinzadeh, M., Rezaee, A. (2020). Energy-aware dynamic-link load balancing method for a software-defined network using a multi-objective artificial bee colony algorithm and genetic operators. IET Communications, 14(18): 3284-3293. https://doi.org/10.1049/iet-com.2019.1300
[37] Salayma, M., Al-Dubai, A., Romdhani, I., Nasser, Y. (2018). Wireless body area network (WBAN): A survey on reliability, fault tolerance, and technologies coexistence. ACM Computing Surveys, 50(1): 1-38. https://doi.org/10.1145/3041956
[38] Anguraj, D.K., Smys, S. (2019). Trust-based intrusion detection and clustering approach for wireless body area networks. Wireless Personal Communications, 104: 1-20. https://doi.org/10.1007/s11277-018-6005-x
[39] Hameed, S.S., Hassan, W.H., Latiff, L.A., Ghabban, F. (2021). A systematic review of security and privacy issues in the Internet of medical things; the role of machine learning approaches. PeerJ Computer Science, 7: e414. https://doi.org/10.7717/peerj-cs.414
[40] Chowdhury, S.M., Hossain, A. (2020). Different energy saving schemes in wireless sensor networks: A survey. Wireless Personal Communications, 114(3): 2043-2062. https://doi.org/10.1007/s11277-020-07461-5
[41] Kalpana, R.N.L.S., Nageshwar Rao, D., Patro, A.K. (2022). A survey on deep learning techniques for anomaly detection in human activity recognition. In: Patnaik, S., Kountchev, R., Jain, V. (eds) Smart and Sustainable Technologies: Rural and Tribal Development Using IoT and Cloud Computing. Advances in Sustainability Science and Technology. Springer, Singapore. https://doi.org/10.1007/978-981-19-2277-0_31
[42] Ganaie, M.A., Tanveer, M., Jangir, J. (2022). EEG signal classification via pinball universum twin support vector machine. Annals of Operations Research, 1-42. https://doi.org/10.1007/s10479-022-04922-x
[43] Aotoban, H.N.N., Al_handali, K.A., Al_sharafi, Z.M., AL-hamadi, Z.M. (2022). Design and implementation of a smart WBAN for diabetes management in healthcare. In book: Design and Implementation of a Smart WBAN for Diabetes Management in Healthcare, vol. 9124, Bramhall, Stockport, UK: EasyChair.
[44] Sengan, S.V.S., Jhaveri, R.H., Varadarajan, V., Setiawan, R., Ravi, L. (2021). A secure recommendation system for providing context-aware physical activity classification for users. Security and Communication Networks, 2021: 1-15. https://doi.org/10.1155/2021/4136909
[45] Garg, V., Gupta, T., Rani, S., Bandyopadhyay-Ghosh, S., Ghosh, S.B., Qiao, L., Liu, G. (2021). A hierarchically designed nanocomposite hydrogel with multisensory capabilities towards wearable devices for human-body motion and glucose concentration detection. Composites Science and Technology, 213: 108894. https://doi.org/10.1016/j.compscitech.2021.108894
[46] Kaur, M., Bajaj, R., Kaur, N. (2021). A review of mac layer for wireless body area network. Journal of Medical and Biological Engineering, 41(6): 767-804. https://doi.org/10.1007/s40846-021-00669-1
[47] Kachuee, M., Fazeli, S., Sarrafzadeh, M. (2018). ECG heartbeat classification: A deep transferable representation. In 2018 IEEE International Conference on Healthcare Informatics (ICHI), New York, USA, pp. 443-444. https://doi.org/10.1109/ICHI.2018.00092
[48] Jena, M., Behera, R.K., Dehuri, S. (2022). Hybrid decision tree for machine learning: A big data perspective. In: Dehuri, S., Chen, YW. (eds) Advances in Machine Learning for Big Data Analysis. Intelligent Systems Reference Library, vol. 218. Springer, Singapore. https://doi.org/10.1007/978-981-16-8930-7_9
[49] Wang, J., Li, P., Ran, R., Che, Y., Zhou, Y. (2018). A short-term photovoltaic power prediction model based on the gradient boost decision tree. Applied Sciences, 8(5): 689. https://doi.org/10.3390/app8050689
[50] Hafeez, M.A., Rashid, M., Tariq, H., Abideen, Z.U., Alotaibi, S.S., Sinky, M.H. (2021). Performance improvement of decision tree: A robust classifier using tabu search algorithm. Applied Sciences, 11(15): 6728. https://doi.org/10.3390/app11156728
[51] Saremi, S., Mirjalili, S., Lewis, A. (2017). Grasshopper optimisation algorithm: Theory and application. Advances in Engineering Software, 105: 30-47. https://doi.org/10.1016/j.advengsoft.2017.01.004
[52] Moayedi, H., Mosavi, A. (2021). Double-target based neural networks in predicting energy consumption in residential buildings. Energies, 14(5): 1331. https://doi.org/10.3390/en14051331
[53] Hussein, S.S., Rashidi, C.B.M., Alrikabi, H.A., Aljunid, S.A., Salih, M.H., Abuali, M.S. (2019). Wireless body area sensor network: Tutorial review. Journal of Computational and Theoretical Nanoscience, 16(11): 4839-4852. https://doi.org/10.1166/jctn.2019.8396