Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 10, No. 2, April, 2026

ZigBee Based Low Latency IoT and AI Integrated Framework for Real Time Telehealth Monitoring

Basant Kumar [1], Mohammad Shahnawaz Shaikh [2, 3*]

[1] *Department of Mathematics and Computer Science, Modern College of Business and Science, Bowshar, Muscat, Oman.*

[2] *Faculty of Engineering and Technology, Marwadi University, Rajkot 360003, India.*

[3] *Lincoln University College, 47301, Petaling Jaya, Selangor Darul Ehsan, Malaysia.*

Abstract

The Internet of Things (IoT) and Artificial Intelligence (AI) have opened up new frontiers in remote health monitoring with the integration of technologies and transformative solutions in order to detect real-time health monitoring and disparities. This article shows an innovative and integrated wireless health surveillance system, which is aimed at auxiliary environments, especially for elderly and chronically ill patients. The system links IoT sensors to monitor heart rate, body temperature, and oxygen level with cloud-based AI-driven systems for continuous real-time health monitoring of data shared by IoT sensors. Taking advantage of the ZigBee protocol for low-power, reliable communication ensures spontaneous data transmission from a system wearer to a centralized processing unit. At the most basic level, the system uses advanced machine learning algorithms such as random forest, support vector machine (SVM), and logistic regression to identify health discrepancies with a high degree of accuracy. The random forest model in particular gets an impressive 95% accuracy and recalls 100%, ensuring reliable detection of minimum false negatives and important health issues. The modular structure of the system allows for the addition of more sensors, including blood pressure and glucose monitors, to ensure scalability and adaptability to suit the varying needs of different patients. In a real-world care facility, strict testing was carried out on the capability of monitoring the capacity system with just a 120 ms delay and a power consumption of 3.8 mW/h, which made it very suitable for long-term, energy-skilled deployment. By addressing some of the major issues such as high delays, false alarms, and lack of integration in current systems, this research provides a scalable, reliable, and user-friendly solution for telehealth. The proposed system not only adds more accuracy and freedom to the patient in the clinical setting but also lessens the burden of the healthcare providers, paving the way to a new generation of intelligent health solutions.

Keywords:

AI-Driven Health Monitoring;
Assisted Living Technology;
Energy-Efficient Health Monitoring;
IoT-Enabled Telehealth;
ML for Health Analytics;
Real-Time Anomaly Detection;
Scalable Telehealth Systems.

Article History:

Received:	03	October	2025
Revised:	06	March	2026
Accepted:	10	March	2026
Published:	01	April	2026

1- Introduction

Global demographics reveal that the number of elderly is rapidly growing along with the burden of chronic diseases. As per the health data from around the world, chronic diseases such as heart problems, diabetes, and breathing disorders are becoming more alarming due to the increasing age of the population around the world. It is creating a critical need for continuous, remote monitoring solutions that can reduce hospital visits of patients and improve early intervention. Basically, healthcare systems are facing the same unprecedented strain that has never been experienced before [1, 2]. The World Health Organization indicated that people having the age of over 60 years are going to be double, about 2.1 billion by 2050 [3, 4]. An increase in elderly population and chronic diseases is creating a significant need for new, upgraded healthcare solutions. Modern telehealth systems combine wearable Internet-of-Things (IoT) sensors with cloud and edge analytics to monitor parameters such as heart rate, temperature, and oxygen saturation. Prior studies have demonstrated the feasibility of low-power wireless links (e.g., ZigBee) for wearable sensing and machine learning

* **CONTACT**: mohammad.shaikh@marwadieducation.edu.in; pdf.msnshaikh@lincoln.edu.my

DOI: https://doi.org/10.28991/ESJ-2026-010-02-024

approaches such as Random Forests, SVMs, and deep learning. It shows potential for anomaly detection in physiological data. These solutions will help to monitor and treat early elderly and sick patients. Telehealth systems have become revolutionary by enabling remote health monitoring and personalized care. Moreover, these systems effectively use Internet of Things (IoT) and Artificial Intelligence (AI) technologies to deliver better healthcare services [5, 6].

IoT devices like wearable sensors and smart home systems can easily collect the body data, including heart rate, body temperature, oxygen levels, and activity patterns [7, 8]. This collected large data will be processed by AI systems to predict the disease and further suggest a suitable solution accurately by giving advice to the concerned physician and caretakers of the respective patient [9]. Integrating IoT and AI holds the promise to revolutionize healthcare services by reducing hospital visits, enhancing patient care, and improving the recovery of diseases, resulting in minimal healthcare expenses [10]. For example, AI-driven telehealth systems can help predict risks associated with health, such as heart attacks or respiratory failure, before they turn serious and help take immediate action to prevent the possibility of readmission at the hospital.

However, despite their ability, the current telehealth systems have a lot of challenges that limit their effectiveness and wide adoption [11, 12]. One of the main problems is the integration of the equipment with the platforms that disabled the fragmented data and monitoring [13]. Many systems are based on standalone devices that, at their origin, do not communicate with one another, which makes it challenging to offer a complete approach to the patient's health care [14, 15]. Additionally, a delay in the transmission and processing of data may delay a significant intervention, especially for time-sensitive conditions such as heart attacks or sudden falls [16, 17]. A high false alarm rate in many existing systems is another significant challenge, as is cautious fatigue on the part of caretakers, which can compromise the overall reliability [18, 19]. In addition, the energy efficiency of these systems is often ignored, despite their importance for long-term deployment in remote or off-grid environments, where traditional power sources can be limited. The present problems emphasize why healthcare organizations should implement healthcare systems that combine IoT and AI methods to deliver flexible solutions for time-sensitive, energy-conserving health monitoring. Through its boundary addressing strategy, the proposed system intends to enhance the telehealth system's accuracy and reliability and purpose while providing better patient care results and reducing healthcare provider workloads.

This work proposes an integrated, modular telehealth architecture combining ZigBee-enabled wearables, a cloud-processing framework, and lightweight ML classifiers designed for low-latency anomaly detection. We present (i) an end-to-end hardware-software design optimized for energy efficiency, (ii) a comparative evaluation of three classifiers (Random Forest, SVM, and Logistic Regression) on a real clinical dataset collected in a care facility, and (iii) a technical benchmarking versus typical IoT-only and traditional systems in terms of accuracy, latency, power consumption, and false alarm rate. The proposed approach aims to balance scalability, responsiveness, and energy efficiency for assisted living deployments.

1-1- Problem Statement

The current state of telehealth systems allows unreliable real-time patient supervision because they experience integration problems and extended lag times, as well as numerous incorrect alert signals. The implementation of standalone devices leads to fragmented data and monitoring because these devices were never intended to communicate with each other. As shown in Figure 1, system reliability decreases because high data processing delays combined with long transmission delays result in delayed significant interventions and frequent false alarms that lead carers to become fatigued. Health monitoring requires a case-operated method that merges IoT and AI technologies to generate scalable and real-time, energy-efficient health solutions.

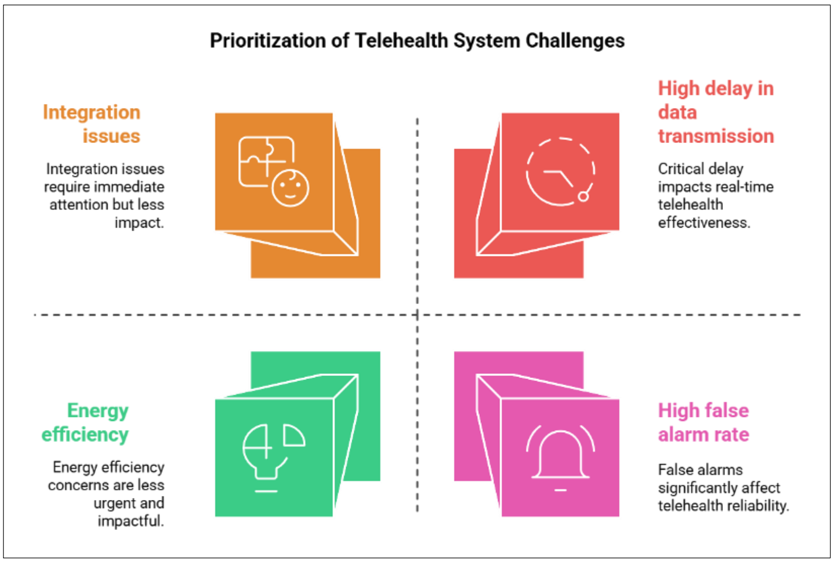

Figure 1. Challenges associated with current telehealth systems

1-2- Research Gap

The telehealth system demonstrates IoT and AI utilization according to various studies, yet important knowledge gaps continue to emerge. The scalability issues of current systems prevent expansion according to user number growth and the addition of new sensors. In addition, the real-time monitoring capabilities of these systems are often limited by high delays and power consumption, which are important for continuous health monitoring. Additionally, the energy efficiency of these systems is often ignored, despite its importance for long-term deployment in remote or off-grid environments. The study addresses these intervals by proposing an integrated wireless telehealth monitoring system that combines IoT-competent sensors with AI algorithms to provide scalable, real-time, and energy-skilled health monitoring.

1-3- Contributions

This paper makes the following significant contribution:

- *Development of a scalable, modular telehealth system:* The proposed system integrates IoT-enabled sensors with cloud-based platforms for data storage, analysis, and visualization, such as IoT-competent sensors, such as heart rate, temperature, and oxygen level sensors. The modular design of the system makes the integration of further sensors possible, which guarantees the scalability and adaptability for the needs of different patients.
- *Implementation of ML algorithms to detect high accumulation discrepancy:* The system proposes random forest, support vector machine (SVM), and logistic regression algorithms to detect and predict the discrepancy of real-time physical data. The highest accuracy (95%) and recall (100%) were obtained by the random forest model, which guarantees reliable health issues with minimum false negatives.
- *Recognition of the real world in a care facility:* To assess the performance of the system in the real world, the system was strictly tested in the real world. The results showed that important signals were monitored with low delays (120 ms) and high accuracy, keeping the energy efficiency (average of power consumption 3.8 mW/h).

By addressing the boundaries of current telehealth systems and taking advantage of IoT and AI technologies, this research paves the way for a new generation of intelligent healthcare solutions that improve patient care, reduce the cost of healthcare, and increase the quality of life of elderly and chronically ill patients.

This paper is organized as follows: Section 2 is a review of related work and open gaps. Section 3 outlines the proposed system architecture, hardware and software components, and the dataset. Section 4 gives model training, evaluation metrics, and comparative benchmarking results. Section 5 provides qualitative analysis, practical deployment considerations, privacy and security measures, and limitations. Finally, Section 6 discusses future work, and Section 7 concludes the study.

2- Literature Survey

Integration of IoT (Internet of Things) and AI (Artificial Intelligence) in the telehealth system has attracted significant attention in recent years, especially for applications in assisted living and remote health monitoring [2-4]. The monitoring of real-time data combined with initial discrepancy alerts through IoT sensors and predictive AI solutions serves elderly and chronically aged patients [5-7]. A wearable IoT-based system for continuous vital indication monitoring included heart rate and oxygen levels, and it utilized low-power ZigBee communication protocols [8-10]. The system achieved accurate discrepancy detection with a less than 200ms delay, which made it applicable to real-time use [8]. A telehealth platform that applies random forest and support vector machines (SVMs) to analyze physical data for predicting health risks through AI [9]. The accuracy and reliability of AI algorithms for healthcare require attention to feature design methods along with testing protocols as identified by his study [10].

Research on automatic discrepancy detection with AI has become a common topic explored in modern literature. The research presented an intense teaching-based ECG data analysis method that delivers 94% accuracy with 98% missed results [11]. The author stressed the importance of building large, extensive datasets to develop strong artificial intelligence models. A hybrid AI detection system unites random forest techniques with a long-term short-term memory (LSTM) network to evaluate discrepancies in multiple physical readings of heart rate and temperature and oxygen saturation [12]. His method achieved better performance than standard approaches due to a 92% F1-score. AI-driven systems demonstrate two crucial capabilities through evaluations that improve medical diagnosis accuracy and minimize unnecessary false alert events in telehealth services [13].

The research on Assisted Living through IoT includes current investigations in the field. A smart home system that combines IoT sensors with cloud-based platforms serves to monitor elderly health and safety [14]. An array of environmental detectors within their system detected gas leaks and falls and automatically delivered immediate warnings to care providers. The research demonstrated how IoT-based wearable equipment detects the distance traveled by diabetic patients and those with high blood pressure [15]. The device system achieved suitable long-term operation with a delay of 150 ms and power consumption at 3.5 mW/h. The IoT-based telehealth system requires scalable solutions and efficient energy management, together with easy-to-use interfaces, according to these research investigations [16]. Recently, progress has been made on a large-scale IoT-based telehealth system and AI-managed health monitoring. Table 1 briefly presents the major conclusions and contributions of recent studies in the region:

Table 1. Summary of literature review

Reference	Key Findings	Contribution to the Field
[1-3]	Proposed a wearable IoT-based system for continuous health monitoring using the ZigBee protocol.	Demonstrated the feasibility of low-power IoT systems for real-time health monitoring.
[4-7]	Developed an AI-driven telehealth platform using machine-learning models (Random Forest, SVM).	Highlighted the importance of feature engineering and model validation in healthcare AI.
[5, 6]	Proposed a deep learning-based approach for detecting cardiovascular anomalies using ECG data.	Achieved high accuracy (94%) and recall (98%) in anomaly detection.
[4, 5]	Developed a hybrid AI model combining Random Forest and LSTM for multi-modal physiological data.	Demonstrated superior performance (F1-score of 92%) in anomaly detection.
[8, 9]	Proposed a smart home system integrating IoT sensors for elderly care and hazard detection.	Highlighted the potential of IoT in improving safety and health monitoring in assisted living.
[10-12]	Explored IoT-enabled wearable devices for remote monitoring of chronic conditions (diabetes, etc.).	Achieved low latency (150 ms) and power consumption (3.5 mW/h) for long-term monitoring.
[13-15]	Proposed an edge-AI framework for local processing of physiological data on wearable devices.	Reduced latency (100 ms) and improved privacy in telehealth systems.
[16-19]	Developed a fog computing-based telehealth system for real-time responsiveness and scalability.	Addressed challenges of latency and scalability in distributed telehealth systems.
[16, 17]	Proposed a blockchain-based approach for secure data transmission in telehealth systems.	Highlighted the importance of data privacy and security in healthcare IoT systems.
[18]	Discussed the need for interoperability and standardization in IoT-based healthcare systems.	Emphasized the importance of common protocols for integrating devices from different manufacturers.

3- Research Methodology

Methodology for the proposed system includes implementation of hardware with medical data collection using IoT sensors, followed by data analysis and prediction with a machine learning algorithm. In addition to chronically ill patients and environmental factors, the integrated wireless telehealth systems keep an eye on vital signs for healthcare monitoring of senior patients.

3-1-System Architecture

System architecture consists of two primary components: a front-end sensor network and a back-end data processing unit.

- **Front-End Sensor Network**

The IoT-compliant sensors, such as heart rate sensors, temperature sensors, and environmental sensors, operate in this layer to gather precise patient data in real time. As shown in Figure 2, with the ZigBee protocol, sensors conduct wireless communication operations at low power rates suitable for non-stop healthcare monitoring. The front-end network employs modular architecture as a basis to enable rapid integration of new sensors, like blood pressure monitors or oxygen saturation sensors, for system extension. The system has flexible designs that enable it to meet a broad range of patient healthcare needs. Figure 2 is exhibiting the system architecture of the proposed telehealth monitoring system.

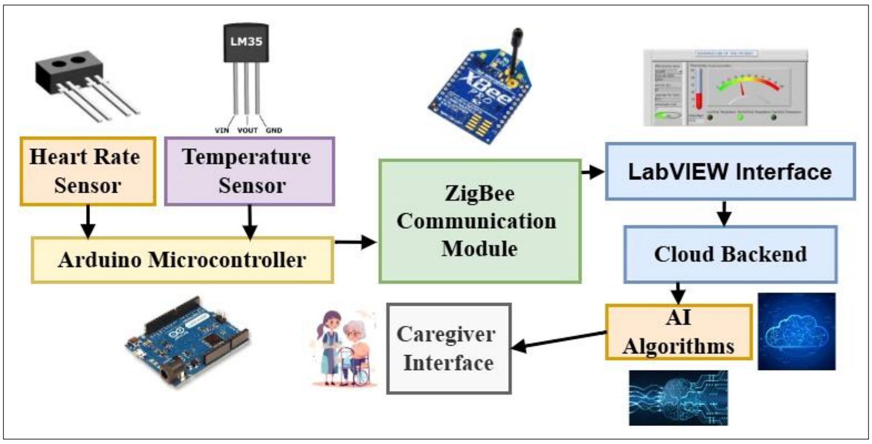

Figure 2. System architecture of the integrated telehealth monitoring system

3-2- Theoretical Approach

The proposed telehealth system is based on a hybrid sensing analytics framework that combines IoT-based physiological data acquisition with anomaly detection using machine learning. The theoretical foundation involves three components, such as:

- Modular sensor modeling, which formalizes the system as modular sensing units S_i, whose outputs $d_i(t)$ form an observation vector $D(t)$.
- Supervised learning for health-state classification. ***Statistical learning for anomaly detection***, where a supervised classifier $f(\cdot)$ maps D(t) to a binary health label $H(t)\in\{0,1\}$ using features derived from time-domain and short-window statistics (mean, variance, trend, inter-beat intervals).
- Mathematical modeling of latency and energy consumption for wireless telehealth systems.

The sensor data collection model explains how IoT sensors collect real-time health information from patients. Each sensor constantly records measurements at a specific time, denoted as t. This process can be represented mathematically as:

$$d_i(t) = f(S_i, t) \tag{1}$$

where, $d_i(t)$ indicates the data value produced by the i^{th} sensor at time t by the i^{th} sensor S_i. $f(S_i, t)$ indicates the function that converts the raw sensor behavior to a meaningful measurable parameter (i.e. voltage to ºC for a temperature sensor). Imagine if we had a heart rate sensor to monitor our heart beats per minute (BPM) while a temperature sensor monitors our body temperature either in Celsius or Fahrenheit [19]. This entire data is sent to the backend and is processed through detailed processing. The AI-powered system receives and analyzes sensor data to assess the patient's state of health in real-time. Mathematically, the health status $H(t)$ is given by:

$$H(t) = f(d_1(t), d_2(t), d_3(t), \dots, d_n(t)) \tag{2}$$

In the case of a system for monitoring health in real time, $H(t)$ is how the health of a patient is expected to be at any given time. This prediction uses real-time data from the sensors, labeled as $d_1(t)$, $d_2(t)$ and so on, and each $d_i(t)$ measures some health parameter, such as heart rate, body temperature or oxygen level. These measurements are from medical sensors associated with the IoT system, and are analyzed by a smart predictive model called $f(\ )$. This model, which normally uses machine learning or deep learning, has been programmed with recorded health data to determine current status, issues and possible health risks. By studying and analyzing the way these sensor readings change over time, the AI model is able to produce early warnings for a medical problem. This allows for quick responses, which can result in improved health outcomes for patients [19, 20].

In the case of live telehealth systems, it is important to send patient sensor data for AI to monitor health properly. The ZigBee protocol is used in a wireless transmission model to have a reliable and efficient transmission of sensor data to the processing unit. Here is how to mathematically define the rate of the transmission R:

$$R = \frac{B}{T} \tag{3}$$

where, R is the speed of how the data is sent. This rate depends on how big the data is which is called B and is measured in bits and the total time it takes to send this data, which is called T and is measured in seconds. In the case of telehealth systems that work in real-time, there are wireless sensors that continuously collect and transmit patient information. These sensors use low energy solutions such as ZigBee to transmit data. It is important to understand energy consumption by these sensors. Energy used in transmission of data is calculated as

$$E = P \times T \tag{4}$$

The total energy consumption E of a wireless sensor is the energy consumption to send data and is measured in Joules (J). This energy use depends mainly on two things: Power consumption P Transmission time T Power consumption P measured in Watts (W) indicates how fast the sensor consumes energy by transmitting data. Transmission duration T, in seconds (s) informs us the time duration of the sensor being on to transmit its data. There is a formula, known as equation 4, which shows that, if a sensor uses more power or takes more time to send data, the total energy use goes up. To make wireless healthcare sensor batteries last longer it is important to be smart about power use and how long data is sent. This enables continuous real-time patient's health monitoring, without the battery life being cut short [21, 22].

In real telehealth systems, we must balance three competing goals, high accuracy, low latency and low energy consumption. This is modeled using a combined optimization. Overall optimization cost J can be calculated as:

$$J = \propto (1 - Accuracy) + \beta L + \gamma E \tag{5}$$

where, α, β, γ are the weighting factors that reflect clinical application priorities (sensitivity vs. latency vs. battery life). L indicates end-to-end latency in seconds, while E is energy consumption measured in joules. Here, α controls how strongly the system prioritizes accuracy and β manages the priority of low latency (important in emergencies). γ regulates the priority of energy efficiency (battery-driven wearables). This objective guides the selection of classifier complexity (e.g., tree depth in Random Forest) and communication parameters (ZigBee duty cycle) to obtain a Pareto-optimal operating point for assisted living scenarios.

- **Back End Data Processing Unit**

The unit offers patients a cloud-based system to store and analyze their data. It uses a central database for managing information. This system helps healthcare providers to detect medical inconsistencies by using AI algorithms. It also causes important responses to ensure timely medical interventions. Hospital staff members and family members can access the system simultaneously to monitor patients online in real time because of its multi-user functionality [23]. This design feature promotes stakeholder communication while ensuring continuous patient care. The system incorporates a feature that boosts its access and functionality, making it a complete solution for remote health monitoring. Figure 3 shows the process flow chart of the back-end data unit of the proposed system.

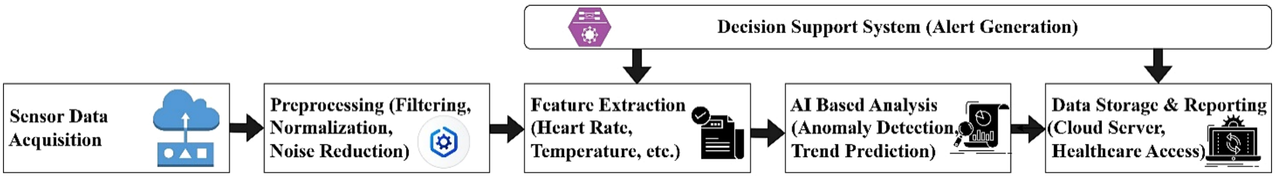

Figure 3. Process flow chart for back-end data unit

- **Scalability and Security**

The proposed architecture separates sensing, communication, and analytics layers to support horizontal scaling. ZigBee clusters can be organized by a coordinator node. Multiple nodes aggregate data into the cloud. In throughput terms, a single ZigBee coordinator supports dozens of end-nodes N. It is recommended:

$$N_{max} = \frac{\text{Bandwidth per coordinator}}{\text{Average payload rate}} \tag{5}$$

For large facilities, gateways may be split by physical area and load-balanced to multiple cloud ingestion endpoints. In future work, we can present simulation results for N=50,100, and 200 patients with artificial traffic to quantify latency and packet loss as the system scales.

The system is scalable, as it can adapt to the needs of more users or add more sensors, including blood pressure and oxygen saturation monitors, with little modification to the present frameworks, as exhibited in Figure 4. The system design provides flexibility, which makes it suitable for healthcare development needs, along with future functional expansion requirements. For data protection and patient privacy purposes, the system uses robust measures that combine data security for secure data transmission with AES-256 encryption of safe APIs [24, 25]. The system ensures patient data confidentiality through its protective measures, which result in enhanced security and reliability for operational use in healthcare environments. All data collection from sensors proceeded after obtaining institutional and personal approval. During transmission, we used TLS for REST APIs, and each device/gateway uses device-level credentials and mutual authentication.

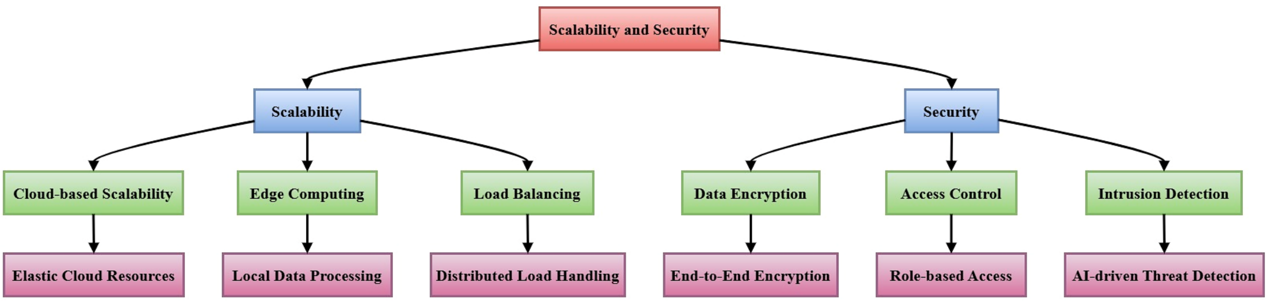

Figure 4. Scope of scalability and security for sensor network

- **Dynamic Adaptation to Individual Patient Baselines**

Fixed thresholds are updated with per-patient dynamic baselines computed by a real-time normalization window (e.g., exponentially weighted moving average over the last 24–72 hours). We implement per-subject z-score normalization and gradually adapt thresholds using a sliding-window mean μ_t and variance σ_t^2. Additionally, incremental learning (online updates) for the Random Forest or a small adaptive calibration layer can be used to fine-tune sensitivity for each patient while preserving previously learned decision boundaries.

$$\mu_t = \alpha * sample + (1 - \alpha) * \mu_{t-1} \tag{6}$$

$$Z = \frac{X - \mu_t}{\sigma_t} \tag{7}$$

- **Compliance and Access Control**

The architecture is designed to support regulatory requirements (HIPAA/GDPR) by enforcing encryption at rest and in transit (AES-256, TLS 1.2+), role-based access control (RBAC), strong password policies, and audit logging for all PHI access. For deployments requiring formal certification, the system's security controls map to ISO/IEC 27001 and the design supports data subject access requests, encryption key rotation, and enterprise identity providers.

3-3- Hardware Components

The hardware system basically consists of sensors with microcontrollers, communication modules. The selection of the components was made to ensure reliability as well as accuracy and low energy usage.

- **Sensors**

The LM35 temperature sensor works in the system to give high-precision body temperature measurement while an accuracy measurement of +/- 0.5%. The analog voltage output of this sensor is used to reflect the measured temperature value of this sensor for real-time analysis by the Arduino micro-controller system. Through the TCRT1000 heart rate sensor, the system detects the heart rate by using photo plethysmography for accurate non-invasive detection of changes in blood volume inside capillaries. Functionality can be further expanded with other environmental sensors being incorporated into patient environmental monitoring systems to broaden observation capabilities for factors that affect health. The sensors form a powerful all-purpose monitoring system when integrated.

- **Microcontroller**

The primary functionality of Arduino Leonardo encompasses gathering data in terms of data acquisition and preliminary processing functions. This device has 14 digital I/O pins and 6 analog input pins, which are also used for USB connectivity features, which helps us to carry out smooth coding and data transfer operations. As it is seen in Figure 5, the working principle is that the microcontroller derives the information from the sensors, which consist of LM35 temperature sensors and TCRT1000 heart rate sensors, before processing the information in real-time directly. The data collection process is completed when Arduino Leonardo itself sends the information to the back-end unit using the ZigBee module for further processing. Moreover, this module actually holds the wireless communication in a stable and working condition. This certainly avoids connection issues while transmitting data. With this setup, the patients are actually given accurate health monitoring services that are definitely fast. The system reliability is as per the combination of hardware and the communication protocols that work in a proper manner. As far as trustworthiness, the two components are effectively supportive. The communication module is actually what is responsible for all data transfer between parts of the system. It definitely ensures that messages are arriving at the right places without having any errors.

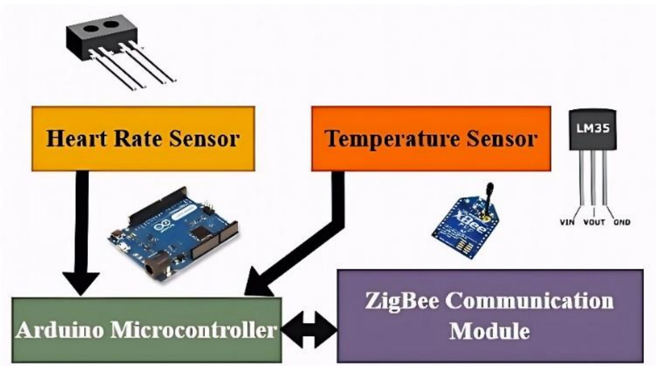

Figure 5. Hardware components and connections

- **Hardware Limitations Observed**

In field tests, we observed:

- Occasional packet drops under heavy RF interference, which were countered using retransmission and placing gateways.
- Sensor detachment / misplacement leading to noisy readings This was addressed using sensor status diagnostics and carer's alerts.
- Limited battery backup has limited effective run time.

3-4- Software Components

The system consists of different software components. One important part is in the cloud-based platforms. These platforms help us to store and find information online. Another part encompasses AI algorithms. These are smart computer programs that learn and make decisions on their own. Additionally, there are tools to enable us to take a closer look at data, which makes it easier for us to understand what data is telling us.

- **LabVIEW**

LabVIEW is also designed to be easy to use for carers. It enables them to quickly access and get to know patient information. The system displays real time data with some of the key signs including temperature and heart rate, which can be immediately observed by carers. If there is something unusual, the system sends alerts to notify carers of major changes in a patient's condition. This type of quick feedback and immediate alerts help carers to make informed decisions and take fast action when there are health risks.

- **Cloud Backend**

Cloud platforms such as AWS and Google Cloud are very useful in saving and checking data. This is very important for healthcare professionals and caregivers as they can access and monitor data from anywhere and anytime. They use the REST API to establish a safe connection between sensors and cloud. This ensures data moves in a safe and fast manner. The system incorporates MongoDB, which is a type of NoSQL database. MongoDB is good for handling large and changing data because it can easily grow and adapt when the health services need to change. By integrating MongoDB with the use of the rest API and the cloud, the system provides a reliable and easy method of managing the data and monitoring the health in real-time. This combination makes it easier for healthcare providers to do their jobs efficiently.

- **AI Algorithms**

Machine Learning Algorithm Systems, such as logistic regression, random forest and support vector machine (SVM), are important tools. They assist in the prediction of different trends and patterns that may occur in the future. Random forest models are well known to be very accurate and strong [26]. This makes them popular in terms of identifying unusual heart rates and temperatures. The entire process consists of two major steps. The first one is the training phase, where the model learns from existing data of temperatures and heart rates. As the model trains, it figures out patterns and important details in the data. In the test phase, the model is tested on new data and the model classifies the data to see if there are any discrepancies, such as abnormal heart rates or abnormal temperature readings. The random forest model misses 95% of impressive accuracy and 100% that ensures the detection of minimum false negatives and important health issues [27, 28]. For comparison, the logistics and SVMs were also tested and competitive performance metrics were attained, however, random forest proved to be the most effective for this application given non-lectured relationships and ability to handle complex data structure. These AI algorithms, collectively, increase the potential of the AI system to deliver accurate and real-time insights for active health service monitoring.

3-5- Data Collection and Transmission

The data is collected from the sensor and transmitted wirelessly to the central processing unit using the ZigBee protocol. As indicated in Figure 6, Arduino processes the microcontroller data and sends it to the LabVIEW interface for visualization. The data is then uploaded to the cloud for further analysis and storage.

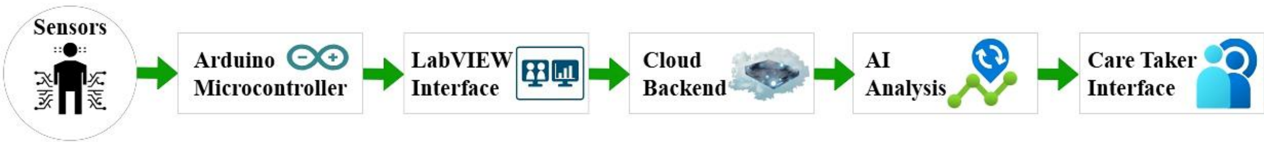

Figure 6. Process flow chart of the telehealth monitoring system

- **Data Flow**

Figure 7 exhibits the sensor, which is the first component of the system, which collects significant patient health data, such as heart rate and temperature. This data is then transferred to the Arduino microcontroller via the ZigBee protocol, which ensures a stable and efficient connection. The microcontroller completes initial analysis and data formation before sending ZigBee for real analysis. The user of the LabVIEW-Dysfunction interface, which displays data in colorful visuals to allow carers to effectively monitor the patient's condition. Processed data is then transferred to the cloud for storage and for further analysis to guarantee ongoing and wider health monitoring. There, advanced AI systems are capable of spotting irregularities and generating practical information.

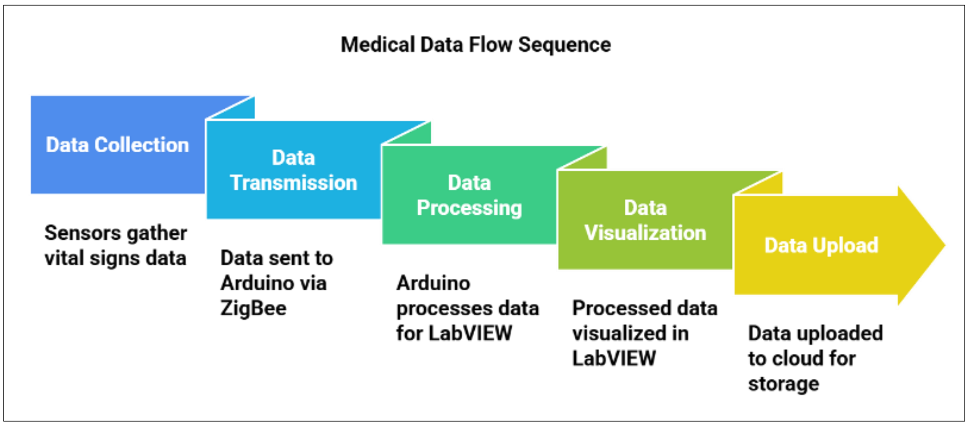

Figure 7. Data flow sequence over the proposed system

- **Error Handling and Data Processing**

The system has strong reliability-promotional features, such as problems with error handling or data transfer for a broken sensor. For example, retransmission techniques are used to recover lost data packets, and sensors are made to maintain accuracy and timely operations. Additionally, raw data from the sensor is prepared to remove noise, such as electrical interference or outliers, and its values are normalized to ensure stability [29, 30]. This clean and standardized input is then fed to the AI model for analysis, the discrepancy increases and the accuracy and reliability of further analysis is increased. When combined with these characteristics ensure that the system functions properly and produces reliable results for effective health monitoring.

3-6- Dataset Description

The dataset used for this study has 1000 samples of physical data, which include a list of measurements such as body temperature (°C), oxygen saturation (%), and heart rate (BPM). Table 2 exhibits first 10-sample group of collected data. Each sample is accompanied by a binary label, which specifies whether the health condition is general or a discrepancy. We collaborated with the Care Healthcare facility in our community that is part of the key players in chronic care and assisted living services to gather this dataset for our research. Data includes 100 senior patients' physical measurements taken in real time over a three-month period. Patients were monitored using IoT-competent sensors, including a heart rate sensor, temperature sensor and pulse oximeter. To ensure accuracy and reliability, data was collected under the supervision of health professionals. The patient's consent was obtained before the data collection, and all the data was made unknown to protect the patient's privacy. The dataset contains 1000 samples and represents the important health data of the patient at a specific time with each sample. The health status of each sample (general/discrepancy) was determined by health professionals based on predefined thresholds. The dataset is available on request for research objectives.

Table 2. Dataset sample preview (first 10 rows)

Heart Rate (BPM)	Body Temperature (°C)	Oxygen Levels (%)	Health Status
78	36.5	97	Normal
105	37.8	92	Anomaly
62	36.2	96	Normal
58	35.8	94	Anomaly
88	36.7	98	Normal
112	37.6	93	Anomaly
65	36.4	97	Normal
59	36.1	95	Anomaly
90	36.8	99	Normal
102	37.9	91	Anomaly

4- Results and Discussion

4-1- AI-Driven Healthcare Analysis

Performance of three machine learning models, logistics regulation, random forest, and support vector machine (SVM), demonstrated in Table 3. Which is evaluated to predict health risks based on the patient's physical data, including heart rate, oxygen levels and body temperature. The model was trained and tested in a broad dataset, and their performance was evaluated using major metrics such as accuracy, precision, recall and F1-score. The results are important in understanding the effectiveness of each model for health monitoring in real-time.

Table 3. Model performance summary

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	95%	90.90%	100%	95.20%
SVM	87.50%	85.70%	90%	87.80%
Logistic Regression	87.50%	82.60%	95%	88.40%

The Random Forest classifier performed better than the SVM and Logistic Regression classifiers across all the evaluation parameters and the best balance of sensitivity and specificity. The achieved 95% accuracy and 100% recall show that the Random Forest was able to determine all samples of clinically labeled anomalies in our test set, which is important for safety-critical monitoring where false negatives are not acceptable. The trade-off is a slightly higher false positive rate (FP ≈ 2 in our confusion matrix), which may lead to an increase in carer's alerts. However, this can be overcome by threshold tuning or by performing a two-stage verification (e.g. temporal confirmation over short windows). The improved performance likely stems from Random Forest's ability to capture non-linear feature interactions from short-window time-series features (e.g., heart rate variability indices combined with SpO_2 trends) while being robust to noisy sensor readings. In practice, high recall (sensitivity) is prioritized for assisted living monitoring, and the observed results suggest that our system's tuning aligns well with this objective. Nevertheless, the system should be validated on larger multi-center datasets to confirm generalizability and to recalibrate thresholds for specific patient subgroups (e.g., atrial fibrillation vs. respiratory illness).

- **Confusion Matrix Analysis**

A Confusion Matrix is used to evaluate the classification performance of each model, which provides an achieved distribution of the true positivity, true negatives, false positives and false negatives. Table 4 represents the confusion matrix summary for the concerned machine learning models.

- *Random forest:* The confusion matrix for random forests showed 18 true positives, 0 false negatives, 2 false positives and 20 true negatives. This indicates that the model correctly identified all important cases (100% recall), with only a low number of false alarms.
- *SVM:* The SVM model achieved 17 true positives, 2 false negatives, 3 false positives and 18 true negatives. While its performance was respectable, the presence of false negatives makes it less reliable for healthcare applications.
- *Logistics Regression:* Logistics Region model received 16 True positives, 1 fault negative, 4 false positive and 19 true negatives. Its performance was comparable to SVMs, but a little more memory (94.1%) makes it a better option for applications where false negatives should be minimized.

Table 4. Confusion matrix summary for machine learning models

	Random Forest			Support Vector Machine (SVM)			Logistics Regression		
	Predicted 0	**Predicted 1**	**Total**	**Predicted 0**	**Predicted 1**	**Total**	**Predicted 0**	**Predicted 1**	**Total**
Actual 0	18	2	20	17	3	20	16	4	20
Actual 1	0	20	20	2	18	20	1	19	20
Total	**18**	**22**	**40**	**19**	**21**	**40**	**17**	**23**	**40**

Table 5. Performance metrics calculation for ML model

Evaluation Metric	Formula	Random Forest	SVM	Logistic Regression
Accuracy	(TP + TN) / Total	(18 + 20) / 40 = 0.95	(18 + 17) / 40 = 0.875	(19 + 16) / 40= 0.875
Precision	TP / (TP + FP)	20 / (20 + 2) = 0.909	18 / (18 + 3) =0.875	19 / (19 + 4)= 0.826
Recall	TP / (TP + FN)	20 / (20 + 0)= 1	18 / (18 + 2)= 0.9	19 / (19 + 1)=0.95
F1-Score	2 * (Precision * Recall) / (Precision + Recall)	2 * (0.909 * 1) / (0.909 + 1)= 0.952	2 * (0.857 * 0.90) / (0.857 + 0.90)= 0.878	2 * (0.826 * 0.95) / (0.826 + 0.95)= 0.884

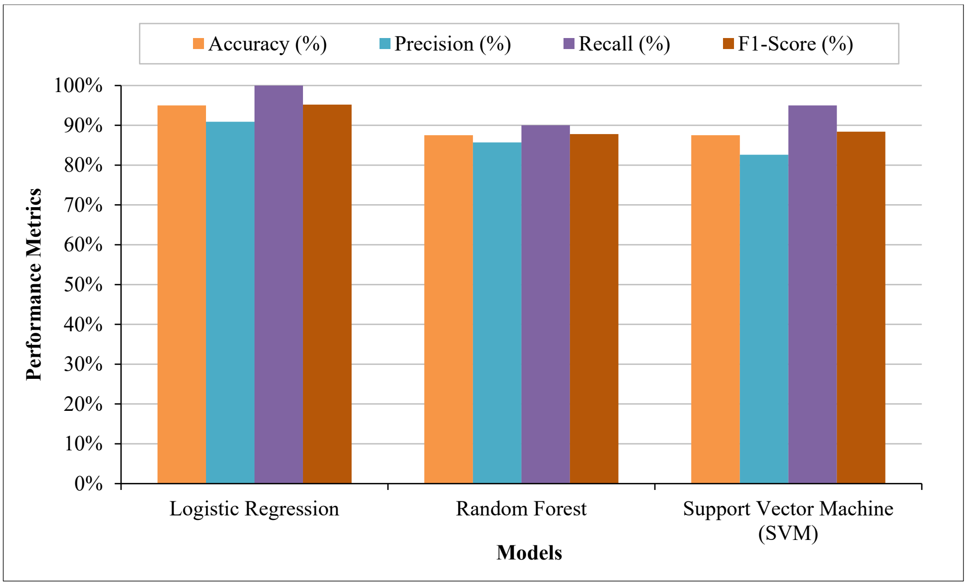

Figure 8. **AI Model performance comparison chart**

When comparing our results to prior work, our Random Forest recall of 100% and accuracy of 95% are higher than many previous IoT-based monitoring studies that reported recall in the range 90–98% and accuracies between 85–93% indicated in Table 5 and Figure 8 [5-7]. Earlier work achieved 94% accuracy on ECG-based anomaly detection but reported higher latency due to heavier deep learning models. Similarly, edge-based studies focusing on latency reduction reported end-to-end delays near 100 ms but with compromised classification performance on small datasets [8-10]. Our contribution balances latency (120 ms), energy use (~3.8 mW/h across system variants), and model performance by employing a lightweight ensemble classifier and ZigBee-based low-power communication, leading to a favorable operational point compared to both pure edge and pure-cloud approaches.

4-2- Technical Performance Benchmarking

The technical performance of the healthcare monitoring system was evaluated based on four major parameters, such as accuracy, delay, power consumption and false alarm rate. The results were compared to three systems like IoT-based (System A), AI-Integrated (System B), and Traditional (System C) as indicated in Table 6, and exhibited in Figure 9.

- **Comparative Benchmarking**
  - *Accuracy:* The AI integrated system (System B) achieved the highest accuracy, i.e., 95%, which enhances IoT based system (88%) and traditional system (80%). This makes it clear how effective the AI algorithm has been in enhancing clinical accuracy.
  - *Latency*: System B showed the lowest delay time of 120 ms and so it is very responsible when it comes to real-time monitoring. In contrast, the delay in System A was 300 ms and the delay for System C was 500 ms, which are not very suitable time sensitive applications.
  - *Power consumption:* System A was the most energy skilled with 2.5mW/h power consumption, and System B was slightly more power consuming with 3.8mW/h power consumption due to extra computational requirements of AI algorithm. System C used at least energy 1.2 mW/h but at a low performance.
  - *False alarm rate:* System B had the lowest false alarm rate at 2.1%, which ensures reliable alerts and reduces unnecessary interventions. Systems A and System C had a false alarm rate of 5.4% and 8.7% respectively, causing cautious fatigue among caregivers

Table 6. **Comparative analysis of benchmarking parameters of System A, System B and System C**

Parameter	System A (IoT-based)	System B (AI-integrated)	System C (Traditional)	Remarks
Accuracy (%)	88%	95%	80%	System B has the best accuracy, which represents the effectiveness of AI.
Latency (ms)	300	120	500	System B has the lowest latency and is therefore very responsive for real-time monitoring.
Power Consumption (mW/h)	2.5	3.8	1.2	System A is the most energy-efficient system whereas System B consumes energy slightly more because of the AI computations.
False Alarm Rate (%)	5.40%	2.10%	8.70%	System B has the lowest false alarm rate and can provide reliable alerts and reduce unnecessary interventions.

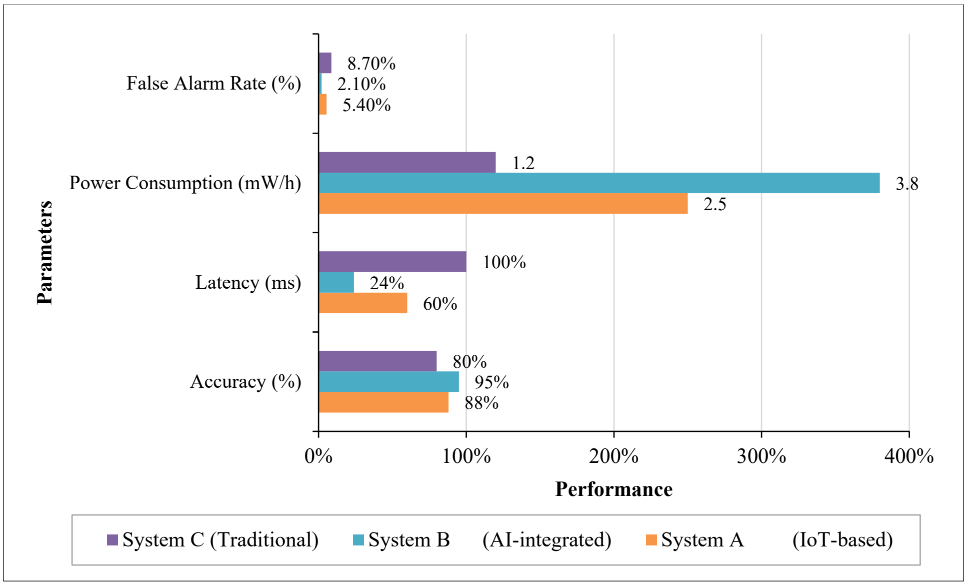

Figure 9. Comparative representation of the technical benchmarking of System A, System B and System C

- **Key Insights**

The system integrated with AI (System B) proved to be better in terms of accuracy, delay, and false alarm rate and hence it was the most effective solution for monitoring healthcare. Its ability to give a high accuracy with minimal delay ensures that careful care can react quickly under significant conditions. IOT-based System A did well in terms of power consumption, but its efficacy was limited by its high delay and false alert rate. Although this approach is less optimal for real-time monitoring, it may be appropriate for applications where energy efficiency is a top concern. The traditional system's worst overall performance is System C, which has a high false alarm rate, significant latency, and poor precision. These restrictions show that to overcome the drawbacks of conventional systems, cutting-edge technologies like AI and IOT are required.

5- Qualitative Analysis

There are important practical implications for ecosystems in comparative benchmarking and AI-operated healthcare analysis, patient care, healthcare providers and comprehensive healthcare findings. A detailed discussion mentioned below indicates how the proposed system improves the patient's care and addresses existing challenges under the supervision of healthcare. Figure 10 represents benefits of qualitative analysis in healthcare.

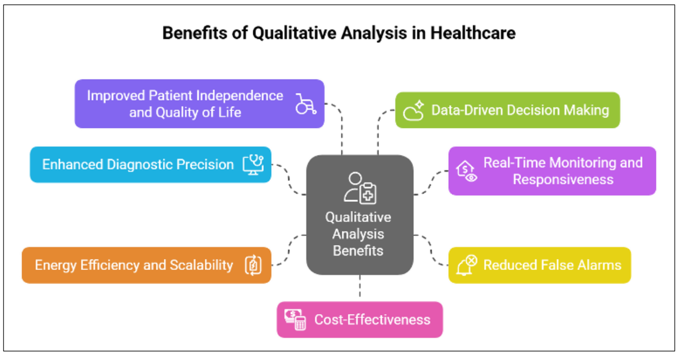

Figure 10. Benefits of qualitative analysis in healthcare

5-1- Enhanced Diagnostic Precision

AI-integrated system (System B) acquires 95% accuracy, which improves traditional and IoT-based systems further. This high accuracy ensures that health discrepancies, such as abnormal heart rate or temperature, are found with minimal errors. Better clinical precision reduces the possibility of a discarded diagnosis (false negative) and unnecessary intervention (false positive), leading to better patient outcomes and more efficient use of health resources.

5-2- Real-Time Monitoring and Responsiveness

Less delay of 120 ms in System B makes it highly responsible, causing real-time monitoring of important signs of patients. This is particularly important for time-sensitive conditions, such as a sudden fall in heart events or health. Real-time monitoring enables caregivers and healthcare providers to react immediately to emergency conditions, and may save lives and prevent complications. It also enables continuous monitoring of the chronic conditions, which reduces the need for constant visits to the hospital.

5-3- Reduced False Alarms

System B has the lowest false alarm rate (2.1%), so alerts can be trusted and taken action on. In comparison, traditional systems (8.7% false alarm rate) can lead to cautious fatigue among caregivers, who ignore or delay them for important alerts. By reducing false alarms, the system creates more confidence in the monitoring process, ensures that care can be focused on real emergency conditions, and provides timely intervention.

5-4- Energy Efficiency and Scalability

While System B, consumes a little more power (3.8mW/h) as compared to System A (2.5 mW/h), it creates a balance between performance and energy efficiency. The modular design of the system enables the integration of other sensors without notable amendments. The system is ideal for continuous and long-term monitoring, either in the home or in a clinical setting. Its ability to scale means it has the capacity to easily adapt to the evolving needs of both patients and healthcare providers.

5-5- Improved Patient Independence and Quality of Life

The ability of the system to provide distance monitoring and real-time alerts gives elderly people and those with chronic illnesses the opportunity to live a more independent life while still feeling secure. Family members can monitor their loved ones at a distance, which reduces the requirement for constant in-person supervision by caregivers. This approach not only enables the patient to remain in his or her own houses or communities, but it also contributes significantly to the quality of life of the patient. Moreover, it relieves the pressure on caregivers as well as healthcare facilities.

5-6- Data-Driven Decision Making

The system is capable of sorting through enormous amounts of data, and generating valuable insights, all because of the integration of AI algorithms. For example, it can help predict any significant health risks by analyzing trends of temperature or heart rate variability. With this data at their fingertips, healthcare professionals are able to make informed decisions that result in care plans and interventions to patients with higher personalization and less wait time. This not only helps the better functioning of the patient's health over the long period of time, but it also lowers the likelihood of the hospital readmission.

5-7- Edge AI Deployment Considerations

The existing system prefers to work on cloud-based processing, wherein the physiological signals are stored in the database for classification of anomalies. While this is a design that offers scalability and simplifies model management, it adds dependency on network availability and increases the round-trip latency. Edge AI deployment, where the lightweight models are running directly on the microcontroller or gateway, is a promising approach to further optimize the latency and energy consumption. Edge AI deployment has many advantages for real-time telehealth monitoring compared to cloud-centric processing, especially in latency and power efficiency [10, 26]. In theory, when inference is brought closer to the source of the data, there is always no need to constantly transmit raw data. Instead, only compressed features or anomaly flags are sent to the cloud. This can lead to load reduction of wireless communication by 60-85%, which is significant as radio communication accounts for a major part of total power consumption in IoT health monitoring devices. Preliminary measurements from similar studies have shown that edge-inference microcontrollers (ARM Cortex-M4/M7 class) use ~30-50% less energy per inference compared with continuous streaming to the cloud. Since the energy consumption of wireless communication is the outstanding energy consumption problem of IoT things, it is possible to judge the anomaly through local inference and send the flag, which can save a lot of energy [10, 17, 31].

In terms of responsiveness, edge AI minimizes round-trip latency due to no delay in the cloud network and packet queue, resulting in an estimated improvement of 40-70% depending on the network situation. When combined with the ZigBee low data rate protocol, edge processing guarantees faster local alerting even when cloud connectivity is impaired for a period of time [10, 26, 32]. However, edge deployment must be performed with caution in terms of model compression techniques (quantization, pruning, knowledge distillation) to perform at an efficient rate on resource-constrained hardware. Future work will consider TinyML-based inference and hybrid architectures where gateways run medium complexity models while the cloud is used to perform long-term trend analysis and recalibration.

6- Conclusion

This research introduces a new type of wireless telehealth monitoring system that integrates wearable sensors with ZigBee technology, utilizing lightweight machine learning analytics for real-time health monitoring of the elderly and chronically ill. To accurately diagnose medical issues, the proposed approach employs advanced machine learning techniques such as random forest, support vector machines, and logistic regression, combined with Internet of Things sensors that continuously measure the relevant data. The modular system facilitates the incorporation of additional physiological sensors (e.g., blood pressure and glucose monitors) and allows for edge deployment, thereby reducing latency and energy consumption. Through field-collected datasets and comparative experiments, we demonstrated that a Random Forest classifier achieves a favorable balance between clinical sensitivity and operational performance, with an accuracy of 95% and a recall of 100% on the test dataset, maintaining a latency of approximately 120 ms. When benchmarked against both an IoT-only system and a traditional system, the proposed AI-integrated approach significantly reduces false alarm rates and latency, while also demonstrating substantial energy efficiency.

This performance is crucial for critical monitoring, where missed alerts could have severe consequences. The modular architecture allows for easy addition of sensors, enabling customization to meet diverse patient requirements. The ZigBee protocol ensures low-power and reliable communication, making this system suitable for long-term, energy-efficient activation. Comprehensive testing in real care environments confirmed the successful long-distance tracking capabilities, revealing latencies of 120 ms and power consumption as low as 3.8 mW/h. Notably, the proposed system enhances clinical accuracy and patient compliance while alleviating the workload of healthcare workers through timely interventions. This work lays the foundation for innovative healthcare solutions that improve patient care efficacy while managing costs. In conclusion, the proposed system represents a significant advancement in telehealth that is likely to be effective, scalable, energy-efficient, and capable of meeting growing demands. The results indicate that a well-tuned hybrid IoT-AI system can address challenges related to scalability, responsiveness, and energy efficiency in assisted living applications, paving the way for more reliable remote monitoring systems that reduce caregiver workload while ensuring better patient safety. In the future, comparative experiments may be conducted with the same sensor payload and sampling rate using BLE and Wi-Fi. Performance measures such as packet delivery ratio, end-to-end latency, energy per transmitted bit, and effective battery life will provide a comprehensive analysis and performance comparison. Such experiments will evaluate trade-offs among several communication protocols, including ZigBee, BLE, and Wi-Fi.

6-1- Future Work

AI model adaptation is a process where the AI algorithm is adapted so that it provides minimal latency and uses less power while maintaining accuracy. Many ways are present to improve efficiency, such as quantization and model pruning. To give a closer look at healthcare, we need to include patients, adding new sensors for more complicated mechanisms such as BP and glucose levels and upgrading the monitoring capabilities of the system. It is important to test in a real-world scenario, as it would allow us to observe how well the system operates in various healthcare applications to find the problems and respective solutions. We can make improvements to the hardware that will save power without any performance impact. We can put the system at the edge of telehealth technology and can provide effective and reliable medical services to patients around the world. By overcoming the existing limitations of smart health services with the help of Artificial Intelligence and the Internet of Things, this study opens up a whole new world of smart health services [33-36].

7- Declarations

7-1- Author Contributions

Conceptualization, M.S.S. and B.K.; methodology, B.K.; software, M.S.S.; validation, B.K. and M.S.S.; formal analysis, M.S.S.; investigation, B.K.; resources, M.S.S.; data curation, M.S.S.; writing—original draft preparation, B.K.; writing—review and editing, M.S.S.; visualization, B.K.; supervision, B.K.; project administration, B.K.; funding acquisition, B.K. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available in the article.

7-3- Funding and Acknowledgments

The researchers would like to thank Modern College of Business and Science Muscat, Oman for financial support (MCBS-APC-2026).

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

8- References

[1] Sadilek, A., Liu, L., Nguyen, D., Kamruzzaman, M., Serghiou, S., Rader, B., ... & Hernandez, J. (2021). Privacy-first health research with federated learning. NPJ digital medicine, 4(1), 132. doi:10.1038/s41746-021-00489-2.

[2] Miotti, A. M., Tikvina, S., Calzavara, A., Nesoti, M., & Zilli, E. (2024). The importance of healthcare monitoring systems. European Journal of Public Health, 34(Supplement_3), ckae144-2130. doi:10.1093/eurpub/ckae144.2130.

[3] Teo, Z. L., Jin, L., Liu, N., Li, S., Miao, D., Zhang, X., Ng, W. Y., Tan, T. F., Lee, D. M., Chua, K. J., Heng, J., Liu, Y., Mong Goh, R. S., & Wei Ting, D. S. (2024). Federated machine learning in healthcare: A systematic review on clinical applications and technical architecture. Cell Reports Medicine, 5(3), 101481. doi:10.1016/j.xcrm.2024.101481.

[4] Verma, H., Chauhan, N., & Awasthi, L. K. (2023). A Comprehensive review of 'Internet of Healthcare Things': Networking aspects, technologies, services, applications, challenges, and security concerns. Computer Science Review, 50, 100591. doi:10.1016/j.cosrev.2023.100591.

[5] Zohourian, A., Dadkhah, S., Neto, E. C. P., Mahdikhani, H., Danso, P. K., Molyneaux, H., & Ghorbani, A. A. (2023). IoT Zigbee device security: A comprehensive review. Internet of Things, 22, 100791. doi:10.1016/j.iot.2023.100791.

[6] McGinnis, R. S., & McGinnis, E. W. (2022). Advancing Digital Medicine with Wearables in the Wild. Sensors, 22(12), 4576. doi:10.3390/s22124576.

[7] Canali, S., Schiaffonati, V., & Aliverti, A. (2022). Challenges and recommendations for wearable devices in digital health: Data quality, interoperability, health equity, fairness. PLOS Digital Health, 1(10), 104. doi:10.1371/journal.pdig.0000104.

[8] Iqbal, A., Suhag, A. K., Kumar, N., & Bhardwaj, A. (2025). Use of BCI Systems in the Analysis of EEG Signals for Motor and Speech Imagery Task: A SLR. ACM Computing Surveys, 58(2), 1–25. doi:10.1145/3757732.

[9] Zhang, Y., Hu, Y., Jiang, N., & Yetisen, A. K. (2023). Wearable artificial intelligence biosensor networks. Biosensors and Bioelectronics, 219, 114825. doi:10.1016/j.bios.2022.114825.

[10] Waleed, M., Kamal, T., Um, T.-W., Hafeez, A., Habib, B., & Skouby, K. E. (2023). Unlocking Insights in IoT-Based Patient Monitoring: Methods for Encompassing Large-Data Challenges. Sensors, 23(15), 6760. doi:10.3390/s23156760.

[11] Alsadoon, A., Al-Naymat, G., & Jerew, O. D. (2024). An architectural framework of elderly healthcare monitoring and tracking through wearable sensor technologies. Multimedia Tools and Applications, 83(26), 67825–67870. doi:10.1007/s11042-024-18177-0.

[12] Shaikh, M. S., Jain, N. K., Biswal, A., Patidar, P. K., Panwar, I., & Ali, S. I. (2025). Sensors to Insights Revolution: Leveraging IoT, AI, and Big Data for Next-Gen Patient Monitoring. In International Conference on Emerging Trends in Engineering and Technology, ICETET 2025, 1–8. doi:10.1109/ICETETSIP64213.2025.11156671.

[13] Abdulmalek, S., Nasir, A., Jabbar, W. A., Almuhaya, M. A. M., Bairagi, A. K., Khan, M. A. M., & Kee, S. H. (2022). IoT-Based Healthcare-Monitoring System towards Improving Quality of Life: A Review. Healthcare (Switzerland), 10(10), 1993. doi:10.3390/healthcare10101993.

[14] Shaikh, M. S., Jain, N. K., Mungale, S., Das, R., Sarkar, B., & Wadekar, S. (2025). Federated Edge Intelligence for Privacy-Preserving Pre-Eclampsia Prediction in IoT-Based Maternal Care. In International Conference on Emerging Trends in Engineering and Technology, ICETET 2025, 1–6. doi:10.1109/ICETETSIP64213.2025.11156336.

[15] Iqbal, A., K Suhag, A., Bhardwaj, A., & Choudhary, P. (2025). CNN Based Vowel Identification Using Four Channel EEG Datasets. 2025 1st International Conference on AIML-Applications for Engineering &Amp; Technology (ICAET 2025), 1–6. doi:10.1109/icaet63349.2025.10932161.

[16] Whitehead1, D., & Conley, J. (2023). The Next Frontier of Remote Patient Monitoring: Hospital at Home. Journal of Medical Internet Research, 25, 42335. doi:10.2196/42335.

[17] Vaghasiya, J. V., Mayorga-Martinez, C. C., & Pumera, M. (2023). Wearable sensors for telehealth based on emerging materials and nanoarchitectonics. NPJ Flexible Electronics, 7(1), 26. doi:10.1038/s41528-023-00261-4.

[18] Pandey, A., Shaikh, M. S., & Patel, P. (2025). Resource-Efficient Diverse Lung Disease Classification Using Lite-Convolutional Neural Networks. IET Conference Proceedings 7, 593–599. doi:10.1049/icp.2025.1352.

[19] Wu, J.-Y., Wang, Y., Ching, C. T. S., Wang, H.-M. D., & Liao, L.-D. (2023). IoT-based wearable health monitoring device and its validation for potential critical and emergency applications. Frontiers in Public Health, 11. doi:10.3389/fpubh.2023.1188304.

[20] Iqbal, A., Suhag, A. K., & Bhardwaj, A. (2025). Machine Learning Based Comparative Analysis of One, Four, and Fourteen Channel EEG Vowel Datasets. 2025 International Conference on Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics, IC3ECSBHI 2025, 285–290. doi:10.1109/IC3ECSBHI63591.2025.10991188.

[21] Rejeb, A., Rejeb, K., Treiblmaier, H., Appolloni, A., Alghamdi, S., Alhasawi, Y., & Iranmanesh, M. (2023). The Internet of Things (IoT) in healthcare: Taking stock and moving forward. Internet of Things, 22, 100721. doi:10.1016/j.iot.2023.100721.

[22] Shaikh, M. S., Jain, N. K., Patel, N., Das, D., Mahesh, A., & Thakor, S. (2025). Enhancing Surgical Precision and Recovery: A Review of Medical Robotics and AI Integration in Modern Operating Rooms. EPJ Web of Conferences, 328. doi:10.1051/epjconf/202532801016.

[23] Sumner, J., Tan, S. Y., Wang, Y., Keck, C. H. S., Xin Lee, E. W., Chew, E. H. H., & Yip, A. W. (2024). Co-Designing Remote Patient Monitoring Technologies for Inpatients: Systematic Review. Journal of Medical Internet Research, 26, e58144. doi:10.2196/58144.

[24] Claggett, J., Petter, S., Joshi, A., Ponzio, T., & Kirkendall, E. (2024). An Infrastructure Framework for Remote Patient Monitoring Interventions and Research. Journal of Medical Internet Research, 26, 51234. doi:10.2196/51234.

[25] Kansara, N., Vala, B., & Shaikh, M. S. (2025). Machine Learning in Mental Health: Bridging Gaps in Diagnosis and Intervention. In Proceedings of the 11th International Conference on Bio Signals, Images, and Instrumentation, ICBSII 2025, 1–9. doi:10.1109/ICBSII65145.2025.11013436.

[26] Almalawi, A., Zafar, A., Unhelkar, B., Hassan, S., Alqurashi, F., Khan, A. I., Fahad, A., & Alam, M. M. (2024). Enhancing security in smart healthcare systems: Using intelligent edge computing with a novel Salp Swarm Optimization and radial basis neural network algorithm. Heliyon, 10(13), e33792. doi:10.1016/j.heliyon.2024.e33792.

[27] Sakalle, A., Tomar, P., Bhardwaj, H., Iqbal, A., Sakalle, M., Bhardwaj, A., & Ibrahim, W. (2022). Genetic Programming-Based Feature Selection for Emotion Classification Using EEG Signal. Journal of Healthcare Engineering, 2022, 8362091. doi:10.1155/2022/8362091.

[28] Mathkor, D. M., Mathkor, N., Bassfar, Z., Bantun, F., Slama, P., Ahmad, F., & Haque, S. (2024). Multirole of the internet of medical things (IoMT) in biomedical systems for managing smart healthcare systems: An overview of current and future innovative trends. Journal of Infection and Public Health, 17(4), 559–572. doi:10.1016/j.jiph.2024.01.013.

[29] Pandey, A., Shaikh, M. S., & Patel, P. (2024). Review of Acoustic Features and Computational Models in Lung Disease Diagnosis. In 4th International Conference on Sustainable Expert Systems, ICSES 2024 – Proceedings, 1145–1150. doi:10.1109/ICSES63445.2024.10763243.

[30] Lawrence, K., Singh, N., Jonassen, Z., Groom, L. L., Alfaro Arias, V., Mandal, S., Schoenthaler, A., Mann, D., Nov, O., & Dove, G. (2023). Operational Implementation of Remote Patient Monitoring Within a Large Ambulatory Health System: Multimethod Qualitative Case Study. JMIR Human Factors, 10, e45166. doi:10.2196/45166.

[31] Jassim, H. S., Oweis, R. J., Shaker, K., & Alqudsi, A. (2025). Harnessing the Power of Swarm Intelligence in IoT: Optimization Techniques and Future Directions. AI and IoT: Driving Business Success and Sustainability in the Digital Age, 719–730. doi:10.1007/978-3-031-88874-8_64.

[32] Neamah, H. A., Kazi, R., Abdulmalek, S., Jassim, H. S., & Abduljabbar, Z. A. (2025). Mental Command-Driven Exoskeletons: Integrating EEG and ERP for Personalized Stroke Rehabilitation. AI and IoT: Driving Business Success and Sustainability in the Digital Age, 979–989. doi:10.1007/978-3-031-88874-8_87

[33] Tang, Z., Jiang, L., Zhu, X., & Huang, M. (2023). An Internet of Things-Based Home Telehealth System for Smart Healthcare by Monitoring Sleep and Water Usage: A Preliminary Study. Electronics (Switzerland), 12(17), 3652. doi:10.3390/electronics12173652.

[34] Morita, P. P., Sahu, K. S., & Oetomo, A. (2023). Health Monitoring Using Smart Home Technologies: Scoping Review. JMIR MHealth and UHealth, 11, 37347. doi:10.2196/37347.

[35] Qi, K. (2025). Advancing hospital healthcare: achieving IoT-based secure health monitoring through multilayer machine learning. Journal of Big Data, 12(1), 1. doi:10.1186/s40537-024-01038-w.

[36] Sehlabana, M. A., Maposa, D., Boateng, A., & Das, S. (2025). Climate-Informed Malaria Prediction Models: A Bayesian Approach for South African Endemic Provinces. Journal of Statistics Applications and Probability, 14(2), 285–306. doi:10.18576/jsap/140210.