Energy-efficient early emergency detection for healthcare monitoring on WBAN platform

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Abstract

This dissertation introduces an innovative structure aimed at improving anomaly detection and predictive analyses in Wireless Body Area Networks (WBANs), a crucial technology within the realm of digital healthcare. Motivated by the need to improve diagnostic precision and clinical decision-making, especially in environments constrained by the computational limitations of edge devices, this research aims to revolutionise patient monitoring systems. The research begins with a comprehensive review of current WBAN technologies and their applications in healthcare. It identifies a distinct gap in the ability of these systems to adapt to the dynamic and complex nature of patient health monitoring. Traditional WBAN methodologies, heavily reliant on static thresholds and centralised cloud-based processing, often fall short of effectively managing the nuanced and varied data derived from patient monitoring, leading to real-time responsiveness and energy efficiency challenges.

The research progresses from static to dynamic threshold to address these challenges, enhancing the system's adaptability to fluctuating health indicators. The Multi-Level Classification Threshold Algorithm (MLCTA) was formulated to refine the classification of health-related data. The study subsequently presents a compound method that combines threshold-based techniques with linear regression analysis. This integration significantly bolsters the model's predictive capacity for health incidents by providing a more profound comprehension of vital sign patterns. When used in conjunction with actual patient data, this approach notably heightens the precision of health event forecasts.

The framework includes a series of progressively advanced algorithms: The Modified Adaptive Local Emergency Detection (MALED) lays the groundwork with its adaptive response to health data changes. This is enhanced by the Differential Change Analysis (DCA), which introduces sensitivity to the rate of change in vital signs for early anomaly detection. The Local Emergency Detection Algorithm Using Adaptive Sampling (LEDAS) further optimises this framework by implementing adaptive sampling based on the patient's health status, ensuring efficient data collection. The pinnacle of this progression is the Sequential Multi-Dimensional Trend Analysis (SMDTA), which offers a comprehensive multi-dimensional analysis of health data, identifying intricate patterns and relationships among various vital signs for precise health predictions. Additionally, incorporating dynamic thresholds across these algorithms refines anomaly detection, making the system more flexible and responsive to changing

patient health dynamics. Together, these algorithms represent a significant leap from basic monitoring systems to advanced networks capable of sophisticated multi-dimensional health analysis.

Empirical evaluation using actual patient data from clinical databases demonstrated the superior efficacy of the proposed framework. Notably, the hybrid approach combining linear regression with threshold-based methods achieved near 96% accuracy in anomaly detection, significantly reducing the false-positive rate to 2%. Furthermore, the optimised local emergency detection strategies led to an average 85% reduction in data transmissions, contributing to a 19% decrease in energy consumption compared to existing methods, thereby underscoring the system's suitability for energy-constrained environments. The results of this research highlight not only the potential of advanced WBAN systems in enhancing healthcare delivery but also pave the way for future developments in medical technology. The proposed framework and its algorithms open new avenues in clinical decision-making, offering robust, efficient, and user-friendly solutions for healthcare professionals and patients.

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Abbreviations

ADC Analogue-to-digital converter

AP Access Point

AUC The Area Under This Curve

ANN Artificial Neural Network

BER Bit Error Rate

BN Bayesian Network

BP Blood pressure

BPM Beats Per Minute/ Breaths Per Minute

BS Base Station

CPU Central processing unit

DCA Differential Change Analysis

DSW Dynamic Slide Window

ECG Electrocardiography

EEG Electroencephalography

EHRs Electronic Health Records

GP General Practitioner

IEEE Institute of Electrical and Electronics Engineers

FN False Negative

FP False Positive

FPR False Positive Rate

FNR False Negative Rate

HR Heart rate

ISM Industrial, Scientific and Medical

KF Kalman Filter

KNN K- Nearest neighbour

LR Linear Regression

LPU Local Processing Unit

MAC Media Access Control

MD Mahalanobis Distance

MAD Median Absolute Deviation

mmHg millimetres of mercury

MM Markov Model

MV Majority Voting

NB Naive Bays

NPV Negative Predictive Value

NHS National Health Service

PPV Positive Predictive Value

PSA Principal Statistic Analysis

PS Personal Server

PS Personal Device

QoS Quality of Service

QoE Quality of Experience

RF Random Forest

ROC Receiver Operating Characteristic

RR Respiration rate

RRT Rapid Response Team

SMO Sequential Minimal Optimization Regression

SVM Support Vector Machine

TDMA Time Division Multiple Access

Temp Temperature

TP True Positive

TN True Negative

Sp Oxygen saturation

SH-Base Shapelets Base

WBAN Wireless Body Area Network

WBSN Wireless Body Sensor Network

WMA Weighted Moving Average

WPAN Wireless PersonalAreaa Network

WSN Wireless Sensor Network

WWAN Wireless Wide Area Network

Chapter 1

1. Introduction

This chapter offers a comprehensive exposition of the distinctive traits and complexities associated with healthcare anomaly detection while delving into prospective solutions to surmount these challenges. Subsequently, it furnishes compelling reasons for delving into the targeted research domain, aligning the study's motivations with the broader landscape of anomaly detection in healthcare. Moreover, it addresses diverse hurdles encountered in customising anomaly detection techniques for specific applications. The research study's primary aim and objectives are expounded upon, laying the groundwork for the ensuing investigation. The adopted methodology to conduct this research is succinctly delineated, providing a clear and concise road map for the scientific inquiry. Furthermore, a succinct and cogent summation of the research study's significant contributions to knowledge is offered, highlighting its potential impact in advancing the frontiers of healthcare anomaly detection. Finally, concluding this chapter, a detailed outline of the report's organisation is presented, signposting the logical progression of the ensuing discourse.

1.1 Background and Motivation

The contemporary healthcare landscape is teeming with an array of challenges that necessitate innovative solutions. With an increasingly ageing global population, healthcare systems face mounting pressures [1]. These challenges encompass not only a surge in healthcare costs but also escalating queues for essential services and a disconcerting prevalence of delayed diagnoses. Considering the cost, astonishingly in the United States, healthcare spending jumped from $250 billion in 1980 to an astonishing $4.3 trillion in 2021 [2]. Projections suggest continued growth, reaching an estimated $6.2 trillion by 2028 [3]. On the other hand, in the United Kingdom, healthcare spending has notably increased, with the National Health Service (NHS) net budget rising from £78.881 billion in 2006/07 to £202.9 billion in 2021/22. Projections indicate planned expenditures of £182 billion for 2023/24 and £184.5 billion for 2024/25. Notably, per capita health spending in the UK surged from £2,106 in 2015/16 to £4,188 in 2021/22 [4]. This dramatic growth mirrored globally, underscores the pressing need for innovative strategies to navigate the ever-intensifying challenges of an ageing population and their profound impact on healthcare systems.

In the face of these challenges, technology has emerged as a beacon of hope [5], offering a means to revolutionise patient care, treatment outcomes, and the overall efficiency of healthcare delivery. Among the myriad technological advancements, Wireless Body Area Networks (WBANs) [6] hold significant promise. These networks, comprising low-power, miniature wireless devices operating close to the human body, provide real-time health data collection, opening new horizons for patient care and well-being [7].

In 2019, the NHS acknowledged the transformative impact of technology on healthcare and the need for adaptation to benefit patients and caregivers [8]. This perspective is rooted in the shift towards an ageing population dealing with medical challenges [9, 10]. Consequently, hospitals grapple with mounting pressures, leading to increased queues for emergency care and a notable prevalence of incorrect diagnoses. Research from 1985 to 2020 indicates that more than a quarter of individuals experienced misdiagnoses [11]. Manual handling issues and extended waiting times in the United Kingdom's accident and emergency departments exacerbate these challenges.

Healthcare, a critical domain, generates extensive data from various sources, offering the potential for improving patient care, treatment outcomes, and overall efficiency. However, the complexity and volume of healthcare data present challenges, including anomaly detection [12, 19-23] and process optimisation. Anomaly detection techniques play a vital role across domains, including healthcare, by identifying issues at early stages, enabling timely intervention, and improving outcomes. In healthcare, early detection [13] enhances treatment effectiveness, reduces costs, and eases the burden on the healthcare system. Despite their importance, current healthcare early detection techniques have limited accuracy, invasiveness, cost, and accessibility issues. Additionally, in the context of WBANs, sensors collect vital signs [14] data for further processing, which can be quite challenging when performed at the local node, mainly due to the traditional WBAN architecture. Typically, in the conventional architecture of WBANs, a bridging point is established between the sensor infrastructure network and the Internet. This bridging point primarily serves basic functions, such as facilitating the transformation of data between the Internet and sensor networks. Nevertheless, there is a need to provide various higher-level services, including local storage, real-time local data processing, and decision-making, at the local node. This approach aims to minimise energy consumption and enable real-time decision-making capabilities while enabling the system to support seamless mobility.

Therefore, this thesis addresses the challenges faced by resource constrained WBANs, aiming to enable an innovative approach to early anomaly detection. It accomplishes this by introducing a comprehensive WBAN architecture, an anomaly detection scheme, and optimisation for local emergency detection. Collectively, these enhancements improve the effectiveness of anomaly detection, fostering an energy-efficient environment. By implementing these proposed schemes, the thesis offers robust solutions for identifying anomalies and early emergencies in patients' healthcare data. Moreover, the unified framework reduces energy consumption throughout the network while maintaining a satisfactory level of reliability.

1.2 Wireless Body Area Network: Applications and Requirement

WBANs facilitate a wide range of innovative applications, which can be categorised based on their respective domains. WBANs find diverse applications in both the medical and non-medical sectors. Figure 1.1 illustrates a more detailed classification of these applications within the medical and non-medical domains.

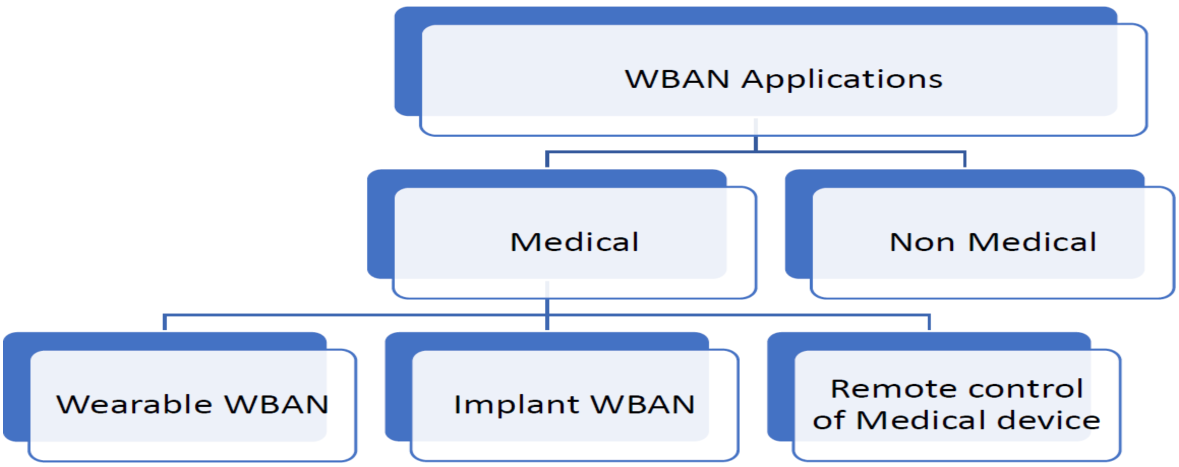


Figure 1. 1: Applications of WBAN.

In the medical field, WBANs serve diverse purposes, with applications ranging from wearable devices to implantable and remote-controlled systems. These applications can be further categorised based on the wearable or implanted techniques employed. Wearable or on-body medical applications encompass health monitoring for rehabilitation, asthma management, electrocardiogram analysis, and sleep stage tracking. Additionally, they support remote control of medical devices like telemedicine systems and ambient assisted living. In the non-medical domain, wearable applications extend to sports training, baby monitoring, and soldier fatigue assessment. On the other hand, implanted or in-body applications involve monitoring and reconfiguration of pacemakers, cardiovascular disease management, diabetic control, cancer detection, and retinal implants. As exemplified in Figure 1.2 [15], WBANs are utilised for patient monitoring, wherein multiple sensors are placed in clothing, vests, directly on the body, or even beneath the skin to measure vital signs like temperature, blood pressure (BP), heart rate (HR), ECG, and respiration rate.

In the context of WBANs, two primary types of devices can be distinguished:

- Wireless Sensor Node: This device is responsible for detecting and collecting data pertaining to physical stimuli. It processes the data when necessary and transmits it wirelessly. The wireless sensor node comprises various components, including sensor hardware, a power unit, a processing unit, memory, a transceiver, and a transmitter.
- Wireless Actuator Node: Acting in response to data received from sensors or other sources, the wireless actuator node executes specific actions. It comprises actuator hardware, a power unit, a processing unit, memory, a transmitter, and a transceiver.
- The wireless personal device serves as a central hub that aggregates data acquired from sensors and actuators. It processes the data when necessary and communicates the results to the user through an external gateway. This device encompasses essential components, including a processor, power unit, memory, transceiver, and more.

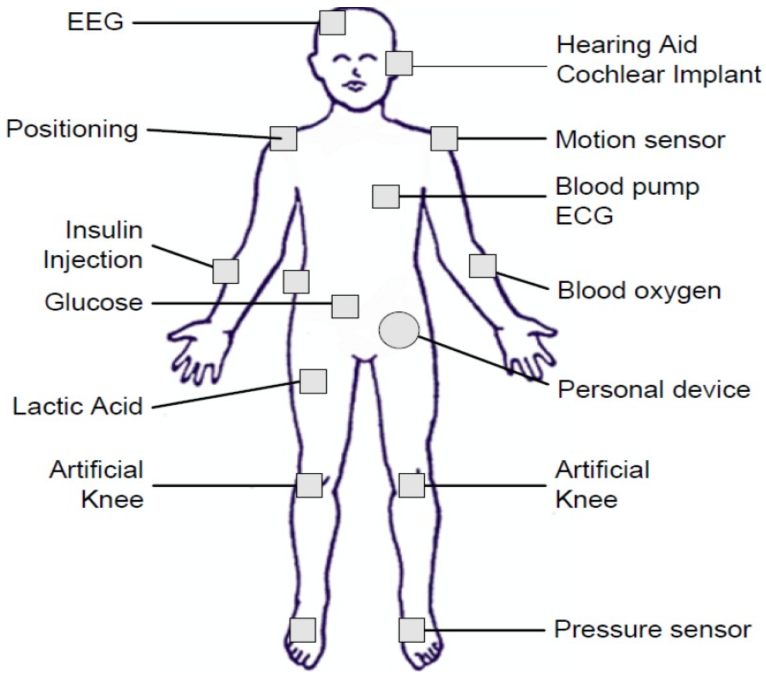


Figure 1. 2: Example of different sensors used in a WBAN.

Existing WBAN standards include: -

- Bluetooth.
- Bluetooth low energy.
- Zigbee.
- IEEE 802.11.
- IEEE 802.15.6.

The healthcare application of WBANs necessitates several user-oriented requirements to ensure a standard level of satisfaction. These requirements encompass:

1. Quality of Service: Due to its intimate connection to human well-being, the healthcare application demands a high standard of service and is capable of handling a vast amount of physiological data continuously. The WBAN should distinguish between critical and non-critical data to maintain service quality.

2. Real-time Performance: The WBAN is expected to operate in real-time, providing instantaneous support for critical healthcare situations. To achieve this, the data processing involved in the WBAN life cycle should be swift and uncomplicated to reduce processing time.

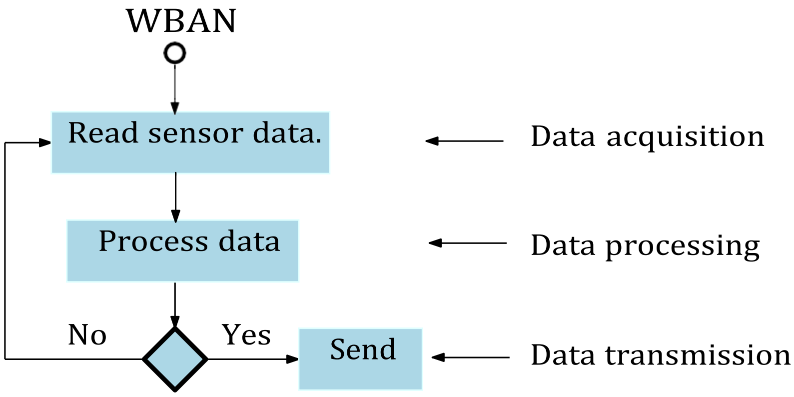


Figure 1. 3: Data flow for a typical WBAN

3. Accuracy: Healthcare support mandates precision, given the critical nature of human well-being events. The WBAN's processes should yield accurate data collection, processing, and transmissions, with algorithms effectively defining and distinguishing critical data.

4. Mobility: To ensure smooth operation, the WBAN system development must consider patient mobility. System devices should be portable and easy to carry, allowing seamless connectivity with different communication channels and mediums during patient movement.

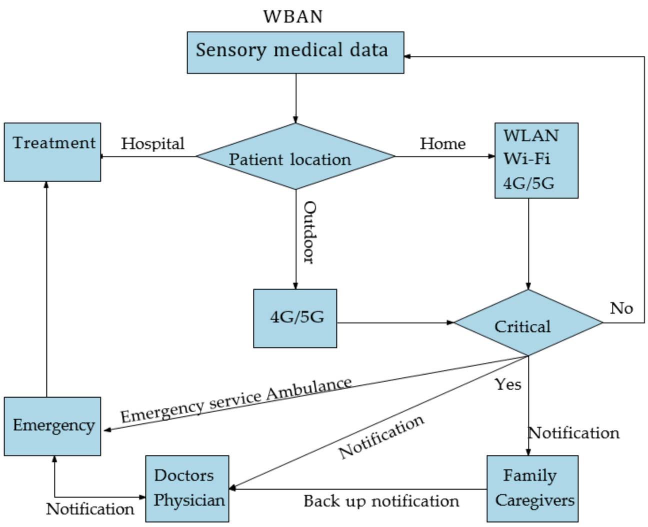


Figure 1. 4: Typical WBAN mobility model

5. Connectivity: Connectivity to the internet is essential for the WBAN system's development. The patient's ability to move freely necessitates continuous monitoring by the WBAN system, requiring various connection mediums beyond location constraints.

6. System Lifetime: Prolonging the system life is of utmost importance for WBAN healthcare applications. Careful measures must be employed to extend the wireless system's limited lifetime effectively.

7. Robustness: To counter system failures and ensure data integrity, the WBAN should incorporate multi-sensor fusion, bolstering the robustness of the system.

8. Security: Given the sensitive nature of medical information, WBAN healthcare applications must implement robust security mechanisms to safeguard data collection, processing, transmission, and storage.

9. Privacy and Integrity: To protect patient privacy and maintain service integrity, privacy mechanisms should be employed within the WBAN healthcare application, thereby enhancing patient trust and acceptance of the system.

10. Reliability: Every aspect of the user's concern should be met with reliability in WBAN healthcare applications, from the system's design and behaviour to its overall performance. Patients should be able to place their trust in the system with confidence.

1.3 Aim and Objectives

This research aims to develop a resilient clinical decision-making framework by harnessing collaborative data from sensors within resource-constrained WBANs for healthcare applications. Through early detection of anomalies, this integrated model aims to improve the precision and reliability of clinical decisions based on patient medical histories. The intention is to optimise clinical decision-making within the limited resource environment of WBANs, ensuring more effective and reliable healthcare outcomes.

The study outlines the following objectives:

- Conduct a comprehensive literature search on existing WBAN techniques and their diverse applications, encompassing healthcare, assisted living, fitness, exercise, emergency services, security, and remote monitoring, among others.

- Investigate the limitations of current WBAN systems concerning critical decision-making that relies on sensor data in a resource-constrained environment.
- Explore the challenges associated with implementing critical decision-making algorithms, including anomaly detection, local emergency detection, and adaptive sampling within the WBAN context.
- Develop a reliable and robust decision-making framework based on collaborative data for bespoke applications, specifically tailored to the constraints of energy limited WBANs.
- Devise a simple, user friendly anomaly detection method utilising sensor data within the WBAN environment.
- Develop a method for optimising local emergency detection using WBANs.
- Formulate a data reduction technique for low-power healthcare framework using WBAN technology.
- Evaluate and compare the performance of the proposed unified framework against existing state-of-the-art techniques to gauge its efficacy and superiority.

1.4 Research Methodology

This section encompasses the methodologies utilised throughout the research process, incorporating extensive theoretical analysis, simulations, and experimentations. The study commenced with a thorough examination of the existing literature on WBANs and their diverse applications in healthcare systems, including clinical diagnosis, decision-making, assisted living, privacy and security, clinical prediction models, and healthcare frameworks. To fulfil the research objectives, a mixed-methods approach, combining both qualitative and quantitative methodologies, has been adopted. For experimental purposes, a customer clinical database has been employed, along with the use of large collections of recorded physiologic signals from PhysioBank [48], subject to ethical considerations and institutional validation. Figure 1.5 visually depicts the research methods employed in this study, outlining the various stages after the literature review.

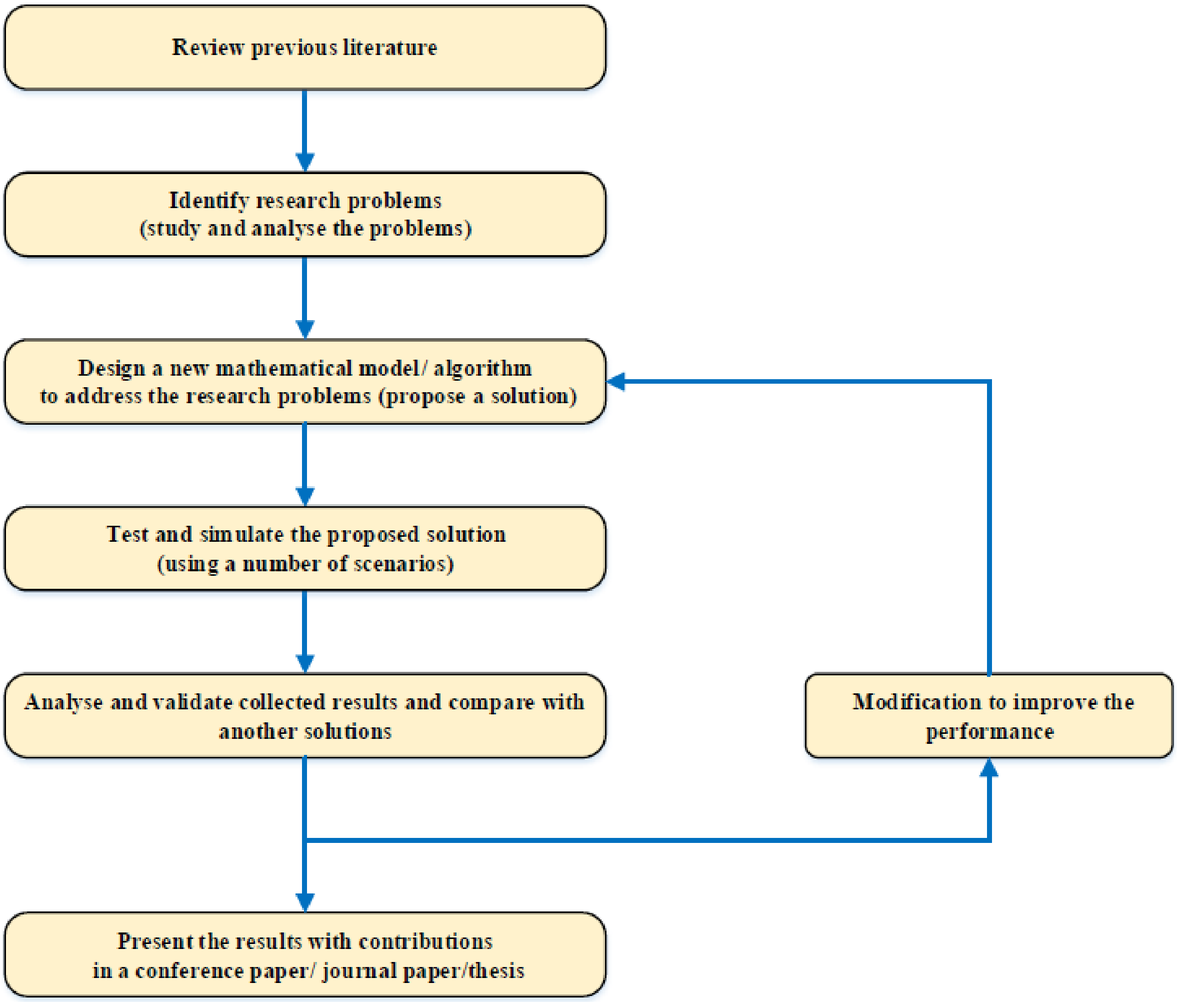


Figure 1. 5: The main steps of methodology

The research study progresses through distinct stages, as outlined below:

- Investigation of existing research works to identify challenges pertaining to the design and optimisation of WBAN healthcare systems.
- Formulation of research aims and objectives, leading to the development of an in-depth research plan.
- Accessing the clinical database to comprehend the information and preparing the data set for experimentation.
- Development of a WBAN system model tailored for healthcare applications, specifically for patient medical condition decision-making.
- Validation of the proposed WBAN framework's reliability through the utilisation of an appropriate simulation platform
- Design and development of a low-power and secure WBAN framework

- Evaluating the reliability of the proposed framework compared to other existing works using appropriate simulation platforms.

1.5 Limitations of Existing Solutions

A wide variety of healthcare solutions utilising wireless healthcare systems for anomaly detection are available, with research often limited to specific domains or services, including patient monitoring [104-107, 111], foetal health monitoring [108], medication management [112], elderly care and fall detection [109], surgical and anaesthesia monitoring [110], telemedicine and virtual consultations [113], infection control [114], and behavioural health monitoring [106]. There is no precise standard found in the literature for generalised healthcare anomaly detection, which can eventually provide patient-specific solutions. Most of these solutions address a specific challenge in detecting anomalies during ongoing incidents. They lack the capability to model each user state individually and predict future anomalies in advance. Additionally, very few of them support the storage and reuse of data for future reference. Consequently, most systems are unable to accurately generate personalised insights due to their limited ability to preserve long-term histories. Existing monitoring systems exhibit high false alert rates and rely on manual observations by medical experts following anomaly detection. While some models can accurately predict changes in specific physiological parameters [115], building models that monitor and correlate multiple bio-signals while retaining interpretability is challenging due to the evolving and variable nature of biomedical data over time. Limited research has also aimed to predict various clinical events using multi-parameter data from a substantial patient pool [116]. Prior studies often employ a small data sample (a few megabytes) from a limited patient group, offer short forecasting windows (typically one hour), and focus on a single parameter like blood pressure [117] or ECG [118]. These models utilise a small feature set for training and exclusively forecast specific clinical events. As patient populations grow, these systems encounter higher misclassification rates, especially when data uncertainty rises.

A broad range of energy consumption solutions have been explored on the wireless healthcare platform. These solutions encompass various techniques, including sensor set selection [119, 120, 136], context-based pull [121, 122], data reduction [34, 123, 124, 137], radio optimisation [125, 126], energy-efficient routing protocols [127-129, 138], sleep/wake schemes [130, 131], feature selection [132, 133], and adaptive classifier selection [134, 135, 139]. However, not all of these techniques are suitable for the general WBAN architecture, where anomaly detection is intended to be processed at the local node. Among various energy-efficient techniques, reducing data transmission can significantly contribute to lowering power consumption. Data reduction is particularly suitable for wireless systems where anomaly detection can be performed at the local node. Adaptive sampling [31, 140–148] stands out as one of the most suitable techniques in this context. However, it's noted that most of the existing research lacks a clear focus on practical applications. This dissertation aims to address the issue of detection quality and implement improved adaptive solutions to achieve better energy savings compared to current solutions. A common problem in the majority of the existing anomaly detection approaches in medical WBANs is the disregard for a fit in real-world medical conditions. The study also found that there is a lack of simple, user-friendly solutions that can be run close to the data source and save energy. The research issues mentioned above for this thesis are summarised in Figure 1.6.

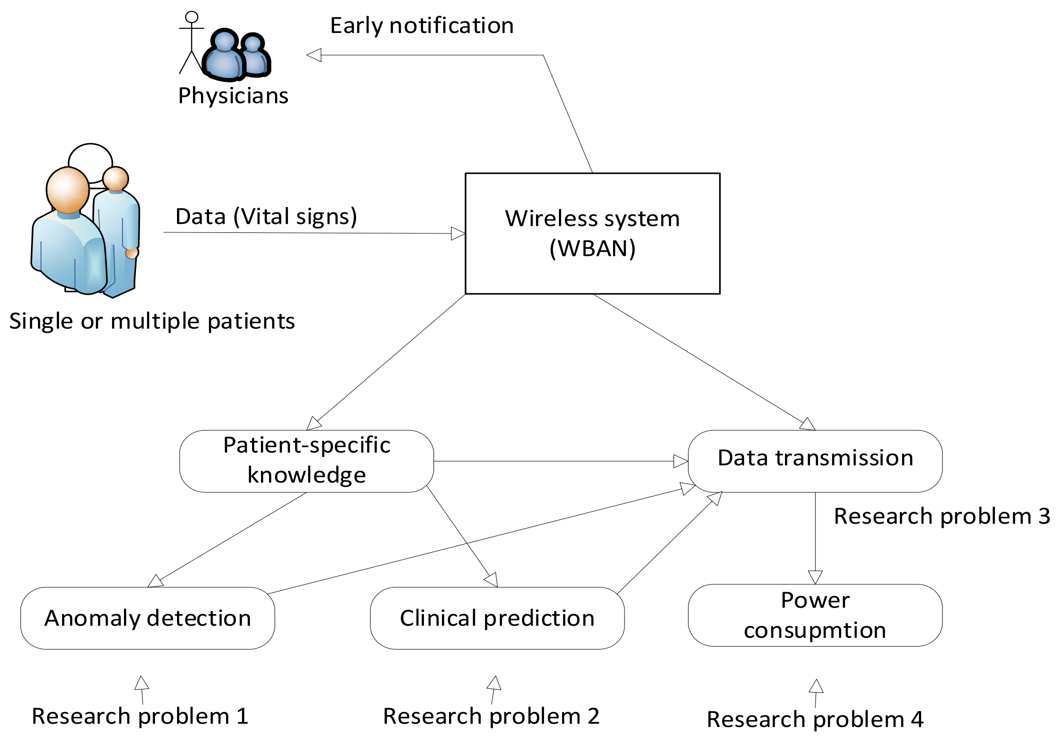


Figure 1. 6: Research problems

1.6 Research Contributions

The following list is a summary of the contributions to knowledge achieved in this

thesis

- Developed a novel WBAN framework integrating personalised monitoring with energy conservation. Algorithms like MALED and SMDTA dynamically adapt to individual patient profiles, while edge computing enables efficient near-source data processing. This approach innovatively addresses energy constraints in WBANs, enabling quicker and more effective responses to patient health changes, thus saving energy and enhancing system responsiveness.

- Devised an innovative resource optimisation strategy within WBANs, exemplified by the LEDAS algorithm. This strategy intelligently adjusts the data acquisition rate based on the urgency of patient conditions, conserving energy and computational resources. By modulating data collection frequency in response to patient health status, LEDAS ensures effective monitoring without excess energy use, marking a significant advancement in WBAN sustainability.

- Enhanced clinical decision-making in WBANs with the introduction of advanced data analysis algorithms, notably DCA. This novel method facilitates early anomaly detection and comprehensive health trend analysis, enabling quicker and more accurate clinical interventions. Its innovation lies in processing complex health data in real-time, significantly improving upon traditional health monitoring systems.

- Pioneered a range of novel methods, including adaptive threshold algorithms and data reduction techniques, to optimise emergency detection and data management in WBANs. Techniques such as differential change analysis and multi-dimensional trend analysis markedly improve the WBAN's capability to detect emergencies efficiently while minimising the volume of data transmitted. These methods enhance WBAN operational efficiency and conserve critical resources like bandwidth and power.

This thesis makes significant contributions within the context of the limitations identified in the existing literature, as summarised in Figure 1.7.

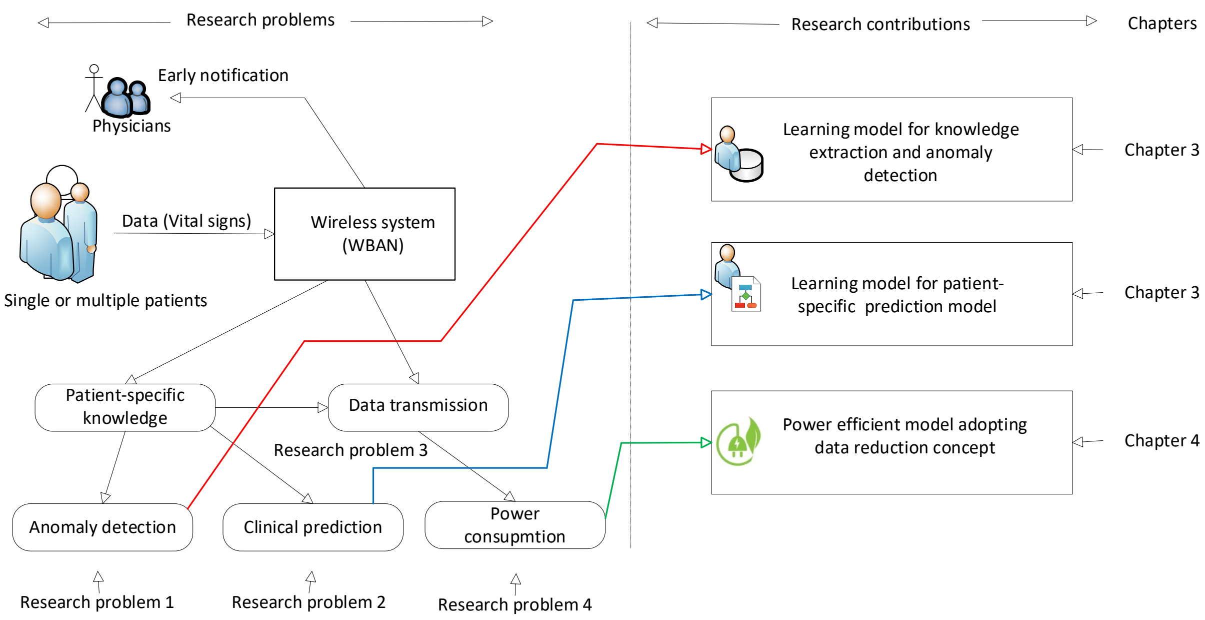


Figure 1. 7: An overview of the contributions made by this thesis against the limitations identified in the existing literature.

1.7 Thesis Organisations

The thesis comprises several well-organised chapters, structured as follows:

Chapter 1:

In this chapter, the project background and motivation are expounded, providing insight into the driving force behind the research. The objectives and aims of the study are clearly defined, while a concise research method and scope of applications are presented. Additionally, a summary of the contributions made to knowledge is articulated.

Chapter 2:

This chapter presents a comprehensive survey of notable state-of-the-art techniques for anomaly detection and early emergency detection. Additionally, energy-efficient approaches within anomaly detection are discussed. The chapter also addresses the limitations of existing techniques in the context of resource-constrained scenarios.

Chapter 3:

This chapter introduces the proposed system model, encompassing the theoretical underpinnings of the research, including performance analysis techniques and system model validation. Furthermore, this chapter outlines a series of enhancements, moving from static threshold algorithms to dynamic threshold algorithms. Also depicted is the multilevel classification of patient data status and the use of a hybrid model for clinical predictions.

Chapter 4:

This chapter explains the suggested local emergency detection method, which uses a novel and more straightforward threshold strategy. Moreover, it discusses the proposed methods designed to optimise decision-making through adaptive sampling, intending to minimise data transmission and boost the system's energy efficiency.

Chapter 5:

This concluding chapter provides a comprehensive summary of the thesis, encompassing an overview of the proposed schemes. Additionally, it discusses the future scope of work, building upon the concepts and frameworks presented in this research. Finally, concluding remarks are provided to highlight the significance and potential impact of the research.

The subsequent chapter presents an illustration of state-of-the-art techniques concerning anomaly detection, early emergency detection, and power consumption, among other relevant aspects.

Chapter 2

2. State-of-the-art in Healthcare Anomaly Detections

2.1 Introduction

This chapter explores the state of the art of existing healthcare anomaly detection in a resource-constrained and heterogeneous environment. In health care, technology plays a vital role in almost all processes, from the start to the end of the patient journey. The recent development of data analytics for medical healthcare and its potential for patients and medical professionals are analysed. In the existing literature, emerging techniques for healthcare such as anomaly detection, local emergency detection, and decision making are presented. The existing scholarly knowledge is reviewed for healthcare applications to find gaps and limitations.

This exploration into the state-of-the-art in healthcare anomaly detection and optimisation will delve into the latest breakthroughs, methodologies, and real-world applications. This will uncover how advanced machine learning algorithms can sift through vast medical datasets to identify anomalies indicative of diseases, adverse events, or unusual patterns in patient health.

2.2 Anomaly Detection Technique

In today's rapidly evolving technological landscape, the volume and complexity of data generated are greater than ever before. Within this data deluge, hidden among the normal patterns, anomalies lurk. These anomalies represent abnormal events or outliers that deviate significantly from the expected behaviour. Detecting these anomalies is of paramount importance in various industries, as they can signify critical issues, security breaches, or unusual events that demand immediate attention.

Anomaly detection [15, 19-23, 26-27, 29, 97], also known as outlier detection [19], is the process of identifying these rare occurrences within datasets. Leveraging cutting-edge machine learning techniques [16], statistical methods [17], and data analytics, anomaly detection algorithms seek to highlight deviations that might otherwise go unnoticed.

This introductory exploration into anomaly detection will delve into the fundamental principles, methodologies, and real-world applications of this crucial field. By understanding the intricacies of anomaly detection, it is better to safeguard against potential threats, enhance predictive maintenance, optimise business processes, and make informed decisions based on actionable insights.

Anomalies can be detected within a system for various reasons, including abnormal or emergency readings, faulty nodes, network failures, and other malfunctions. The process of anomaly detection can be distinguished based on the indicators utilised, with two primary categories being parametric and non-parametric approaches [20]. Parametric methods, also known as statistical methods, are well-suited for stable environments where data remains relatively unchanged. Conversely, non-parametric methods are more appropriate for dynamic environments, where the statistical distribution is either unknown or subject to frequent changes. Parametric methods offer quicker detection, whereas non-parametric methods can be more challenging to process. Figure 2.2 [20] presents a concise summary of the basic classification of anomaly detection methods.

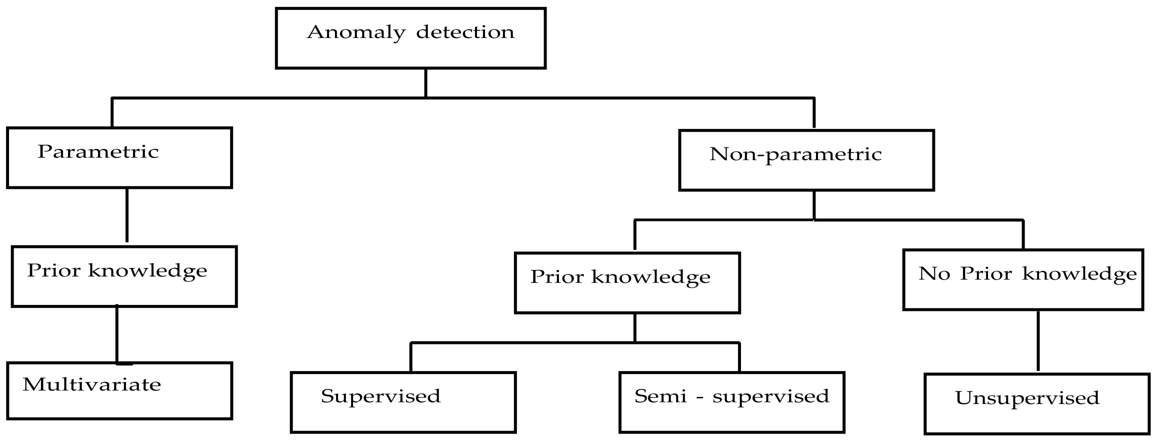


Figure 2. 1: Anomaly detection classification summary

Anomaly detection techniques have found wide-ranging applications across diverse domains, offering valuable insights by identifying patterns and instances that deviate significantly from the norm. In this context, anomaly detection serves as a powerful tool for enhancing security, accuracy, and efficiency in various fields. From safeguarding network infrastructures against cyber threats to detecting fraudulent activities and ensuring patient safety in healthcare, anomaly detection plays a pivotal role in addressing critical challenges.

This exploration delves into the multifaceted applications of anomaly detection techniques, categorising them into distinct sub-domains that highlight their relevance and impact. From the realm of cybersecurity [23], where intrusion detection and network monitoring shield against unauthorised access, to the financial sector, where fraud detection [49] prevents economic losses, anomaly detection offers proactive measures to mitigate risks.

In healthcare [21], anomaly detection contributes to patient monitoring, early disease detection, and medication error prevention, fostering improved clinical outcomes. Furthermore, industrial domains [22] leverage these techniques to monitor equipment health, enhance manufacturing quality control, and predict maintenance needs, thus ensuring operational continuity and resource optimisation.

Across a diverse spectrum of anomaly detection techniques, applications are meticulously categorised according to distinct domains. This categorisation is elucidated by a hierarchical structure where primary branches delineate specific application domains, and subordinate sub-branches encapsulate refined sub-domains or precise applications intrinsic to each domain.

In the realm of healthcare [21], anomaly detection techniques hold substantial promise for enhancing patient safety, early disease detection, and overall clinical efficacy. This branch encompasses applications [18] where anomaly detection contributes to accurate diagnostics and proactive healthcare management. These areas encompass patient monitoring, which involves detecting anomalies in patients' physiological data or health records; disease outbreak detection focused on identifying abnormal patterns in disease occurrence; medication error detection, targeting errors in medication administration or dosage; and medical image diagnosis, identifying anomalies in medical images like X-rays or MRI scans; clinical trial safety, involving the monitoring of clinical trial data for safety-related anomalies; EHR anomaly detection, which detects anomalies in electronic health records; early disease detection, aimed at identifying anomalies in data that may indicate early disease development; and remote health monitoring, which entails monitoring patients' health remotely and detecting anomalies.

In the realm of cybersecurity [23], anomaly detection emerges as a potent tool for safeguarding digital landscapes against intrusive and malicious activities. The branch encompasses a range of applications [48] that target diverse anomalies within network ecosystems, ensuring the fortification of digital infrastructures against potential threats. The most common anomalies occur in various areas, including intrusion detection, which detects unauthorised or malicious activities in computer networks; insider threat detection, which identifies abnormal behaviour by authorised users indicating insider threats; denial of service detection, which identifies attempts to overwhelm a network or service with excessive traffic; botnet detection, which detects networks of compromised devices used for malicious activities; malware detection, which identifies the presence of malicious software or code; and DNS anomaly detection [95], which identifies anomalies in domain name system (DNS) traffic.

Fraud detection constitutes a pivotal application of anomaly detection techniques [49], encompassing a range of domains where anomalies indicate potentially fraudulent activities. The branch underscores the significance of anomaly detection in preserving financial integrity and curtailing fraudulent behaviour. The most common fraud detection techniques encompass credit card fraud detection, which identifies fraudulent credit card transactions; insurance claims fraud detection, which detects fraudulent insurance claims; tax evasion detection, which identifies anomalies in tax-related data; payment fraud detection, which detects fraudulent payment transactions; healthcare fraud detection, which identifies fraudulent activities in healthcare claims and billing; e-commerce fraud detection, which detects anomalies in online shopping transactions; and identity theft detection, which identifies unauthorised use of personal information.

The industrial domain benefits significantly from anomaly detection techniques [50], which play an essential role in maintaining operational efficiency, quality control, and predictive maintenance. This branch encompasses applications where anomaly detection optimises industrial processes and equipment management. Most common industrial anomaly detection techniques are equipment failure detection, that identifying anomalies in industrial machinery or equipment to prevent failures; manufacturing quality control that detecting defects in manufacturing processes; predictive maintenance that identifying potential equipment failures in advance for maintenance scheduling; industrial process anomalies that detecting anomalies in manufacturing and production processes. energy consumption anomalies that identifying deviations in energy consumption patterns.

As discussed before clinical decision-making from data involves using information derived from various sources, such as patient records, medical imaging, and research studies, to inform healthcare professionals' choices regarding diagnosis, treatment, and patient care. By analysing and interpreting this data, clinicians can gain insights into a patient's condition, predict potential outcomes, and make informed decisions that align with evidence-based practices. This data-driven approach enhances the accuracy of diagnoses, optimises treatment plans, and ultimately contributes to improved patient outcomes while ensuring that medical decisions are grounded in objective information and current medical knowledge.

In the work presented in [31], a proposition is put forth wherein a data management framework is introduced to facilitate the sampling of sensor data and subsequent decision-making contingent upon the data's value. This endeavour incorporates a decision matrix and employs fuzzy set theory at the coordinator level, introducing a data fusion model. However, it is notable that this particular undertaking fails to account for other influential factors such as the patient's preceding medical history, physical activity, and individual attributes encompassing height and weight, amongst others. An energy-efficient approach that aims to curtail energy consumption, is adopted by executing sampling prior to decision-making; however, this strategy potentially compromises the authenticity of the data. Another initiative, depicted in [32], endeavours to establish a collaborative medical decision-making process; nevertheless, it confines its methodology solely to interview-based assessments. Given the inherent nature of this approach, there exists an inherent temporal delay, precluding the provisioning of instantaneous feedback. A parallel pursuit, stemming from aerospace multisensory data fusion concepts and expounded upon in [33], leverages multiple datasets to formulate a data fusion model enabling decision-making external to the confines of the sensor coordinator. Regrettably, even this endeavour falls short in delivering real-time feedback, as it abstains from harnessing real-time data derived from sensors. Within the domain of [34], a framework elucidating collaborative computing and multi-sensor data fusion is posited, underscoring a system reliant on a multisensory data fusion scheme for the automated detection of handshakes between two individuals, while additionally assessing the heart rate in relation to the emotional comportment of the patient. Notably, although this framework integrates data fusion techniques, its suitability for medical decision-making within an assisted living context remains constrained by its absence of real-time feedback. The realm of sensor-based decision-making has witnessed diverse manifestations across various domains, addressing applications ranging from monitoring water status in rivers and lakes [35], to optimising water pump efficiency [36], and ameliorating energy consumption [37].

The imperative of real-time clinical decision-making, replete with the potential to avert patient mortality and empower independent living, looms paramount. Indeed, meticulous consideration of an exhaustive spectrum of facets is pivotal to engendering precise diagnoses, encompassing diverse sensor data and personal attributes comprising the individual's profile, encompassing height, weight, ethnicity, antecedent medical history, behavioural patterns, and physical activity. A pivotal attribute pertains to the augmentation of clinical diagnostic accuracy through the integration of real-time feedback. Noteworthy is the observation that extant literature, as evidenced in [26- 29], pertains to context-specific applications, potentially inapplicable to the generic and tailored applications contemplated within the purview of this present research endeavour.

Therefore, the prevailing emphasis within healthcare data revolves around two primary spheres of concern: early detection and local emergency detection.

2.3 Healthcare Anomaly Detection

Anomaly detection techniques in healthcare data analysis offer both advantages and limitations. Understanding their Advantages and limitations is essential for selecting the most suitable method for a specific healthcare application. Anomaly detection techniques offer several advantages [21] in healthcare. They enable the early identification of abnormal patterns or deviations from normal behaviour, facilitating the timely recognition of potential health issues and medical errors. This timely detection enhances patient safety, particularly in critical care settings where immediate action is vital. These techniques also provide automated surveillance of healthcare data, reducing the need for manual observations and the associated risk of human errors. Moreover, anomalies detected in healthcare data yield valuable insights for data-driven decision-making, allowing for optimised treatment plans and resource allocation. Integration with Clinical Decision Support Systems (CDSS) [51] enables healthcare professionals to make informed decisions and issue real-time alerts. Personalised patient care is another benefit, as individual patient data anomalies enable tailored treatments and interventions. Lastly, detecting anomalies in healthcare claims data can effectively prevent fraud and abuse, resulting in substantial cost savings for healthcare systems and insurers.

However, anomaly detection techniques in healthcare come with certain limitations [52]. These include the potential for false positives and false negatives, where normal data can be misclassified as anomalies or anomalies can be missed altogether, making it challenging to strike the right balance. Imbalanced data, where normal instances significantly outnumber anomalies, can bias detection towards normal patterns. Issues with data quality and missing values, common in healthcare data, can affect the reliability of results. Additionally, some advanced anomaly detection methods, like deep learning models, may lack interpretability, making it difficult to explain detected anomalies to healthcare professionals. Scalability can be a concern, particularly for real-time applications with large, high-frequency healthcare data streams that require rapid processing. Some complex anomaly detection algorithms, such as deep learning models, may demand significant computational resources, limiting their use in resource-constrained environments. Finally, implementing and training these techniques often necessitate domain expertise and sufficient labelled training data, which can be limited in healthcare settings. imbalanced data: healthcare data is often imbalanced, with normal instances significantly outnumbering anomalies. anomaly detection in such scenarios can be biased towards normal patterns.

2.3.1 Anomalies in Healthcare Data

The healthcare domain presents a complex landscape where anomalies can manifest across various aspects of patient care, medical processes, and data [53, 54, 64]. This classification delves into the diverse types of healthcare anomalies, categorising them based on their distinct characteristics and implications. Anomalies in healthcare data cover various critical categories. Patient vital sign anomalies, encompassing deviations in heart rate, blood pressure, respiratory rate, and temperature, can indicate health deterioration or adverse conditions. Medication administration anomalies, including dosage errors and improper routes, are vital for patient safety. Disease occurrence anomalies, like unexpected disease prevalence changes, signal outbreaks, or epidemiological anomalies in medical image anomalies in X-rays, MRI scans, and CT scans, support accurate diagnoses. Healthcare fraud anomalies help preserve financial integrity. Electronic health record (EHR) anomalies are essential for accurate patient records. Diagnostic test result anomalies indicate health conditions. Telemedicine data anomalies track remote health monitoring. Laboratory data anomalies ensure precision in disease assessment. Treatment response anomalies highlight deviations from expected therapeutic outcomes. Workflow anomalies impact care efficiency. Patient demographic anomalies can lead to errors in care, billing, and medical history.

In clinical decision-making within the UK NHS, certain significant features are commonly used to estimate the likelihood of specific outcomes or conditions. These features help healthcare professionals make informed decisions and provide appropriate care [53]. There are some of the main significant features used for clinical decision-making and prediction in the NHS UK.

Demographic information [55], including age, plays a critical role in predicting health outcomes, as certain conditions are more prevalent in specific age groups. Gender also holds significance, as some diseases exhibit gender-specific prevalence and risks. Ethnicity is another important factor, as certain conditions are more common in specific ethnic groups, influencing risk assessments and treatment approaches. Additionally, a patient's medical history [56], encompassing previous medical conditions, chronic diseases, prior surgeries, and overall health status, offers valuable insights into potential complications. Chronic diseases like diabetes, hypertension, and cardiovascular conditions significantly impact outcomes for various health events, while a patient's surgical history can affect the risk of complications and recovery from new procedures.

Symptoms and signs [57], patient-reported symptoms, and symptoms reported by the patient (e.g., pain, shortness of breath) provide valuable clues to the underlying condition. Physical examination findings, and clinician-assessed physical signs (e.g., fever, abnormal heart sounds) aid in diagnosis and prognosis. Vital signs [58, 63] such as heart rate, and an elevated or irregular heart rate can indicate cardiac stress or arrhythmias. Blood pressure and abnormal blood pressure levels can indicate cardiovascular risks. Respiratory rate, deviations from the normal range can signify respiratory distress. Temperature, fever or hypothermia can indicate infection or metabolic disturbances. Oxygen saturation, low oxygen saturation can indicate respiratory or cardiovascular issues.

Laboratory tests [59], including blood tests such as complete blood count, blood glucose levels, and liver function tests, offer insights into overall health and specific conditions. Urine tests aid in detecting kidney function, infections, and other medical conditions. Additionally, diagnostic imaging results obtained from X-rays, CT scans, and MRI scans provide detailed information about anatomical structures, helping identify abnormalities, tumours, fractures, and other structural issues.

Clinical scores and scales [60] encompass various tools for assessing and quantifying medical conditions and patient health. The Charlson comorbidity index [149] is an assessment that considers a range of medical conditions to predict mortality risk. The Glasgow coma scale evaluates neurological function, particularly after a traumatic brain injury, providing valuable insights into the patient's cognitive status. Additionally, the APACHE II score is a predictive tool to gauge the severity of illness among critically ill patients, aiding in their management and treatment decisions.

Risk factors [61] encompass various elements that can significantly influence an individual's susceptibility to certain diseases and health conditions. Smoking, for instance, is a well-established risk factor associated with numerous ailments, such as lung cancer and cardiovascular diseases. Similarly, obesity is a contributing factor that elevates the risk of conditions like diabetes, heart disease, and certain types of cancer. Moreover, environmental exposures in occupational settings, including contact with chemicals, radiation, and pollutants, have the potential to impact health outcomes, emphasising the importance of workplace safety measures and protective measures for individuals in such environments.

Observations:

These significant features are crucial components of clinical prediction in the NHS UK, enabling healthcare professionals to make accurate assessments and personalised decisions to improve patient outcomes. Among them, vital signs are fundamental physiological measurements that play a pivotal role in healthcare assessment and decision-making. They serve as critical early indicators of physiological disturbances, facilitating the early detection and diagnosis of underlying medical conditions. By establishing baseline measurements and monitoring trends over time, healthcare professionals can evaluate the effectiveness of treatments, interventions, and medications. Vital signs are vital in emergency situations, guiding rapid responses and interventions. Moreover, they contribute to clinical decision-making, anaesthesia management, and the assessment of patient wellness. As standardised indicators, vital signs enable effective communication and documentation among healthcare teams. Overall, vital signs are a cornerstone of medical practice, providing essential data points that aid in diagnosis, treatment, and patient care across diverse healthcare settings.

2.3.2 Anomalies from Vital Signs

Vital signs [58, 62, 63] are a set of measurable physiological parameters that provide important information about the body's overall health and functioning. Vital signs encompass a set of essential physiological measurements that provide valuable insights into an individual's overall health and well-being. These measurements include Heart rate, which quantifies the number of heartbeats per minute and is typically measured at the radial or carotid arteries, serving as an indicator of cardiovascular health and response to stress or activity. Respiratory rate, indicating the number of breaths taken per minute, reflects lung function and respiratory responses to stress or illness. Blood pressure, recorded as systolic and diastolic pressures, reflects cardiovascular health and circulatory efficiency. Body temperature, measured via various methods, indicates metabolic activity and can signal fever or hypothermia. Oxygen saturation (SpO2), usually assessed with a pulse oximeter [150], reflects respiratory and circulatory function as well as oxygen delivery to tissues. Normal ranges for these vital signs may vary depending on age, activity level, and measurement method, but collectively, they offer critical information for health assessment and diagnosis.

While each vital sign provides specific information about different aspects of the body's functioning, they are interconnected and can influence each other in various ways:

Heart rate and blood pressure are closely interconnected; when the heart rate increases, it can lead to elevated blood pressure as the heart pumps more frequently, exerting greater force against the arterial walls. This relationship is vital for clinicians as it aids in evaluating cardiovascular health, identifying stressors, and understanding the body's compensatory mechanisms. Likewise, heart rate and respiratory rate exhibit synchronisation, particularly during physical exertion or stress, when both may rise to meet the heightened demand for oxygen and energy. Monitoring this coordination assists clinicians in assessing the responsiveness of the cardiovascular and respiratory systems to physiological demands. Blood pressure plays a pivotal role in oxygen delivery to tissues, impacting oxygen transport to cells. Consequently, healthcare providers consider the association between blood pressure and oxygen saturation when assessing circulatory and respiratory function, recognising that low blood pressure can affect oxygen delivery and low oxygen saturation can induce vasoconstriction and impact blood pressure. Respiratory rate and oxygen saturation are intricately related, with respiratory rate determining the efficiency of lung gas exchange. A higher respiratory rate may help maintain sufficient oxygen levels in the bloodstream. This balance between respiratory rate and oxygen saturation is crucial for assessing respiratory health and ensuring adequate oxygen supply to tissues. Finally, temperature and heart rate exhibit a direct relationship, elevated body temperature, often due to fever or inflammation, results in an increased heart rate. Clinicians monitor this correlation to identify febrile conditions and gauge the body's immune response. Additionally, body temperature can influence blood vessel dilation and constriction, thereby affecting blood pressure. Recognising the interplay between temperature and blood pressure aids healthcare professionals in interpreting changes in blood pressure readings, especially in cases involving fever or hypothermia.

Observations:

The relationships between these vital signs provide a comprehensive picture of a patient's physiological state. When making clinical decisions, healthcare professionals consider how deviations from normal values in one vital sign can impact others. For example:

- A patient with an elevated heart rate, low blood pressure, and low oxygen saturation might be experiencing septic shock, prompting immediate intervention.
- A patient with a rapid respiratory rate, an increased heart rate, and a high fever could be showing signs of pneumonia or another respiratory infection.

By recognising the interconnectedness of vital signs and how they respond to different conditions, clinicians can make more accurate diagnoses, tailor treatment plans, and monitor the effectiveness of interventions [192]. Decisions are based on a holistic assessment of the patient's vital sign trends, medical history, symptoms, and other clinical information.

2.3.3 Common Health Care Anomaly Detection Techniques

Anomaly detection in healthcare is a critical area of research and application that plays a vital role in ensuring patient safety, early disease diagnosis, and efficient healthcare delivery [64]. Healthcare data, whether originating from electronic health records, medical imaging, physiological signals, or wearable devices, is inherently complex and dynamic. Detecting anomalies in such data can help identify abnormal patterns, potential health risks, and adverse events, enabling timely interventions and improving patient outcomes.

Anomalies in healthcare data can take various forms, such as rare diseases, abnormal physiological trends, irregular medical image findings, or unexpected patterns in patient behaviour [15]. Detecting these anomalies is challenging due to the vast amount of data generated, the presence of noise and missing values, and the need to distinguish between normal variations and true abnormalities. As a result, advanced analytical techniques, including machine learning, deep learning, and statistical methods, are employed to sift through the data and identify deviations from the norm.

In this context, the exploration of anomaly detection in healthcare takes on a multidisciplinary approach, involving experts from data science, medical professionals, and domain-specific researchers. By harnessing the power of cutting-edge technologies and domain expertise, anomaly detection in healthcare is promising for revolutionising patient care, automating diagnostics, and optimising healthcare workflows.

Researchers delve into the various anomaly detection techniques, their applications in different healthcare domains, and the potential challenges and opportunities in this ever-evolving field. From early detection of life-threatening conditions to personalised medicine, anomaly detection in healthcare continues to make significant strides towards delivering safer, more efficient, and data-driven healthcare solutions [25].

Statistical Methods

Statistical methods [23, 26] are fundamental in healthcare anomaly detection, offering a structured approach to identifying deviations from expected patterns in patient data and vital signs. These techniques rely on established statistical measures to quantify the normal behaviour of data, making them valuable for detecting anomalies in healthcare settings. In healthcare data analysis, several common statistical anomaly detection techniques are applied. The Z-Score [65], for instance, quantifies the number of standard deviations a data point deviates from the mean, flagging outliers as anomalies. The modified Z-Score improves upon this method, enhancing robustness to outliers. Percentiles also serve to detect anomalies by identifying data points falling below or above specific percentiles within the distribution. Additionally, moving average [66] and moving standard deviation [67] techniques are employed to uncover anomalies in time-series data by comparing present values to historical averages and standard deviations. These statistical methods offer a structured approach to anomaly detection, proving accessible for healthcare professionals and applicable to both univariate and multivariate data analysis. However, they may struggle with complex, non-linear relationships and subtle anomalies, and determining appropriate thresholds and parameters can be subject to subjectivity and complexity.

Machine Learning-Based Techniques

Machine learning uses algorithms to train models on historical data and then apply these models to new data for anomaly detection. Three primary approaches are highlighted in this comprehensive exploration of machine learning-based techniques [27, 68, 69] used in healthcare anomaly detection. Firstly, supervised learning [70] uses labelled data to train models for distinguishing between normal and anomalous instances, employing algorithms such as Support Vector Machines (SVM) [71], Decision Trees [72], K-Nearest Neighbour (K-NN) [87], linear regression [201] and Random Forests [73]. Secondly, unsupervised learning [74], which operates without the need for labelled data, aims to unveil patterns and anomalies through techniques like K-Means clustering [75], Once class SVM (OC-SVM) [76, 116] and DBSCAN-based density analysis [77]. Finally, semi-supervised learning [78] combines labelled and unlabelled data to enhance anomaly detection, particularly when labelled data is scarce. The advantages of machine learning techniques lie in their ability to capture intricate relationships and patterns that can prove challenging for rule-based or statistical methods, their adaptability to diverse healthcare data types, and their capability to handle high-dimensional data and large datasets. However, they face limitations, including the requirement for substantial labelled training data, sensitivity to data quality, preprocessing, feature selection, and potential computational intensity for complex models like deep learning architectures.

Deep Learning-Based Techniques

Deep learning-based techniques [28, 79] have revolutionised healthcare anomaly detection by leveraging complex neural architectures to automatically learn intricate patterns in data. In healthcare anomaly detection, deep learning-based techniques offer a comprehensive exploration, each with its advantages and limitations. Long Short-Term Memory (LSTM) [80] networks excel at capturing temporal dependencies in patient records and time series data. Convolutional Neural Networks (CNNs) [81] are adept at identifying anomalies in medical images, which is handy for conditions like tumours or fractures. Recurrent Neural Networks (RNNs) [80], including LSTM networks and Gated Recurrent Units (GRUs) [82], handle sequential data by considering temporal dependencies. Generative Adversarial Networks (GANs) [83] operate with a generator and discriminator in competition, generating and evaluating data authenticity, respectively. These techniques are advantageous for capturing intricate patterns in complex healthcare data and handling substantial data volumes. Still, they require significant labelled data for training, are computationally intensive, and may lack interpretability.

Time-Series Analysis

By analysing sequential data points over time, healthcare professionals can gain insights into changes in patient conditions, enabling early detection of anomalies and timely interventions [29, 90]. A comprehensive exploration of time-series analysis techniques in healthcare anomaly detection reveals several valuable methods. Moving Average and Exponential Smoothing techniques, for instance, effectively smooth out noise in time-series data to reveal underlying trends. Anomalies become apparent when deviations from these smoothed trends occur. Autoregressive Integrated Moving Average (ARIMA) [84], a popular method for time series forecasting, identifies anomalies when observed data significantly deviates from forecasted values. Seasonal Decomposition of Time Series (STL) [85] decomposes time series data into seasonal, trend, and residual components, with anomalies detected in the residual component, signalling deviations from expected behaviour. Dynamic Time Warping (DTW) [86] measures the similarity between two time-series sequences, and anomalies are pinpointed when the alignment distance between a query sequence and a reference sequence exceeds a threshold. Time-series analysis offers the advantage of specialising in capturing temporal patterns, making it ideal for evolving healthcare data. It excels at identifying subtle anomalies and providing insights into disease progression and treatment effectiveness. However, limitations include the need for historical data, potential challenges in handling missing or irregular data, and difficulty in detecting abrupt changes in data patterns.

Domain-Specific Techniques

Healthcare anomaly detection requires specialised techniques that cater to the unique characteristics of medical data and the intricacies of clinical contexts. These domain-specific methods [30] leverage medical knowledge, physiological understanding, and clinical expertise to enhance the accuracy and relevance of anomaly detection. Domain-specific techniques play a crucial role in enhancing anomaly detection accuracy by leveraging the depth of medical expertise. They are well-suited to handle the intricacies of medical data, characterised by complex and non-linear relationships. By incorporating clinical knowledge and standards, these methods provide valuable insights and can assist healthcare professionals in making informed decisions. However, their effectiveness depends on the availability and accuracy of medical knowledge, and they may not always capture emerging or rare anomalies that are not explicitly defined. Additionally, the interpretability of their outputs can vary, emphasising the need for ongoing validation and refinement to ensure reliable anomaly detection in healthcare settings.

2.3.4 Performance Evaluation Metrics

Performance evaluation metrics are crucial for assessing the robustness and accuracy of anomaly detection models applied to healthcare data. These metrics help quantify how effectively a model distinguishes between anomalous and normal instances. Key metrics include True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) [91, 92], which are used to compute Sensitivity, Specificity, Precision, Negative Predictive Value, and the F1-Score [91, 92]. In addition to these, the Receiver Operating Characteristic (ROC) [91] curve and the Precision-Recall curve [92] provide valuable insights into the trade-offs between sensitivity and specificity at various decision thresholds. Metrics such as Accuracy [91], Matthews Correlation Coefficient (MCC) [93], and the Area Under the Precision-Recall Curve (AUC-PR) [94] offer comprehensive performance assessments, aiding in the selection and fine-tuning of anomaly detection algorithms. The choice of which metric to prioritise depends on the nature of the healthcare dataset, the clinical context, and the specific objectives of the anomaly detection task.

Observations:

It is observed that there are three main categories of anomaly detection techniques in healthcare data:

Data Types: This category encompasses various types of healthcare data amenable to anomaly detection, including structured data, unstructured data, and time-series data. Structured data typically consists of organised tabular datasets, like electronic health records (EHRs) [56] and administrative data, featuring well-defined columns and rows. In contrast, unstructured data encompasses non-tabular formats like medical imaging (e.g., X-rays, MRI scans) and clinical notes, which lack the neat organisation of structured data. Lastly, time-series data involves temporal information with a series of values recorded over time, such as patient vital signs, continuous monitoring data, and patient activity logs, providing valuable insights for anomaly detection in healthcare.

Techniques: This category represents the different approaches and methodologies used for anomaly detection in healthcare data. This category encompasses diverse methodologies and approaches employed for anomaly detection in healthcare data. It includes conventional statistical methods like mean, standard deviation, and z-scores, which are used to pinpoint outliers and anomalies in healthcare datasets. Machine learning methods, such as SVM, k-NN, and random forests, are harnessed to learn patterns from historical data for detecting anomalies across various healthcare datasets. Deep learning techniques, powered by advanced neural network architectures like CNNs and LSTM networks, come into play for anomaly detection in medical imaging and time-series data. Ensemble approaches, incorporating the amalgamation of multiple models or techniques like bagging and boosting, aim to enhance anomaly detection accuracy while reducing false positives. Additionally, threshold-based alarms employ straightforward rules and predefined threshold values for specific vital signs or attributes to trigger alarms upon detecting anomalies.

Data Sources: This category encompasses various sources of healthcare data where anomaly detection is deployed. It includes hospital data, where anomaly detection is applied to information gathered within hospital settings, encompassing EHRs, patient demographics, and administrative data. Moreover, medical imaging constitutes another facet where anomaly detection is utilised to scrutinise medical imaging data such as X-rays, CT scans, and MRIs, to discern and flag abnormalities and diseases. Patient monitoring is an integral component, involving real-time tracking of a patient's vital signs and physiological data for the detection of anomalies and critical events. Lastly, the category extends to IoT and wearable devices, facilitating anomaly detection through data collected by wearable devices and Internet of Things (IoT) [88] devices, thereby enabling continuous patient monitoring beyond the confines of healthcare facilities.

2.3.5 Summary Observation

Salem [104] introduces a methodology that merges linear regression with the Support Vector Machine (SVM) technique. However, SVM tends to underperform when working with extensive datasets while demonstrating better results for smaller ones, as addressed in [222]. Using SVM in resource-limited settings might not be suitable due to its high energy requirements. Additionally, the approach discussed compromises the false alarm rate to maintain a high detection ratio. Salem et al. [105] proposed an online anomaly detection system utilising the Mahalanobis distance (MD). However, in their work, a threshold approach with the MD was employed, which was found to be unsuitable for real-time healthcare systems. While calculating the MD can be done smoothly, the process as a whole can be unstable and potentially hazardous for healthcare applications. Table 2.1 shows a summary of anomaly detection techniques from literature.

Table 2. 1: Existing anomaly detection techniques in the literature

Year	Author	Purpose	Techniques	Limitations
2014	O salem [104]	Anomaly detection	SVM, LR	Sensitive to missing data, high power consumption
2014	O salem [105]	Anomaly detection	MD	High processing time, did not used IEEE 802.15.6
2015	SA Haque [106]	Anomaly detection	SMO, MV, DSW	High processing time, did not used IEEE 802.15.6
2015	Pachauri [107]	Anomaly detection	J48, RF, K-NN	High processing time
2017	S Xie [108]	Anomaly detection	PSA, BN	2 Steps of process, high complexity
2017	Temilola [109]	Outlier detection	MAD, MV	Working only for a fixed threshold
2017	Khan [110]	Anomaly detection	MM	Less effective in heterogenous environment
2018	O salem [111]	Event detection	KF	High energy consumption
2019	Saraswathi [112]	False alarm detection	RF	Processing time high
2019	Sun [113]	ECG anomaly detection	SH-Base	Only for a particular disease
2019	S Kumar [114]	Anomalous Data	ANN, LR	High computational complexity
2019	Smrithy [226]	Anomaly detection	WMA	Sensitive to old data
2021	Dwivedi[227]	Anomaly detection	Gaussian based	Power consumption, latency

Haque et al. [106] utilised the Sequential Minimal Optimization (SMO) algorithm and Majority Voting (MV) algorithm for anomaly detection. However, this effort wasn't tailored to the IEEE 802.15.6 standard and demanded a considerable amount of processing time, making it unsuitable for healthcare applications. Further, the authors incorporated the Dynamic Sliding Window (DSW) algorithm, which is known for its high computational cost. In a similar context, G Pachauri et al. [107] proposed an anomaly detection system that employed a combination of three algorithms - J48, Random Forest (RF), and the k-nearest neighbours algorithm (k-NN). While this arrangement proved effective, its training and processing times were high. This excess time consumption could potentially jeopardize patient health in urgent medical scenarios.

Xie et al. [108] introduced an anomaly detection methodology using Principle Statistic Analysis (PSA) and Bayesian Network (BN). Their proposal was organised into two steps, focusing on anomaly detection and redundancy elimination. However, due to its high complexity, it's not very suitable for environments where power consumption is a vital constraint. On a similar note, Temilola et al. [109] applied Median Absolute Deviation (MAD) and MV for their outlier detection techniques. They utilised a fixed threshold, which unfortunately didn't effectively handle dynamic scenarios. A Markov Model (MM) was proposed in [110], but it didn't perform well in heterogeneous environments. In a different vein, Salem et al. [111] put forward an event detection method using the Kalman Filter (KF). Despite the authors claiming an impressive detection rate, this approach came with a significant downside, namely its high power consumption.

Saraswathi et al. [112] implemented the Random Forest (RF) algorithm to decrease the rate of false alarms. However, the long processing time it required made it unsuitable for healthcare applications, where short response times are crucial. A Shapelets-base (SH-Base) was employed in [113] for a specific electrogastrogram (EGG) to spot any EGG anomalies. Kumar et al. [114] improved upon both fault detection and anomaly data detection techniques by making use of an ANN. Moreover, they adopted Linear Regression (LR) for their proposed solution. A downside of this work, however, was its need for vast computational capacity, making this approach less effective in environments where resources are scarce or limited.

2.4 Anomaly Detection Using Vital Signs

Monitoring vital signs enables healthcare professionals to identify potential problems before they become severe, allowing for timely intervention and improved patient outcomes. The literature emphasises the significance of early detection of patient vital signs across various medical conditions. Here are key findings from the literature:

The significance of vital signs, notably heart rate, respiratory rate, and temperature, in the early detection of life-threatening conditions like sepsis, is underscored in the realm of sepsis detection [38]. Extensive research demonstrates that swift changes in vital signs can serve as precursors to sepsis, facilitating timely intervention and mitigating mortality rates. The role of abnormal vital signs, including heightened heart rate and blood pressure, in predicting cardiovascular events such as heart attacks and strokes is illuminated within the context of cardiovascular events [39]. By vigilantly monitoring fluctuations in these vital signs, clinicians can identify individuals at risk and navigate pre-emptive measures and interventions. Respiratory distress [40] involves irregularities in vital signs such as respiratory rate and oxygen saturation, serving as indicators of potential conditions like Acute respiratory distress syndrome (ARDS) [89]. Monitoring these vital signs aids in identifying respiratory distress and facilitating timely intervention for improved patient outcomes. Scholarship suggests that vigilant monitoring of these indicators empowers healthcare providers to intercede expeditiously, ultimately enhancing patient outcomes. The pivotal role of vital signs, particularly blood pressure and heart rate, in haemorrhage and shock detection [41] takes precedence, with the literature accentuating the necessity of closely tracking these vital signs in trauma and surgical patients to discern indications of internal bleeding or compromised circulatory states. Neonatal care [42], in a similar vein, emphasises the imperative of promptly detecting anomalies in vital signs to identify conditions such as neonatal sepsis and respiratory distress syndrome. The literature underscores the employment of continuous vital sign monitoring to forestall complications and diminish neonatal mortality. Shifting the discourse towards Cancer and Chemotherapy monitoring [43], scholarly discourse expounds upon the role of vital signs in monitoring cancer patients undergoing chemotherapy, given chemotherapy's potential impact on heart rate, blood pressure, and other vital signs. Early identification of treatment-induced vital sign alterations can facilitate the tailoring of chemotherapy regimens and the effective management of prospective side effects. In the realm of Acute Pain and Postoperative care [44], vital signs manifest as invaluable indicators of acute pain, frequently coinciding with alterations in heart rate, blood pressure, and respiratory rate. The diligent monitoring of vital signs post-surgery aids in the detection of pain-related complications and ensures the judicious management of pain. Concerning diabetes and glycemic control [45], studies underscore the pivotal role of vital signs, particularly blood pressure and heart rate, in the management of diabetes to avert complications and oversee glycemic control. The prompt identification of aberrant vital signs can guide refinements in diabetes treatment strategies. The landscape of Remote Monitoring and Telehealth [46] delineates the integration of wearable devices and telehealth platforms to facilitate continuous remote monitoring of vital signs. Scholarly discourse deliberates on the potential of pre-emptive detection through remote monitoring, thereby equipping healthcare providers with the means to intervene based on real-time data.

Observations:

Current solutions for early detection of patient vital signs face limitations mainly due to their reliance on complex algorithms, resulting in interpretability issues that complicate clinical understanding and acceptance. Moreover, the intricate nature of some techniques, like deep learning, can hinder real-world implementation due to their resource-intensive requirements. In the quest for effective and practical solutions, there's a growing need to strike a balance between accuracy and simplicity, ensuring that healthcare professionals can easily comprehend and integrate these systems into their workflows, ultimately improving patient care.

A straightforward algorithm for healthcare anomaly detection from patient vital signs is the threshold-based anomaly detection algorithm [47]. It involves selecting vital sign parameters (e.g., heart rate, blood pressure, temperature, and respiratory rate) for monitoring and setting upper and lower thresholds for each parameter based on reference ranges or clinical guidelines. Patient vital signs data is continuously monitored, and at regular intervals, the current values are compared to the predefined thresholds. If any vital sign data surpasses the thresholds, an anomaly alert is triggered, such as an alarm or notification. This approach is advantageous for its simplicity, real-time monitoring, and low computational overhead. However, it has limitations in that static thresholds may not adapt well to individual patient variations, leading to potential false positives or false negatives. Additionally, it lacks the ability to offer clinical insights or predictive capabilities beyond threshold-based alerting.

Threshold-Based Alarm Systems in healthcare [47] refer to a monitoring approach where predefined thresholds are set for specific physiological parameters, such as vital signs or other health-related measurements. These thresholds act as triggers to generate alarms or alerts when the monitored values exceed or fall below the established limits. The purpose of these alarms is to promptly notify healthcare providers or medical staff of potential abnormalities, allowing them to take immediate action and provide timely interventions for patients in critical or deteriorating conditions.

In their work, the authors of reference [220] question the scientific validity of the conventional method of instability detection, which relies on threshold breaches. They claim that this method is inadequate for early detection of instability, leading to numerous inexplicable in-hospital fatalities. A threshold technique was proposed using a machine learning algorithm in [221]. However, this method requires significant computational resources. They developed an early warning system focused on predicting organ system failures in ICU EHRs, particularly for circulatory system failure. The system includes data processing, clinical endpoint definition, supervised learning using a gradient-boosted decision tree ensemble, alarm generation, and clinical setting evaluation.

For instance, in an intensive care unit (ICU) scenario, a threshold-based alarm system might be set to trigger an alert if a patient's heart rate goes above a certain value or if their blood pressure drops below a certain level. Similarly, in remote patient monitoring, if an individual's blood oxygen saturation falls below a predetermined threshold, an alarm could be sent to their healthcare provider's dashboard or mobile device. While threshold-based alarm systems offer a simple way to monitor patients' well-being and quickly respond to changes, they also come with challenges. Over time, healthcare providers can become desensitised to frequent alarms, leading to alarm fatigue and potentially causing them to overlook critical alarms. Additionally, fixed thresholds may not account for individual patient variability or contextual factors, resulting in false alarms or missed genuine health concerns.

Therefore, refining and personalising threshold-based alarm systems is crucial to balancing sensitivity and specificity, improving their effectiveness in clinical settings. By combining traditional approaches with advanced analytics and user-centred design, researchers aim to enhance the utility of these systems, ultimately contributing to better patient care and outcomes.

However, this does not contain predictive capabilities and can only minimise the time of occurrence of critical clinical situations.

Observations:

Threshold-Based Alarm Systems in healthcare monitor specific physiological parameters using predefined thresholds, triggering alerts when readings exceed or fall below these limits. These systems aim to facilitate prompt responses to potential health abnormalities. However, their scientific validity is questioned, especially as they may not detect early instabilities, potentially causing in-hospital fatalities. A machine-learning based approach has been proposed but requires substantial computational resources. Though these systems provide quick responses, they can lead to alarm fatigue and overlook individual patient variability or context, causing false or missed alarms. Refining these systems may improve their effectiveness, but current models lack predictive capabilities, reducing their ability to anticipate critical clinical situations.

In your narrative, you highlighted the importance of two primary metrics in the performance analysis of anomaly detection algorithms: detection rate (DR) and false positive rate (FPR). These metrics can be illustrated on a receiver operating characteristic plot. Broadly, the detection rate measures the percentage of actual anomalies correctly identified, while the false positive rate indicates the proportion of normal instances incorrectly labelled as anomalies. It has been noted that sensor data can occasionally be marked as anomalous due to several factors, such as hardware failure, sensor malfunction, excess energy consumption, or incorrect calibration. In the work referenced as number 223, an anomaly detection method was put forward involving a two-phased algorithm. This method employed a support vector machine for detecting anomalies and a nearest neighbour approach to reduce the occurrence of false alarms. This research was implemented in the context of a wireless sensor network. On the other hand, in the document referenced as number 224, a Gaussian mixture model was utilised to differentiate between normal and abnormal data. Additionally, an Ant Colony algorithm was harnessed to detect erroneous sensor readings. In this case, the detection rate and false positive rate were recorded at 100% and 9%, respectively. Lastly, in the study referenced as number 225, the Mahalanobis Distance was implemented for measuring sample anomalies, and the Kernel Density Estimator was adopted to evaluate correlation. In this scenario, the detection rate and false positive rate were reported as 100% and 5.5%, respectively.

2.5 Local Emergency Detection

Detecting local emergencies entails identifying any abnormal or unexpected occurrence within the local node. This concept is referred to by various terms in literature, including outlier detection, anomaly detection, and emergency detection. The primary goal here is to identify unexpected behaviours or patterns locally, which helps to reduce the amount of data to be transmitted. Various methods have been observed in the literature, with statistical analyses standing out as particularly effective. However, while statistical analysis can effectively address this issue, it may not be universally applicable.

Elghers et al. [140] proposed a local emergency technique using WBANs for healthcare applications. The Early Warning Score is used for the proposed algorithm to detect emergency in the local node. The ultimate idea was to conserve energy by reducing data transmission. The limitation of the proposed technique is that it sends all the data that detects an emergency. The positive aspect of the proposed work is that it uses Early Warning Scoring data to classify the emergency data.

Thamilarasu et al. proposed a local emergency detection system in their study [235], devised to secure the system. The authors put forward an autonomous, mobile agent-based intrusion detection architecture to identify any emergent situations. While the authors applied this algorithm to WBAN, the usage is primarily centred on security-focused applications. As such, the proposed system does not concentrate on energy-saving or data sampling strategies.

Salim et al. [141] presented a local emergency detection system using statistical variance analysis in their study. It remains uncertain whether data calibration will occur locally or centrally and how this will function in a practical context. Also, please note there may be a typo in your sentence; "spell" is the correct English term. Habib et al., in their work cited as [31], improved the Light Emitting Diode (LED) system [140] to avoid transmitting all data collected from the system. The authors suggested a revised algorithm as a countermeasure to the existing LED algorithm. This advanced warning system is utilized to compute the score on a local node, thereby eliminating the need to transmit every piece of data. A significant flaw in the proposed method is that this algorithm replaces the old score with a new one. If the subsequent score varies from the prior score, the system determines whether it's an emergency or not. Nevertheless, the suggested system doesn't delve into individual levels for further scrutiny. This vulnerability makes the recommended algorithm, known as MLED, susceptible. The aggregate score, unfortunately, could closely resemble the score of a high-risk individual.

Odesile et al., in their paper referenced as [236], present work akin to that in [235] for the early detection of emergencies, aiming to safeguard the system from potential attacks. Techniques incorporated are intruder system methods utilising a mobile agent with the primary objective of securing the system against attacks. Massoud et al., in paper [237], recommended a local emergency system applying Null Hypothesis. Chi-square statistics are utilised in formulating this algorithm. However, the limitations include the fact that chi-square works only with independent variables. Consequently, the proposed method is not suitable for heterogeneous systems.

In [238], Shaikh and his team propose a local emergency detection method utilising the statistical mean, a strategy found to be unreliable in WBANs healthcare applications. A different approach using mostly statistical analysis for local emergency detection is presented by Arafoui and his colleagues in [239]. This involves using standard deviation for variation calculations and the Mahalanobis Distance (MD) for distance computations. However, the proposed method requires significantly high computation in comparison to other suggested processes.

Additionally, Sawqi et al. put forward local emergency techniques in [142] that employ adaptive rate. The proposed system comprises a two-stage calculation process, which escalates the computational workload. Notwithstanding, a key drawback of this system lies in its usage of the LED algorithm. This LED algorithm, as presented in [140], transmits all data identified as emergency data.

2.6 Energy Optimisation Techniques Used in Healthcare Emergency Detection

2.6.1 Power Consumption Techniques

Since WBAN operate wirelessly, one of the crucial factors to consider during their development is power consumption. Power consumption can be classified based on its component-based and they are:

- Sensing
  - Sensor set selection [228, 229]
  - Context based pull [121, 231]
- Communication
  - Data reduction [34, 123, 230]
  - Radio optimisation [125, 126]
  - Energy-efficient routing protocol [127–128]
  - Sleep/Wake scheme [130, 131]
- Processing

– Feature selection [132, 133]

– Adaptive classifier selection [1345, 135]

Most popular energy-efficient methods are:

- Adaptive classifier selection
- Adaptive sampling
- Compressive sensing
- Context-based pull
- Context-aware routing protocol
- Energy-efficient routing protocols
- Feature selection
- Radio optimisation
- Sensor set selection
- Sleep/wakeup schemes

In [232], it is highlighted that power inefficient protocols are the main contributors to energy usage. An effective routing protocol that is compatible with the Media Access Control (MAC) layer was also suggested in the same paper. Paper [233] put forth a MAC protocol for a specific scenario where human body circuitry is low. In this context, it was demonstrated that multi-hop communication is more efficient than single-hop communication.

The classification of a patient's health is determined based on the collected vital signs data, which is identified as either within or outside the normal range. Two types of classifiers are used: one for the standard data range, and a prioritised queue for when the vital signs data deviates from this range [211]. Despite that, the primary emphasis of this paper is on energy conservation using queuing techniques during data transmission.

Activity recognition models are proposed in [234], using feature extraction and classifiers such as naive Bayes, decision tree, and Bayesian. Fortino [34] suggested using data fusion and analysis to generate valuable information for the proposed model. However, these proposed solutions are based on specific criteria and do not provide support for general purposes.

2.6.2 Adaptive Sampling

A significant body of work has already been published regarding sensor data for healthcare applications. Specifically, this review focuses on the research related to the study at hand. The role of sensing rate in wireless body area network (WBAN) healthcare applications is highlighted, primarily due to its impact on understanding patient wellbeing. Patients' health conditions can fluctuate rapidly, necessitating the need to adjust the sampling rate to respond effectively and promptly. Moreover, adjusting the sampling rate also serves as an efficient technique for reducing energy usage in WBAN. An Internet of Things (IoT)-driven Early Warning Score System (EWS) is suggested in a study [191] to predict patients' health deterioration using vital signs. However, considerations related to energy usage and local emergency detection were not addressed in this approach. On the other hand, a study [140] proposes an algorithm for early emergency detection aimed at energy conservation. This research, however, advocates the transmission of all critical data, potentially impacting energy conservation negatively. As an alternative, Study [31] introduces a local data sampling technique intended for early emergency detection and periodic local decision-making.

In their work [140], Elghers and his team introduced an adaptive sampling method to regulate the amount of data to be transmitted. They utilized the LED algorithm, also developed by them, to identify emergencies, dictating the sampling rate to be used accordingly. According to the design of the LED algorithm, data is only transmitted when the EWS score surpasses zero. Compared to other available solutions, local emergency detection is efficient, leading to a higher sampling frequency. However, this ultimately escalates energy consumption in WBAN-based applications. Similarly, Salim and his colleagues proposed another adaptive sampling method in [146], leveraging the use of a Fisher test algorithm. Despite its primary basis in statistical analysis, this proposed approach might not be a suitable fit for WBAN healthcare applications.

In their paper [31], Habib and others have refined the energy usage method by employing an adjustable sampling technique. They utilize ANOVA (Analysis of Variance) and behavioural functions to assess a patient's risk level and set the sampling accordingly. This approach stands out among existing methods for its effectiveness. The included system upgrade from LED to MLED helps in reducing the data that needs to be transmitted. Moreover, a Fisher test is incorporated in the suggested methods to facilitate the process of determining the patient's risk level. Nonetheless, there are certain limitations in variance analysis when dealing with data that lacks variation. For instance, if the Early Warning Score (EWS) escalates and maintains a consistent high, the proposed ANOVA may not be adequate to identify the emergent situation.

An optimised data gathering approach is presented by Xiaobin et al. in [143], utilising an adaptive sampling-based information collection method. However, this study does not concentrate on energy conservation. Lee et al. in [144] introduced energy-conscious local emergency detection methods. Their proposed methods employed adaptive sampling and harvesting techniques. The complexity of the suggested work's system design might not be suitable for a heterogeneous environment. An energy-saving technique proposed by Ting Lu et al. in [145] employs a sampling rate allocation method. However, requiring a rechargeable sensor for the system design makes this solution expensive.

Fathy et al. [146] proposed an adaptive enhanced data reduction technique using the Adaptive Method for Data Reduction (AM-DR). However, this suggested solution is not applicable for Wireless Body Area Networks (WBAN) but is suitable for Wireless Sensor Networks (WSN). Given its computational nature, it may not be feasible in a heterogeneous environment. Azar et al. [147] presented a data reduction technique that utilises the Wavelet Transform Lifting Scheme. This work, however, predominantly focuses on statistical analysis and does not address real-world applications.

In their paper [148], Bacsaran and his team introduced techniques to reduce data with the aim of conserving energy. They employed a wavelet filter-based adaptive sampling method designed for wireless sensor networks. Despite this, the potential application within healthcare settings was not discussed. Similarly, Shawqi and his colleagues proposed [142] a method involving adaptive rates to enhance energy efficiency. The approach includes a two-stage procedure, which unfortunately introduces computational complexity. An additional issue was the use of the LED algorithm for data sampling; as previously mentioned, it too had its drawbacks.

Observations:

Several existing energy-aware adaptive sampling techniques found in the literature are reviewed. It is noted that a key limitation is that most of the proposed work is primarily research-based and doesn't clearly address its applications. The two most effective solutions observed are referenced as [140] and [31]. Both employ the Early Warning Score (EWS) system to detect pressing emergencies, adapting a scoring mechanism in the process. The EWS system is a commonly utilized solution in both hospital and pre-hospital environments, making their local emergency detection methods realistic for healthcare applications. However, these two proposals' limitations lie in their respective algorithms.

For instance, the Local Emergency Detection (LED) approach fails to minimize the amount of data sent, as it transmits all emergency data. Conversely, the Modified Local Emergency Detection (MLED) has flaws within its local emergency detection algorithm, as previously discussed. The aim of this dissertation is to address these issues, specifically focusing on improving quality detection and implementing superior adaptive solutions for better energy conservation than what's offered by LED and MLED.

2.6 Summary

In the realm of WBANs, both threshold-based and hybrid algorithms play pivotal roles in health monitoring. However, existing literature highlights several limitations inherent in these approaches. Threshold-based algorithms, fundamental in anomaly detection, often employ fixed threshold values, which may not accommodate the physiological variability between individuals. This lack of personalisation can lead to false alarms or missed detections, as what constitutes an anomaly for one patient might be within the normal range for another. These algorithms also tend to be reactive, typically alerting only after a threshold breach, which can delay intervention in emerging health issues. Moreover, setting appropriate threshold levels is challenging; overly sensitive thresholds can lead to frequent false positives, whereas high thresholds might overlook critical health changes. In dynamic health scenarios, these algorithms may not adapt swiftly to changing patient conditions, potentially resulting in outdated or irrelevant threshold settings. On the other hand, hybrid algorithms, which aim to amalgamate the immediacy of threshold methods with the predictive capabilities of more complex models like linear regression, face their own set of challenges. One major limitation is achieving a balance between the sophistication of the predictive model and the practical constraints of WBANs, such as limited computational power and energy resources. These hybrid models can be computationally intensive, straining the resources of WBANs and potentially impacting their sustainability. Additionally, integrating different methodologies within a hybrid system poses challenges in ensuring efficiency, accuracy, and real-time responsiveness. Another concern is the interpretability of the outputs from these hybrid models; the complexity of the algorithms can make it difficult for healthcare providers to understand and act on the system's predictions and alerts. This complexity also raises concerns about the generalizability of these models across different patient profiles, given the diversity in health patterns and conditions. Furthermore, the literature indicates that long-term clinical validation of these hybrid models in real-world settings is often limited, raising questions about their reliability and consistency over time. Addressing these limitations is crucial for the advancement of threshold-based and hybrid algorithms in WBANs, ensuring they are both effective in monitoring patient health and practical for widespread implementation.

Adaptive sampling, a pivotal technique in Wireless Body Area Networks (WBANs) and other health monitoring systems, is designed to optimize data collection based on the varying needs of a patient's health status. Despite its importance, existing literature reveals several limitations that can affect its efficacy. Firstly, determining the optimal sampling rate that strikes a balance between adequate data collection for accurate health monitoring and the conservation of energy and computational resources is a significant challenge. Adaptive sampling methods often struggle to quickly respond to sudden and significant changes in health indicators, potentially leading to delayed data capture during critical health events. This is particularly concerning in emergency situations where real-time data is crucial. Additionally, there's a complexity in seamlessly integrating adaptive sampling techniques with other components of the WBAN ecosystem, such as data transmission protocols and power management systems. The existing algorithms may not always be efficient in contexts where rapid changes in physiological parameters occur, and they may not account for the multifaceted nature of a patient's health condition, especially in cases of chronic or complex diseases. Furthermore, while adaptive sampling can reduce the volume of data transmitted and thus conserve energy, this reduction could sometimes lead to the loss of crucial health information, creating a trade-off between data comprehensiveness and system sustainability. Another limitation is the potential for increased computational complexity, as adaptive sampling algorithms need to continuously analyse incoming data to adjust sampling rates, which can be resource-intensive. The literature also points to a gap in the long-term validation of these methods in real-world scenarios, questioning their reliability and consistency over extended periods. In addition, issues related to data privacy and security are amplified in adaptive sampling systems due to the variable nature of the data transmission, posing challenges in maintaining consistent security protocols. Finally, ensuring user-friendliness and accessibility of these systems remains a concern, as complex adaptive sampling mechanisms can be difficult for patients and healthcare providers to understand and manage, potentially hindering their wider adoption. Addressing these limitations is crucial for advancing the effectiveness of adaptive sampling methods in health monitoring applications.

Considering the limitations of current threshold-based and hybrid algorithms for WBANs, future research is needed. Enhancing personalisation and adaptability is crucial, moving beyond the one-size-fits-all approach to tailor algorithms to individual patient profiles and their unique health histories. Improving the predictive accuracy of hybrid algorithms by better integrating methods like linear regression with threshold techniques will be essential for more effective proactive health monitoring. Addressing computational efficiency is also paramount to ensuring these sophisticated algorithms are viable in resource-constrained WBAN environments. This includes optimising the real-time data processing capabilities for quicker responses to health changes, particularly in emergency scenarios. Additionally, making the complex data outputs of these hybrid models more accessible and interpretable for healthcare providers will enhance usability and clinical adoption. Expanding clinical validation and generalizability through extensive trials across diverse patient populations and settings will ascertain the reliability and applicability of these algorithms. Lastly, given the sensitive nature of the data handled by WBANs, enhancing data security and privacy remains a crucial area of focus, especially as the systems become more complex. Addressing these aspects will significantly advance the field of WBANs, making them more effective, reliable, and tailored to individual healthcare needs.

Chapter 3

3. Unified Anomaly Detection Schemes (UADS)

3.1 Introduction

Recent developments in electronics, embedded systems, and wireless communication technologies allow the creation of tiny, intelligent sensors for use on the human body to track health. A wide array of robust and high-performing biometric sensors, such as those for electrocardiograms, electroencephalograms, electromyograms, blood pressure, body temperature, blood glucose, heart rate, and oxygen saturation, are now deployed for ongoing human health monitoring. The application of these sensors carries several beneficial impacts: (i) they decrease medical errors, (ii) alleviate the workload for hospital staff, (iii) enhance patient comfort, (iv) enable highly sensitive health-related decisions, (v) deliver highly accurate data at a relatively low cost, and (vi) simplify the analysis and reduce the time required to process medical data [154].

This chapter serves as an exposition of the system model and theoretical framework that underpin our extensive research endeavour. Specifically, it outlines the development of an anomaly detection system utilising WBANs within the healthcare domain. The primary goal is to enhance clinical decision-making efficiency across diverse environments. This system incorporates anomaly detection techniques derived from the existing body of literature and aims to deliver robust performance characterised by early anomaly detection, precision in decision-making, and minimal power consumption. The chapter further elucidates the preliminary aspects, provides insights into related work, offers a detailed methodology of the threshold-based approach, and conducts a comparative analysis with machine learning approaches.

This research places significant emphasis on vital signs for the purpose of decision-making and prediction. Existing literature indicates that the interplay between these vital signs offers a holistic view of a patient's physiological condition, with changes in various vital signs demonstrating strong correlations. It is evident that more accurate predictions can be achieved when the alterations in multiple vital signs are collectively considered rather than estimating them in isolation. This chapter introduces a novel anomaly detection approach that leverages vital signs and their correlations to enhance predictive capabilities in healthcare.

3.2 Preliminaries

A typical architecture in a wireless healthcare system involves WBANs, wireless networks, actuators, and software services that collect data from a target user who requires such support due to medical conditions [9]. Wearable and implantable data collection devices [96] are available at a low cost. These devices can provide real-time physical and medical information about the user. These sensors exhibit key configurations and infrastructure, enabling easy implantation or wearability on the human body, with some being designed as wearable textile sensors that offer low power consumption, wireless communication, and the ability to monitor the user's health status and activity. In addition to a local processing point where data is initially transmitted, such as a workstation, smartphone, or tablet, all these sensors and devices are integral components of this healthcare system. Data in this healthcare system is continuously collected at various times of the day and, in some cases, on-demand. The data can encompass physiological information (e.g., heart rate, blood pressure, ECG) or information retrieved from persistent storage, such as a patient's profile, including historical and medical records.

The WBAN utilises bandwidth-limited low-power communication protocol devices such as WPAN, Zigbee, Bluetooth, etc. to transmit data using single hop or multi-hop between the sensor and Base Station (BS) [155]. The limitations of resources in networks, including restricted bandwidth, buffer memory, and battery power, necessitate an effective routing protocol for timely data transmission using minimal resources. Issues such as congestion and energy utilisation are significant in WBAN communication. Network traffic load escalation often results in buffer overload and repeated data retransmission. This, in turn, degrades the Qos, affecting latency, packet loss, throughput, and energy use [156]

In the context of most WBAN healthcare systems, data is typically transmitted to cloud storage [98] or hospital data repositories for decision-making based on patient data. However, this approach comes with several drawbacks, including high power consumption due to the transmission of extensive data, a lack of real-time processing, significant costs, and a heavy reliance on internet connectivity. In light of these challenges, it is advisable to conduct anomaly detection within a WBAN at the local node rather than relying on cloud-based processing. This underscores the need for an intermediary layer of computation, where a geo-distributed network of smart gateways offers intelligence at the network's edge. It facilitates the interaction between the sensors' layer and the cloud layer. This paradigm, alternatively known as edge computing, addresses this requirement [101,153]. A few WBAN architectures can be considered, where decisions can be made at the local node before transmitting data to the cloud.

In the distributed processing architecture approach [99], data from WBAN sensors undergoes local processing either on the WBAN device itself or on a nearby edge device. This configuration enables the integration of anomaly detection algorithms directly on the sensor nodes or edge devices, facilitating real-time anomaly detection without the need to transmit data to the cloud. This method offers the benefits of low-latency processing, minimised data transmission, and enhanced privacy. However, it faces limitations due to the computational constraints on the sensor nodes, posing challenges for complex processing tasks.

The fog computing architecture [100] extends the cloud's influence towards the network edge, enabling data processing at intermediary nodes within the network. Within a WBAN context, this approach may involve tasks like data aggregation and anomaly detection being performed at a nearby gateway device. Advantages include reduced latency, improved scalability, and efficient data processing. Nevertheless, the complexity of setting up and maintaining fog nodes can present challenges in implementation.

In the context of edge computing architecture [101] within a WBAN, the core idea is to bring data processing and computation as close as possible to where the data is generated. This involves processing vital signs and health-related data on wearable devices or nearby dedicated edge servers rather than sending all raw data to a remote cloud server. The benefits include those similar to fog computing and not limited to low-latency, real-time processing critical for healthcare applications, reduced data transmission, aiding in power consumption, and maintaining privacy. However, the limited computational capabilities of edge devices can pose constraints.

In the decentralised peer-to-peer architecture [102], each sensor node within the WBAN operates as both a data source and a processing unit. Anomaly detection can be executed collaboratively or independently on each sensor node. This approach provides high fault tolerance and minimal data transmission requirements. However, the limited processing power on sensor nodes may impact the complexity and real-time capabilities of anomaly detection algorithms.

As noted earlier, the edge computing architecture presents substantial benefits, making it a compelling option for crucial applications such as healthcare anomaly detection in WBANs. This WBAN architecture is depicted in Figure 3.1.

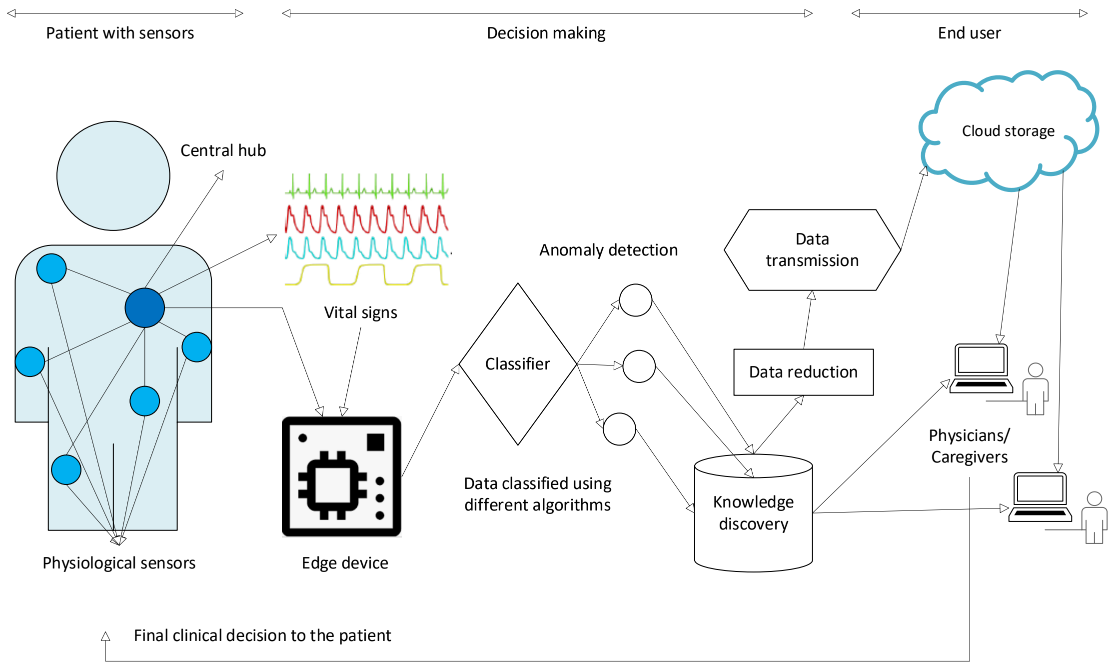


Figure 3. 1 The WBAN architecture includes edge devices for classification, prediction and decision-making.

Edge computing is a superior choice over cloud processing for healthcare anomaly detection due to several key advantages [98,101,103]. It offers low-latency, real-time processing, ensuring rapid response to anomalies, a crucial requirement in healthcare. This approach significantly enhances data security and privacy by keeping sensitive patient information within the local network. Despite its limited computational capabilities, edge computing proves cost-effective by reducing data transfer costs, making it particularly well-suited for applications with high data volumes and predictable workloads, such as vital sign monitoring. While cloud processing offers redundancy and fault tolerance, edge computing excels in simplicity and efficiency, and real-world case studies illustrate its successful deployment, showcasing improved patient outcomes.

When it comes to edge devices, there are several options available that can support the desired WBAN healthcare system. These devices vary in terms of their computational power, power consumption, data rate capabilities, cost, and more. Table 3.1 provides a summary of the available edge devices.

Table 3. 1: A summary of edge devices that can be used in a WBAN healthcare system.

Features	**Arduino Nano 33 BLE Sense**	**Raspberry Pi Zero W**	**Microsoft Azure Sphere**	**Intel Curie**	**Nordic Semiconductor nRF52840**	**Microchip ATmega328P**
Microcontroller	Nordic Semiconductor nRF52840	Broadcom BCM2835	Microsoft Pluton security subsystem	Intel Curie module	Nordic Semiconductor nRF52840	Microchip ATmega328P
CPU	ARM Cortex-M4F	ARM1176JZF-S	Dual-core ARM Cortex-A7	x86 Quark SE	ARM Cortex-M4	8-bit AVR
Clock Speed	64 MHz	1 GHz (single core)	500 MHz	32 MHz	64 MHz	16 MHz
Flash Memory	1MB	-	4-8 MB	384KB	1MB	32KB
RAM	256KB	512MB	8-9 MB	80KB	256KB	2KB

Connectivity	Bluetooth Low Energy (BLE)	Wi-Fi and Bluetooth	Wi-Fi and Ethernet	Bluetooth and Wi-Fi	Bluetooth 5, Zigbee, and Thread	Limited to GPIO pins.
Sensors	Various built-in sensors	Non-built-in	Supports external sensors	Includes motion sensors	Supports external sensors	Supports external sensors
User Friendly	User-friendly	User-friendly	User-friendly	User-friendly	Technical expertise required	User-friendly
Cost (£)	20-25	10-12	15-25	8-12	12-15	5

3.3 Related Works

Edge computing in the IoT is a growing field that is relatively new in the healthcare industry. It lacks established standards and focused research, which results in potential gaps in areas like healthcare solutions based on WBAN. Existing studies have predominantly focused on cloud scenarios due to the historical prevalence of cloud-based systems in data management. This emphasis on cloud computing has led to shortcomings in resource management within edge computing. However, this presents an opportunity for innovation and the development of new standards that cater specifically to the needs of healthcare. By adopting WBAN, these standards can enhance data processing from wearable devices by carrying out computations closer to the data source, reducing latency, and optimising resources. As a result, most of the current solutions utilising edge computing are about IoTs. Despite the lack of established standards, further research in edge computing promises to advance healthcare technology solutions.

The swift progress in information technology allows an increasing number of people to store various data through mobile devices online. This has revolutionised our lifestyle and work by merging physical reality with digital space. However, the data explosion challenges traditional architectures' handling power. Temporarily, cloud computing, rich in computing and storage resources, helps manage this issue. Nevertheless, uploading data to remote clouds from mobile devices leads to significant user delays. This latency situation can even be life-threatening in certain contexts, like heart failure patients. Fortunately, using edge data processing close to mobile devices effectively addresses these problems. Edge devices can directly interact with the nearest edge node, substantially reducing data latency when uploading or requesting data. Edge computing faces issues like potential data breaches, inefficient resource allocation leading to task failures, and vulnerability to attacks due to limited computing and caching capabilities.

The growth of the Internet of Things (IoT) and the success of cloud services have expanded the boundaries into a novel computing model known as edge computing, which envisages processing data closer to its source [157]. Edge computing's main principle involves transferring part or all of the computing work typically handled by centralised cloud computing hubs to the periphery, near where the data originates. This approach gives edge computing immense potential to address limitations associated with the cloud [158].

The study outlined in [159] introduces a new strategy for using edge nodes to assist in data transmission within a cloud-centric IoT structure as a means to tackle the challenge of excessive bandwidth utilisation in the cloud. It highlights the utility of edge nodes' bandwidth resources by expanding the existing framework of edge computing within a cloud-focused IoT design. Research in [160] examines the issue of computation offloading for multiple users in mobile-edge cloud computing within a multi-channel wireless interference context. A distributed computation offloading algorithm is designed in this study, which demonstrates remarkable performance in computation offloading capacity and scalability as the number of users increases. The paper [161], delves into the synchronised allocation of communication and computational resources to reduce the aggregate weighted-sum delay of all devices within a cloud-edge collaborative system.

A prototype platform was developed to run a facial recognition application, as outlined in [162]. With this platform, executing operations moved from the cloud to the edge, subsequently reducing response time significantly from 900 ms to 169 ms. Additionally, [163] employed cloudlets to delegate computing tasks for wearable cognitive assistance applications. This technique exhibited substantial enhancements in response time, ranging from 80 ms to 200 ms. Importantly, the energy consumption was decreased by 30%–40% via cloudlet offloading. CloneCloud, mentioned in reference [164], incorporated methods like partitioning, migration, merging, and on-demand instantiation of partitioning between mobile and cloud computing. The demonstrated prototype led to a 20-fold improvement in runtime and energy efficiency for the tested applications.

Porambage et al. [165] provide a thorough analysis of edge computing architecture and the benefits of computation offloading. Ning et al. [166] proposed a system that uses multi-access edge computing for in-home health monitoring. In this system, they modelled the task offloading challenge as a weighted potential game, taking into account the computational costs of each user in the WBAN. In this model, a balance (or Nash equilibrium) among WBAN users is reached in a decentralised manner. Similarly, Yuan et al. [167] put forth a task offloading method that aims to minimise delay and energy consumption in edge-enabled WBAN systems. They framed this challenge as a two-stage optimisation problem: initially, WBAN users determine their offloading choices based on their benefits and penalties. Roy et al. (168) proposed a task-offloading approach within healthcare systems facilitated by cloud and edge computing. They modelled the challenge as a bargaining problem. In this scenario, users from the WBAN negotiate with one another to determine whether tasks should be offloaded to the cloud or a fog server. Addressing resource allocation for computation offloading within edge computing, Merluzzi et al. (169) suggested a stochastic algorithm. The purpose of this algorithm is to dynamically assign computation resources based on the system's needs. Safar et al. (170), on the other hand, offered a distinctive framework. This framework accommodates users within the WBAN who wish to offload their computational tasks to nearby mobile users with higher computational capacities. The primary objective behind this arrangement is to minimise the network's total energy consumption.

Wan et al. [172] suggested a model of energy-conscious load balancing and scheduling through the use of a swarm optimisation algorithm, thereby improving balancing efficiency. In a separate study, Isa et al. [171] introduced a fog-based architecture for healthcare monitoring, addressing the system's energy efficiency problem using mixed integer linear programming. From a network operator's perspective, Yosuf et al. [173] understood the problem of energy efficiency within IoT architecture as a mixed integer linear programming problem, proposing a heuristic algorithm as a solution.

Merluzzi et al. [174] investigated the problem of energy management in mobile edge computing, viewing it as a stochastic optimisation problem. They considered both the energy usage of end-users and MEC servers. They came up with the innovative concept of a low-power sleep mode for mobile edge computing servers to reduce excessive energy consumption. At the same time, Sharma et al. [176] proposed strategies to conserve power and promote environmentally friendly computing. These authors suggested using a combination of virtualization and recycling techniques to decrease energy usage in computing facilities. Similarly, Ranadheera et al. [175] focused on optimising the energy usage of mobile edge computing servers while satisfying users' Quality of Experience (QoE) requirements. To achieve this dual objective, they proposed a minority game-based algorithm for efficient server activation management.

Xiao and Krunz [177] tackled the intricate balance between power efficiency and users' QoE satisfaction within a fog and edge environment. They put forward a framework that leverages the symbiotic relationships between different fog nodes. Furthermore, they crafted a distributed optimisation framework and, under this umbrella, proposed two robust distributed algorithms [178]. From another perspective, Apostolopoulos et al. [179] scrutinised the risky behaviours exhibited by mobile users when offloading computations, all within a multi-mobile edge computing server environment. Their approach was grounded in a non-cooperative game-theoretic analysis. The challenge of data offloading in a multi-mobile edge computing server scenario, encompassing scheduling and multi-mobile edge computing server selection, is tackled through a coalition game [180].

The presented discussion emphasises the importance of edge computing in addressing latency and energy-saving issues associated with traditional architectures like cloud computing. Edge devices allow for direct interaction with the nearest edge node, thereby reducing data delay. The research covers various aspects, including resourcefulness of bandwidth, offloading of computation, and reduction of response time. In particular, studies have shown the benefits of using edge devices in healthcare monitoring. Facial recognition software prototypes, for example, demonstrated a significant reduction in response time through the use of edge computing. Moreover, further research highlights the potential for energy management and improved computational efficiency, as seen in discussions on sleep modes and minority game-based algorithms for server management. Various tasks and strategies for offloading energy, such as bargaining and weighted potential game analyses, have been proposed to optimise network resource allocation and energy consumption.

Ultimately, the literature demonstrates the potential of edge devices for task optimisation within the WBAN architecture. Focusing on an anomaly detection experiment using edge devices in the WBAN architecture can enhance network performance, reduce latency, and improve energy efficiency. With the growing need for real-time responses in fields like healthcare monitoring, the reduced latency benefit is crucial. Additionally, efficiently managing resources by determining the correct techniques for task offloading can lead to improved overall network performance and energy savings. Therefore, experimentation with anomaly detection at the edge local nodes of a WBAN can be instrumental in anticipating potential issues and ensuring system reliability and performance. Based on the comprehensive examination and research outlined above, the hybrid healthcare architecture that integrates WBAN, edge, and cloud technologies, as proposed in source [159], is considered throughout the experiment.

3.4 Performance Analysis Techniques

In assessing the effectiveness of decision-making, the most frequently used metrics include the probability of detection (Pd), measurable via the Likelihood ratio, and the probability of false alarm (Pfa). For this research, the principles of sensitivity, specificity, and receiver operating characteristics (ROC) [185] are employed, as they represent the best methods available.

The key terms often used to assess a clinical test are referred to as sensitivity and specificity [185]. Commonly considered for a clinical test are positive and negative predictive values, which rely on the existence of the disease being studied. Generally, sensitivity and specificity are quantitative tests that hinge on a cut-off value that surpasses or falls short of a given limit. As a rule, they are generally inversely related; as sensitivity increases, specificity typically decreases, and vice versa. The potential results of a clinical test are depicted in Table 3.2 [185]. Understanding the following key terms is crucial for measuring the performance of clinical tests:

Table 3. 2: Truth table for a clinical test

Status	Disease present	Disease absent
Test positive	True positives	False positives
Test negative	False negative	True negatives

True positive (TP): The patient has the disease, and the test result is positive.

False positive (FP): The patient does not have the disease, but the test result is positive.

True negative (TN): The patient does not have the disease, and the test result is negative.

False negative (FN): The patient has the disease, but the test result is negative.

Sensitivity: This is also called Recall and in more common terms, sensitivity refers to a clinical test's ability to accurately identify a patient who has a particular disease. A test with 100% sensitivity implies that it can accurately diagnose the disease in every patient who has it. However, a test with a 75% sensitivity can only correctly identify the disease in 75% of the patients who have it. It misses or fails to detect the disease in the remaining 25% of the cases, leading to false-negative results. To ensure a dependable diagnosis, it's preferable for a clinical test to have a high sensitivity percentage. In probability notation:

$$P_{sn}(T^+|D^+) = TP/(TP + FN)$$

where P_{sn} , T^+, D^+, TP and FN refer Probability of the sensitivity, Test positive, Disease positive, True positive and False negative respectively.

Specificity: Specificity is a concept used in clinical testing, indicating the ability of a test to accurately identify individuals who don't have the disease. A test boasting a 100% specificity would correctly identify all disease-free individuals. In the case of a test with 75% specificity, it indicates that the test correctly identifies 75% of disease-free cases (true negatives), but wrongly flags 25% of healthy individuals as having the disease (false positives). In probability notation:

$$P_{sp}(T^-|D^-) = TN/(TN + FP)$$

where P_{sp} , T^-, D^-, TN and FP Probability of the specificity, Test negative, Disease negative, True negative and False positive respectively.

The concepts of sensitivity and specificity are used to evaluate how effectively a clinical test can differentiate between patients who have a certain disease and those who don't. In the context of a specific test, the likelihood of the disease being present is termed as, the test's predictive value. The term Positive predictive value (PPV) also called Precision, in terms of probability, refers to the likelihood that a person has the disease given a positive test result. In probability notation:

$$T^{+}|D^{+}) = TP/(TP + FP)$$

For Negative predictive value (NPV) in probability notation:

$$T^{-}|D^{-} = TN/(TN + FN)$$

The **F1 Score** is the harmonic mean of precision and recall, providing a balance between the two metrics. It is particularly useful when the distribution of the classes is imbalanced. In mathematical notation

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Or

$$F1 = \frac{2TP}{2TP + FP + FN}$$

Accuracy in the context of classification is defined as the proportion of true results (both true positives and true negatives) among the total number of cases examined.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

A key term associated with diagnostic testing is the Likelihood ratio. This term establishes the comparison between the chances of a patient testing positive having the disease versus those who tested negative.

$$Likelihood\ ratio = Sensitivity/1 - Specificity$$

The Receiver Operating Characteristic (ROC) curves, as depicted in Figure 3.2, communicate the proportion of (1-specificity) of a test on the horizontal axis, compared to its sensitivity on the vertical axis, for all potential measurements.

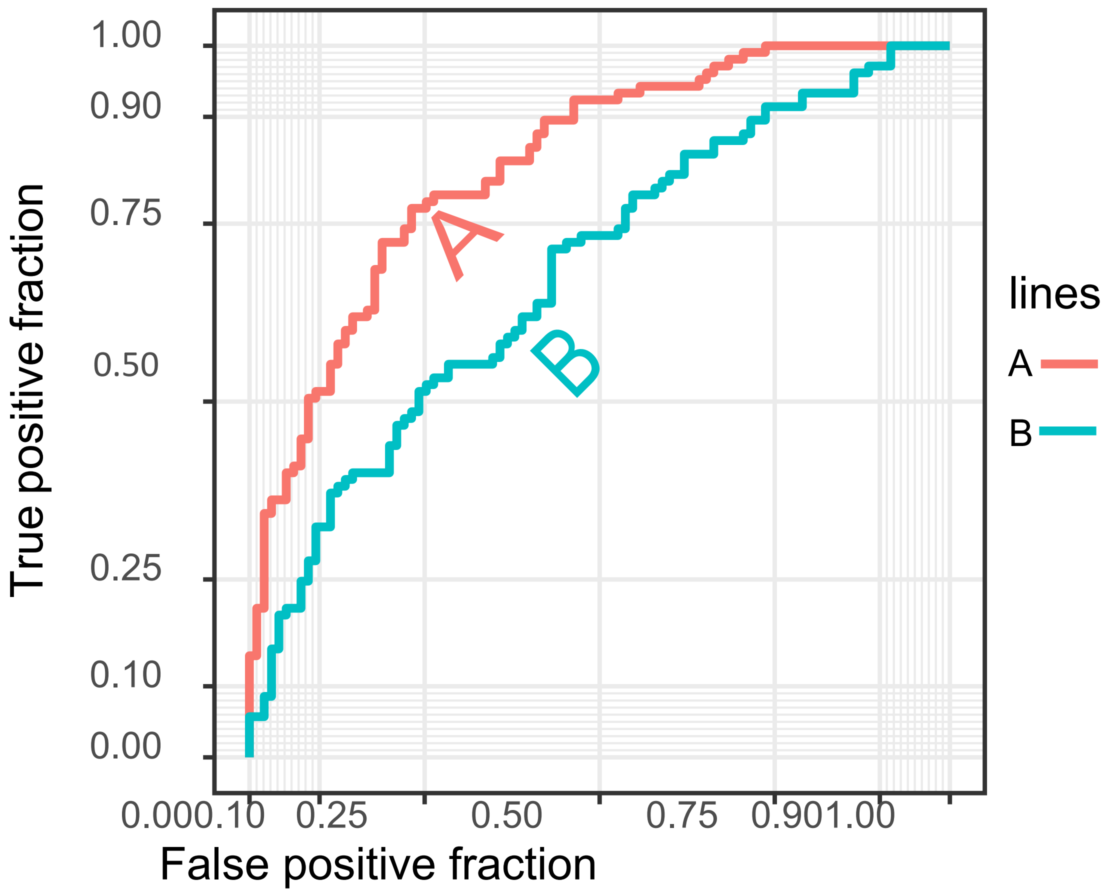


Figure 3. 2: Receiver operator curves (example)

Figure 3.2 depicts a standard ROC curve, which is a graph where the y-axis represents the True positive rate (TPR) of a test and the x-axis shows the False positive rate (FPR). Curve A represents the ideal test scenario, while Curve B signifies the usual outcome in clinical settings. The accuracy of the test is indicated by the Area under the curve (AUC). The ROC curve is an effective mechanism for assessing performance in classification and distribution tasks. Essentially, it's a chart that provides a probabilistic representation, and the AUC demonstrates the model's ability to differentiate between different categories. For any given dataset, the model's power to discern between classes can be articulated using the AUC. A higher AUC score indicates that the model is more successful at correctly identifying positive and negative cases. In a medical setting, an AUC of 1 would mean that the ROC could flawlessly predict whether a patient has a disease or not. A prime example of this is displayed in Figure 3.3, where the model adeptly distinguishes between TP and TN. The ROC curve plots the false positive rate FPR on the x-axis against the true positive rate TPR on the y-axis.

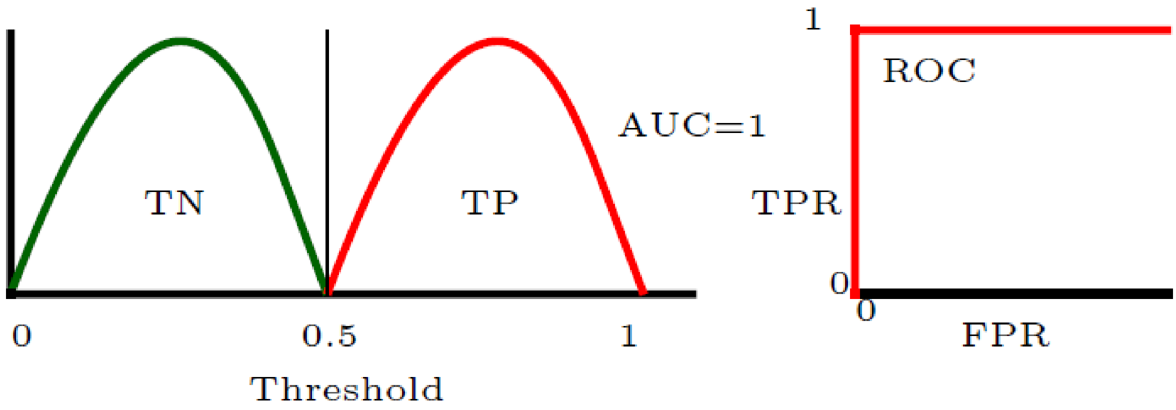


Figure 3. 3: AUC is 1, Perfect scenario; AUC = Area under curve; TPR =True Positive Rate; FPR =False Positive Rate.

Figure 3.4 reveals an AUC score of 0.7, which indicates a 70% probability of accurately predicting both true negatives and true positives. However, the model also introduces two types of errors: false negatives and false positives.

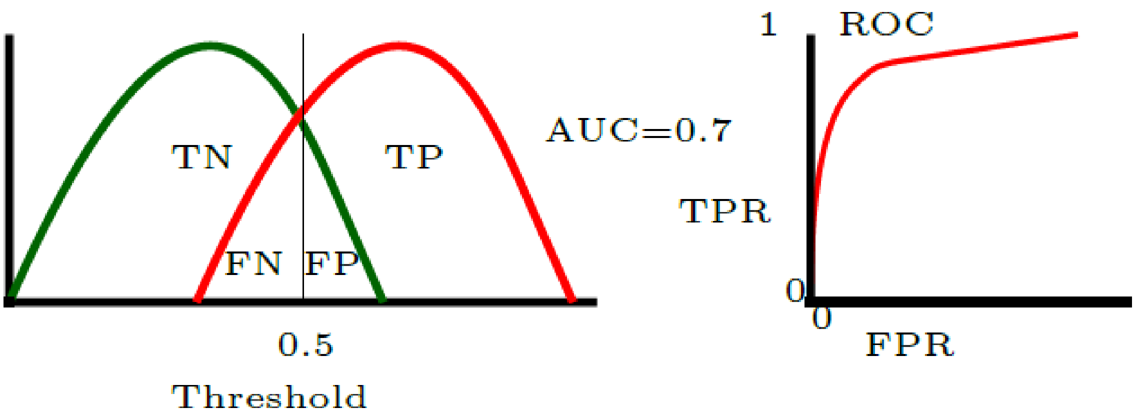


Figure 3. 4: AUC is 0.7, 70% chance the model distinguishes between positive class and negative class.

The illustration referred to as Figure 3.5 displays an AUC of 0.5, indicating an inability to differentiate between the positive and negative classes. Essentially, an AUC of 0.5 implies that the test doesn't exhibit any discerning capability, meaning it can't effectively distinguish between patients who have the disease or condition compared to those who don't.

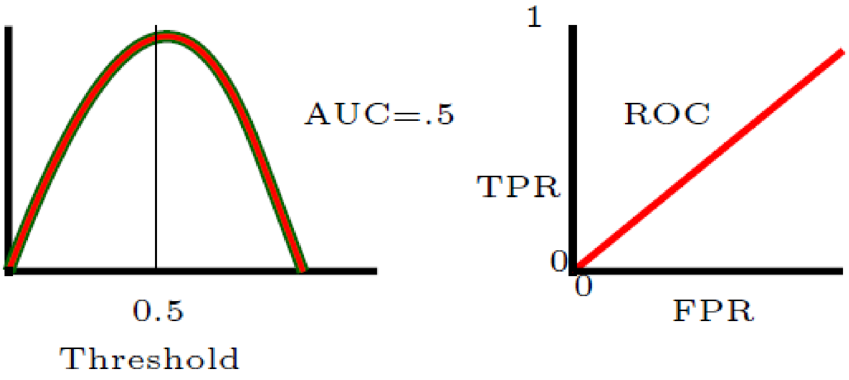


Figure 3. 5: AUC is 0.5, This is the worst situation, the model has no discrimination capacity.

When the AUC is nearly zero, it means the model is incorrectly classifying positive instances as negative and vice versa. In Figure 3.6, the instances that are correctly predicted as negative (true negatives) and those correctly predicted as positive (true positives) are incorrectly labelled as their opposites, i.e., true negatives are labelled as true positives and true positives are labelled as true negatives.

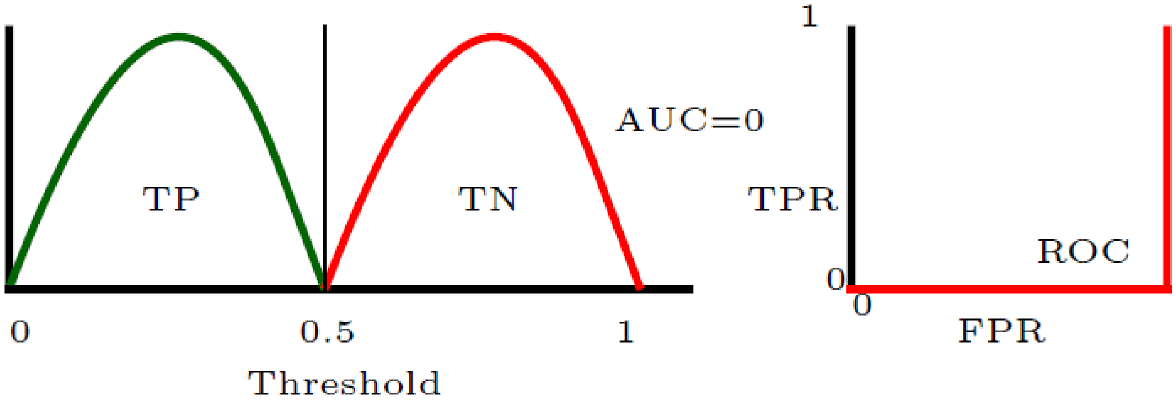


Figure 3. 6: AUC is 0, The model is predicting the opposite.

In a nutshell, an ROC curve illustrates the balance between the true positive rate (sensitivity) and the false positive rate (specificity), resulting in a curve. Typically, the more the curve skews towards the top-left corner, the better the test results. If the curve nears the ROC space's 45-degree diagonal, the test's accuracy declines.

3.5 System Model

Consider a standard WBAN, wherein numerous biosensors are positioned or implanted within the human body. Similar to typical sensors, these biosensors possess three fundamental capabilities: i) sensing, ii) processing, and iii) communication. Following the sensing phase, the biosensors transmit the gathered data to the coordinator, situated in proximity to or on the body. The coordinator then conducts processing based on algorithms implemented for the sink node. Subsequently, the sink node forwards the processed data to the destination.

A system model has been developed based on WBAN technology, with the primary objective of enhancing reliability throughout the clinical decision-making process. The fundamental block diagram outlining the inputs and outputs of the healthcare system is depicted in Figure 3.7. The system model comprises two primary blocks: decision-making and clinical prediction.

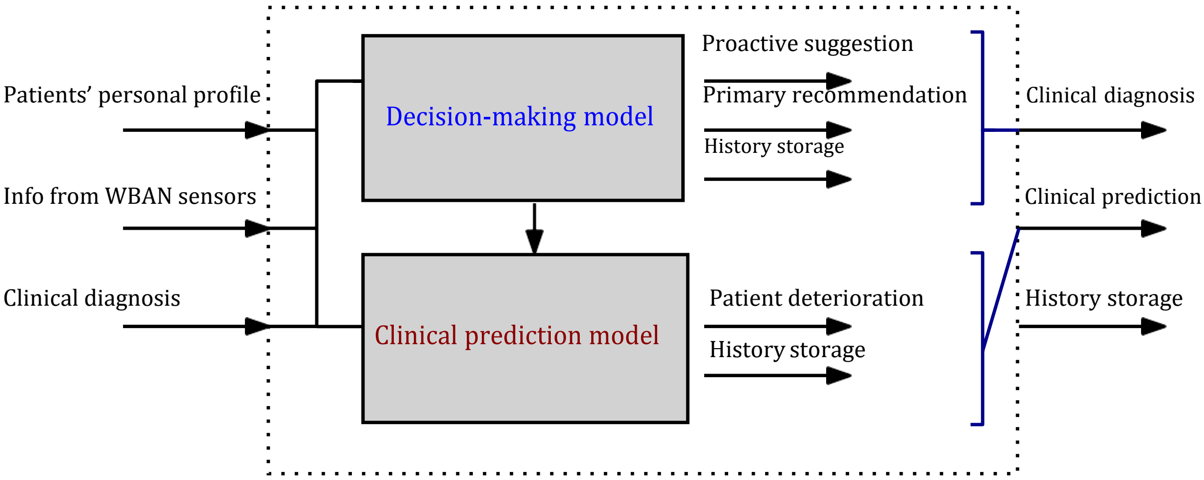


Figure 3. 7: Input and output for the proposed healthcare system.

Within this system model, three inputs are taken into consideration. Firstly, sensor data is anticipated to yield various types of physiological outputs. This physiological data, derived wirelessly from the patient's sensor, constitutes the initial input. The second input is derived from the patient's personal profile, encompassing their historical medical information and physical attributes such as weight, height, and age. To augment the reliability of clinical prediction, a third-input clinical diagnosis is incorporated. The first block of the decision-making model yields three principal outputs: proactive suggestion, primary recommendation, and history storage. Simultaneously, the second block of the clinical prediction model generates two initial outputs: patient deterioration or improvement and history storage. In terms of the overall system model, three primary outputs are established, encompassing clinical diagnosis, clinical prediction, and history storage for subsequent reference.

This system is designed to operate independently, deriving clinical decisions from the provided inputs (see Figure 3.7) and producing anticipated outputs. Leveraging physiological sensor data and the patient's historical clinical information, the system is poised to assess the severity of the patient's clinical condition, categorising it as either emergency, semi-emergency, or non-emergency. In instances classified as non-emergency, the system issues alert to prompt the patient to undertake preventive measures, such as medication or dietary adjustments. Conversely, for emergencies, the system recommends that the patient seek healthcare services, specifying options such as contacting a general practitioner (GP), visiting a walk-in centre, or seeking emergency medical attention. Additional attributes are slated to be incorporated into the system in subsequent phases of experimentation, to enhance overall system performance.

Figure 3.8 illustrates the detailed system model of the proposed WBAN for healthcare. This system is designed to generate dependable clinical decisions and clinical predictions within a resource-constrained environment. It is assumed to be a secure system, safeguarded against both external and internal security breaches.

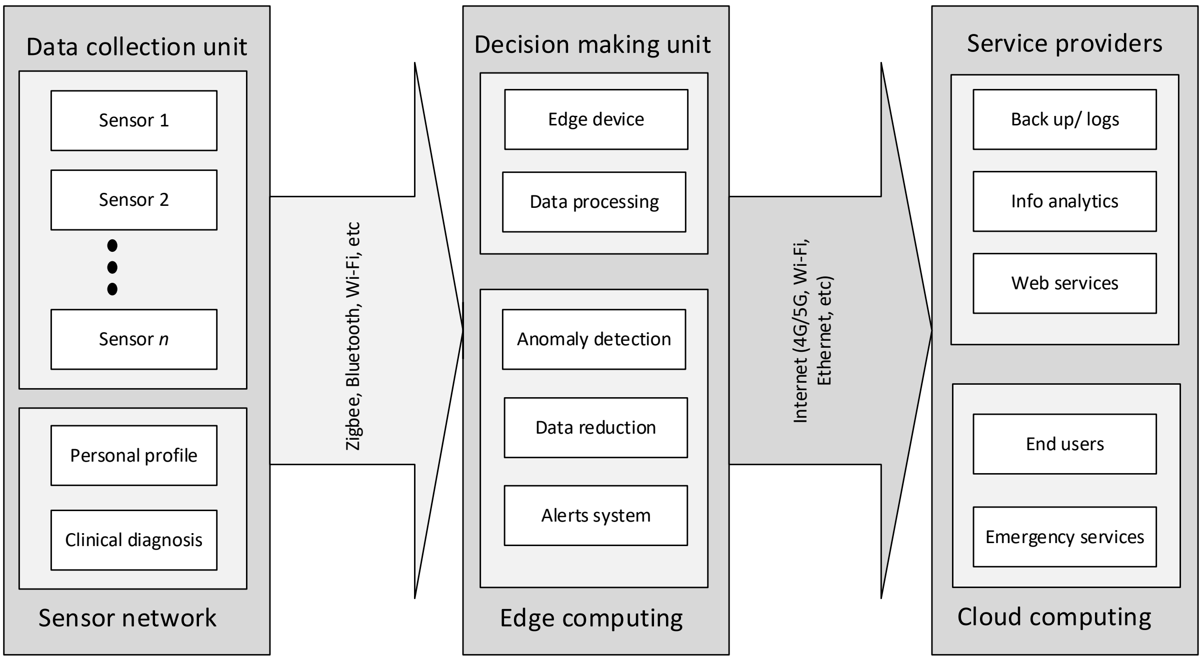


Figure 3. 8: Block diagram of the proposed healthcare framework

The system comprises three distinct components: the data collection unit, the decision-making unit, and the service provider unit. The first unit incorporates physiological sensors responsible for gathering data from a patient's body. Additionally, this unit includes the patient's profile, encompassing medical history. Primarily, it constitutes the body area network connected to an appropriate edge device through low-power technologies like Zigbee, Bluetooth, etc.

The subsequent unit is tasked with knowledge discovery from data to formulate a reliable clinical decision. It considers the data forwarded from the first unit, along with the patient's medical history. This unit comprises an edge device equipped with a mini-storage and the computational ability to process data and make decisions locally. Furthermore, this unit is capable of anomaly detection from vital signs obtained from physiological sensors and medical history, generating alerts for relevant stakeholders. Additionally, by utilising data reduction techniques, this unit minimises the amount of data to be transferred to the cloud. Internet technologies such as 4G, 5G, or Wi-Fi are employed to connect this unit to the next unit.

The concluding segment of the block diagram is the service provider unit on the cloud platform. This unit plays a crucial role in storing and backing up system data. It serves as a web-based service for end-users, including patient carers, physicians, and emergency services. It also serves as a valuable resource for healthcare researchers to conduct their studies. Additionally, physicians can leverage this opportunity to improve their clinical decisions.

Assuming S represents sensors connected to the WBAN, this is expressed as follows:

$$S = [S_i | i = 1,2,3, \dots, n]$$

In this context, each element S_i represents a specific type of sensor, such as pulse, blood pressure, respiration rate, heart rate, temperature, etc., where n denotes the total number of sensors within the WBAN. Every sensor S_i furnishes sensed data with measurements conducted at preset sampling intervals.

It is assumed that each sensor operates in an awake state, adhering to a duty cycle denoted by α in the range [0, 1] for a designated time t_p. Consequently, each node is active during the time interval $\alpha t_p$and inactive during the interval $(1-\alpha)t_p$.

During the awake state of the sensors, let f_s define the sampling frequency, which is assumed to be the same for all sensors within the WBAN. The number of samples acquired during the awake state of each sensor is denoted by k as follows:

$$k = \alpha t_p f_s$$

Hence, the data acquired by any sensor S_i during its awake state can be articulated as:

$$d_i = [d_{ij} | j = 1,2,3, \dots , k]$$

The data obtained from n sensors during one complete awake state can be represented by a matrix D of size $n \times k$.

$$D = \begin{bmatrix} d_{1,1} & d_{1,2} & \dots & d_{1,k} \\ d_{2,1} & d_{2,2} & \dots & d_{2,k} \\ \vdots & \vdots & & \vdots \\ d_{n,1} & d_{n,2} & & d_{n,k} \end{bmatrix}$$

In this WBAN, sensors are expected to operate within the normal range of vital signs, which can be defined by the lower limit γ_i^l and the upper limit γ_i^u. The well-being range of vital signs can vary due to demographic differences, and this range may also vary based on professions. These measurements may have different tolerance levels depending on the type of sensor and the sensitivity of the acquired data. Let δ_i denote the tolerance level for the $i^t h$ sensor node. For instance, for temperature measurements, the lower threshold γ^l and upper threshold γ^u are 37°C and 40°C, respectively, and the tolerance level δ_i may be considered as ±3°C.

In the data pre-processing phase, measurements that fall outside the normal sensing range are categorised as emergency data measurements i.e.

$$d_{i,j} > \gamma_i^l \ - \delta \ \ or \ d_{i,j} > \gamma_i^u \ + \delta$$

Consequently, emergency services will be notified, and simultaneously, a notification will be sent to a support engineer responsible for the WBAN architecture to inspect the system as a precaution. Like a conventional WBAN, each sensor node gathers data and transmits it to the coordinator periodically. Consequently, a substantial volume of data is collected and sent to the coordinator for the decision-making process. In addition to this periodic process, a concurrent, event-driven process is also necessary in a state of emergency. In the event of an emergency, an event-driven approach is prioritised over a periodic approach [31, 152].

Measurements falling within the normal and anticipated sensing range are classified as true data and are subject to processing in the decision-making unit (Figure 3.8). The decision-making strategy can be characterised by intra-sensor (within the same type of sensor) and inter-sensor (group of sensors) criteria. The intra-sensor criteria for decision-making by the i^th sensor node is expressed as:

$$C_{ij} = \begin{cases} 0 & \gamma_i^l \leq d_{ij} \leq \gamma_i^u \\ 1 & otherwise \end{cases}$$

Here, $C_{ij} = 0$ and $C_{ij} = 1$ indicate the likelihood of the j^th sample acquired from the ith sensor representing true and incorrect data, respectively.

In the event of a significant change in measurements, action is initiated when:

$$C_{ij} = \begin{cases} Emergency & \sum_{j=1}^{k} C_{ij} > \delta_1 \\ Log & otherwise \end{cases}$$

Here, δ_1 signifies the threshold for triggering alerts to emergency services.

In cases where the measurements do not explicitly indicate an emergency based on their values but still necessitate attention, they can be defined as:

$$C_{ij} = \begin{cases} Contact\ GP & \sum_{j=1}^{k} \hat{C}_{ij} > \delta_2 \\ Log & otherwise \end{cases}$$

Measurements may only necessitate preventive action by the patient themselves, as defined by:

$$C_{ij} = \begin{cases} Prevention & \sum_{j=1}^{k} \hat{C}_{ij} > \delta_3 \\ Log & otherwise \end{cases}$$

In the suggested WBAN framework, each sensor node is capable of providing readings that fall within an acceptable limit. For adults, there's a certain threshold or acceptable range for specific vital signs, although these ranges differ for children and toddlers. The acceptable range may also fluctuate based on demographic or geographic differences. Appendix A.3 provides a table of acceptable thresholds for an adult, indicating that vital signs are significantly interconnected. Even if all the vital signs fall within an acceptable range, a critical situation could still arise. Such scenarios could be mitigated by harnessing the power of cooperative interaction among WBAN sensors. This would involve implementing an inter-sensor decision-making approach that takes into account the correlation among the relevant vital signs. It's anticipated that this strategy would involve input from all different sensors to boost the effectiveness of the decision-making process.

The WBAN consistently produces both emergency and non-emergency data derived from physiological signs. As detailed in Figure 3.9, sensor data falls into two core categories: abnormal or emergency data and normal data. Emergency data, which could be caused by either a change in patient physiology or system failure, is prioritised for analysis, leading to a clinical decision. On the contrary, non-emergency data undergoes local compression and storage in the cloud. Various compression techniques [181–183] are available, and the proposed system is likely to adopt one or a blend of these methods. With data integrity being paramount, any compression method employed must avoid compromising the original information.

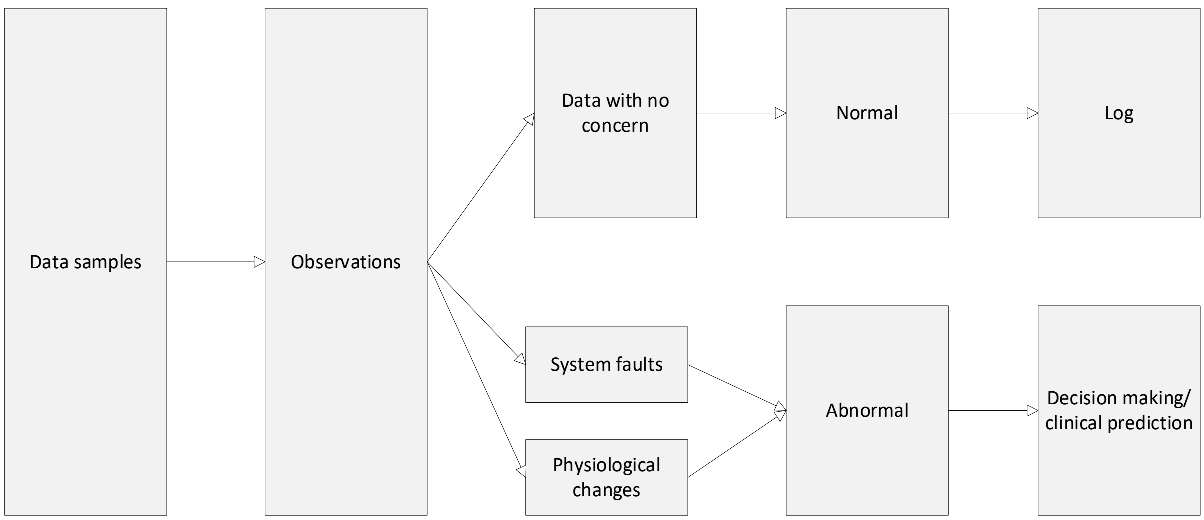


Figure 3. 9: Flow diagram of information

Patient history is extremely important information that should be available to the appropriate parties. Hence, the need arises for a platform that can provide secure and mobile access to this data. Secure cloud storage can effectively meet this need. A variety of techniques and services have been outlined in [184] about cloud services. The proposed system is anticipated to utilise one of these solutions for secure data storage and access.

3.5.1 Data Collection

In a WBAN, data collection begins when the miniature, usually micro-battery-powered, sensors are activated. These sensors, each tailored to monitor specific physiological parameters such as heart rate or body temperature, detect the relevant signals. The data is either gathered continuously or at periodic intervals according to the predetermined requirements. The detected analogue health signals are then converted into digital format by an analogue-to-digital converter (ADC) within the sensor. Once digitised, the health data is temporarily stored in the sensor's integrated storage unit before being transmitted to the central processing unit (CPU). The sensors also implement energy-saving strategies to manage the limited energy supplied by their micro-batteries, with techniques such as duty cycling, where sensors go into sleep mode when not active.

Traditional WBAN systems predominantly forward most data to the cloud, rather than processing the low-level data or performing substantial computations on a local server or mobile device. In the proposed framework, the local server, which can be either a mobile device or an edge device, has a role that goes beyond simply collecting basic data from the WBAN system, such as physiological indicators like blood pressure, heart rate, and respiratory rate. It is also responsible for performing computational tasks before sending all the data to the cloud.

To certify a learning model that relies on extensive data, it's crucial to use data closely resembling real-world data. However, the available real data that could be utilised is limited and often does not encompass a range of physiological indicators. For instance, databases such as those by Faini [186] and Parati [187] possess data, but they are restricted to only two vital signs: BP and heart rate HR. Hence, the dataset from the Physionet MIMIC-II database [188] is utilised as it encompasses a vast range of examples of various vital signs.

This dataset was chosen due to its suitability for evaluating our implementations. It is exceptional because no publicly available dataset provides multiple vital sign measurements from diverse home-monitoring patients, demonstrating different correlations over a long period of time. It is important to note that home-monitoring data shows similar patterns when collected in controlled conditions and under the supervision of a nurse. The MIMIC Database is composed of patients who were admitted to the hospital for various clinical emergencies. The data collected from bedside monitors is divided into several files, each containing 10 minutes of recorded signals. These files are later combined seamlessly to create a continuous recording. The experimental records, which consist of 60-minute segments of information, are used to validate the system.

For the experiment, from MIMIC-II, 100 patient records have been utilised for evaluations. The patients who participated in this study present with a broad range of clinical issues, such as sepsis, respiratory failure, congestive heart failure, pulmonary oedema, myocardial infarction, cardiogenic shock, and acute hypotension. The majority of these clinical instances arise because of simultaneous abnormalities in multiple vital signs.

3.5.2 Data Preprocessing

Similar to other real-world databases, it's necessary to perform several preprocessing steps to enhance the quality of the data prior to deriving the features. This process is crucial when dealing with real-world data. Even in the context of a monitored patient at home, the data may be contaminated with noise and contain outliers. This can result from a variety of circumstances, such as sensor malfunctions, disconnections, changes in equipment, and interruptions in network connections, among others. In the circumstance where all vital sign data is missing for an extended duration, these gaps are deemed to be non-recoverable due to network disruptions or sensor malfunctions, leading to data deletion. However, in situations where one or more vital sign values are missing but other clean values are provided, the data is deemed recoverable and filled by employing methods such as median-pass [189] and k-nearest neighbour [190] filters. In actual patient databases, a median-pass filter can be used to replace each raw record with a median value calculated from nearby records, effectively dealing with observational error data. Furthermore, the k-nearest neighbours algorithm proves to be a valuable technique in tasks like data imputation, where it's used to fill in missing entries in a patient record by evaluating the 'K' most similar records.

Table 3.3 displays the physiological data in the database columns.

Table 3. 3: Data in columns

SL #	SYSTOLICBP	SpO2	HR	PULSE	RESP	TEMP
1	151	97	133	132	32	36.8
2	153	97	133	132	32	36.7
3	154	97	133	132	32	36.6
4	152	97	133	132	29	36.9

The initial column in the figure signifies time (in seconds), while the subsequent columns symbolise blood pressure, oxygen saturation, heart rate, pulse, respiration rate, and temperature, in that order.

3.5.3 System Model Validation

3.5.3.1 Threshold-Based Approach

The introduced system begins its validation process by using a rule-based threshold algorithm. This strategy is based on the fundamental principle that every important vital sign has a specific range of minimum and maximum thresholds. An example of this is the breathing rate shown in Figure 3.10, using NEWS [191] as a benchmark. One advantage of this system is its versatility, as it allows doctors to set personalised threshold ranges to evaluate a patient's health status. If the system detects data that falls outside of these predetermined ranges, it immediately triggers an alarm. The threshold algorithm is both simple and efficient, quickly alerting to significant changes in physiological signs. Since the system's main function is to classify data as either "normal" or "emergency," even the smallest deviations in vital signs are carefully recorded. Although this can lead to a relatively high rate of alarms, there are situations where such algorithms are crucial, especially when changes in vital signs can have a significant impact on decision-making.

PHYSIOLOGICAL PARAMETERS	3	2	1	0	1	2	3
Respiration Rate	≤8		9 - 11	12 - 20		21 - 24	≥25
Oxygen Saturations	≤91	92 - 93	94 - 95	≥96			
Any Supplemental Oxygen		Yes		No			
Temperature	≤35.0		35.1 - 36.0	36.1 - 38.0	38.1 - 39.0	≥39.1	
Systolic BP	≤90	91 - 100	101 - 110	111 - 219			≥220
Heart Rate	≤40		41 - 50	51 - 90	91 - 110	111 - 130	≥131
Consciousness Level				A			V, P, or U

Figure 3. 10: National Early Warning Scoring System [191]

However, doctors also follow existing medical theories and evidence that show how certain vital health metrics are interconnected and often change together in response to specific body conditions. This understanding allows physicians to identify which vital signs should be continuously monitored, and importantly, simultaneous shifts in these selective vital signs could be seen as indicators of deterioration. To manage these situations, two distinct threshold algorithms are proposed. The first Algorithm 1. A is called "Threshold" and alerts medical staff when any of the vital signs exceed the set tolerance range. On the other hand, "Algorithm 1. B" is called 'Threshold (adopted)' aims to reduce false alarms by focusing only on specific vital signs instead of all six, enabling physicians to adjust monitoring based on their clinical judgement or the patient's current condition. The choice between the algorithms primarily depends on the patient's condition and the overall clinical context.

Algorithm 1. A illustrates an algorithm capable of classifying sensor data as either normal or emergency, utilising the tolerance range of vital signs.

Algorithm 1.A. Emergency detection using threshold (Threshold)

Input: A set of patient vital sign data
Output: A classification result indicating a status
Procedure: Classifier ()
begin
Threshold (value, lower_threshold, upper_threshold):
  return value < lower_threshold OR value > upper_threshold
Classify(sensor_data):
  emergency_vital_signs = empty_list()
  for i in range(1, num_vital_signs + 1):
    value = sensor_data[i]

```
      lower_threshold = SetLowerLimit(i)
      upper_threshold = SetUpperLimit(i)
      if Threshold(value, lower_threshold, upper_threshold):
         append_to_list(emergency_vital_signs, i)
      end if
   end for
   if length(emergency_vital_signs) > 0:
      return {"status": "Emergency", "vital_signs": emergency_vital_signs}
   else:
      return {"status": "Normal", "vital_signs": empty_list()}
   end if
Monitor(reading_values):
   sensor_data = reading_values
   result = Classify(sensor_data)
   if result["status"] == "Emergency":
      vital_sign_names = EmergencyVitalSign(result["vital_signs"])
   end if
getLower(vital_sign_number):
   lower_thresholds = SetLowerLimit()
   return lower_thresholds[vital_sign_number]
getUpper(vital_sign_number):
   upper_thresholds = SetUpperLimit()
   return upper_thresholds[vital_sign_number]
EmergencyVitalSign(vital_sign_numbers):
   vital_sign_mapping = getVitalSignMapping()
   vital_sign_names = [vital_sign_mapping[number] for number in vital_sign_numbers]
   return vital_sign_names
end
```

This algorithm represents a vital sign monitoring system that classifies a patient's condition as either "normal" or "emergency" based on readings from different sensors. Here is how it operates: Firstly, it sets the lower and upper thresholds for each vital sign. If a reading from any sensor falls outside of a pre-established normal range (either below the lower or above the upper threshold), that reading is considered a cause for concern. The system iteratively goes through each sensor's data. For each vital sign, it checks whether the sensor's value surpasses the thresholds. If the value does exceed, it adds the vital signs to a list of emergency signs. Once the system has gone through all the sensor data, it checks if there are any signs marked as 'emergency'. If there are, it changes the patient's status to "Emergency" and returns this status along with the specific vital signs causing the alarm. If no sign surpasses the thresholds, it indicates that the patient's status is "normal." Additionally, the system has a mechanism to translate these sensor readings (identified by numbers) into their corresponding names. This is done through a function that maps the vital sign numbers to their names. This feature is mostly used when an emergency is identified and the system needs to specify which vital signs have exceeded their thresholds. Two more helper functions determine the lower and upper thresholds for a particular vital sign. These thresholds are predefined within their corresponding functions. In essence, this monitoring system ensures that the patient's health status is continually monitored. If any alarming changes are detected, it promptly classifies the status as an emergency and identifies the problematic vital signs.

An illustration of patient data for this algorithm includes the following vital signs: heart rate 133, blood pressure 151, respiratory rate 32, temperature 36.8, oxygen saturation 97, and pulse 132.

Example: R Code with this patient data

```
# Function to check if a value is beyond specified thresholds
Threshold <- function(value, lower_threshold, upper_threshold) {
  return(value < lower_threshold | value > upper_threshold)
}
# Function to classify sensor data and identify emergency vital signs
Classify <- function(sensor_data) {
  emergency_vital_signs <- numeric(0)

  for (i in 1:length(sensor_data)) {
    value <- sensor_data[i]
    lower_threshold <- getLower(i)
    upper_threshold <- getUpper(i)
    if (Threshold(value, lower_threshold, upper_threshold)) {
      emergency_vital_signs <- c(emergency_vital_signs, i)
    }
  }
  if (length(emergency_vital_signs) > 0) {
    return(list(status = "Emergency", vital_signs = emergency_vital_signs))
  } else {
    return(list(status = "Normal", vital_signs = numeric(0)))
  }
}
# Function to monitor sensor readings and display classification
Monitor <- function(reading_values) {
  sensor_data <- reading_values
  result <- Classify(sensor_data)
  cat("Classification:", result$status, "\n")
  if (result$status == "Emergency") {
    vital_sign_names <- EmergencyVitalSign(result$vital_signs)
    cat("Emergency Vital Signs:", paste(vital_sign_names, collapse = ", "), "\n")
  }
}
# Function to retrieve the lower threshold for a specific vital sign
getLower <- function(vital_sign_number) {
  lower_thresholds <- SetLowerLimit()
  return(lower_thresholds[vital_sign_number])
}
# Function to retrieve the upper threshold for a specific vital sign
getUpper <- function(vital_sign_number) {
  upper_thresholds <- SetUpperLimit()
  return(upper_thresholds[vital_sign_number])
}
# Function to map vital sign numbers to their names in case of emergency
```

```
EmergencyVitalSign <- function(vital_sign_numbers) {
  vital_sign_mapping <- getVitalSignMapping()
  vital_sign_names <- sapply(vital_sign_numbers, function(number) vital_sign_mapping[number])
  return(vital_sign_names)
}
# Sample patient data
patient_data <- c(HeartRate = 133, BloodPressure = 151, RespiratoryRate = 32,
              Temperature = 36.8, OxygenSaturation = 97, Pulse = 132)
# Execute the Monitor function with the sample patient data
Monitor(patient_data)
```

The algorithm explanation, utilising the provided patient data as an example, is outlined below:

Patient Data:

The patient data consists of vital signs such as HeartRate, BloodPressure, RespiratoryRate, Temperature, OxygenSaturation, and Pulse.

Table 3. 4: Example patient data

HeartRate	BloodPressure	RespiratoryRate	Temperature	OxygenSaturation	Pulse
133	151	32	36.8	97	132

Threshold Checking Loop (Inside Classify Function):

- The `Classify` function iterates through each vital sign in the patient data.
- For each vital sign, it obtains the corresponding lower and upper thresholds using the `getLower` and `getUpper` functions.
- It then uses the `Threshold` function to check if the vital sign value falls beyond the specified thresholds.

Example Checking (For HeartRate):

- For the HeartRate:
  - Lower Threshold: 51
  - Upper Threshold: 90
  - Patient HeartRate: 133

- The `Threshold` function checks if `133` is outside the range `[70, 150]`. Since it is outside, the HeartRate is identified as an emergency vital sign.

For all the vital signs:

Table 3. 5: Example of threshold-based classification.

Vital Sign	Lower Threshold	Upper Threshold	Patient Measurement	Result
Heart Rate	70	150	133	Emergency
Blood Pressure	120	140	151	Emergency
Respiratory Rate	15	25	32	Emergency
Temperature	36	38	36.8	Normal
Oxygen Saturation	90	100	97	Normal
Pulse	60	100	132	Emergency

Overall Result:

- After checking all vital signs, the `Classify` function determines whether any vital signs are identified as emergency based on the thresholds.

Inside Classify Function:

- The `for` loop iterates through each vital sign in the `sensor_data`.

- For each vital sign, it checks if the value is beyond the specified thresholds using the `Threshold` function.

- If the condition is met, it adds the vital sign number to the `emergency_vital_signs` list.

- After processing all vital signs, it checks if any emergency vital signs were identified.

- If yes, it returns a list indicating an "Emergency" status along with the list of emergency vital signs; otherwise, it returns a list indicating a "Normal" status with an empty list.

Classification Result:

- If the classification is "Emergency," the `EmergencyVitalSign` function is called with the identified emergency vital sign numbers.

- The function returns the names of the emergency vital signs, which are then printed:

Emergency Vital Signs: HeartRate, RespiratoryRate, Pulse

To validate the system model, a set of experiments was carried out. Each sample, approximately 20,100 records in size, was examined over one hour.

In the initial stage of the system validation experiment, individual physiological signs are taken into account as displayed in various figures. Specifically, blood pressure. is demonstrated in Figure 3.6, oxygen saturation in Figure 3.7, and heart rate in Figure 3.8 respectively. The early warning scoring system table (refer to Figure 3.5) is used to highlight the normal range of well-being over time. Notably, only a few alarms were observed for blood pressure (as seen in Figure 3.11) based on the available data. In this graph, the y-axis signifies the measurement of blood pressure in millimetres of mercury (mmHg), while the x-axis illustrates the passage of time in seconds. Measurements depicted in blue represent a normal state, whereas those marked in red point to an emergency state. Due to their specific health condition, this particular patient is anticipated to have normal blood pressure while experiencing a higher rate of respiration and heart rate.

Figure 3. 11: Blood pressure, normal and emergency data.

The red vertical lines on the graph symbolise an alert at a specific point in time, while the green horizontal lines mark the maximum and minimum threshold values for all vital sign measurements. Alarms are integrated into the graph following a threshold algorithm, with emergency data marked in red and ordinary data in blue. A significant number of alarms are identified for oxygen saturation (Figure 3.12), heart rate (Figure 3.13), and respiration rate (Figure 3.14), resulting from actual variations in physiological measurements.

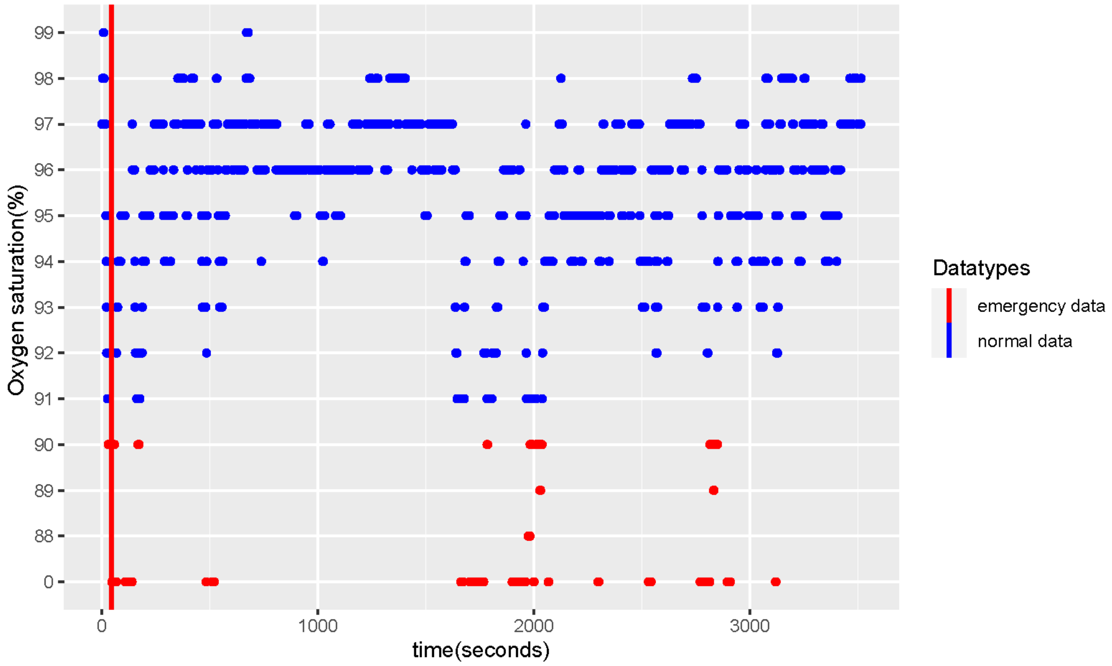


Figure 3. 12: Oxygen saturation, normal and emergency data.

All the vital signs depicted in Figures 3.12 to 3.14 are plotted with time on the x-axis and measurements on the y-axis. Each vital sign is associated with distinct measurement units. Blood pressure, for instance, is quantified in millimetres of mercury (mmHg) and presented as systolic pressure over diastolic pressure (e.g., 120/80 mmHg). Oxygen saturation is represented as a percentage (%), indicating the proportion of oxygen-saturated haemoglobin in the blood. Heart rate is gauged in beats per minute (BPM), denoting the number of heart beats per minute. Similarly, respiration rate is measured in breaths per minute (BPM), signifying the count of breaths taken per minute.

Table 3.6 presents the log documenting alarms triggered by the system for individual sensors. The analysis reveals that the system-generated alarms fall into two distinct categories: emergency data and errors attributed to system failures. A specific entry in the patient log (191) indicates a system failure at the commencement of the record. Notably, alarms related to blood pressure were found to be the result of a faulty system and were treated as errors, as indicated in Table 3.6.

Table 3. 6Table 3.6: Raised alarm for individual vital signs.

Vital signs	Alarm %	Error %
Blood pressure	10	1
Oxygen saturation	37	2
Heart rate	91	2
Respiration rate	94	2

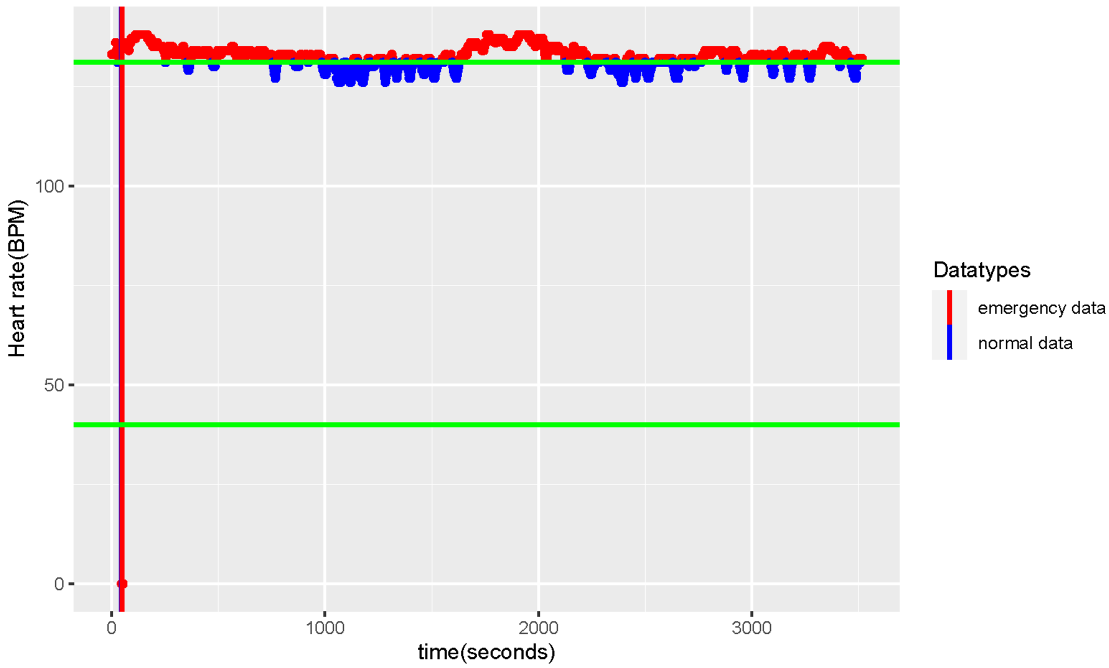


Figure 3. 13: Heart rate, normal and emergency data.

Among the four physiological signs plotted, it is noted that respiration (Figure 3.14) has the highest number of alarms. Conversely, blood pressure exhibits the lowest number of alarms compared to the others. Additionally, it is observed that heart rate and respiration share a similar percentage of alarms.

The sample data used for system validation comes from an ICU patient experiencing respiratory and heart problems. A higher rate of alarms is recorded for heart rate and respiration rate (Table 3.6). The data suggests a correlation between vital signs, and it is noted that at least two or three vital signs may be interlinked [192]. The goal is to design a system for patients, physicians, or carers that is simple, easy to use, and suitable for medical scenarios. In dynamic situations, physicians may look for any changes in vital signs to monitor progress or deterioration. In some scenarios, observing at least two or three vital signs together can provide insights into the patient's overall progress or deterioration, where each vital sign being in an emergency state contributes to determining the overall emergency.

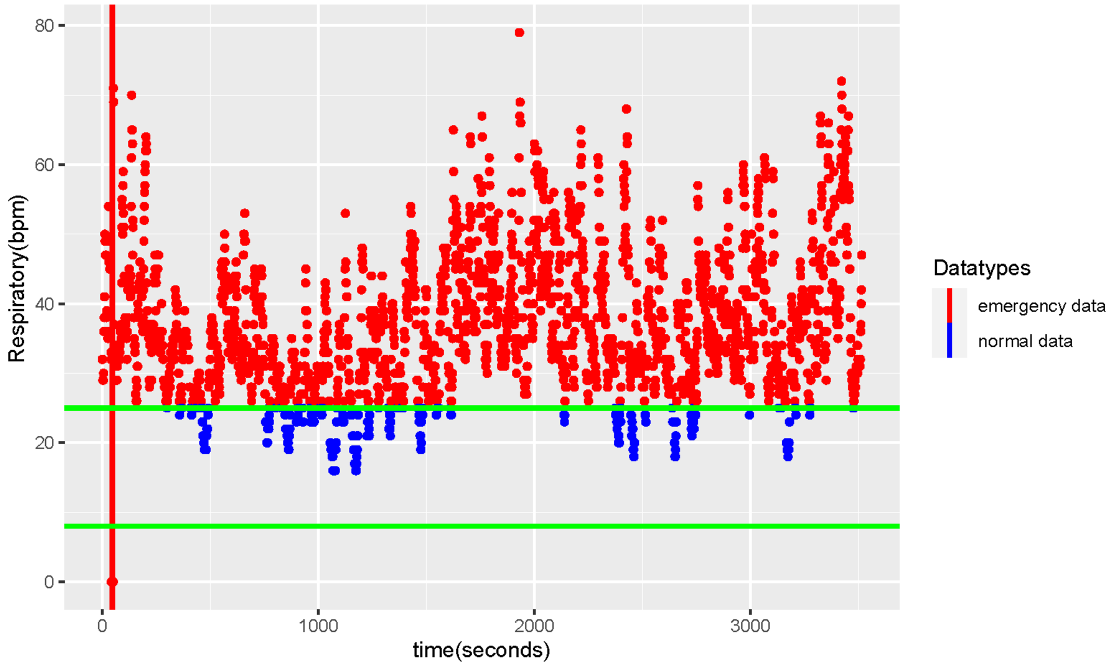


Figure 3. 14: Respiratory rate, normal and emergency data.

Hence, the initially proposed threshold algorithm (1. A) has been expanded to version 1. B, incorporating options where physicians can specifically choose certain sensors and observe them collectively. This modification aims to assist physicians in minimising false alarms and obtaining more accurate observations.

With the implementation of Threshold Algorithm 1. A (Threshold), a mini-experiment for system validation proved successful, as it effectively raised alarms when data fell outside the predetermined thresholds of upper and lower limits for vital signs.

3.5.3.2 Threshold-Based Approach (Selective Vital Signs)

The modified threshold algorithm 1. B (Threshold adopted), derived from threshold algorithm 1. A, is designed to classify data into normal and emergency states. In this algorithm, the classification as an emergency is contingent on all the selected sensor data being in an emergency state. For instance, if three sensors are chosen to observe a patient using this algorithm, all three of them must be classified as emergencies for the system to be classified as an emergency.

Algorithm 1.B. Emergency detection using threshold by selecting sensors (Threshold adopted)

```
Input: A set of patient vital sign data (can select specific vital signs)
Output: A classification result indicating an overall system status
Procedure: Classifier ()
begin
Threshold (value, lower_threshold, upper_threshold):
   return value < lower_threshold OR value > upper_threshold
SetSensor():
Classify(sensor_data, selected_sensors):
   emergency_vital_signs = empty_list()
   for i in selected_sensors:
      value = sensor_data[i]
      lower_threshold = SetLowerLimit(i)
      upper_threshold = SetUpperLimit(i)
      if Threshold(value, lower_threshold, upper_threshold):
         append_to_list(emergency_vital_signs, i)
      end if
   end for
   if length(emergency_vital_signs) == length(selected_sensors)
      return {"status": "Emergency"}
   else:
      return {"status": "Normal"}
   end if
Monitor(reading_values, selected_sensors):
   sensor_data = reading_values
   result = Classify(sensor_data, selected_sensors, )
getLower(vital_sign_number):
   lower_thresholds = SetLowerLimit()
   return lower_thresholds[vital_sign_number]
getUpper(vital_sign_number):
   upper_thresholds = SetUpperLimit()
   return upper_thresholds[vital_sign_number]
end
```

The proposed algorithm is designed to analyse patient vital signs and classify them into either a normal or emergency state. The system allows physicians to choose specific sensors relevant to the patient's condition. The classification process involves setting threshold values for each vital sign, and if the readings surpass these thresholds for all selected sensors, the system declares an emergency. Monitoring is conducted to assess the overall system status based on the classification results. This approach aims to provide flexibility by allowing physicians to tailor the system to specific patient needs, with a focus on accurate emergency detection while minimising false alarms.

An illustration of patient data for this algorithm includes the following vital signs: heart rate 133, blood pressure 151, respiratory rate 32, temperature 36.8, oxygen saturation 97, and pulse 132.

Example: R Code with this patient data

```
# Define Threshold function
Threshold <- function(value, lower_threshold, upper_threshold) {
  return(value < lower_threshold | value > upper_threshold)
}
# Define SetSensor function
SetSensor <- function() {
  # Implement logic to allow physicians to set specific sensors
  # Return a list of selected sensor indices
  return(NULL)  # return value
}
# Define Classify function
Classify <- function(sensor_data, selected_sensors) {
  emergency_vital_signs <- integer(0)
  # Detailed calculations for each vital sign
  for (i in selected_sensors) {
    value <- sensor_data[[i]]
    lower_threshold <- getLower(i)
    upper_threshold <- getUpper(i)
    # Check if the vital sign is outside the normal range
    if (Threshold(value, lower_threshold, upper_threshold)) {
      emergency_vital_signs <- c(emergency_vital_signs, i)
    }
  }
  # Check if all selected vital signs are problematic
  if (length(emergency_vital_signs) == length(selected_sensors)) {
    return(list(status = "Emergency"))
  } else {
    return(list(status = "Normal"))
  }
}
# Define Monitor function
Monitor <- function(reading_values, selected_sensors) {
  sensor_data <- reading_values
  # Call the Classify function
  result <- Classify(sensor_data, selected_sensors)
  # Print the classification status
  cat("Classification:", result$status, "\n")
}
# Define getLower function
getLower <- function(vital_sign_number) {
  lower_thresholds <- SetLowerLimit()
  return(lower_thresholds[[vital_sign_number]])
}
# Define getUpper function
getUpper <- function(vital_sign_number) {
  upper_thresholds <- SetUpperLimit()
  return(upper_thresholds[[vital_sign_number]])
}
# Given patient data
patient_data <- list(
  "heart_rate" = 133,
  "blood_pressure" = 151,
  "respiratory_rate" = 32,
  "temperature" = 36.8,
```

```
  "oxygen_saturation" = 97,
  "pulse" = 132
)
# Selected sensors
selected_sensors <- c("heart_rate", "respiratory_rate", "pulse")
# Monitor patient condition
Monitor(patient_data, selected_sensors)
```

The adjusted threshold algorithm 1.B is designed to empower doctors in choosing particular sensors for patient monitoring. A supplementary function named 'SetSensor' has been integrated into algorithm 1.A to facilitate sensor selection based on the patient's needs. Here's how the process works: Doctors interact with a graphical user interface to define the crucial health sign sensors they wish to use during monitoring. The chosen interface could utilise checkboxes, drop-down menus, or other forms of input. - The internal mechanics of the 'SetSensor' function interpret the doctor's selection and decide which sensors will be involved in the monitoring. For instance, if a doctor opts for "heart rate" and "respiratory rate," the function would yield a list of indices or names that match these chosen sensors. All the vital sign classification calculations are:

Table 3. 7: Example of threshold-based (algorithm 1. B/ Threshold adopted) classification.

Vital Sign	Given Rate	Threshold Range	Calculation	Result
Heart Rate	133	51 to 90	133 is outside the normal range (51 to 90).	Emergency
Respiratory Rate	32	12 to 20	32 is outside the normal range (12 to 20).	Emergency
Pulse	132	51 to 90	132 is outside the normal range (51 to 90).	Emergency

In the initial analysis, each of the four vital signs, namely blood pressure, oxygen saturation, heart rate, and respiration, exhibited emergency data, triggering alarms. Subsequently, a modified threshold approach was introduced, implementing an 'and' logic to examine the correlation between these vital signs. The approach involved considering any two vital signs simultaneously. The outcome revealed a reduction in the number of alarms, as illustrated in Table 3.8.

Table 3. 8: Raised alarm between individual and combined vital signs (Sp = Oxygen saturation, HR = Heart rate, RR = Respiration rate)

Features	Sp	HR	RR	Sp and HR	Sp and RR	RR and HR
Alarm %	37	91	94	24	33	81
Error %	2	2	2	9	2	2

Figures 3.15, 3.16, and 3.17 depict the graphical representation of various combinations of physiological signs and their corresponding alarm tests against the system. An enhancement has been observed in comparison to individual physiological signs, particularly in terms of alarm reduction, as indicated in Table 3.8.

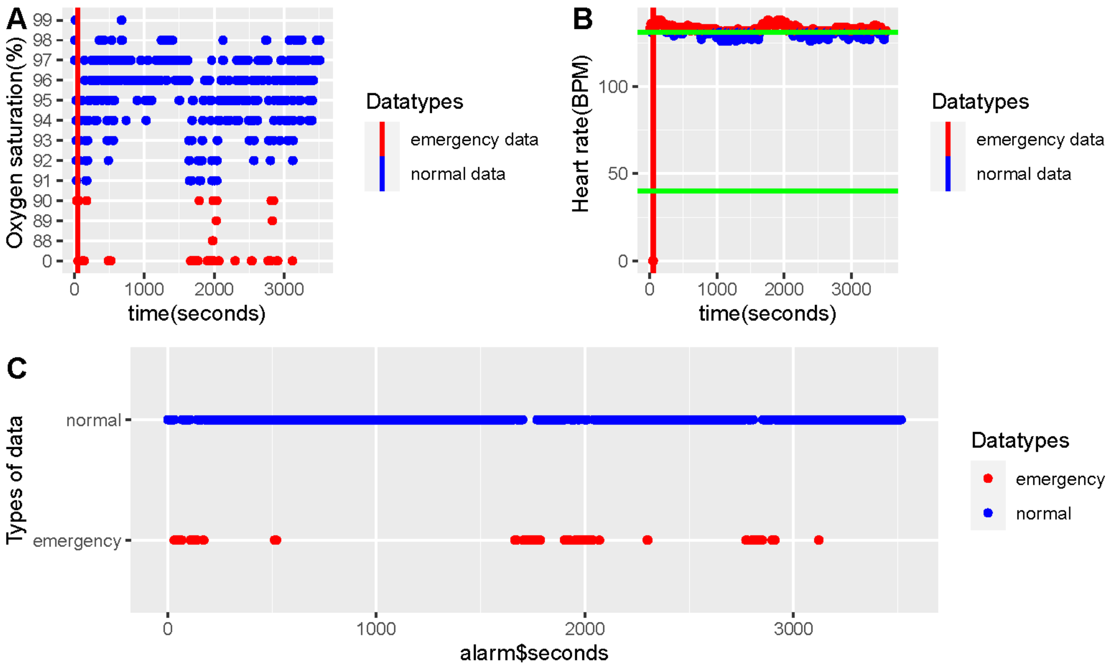


Figure 3. 15: Raised alarms for Oxygen saturation and Heart rate.

The individual alarm rates for oxygen saturation and heart rate were 37% and 91%, respectively. It has been noted that the alarm rate decreases to 24% when a combination of these two is employed for the alarm test (Figure 3.10 and Table 3.8).

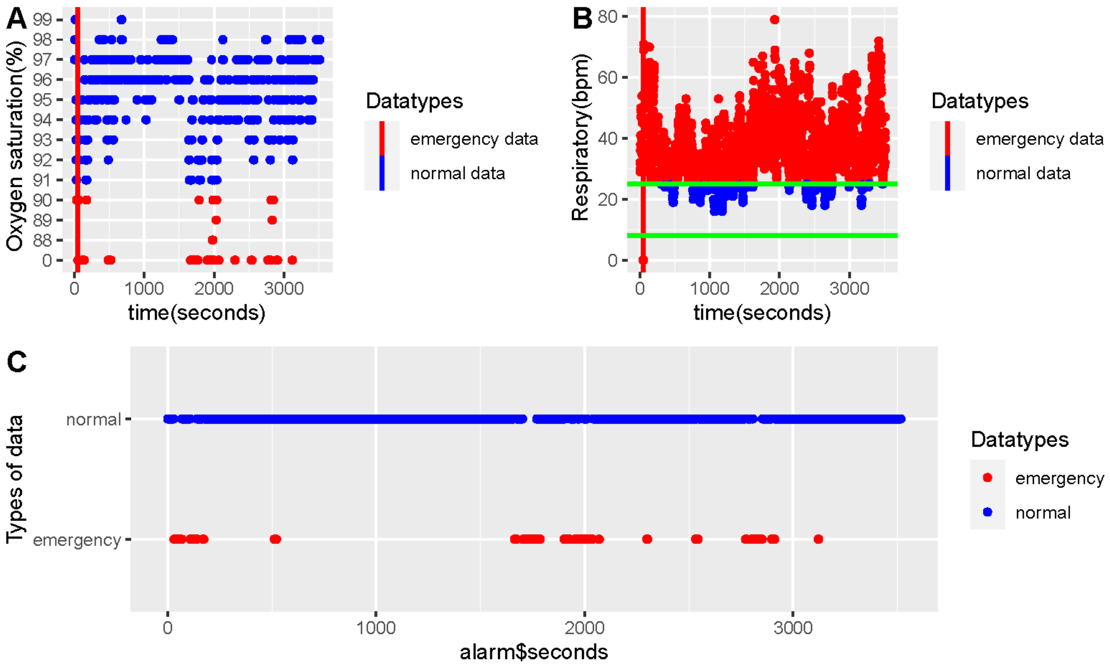


Figure 3. 16: Raised alarms for Oxygen saturation and Respiration rate.

The individual alarm rates for oxygen saturation and respiration rate were 37% and 94%, respectively. It has been observed that there is a reduction of 33% when a combination of these two is used for the alarm test (Figure 3.11 and Table 3.8).

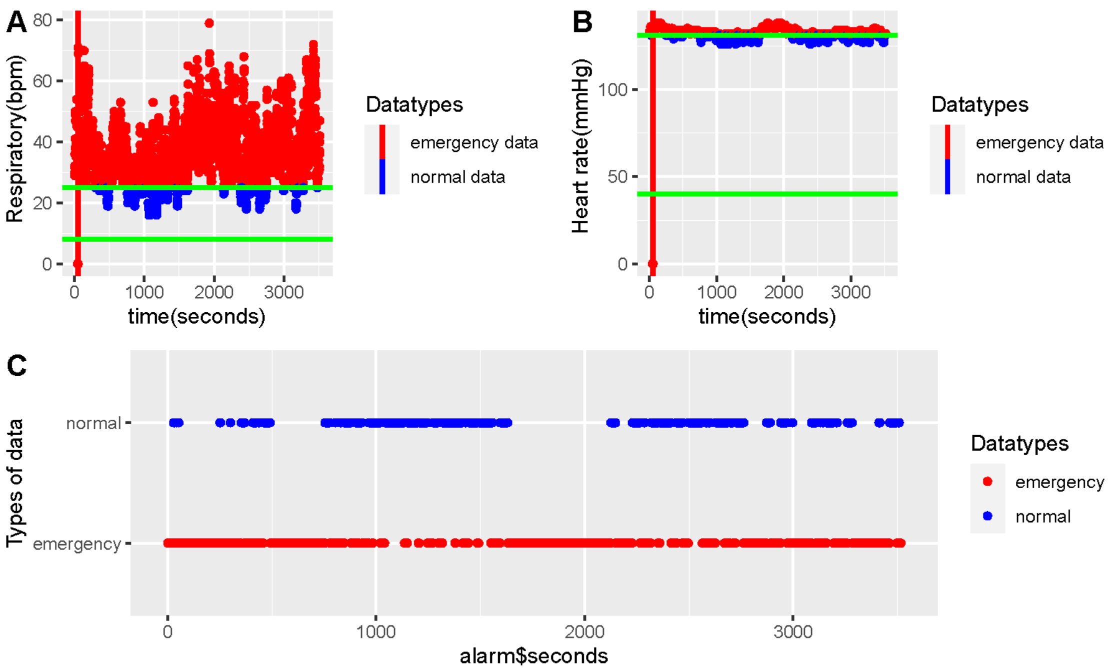


Figure 3. 17: Raised alarms for Respiration rate and Heart rate.

Moreover, figure 3.17 displays the alarm for the combined respiration rate and heart rate, which is observed to be less than the alarm rates for heart rate and respiration rate individually.

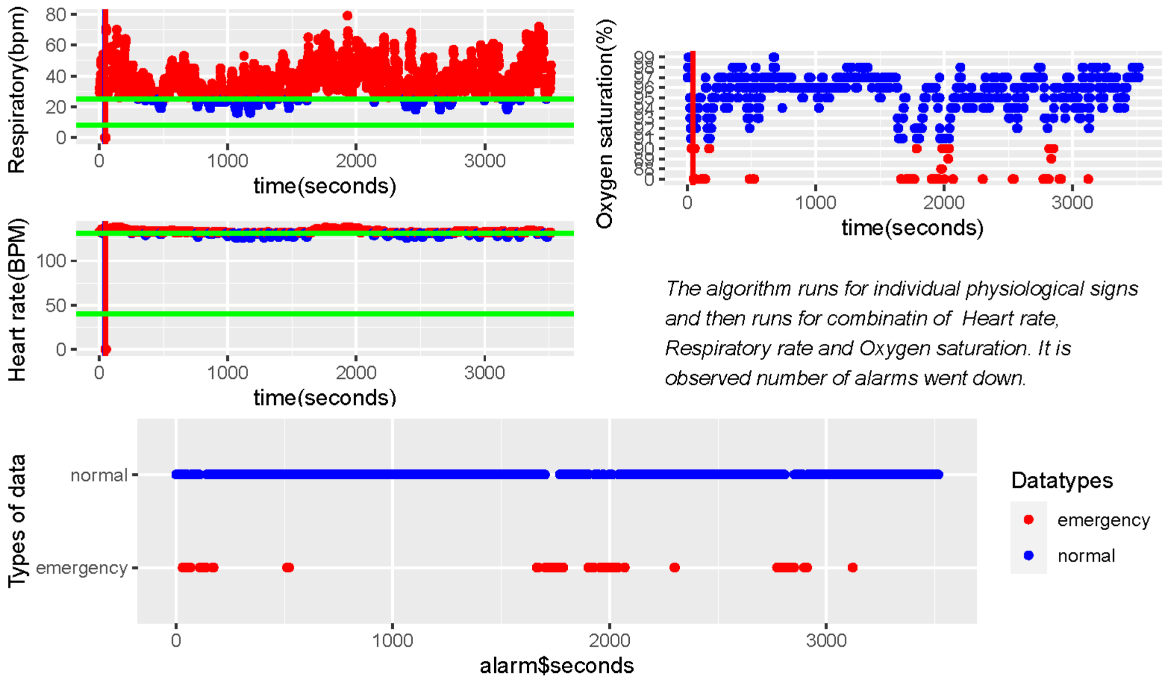


Figure 3. 18: Raised alarms for Respiration rate, Oxygen saturation and Heart rate.

In a subsequent experiment, three physiological signs were chosen for the implementation of algorithm 1. B, and the results are illustrated in graph 3.18. Table 3.9 enumerates the count of alarms triggered by the system for various combinations of physiological signs.

Table 3. 9: Raised alarm between individual and combined vital signs (Sp = Oxygen saturation, HR = Heart rate, RR = Respiration rate, BP =Blood pressure)

Features	Sp & HR	Sp & RR	RR & HR	RR, HR & Sp	BP, RR,HR & Sp
Alarm %	24	33	81	10	10
Error %	9	2	2	2	2

The count of alarms decreased for the combination of three physiological signs (table 3.9) compared to any two combinations. However, this experiment is beneficial only in situations where physicians opt to utilise multiple vital sign combinations to assess emergency conditions.

The numerical and graphical analyses indicate that the system is functioning correctly. The proposed system successfully detects instances where the data values exceed the threshold for individual sensors. Moreover, the system performs accurately when considering combinations of sensors, including random pairs and combinations involving more than two sensors.

Different clinical scenarios, including MI/cardiogenic shock, cardiogenic shock, and respiratory failure, were considered for the system validation experiment. It was observed that the system performed effectively with both proposed threshold-based algorithms. Depending on the physician's observation, either algorithm can be chosen, considering that using fewer sensors is cost-effective and less complex in terms of computational concerns.

3.5.3.3 Dynamic Threshold Approach

In the work [197], Sharma and his team delve into four categories of methods used for fault detection, which include rule-based, estimation-based, time-series analysis, and learning-based techniques. They examine both static and changeable thresholds, linear least squares estimation, ARIMA, as well as the hidden markov model, among others. Their research primarily targets the detection of three types of faults: brief, noise-induced, and constant. They found that not one particular detection method consistently excels for all types of anomalies. Using dynamic thresholds in health monitoring systems allows for customisation according to individual variables and adjustments to new circumstances, which augments precision. However, the computational complexity remains comparable to that of a static threshold. Statistically based parameters, like mean (μ) and standard deviation (σ), are often deployed as dynamic thresholds to identify deviations, such as the z-score or $\mu \pm k\sigma$, within normally distributed values. Nonetheless, when considering approaches like percentage-based thresholds and moving averages [66], the use of moving averages is more prevalent. This method involves calculating the average of the most recent readings over a designated time window. The advantages of moving averages include simplicity in calculation and implementation, live updating of thresholds based on the latest data, and mitigating the impact of short-term fluctuations and data noise. Alternatively, percentile-based Thresholds entail setting limits based on percentiles derived from past records, which is advantageous for establishing personalized thresholds based on a patient's own historical data. However, this method is less suitable for quick-onset conditions where an immediate reaction is crucial.

Dynamic threshold using moving average:

- Let V_i be a list of the most recent readings for the i^{th} vital sign.
- Define N as the window size for the moving average.
- The moving average MA_i for the i^{th} vital sign is calculated as

$MA_i = \frac{1}{N}\sum_{j=1}^{N} V_{ij}$, where, V_{ij} is the j^{th} most recent reading of the i^{th} vital sign.

- Let $offset_i$ be a predefined offset value for the i^{th} vital sign.
- The dynamic lower threshold LT_i and upper threshold UT_i for the i^{th} vital sign are calculated as:

$$LT_i = MA_i - offset_i$$

$$UT_i = MA_i + offset_i$$

- For each vital sign reading R_i compare it against its dynamic thresholds:
- If $R_i < LT_i \ or \ R_i > UT_i$, flag the reading as indicating a potential emergency.

An algorithm named 'Dynamic Threshold', developed for the proposed dynamic threshold approach, is presented below as algorithm 1. C.

Algorithm 1.C. Emergency detection using Dynamic threshold (Dynamic Threshold)

Input: A set of patient vital sign data
Output: A classification result indicating a status
Procedure: Classifier()
begin
  MovingAverage(recentValues, windowSize):
    Calculate and return the average of the last 'windowSize' elements in recentValues
  DynamicThresholds(vitalSign, recentValues, windowSize, offset):
    movingAvg = MovingAverage(recentValues[vitalSign], windowSize)
    lowerThreshold = movingAvg - offset
    upperThreshold = movingAvg + offset
    return lowerThreshold, upperThreshold
  Threshold(value, lowerThreshold, upperThreshold):
    return value < lowerThreshold OR value > upperThreshold
  Classify(sensorData, recentValues, windowSize, offset):
    emergencyVitalSigns = empty_list()
    for i in range(1, num_vital_signs + 1):
      value = sensorData[i]
      lowerThreshold, upperThreshold = DynamicThresholds(i, recentValues, windowSize, offset)
      if Threshold(value, lowerThreshold, upperThreshold):

```
            append_to_list(emergencyVitalSigns, i)
         end if
      end for
      if length(emergencyVitalSigns) > 0:
         return {"status": "Emergency", "vital_signs": emergencyVitalSigns}
      else:
         return {"status": "Normal", "vital_signs": empty_list()}
      end if
   Monitor(readingValues, recentValues, windowSize, offset):
      sensorData = readingValues
      result = Classify(sensorData, recentValues, windowSize, offset)
      if result["status"] == "Emergency":
         vitalSignNames = EmergencyVitalSign(result["vital_signs"])
      end if
   EmergencyVitalSign(vitalSignNumbers):
      vitalSignMapping = getVitalSignMapping()
      vitalSignNames = [vitalSignMapping[number] for number in vitalSignNumbers]
      return vitalSignNames
end
```

A comprehensive experiment was conducted to compare static and dynamic thresholds in terms of their execution time and accuracy in classification. The initial phase of the experiment employed blood pressure data from fourty ICU patients, with 14,4000 data points in total (60*60*40). The next stage considered 12 hours' worth of data, a total of 172,8000 data points (12*60*60*40). Finally, the experiment was extended to 24 hours of data, resulting in a total of 345,6000 data points. Table 3.10 presents a summary of the experimental findings. When analysing smaller datasets, both algorithms demonstrated nearly identical performance. However, when applied to larger datasets, the dynamic threshold exhibited superior accuracy as it could adapt to each patient's unique variations and be capable of tracking trends over time. Nevertheless, in terms of execution time, the dynamic threshold was found to be more time-consuming compared to the static threshold when dealing with large datasets.

Table 3. 10: Comparison of classification accuracy by static and dynamic threshold

	Accuracy (%)			**Execution time (seconds)**		
Duration	1 hour	12 hours	24 hours	1 hour	12 hours	24 hours
Data	144000	1728000	3456000	14400	172800	345600
Static	**99.3**	**98.9**	**98.3**	**1.6**	**7.6**	**56**
Dynamic	**99**	**99.1**	**99.3**	**2.9**	**40**	**206**

3.6 Abnormality Classification

The proposed model possesses the capability for knowledge discovery derived from extensive patient data at the local node through threshold approaches. Consequently, a Unified Anomaly Detection Scheme (UADS) has been developed as an extended version of the basic WBAN system model. This enhanced model incorporates functionalities for learning and the process of knowledge discovery to identify patient-specific anomalies. This involves the utilisation of rule-based thresholds, machine learning, and hybrid approaches.

For the experiment, from MIMIC-II, 100 patient records have been utilised for evaluations. The patients who participated in this study present with a broad range of clinical issues, such as sepsis, respiratory failure, congestive heart failure, pulmonary oedema, myocardial infarction, cardiogenic shock, and acute hypotension. The majority of these clinical instances arise because of simultaneous abnormalities in multiple vital signs.

In the experimental phase, the threshold-based approach is compared with machine learning algorithms. The system aims to achieve simple, user-friendly, clinically fit, computationally low, and energy-efficient anomaly detection, making decisions locally on the edge device. This approach is expected to reduce the amount of data sent to the cloud, thereby lowering overall system energy consumption. As discussed in the previous section, various edge devices with different computational capacities are considered. Amazon EC2 instances (type m1.medium) [193] are created to match the processing capability of Microsoft Azure Sphere (one of the edge devices). The classification process is then executed on the EC2 instance.

In this experiment, apart from the threshold approach for classifying normal or emergency data based on vital signs, two additional machine learning algorithms, namely decision tree [72] and one-class support vector machine [71,76], have been employed. The selection of these two algorithms was meticulous, considering the system model's constraints that support the operation of simpler algorithms. The dataset is partitioned into training and test sets for utilisation with these machine learning algorithms. This careful choice aims to align with the system model and optimise the output for enhanced performance.

Abnormal vital signs pose challenges to standardisation due to variations among patients, influenced by factors like medical history and family profile. These variations may not always indicate danger in practical scenarios. Relying solely on generalised threshold values for patient classification can lead to frequent false alarms. While false alarms may be acceptable in life-threatening situations, it's crucial to factor in correlations with other contextual information when making final clinical decisions.

As detailed in the system model section (3.5), decision support mechanisms are established based on the multiple level of classification results to recommend specific actions for implementation. They are:

1. In the case of a normal situation:
   If $\forall i, j: C_{ij} = 0$, assign a score of 0.
2. If the situation is abnormal but not dangerous and falls within the tolerance range:

   If $\sum_{j=1}^{k} \hat{C}_{ij} > \delta_3$, then issue a warning for preventive action, assign a score of 1.

3. If the situation is abnormal and poses a danger:

   If $\sum_{j=1}^{k} \hat{C}_{ij} > \delta_2$, then send an alert to the doctor and recommend a visit to the general practitioner, assign a score of 2.

4. In the event of an extremely abnormal situation:
   If $\sum_{j=1}^{k} \hat{C}_{ij} > \delta_1$, then notify emergency services, assign a score 3.

Where,

- C_{ij} represents the intra-sensor criteria for the i-th sensor and j-th sample.
- $\hat{C}_{ij}$ represents a modified criteria for specific actions, depending on the context.
- $\delta_1, \delta_2, and\ \delta_3$ are predefined thresholds for triggering different actions.
- $\sum_{j=1}^{k} denotes$ the summation over all samples acquired during the awake state of the sensor.

The suggested threshold method can only categorise the data into two states: normal or emergency. However, machine learning techniques can sort into multiple categories based on set criteria. Therefore, there's a plan to expand this threshold method to enable it to be classified into multiple categories, which would be more beneficial for this model. Afterwards, it will be possible to compare this revised method with the previously discussed machine learning approaches.

There are several straightforward techniques suitable for this system model that can classify various alert levels. Among all available methods, the two most effective are the Mahalanobis Distance (MD) [195] and the Z Score [196]. Z-Score and Mahalanobis distance are both statistical methods used for the classification of data, and while they may seem to perform similar functions, their applications differ in certain contexts.

Z-Score: Measures how many standard deviations a data point deviates from the mean; suitable for univariate (single-variable) data.

Mahalanobis Distance: Measures the distance between a point and a distribution considering covariance; ideal for multivariate data where variables correlate.

For this system model, where values of different signs might affect each other, Mahalanobis distance is preferred. It takes into account correlations between variables, reducing false positives.

3.6.1 Multi Level Classification Using Threshold Approach

The algorithm is described in 1. A and 1. B, and it performs exceptionally well for binary classification. It can accurately classify patient vital signs as either normal or emergency. Afterwards, algorithm 1. D which is called MLCTA introduces an algorithm for multi-level classification, which is presented below.

Algorithm 1.D. Multi-level classification using threshold approach (MLCTA)

```
Input: A set of patient vital sign data
Output: Multi-level classification result indicating an overall system status
Procedure: Classifier ()
begin
Threshold(value, lower_threshold, upper_threshold):
  if value < lower_threshold:
    return "Warning"
  else if value > upper_threshold:
    return "Emergency"
  else:
    return "Normal"
  end if
Alert(value, alert_threshold):
  if value > alert_threshold:
    return "Alert"
  else:
    return "Normal"
  end if
```

```
Classify(sensor_data):
   emergency_vital_signs = empty_list()
   warning_vital_signs = empty_list()
   alert_vital_signs = empty_list()
   for i in range(1, num_vital_signs + 1):
      value = sensor_data[i]
      lower_threshold = SetLowerLimit(i)
      upper_threshold = SetUpperLimit(i)
      alert_threshold = SetAlertLimit(i)
      status = Threshold(value, lower_threshold, upper_threshold)
      if status == "Warning":
         append_to_list(warning_vital_signs, i)
      else if status == "Emergency":
         append_to_list(emergency_vital_signs, i)
      end if
      alert_status = Alert(value, alert_threshold)
      if alert_status == "Alert":
         append_to_list(alert_vital_signs, i)
      end if
   end for
   result = {"status": "Normal", "vital_signs": empty_list()}
   if length(emergency_vital_signs) > 0:
      result = {"status": "Emergency", "vital_signs": emergency_vital_signs}
   else if length(alert_vital_signs) > 0:
      result = {"status": "Alert", "vital_signs": alert_vital_signs}
   else if length(warning_vital_signs) > 0:
      result = {"status": "Warning", "vital_signs": warning_vital_signs}
   end if
   return result
Monitor(reading_values):
   sensor_data = reading_values
   result = Classify(sensor_data)
   output = {"Classification": result["status"]}
   if result["status"] == "Emergency":
      vital_sign_names = VitalSignNames(result["vital_signs"])
      output["Emergency Vital Signs"] = vital_sign_names
   else if result["status"] == "Alert":
      vital_sign_names = VitalSignNames(result["vital_signs"])
      output["Alert Vital Signs"] = vital_sign_names
   else if result["status"] == "Warning":
      vital_sign_names = VitalSignNames(result["vital_signs"])
      output["Warning Vital Signs"] = vital_sign_names
   end if
   return output
VitalSignNames(vital_sign_numbers):
   vital_sign_mapping = getVitalSignMapping()
   vital_sign_names = [vital_sign_mapping[number] for number in vital_sign_numbers]
   return vital_sign_names
End
```

`Threshold’ function evaluates a given `value` against a `lower_threshold` and an `upper_threshold`. It returns an assessment of the situation—either "warning," "emergency," or "normal"—depending on whether the value is below, above, or within the threshold boundaries. `Alert’ function decides whether a received `value` exceeds an `alert_threshold`. If the value is above the threshold, the function delivers an "Alert"; otherwise, it provides a "Normal" status. `Classify function processes sensor data to classify the conditions of various vital signs according to individual thresholds. It maintains three lists for tracking which vital signs are designated as "Warning," "Emergency," or "Alert." Should a vital sign cross its respective threshold, the sign is added to its respective list. Based on these lists, an overall health status is determined at the end of the function, ranging from "normal" to "emergency." The function then returns a dictionary detailing this status and the trigger elements for that status.

‘Monitor function collects sensor'reading_values', conducts a data classification through the `Classify` function, and maps the associated vital signs to their descriptors with the `VitalSignNames` function. If specific conditions ("Emergency", "Alert", or "Warning") are met, it records the related vital sign names within an output dictionary. 5. `VitalSignNames(vital_sign_numbers)`: This function accepts a series of vital sign numbers and translates them into vital sign descriptors based on the `vital_sign_mapping` dictionary, which is assumedly provided by the `getVitalSignMapping()` function.

This study used data from four patients to contrast the traditional threshold classification rule with the UADS scheme, a system designed to offer multi-tiered classifications based on threshold values. Table 3.11 showed a comparison between the typical binary threshold rule (using Threshold algorithm) and the suggested model, which seeks to achieve a multi-level classification stemming from the MLCTA method.

Table 3. 11: Comparison Threshold vs proposed MLCTA.

Patient	Total Data	Threshold approach		UADS model MLCTA			
		Normal	Abnormal	Normal	Warning	Alert	Emergency
Patient 1	36001	3563	32438	12320	17853	5523	305
Patient 2	36492	4012	32480	10153	18997	6952	390
Patient 3	35245	3692	31553	10586	17556	6802	301

Patient 4	34256	1899	32357	10207	19214	4523	312

The results of this experiment demonstrate that multi-level classification performs effectively. Nevertheless, additional testing is needed to compare these findings. The objective of the research is to implement the simplest possible method, ensuring that straightforward techniques are thoroughly examined. Figure 3.19 illustrates a comparative analysis between binary classification and multi-tiered classification, employing two threshold approaches for this system model. The classification categories—warning, alert, and emergency—are broadly grouped under the term 'abnormal' for the sake of maintaining a binary-like classification structure. An observation derived from the chart reveals that proposed MLCTA multi-level classification techniques yield superior results.

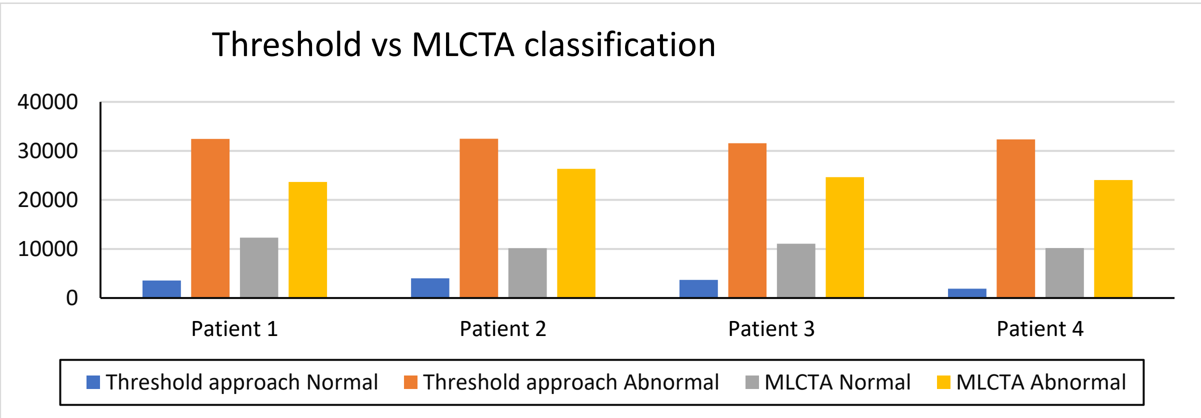


Figure 3. 19: Threshold vs MLCTA classification approach

Observations indicate that the adjusted threshold offers improved classification results in distinguishing between normal and emergency data. In binary classification, an average normal data representation of 9% was observed across four patients, which then escalated to an average of 30%. Similarly, the trend was mirrored for abnormal classification, evident in the reduction from 91% to 70%. As depicted in Figure 3.20, the classification of abnormal data seemingly diminishes linearly when using the multilevel classification method as compared to the binary threshold (Threshold) classification method.

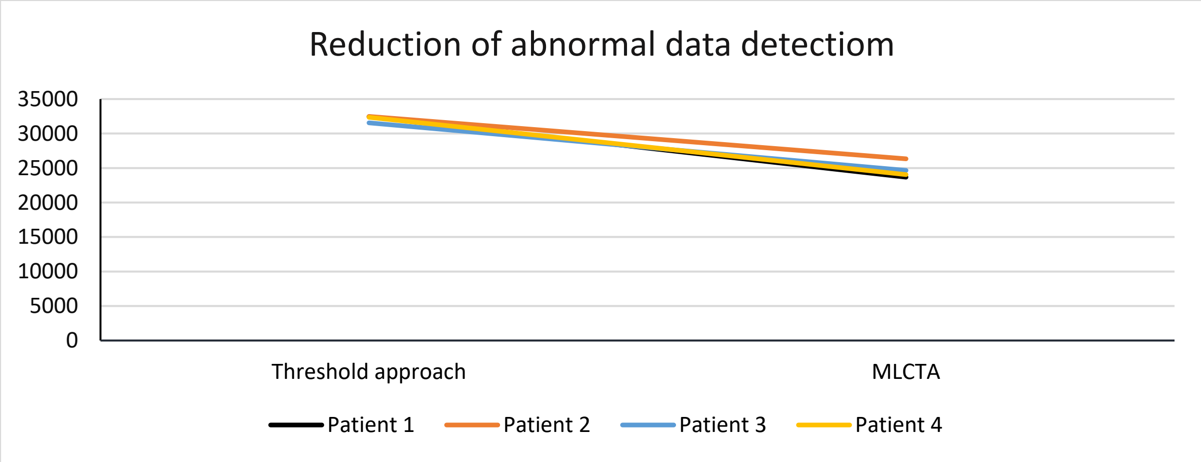


Figure 3. 20Figure 3.15: Comparison for abnormal data tendency (Threshold vs MLCTA)

3.6.2 Mahalanobis Distance Calculation:

There are several simple steps to calculate Mahalanobis distance. First, gather data and ensure that it is in a multivariate format, with observations in rows and variables in columns. Next, calculate the mean value of the dataset, which will serve as the reference point for distance calculation. After that, obtain the covariance matrix of the variables to take into account their variation and correlation. Then, subtract the mean from each variable's value for each observation to centralise the data around the mean. Finally, compute the Mahalanobis distance using the inverted covariance matrix and the centralised data. The distance can be found by taking the square root of the transposed centralised value, then multiplying by the inverted covariance matrix, and then multiplying again by the centralised value itself.

- For each sensor S_i, calculated the mean vector μ_i and covariance matrix C_i from dataset.

$$\mu_i = \frac{1}{k}\sum_{j=1}^{k} d_{ij}$$

$$C_i = \frac{1}{k-1}\sum_{j=1}^{k}(d_{ij} - \mu_i)(d_{ij} - \mu_i)^T$$

- Calculated the inverse of the covariance matrix C_i^{-1} for each sensor S_i
- For each sensor $S_{i,}$ mahalanobis distance MD_i calculated using the below formula.

$$MD_i = \sqrt{(d_i - \mu_i)^T {C_i}^{-1} (d_i - \mu_i)}$$

Where,

d_i is the vector measurements for sensor S_i

μ_i is the mean vector for sensor S_i

C_i is the covariance matrix for sensor S_i

- It is defined four threshold $\delta_1, \delta_2, \delta_3$ and $\delta_4$for the mahalanobis distance corresponding to four alert levels
  - Level 1 (normal): $MD \leq \delta_3$
  - Level 2 (warning): $\delta_3 < MD \leq \delta_2$
  - Level 3 (alert): $\delta_2 < MD \leq \delta_1$
  - Level 4 (emergency): $MD > \delta_1$

This experiment made use of data from 4 patients to compare the conventional threshold classification rule and the UADS scheme, which includes MD is called MDTA (Mahalanobis distance Threshold approach). If the classifiers solely sort situations into normal and emergency categories, the physician must personally review the data before making any decisions. The proposed model, which incorporates MD, yields improved outcomes when determining the severity of data criticality. Table 3.12 illustrates the comparison between the general threshold rule and the proposed model that has incorporated the MD.

Table 3. 12Table 3.12: Comparison Threshold vs proposed MDTA

Patient	Total Data	Threshold approach		UADS model (MDTA)			
		Normal	Abnormal	Normal	Warning	Alert	Emergency
Patient 1	36001	3563	32438	13356	17123	5156	366
Patient 2	36492	4012	32480	11473	18212	6432	375
Patient 3	35245	3692	31553	11681	17235	5978	351
Patient 4	34256	1899	32357	10834	18124	4994	304

This finding suggests that the system can decrease the incidence of false alerts at the receiver's end. Our results haven't found a comparable study in the existing literature, so they are compared with generalised medical observations. In certain healthcare systems, doctors personally calibrate the threshold values in an attempt to mitigate false alerts. However, in the proposed system, there's no need for any manual adjustments. Figure 3.21 illustrates that the proposed threshold method combined with MD delivers superior results for classifying normal and emergency data distributions. The assumption underpinning the use of the MDTA is that, aside from the normal data, all other pieces of data are treated as abnormal. This encompasses warning, alert, and emergency data.

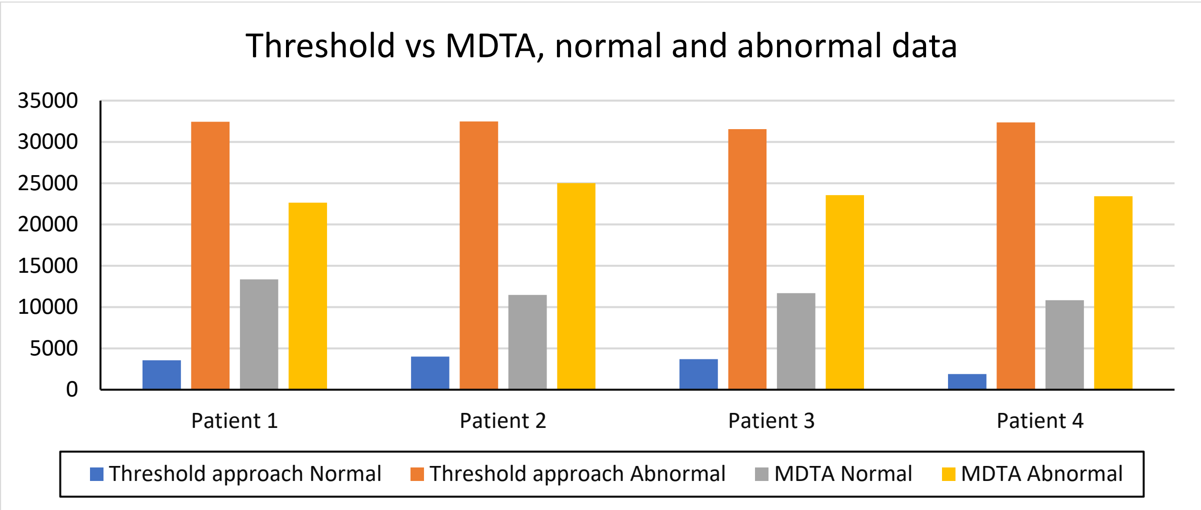


Figure 3. 21: Threshold vs MDTA normal and abnormal classification

Figure 3.22 demonstrates how the combination of threshold and MD leads to an increase in the number of normal data classified, compared to the binary threshold method proposed earlier.

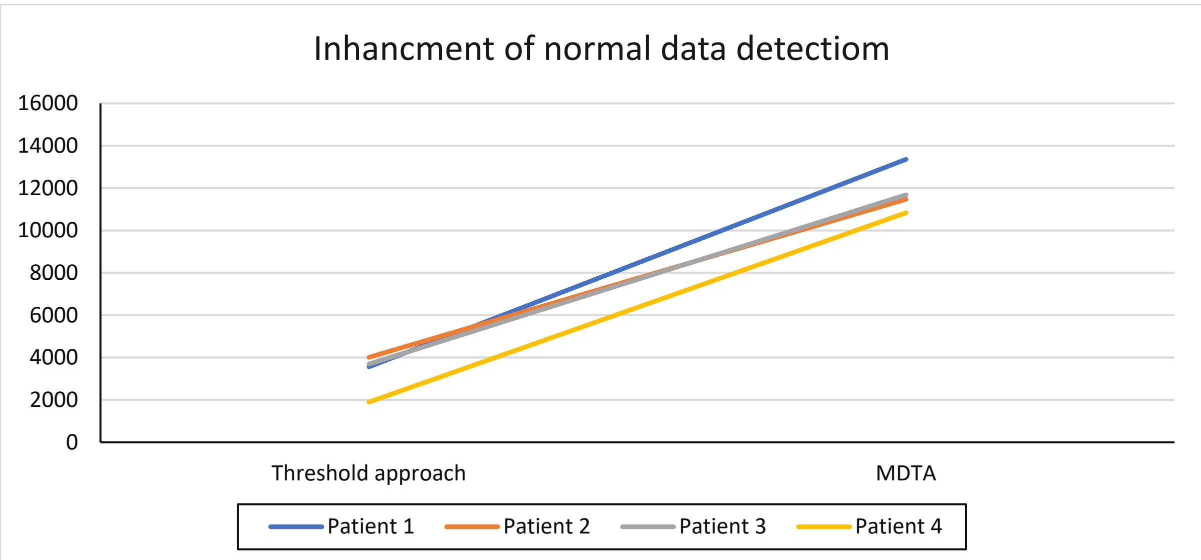


Figure 3. 22: Comparison for normal data tendency Threshold vs MDTA

In the binary threshold classification, it was noted that an average of 91% abnormal data was observed across four patients. This average then decreased to around 67%. In the same manner, the pattern was reflected in the normal classification, as seen by the increase from 9% to 33%.

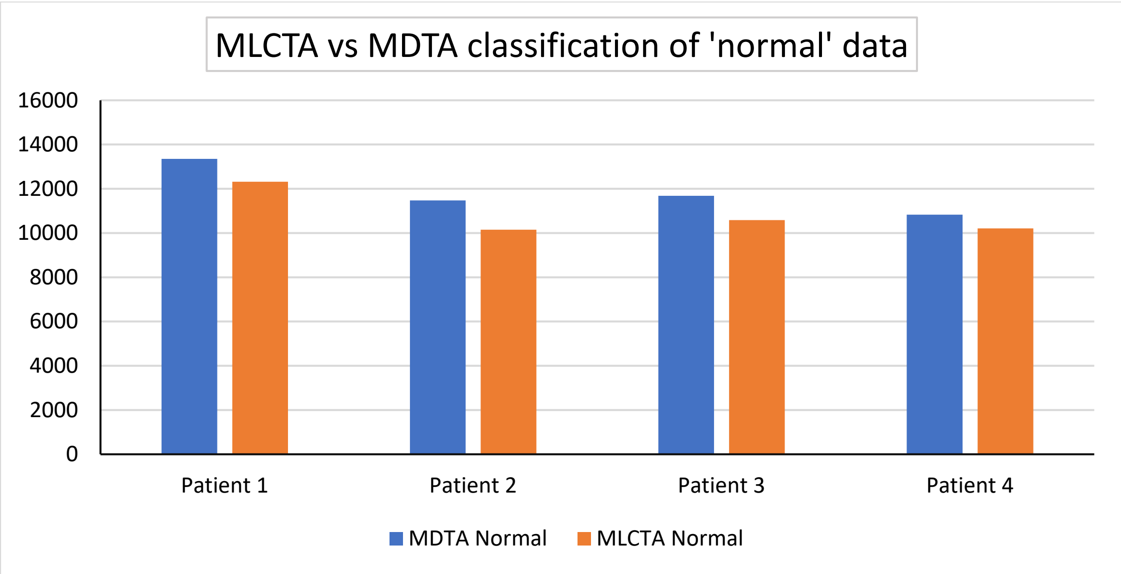


Figure 3. 23: Comparison between MLCTA and MDTA for normal data classification

It has been noted that the proposed MLCTA and MDTA methods are utilised for multi-level classification of normal and emergency data. Furthermore, the data suggests that MDTA is more effective in detecting normal data compared to MLCTA in figure 3.23. Alternatively, figure 3.24 indicates that MLCTA outperforms MDTA in detecting abnormal data.

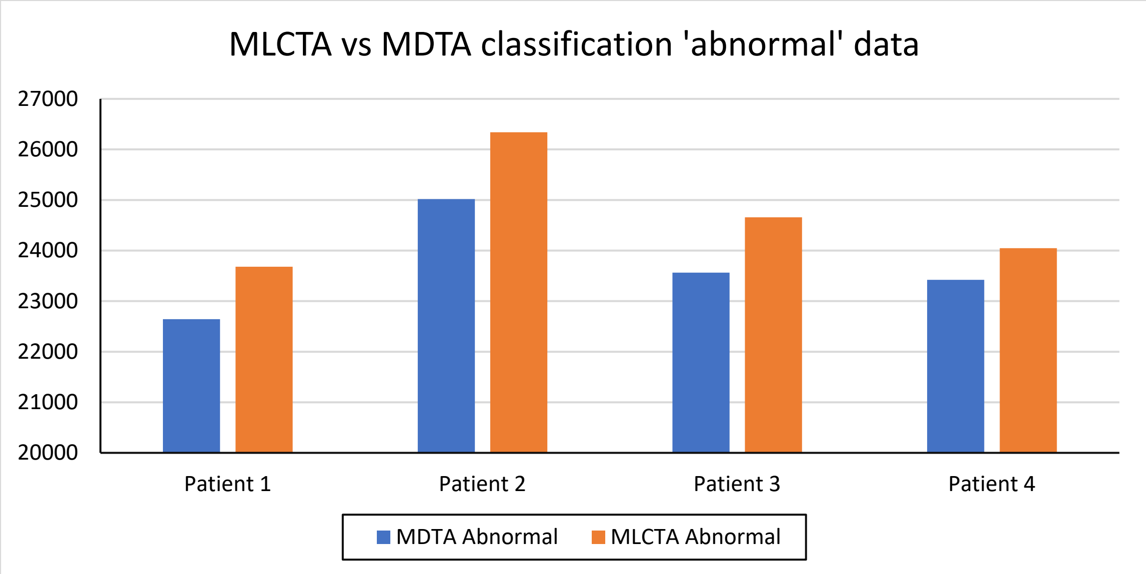


Figure 3. 24: Comparison between MLCTA and MDTA for abnormal data classification

3.6.3 Machine Learning Algorithms for Classification

In the proposed WBAN system, decision-making is conducted on edge devices, and the employment of both one-class SVM [71, 76, 116] and decision trees (C5.0) [72, 198] serves to provide a comprehensive basis for comparison with other classification methodologies like static and dynamic thresholds. The OCSVM is particularly proficient in anomaly detection within the high-dimensional data from WBAN sensors, offering efficient real-time processing crucial for edge computing. Its capability to discern health anomalies in complex data streams is a significant advantage. In contrast, decision trees present a transparent, rule-based classification approach, granting interpretability essential for healthcare decision-making.

3.6.3.1 One Class Support Vector Machine

OCSVM serves as an optimal anomaly detection solution within WBAN systems, aptly designed to highlight deviations signalling potential health risks. This is particularly pertinent in WBAN systems where the objective is identifying atypical readings among known vital sign parameters. OCSVM leverages a hyperplane approach to create a distinct separation between 'normal' sensor readings and outliers, effectively marking a border in the voluminous data retrieved from WBAN sensors. This differentiation expedites the identification and response to variations in vital signs. The hyperplane model is notably adept at managing the high-dimensional WBAN data, making it a clear choice for system implementation. The hyperplane approach, being less computationally intensive, is more suitable for the real-time data processing required in continuous health monitoring. Additionally, the hyperplane model offers a balance between simplicity and effectiveness, which is important considering the high-dimensional nature of WBAN data. This model is not only easier to implement and maintain on edge devices but also aligns well with the data distribution characteristics typically observed in WBAN systems. While the hypersphere model might provide a more nuanced fit for tightly clustered data, the hyperplane approach adequately meets our system's needs, effectively distinguishing between normal operation and anomalies, and ensuring efficient operation within the constraints of edge computing in WBAN environments.

The goal of the OCSVM is to identify a hyperplane within the feature space that maintains the greatest possible distance from the origin. This ensures that there's a noticeable distinction between usual operational data and potential outliers. The mathematical expression for the OCSVM is as follows:

$$min_{\omega,\delta,\rho}\left(\frac{1}{2}||\omega||^2 + \frac{1}{vnk}\sum_{i=1}^{n}\sum_{j=1}^{k}\xi_{ij}\right)$$

Where ω represents the weight vector of the hyperplane, and ξ_{ij} are slack variables associated with each data point d_{ij}. The term ρ denotes the bias of the hyperplane in the feature space. v is a regularisation parameter that controls the trade-off between maximising the margin and minimising misclassification.

The model is subject to the following constraints:

$$\left(\omega.\emptyset\left(d_{ij}\right)\right) \geq \rho - \xi_{ij}, \xi_{ij} \geq 0$$

In these constraints, $\emptyset\left(d_{ij}\right)$ signifies a mapping function that transforms the WBAN data into a higher-dimensional feature space, facilitating the linear separation of data points.

3.6.3.2 Decision Tree (C5.0)

The C5.0 decision tree algorithm is utilised for the effective classification and interpretation of data. This algorithm is recognised for its interpretability and its ability to handle complex, non-linear relationships in data. The C5.0 algorithm forms a decision tree, where every node denotes a decision based on vital sign features, and branches represent the decision outcomes. The operation starts from the tree's root, which includes all the data from the WBAN system. To construct the tree, the first step involves the selection of a feature that differentiates the data into distinct categories most effectively. This selection is based on the principle of information gain, which quantifies how well a feature divides data into groups determined by the target variable. In this scenario, the target variable might consist of categories such as 'normal', 'alert', 'warning', and 'critical'.

Define the Information Gain (IG) for a feature A as:

$$IG(S, A) = H(S) - \sum_{v \in Values\ (A)} \frac{|s_v|}{|s|} H(S_v)$$

Where entropy $H(S)$ is calculated as

$$H(S) = -\sum_{c \in Values\ (A)} p(c) log_2 p(c)$$

Where $p(c)$ is the proportion of elements in class c within the set S.

At each node of the tree, select the feature A that maximise $IG(S, A)$ to split the dataset. This process is recursively applied to each subset until specific stopping criteria, such as maximum tree depth or minimum node size, are satisfied. To classify a new observation d_{new}, traverse the tree from the root to a leaf node based on the feature values of d_{new} with the leaf node providing the predicted classification.

As previously stated, a considerable volume of patient data is being used for this experiment. Initially, it is used 100 patient data sets, spanning over 24 hours each, for the trials. But now, it is expanded this duration to 40 hours to extract more insights from the machine learning algorithm. This extended time frame will also help us test the proposed threshold algorithms. Table 3.13 displays the results of the classifications obtained from the experiments. Five performance criteria were utilized to evaluate their effectiveness. These include accuracy, sensitivity or recall, specificity, precision, and the F1 score. The algorithms assessed included the Multi-Level Classification Threshold Algorithm (MLCTA), Decision Tree (C5.0), Dynamic Threshold, One-Class Support Vector Machine (OCSVM), and Mahalanobis Distance Threshold Approach (MDTA).

Table 3. 13Table 3.13: Evaluating different approaches through performance metrics.

Algorithms	Accuracy	Sensitivity	Specificity	Precision	F1 score
MLCTA	96.19%	96.50%	91.00%	99.29%	97.87%
Decision Tree	91.91%	92.00%	87.50%	99.04%	95.39%
Dynamic threshold	90.55%	90.50%	91.00%	99.03%	94.57%
OCSVM	87.96%	88.00%	93.00%	98.61%	93.01%
MDTA	86.19%	86.50%	83.00%	98.09%	91.93%

The results revealed that MLCTA exhibited superior performance with an accuracy of 96.19%, sensitivity of 96.50%, and an F1 score of 97.87%. These high metrics are indicative of MLCTA's robustness in handling multi-level classifications and its rule-based nature, which allows for granular and tailored analysis.

The Decision Tree algorithm followed with competitive precision (99.04%) and a commendable F1 score of 95.39%, underscoring its capacity to manage complex relationships in the data effectively. However, it showed lower sensitivity and specificity, which might be attributed to potential overfitting or the lack of handling noisy data.

The Dynamic Threshold method demonstrated balanced performance, notably matching the MLCTA in specificity (91.00%). This balance underscores its potential to adapt well to patient data trends, though it may not capture acute anomalies as effectively as MLCTA.

OCSVM specialised in outlier detection; however, it scored lower in sensitivity and accuracy, reflecting a potential trade-off in detecting normal behaviour versus outliers. Its higher specificity (93.00%) suggests a strong ability to identify true negatives.

Lastly, MDTA showed the lowest scores across most metrics but maintained high precision (98.09%). This might be due to its reliance on the assumption of a multivariate normal distribution, which may not always align with real-world medical data characteristics.

The bar chart in Figure 3.25 highlights varying algorithm performances on key metrics. Accuracy spans a wide range, with MLCTA outperforming others, suggesting its robustness in correctly identifying true positives and negatives. In contrast, precision is comparably uniform across algorithms, indicating a consensus on the true positive rate. Sensitivity varies, with MLCTA and the Decision Tree demonstrating heightened ability to detect true positives. Specificity sees OCSVM excel, pointing to its strength in confirming true negatives. The F1 score consolidates these insights, with MLCTA leading, exemplifying its balanced precision and sensitivity.

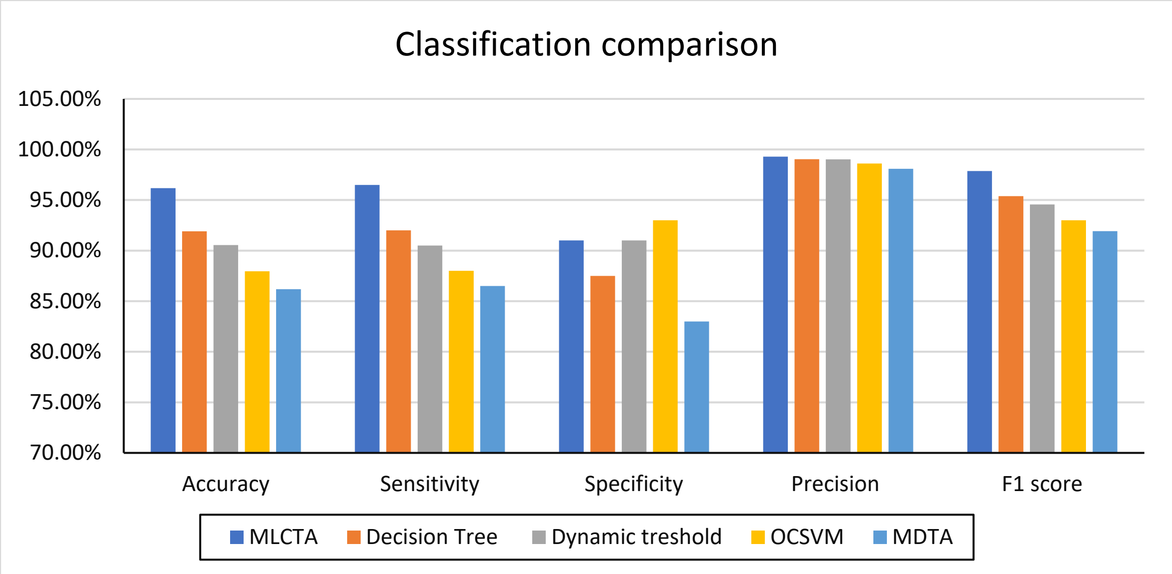


Figure 3. 25: Evaluation of performance by all algorithms.

The experimental output is derived from the data listed in Table 3.13 and illustrated in Bar Chart 3.25. The overarching aim here is to use this data to make informed decisions concerning edge devices. Keep in mind that this scenario requires consideration of additional variables, primarily computational complexity. Computational complexity [199, 200] can substantially dictate the efficiency of the system model in an edge device environment, which is typically resource-limited and where efficiency is vitally important. Dealing with such complexities calls for the use of theory and presumptions. A matrix simplifies comprehension of the system model's behaviour under various conditions. The elements of this matrix receive rankings according to their potential impact on the system's overall performance. The ranking offers a clear hierarchy of factors, each graphically demonstrating their influence, supporting effective strategic tailoring to optimise system performance.

Let's assume there are n data points (patients), each with m features (vital signs), and the focus is on evaluating the complexity of classifying a new data point using each algorithm. Two primary measures to evaluate computational complexity are time complexity (Big O notation) and space complexity (Big O notation). Table 3.14 provides an overview of the computational complexity. Let's presume an order for time and space complexity, along with the rationale for it.

Table 3. 14Table 3.14: Computational complexity assumptions

Rank	Algorithm	Classification Complexity	Training Complexity	Execution Time	Space Complexity	Reasoning
1	MLCTA	$O_{(n)}$	Not Applicable	Fastest	Least	No training phase; simple rule application; and minimal space for rules.
2	Dynamic Threshold	$O_{(n)}$	Not Applicable	Faster	Moderate	No training phase; quick due to incremental updates; moderate space for thresholds.
3	Decision Tree	$O(m.n.\log(n)$	$O(m.n.\log(n$	Moderate to Fast	Moderate	Requires construction of the tree; balanced trees offer better execution efficiency.
4	OCSVM	$O(m.sv)$	$O_{(\mathrm{n}^2)}\ to\ O_{(\mathrm{n}^3}$	Moderate	Moderate to Most	Training involves complex quadratic programming; and storage for support vectors.
5	MDTA	$O_{(m^3)}$	$O_{(m^3)}$	Longest	Most	Intensive matrix operations both in training and classification; substantial space is needed.

It's clear now that MLCTA is the most efficient with respect to both execution time and space complexity. It delivers the quickest execution, making it a prime choice for real-time processing in systems with limited resources, such as WBANs. The dynamic threshold is a close second, providing a good compromise between efficiency and performance. Although the decision tree, OCSVM, and MDTA are indeed effective, they show relatively higher computational complexities. This makes them more appropriate in situations where there is less concern about computational resource constraints.

3.7 Hybrid Approach for Anomaly Detection

In the context of WBANs, where resources such as processing power and energy are constrained, the integration of multiple techniques, such as threshold-based algorithms, machine learning models, and statistical methods, offers a comprehensive solution. These hybrid approaches allow for real-time processing of vital sign data directly at the edge devices, minimising the need for data transmission to central servers and reducing latency. Moreover, they enhance the system's adaptability to varying patient conditions, accommodating both routine monitoring and early detection of anomalies. By combining the strengths of different algorithms, hybrid approaches deliver accurate and context-aware results, ensuring that critical health events are promptly identified while conserving computational resources. This approach optimises the trade-off between computational complexity and accuracy, making it well-suited for the resource-constrained environment of WBANs, ultimately improving the quality of healthcare services and patient outcomes.

The incorporation of linear regression [201] into the healthcare monitoring system represents a strategic enhancement designed to elevate the system's performance and decision-making capabilities. By leveraging linear regression, the system gains the capacity to detect subtle yet crucial trends and deviations in patient vital sign data, thereby significantly improving sensitivity. This enhancement allows for risk stratification, enabling the system to differentiate between low-risk and high-risk patients based on their unique vital sign profiles. Personalised care becomes attainable through patient-specific models and optimising healthcare interventions and treatment plans. Moreover, the inclusion of linear regression contributes to a reduction in false alarms by considering the context and trends in vital sign data, leading to more precise alerts. This precision, in turn, facilitates the efficient allocation of healthcare resources, ensuring that interventions are directed toward patients in need. Lastly, linear regression offers valuable decision support by quantifying the impact of vital sign changes on patient outcomes, empowering clinicians with data-driven insights to enhance patient care decisions. In summary, the integration of linear regression enhances the healthcare monitoring system's ability to detect and respond to vital sign variations, ultimately yielding improved patient outcomes and resource utilisation. Figure 3.26 presents our proposed system model composed of five sensors that measure vital signs such as oxygen saturation (SpO2), body temperature, blood pressure, respiration rate, and heart rate/pulse. This system primarily employs various methods, particularly threshold methods, to identify emergency events in the incoming sensor data. Upon detection of an emergency, we use a continuously updated regression prediction model to analyse the abnormal instance and determine whether the patient is nearing a critical state or if a sensor is presenting incorrect data. For this experiment, we utilised similar data.

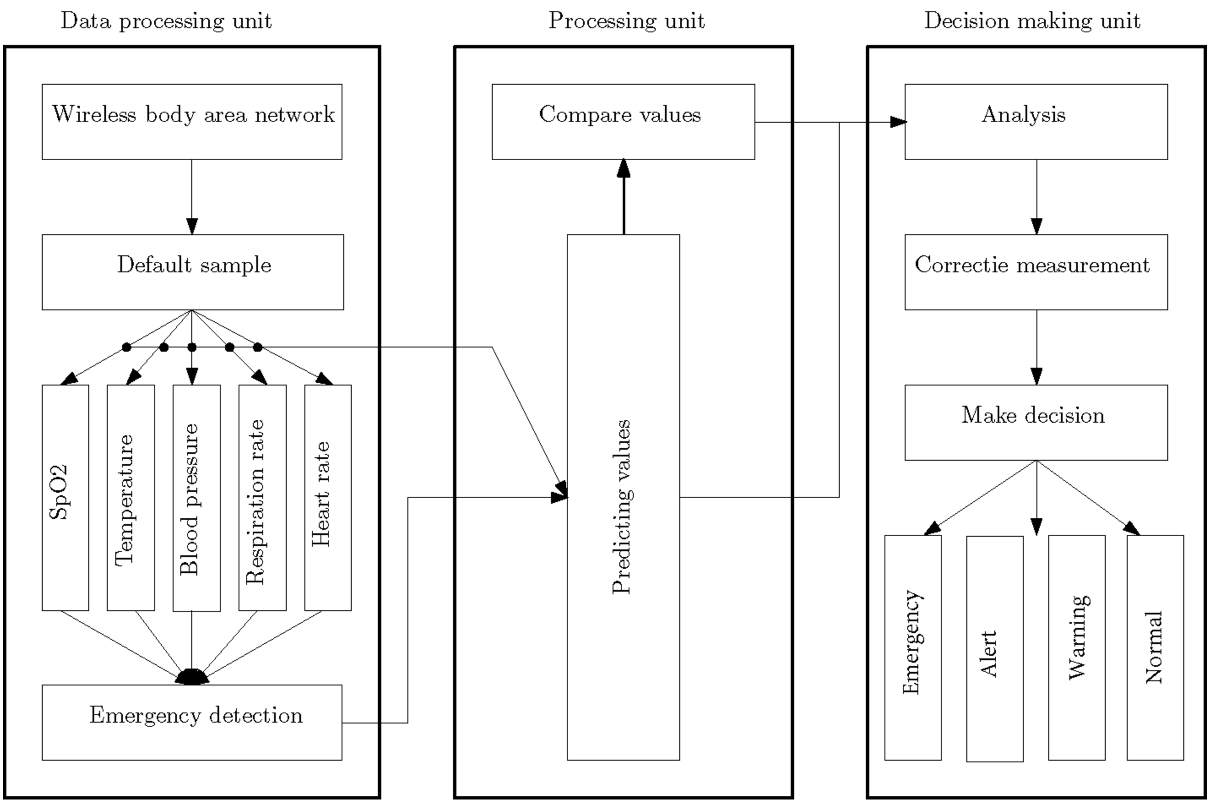


Figure 3. 26: Block diagram of the proposed hybrid system

Given the array of sensors $S = [S_i | i = 1,2,3, \dots, n]$ the proposed WBAN system, each sensor S_i records a series of data points d_{ij} over time. It aims to predict the current value of a specific sensor reading using a linear regression model that exploits the spatial correlation among different sensor readings. The model for predicting the value of a particular attribute (sensor reading) at the j^th instance for the i^th sensor is formulated as:

$$\hat{d}_{ij} = a_0 + a_1 d_{1j} + a_2 d_{2j} + \cdots + a_n d_{nj}$$

where,

- $\hat{d}_{ij}$ is the predicted value for sensor S_i at instance j
- $a_{0,} a_1, a_2 \dots \dots . . a_n$ are the coefficients of the regression model (weights), representing the influence of each sensor's readings.
- The coefficients a_k for each sensor S_k are obtained during the training phase and are calculated as:

$$a_k = \frac{\sum(d_{ki} - \bar{A}_k)(d_{ij} - \bar{A}_\iota)}{\sum(d_{ki} - \overline{A_k})^2}$$

Where,

- $\bar{A}_k$ and $\bar{A}_i$ are the average values of the attributes for sensors S_k and S_i respectively.
- The numerator is the covariance of sensor readings S_k and S_i and the denominator is the variance of sensor S_k

Once the model is computed from the training data, it is used to predict the value of each attribute $\hat{d}_{ij}$ at instance j. Afterward, the predicted value $\hat{d}_{ij}$ is compared with the actual value d_{ij} to determine if it falls within a small margin of error. This comparison helps classify the readings as normal or abnormal, which is crucial for monitoring health status and detecting anomalies in the WBAN system.

The run times for the threshold method and linear regression are less than those of other algorithms [202]. Threshold algorithms are employed to identify abnormalities, while linear regression is used to estimate current values, which can then be compared to the real values. The proposed system that utilises linear regression for detecting anomalies is represented in Algorithm 2.

Algorithm 2 Emergency detection using Hybrid approach (Hybrid)

```
Input: A set of patient vital sign data
Output: A classification result indicating a status
Procedure: Predictor ()
begin
Threshold(value, lower_threshold, upper_threshold):
   return value < lower_threshold OR value > upper_threshold
Classify(sensor_data):
   emergency_vital_signs = empty_list()
   for i in range(1, num_vital_signs + 1):
      value = sensor_data[i]
      lower_threshold = getLower(i)
      upper_threshold = getUpper(i)
      if Threshold(value, lower_threshold, upper_threshold):
         append_to_list(emergency_vital_signs, i)
      end if
   end for
   if length(emergency_vital_signs) > 0:
      return {"status": "Emergency", "vital_signs": emergency_vital_signs}
   else:
      return {"status": "Normal", "vital_signs": empty_list()}
   end if
LinearR(sensor_data, coefficients, intercept):
   selected_sensors = [sensor_data[i] for i in range(1, num_selected_sensors + 1)]
   predicted_value = 0
   for i in range(1, num_selected_sensors + 1):
      predicted_value += coefficients[i] * selected_sensors[i]
   end for
   predicted_value += intercept
   return predicted_value
Monitor(patient_data):
   sensor_data = patient_data
   threshold_result = Classify(sensor_data)
   if threshold_result["status"] == "Emergency":
      coefficients = [0, coefficient_heart_rate, coefficient_blood_pressure,
coefficient_respiratory_rate, coefficient_temperature, coefficient_oxygen_saturation,
coefficient_pulse]
      intercept = trained_intercept
      linear_regression_result = LinearR(sensor_data, coefficients, intercept)
      linear_regression_threshold = 0.0
      if linear_regression_result >= linear_regression_threshold:
         # Perform actions for Emergency (Using Linear Regression)
      else:
         # Perform actions for Normal (Using Linear Regression)
      end if
   else:
      # Perform actions for Normal (Threshold Algorithm)
   end if
end
```

Figure 3.27 displays the alarms as red vertical lines, with various vital signs each represented in a distinct colour. A legend for these colours is placed in the top corner.

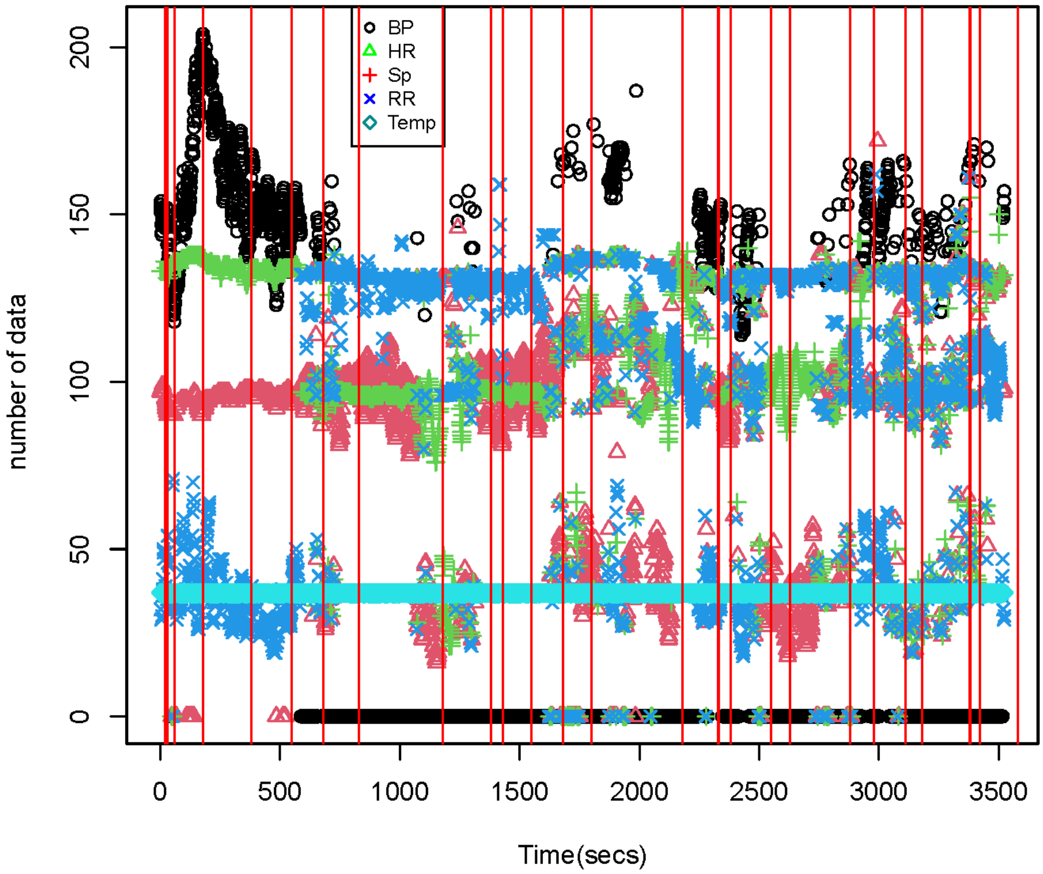


Figure 3. 27: Raised alarms for proposed Threshold approach (all physiological signs)

Salem et al. [104] improved the detection rate by employing SVM and logistic regression. They used almost identical physiological parameters for their study as those used in the proposed optimised early detection algorithm. The authors referred to their methodology as the 'Detection algorithm,' which is the term used for their approach throughout the remaining sections of the paper. The Salem algorithm, demonstrated in the system model, was tested and found to perform almost similarly to the threshold algorithm, as shown in Figure 3.28.

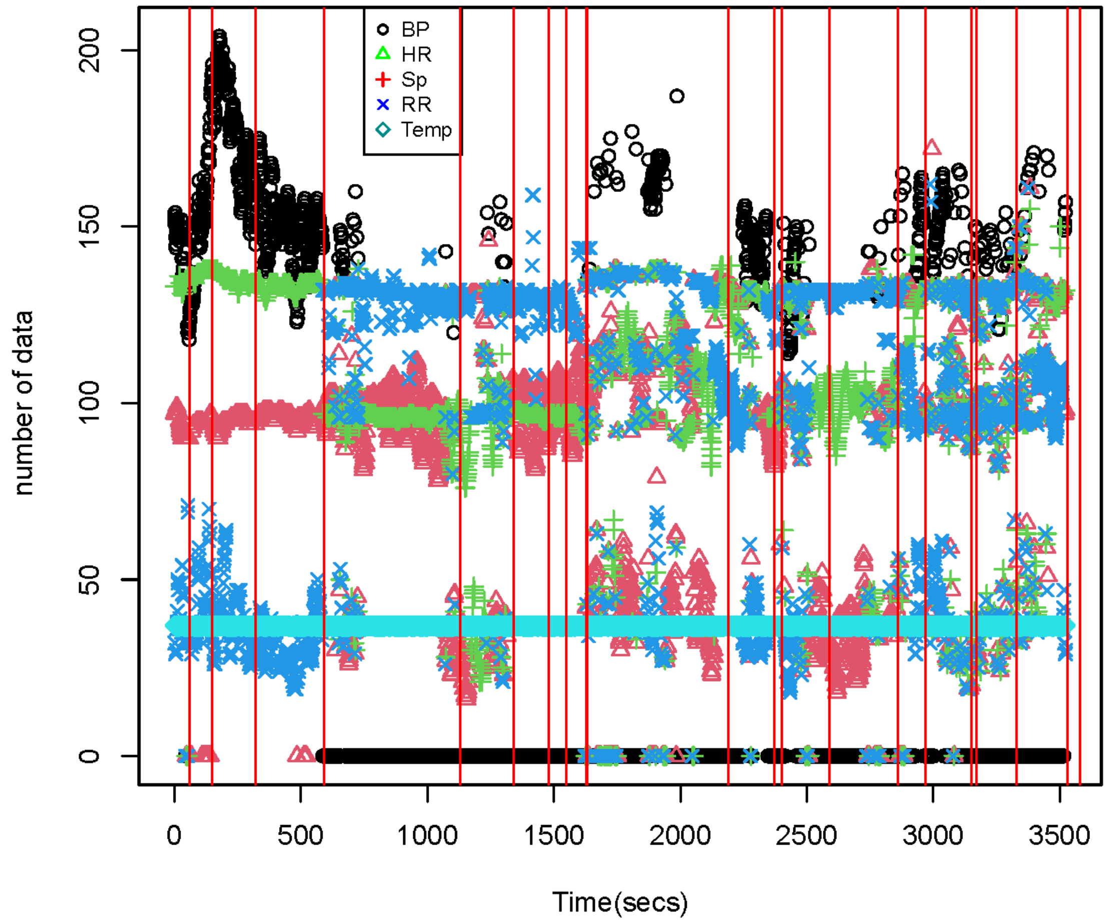


Figure 3. 28: Raised alarms for proposed Detection algorithm [104]

Kumar et al. [114] introduced a method of anomaly detection that makes use of all physiological signs to better identify abnormal data. This method was named the 'Anomaly Detection Algorithm' and is mentioned consistently throughout the remainder of the section. In addition to the algorithms proposed, Salem's [104] and Kumar's [118] methods are also analysed through experimental evaluation of classification.

Table 3.15 presents a comprehensive comparison of various algorithms in terms of their performance metrics in the proposed model. The MLCTA using the threshold rule-based algorithm demonstrates superior performance with an accuracy of 96.19%, a high sensitivity of 96.50%, and an impressive precision rate of 99.29%, leading to an F1 score of 97.87%.

Despite its relatively higher false positive rate (FPR) of 9.00%, it outperforms other algorithms in accuracy and sensitivity. The decision tree algorithm shows commendable results with an accuracy of 91.91% and a slightly higher FPR of 12.50%, suggesting a trade-off between specificity and sensitivity. The dynamic threshold approach that used a moving average method with an accuracy of 90.55% and an FPR equal to MLCTA offers balanced sensitivity and specificity, both at 90.50% and 91.00%, respectively, indicating its effectiveness in distinguishing between normal and abnormal readings. The OCSVM algorithm, while having the lowest accuracy at 87.96%, exhibits the best specificity of 93.00% and the lowest FPR of 7.00%, making it particularly useful in reducing false alarms. Lastly, the MDTA shows the least favourable performance with an accuracy of 86.19% and the highest FPR of 17.00%, which might limit its applicability in scenarios where false positives are a critical concern. This comparative analysis underscores the importance of selecting the appropriate algorithm for WBAN systems based on the specific requirements of accuracy, sensitivity, specificity, and the acceptable level of false positive rates.

Table 3. 15: Performance comparison for all algorithms

Method	Accuracy	Sensitivity	Specificity	Precision	F1 score	FPR
MLCTA	96.19%	96.50%	91.00%	99.29%	97.87%	9.00%
Dynamic Threshold	90.55%	90.50%	91.00%	99.03%	94.57%	9.00%
Decision Tree	91.91%	92.00%	87.50%	99.04%	95.39%	12.50%
OCSVM	87.96%	88.00%	93.00%	98.61%	93.01%	7.00%
Hybrid (linear)	91.15%	92.45%	90.05%	99.56%	95.60%	8.00%
Detection [104]	89.64%	91.30%	90.10%	96.50%	94.60%	10.60%
Anomaly [114]	89.90%	90.80%	89.60%	97.80%	94.20%	11.50%

Based on the provided performance metrics, every technique is ranked from 1 to 7, where 1 indicates the best score and 7 signifies the least favourable one. Marks are given out, with 7 points handed to the top scorer and 1 point to the one with the lowest score, and then these points are combined to establish the overall ranking. Here's how the adjusted calculation looks. For every metric, marks will be distributed according to rank (7 points for the leader, 6 points for the second position, and so on). After this, the points for each technique get accumulated to provide the ultimate score. Since a lower FPR is considered superior, the ranking for FPR will be reversed.

Figure 3.29 presents a bar chart illustrating the classification accuracy of several anomaly detection methods. The vertical axis represents the accuracy as a percentage, clearly quantifying the effectiveness of each method in correctly classifying instances.

The 'MLCTA' method outperforms others with an impressive accuracy of 96.19%, indicating its superior capability in this context. Following are the 'dynamic threshold' and 'decision tree' methods with accuracies of 90.55% and 91.91%, respectively, showcasing robust performances. The 'OCSVM' method exhibits a slightly lower accuracy of 87.96%, which could suggest a need for further optimisation when applied to the same dataset.

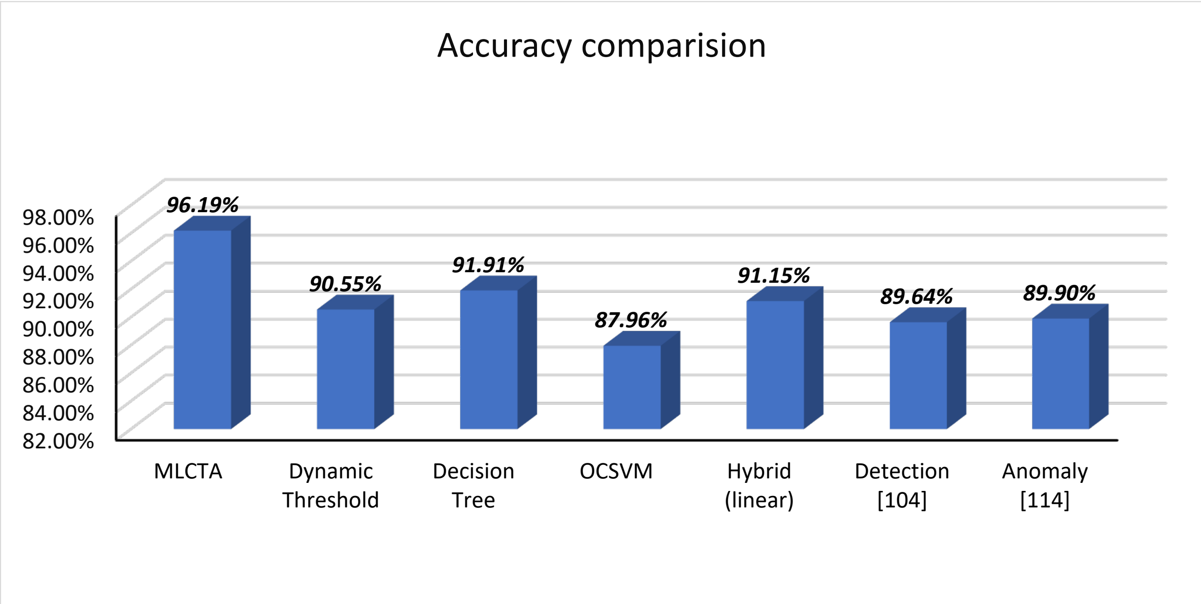


Figure 3. 29: Accuracy comparison by all methods

The 'hybrid (linear)' method, which likely combines linear regression with other classification techniques, achieves an accuracy of 91.15%, signifying a competitive and effective approach. Lastly, the methods labelled 'Detection [104]' and 'Anomaly [114]' have accuracies of 89.64% and 89.90%, respectively. These may refer to specific models or techniques referenced in the study and demonstrate commendable accuracy, albeit slightly lower than the leading methods.

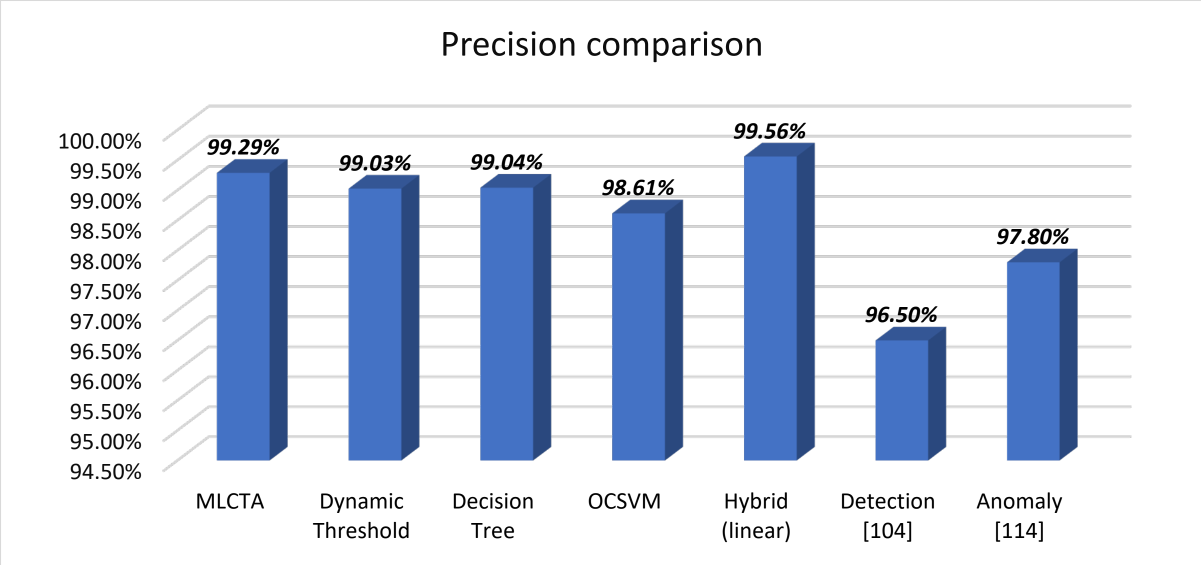


Figure 3. 30: Precision Across Methods

Figure 3.30 displays a concise comparison of the precision achieved by various classification methods. Hybrid (linear) leads with the highest precision at 99.56%, followed closely by MLCTA at 99.29%. The methods exhibit high precision across the board, indicating a strong positive predictive value in their respective classifications.

Figure 3.31 shows the FPR for each method, where lower values are indicative of fewer false alarms. OCSVM has the lowest FPR at 7.00%, suggesting it is the most conservative in terms of incorrectly labelling negative instances as positive. Decision Tree has the highest FPR at 12.50%, pointing to a higher rate of false positives in its classification process.

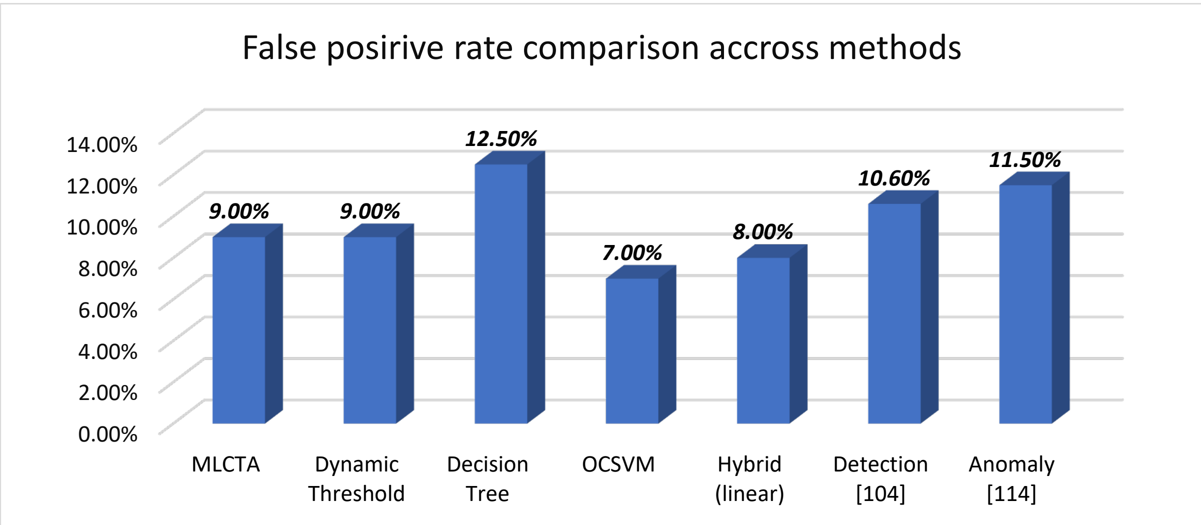


Figure 3. 31: Figure 3.26: False Positive Rate (FPR) Across Methods

Based on the provided performance metrics, every technique is ranked from 1 to 7, where 1 indicates the best score and 7 signifies the least favourable one. Marks are given out, with 7 points handed to the top scorer and 1 point to the one with the lowest score. These points are then combined to establish the overall ranking. Here's how the adjusted calculation looks. For every metric, marks will be distributed according to rank (7 points for the leader, 6 points for the second position, and so on). After this, the points for each technique get accumulated to provide the ultimate score. Since a lower FPR is considered superior, the ranking for FPR will be reversed.

Based on the performance metrics analysed on table 3.16, the MLCTA has demonstrated the most robust performance, leading the table with the highest total score. This reflects its superior accuracy and sensitivity, as well as excellent F1 scores, indicating its effectiveness in a WBAN context. The hybrid (linear) model also shows strong performance, particularly excelling in precision, which suggests its potential for delivering highly accurate predictions when it comes to continuous monitoring.

Table 3. 16: Comparative Performance Analysis of Predictive Models

Method	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**F1 Score**	**FPR**	**Total Score**
MLCTA	7	7	4	6	7	3	***34***
Hybrid (Linear)	4	4	3	7	5	5	***28***
Dynamic Threshold	5	5	5	5	3	4	***27***
Decision Tree	6	6	1	4	4	1	***22***
OCSVM	1	1	7	2	1	6	***18***
Anomaly [114]	3	2	2	3	6	1	***17***
Detection [104]	2	3	6	1	2	2	***16***

The dynamic threshold method presents a balanced performance across the board, indicating its reliability and adaptability in various scenarios within the WBAN framework. On the other hand, the Decision Tree method, while demonstrating good accuracy and sensitivity, falls short in specificity, which may limit its application in environments where false positives are a concern.

OCSVM, although it ranks lowest in accuracy and sensitivity, stands out in specificity, suggesting its utility in scenarios where the correct rejection of non-events is crucial. The anomaly [114] and detection [104] methods follow closely, with moderate scores across the metrics. However, they seem to struggle in certain areas, such as precision and the F1 score for detection [104] and sensitivity for anomaly [114].

The ranking methodology, which inversely correlates the FPR to the scoring, highlights the importance of not only correctly identifying true health events but also minimising false alarms, which is critical in patient monitoring systems.

Figure 3.32 displays the ROC curve for MLCTA. The ROC curve is depicted to illustrate the correlation between TPR, or sensitivity, and FPR, with TPR plotted along the Y-axis and FPR represented on the X-axis.

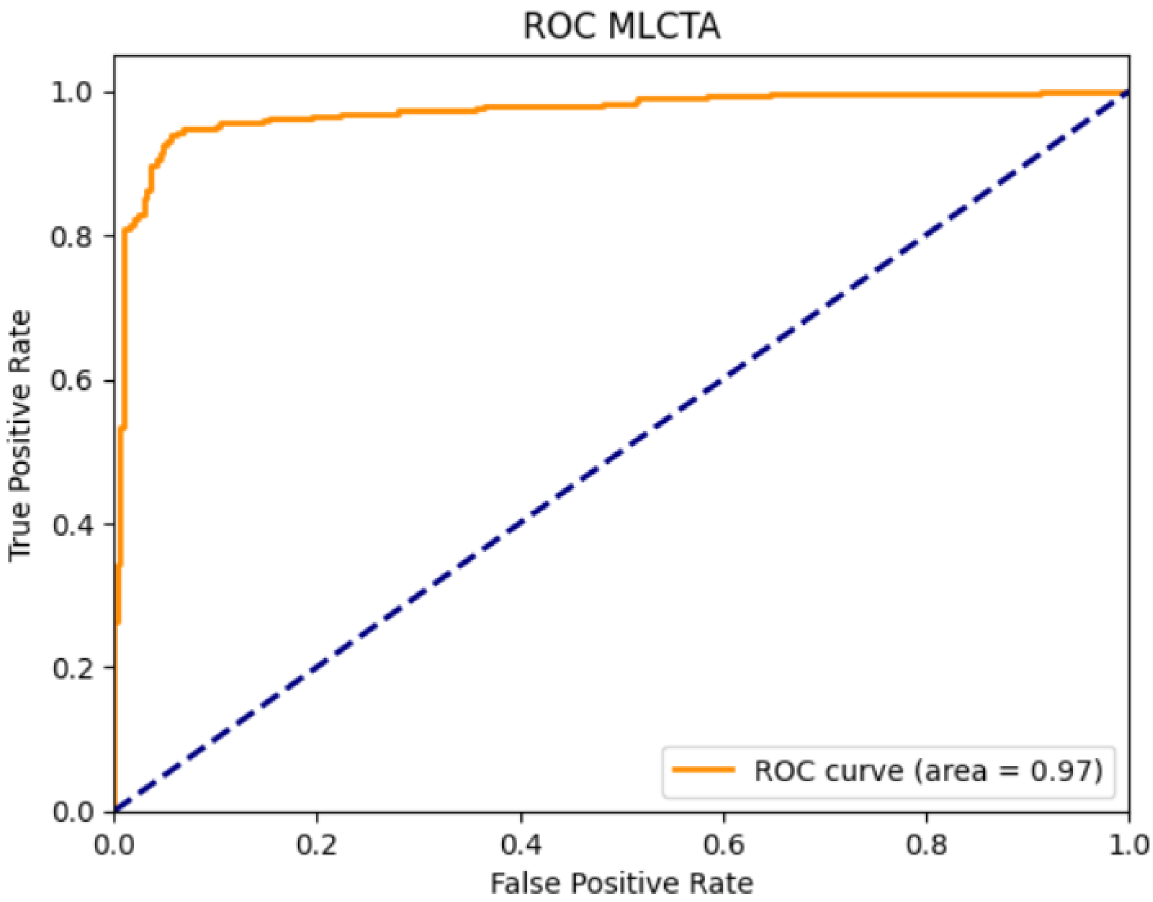


Figure 3. 32: ROC curve for MLCTA

The AUC is a measure of the algorithm's ability to correctly classify the health states as 'normal' or 'critical'. With an AUC of 97%, the MLCTA model demonstrates outstanding performance, indicating a high degree of separability between the health states.

This high AUC value suggests that the MLCTA has a high likelihood of correctly distinguishing between different health conditions, making it an excellent tool for predictive analysis in WBAN systems. The ROC curve's steep ascent and plateau near the top-left corner of the graph signify that the MLCTA achieves high sensitivity without a correspondingly high rate of false positives, which is crucial in medical applications where the cost of a false alarm can be high.

3.8 Summary

The exploration of predictive models within WBANs has culminated in pivotal findings. The performance analysis of a suite of algorithms—including the novel Multi-Level Classification Threshold Algorithm (MLCTA), Dynamic Threshold, Decision Tree, OCSVM, and a novel hybrid linear regression model—has illuminated their respective capabilities and limitations in the nuanced domain of health monitoring.

The MLCTA emerges as a standout with its innovative approach to multi-level classification, showcasing an impressive amalgamation of accuracy and precision. However, its rigidity and a one-size-fits-all thresholding strategy may not fully capture the dynamic and individual variability present in physiological data streams. The novel hybrid model, which synergizes linear regression with threshold-based classification, boasts commendable precision, yet its reliance on linear relationships may curtail its predictive fidelity amidst the complex physiological interplays.

While decision trees and OCSVM each offer distinctive advantages in contending with non-linearities and enhancing specificity, there is an explicit and critical need for more adaptive and patient-centric models. The compatibility of these models with the computational restrictions of edge devices in WBANs also warrants meticulous attention.

The aspiration to refine the MLCTA is propelled by the intent to evolve this robust framework into a more adaptable and personalised health monitoring tool. The forthcoming chapter introduces a novel iteration of the MLCTA, integrated with an innovative pain assessment and escalation mechanism. This advancement seeks to transcend the MLCTA's current constraints by embedding individualised thresholds and real-time adaptability into its structure.

The integration of such a groundbreaking tool aims to elevate the WBAN's acuity in detecting and responding to acute pain manifestations, thereby augmenting patient care and outcomes. By tailoring the MLCTA to encompass subjective pain assessments, the model is poised to transform into a more empathic and precise conduit for patient care, echoing the ethos of personalised medicine.

Energy consumption plays a crucial role in such a WBAN environment, particularly at the edge, where the choice of algorithms is keenly scrutinised for their appropriateness. The subsequent chapter delves further into the appropriation of real clinical scenarios, incorporating a pain assessment and escalation tool to enhance its integration into the clinical setting. Additionally, the chapter investigates adaptive sampling methodologies for data reduction. This approach aims to diminish the volume of data transmitted to the cloud, thereby conserving more energy and enhancing the longevity of the system.

Chapter 4

4. Local Emergency Detections Enhancement

4.1 Introduction

In WBANs, a critical concern for most healthcare applications is managing power consumption to keep the system operational. The primary purpose of these systems is to safeguard patient health, making energy conservation indispensable for maintaining system longevity as much as possible. Concurrently, it's vitally important that the proposed solutions are clinically justified. Various strategies to conserve energy for WBANs in healthcare applications have been discussed in the academic literature. The core strategies identified include optimising radio utilisation, reducing data, implementing sleep/wake routines, utilising energy-efficient routing, and managing battery depletion. Adaptive sampling [31, 140–148] is highlighted as one of the most viable data reduction techniques for preserving energy. Numerous related works featuring these strategies have been reviewed. In WBAN healthcare applications, the sampling rate is a crucial element to manipulate based on the severity of a patient's condition. Since a patient's health can fluctuate rapidly, the sampling rate needs to be adjusted accordingly to respond to potential changes efficiently. Patient vital signs can shift from normal to emergency conditions. The speed of these changes can be either very fast or slow, depending on the specific circumstances of the patient's condition.

In practical medicine, there is a standard range for physiological signs, which can vary due to various factors, including demographic and geographic differences. Utilising these established ranges, a widely used scoring system in medical practice, known as the EWS [191], has been developed. Leveraging this scoring system and its associated ranges, there is a proposal to develop a pain assessment tool and an escalation process. These are intended to be incorporated into the MLCTA (algorithm 1.D from chapter 3.6) for modification to better adapt it to clinical condition

Vigilant patient monitoring is essential for healthcare professionals to evaluate the health status of patients, particularly in areas like the intensive care unit where individuals are battling potentially life-threatening conditions. In such settings, continuous and detailed observation of physiological signs using a variety of medical instruments, coupled with professional expertise, allows an immediate response to any changes in a patient's health. However, a significant reduction in this thorough monitoring is observed when patients are transferred from these high-intensity areas, such as intensive care or operating theatres, to a more conventional ward. In this setting, the monitoring of health parameters is less frequent and covers fewer aspects due to an increased ratio of patients to healthcare professionals. Key health evaluations, like those carried out by a nurse every six hours, may not detect deterioration that occurs between these checks. Diseases such as sepsis, which remains a leading cause of death in hospitals and can progress unpredictably, concealing early signs, require rapid detection. Swift diagnosis and effective management of these conditions greatly improve the chances of favourable patient outcomes. A global research project was carried out in 2011 to analyse postoperative death rates among patients who had non-cardiac surgery. The research gathered information from around 500 hospitals in 30 European countries. A total of 46,000+ patients participated in this study. The findings indicated that out of these 1864, around 4% of patients died during their hospital stay. Interestingly, it was found that around 70%+ patients who died never received critical care at any point post-surgery." Moreover, around 44% of patients who died after being admitted to critical care passed away after being relocated from the critical care unit to a regular ward [210].

4.2 Related Works

Churpek et al. (210) carried out a research project in which they analysed the effectiveness of various machine learning techniques against a modified early warning score (MEWS) to forecast possible patient decline within hospital medical-surgical units. They found that the respiratory rate and heart rate were the most crucial predictive factors for the random forest model.

In the context of diminished direct supervision during the night, medical trainees are necessary to accurately judge patients potentially facing clinical instability and bring matters to the attention of supervising practitioners. Negligence in escalating such situations contributes to unfavourable patient safety occurrences [205]. The paper discovered that the implementation of the EoC protocol standardised resident escalation during unsupervised periods, enhancing the perception of patient safety from the residents' perspective and increasing confidence among interns to escalate. Faye et al. [203] Faye and her team conducted a study using a method to assess heart rate variability in infants experiencing chronic pain. They separated these infants into groups of low and high pain. This study explored the correlation between chronic pain and various cardiovascular data using average heart rate, respiration rate, and blood oxygen saturation, as well as the high-frequency variability index. The investigation highlighted notable differences in heart rate variability between the two groups, while other vital signs remained steady. The study suggested that the high-frequency variability index could be a reliable tool to measure pain, demonstrating a high level of sensitivity and specificity. Though correlations between changes in vital signs and pain have been reported, fluctuations in these signs can also be linked to non-pain emotions (like hunger or fear) or an underlying illness [204]. Clinical escalation protocols and rapid response systems (RRS) are designed to mitigate the "failure to rescue" rates in deteriorating hospitalized patients, either due to their medical condition or a treatment complication. The objective is to discern physiological anomalies (the afferent arm) and activate an effective response (the efferent arm), which could include the patient’s primary carers, nurse practitioners, or a specialised rapid response team. Escalation protocols use electronic observation systems to implement a specific healthcare strategy. This mechanism prompts automatic escalations for less experienced doctors and certain medical teams based on a predetermined scale. The introduction of this health strategy led to an increase in escalations, significantly adding to the time needed for review and management monthly. The volume of patients escalated within a day has doubled per month, with a noticeable rise in patients escalated multiple times in a single day. [206]. Lastly, Hugo et al.'s [209] study exhibits a limitation, as the moving average filter-based algorithm might fail to identify an emergency if the time-monitoring window does not capture a variation.

'Neill et. al. [213] identified a range of obstacles and enablers to the increase in care according to the EWS protocols. The primary challenges consist of inconsistencies, shortage of resources, absence of responsibility, behaviours of the Rapid Response Team (RRT), apprehension, organisational hierarchy, heightened conflict, overconfidence, lack of confidence, and patient variability. The key drivers, on the other hand, encompass responsibility, uniformity, availability of resources, behaviours of RRT, expertise, supplemental assistance, permission to escalate care, ability to cross barriers, and clinical experience.

In the context of the obstacles and enablers to care escalation as delineated by Neill et al. [213], the development of a WBAN system with an integrated predictive model has the potential to significantly mitigate many of the identified challenges within healthcare settings. By providing consistent and accurate monitoring of patient vitals, such a system addresses the inconsistency issue and optimises the use of scarce healthcare resources.

The predictive nature of the WBAN model is designed to reinforce responsibility across healthcare teams by offering clear indicators for patient status, which can reduce ambiguity and foster decisive action. This is particularly beneficial in scenarios that involve the Rapid Response Team (RRT), where the timely and precise data provided by the WBAN system can inform and expedite appropriate interventions.

Moreover, the predictive model within the WBAN system can contribute to reducing apprehension among healthcare providers by offering objective data that supports clinical decisions, thus helping to navigate the complexities of organisational hierarchies and interprofessional dynamics. It can also diminish conflict and the paradox of overconfidence or lack of confidence by providing a reliable basis for escalating care.

The WBAN model's utility extends to facilitating the escalation of care by empowering clinicians with real-time data and trend analysis, which are critical in high-stakes environments where the ability to act swiftly can have profound implications for patient outcomes. The system's design allows it to integrate seamlessly into the workflow, aiding in overcoming barriers to care and enhancing the overall capacity for clinical response.

By capitalising on these strengths, the WBAN system, with its predictive analytics capability, emerges as a key driver in healthcare, aligning with the enablers of care escalation. It underscores the importance of leveraging technology to augment clinical expertise, streamline the escalation process, and ultimately contribute to the delivery of high-quality, responsive patient care.

4.3 Early Emergency Detection

The same WBAN model is examined, wherein a Modified Adaptive Local Emergency Detection (MALED) algorithm is proposed to enhance the precision of local emergency detection and inform clinical decisions. The recommended model, as demonstrated in Figure 4.1, consists of five sensors to measure key vital signs: oxygen saturation, body temperature, blood pressure, respiration rate, and heart rate. It is composed of three units: a data processing unit, an early warning scoring unit, and a decision-making unit.

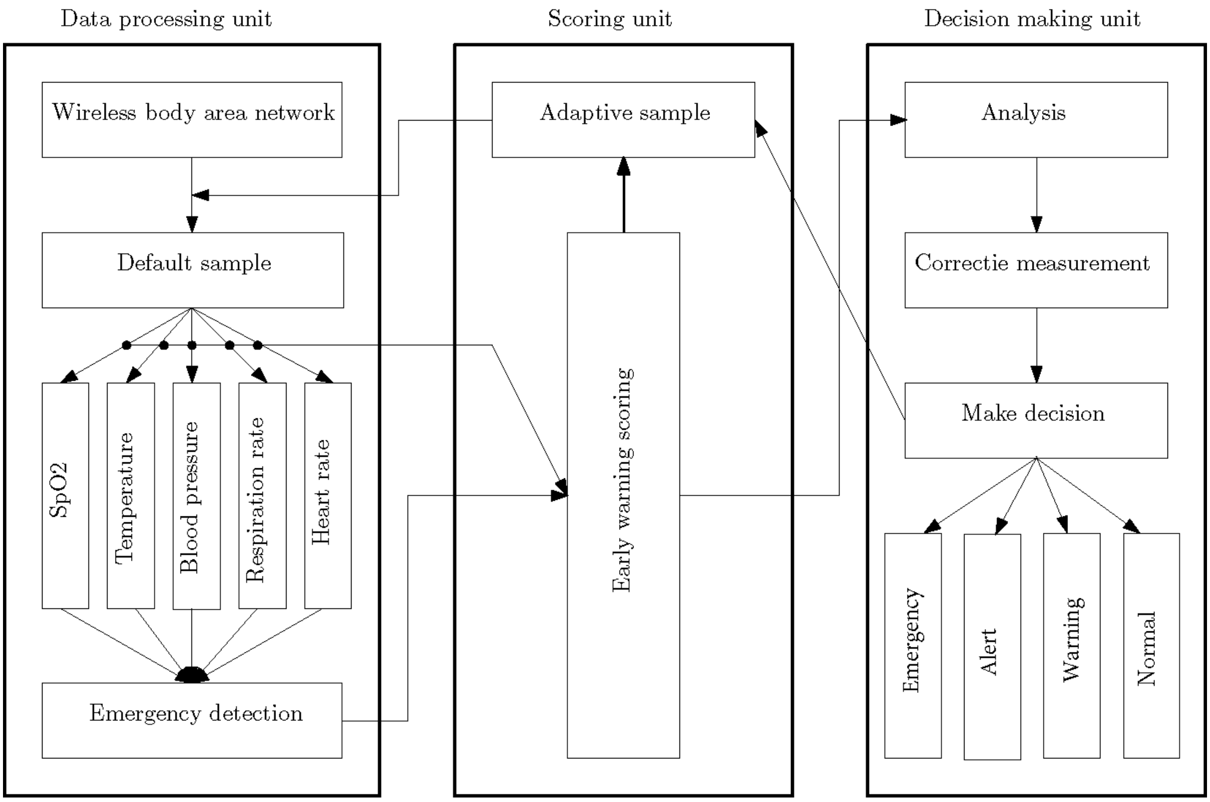


Figure 4. 1: Block diagram of proposed system model for MALED

The sensors begin recording at their maximum sampling rates, which eventually adapt to system dynamics. An initial emergency is expected to be detected through sensor samples based on predefined healthy vital sign ranges. Various local emergency detection methods have been adopted to provide early alarms in this system model.

Information is sent to the scoring unit once an emergency is detected. This unit then forwards the data to the decision-making unit for further analysis. An adaptive sampling request is sent to customise the sampling rate based on the assessment situation. The decision-making unit then analyses the emergency details, carrying out fault isolation before deciding between the states of severe, moderate, and normal. The proposed methods aim to assist, not replace, immediate human clinical attention.

It should be noted that a standard WBAN gathers sizable data amounts and sends them periodically to the coordinator. This period adjusts based on the patient's medical condition. However, concerns arise due to the volume of the data and the potential for an event to occur between samples. The main goal is to identify emergency data from routinely collected data, incorporating any additional emergency data from intervening periods. An 'emergency event' is defined by data differing from expected ranges, and it's vital to identify this 'emergency data' to determine patient risk levels and aid in clinical decision-making. There are multiple methods to detect these deviations, which is the focus of the experiments in this section. This approach not only aids emergency identification but also conserves power. Figure 4.2 presents a flow diagram illustrating the proposed system model for this experiment.

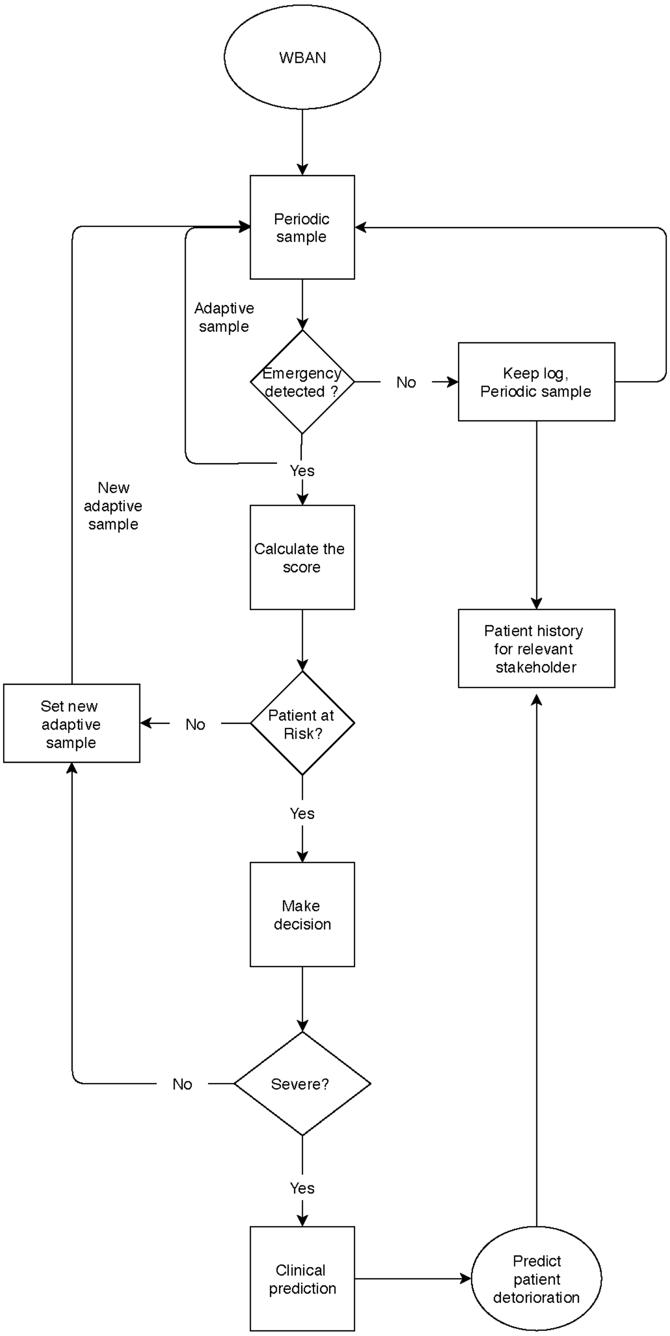


Figure 4. 2: Process flow of the work

4.3.1 Clinical Consideration- News and Pain Assessment Tool

To medically evaluate this experiment, the number of suggested studies was examined, and several complexities, including processing time, computational complexity, and cost, were taken into account. Despite these considerations, the perspective of medical practitioners remains the most critical. In this regard, the NEWS [191], a standard for evaluating the severity of acute illness in the NHS proposed by the Royal College of Physicians, plays a crucial role in many parts of this chapter.

The proposed Early Warning System (EWS), also known as NEWS, represents a practical approach frequently used in hospitals and pre-hospital care. It has four trigger levels, indicating the need for a clinical alert and necessitating a clinician's assessment based on the NEWS [191] scoring system:

- LOW score: a total score of 1-4
- A single red score: a score of 3 for any individual physiological parameters
- Medium score: a total score of 5–6
- High score: a total score of 7 or more

These trigger levels must be treated with urgency and require a clinical response, with expected actions as follows:

- A low NEWS score (1-4) necessitates a prompt assessment by medical staff, typically a registered nurse.
- A single red score (3 in a single parameter) is unusual and needs to be assessed by a doctor.
- A medium NEWS score (5–6) requires urgent assessment and a determination regarding the need for critical care.
- A high NEWS score (7 or above) necessitates immediate assessments and patient transfer to a high-dependency care area.

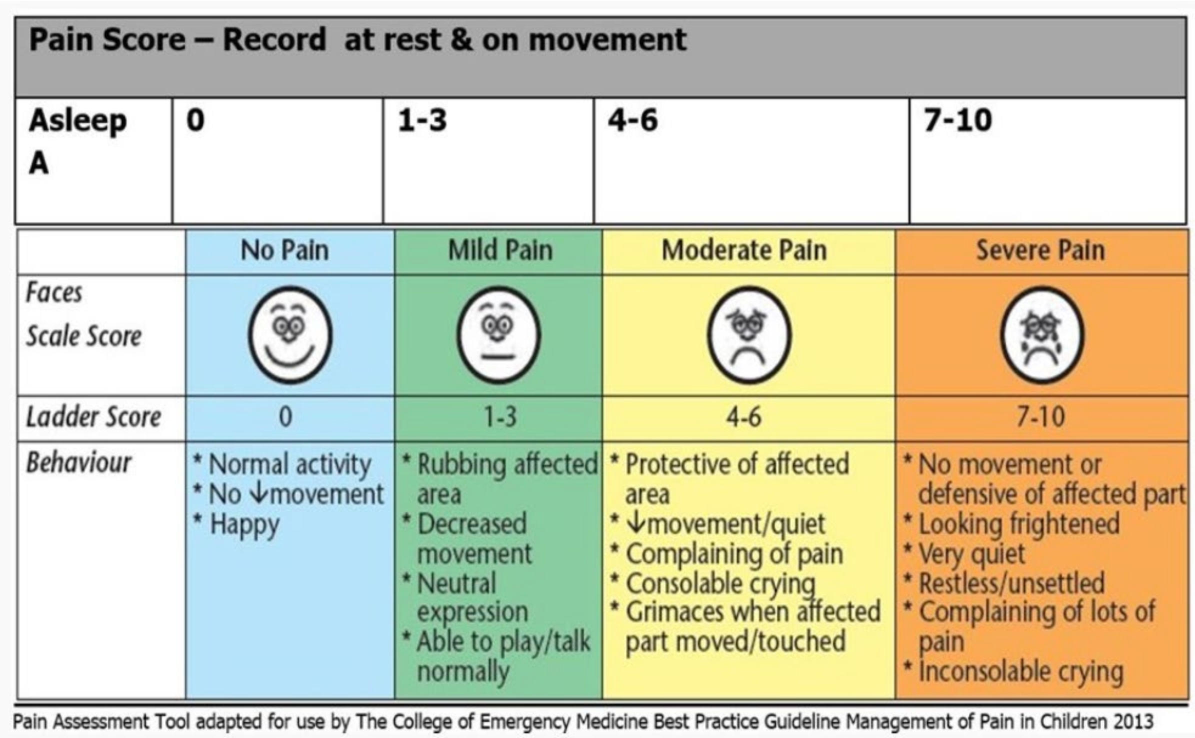
Figure 4.3 depicts the thresholds and trigger system of NEWS.

NEW score	Clinical risk	Response
Aggregate score 0–4	Low	Ward-based response
Red score Score of 3 in any individual parameter	Low–medium	Urgent ward-based response*
Aggregate score 5–6	Medium	Key threshold for urgent response*
Aggregate score 7 or more	High	Urgent or emergency response**

* Response by a clinician or team with competence in the assessment and treatment of acutely ill patients and in recognising when the escalation of care to a critical care team is appropriate.

**The response team must also include staff with critical care skills, including airway management.

Figure 4. 3: NEWS thresholds and triggers



Pain Score – Record at rest & on movement				
Asleep A	0	1-3	4-6	7-10

	No Pain	Mild Pain	Moderate Pain	Severe Pain
Faces Scale Score				
Ladder Score	0	1-3	4-6	7-10
Behaviour	* Normal activity * No ↓movement * Happy	* Rubbing affected area * Decreased movement * Neutral expression * Able to play/talk normally	* Protective of affected area * ↓movement/quiet * Complaining of pain * Consolable crying * Grimaces when affected part moved/touched	* No movement or defensive of affected part * Looking frightened * Very quiet * Restless/unsettled * Complaining of lots of pain * Inconsolable crying

Pain Assessment Tool adapted for use by The College of Emergency Medicine Best Practice Guideline Management of Pain in Children 2013

Figure 4. 4: Pain score [191]

4.3.2 Local Emergency Detection

Within this system, each sensor has a specified normal range, defined by a lower boundary γ_i^l and an upper boundary γ_i^u. If a sensor reading falls outside this normal range, it is identified as an urgent emergency signal. The system features an adjustable, event-driven sample time interval that regularly checks for any deterioration in a patient's condition. When such potential emergencies are indicated by vital sign readings, the NEWS algorithm is applied. The NEWS score, which is referred to as SC, sets its initial conditions at zero as $SC = 0 = SC_a$, otherwise known as SC_a (adaptive score). This adaptive score is designed to be particularly patient-specific, meaning it can dynamically adapt based on the patient's medical history and their current health status.

Let's say the tolerance range for the respiration rate is represented by ζ_{rr} , and for the heart rate, it is represented by ζ_{hr}. In the framework of the proposed method, a threshold algorithm is considered, and by leveraging NEWS, a tolerance range ζ_i is established. The following run is scheduled at a time ' t ', which is denoted as R_{nr} (Next Runtime). To improve the robustness of this setup, the Next Runtime can be made adaptable.

When the set time surpasses the Next Runtime, the proposed algorithm will initiate automatically. As the biosensor begins to perform its sensing functions, threshold methods are employed to check if the data falls within the tolerance range. If the sensor data is found outside this range, the NEWS system is invoked to compute the SC_i value. The system only transmits the sensed data if the calculated SC_i value exceeds the SC_a value. If not, the system turns to inspecting the respiration rate ζ_{rr} and heart rate ζ_{hr}. The Royal College of Physicians has noted and recommended that the most crucial physiological signs to be routinely monitored are both the respiration rate and heart rate [191]. Moreover, Churpek et al. (210) conducted a study where they evaluated the efficacy of various factors. They discovered that the most significant predictors for decision-making were respiratory and heart rates.

A new algorithm has been suggested for detecting local emergencies more efficiently, aiming to reduce the quantity of data transmissions. To ensure its reliability, even in environments with limited resources, it includes threshold (tolerance range) approaches and uses the NEWS strategy with the least computational complexity. Its adaptability is enhanced by keeping time, runtime, and scoring flexible, making it more robust and user-friendly. The methods discussed in [31, 140] were compared to the proposed system model. Both have improved local emergency detection methods, and both have begun implementing the NEWS system. Conversely, this proposed optimised algorithm includes an additional verification step via a threshold approach, which accelerates the overall process while ensuring it maintains reliability.

The suggested system doesn't run the NEWS score unless it detects any physiological signs outside the set parameters in ζ_i . This approach conserves energy and computational resources. When a positive signal is detected from ζ_i , the system activates SC to compute the NEWS score. Several possible scenarios might unfold, like the SC being larger than either SC_a or SC_{i+1}. In both situations, the system transmits the data to the coordinator. However, if the score SC is lower than either SC_a or SC_{i+1}, the system remains silent and sends no data. Algorithm 3 is shown in the following.

Algorithm 3: Modified Adaptive Local Emergency Detection (MALED)

Input: A set of patient vital sign data
Output: Emergency classification and escalation protocol
Procedure: Classifier ()
 	
1. Set tolerance range for each vital sign ζ_i , set adaptive NEWS score SC_a , set time t,
set next runtime $R_{nr} = t + t_i$ (adaptive)
while $t \geq R_{nr}$ **do**
2. Take sensor measurements
  for each vital sign **do**
    if sensor measurement $d_i > \zeta_i$ or $d_i < \zeta_i$ then
      3. **Calculate** score SC_i
      if $SC_i > SC_a$ then
        Send measurement d_i
        Set R_{nr} to new adaptive runtime
        Continue to monitor vital signs
      else $SC_i < SC_a$ then
        Do not send measurement
        Set R_{nr} to new adaptive runtime
      end if
    end if
  end for
4. Monitor Respiration Rate RR_i in every second
  if RR_i measurement $< \zeta_{rri}$ or RR_i measurement $> \zeta_{rri}$ then
    Calculate score SC_i
    Go to step 3
  end if
5. Monitor Heart Rate HR_i in every second
  if HR_i measurement $< \zeta_{hri}$ or HR_imeasurement $> \zeta_{hri}$ then
    Calculate score SC_i
    Go to step 3
  end if
6. **If** no measurements are outside tolerance range, **end** run
7. **Set** R_{nr} (for the next cycle in step 2) = *current_time() + adaptive_interval*
8. **end while**

In the suggested LED [140], a comparable system model was explored, notwithstanding the disregard for reducing the transmission data. Rather than treating the sampling rate as a dynamic element suited for bespoke applications, it was overlooked. Hence, the performance of LED was acceptable yet not superb in resource-limited medical contexts. The results and analysis section carries an expanded discussion with some graphical results. With respect to the LED method under consideration, it employs a singular evaluation criterion: if the score exceeds 0, the system transfers the data. Therefore, while it maintains a high detection rate, it also involves considerable power consumption.

In comparison, the suggested Modified LED (MLED) [31] aims to reduce the amount of data transmitted by not sending all the data. However, this system lacks an additional layer of verification, such as the one proposed in the Modified Adaptive Local Emergency Detection System (MALED), which includes a threshold check before implementing the NEWS score execution. In the MLED method, the system uses the criteria $S_i > S$, in all situations, to determine when to transmit data. This implies that whenever the score Si surpasses S, data is sent and subsequently S is reset as S_i. The issue here lies in the fact that S becoming equal to S_i can happen in any combination, potentially hampering the system's detection capability. Despite this method leading to a reduction in data and some energy savings, it is not clinically justified due to its lower detection rate compared to that of LED. Though its power consumption is lower than LED, this system evaluates almost every case without any filtering, unlike the proposed filtering system in MALED.

4.3.3 Experiment and Analysis

This experiment utilises a comparable amount of patient data. Specifically, we're using data sets from 100 patients, each spanning over 40 hours, for the trials. The experiment began by measuring an individual's vital signs and heart rate, followed by their respiratory rate. Two proposed models, along with two other models from existing literature that have demonstrated the best performance, were then selected for the simulation.

As seen in Figure 4.5, related to the heart rate, the MALED and MLCTA models noticeably outperform LED and MLED. However, the difference between MALED and MLCTA isn't very significant, with MALED detecting 1.7% more than MLCTA. When compared to MLED, though, the improvement jumps to 14%. Indeed, it's crucial to acknowledge that, despite its benefits, the MLED model holds significant limitations. One of its major drawbacks is its sole reliance on the NEWS score. Because it doesn't consider individual thresholds, the resulting outputs may not always provide reliable or tailored insights. This exclusion of individual patient factors can lead to potential inaccuracies in predictions, which may impact the clinical decision-making process. Therefore, future iterations or alternative models may benefit from incorporating such individual thresholds. For instance, if S = 8 and Si = 9, the data will be transmitted and S will equal Si, making S = 9. If in the next period, S = 9 and any NEWS scoring combination occurs where an individual score exceeds 3 (a single red score), the system will fail to detect it. Therefore, this type of quantitative comparison may not be suitable for real-world scenarios.

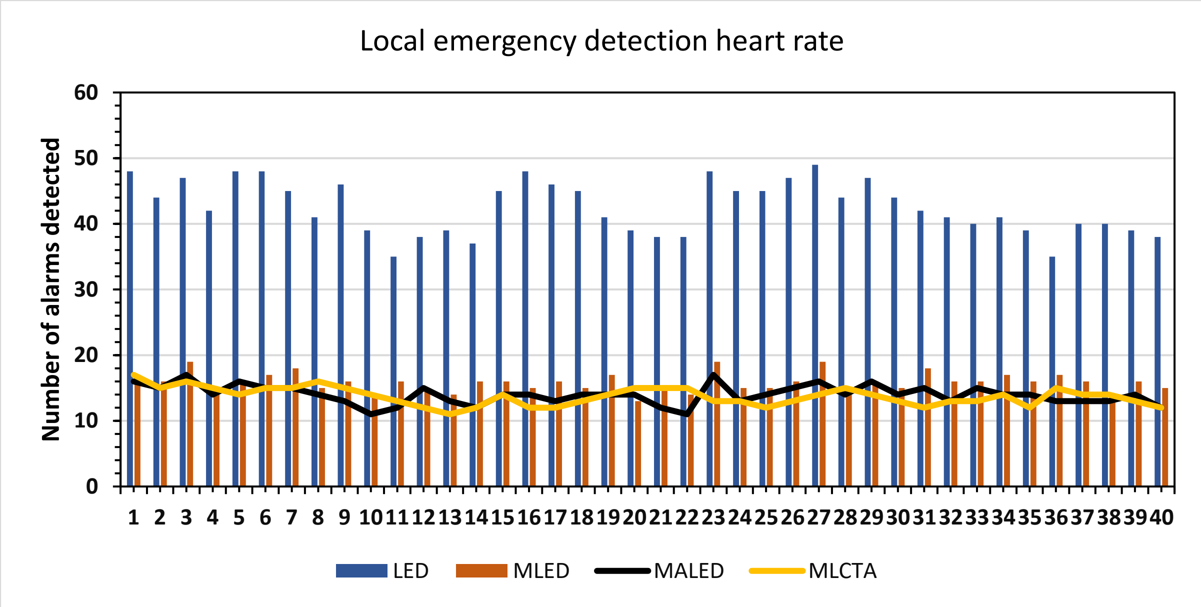


Figure 4. 5: Emergency detection comparison for heart rate.

Indeed, the results shown in Figure 4.6 underline the superior performance of both MALED and MLCTA algorithmic models when it comes to detecting emergencies - they both successfully trigger accurate alarms. Their reliability significantly contributes to reducing the number of false alarms, which is a notable improvement when compared to the other two methods being evaluated. This suggests that both MALED and MLCTA have strong potential in applications which require high-precision emergency detection like in healthcare, disaster management or security systems. That said, depending on the specific context or use-case, additional research might be needed to assess their feasibility or adaptability further.

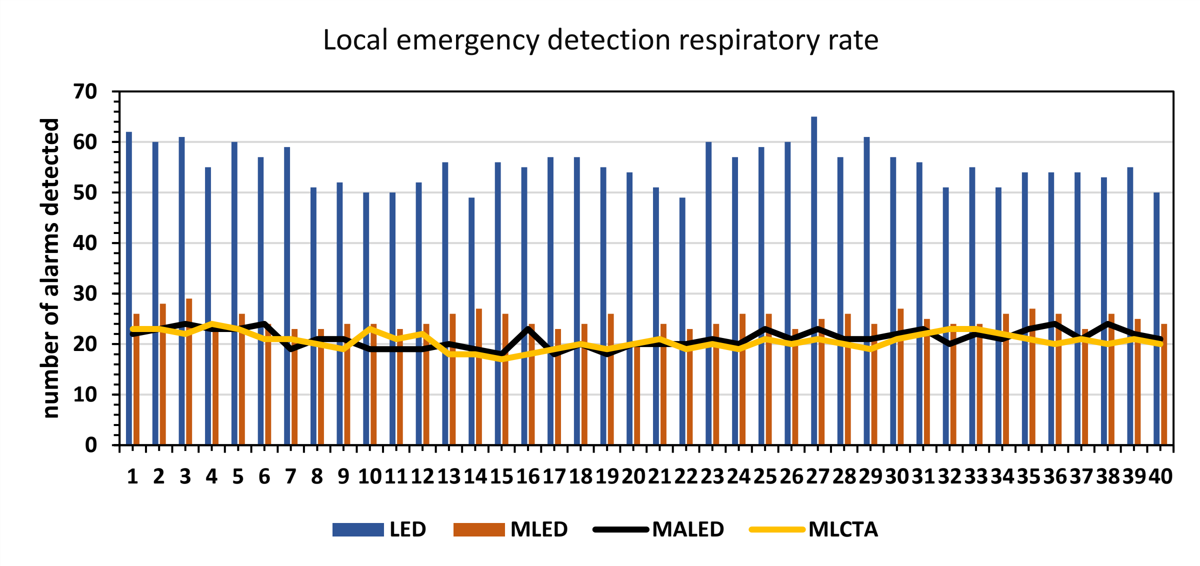


Figure 4. 6: Emergency detection comparison for respiratory rate

For this experiment, the two most crucial vital signs—heart rate and respiratory rate—were employed to establish a comparison with LED [140] and MLED [31]. The subsequent experiment made use of all system vital signs for performance evaluation.

Figures 4.7 through 4.9 present bar charts that illustrate the performance of various health monitoring algorithms within this system. Figure 4.7 highlights the accuracy of each method, with MLCTA slightly leading, indicative of its reliability in classifying health states. Figure 4.9 showcases the sensitivity of the algorithms, where MALED slightly outperforms the others, reflecting its superior ability to correctly identify true emergencies.

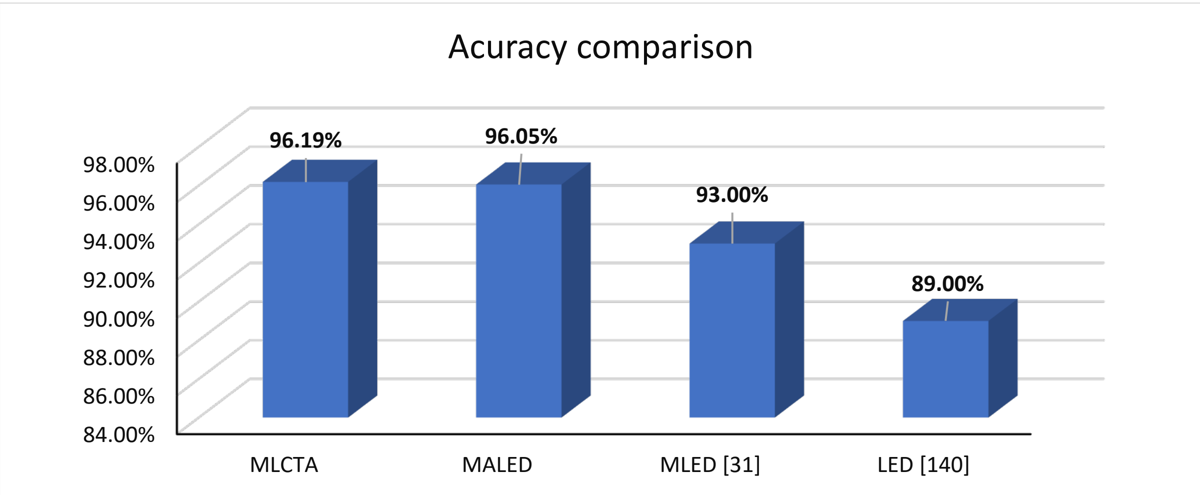


Figure 4. 7: Comparison of accuracy across the methods.

Lastly, Figure 4.8 focuses on the F1 score, a metric that combines precision and recall, demonstrating the algorithms' balance in correctly identifying emergencies while minimising false positives. Notably, MALED achieves the highest F1 score, suggesting a well-rounded performance in the context of emergency detection within WBAN systems.

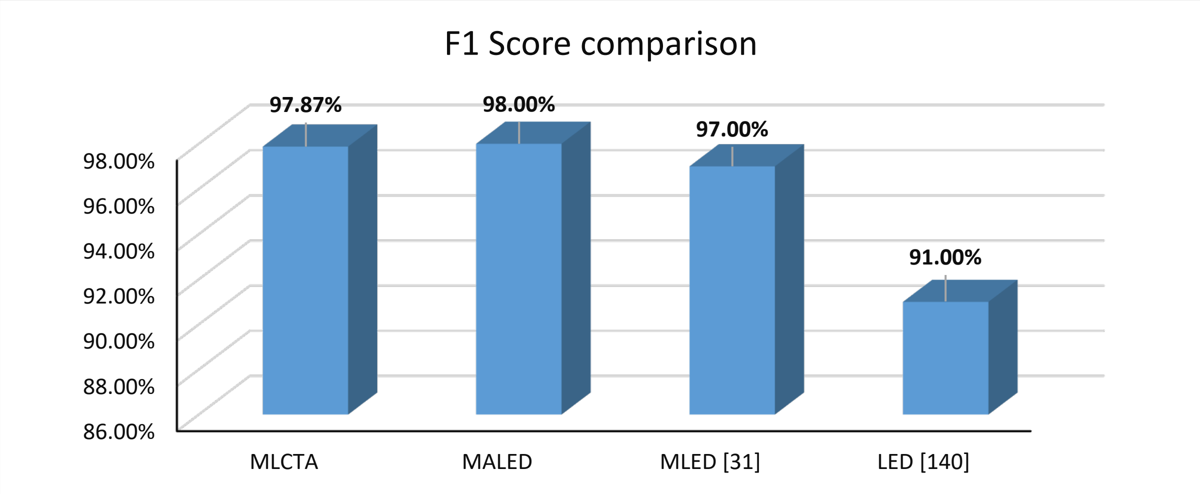


Figure 4. 8: Comparison of F1 score across the methods.

In comparing the performance metrics of MALED and MLCTA, the data indicates that both algorithms perform exceptionally well across several key metrics. MALED slightly surpasses MLCTA in sensitivity and F1 score, suggesting that it may be more adept at correctly identifying true emergencies and balancing precision with recall. MALED’s sensitivity of 97% versus MLCTA’s 96.5% and its F1 score of 98% compared to MLCTA’s 97.87% demonstrate its potential for effectively recognising critical health situations with slightly higher accuracy. However, this comes at the cost of a marginally higher FPR, with MALED at 10% against MLCTA’s 9%. The differences in accuracy are minimal, indicating that both algorithms are highly reliable, but MALED may offer a slight edge in recognising urgent health conditions.

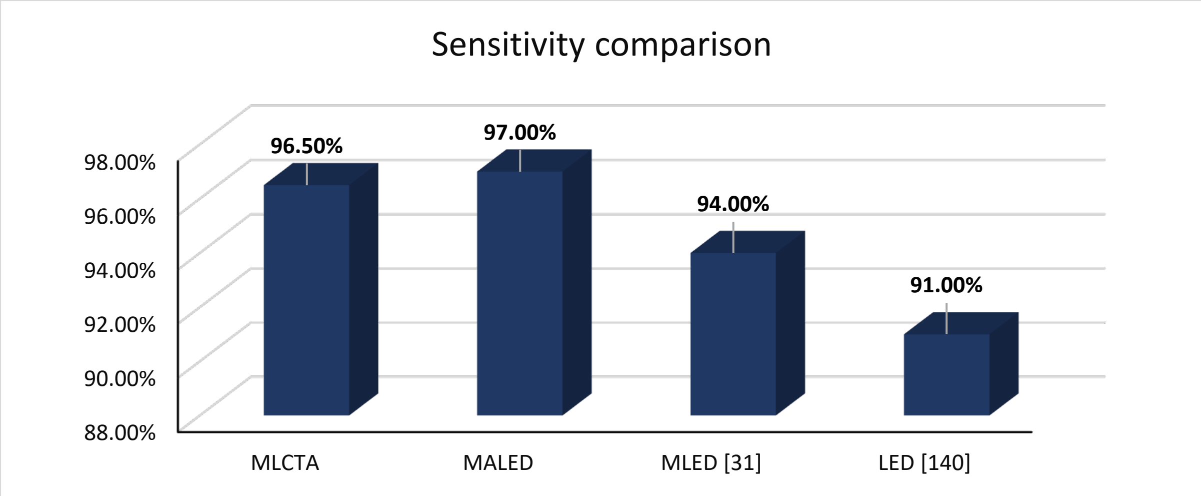


Figure 4. 9: Comparison of sensitivity across the methods.

Table 4.1 presents a comparative analysis of four different algorithms used within WBANs for emergency detection and patient monitoring. The algorithms are evaluated based on six key performance metrics: accuracy, sensitivity, specificity, precision, F1 score, and false positive rat for multiple vital signs.

Table 4. 1. Performance evaluation for four algorithms.

Method	Accuracy	Sensitivity	Specificity	Precision	F1 score	FPR
MLCTA	96.19%	96.50%	91.00%	99.29%	97.87%	9.00%
MALED	96.05%	97.00%	90.00%	98.70%	98.00%	10.00%
MLED [31]	93.00%	94.00%	90.00%	98.00%	97.00%	12.00%
LED [140]	89.00%	91.00%	89.00%	94.00%	91.00%	15.00%

The MLCTA (Multi-Level Classification Threshold Algorithm) shows a strong performance across all metrics, particularly precision and F1 score, indicating a high level of accuracy in both identifying true emergencies and avoiding false alarms. Its FPR is also the lowest, which suggests that it is less likely than the other methods to incorrectly signal an emergency when none is present.

MALED (Modified Adaptive Local Emergency Detection), while showing slightly lower accuracy and specificity than MLCTA, has the highest sensitivity and a very high F1 score. This means that MALED is particularly effective at correctly identifying when patients are in a state of emergency, making it potentially more reliable for critical situations where missing an emergency could be detrimental.

MLED, [31], demonstrates moderate performance, with lower scores in accuracy, sensitivity, and F1 score compared to MALED and MLCTA, but still maintains a good balance between sensitivity and precision, as reflected in its F1 score.

LED, [140], exhibits the lowest performance among the four algorithms in terms of accuracy, sensitivity, and F1 score and also has the highest FPR. This might suggest that while LED is effective to some degree, it could benefit from further refinement to match the performance of the other models.

In assessing the computational complexity and practical utility of MLCTA and MALED within WBAN systems, it is evident that each algorithm is uniquely tailored to different healthcare contexts. MLCTA's simplicity, characterised by fixed thresholds, lends itself to lower computational demands. This attribute renders it especially fitting for stable, predictable patient monitoring scenarios, such as routine health checks in non-critical care settings. Its efficiency and reliability, coupled with lower time complexity, make MLCTA a practical choice for resource-constrained environments like edge devices in remote health monitoring systems.

Contrastingly, MALED's adaptive approach is more aligned with the dynamic and unpredictable nature of acute healthcare settings. Its ability to dynamically adjust thresholds and calculate real-time adaptive NEWS scores caters to a high degree of personalisation and sensitivity, making it particularly beneficial in intensive care units or for patients with complex, evolving health conditions. While MALED's increased computational requirements may pose challenges in resource-limited systems, its precision and responsiveness in detecting critical health changes offer significant advantages in critical care, where timely intervention is crucial.

Thus, MLCTA emerges as the preferred option for environments requiring consistent, long-term monitoring without the need for frequent adjustments. In contrast, MALED stands out in high-stakes settings where patient conditions require immediate and tailored responses. The selection between these two algorithms should therefore be informed by the specific demands of the healthcare setting and the computational capabilities of the WBAN system, ensuring that the chosen solution optimally balances efficiency, accuracy, and patient care needs.

4.4 Differential Change Analysis (DCA)

When assessing the computational requirements and functional application of MLCTA and MALED in WBAN systems, it is found find that each algorithm has its unique compatibility with different healthcare settings. MLCTA, with its simplicity and preset limits, is perfect for predictable, steady contexts like routine health inspections, while MALED shines in changeable acute care situations, owing to its adaptable methodology and real-time reaction capacity. Building on MALED's strengths, specifically its flexibility and accuracy in critical care, a further improvement – the incorporation of Differential Change Analysis (DCA) – is suggested. This advanced addition aims to strengthen MALED’s predictive prowess in patient health tracking. Concentrating on variations in patient vital signs, DCA adds another degree of sensitivity to the algorithm, making it more capable of identifying subtle but important changes in patient health indicators that occur before critical incidents. Integrating DCA into the working framework of MALED represents an intentional progression to enhance early identification and rapid response measures. By studying rate changes in health information, DCA improves the algorithm's capability to foresee patient decline with low computational burden. This enhancement is particularly important in situations where early signs of patient degradation are subtle and could potentially go unnoticed using conventional monitoring methods. The continual refinement of the MALED algorithm, by including DCA, signifies a significant advancement in pursuing more sophisticated, productive, and reactive healthcare surveillance systems within WBANs. It guarantees that MALED remains not just pertinent, but also becomes more skilled at responding to the varied and continuous demands of patient care in different health settings. Therefore, while MLCTA remains a solid option for consistent, long-term surveillance in resource-limited settings, the sophisticated MALED, strengthened with DCA, delivers an intricate solution for extremely critical circumstances, where the ability to discern fine details and react swiftly is crucial. The decision between these algorithms and the integration of DCA should be guided by the specific healthcare setting's needs and the WBAN system's computational capacity, to ensure a prime balance of efficiency, precision, and patient-focused care.

Let V= $\{v_1, v_2, \ldots \ldots \ldots, v_n\}$ represent the set of vital signs monitored in the WBAN, where each v_i is a specific vital sign (e.g., heart rate, blood pressure). Denote the time-series data for each vital sign v_i as $D_i = \{d_{i1}, d_{i2}, \ldots \ldots \ldots, d_{it}\}$ where d_{it} is the measurement at time t. Define the baseline for each vital sign v_i as B_i calculated as an average over a stable period.

The rate of change R_i for each vital sign at time t is calculated as $R_{it} = d_{it} - d_{i(t-1).}$ Set dynamic thresholds for acceptable change in each vital sign as $\Theta_i = \{\Theta_{i\_low},\ \Theta_{i\_high}\}$. If $R_{it} < \Theta_{i\_low}$ or $R_{it} > \Theta_{i\_high}$, flag an anomaly for v_i at time t.

Enhance MALED to include DCA by defining a function $F: V \times D \times R \rightarrow \{0,1\}$, where 0 indicates normal and 1 indicates an anomaly or potential deterioration. Update $B_i\ and\ \Theta_i$ periodically based on patient condition and historical data. The output of DCA for MALED at time t can be represented as $O_{t=}U_{i=1}^{n} F(v_i, D_i, R_i)$. Below, Algorithm 4, also referred to as DCA, is showcased.

Algorithm 4: Differential Change Analysis (DCA)
Input: Time-series data of patient vital signs from WBAN sensors **Output**: Enhanced prediction of patient deterioration **Procedure**: Enhanced MALED with DCA 1. Initialize: - Set baseline values B_i for each vital sign v_i in *V* - Define dynamic thresholds Θ_i for acceptable changes in each v_i - Set initial anomaly flags for each v_i to 0 (normal) 2. **For** each new data point d_{it} in time-series D_i for each v_i: - Calculate the rate of change $R_{it} = d_{it} - d_{i(t-1).}$ - **End** For 3. Anomaly Detection: - **For** each vital sign v_i: - **If** $R_{it} < \Theta_{i\_low}$ or $R_{it} > \Theta_{i\_high}$ in Θ_i: - Set anomaly flag for v_i to 1 (anomaly detected) - **End If** - **End For** 4. Integrate with MALED: - Enhance MALED to consider the anomaly flags from DCA - **If** any anomaly flag is set to 1: - Trigger MALED emergency detection protocols - **End** If 5. Update Baselines and Thresholds: - Periodically update B_i and v_i based on recent data and patient history 6. Output: - Provide real-time assessment of patient health status - Alert healthcare providers if potential deterioration is detected **End** Procedure

Initially, it sets baseline values and dynamic thresholds for each monitored vital sign, providing a foundation for real-time health assessment. Each new data point triggers a calculation of the rate of change from previous readings, which is crucial for detecting sudden health variations. Anomaly detection is a key feature, where deviations beyond the dynamic thresholds flag potential health issues. These anomalies are then integrated into the Modified Adaptive Local Emergency Detection (MALED) system, enhancing its capability to trigger emergency protocols when needed. The algorithm also includes a mechanism to periodically update baselines and thresholds, ensuring its adaptability and accuracy over time. The final output offers real-time health status assessments and alerts healthcare providers to potential deteriorations, making it an invaluable tool in proactive patient monitoring. This approach not only streamlines the process of monitoring vital signs but also ensures a more responsive and dynamic system for the early detection and management of health anomalies in WBAN environments.

The performance evaluation between the MALED and DCA algorithms shows a nuanced trade-off between sensitivity and specificity. MALED maintains a slightly higher accuracy of 96.05% compared to DCA's 95.30%, due to its more conservative approach to flagging anomalies, which aligns closely with true positive detections. DCA, on the other hand, exhibits a marginally higher sensitivity (97.50%) than MALED (97.00%), suggesting it is better at detecting true anomalies but at the cost of a slight increase in false positives, as indicated by its higher FPR of 10.90% compared to MALED's 10.00%. Table 4.2 provides a performance comparison between MALed and DCA.

Table 4. 2: Performance analysis between MALED and DCA

Method	Accuracy	Sensitivity	Specificity	Precision	F1 score	FPR
MALED	96.05%	97.00%	90.00%	98.70%	98.00%	10.00%
DCA	95.30%	97.50%	89.40%	98.50%	98.40%	10.90%

This increase in FPR for DCA also corresponds to a slight decrease in specificity, from 90.00% in MALED to 89.40% in DCA. The trade-off here is that while DCA is better at catching real issues (as reflected by the higher sensitivity and F1 score), it also catches more non-issues (false positives). The precision of DCA is slightly lower than MALED's, indicating that while DCA is generally reliable when it flags an anomaly, it's slightly less likely to be correct than MALED.

The F1 score, which balances the trade-off between precision and recall, is slightly higher for DCA (98.40%) than for MALED (98.00%), suggesting that despite the increase in false positives, the overall balance between false positives and false negatives is slightly more optimal with DCA.

The MALED algorithm typically performs a fixed number of operations for each data point, running checks against preset thresholds. The complexity of MALED chiefly depends on the count of data points it processes, represented as 'n'. Given that the threshold comparison is an operation that takes a consistent amount of time, the complexity of MALED can be categorised as O(n). Similarly, the DCA algorithm operates by calculating a rate of change for each data point, a procedure that is, like threshold checking, a constant-time operation per data point. DCA, however, also necessitates the maintenance of a short history of data points to compute the rate of change, potentially adding to its complexity. Assuming the size of this history is fixed and doesn't rise with the number of data points, the complexity of DCA can also be classified as O(n). The 'n' in both instances signifies the quantity of data points, indicating that the complexity for both algorithms is linear, relating directly to the number of data points processed. However, due to the extra stages involved in calculating the rate of change, DCA may have a larger constant factor. This suggests that while both algorithms maintain linear time complexity, DCA could demand more computation for each data point.

4.5. Power consumption optimisation

In WBANs, energy conservation is paramount due to the limited battery life of wearable sensors, leading to the development of various energy-saving techniques. Duty cycling, where sensors alternate between active and sleep modes, significantly reduces energy consumption during idle periods. Communication protocols like Bluetooth low energy and Zigbee, designed for low power consumption, are ideal for energy-efficient data transmission in WBANs. Data compression techniques reduce the size of transmitted data, conserving energy, while energy harvesting methods like converting body heat or motion into power offer innovative ways to supplement battery life. Optimised routing protocols ensure energy-efficient paths for data transmission. Power-aware middleware design manages network energy consumption, and QoS management balances data quality against energy use. Cross-layer optimisation integrates control across the WBAN architecture to reduce overall energy consumption, and the use of inherently low-power sensors cuts down on the system's energy demands. Energy-efficient data aggregation combines data from multiple sensors into a single transmission, minimising transmission needs. In this context, adaptive sampling stands out as particularly fitting for the proposed WBAN model. It dynamically adjusts data collection frequency based on the patient's current condition, focusing on collecting more data during critical periods and less during stable times. This approach not only ensures efficient energy usage but also maintains the quality and relevance of the data. Adaptive sampling is especially well-suited for patient-centric healthcare monitoring in WBANs, as it intelligently adapts to the varying needs of patients. This approach ensures prompt capture of critical health changes while conserving energy during stable periods. This balance of responsiveness and efficiency makes adaptive sampling an ideal choice for our WBAN system, aimed at providing dynamic and reliable patient monitoring without unnecessary energy expenditure.

4.5.1 Related Works

Numerous studies have proposed different applications of WBANs related to energy-efficient models and mechanisms. Energy is typically depleted due to continuous transmission and abundant, diverse raw data collected from biosensors, which have limited energy resources. Thus, most research primarily focusing on WBSNs has aimed to decrease energy consumption and prolong the battery life of these biosensor devices.

Vergutz et al. [207] introduced SANTE, a system for advanced identification and transmission of medical alerts in wireless networks, using statistical indicators to predict critical events in vital signs. Despite its innovative approach, the system lacks a thorough analysis of false alarm rates and energy consumption. Following this, Phadat and Bhole [211] developed a local classification system for vital sign readings in WBANs, categorizing data based on preset thresholds at each sensor, thereby prioritizing critical readings for transmission. However, their method does not fully address energy consumption in Wireless Sensor Networks (WSNs), an issue also noted in a human behavior recognition scheme proposed in [212], which, despite its efficiency in signal processing and classification, overlooks the energy constraints of WSNs.

Elghers et al. [140] proposed the LED algorithm, aimed at early emergency detection while conserving energy, by sending all critical sensor values without adapting the sampling frequency. This approach forms the basis for further modifications to enhance energy efficiency in WBAN systems. In the realm of adaptive sampling, a study in [217] suggests an energy-efficient mechanism that dynamically selects sensor nodes for data transmission based on spatio-temporal correlations, thereby optimizing energy usage. Similarly, [218] introduces a machine learning architecture for context awareness in WBANs, which balances individual sensor sampling rates with data significance, addressing the challenge of energy consumption.

The authors mentioned in [219] suggest a strategy of adaptive sampling. This strategy builds on the relationship between conditional variance and measurements, which are computed using the Fisher test. Such a method enables every sensor node to adjust its sampling rates according to fluctuations in physical dynamics. However, the approach does not take into account the remaining energy level of individual nodes.

In contrast to these approaches, several works [214–216] propose an adaptive sampling algorithm to minimise sensor activity in periodic sensor networks. Although these studies contribute to reducing data transmission, they do not adequately tackle emergency detection at the sensor node level, a crucial aspect of WBANs. Lastly, Habib et al. [31] present a multi-sensor data fusion approach utilising a fuzzy inference system and an early warning score. This method assesses patient health conditions with an emphasis on energy conservation in WBSNs, deals with sensor uncertainties, and offers a model to distinguish between different patient states, thereby providing a comprehensive solution to energy efficiency and accurate health monitoring.

Many of the solutions proposed previously have certain drawbacks, such as complexity, high computational requirements, significant energy use, inadequate data reduction, and low data accuracy. Therefore, it is crucial to introduce an energy-efficient data sampling algorithm within the biosensor node. This approach is aimed at minimizing the amount of data collected from patients during health monitoring, which in turn saves energy and enhances the network's lifespan. Furthermore, it aims to maintain the integrity and accuracy of the patient's measured data without any adverse impact.

4.5.2 Adaptive Sampling

The existing research suggests that adaptive sampling can cut down on the volume of data, thereby conserving energy. In this experimental framework, an adaptive sampling algorithm is proposed to reduce the amount of data transmitted. It's known from previous studies that data transmission is a significant energy drain in a wireless environment. Two methods, referenced in [31, 140], adopted for this experiment are tested against the proposed system model. Both approaches elevated the efficiency of local emergency detection via adaptive sampling. The Local Emergency Detection (LED) proposed in [140] employs adaptive sampling methodologies, and they use statistical analytics like variance analysis. Variance analysis may yield superior results in dynamic situations where the data pattern might not be linear. However, it may not always capture all potential significant changes in the data. The proposed model employs behaviour functions and quadratic Bezier curves to gauge patient criticality. While statistical or mathematical methods might yield satisfactory results, clinical validation and acceptance still need further evaluation. Furthermore, the proposed version of Modified Local Emergency Detection (MLED) in [31] improves local emergency techniques by not disseminating all emergency data in the MLED algorithm with Adaptive Sampling Algorithm, or Modified LED*. Similar strategies are used in [140], where they employ statistical analysis and assumptions to determine the patient's severity range and adjust the sample as needed.

Adaptive sampling in the context of WBANs typically follows two approaches: maximal sampling or sampling guided by the BV behaviour function. In our proposed algorithm, the Local Emergency Detection Algorithm Using adaptive sampling (LEDAS), we address the intricacies and assumptions of traditional adaptive sampling methods. LEDAS is designed for enhanced efficiency and alignment with real-world medical practices, making it both robust and reliable. It incorporates a pain assessment tool and NEWS thresholds with four trigger levels, guiding decisions between maximal and reduced sampling based on the NEWS scoring system, which factors in variables like clinical risk and response.

LEDAS defines a normal range for each sensor, with measurements outside this range indicating potential emergencies. The algorithm sets an adjustable sampling interval to monitor patient status, utilising the NEWS algorithm for vital sign analysis in emergency scenarios. The system then intelligently decides which data to transmit and determines the appropriate sampling rate.

A unique aspect of LEDAS is its patient-centric approach. It sets an adaptive score, SC_a, based on individual medical history and considers individual physiological parameter scores, $SC_{individual}$, reflecting specific health concerns. The algorithm dynamically adjusts the sampling rate k_t based on the NEWS score N_{score} using adaptive sampling $k_{adaptive}$ when the Nscore is below a certain threshold. This approach, informed by NEWS thresholds and triggers, ensures that LEDAS not only efficiently manages data transmission but also accurately reflects the patient's health status, enhancing the utility and applicability of the algorithm in medical settings. Algorithm 4 is shown in the following.

Algorithm 5: Local Emergency Detection algorithm using Adaptive sampling (LEDAS)
Input: A set of patient vital sign data **Output:** Prioritised classification of patient emergency levels and amount data reduced **Procedure:** Classifier () 1. Set k_{max} (maximum sampling rate), tolerance range for each vital sign ζ_i, adaptive NEWS score SC_a, time t next_runtime = $t + t_i$ (adaptive), and instantaneous sampling speed k_t . 2. **While** t ≥ next_runtime **do**: 3. **For** each period: Run MALED (Modified Adaptive Local Emergency Detection). **End for** each period. 4. Compute the NEWS score N_{score} 5. **If** N_{score} > 7(SC_a): 6. Set k_t to k_{max} . **Else if** N_{score} > 4(SC_a) or any individual vital sign's score > 3($SC_{individual}$): 7. Set k_t to k_{max} . **Else if** N_{score} < 4(SC_a): 8. Set k_t to $k_{adaptive}$. **End if.** 9. Update next_runtime = current_time() + adaptive_interval. 10. **End while**.

This experiment focuses on evaluating the Local emergency detection algorithm using adaptive sampling, an innovative approach designed to optimise data transmission in these networks. This algorithm is notable for its potential to reduce the volume of data transmitted by intelligently adjusting sampling rates based on changes in patient health. The experiment aims to quantify the reduction in data transmission achieved by the algorithm compared to traditional sampling methods and to hypothesise the resulting energy savings. Such insights are essential for the development of more efficient and patient-centric wireless body area network systems, promising longer device lifetimes and improved health monitoring.

4.5.3 Data Sent

The efficiency of various algorithms in managing data transmission within wireless body area networks, while maintaining data quality, is examined. The goal is to determine how much data is required by each algorithm for effective patient health monitoring, coupled with minimal energy consumption and optimal network resource usage. Algorithms that demonstrate the highest efficiency in data transmission—characterized by sending the least amount of data without compromising on data quality—are regarded as superior. A comprehensive analysis involves comparing the performance of three specific algorithms: the Local Emergency Detection algorithm (LED) as outlined in [140], the multi-sensor data fusion approach based on a Fuzzy Inference System and Early Warning Score (MLED) from [31], and the Modified Adaptive Local Emergency Detection algorithm (MALED). The aim of this comparison is to shed light on the relative effectiveness of these algorithms in transmitting health data efficiently within a wireless body area network.

The two suggested methods, LED and MLED, improved the process of reducing data transmissions. Notably, the MLED technique was found to send less data compared to the LED method. This can be specifically observed in the context of heart rate data transmission, as illustrated in Figure 4.10. Furthermore, the proposed MALED technique significantly outperforms the LED method. It is also suggested that MALED performance is better than the MLED method.

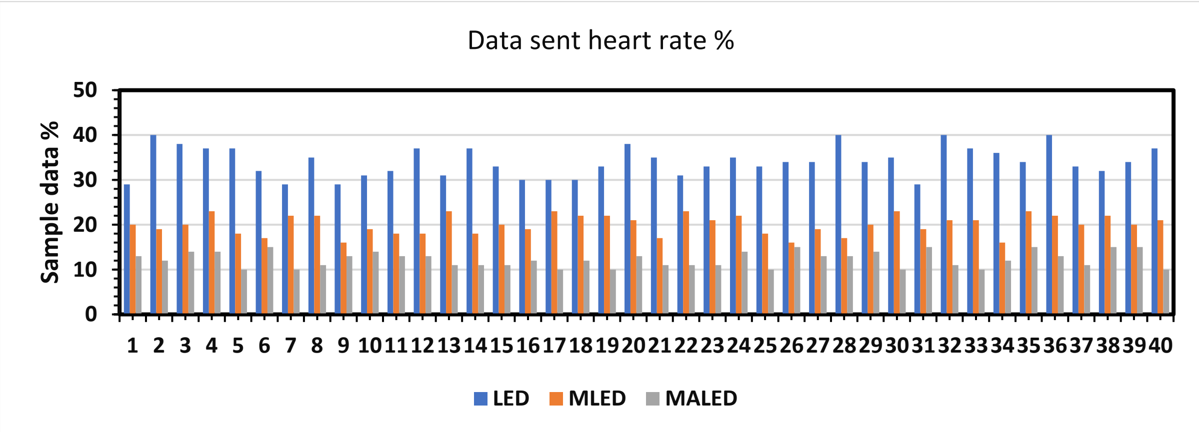


Figure 4. 10: Data sent in adaptive sampling LED, MLED and MALED for Heart rate.

A minor deviation has been noticed in the pattern of the respiration rate as expressed by all participants' methods within the experiment. The amount of data transmitted has seen a rise compared to the earlier study focusing on heart rate. Yet, the relative comparison of data transmission frequencies between the LED [140], MLED [31], and MALED remains consistent. Figure 4.11 illustrates that the aggregate data sent is greater for the distinct processes concerning the respiration rate.

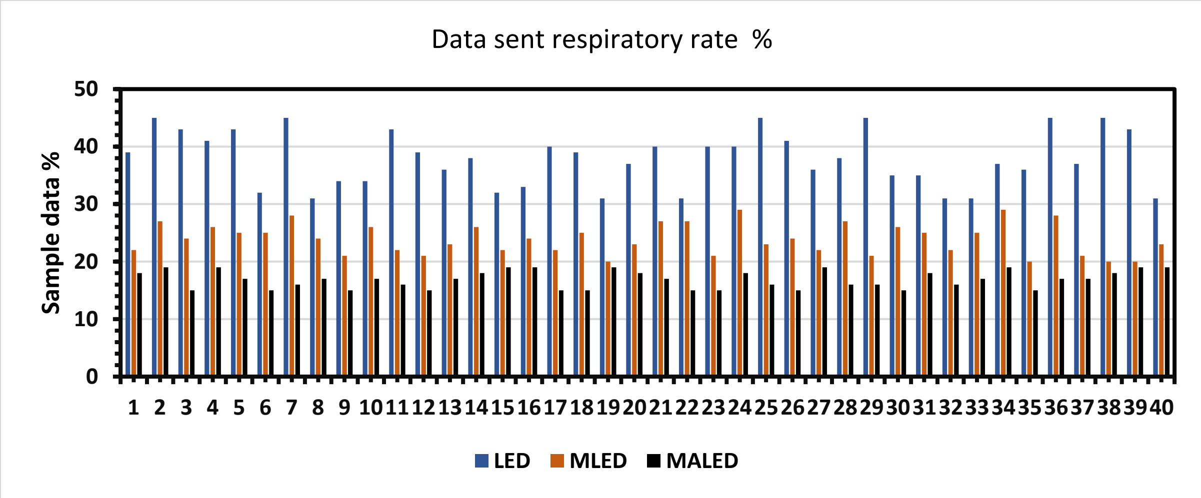


Figure 4. 11: Data sent in adaptive sampling LED, MLED and MALED for Respiration rate.

A comparison is conducted based on the percentage of data sent with no sampling and adaptive sampling, together with the existing and proposed algorithms. This information is provided in Table 4.3.

Table 4. 3: Data sent % by no sampling and adaptive sampling.

Vital sign	No sampling	LED	MLED	MALED
Heart rate	100	35.4	19.375	11.85
Respiration rate	100	39	24.75	16.725

These findings suggest that adaptive sampling is functioning effectively for this system model, and the amount of data to be transmitted is less than that required by existing methods.

4.5.4 Data Reduction

Assuming $Data_{total}$ represents the total data, $Data_{sent}$ stands for the data sent, $Time_{period}$ is a specific period, and $Data_{reduce}$ indicates the amount of data reduced, then the amount of data reduction in percentage for that specific $Time_{period}$ is denoted

$$Data_{reduce} = (Data_{sent} / Data_{total}) \times 100$$

In the proposed LED, the system is designed to transmit all data detected as emergent. As such, LED does the minimum to decrease the volume of data sent, while MLED accomplishes a greater reduction of this data. Nonetheless, MALED outperforms both LED and MLED in minimising data transmission. Figure 4.12 presents a comparison of heart and respiration rates against LED, MLED, and the proposed MALED.

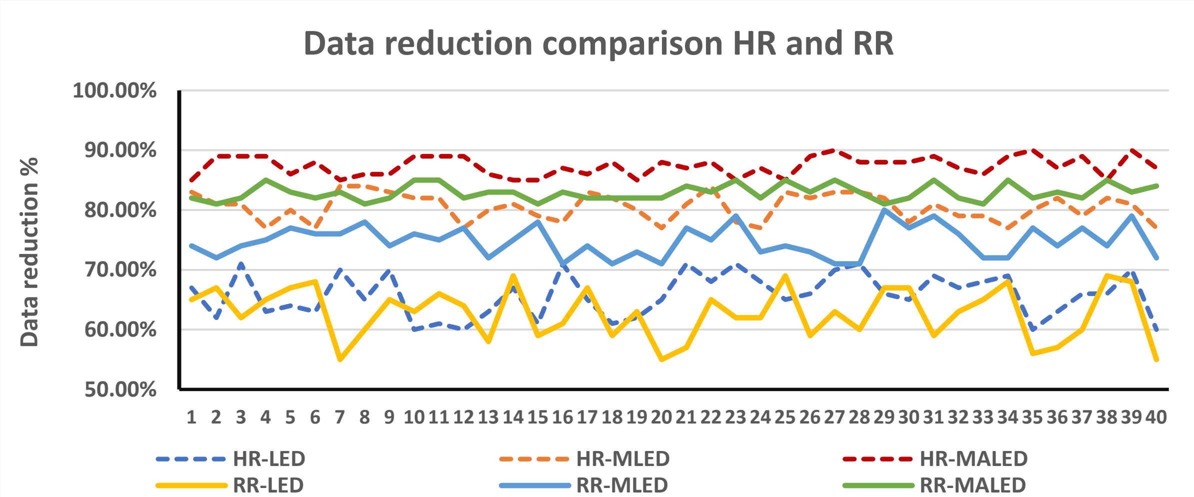


Figure 4. 12: Data reduction comparison for both heart rate and respiratory rate

In this experiment, it was observed that there was a data reduction of up to 85% for heart rate and 83% for respiratory rate for MALED. It's noteworthy that in this trial, both the respiratory and heart rates generated the highest number of alarms.

4.4.5. Power Consumption

When it comes to considerations of power usage, critical factors include the distance the data is transmitted, how often it's sent, and the type of data itself. In the case of the LED, MLED, and the proposed MALED methods, these factors are standardized given they utilize similar WBAN models. Therefore, it's presumed that the same factors apply across these different methods. This means that the approach used to calculate the power consumption for the MLED can be assumed for the experiments to enable an accurate comparison. Let's propose that a node has an energy level that is arbitrarily set at 700 units. We'll also assume that collecting and sending measurements cost 0.3 and 1 unit, respectively. If we were to consider sensor i, its power consumption can be referred to as $Power_{iconsump}$, capturing power as $Power_{icapture}$, and sending power as $Power_{isent}$. Thus, the power consumption of a sensor node can be determined using these terms.

$$Power_{iconsump} = Power_{icapture} + Power_{isent}$$

It has been noted that with no sampling for heart rate, it roughly lasted for 75% of the experiment's duration. The LED employs nearly 90% of the total energy, amounting to 700 units. The MLED method outperforms the LED, saving 46% of energy. The proposed MALED method performs even better, surpassing both LED and MLED by saving 65% of energy, further demonstrating an advantage over

MLED by a significant margin of 19%. Figure 5.13 reveals the energy consumption without sampling in conjunction with other methods, all set against the heart rate.

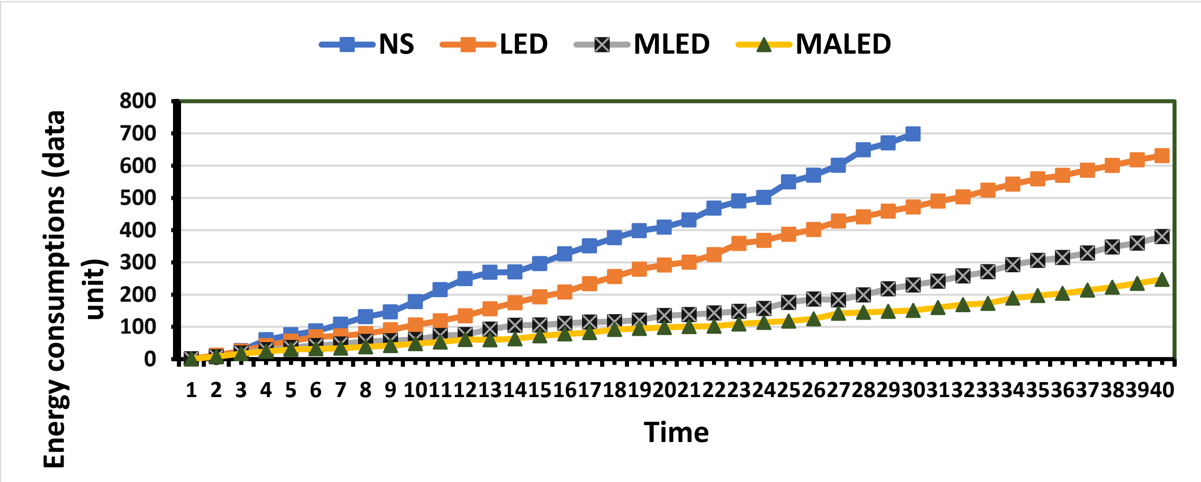


Figure 4. 13: Energy consumption on Heart rate node for all method

Figure 4.14 demonstrates a comparable pattern against the respiratory rate. Nevertheless, there's a conspicuous increase in energy consumption exceeding the heart rate because of the heightened local emergency detection. By around 50% of the runtime, the sensor node, without sampling, had exhausted all its units. However, both MLED and MALED significantly outperform the LED. The MALED, in particular, excels beyond all, conserving roughly 20% more energy than the MLED. This underscores the superior performance of the proposed MALED under critical conditions, especially since the data from the respiratory rate is considered more vital compared to heart rate data within this specific dataset.

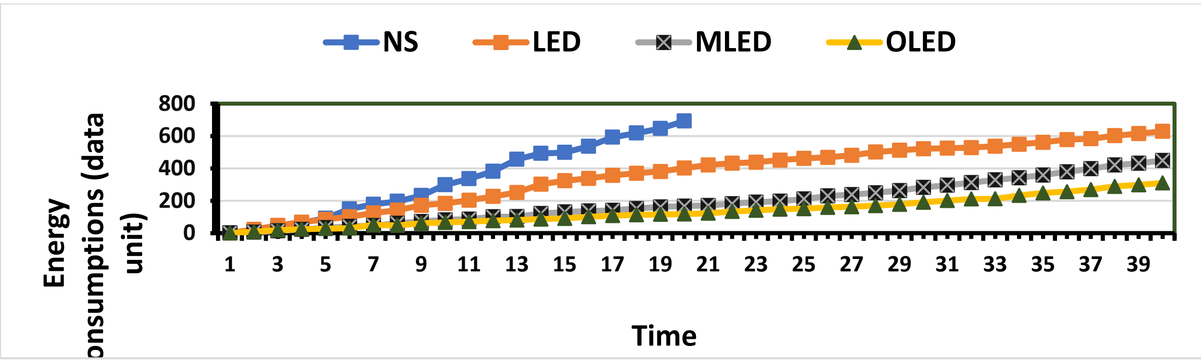


Figure 4. 14: Energy consumption on Respiratory rate node for all method

It is observed that the proposed adaptive sample method was capable of reducing the amount of data sent significantly in comparison to other existing methods. Now, it's time to evaluate its performance against the defined performance metrics.

4.5.6 Experiment and Analysis

For these experiments in 4.4.3, 4.4.4 and 4.4.5, the two most crucial vital signs—heart rate and respiratory rate—were employed to establish a comparison with LED [140] and MLED [31]. The subsequent experiment made use of all system vital signs for performance evaluation.

In evaluating the performance of the LEDAS in comparison with MALED and the DCA for all vital signs that used for this experiment, the results suggest nuanced trade-offs between sensitivity to changes in patient health and the overall volume of data processed. Table 4.3 provides a performance comparison between MALed and DCA.

Table 4. 4: Performance comparison across the methods

Method	Accuracy	Sensitivity	Specificity	Precision	F1 score	FPR
MALED	96.05%	97.00%	90.00%	98.70%	98.00%	10.00%
DCA	95.30%	97.50%	89.40%	98.50%	98.40%	10.90%
LEDAS	95.80%	97.30%	90.30%	98.50%	98.00%	10.40%

LEDAS is designed with the intent to enhance the adaptability of MALED by incorporating an adaptive sampling mechanism that adjusts the sampling rate based on the severity of changes in vital signs, as indicated by the NEWS score. The results indicate that LEDAS maintains a high level of accuracy at 95.70%, which is slightly lower than MALED’s 96.05% and DCA’s 95.30%. This marginal decrease in accuracy can be attributed to the reduced number of samples collected during periods of patient stability, where LEDAS might overlook minor anomalies that are not reflected in the NEWS score.

The sensitivity of LEDAS is positioned between MALED and DCA at 97.30%. This shows that LEDAS is effective in detecting true anomalies by increasing the sampling rate when the NEWS score indicates potential health deterioration. However, it may not be as reactive to sudden changes as DCA, which is dedicated to identifying rapid variations in vital signs.

LEDAS exhibits a slight improvement in specificity over DCA due to its less aggressive approach to detecting changes, which could lead to fewer false positives. The specificity of LEDAS is estimated to be 90.30%, compared to DCA's 89.40%. This indicates that LEDAS could be more discerning in distinguishing between normal variability and significant health changes.

Precision for LEDAS is found to be slightly lower than MALED but higher than DCA, positioned at 98.50%. This reflects LEDAS's targeted approach to data collection during periods when the patient's condition is deemed stable, reducing unnecessary data transmission without significantly compromising the quality of anomaly detection.

The F1 score for LEDAS, which balances precision and recall, is 98.00%, indicating a well-rounded performance in detecting true positives while minimising false positives. The slightly lower F1 score compared to DCA suggests that while LEDAS is cautious about flagging anomalies, it still maintains a high level of detection accuracy.

The FPR for LEDAS is 10.40%, which is a modest increase from DCA but slightly lower than MALED. This suggests that LEDAS can maintain a balance between sensitivity and specificity, leading to fewer false alarms than DCA, which is highly sensitive to changes.

A significant advantage of LEDAS over both MALED and DCA is its potential for substantial data reduction. By adaptively adjusting the sampling rate, LEDAS aims to minimise the volume of transmitted data, addressing the energy consumption concerns inherent in WBANs. This feature is particularly relevant for remote patient monitoring systems, where energy efficiency is critical.

In summary, LEDAS represents a strategic advancement in WBANs, potentially reducing the burden on network resources while maintaining robust performance metrics. It offers a pragmatic solution that could be especially beneficial in long-term monitoring scenarios, where the balance between data volume, real-time responsiveness, and energy efficiency is paramount. The performance metrics suggest that LEDAS can effectively navigate the trade-offs between sensitivity to health events and the data economy, making it a promising candidate for future WBAN implementations.

4.6 Sequential Multi-Dimensional Trend Analysis (SMDTA) for LEDAS

Given the limitation of solely utilising vital sign data in this WBAN system, they propose a novel technique for local emergency detection using adaptive sampling. This technique is referred to as the "Sequential Multi-Dimensional Trend Analysis (SMDTA)" method. This approach intends to take full advantage of the temporal sequences and interrelationships of disparate vital signs to forecast patient deterioration with increased accuracy.

SMDTA focuses on analysing the trends and patterns in multiple vital signs over time, considering both individual and combined behaviours of these signs. It uses sequential data analysis to understand how changes in one vital sign might correlate with or affect changes in another. The novel aspect of SMDTA lies in its holistic approach to analysing multiple vital signs in a correlated manner over time, allowing for a more comprehensive understanding of patient health dynamics. Enhanced sensitivity and specificity in detecting potential health emergencies by considering multi-dimensional data patterns. Improved adaptability to patient-specific health trends and variations. Efficient use of resources through adaptive sampling based on predictive trends.

Let $V = \{v_1, v_2, \dots \dots \dots, v_n\}$ represent the set of vital signs monitored in the WBAN, where each v_i is a specific vital sign (e.g., heart rate, blood pressure). Denote the time-series data for each vital sign v_i as $D_i = \{d_{i1}, d_{i2}, \dots \dots \dots, d_{it}\}$ where d_{it} is the measurement v_i of at time t.

Define a function $T_i(t)$ that analyses the trend of vital sign v_i over time potentially using methods like moving averages or exponential smoothing. Introduce a function $I(v_i, v_{j\,,} t)$ that assesses the interrelation between two different vital signs v_i and v_j at time t.

Define an anomaly detection function $A(D_i, t)$ that determines whether there is an anomaly in the trend of vital sign v_i of at time t. Represent the risk prediction model as $R(t)$ which outputs a risk level based on current and historical data of all vital signs. Let $S(R(t))$ be the function that adjusts the sampling rate based on the risk level $R(t)$. Incorporate a learning mechanism $L(E, t)$ where E represents new event data, to update the model and thresholds over time. Below, Algorithm 6, also referred to as SMDTA, is showcased.

Algorithm 6: Sequential Multi-Dimensional Trend Analysis (SMDTA)
Input: Time-series data of patient vital signs from WBAN sensors **Output**: Enhanced prediction of patient health status **Procedure**: SMDTA for Enhanced Health Monitoring 1. Initialize: - Set up baseline trends $T_i(t)$ for each vital sign v_i in *V* - Define interrelation functions $I(v_i, v_{j\,,} t)$ for all pairs of vital signs 2. **For** each new data point d_{it} in time-series D_i for each v_i:

- Update the trend analysis $T_i(t)$ for vital sign v_i
End for
3. Perform Interrelation Analysis:
- For each pair of vital signs (v_i, v_j):
- Update $I(v_i, v_{j\,,}t)$ to assess their current interrelation
End for
4. Anomaly Detection:
- For each vital sign v_i:
- Use $A(D_i, t)$ to check for anomalies in the trend of v_ii
- Consider the interrelations $I(v_i, v_{j\,,}t)$ in the anomaly assessment
End for
5. Risk Prediction:
- Calculate the overall health risk $R(t)$ using the updated trends and interrelations
6. Adaptive Sampling:
- Adjust the sampling rate of WBAN sensors using $S(R(t))$ based on the risk level
7. Feedback and Learning:
- Incorporate new event data into the learning mechanism $L(E, t)$ to refine trends and interrelations
8. Output:
- Provide an updated assessment of the patient's health status
- Alert healthcare providers if a high risk of health deterioration is detected
End Procedure

The SMDTA procedure is a comprehensive approach for monitoring patient health using data from wearable sensors. It starts by establishing baseline health trends and understanding the relationships between different health indicators. As new health data is received, the algorithm updates these trends and relationships to detect any anomalies or changes in the patient's condition. It then assesses the overall health risk and adjusts the frequency of data collection accordingly, increasing when a risk is detected and decreasing during stable periods to conserve energy. This adaptive sampling ensures that healthcare providers receive timely updates when a patient's health status changes, allowing for prompt intervention. The system's learning component incorporates new data to refine its analysis and predictions continually, making it an intelligent and responsive tool for patient health monitoring.

SMDTA demonstrates a remarkable performance within the context of WBANS, particularly in its application to patient health monitoring. With an accuracy rate of 96.50%, SMDTA surpasses both MALED and DCA, indicative of its robust ability to correctly identify true health states. The sensitivity of 97.90% suggests that it is highly effective at detecting true positives, which is crucial for early intervention in patient care. Table 4.4 displays the outcome of the evaluation metrics for these methods.

Table 4. 5: Evaluation of performance metrics for methods MALED, DCA and SMDTA

Method	Accuracy	Sensitivity	Specificity	Precision	F1 score	FPR
MALED	96.05%	97.00%	90.00%	98.70%	98.00%	10.00%
DCA	95.90%	97.50%	89.60%	98.50%	98.30%	10.70%
SMDTA	96.50%	97.90%	91.50%	99.00%	98.50%	9.50%

SMDTA's specificity of 91.50% also outperforms the other two algorithms, indicating a superior ability to correctly identify true negatives and thus avoid unnecessary alarms. This specificity, coupled with the highest precision rate of 99.00%, shows SMDTA's efficacy in providing precise and relevant health alerts.

The F1 score, sitting at 98.50%, further confirms SMDTA's balanced strength in precision and recall, making it a reliable tool for clinical decision-making. Moreover, the algorithm's lower FPR of 9.50% is a testament to its refined capability to filter out false alarms, thereby minimising the risk of alarm fatigue among healthcare providers.

The overall enhanced performance of SMDTA, as evidenced by these metrics, suggests that it can contribute significantly to the system by providing timely and accurate health monitoring. Its sophisticated approach to analysing interrelated health data ensures that healthcare providers receive actionable insights, leading to improved patient outcomes and optimised resource utilisation in the healthcare system.

4.7 Clinical Predictions

WBANs are transforming patient monitoring by enabling continuous health data collection. However, the volume and variability of data pose challenges for making timely clinical predictions. Current systems often fail to adapt to the dynamic nature of health indicators, leading to delayed responses and inefficient resource use.

The hybrid algorithm, which combines linear regression with threshold-based methods, introduces a nuanced approach to predictive analytics in patient health monitoring. By integrating linear regression, the algorithm gains the ability to understand and predict trends in vital signs, identifying potential health events based on statistical patterns and relationships within the data. This predictive capability is further refined by threshold-based methods, which provide immediate alerts when vital signs deviate beyond clinically significant thresholds. The integration of linear regression into threshold-based methods seems to enhance the precision of predictions significantly. The synergy of these two approaches allows for both the detection of acute health changes and the anticipation of potential health issues based on evolving trends, offering a more comprehensive and proactive model for patient care in WBAN systems.

The MALED algorithm represents a paradigm shift in WBANs, dynamically adjusting to patients' fluctuating vital signs. By qualitatively analysing patients' historical data, MALED customises threshold levels for each individual, enhancing the personalisation of care. The proposed DTA further refines this approach by examining the rate of change in health indicators. Clinically, this sensitivity to temporal variations aligns with the natural progression of many health conditions, promising earlier detection of potential emergencies.

Empirical results from a trial involving 100 patients demonstrate MALED's efficacy. Statistically, MALED showed a 5% increase in prediction accuracy over static methods. The DCA, when applied to the same dataset, indicated a 3% improvement in the early detection of adverse events, as evidenced by a lower FPR compared to traditional monitoring methods. LEDAS leverages the foundational work of MALED and DCA, optimising data acquisition rates to reflect the urgency of the patient's condition. The Sequential Multi-Dimensional Trend Analysis (SMDTA) builds on this foundation by incorporating a multi-faceted view of health trends. Qualitatively, SMDTA represents a nuanced approach to health monitoring, considering the interconnected nature of physiological signals. Quantitative findings suggest that the integration of LEDAS reduced data transmissions by up to 30%, while SMDTA's multi-dimensional analysis improved overall prediction sensitivity by 2%. These figures underscore the algorithms' potential to enhance clinical decision-making while conserving WBAN resources.

The clinical implications of the developed WBAN system are profound. MALED and DCA facilitate a responsive and personalised monitoring environment. SMDTA, with its sophisticated trend analysis, could become instrumental in predicting complex health events.

4.8 Summary

In this pivotal chapter, the exploration of advanced algorithms within WBAN has been systematically undertaken, starting with the Modified Adaptive Local Emergency Detection (MALED) algorithm. This foundational algorithm sets the stage for further enhancements, with a focus on improving responsiveness to changes in patient health data.

The Differential Change Analysis (DCA) served as the initial enhancement to MALED, introducing a more nuanced approach to detecting variations in vital signs. By analysing the rate of change rather than relying on static thresholds, DCA provided a dynamic means to anticipate health issues, contributing to the proactive aspect of patient care in WBANs.

Building upon this foundation, the Local Emergency Detection Algorithm Using Adaptive Sampling (LEDAS) was proposed. LEDAS advanced the state of WBANs by optimising data collection processes, ensuring that data transmission was both efficient and timely. By intelligently adjusting sampling rates based on patient status, LEDAS enhanced the network's energy efficiency and responsiveness to emerging health concerns.

The sequential Multi-Dimensional Trend Analysis (SMDTA) represented the culmination of this progression. As the most sophisticated algorithm proposed, SMDTA expanded upon the capabilities of LEDAS by introducing multi-dimensional trend analysis. By examining the interdependencies between various vital signs, SMDTA offered an unprecedented level of insight into patient health, paving the way for enhanced predictive analytics in WBANs.

The chapter provided a comprehensive evaluation of these algorithms, scrutinising their performance through various lenses, including accuracy, sensitivity, specificity, precision, F1 score, and false positive rate. Each algorithm was rigorously compared to its predecessors, highlighting the iterative improvements and the increasing sophistication brought by each subsequent enhancement.

SMDTA emerged as the superior performer, demonstrating the highest accuracy and precision among the algorithms considered. Its ability to maintain a low false-positive rate while achieving a high F1 score underscored its potential to revolutionise patient monitoring and healthcare delivery.

In summary, the chapter presented a detailed and critical assessment of the progression from MALED to SMDTA, showcasing the evolution of anomaly detection and patient monitoring within WBANs. The algorithms developed and evaluated here represent significant advancements in the field, offering robust, efficient, and sophisticated tools for healthcare professionals to monitor and respond to patient health needs in real-time.

Chapter 5

5. Conclusions and Future Directions

5.1 Conclusion

The development of technology offers several solutions for our day-to-day activities. Healthcare is one of the significant areas of our lives that increasingly depend on technology. With the technological revolution, healthcare has now developed beyond what it was previously. One of the blessings of technology is biosensors, and more specifically, wireless body area networks (WBAN). Many research papers have noted endeavours to create a robust solution using WBANs for healthcare applications. WBANs are primarily used for healthcare or healthcare-related applications to assist medical practitioners. As such, medical practitioners can gain confidence with the aid of technology. Several solutions have been proposed by researchers to address the ongoing problems in WBAN healthcare applications. A WBAN can be a potential solution for patient-assisted living. This is because most of the solutions offered for patient well-being require high reliability. A WBAN healthcare application is expected to perform quickly and accurately. Human health is the most dynamic area, and it is difficult to offer a one-stop solution with WBANs. Consequently, there is a trade-off dilemma for the time and accuracy of these applications. The thesis, firstly, presents a comprehensive survey on anomaly or emergency detection and energy consumption.

The research set out with specific goals, including developing a robust decision-making framework, devising a user-friendly anomaly detection method, optimising local emergency detection, formulating a data reduction technique for low-power healthcare frameworks, and evaluating the performance of these systems against state-of-the-art techniques. - The research successfully integrated algorithms like MALED, DCA, and SMDTA into WBANs. These algorithms demonstrated a marked improvement in decision-making accuracy and responsiveness to patient health changes. For instance, MALED showed an accuracy of 96.05% and a sensitivity of 97.00%, highlighting its effectiveness. - The incorporation of DCA into the WBAN framework significantly enhanced the system's ability to detect anomalies early, with a 3% improvement in early detection of adverse events compared to traditional monitoring methods. This approach made anomaly detection more accessible and interpretable for healthcare practitioners. - The implementation of LEDAS, modified later with

SMDTA, optimised emergency detection by intelligently adjusting data acquisition rates. This optimisation was evident in the reduced data transmissions, conserving resources while maintaining effective patient monitoring. - The research effectively addressed the challenge of data volume in WBANs. For example, the integration of LEDAS reduced data transmissions by up to 30%, demonstrating the success of the data reduction techniques in minimising energy consumption without compromising the quality of health monitoring. - The performance of the proposed frameworks was rigorously evaluated and compared with existing techniques like OCSVM and decision trees. The results consistently indicated superior performance of the proposed models, both in terms of predictive accuracy and resource efficiency. It is found that the research has successfully met its stated objectives, making substantial contributions to the field of WBANs. The development and integration of advanced algorithms have not only enhanced the accuracy and efficiency of patient health monitoring but also ensured that these improvements are aligned with the practical constraints of WBANs, such as limited energy resources. The research outcomes demonstrate a significant advancement over traditional methods, indicating a promising future for WBAN technologies in healthcare. Through this work, WBANs have been shown to be capable of supporting more responsive, reliable, and patient-centered healthcare, paving the way for their broader adoption in various healthcare settings.

In Chapter 2, an extensive literature review is conducted. Several crucial factors condition the deployment of WBANS using edge devices in healthcare anomaly detection. These are shaped around key areas like threshold algorithms, decisions from vital signs, prediction accuracy, and personalised solutions, along with balancing energy efficiency and employing data reduction mechanisms like adaptive sampling. It has been found that the key to any WBAN system implementation is the detection algorithm, which is typically set around thresholds. However, threshold settings become significant limitations in this context. Due to individual physiological variations, one-size-fits-all threshold settings are challenging to implement. They can lead to false positives or negatives if they aren't adequately attuned to the individual user's typical vital sign patterns. Custom thresholds are an ideal solution but come with their own difficulties, such as the requirement for more complex computation and higher energy usage. Furthermore, the decision-making accuracy of the gathered vital signs is another significant limitation. It hinges on prediction issues such as the false prediction of anomalies due to erratic but non-critical fluctuations in vital signs. This may lead to unnecessary panic and medical interventions, posing an issue for the reliability of this technology. Edge computing can be employed to improve the accuracy of decision-making quickly, but it introduces challenges about data privacy, latency, and energy consumption. Personalised solutions are key to addressing the above challenges, but they introduce their complexities. Personalising WBAN systems demands significant input from machine learning algorithms, which can tax the computational capabilities of edge devices. Furthermore, ensuring that these individualised solutions remain adaptable to changing user needs over time requires constant updates and recalibrations, significantly impacting the energy efficiency of the device. Energy efficiency itself is crucial to the functioning of edge devices in WBAN. The devices are often mobile and should work for extended periods without requiring frequent charging. Furthermore, ensuring that the devices can process and transmit data while consuming minimal energy is a considerable challenge in this application, and it is further accelerated by the demands of complex decision-making or adaptive algorithms. Lastly, data reduction techniques such as adaptive sampling can mitigate some of the issues presented by high data volumes, but they are not without their problems. While such methods can prevent unnecessary data transfer and computation, they also risk missing vital sign anomalies if the sampling isn't thorough enough. Balancing comprehensive data capture and computational efficiency is hence a significant limiting factor in using edge devices with WBAN for health anomaly detection. In conclusion, while considerable strides have been made in employing edge devices with WBAN in healthcare, there are still substantial limitations to be addressed. Balancing the accuracy of anomaly detection, responsive personalisation, and energy efficiency alongside appropriate data reduction poses a significant challenge. Resolving these concerns involves complex interplay between technological advances, algorithmic fine-tuning, and sensitive prioritisation of user needs.

Chapter 3 of the research presents an in-depth exploration of various algorithms and methods aimed at enhancing patient monitoring in WBANs. The chapter kicks off with the deployment of a simple threshold approach, acting as a basic method for detecting abnormalities in patient vital signs. While this approach is fundamental, it provides an essential framework for more refined enhancements. However, despite its effectiveness in certain circumstances, there are restrictions on its adaptability and sensitivity to individual patient variations.

Acknowledging these restrictions, the research advances towards an enhanced model that incorporates input from physicians for the selection of sensors. This considerable step adds a layer of clinical relevance and expertise to the monitoring system. The system becomes more bespoke and patient-focused through the selection of specific sensors based on patients' needs by physicians. This focus could potentially lead to more accurate and clinically relevant monitoring outcomes. Nevertheless, the static nature of these thresholds still poses challenges in addressing the fluid nature of physiological data. The adoption of a dynamic threshold approach using moving averages introduces further advancements. This method is superior to the straightforward threshold technique as it allows the system to adapt to patients' condition changes over time, therefore providing a more reactive and accurate monitoring solution. While this was a significant progression, there was still potential for further enhancement since this only provides a binary outcome of normal or emergency. Threshold methods, while competent at simple anomaly detection, lacked the refinement needed for more complex and varied medical scenarios. A multi-level classification system bridges this gap by offering a layered approach to categorising patient health statuses. This system suggests multiple levels of health states, such as normal, warning, alert, and emergency, as opposed to a binary classification (normal or abnormal). This detail allows for a more nuanced understanding of a patient's health, enabling healthcare providers to make more informed decisions. For instance, a 'warning' status could indicate the need for heightened monitoring, while an 'emergency' status could prompt immediate medical intervention. This level of detail is vital in situations where patient conditions are intricate and require in-depth analysis. However, the inclusion of the Mahalanobis distance into the model—while it enhances predictive accuracy—brought its own set of challenges, especially concerning computational complexity. The Mahalanobis distance requires the computation of covariance matrices and their inverses, which can be computationally demanding, particularly as the number of monitored vital signs increases. This computation requires not only more processing power but also consumes more energy, a critical factor in resource-limited WBAN environments. These complex calculations could potentially slow down the real-time processing capabilities of the system, a limitation significant in emergency contexts where swift response is imperative. Additionally, the chapter includes a comparative analysis of well-established algorithms such as the One-Class Support Vector Machine (OCSVM) and Decision Tree. These comparisons are essential in assessing the utility of the newly developed methods against existing superior techniques. Known for their robustness in various applications, the OCSVM and Decision Tree methods provide a benchmark for evaluating the improvements made by the newly proposed methods. In this system model, the trial of machine learning algorithms like OCSVM and decision trees was a significant undertaking, intended for comparison with traditional methods. These algorithms were selected for their advanced capabilities in pattern recognition and data analysis, considered indispensable for enhancing the precision and reactivity of WBAN health monitoring systems. However, the findings obtained from these algorithms provided revealing insights about their applicability in WBAN scenarios. The OCSVM algorithm demonstrated potential in specificity but lagged in overall accuracy compared to other developed models. This discrepancy suggests limitations in its ability to comprehensively detect all relevant health emergencies. In contrast, the decision tree model performed better in both accuracy and sensitivity. It was more proficient at identifying true-positive cases but had a higher false-positive rate, suggesting premature flagging of normal scenarios as emergencies. These outcomes highlight the need to strike a critical balance between the sensitivity and specificity intrinsic to these models. From these outcomes, we could derive several key aspects. Firstly, both OCSVM and decision trees demanded significant computational complexity. This demand resulted in higher energy consumption, a crucial concern given WBAN environments' energy constraints. Secondly, the processing speed of these models posed a challenge, as patient monitoring requires real-time or near-real-time analysis. The time required to train and execute these models did not always align with the immediate response requirements of WBAN systems. Furthermore, while the decision trees were more sensitive to health changes, they were less specific, leading to unnecessary alerts. In contrast, while the OCSVM was more specific, it sometimes failed to detect vital health events, thus compromising sensitivity. Their general applicability across a diverse range of patient profiles and health conditions also raised concerns. This exploration led to the realisation that whilst OCSVM and Decision Trees brought valuable data analytics capabilities to WBAN health monitoring, they faced substantial limitations within the unique WBAN context. These included challenges related to computational demand, energy efficiency, real-time data processing, and achieving a balance between sensitivity and specificity. These insights were pivotal in guiding the research towards the development of more suitable models for WBANs. The subsequent creation of hybrid models, which combined the immediacy of threshold-based methods with the predictive accuracy of linear regression, aimed to strike a harmonious balance between computational efficiency, accuracy, and practical applicability. This approach sought to optimise patient health monitoring in WBANs, addressing the critical need for timely, accurate, and energy-efficient health data analysis. In Chapter 3, at the end we developed a hybrid approach that effectively amalgamated the immediacy of threshold-based methods with the predictive accuracy of linear regression, addressing the significant challenges of computational complexity and energy efficiency in WBANs. This innovative model was specifically designed to provide a more balanced, efficient, and accurate solution for patient health monitoring within the constraints of WBAN environments. The primary motivation for adopting this hybrid model was to overcome the limitations observed in previous approaches. Purely threshold-based methods, while excellent for quick anomaly detection, lacked the depth to predict health events based on evolving trends. On the other hand, linear regression excelled in trend analysis and predictions but often lagged in an immediate response to acute health changes. By integrating these two methodologies, the hybrid approach offered both rapid detection capabilities and insightful trend analysis. One of the most significant achievements of the hybrid model was its improved accuracy and sensitivity in monitoring patient health. It proved highly effective in detecting subtle yet critical changes in health data, which was a considerable advancement over the single-method models. Additionally, this approach achieved a reduction in false positives, a crucial aspect of avoiding unnecessary alarms and interventions in patient care. The adaptability of the hybrid model to individual patient data was another key advantage, enhancing its suitability for personalised healthcare monitoring. This adaptability is vital in tailoring care to the specific needs and conditions of individual patients, a growing trend in modern healthcare. Moreover, the hybrid model addressed the challenge of computational load, striking a balance between the simpler computations of threshold methods and the more intricate calculations of linear regression. This balance was crucial in making the model viable for WBANs, which typically operate with limited computational resources and energy constraints. In summary, the hybrid approach developed in our WBAN research represents a significant breakthrough, offering a practical and effective solution for real-time health monitoring. It combines the strengths of different analytical techniques to provide accurate, timely, and patient-specific health data analysis, setting a new standard for future developments in WBAN systems and highlighting the potential for innovative solutions in the field of health monitoring technology. The chapter also delves into the computational complexity of each method. The simple threshold and physician-informed sensor selection methods are relatively less computationally intensive, making them suitable for real-time applications. However, the dynamic threshold and multi-level classification methods, along with the Mahalanobis distance approach, introduce increased complexity but offer higher accuracy and sensitivity. The hybrid algorithm, while being the most computationally demanding among the methods discussed, balances this complexity with significant improvements in prediction accuracy and system responsiveness. The chapter provides a detailed evaluation of various advancements in WBANs for patient monitoring, each contributing to a more accurate, responsive, and efficient system. The development of these methods, particularly the novel hybrid algorithm, marks a significant step forward in the field of healthcare technology, offering promising implications for future applications in patient monitoring and clinical decision-making. However, all the methods still do not provide a high standard of personalised, robust systems where energy can be saved while the system can detect early emergencies.

Chapter 4 of the research builds upon the advancements made in Chapter 3, where the exploration of predictive models in Wireless Body Area Networks (WBANs) transitioned from simpler algorithms to more complex ones. The progression from the Multi-Level Classification Threshold Algorithm (MLCTA) to the Modified Adaptive Local Emergency Detection (MALED) marked a significant change in approach, driven by the need for greater personalisation and adaptability in patient health monitoring. The shift to MALED was necessitated by certain limitations of MLCTA, particularly its rigid thresholding strategy, which couldn't adequately capture the dynamic and individual variability present in physiological data. While MLCTA excelled in offering a nuanced classification of patient health status, it lacked the adaptability to cater to the unique and evolving health patterns of individual patients. MALED addressed this gap by implementing a model that not only used threshold levels for emergency detection but also adapted these thresholds based on each patient's historical health data. This approach significantly enhanced the precision and personalisation of the WBAN system. Despite the advancements with MALED, there was a continual drive for improvement, particularly in terms of predictive capabilities and resource efficiency. The integration of Differential Change Analysis (DCA) into the MALED framework was a response to this challenge. DCA was proposed to address the need for a more proactive approach to predicting health events, enhancing the sensitivity of WBAN systems to subtle physiological changes that may not trigger conventional threshold-based alarms. By analysing the rate of change in health indicators, DCA provided an early warning system for potential health issues, offering deeper insights into patient health trends. This enhancement not only improved the predictive capabilities of WBAN systems but also refined patient monitoring by differentiating between normal fluctuations and signs of emerging health concerns, thereby reducing false alarms and enabling more targeted interventions. The integration of DCA thus represented a crucial step in evolving WBAN systems towards more accurate, reliable, and anticipatory health monitoring solutions. However, the application of MALED and DCA, while effective in anomaly detection and trend analysis, highlighted the need for optimising data acquisition rates. This led to the development of the local emergency detection algorithm using adaptive sampling (LEDAS). LEDAS was particularly focused on optimising the energy efficiency of the WBAN system. It dynamically adjusted the data collection frequency according to the urgency of the patient's condition, ensuring that resource consumption was aligned with the need for monitoring.

The final stage in the evolution presented in Chapter 4 was the incorporation of sequential multi-dimensional trend analysis (SMDTA) into the LEDAS framework. SMDTA marked a substantial enhancement by offering a multi-dimensional analysis of patient health. The SMDTA in this system was driven by the need to provide a more holistic and comprehensive analysis of patient health data. SMDTA was designed to go beyond single-parameter analysis, integrating multiple vital sign data to understand the complex interrelations and dependencies among various health indicators. This approach enabled the WBAN system to not just monitor individual health metrics in isolation but to interpret them in the context of a broader physiological landscape. The achievement of SMDTA lies in its ability to offer a nuanced view of patient health, improving the accuracy and sensitivity of health predictions. By considering the multi-dimensional nature of human physiology, SMDTA enhanced the predictive capabilities of the WBAN system, allowing for earlier and more precise detection of potential health issues. This comprehensive analysis also played a crucial role in minimising false positives and negatives, leading to more effective and efficient patient monitoring and care management. The integration of SMDTA thus marked a significant advancement in the field of WBANs, pushing the boundaries of what these systems can achieve in terms of patient health monitoring and predictive analytics. In a nutshell, Chapter 4 presents a continuous narrative of enhancing and refining WBAN predictive models, where each development phase, from MLCTA to SMDTA, was aimed at addressing specific limitations of the preceding models. This journey reflects a commitment to advancing WBAN technology to meet the complex demands of patient health monitoring, ultimately aiming to create a system that is both sophisticated and sensitive to the nuanced needs of healthcare.

5.2 Future Direction

The thesis is centred around a variety of simulation-based experiments, with real clinical data serving as the backbone for these experiments. Despite proposing potential solutions, these have not yet been practically implemented or tested. One key future direction includes the establishment of an actual WBAN system to conduct this research in a real-world network environment. This would bolster the credibility and reliability of the results, enabling more straightforward data interpretation without the need for assumptions. In addition, it would offer the possibility of evaluating other variables like costs or comfort to the wearer.

Moreover, the synergy of WBANs with emerging technologies like Artificial Intelligence (AI), 5G, and the Internet of Things (IoT) have the potential to drastically enhance data transfer rates, analytic capacity, and the overall efficiency of the system. This combination could pave the way for real-time monitoring and predictive analytics of high precision, thereby enriching the standard of patient care. It is also intend to incorporate contextual analysis to make decision such as personal attributions and physical analysis such as motion, walking style, sleeping state, facial reaction etc.

Within the domain of healthcare applications utilising WBANs, time turns out to be the most crucial element. However, computing the processing time is no simple feat. A WBAN comprises a range of biosensors, each with its own unique computational capabilities, making the situation even more complex. Furthermore, a WBAN might be connected to several different networks, such as LAN, WiFi, and cellular networks. Given the diverse array of biosensors produced by various manufacturers, accurately calculating the processing time from an algorithm's runtime becomes a challenging task. For instance, while R is capable of calculating the processing time of an algorithm, the final output is subject to the system where R is deployed. In this research, we propose a hypothetical computational complexity using both mathematical and practical approaches, which could extend to future studies. The concept of time complexity has sparked considerable interest among researchers. Big-O notation, a prevalent method for computing time complexity, signifies both the execution duration of a task and the steps it entails for completion. Calculating time complexity proves to be vital in evaluating the effectiveness of existing solutions regarding processing time reliability.

The sentiment shared is indeed an insightful one that touches on the very core of the challenges facing healthcare. The introduction of AI and machine learning systems in healthcare has undeniably offered a plethora of possibilities, but it also reveals the gaps that need to be addressed. In many of the systems currently researched or deployed, overemphasis on standard physiological data gathered by WBAN systems leaves out the rich tapestry of information that clinical carers often use to assess the condition of a patient. Surely, probing the heart rates, blood pressure levels, and body temperature offers useful information, but it is not the comprehensive range of criteria that medical practitioners deploy in framing a patient's health status. The key to actualizing an effective clinical prediction tool, therefore, lies in developing a model that considers a broad array of health indicators. A tool that incorporates past medical records, patient responses to prior treatments, and real-time physiological data can offer predictions that are more holistic, reliable, and actionable. Interdisciplinary collaboration comes into play here, which is extraordinarily significant. Medical professionals, AI experts, and data scientists need to pool their knowledge together to build these comprehensive systems. Rigorous clinical trials would ensure the predictions from such systems align with the real-world medical scenario and hold practical utility in healthcare settings. With the continuously growing focus on data in decision-making, considering the ethical aspects of data becomes increasingly significant. Ensuring data privacy and achieving informed consent from patients for their data usage sets an ethical standard for these AI-based tools and systems. In essence, the evolution of clinical prediction tools hinges on making full use of machine learning while staying tethered to real-world medical practices that are comprehensive and holistic. This can enhance the reliability of the systems and ensure the developed tools offer actionable insights to aid healthcare practitioners in patient care.

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‘Appendix

A.1 Anomaly detection

Anomaly detection techniques in healthcare data analysis offer significant benefits, including early detection, improved patient safety, and automated surveillance. However, challenges like false positives, imbalanced data, and interpretability need to be addressed to ensure the reliability and effectiveness of these methods. Selecting the most appropriate technique should consider the specific healthcare application, the quality of the available data, and the resources and expertise available for implementation.

The following are the most common applications of healthcare anomalies, highlighting their significance and impact:

- Patient Monitoring and Safety: Anomaly detection plays a pivotal role in continuously monitoring patients' vital signs and physiological parameters. By identifying deviations from established norms in heart rate, blood pressure, respiratory rate, and temperature, healthcare professionals can intervene promptly to prevent adverse events and ensure patient safety. This application is particularly critical in intensive care units (ICUs) and critical care settings, where rapid responses are vital for patient well-being.
- Early Disease Detection: Anomaly detection contributes to early disease detection by identifying subtle deviations in patient data that may signify the onset of health conditions. Timely recognition of anomalies in physiological patterns or diagnostic test results allows for

early interventions and improved disease management. This application holds immense potential for enhancing public health efforts, preventing disease outbreaks, and optimising treatment outcomes.

- Medication Error Prevention: Anomaly detection is instrumental in preventing medication errors by scrutinising medication administration records for irregularities. Detecting discrepancies such as incorrect dosages, missed doses, or improper administration routes ensures patient safety and reduces the risk of adverse drug reactions. This application minimises the potential harm associated with medication errors and contributes to improved treatment adherence.
- Healthcare Fraud Detection: Anomaly detection serves as a powerful tool in detecting fraudulent activities within healthcare billing, insurance claims, and reimbursement processes. By identifying anomalous patterns in financial transactions and claims data, anomaly detection helps combat healthcare fraud, ensuring accurate allocation of resources and preserving the financial integrity of healthcare systems.
- Early Disease Detection: Anomaly detection contributes to early disease detection by identifying subtle deviations in patient data that may signify the onset of health conditions. Timely recognition of anomalies in physiological patterns or diagnostic test results allows for early interventions and improved disease management. This application holds immense potential for enhancing public health efforts, preventing disease outbreaks, and optimising treatment outcomes.
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- Healthcare Fraud Detection: Anomaly detection serves as a powerful tool in detecting fraudulent activities within healthcare billing, insurance claims, and reimbursement processes. By identifying anomalous patterns in financial transactions and claims data, anomaly detection helps combat healthcare fraud, ensuring accurate allocation of resources and preserving the financial integrity of healthcare systems.
- Diagnostic Test Result Anomalies: Anomaly detection techniques are utilised to detect deviations in diagnostic test results, such as blood tests or genetic analyses. Detecting anomalies in test data allows for the early identification of underlying health conditions,

facilitating accurate diagnoses and tailored treatment strategies. This application optimises disease assessment and management.

- Workflow Optimisation: Anomaly detection extends to optimising healthcare workflows by identifying deviations from established protocols, resource utilisation patterns, or delays in patient care processes. By highlighting workflow anomalies, healthcare administrators and providers can streamline operations, improve efficiency, and enhance the quality of patient services.
- Predictive Analytics: Anomaly detection techniques enable predictive analytics by identifying trends and patterns that deviate from expected norms. By analysing historical patient data, anomaly detection can forecast potential health risks, disease progression, or treatment responses. This application supports proactive healthcare interventions and personalised treatment planning.

A.2 Vital Signs

Set of factors that reflect physical health classified as 'physiological signs' or 'vitalsigns'. Generally it consist the following vital signs:

- Respiratory rate (breaths/min);
- Oxygen saturation;
- Temperature (C);
- Blood Pressure;
- Heart rate (beats/min);

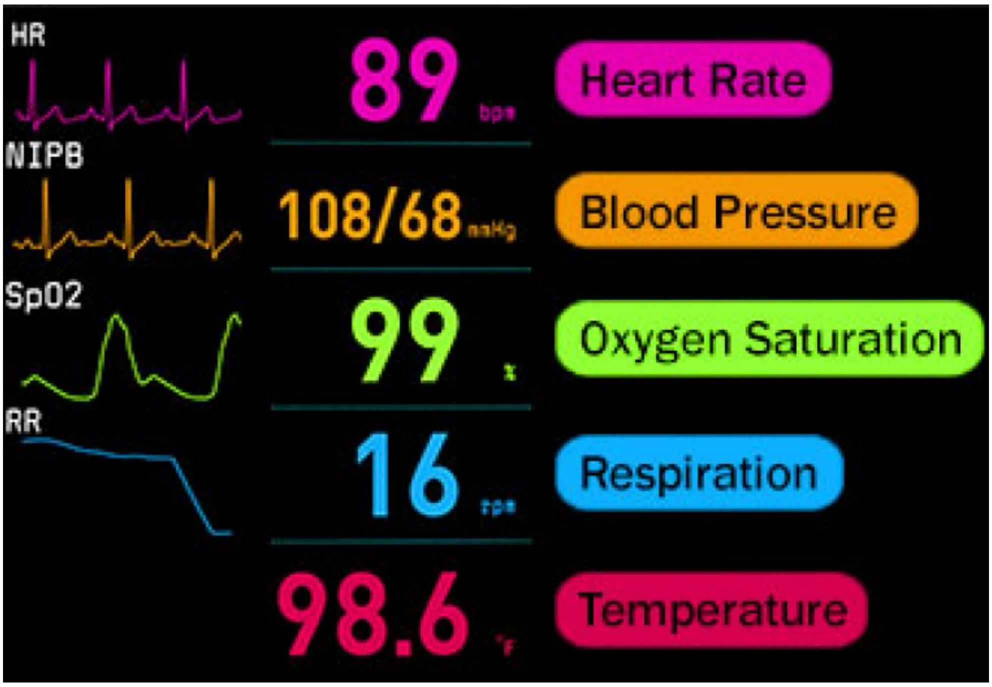

Figure A.2: Vital signs.

A.3 Normal Range of vital signs

Table A.3: Normal Range of vital signs

Normal ranges: respiratory rate (RR), heart rate (HR) and blood pressue (BP)

Age	Guide weight (kg)		RR At rest Breaths per minute	HR Beats per minute	BP Systolic		
	Boys	Girls	5th–95th centile	5th–95th centile	5th centile	50th centile	95th centile
Birth	3.5	3.5	25–50	120–170	65–75	80–90	105
1 month	4.5	4.5					
3 months	6.5	6	25–45	115–160			
6 months	8	7	20–40	110–160			
12 months	9.5	9			70–75	85–95	
18 months	11	10	20–35	100–155			
2 years	12	12	20–30	100–150	70–80	85–100	110
3 years	14	14		90–140			
4 years	16	16		80–135			
5 years	18	18			80–90	90–110	111–120
6 years	21	20		80–130			
7 years	23	22					
8 years	25	25	15–25	70–120			
9 years	28	28					
10 years	31	32					
11 years	35	35					
12 years	43	43	12–24	65–115	90–105	100–120	125–140
14 years	50	50		60–110			
Adult	70	70					

A.4 Pain Response

NEWS SCORE	FREQUENCY OF MONITORING	CLINICAL RESPONSE
0	Minimum 12 hourly	• Continue routine NEWS monitoring with every set of observations
Total: 1-4	Minimum 4-6 hourly	• Inform registered nurse who must assess the patient; • Registered nurse to decide if increased frequency of monitoring and / or escalation of clinical care is required;
Total: 5 or more **or** **3 in one parameter**	Increased frequency to a minimum of 1 hourly	• Registered nurse to urgently inform the medical team caring for the patient; • Urgent assessment by a clinician with core competencies to assess acutely ill patients; • Clinical care in an environment with monitoring facilities;
Total: 7 or more	Continuous monitoring of vital signs	• Registered nurse to **immediately** inform the medical team caring for the patient – this should be at least at Specialist Registrar level; • Emergency assessment by a clinical team with critical care competencies, which also includes a practitioner/s with advanced airway skills; • Consider transfer of Clinical care to a level 2 or 3 care facility, i.e. higher dependency or ITU;

Figure A.4: Pain response table.

A.5 Pain Assessment Tool

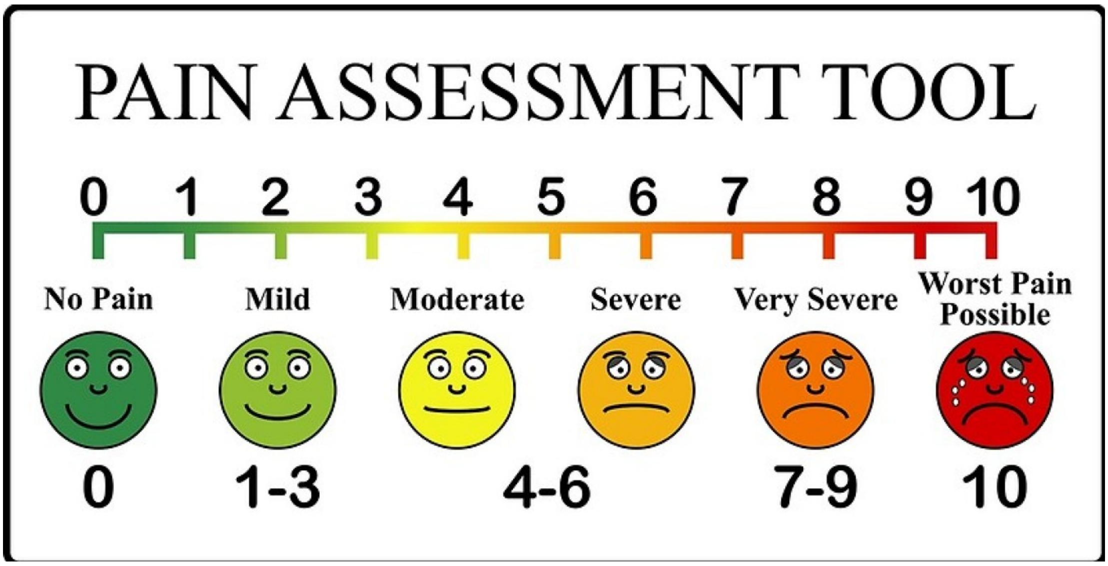

Figure A.5: Pain assessment tool

A.6 Sample data looks like

Table A.6: Sample data

SL #	SYSTOLICBP	SpO2	HR	PULSE	RESP	TEMP
1	151	97	133	132	32	36.8
2	153	97	133	132	32	36.7
3	154	97	133	132	32	36.6
4	152	97	133	132	29	36.9
5	147	98	133	132	29	36.8
6	144	98	133	132	29	36.6
7	154	98	133	132	30	36.6
8	147	98	133	132	36	37.1
9	149	99	133	115	36	36.5
10	151	99	133	115	38	36.5

A.7: Physionet data training certificate

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COMPLETION REPORT - PART 1 OF 2
COURSEWORK REQUIREMENTS*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- **Name:** Masum Billah (ID: 6223748)
- **Institution Affiliation:** Massachusetts Institute of Technology Affiliates (ID: 1912)
- **Institution Email:** masum.billah@research.staffs.ac.uk
- **Institution Unit:** Science and engineering
- **Phone:** 00447816584267

- **Curriculum Group:** Human Research
- **Course Learner Group:** Data or Specimens Only Research
- **Stage:** Stage 2 - Refresher Course

- **Record ID:** 22577648
- **Completion Date:** 10-Mar-2017
- **Expiration Date:** 09-Mar-2020
- **Minimum Passing:** 90
- **Reported Score*:** 100

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
SBE Refresher 1 – Defining Research with Human Subjects (ID: 15029)	10-Mar-2017	2/2 (100%)
SBE Refresher 1 – Privacy and Confidentiality (ID: 15035)	10-Mar-2017	2/2 (100%)
SBE Refresher 1 – Assessing Risk (ID: 15034)	10-Mar-2017	2/2 (100%)
SBE Refresher 1 – Research with Children (ID: 15036)	10-Mar-2017	2/2 (100%)
SBE Refresher 1 – International Research (ID: 15028)	10-Mar-2017	2/2 (100%)
Biomed Refresher 2 - Instructions (ID: 764)	10-Mar-2017	No Quiz
Biomed Refresher 2 – History and Ethical Principles (ID: 511)	10-Mar-2017	3/3 (100%)
Biomed Refresher 2 – Regulations and Process (ID: 512)	10-Mar-2017	2/2 (100%)
Biomed Refresher 2 – SBR Methodologies in Biomedical Research (ID: 515)	10-Mar-2017	4/4 (100%)
Biomed Refresher 2 – Genetics Research (ID: 518)	10-Mar-2017	2/2 (100%)
Biomed Refresher 2 – Records-Based Research (ID: 516)	10-Mar-2017	3/3 (100%)
Biomed Refresher 2 - Populations in Research Requiring Additional Considerations and/or Protections (ID: 519)	10-Mar-2017	1/1 (100%)
Biomed Refresher 2 – HIPAA and Human Subjects Research (ID: 526)	10-Mar-2017	5/5 (100%)
Biomed Refresher 2 – Conflicts of Interest in Research Involving Human Subjects (ID: 681)	10-Mar-2017	3/3 (100%)
How to Complete the CITI Refresher Course and Receive a Completion Report (ID: 922)	10-Mar-2017	No Quiz

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

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COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COMPLETION REPORT - PART 2 OF 2

COURSEWORK TRANSCRIPT**

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

- **Name:** Masum Billah (ID: 6223748)
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- **Stage:** Stage 2 - Refresher Course

- **Record ID:** 22577648
- **Report Date:** 10-Mar-2017
- **Current Score**:** 100

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Biomed Refresher 2 - Instructions (ID: 764)	10-Mar-2017	No Quiz
Biomed Refresher 2 – History and Ethical Principles (ID: 511)	10-Mar-2017	3/3 (100%)
Biomed Refresher 2 – Regulations and Process (ID: 512)	10-Mar-2017	2/2 (100%)
Biomed Refresher 2 – SBR Methodologies in Biomedical Research (ID: 515)	10-Mar-2017	4/4 (100%)
Biomed Refresher 2 – Records-Based Research (ID: 516)	10-Mar-2017	3/3 (100%)
Biomed Refresher 2 – Genetics Research (ID: 518)	10-Mar-2017	2/2 (100%)
SBE Refresher 1 – International Research (ID: 15028)	10-Mar-2017	2/2 (100%)
Biomed Refresher 2 - Populations in Research Requiring Additional Considerations and/or Protections (ID: 519)	10-Mar-2017	1/1 (100%)
SBE Refresher 1 – Defining Research with Human Subjects (ID: 15029)	10-Mar-2017	2/2 (100%)
SBE Refresher 1 – Assessing Risk (ID: 15034)	10-Mar-2017	2/2 (100%)
SBE Refresher 1 – Privacy and Confidentiality (ID: 15035)	10-Mar-2017	2/2 (100%)
SBE Refresher 1 – Research with Children (ID: 15036)	10-Mar-2017	2/2 (100%)
Biomed Refresher 2 – HIPAA and Human Subjects Research (ID: 526)	10-Mar-2017	5/5 (100%)
Biomed Refresher 2 – Conflicts of Interest in Research Involving Human Subjects (ID: 681)	10-Mar-2017	3/3 (100%)
How to Complete the CITI Refresher Course and Receive a Completion Report (ID: 922)	10-Mar-2017	No Quiz

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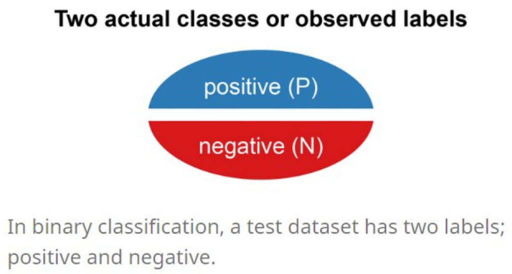
A.8 Distribution and Cut of point

Table A.8: TP, TN, FP, FN measurements as outcomes

Case	Prediction or test outcome	Reality or truth
False Positive (FP)	Anomaly	Normal
False Negative (FN)	Normal	Anomaly
True Positive (TP)	Anomaly	Anomaly
True Negative (TN)	Normal	Normal



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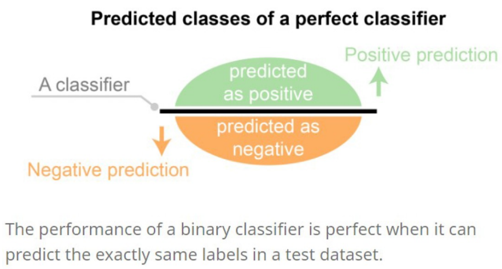

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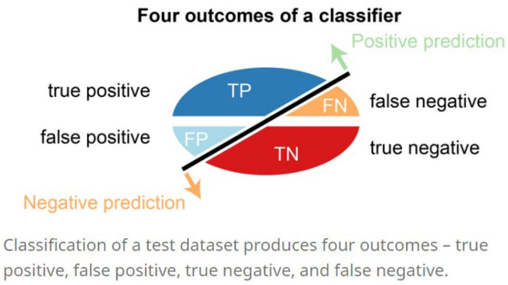

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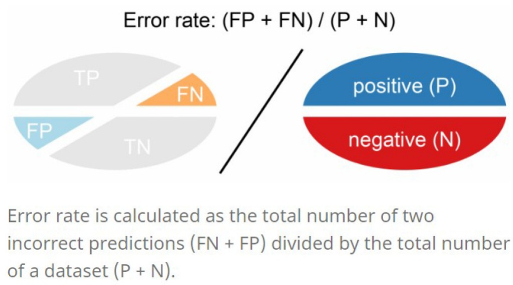

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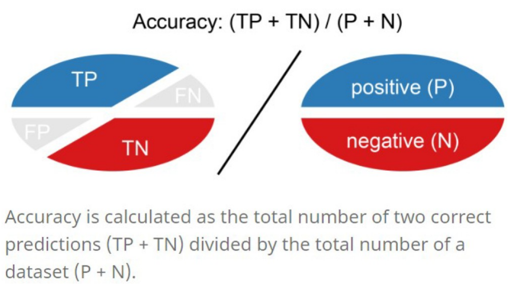

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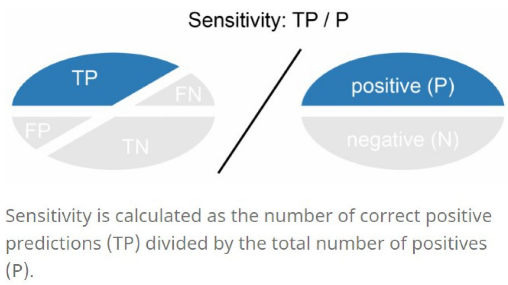

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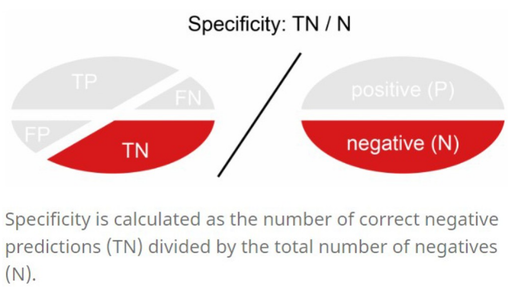
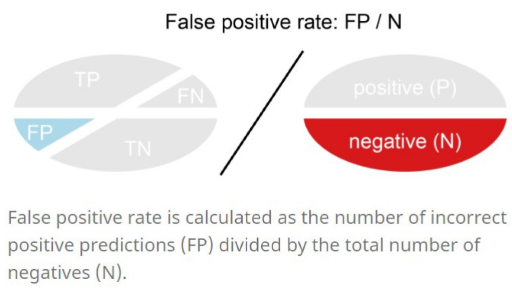


(g)



(h)

A.9 : R code linear regression algorithm

Example: R Code with this patient data

```
Threshold <- function(value, lower_threshold, upper_threshold) {
 return(value < lower_threshold | value > upper_threshold)
}
Classify <- function(sensor_data) {
 emergency_vital_signs <- c()
 for (i in 1:num_vital_signs) {
  value <- sensor_data[i]
  lower_threshold <- getLower(i)
  upper_threshold <- getUpper(i)
  if (Threshold(value, lower_threshold, upper_threshold)) {
   emergency_vital_signs <- c(emergency_vital_signs, i)
  }
 }
 if (length(emergency_vital_signs) > 0) {
  return(list("status" = "Emergency", "vital_signs" = emergency_vital_signs))
 } else {
  return(list("status" = "Normal", "vital_signs" = integer(0)))
 }
}
LinearR <- function(sensor_data, coefficients, intercept) {
 selected_sensors <- sensor_data[1:num_selected_sensors]
 predicted_value <- 0
 for (i in 1:num_selected_sensors) {
  predicted_value <- predicted_value + coefficients[i] * selected_sensors[i]
 }
 predicted_value <- predicted_value + intercept
 return(predicted_value)
}
Monitor <- function(patient_data) {
 sensor_data <- patient_data
 threshold_result <- Classify(sensor_data)
 if (threshold_result$status == "Emergency") {
  coefficients <- c(0, coefficient_heart_rate, coefficient_blood_pressure, coefficient_respiratory_rate,
coefficient_temperature, coefficient_oxygen_saturation, coefficient_pulse)
  intercept <- trained_intercept
  linear_regression_result <- LinearR(sensor_data, coefficients, intercept)
  linear_regression_threshold <- 0.0
  if (linear_regression_result >= linear_regression_threshold) {
   # Perform actions for Emergency (Using Linear Regression)
   cat("Final Status: Emergency (Using Linear Regression)\n")
  } else {
   # Perform actions for Normal (Using Linear Regression)
   cat("Final Status: Normal (Using Linear Regression)\n")
  }
 } else {
  # Perform actions for Normal (Threshold Algorithm)
  cat("Final Status: Normal (Threshold Algorithm)\n")
 }
}
# Assuming you have appropriate values for num_vital_signs, num_selected_sensors,
# coefficient_heart_rate, coefficient_blood_pressure, etc.
# and the required functions getLower, getUpper, and trained_intercept
# Example usage:
# Monitor(patient_data)
```