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An IoT healthcare system with Deep Learning functionality for patient monitoring

Ali Hamza Najim[1], Kareem Ali Malalah Al-sharhanee[2], Istabraq M. Al-Joboury[3], Dimitris Kanellopoulos[4]*, Varun Kumar Sharma[5], Mustafa Yahya Hassan[6], Walid Issa[7], Fatima Hashim Abbas[8], and Ali Hashim Abbas[9]

[1] Department of Computer Technical Engineering, Imam Al-Kadhim College (IKC) Al-Diwaniyah, Iraq. alihamza@alkadhum-col.edu.iq

[2] Department of Communication Technical Engineering, Al-Farahidi University Baghdad, Iraq. kareemali@uoalfarahidi.edu.iq

[3] College of Technical Engineering, Al-Bayan University, Baghdad, Iraq, istabraq.m@albayan.edu.iq

[4] Department of Mathematics, University of Patras, Greece. d_kan2006@yahoo.gr

[5] Department of Computer Science and Engineering, The LNM Institute of Information Technology, Jaipur 302031, India. varunksharma.102119.cse@gmail.com

[6] Department of Computer Science and Information Technology, University of Al-Qadisiya, Iraq. mustafa.yahya@qu.edu.iq

[7] Engineering and Mathematics Dept. Sheffield Hallam University Sheffield, UK. walid.issa@shu.ac.uk

[8] Medical Laboratories Techniques Department, Al-Mustaqbal University College, Hillah 51001, Iraq. fatimahashim@mustaqbal-college.edu.iq

[9] College of Information Technology, Imam Ja'afar Al-Sadiq University, Al-Muthanna 66002, Iraq. alsalamy1987@gmail.com

***Author in correspondence**

Abstract. Currently, healthcare systems operate under conventional management practices and entail storing and processing substantial medical data. Integrating the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) technologies has facilitated the development of IoT-enabled healthcare, which possesses advanced data processing capabilities and extensive data storage. This paper proposes a WSN and IoT framework for patient monitoring in high-speed 5G communications. Based on an Artificial Neural Network (ANN), an intelligent health monitoring system was developed using IoT technology to monitor a person's blood pressure, heart rate, oxygen level, and temperature. Furthermore, the system helps the elderly being in critical cases in their homes to communicate and update their medical condition with the hospital, especially in critical cases, to be treated as soon as possible, especially in remote areas. The experimental results showed the superiority and effectiveness of the proposed system. Moreover, relying on ANNs to extract the basic features, the accuracy reached (96%). The proposed system was implemented practically, and the results were displayed in real-time and compared with commercial medical devices. Maximum Relative errors are heart rate (2.19), body temperature (2.94), systolic blood pressure (3.4), diastolic blood pressure (2.89), and SpO2 (1.05). On the other hand, the proposed system is much faster than other wireless communication methods, regardless of the detection quality.

Keywords: WSN, medical IoT, 5G, LAN, Raspberry Pi, ANN.

1. Introduction

In recent years, the healthcare business has undergone a substantial transformation and has become a major contributor to revenue and jobs [1]. Patients typically spend a significant amount of time in the hospital as a result of traditional methods of disease diagnosis, which require in-depth physical examinations performed in a medical setting. This strategy led to increased healthcare costs and much pressure was put on the healthcare facilities, especially in the rural and inaccessible regions. Advances in technology for instance use of small gadgets instance as smart-watches have led to diagnostics of various diseases/illnesses and over-monitoring of health. These have led to changes from the hospital-centred system towards patient-centred health care [2]. Additionally, there are aging population and increased reports of chronic diseases have exerted much pressure on health facilities. Hence, applying remote health monitoring has become a solution to improve the levels of patient care, reduce healthcare costs, and minimize hospitalization [3]. It entails collecting a plethora of other physiological data, such as blood oxygen level, heart rate, temperature, electroencephalogram (EEG), and electrocardiogram (ECG), which can be evaluated to identify any preexisting health issues and give healthcare professionals immediate feedback. [4]. The concept known as the Internet of Things (IoT) entails the incorporation of computing and communication functionality into ordinary objects to drive various advantages in domains including eHealth [5]. Nevertheless, with the increasing use of sensors, the accumulation of large amounts of data, and the use of artificial intelligence, machine learning, and cloud computing, the above issues are still causing more problems than solving them. Broadband wireless access technologies have record growth over the years. 5G is the next generation of mobile networks: implementation involves the application of densely positioned microcells. The system will provide a substantial boost in bandwidth and ensure a high level of Quality of Service (QoS) for the users [6]. The benefits of 5G enable it to offer a wide range of services including Internet of Things (IoT), cloud computing, high-definition 3D video streaming, and applications that are interactive for mobile users. Nevertheless, the assessment of this type of technology is mostly centred on enhancing the velocity at which data is transferred. Consequently, it is anticipated that by the end of 2020, there will be 50 billion ubiquitous gadgets linked to the cellular network. Moreover, about two-thirds of the overall IP traffic will be attributed to the traffic generated by mobile devices [7,8]. Thanks to advancements in remote health monitoring and early problem detection made possible by the convergence of IoT-5G and deep learning, home medical systems have undergone a dramatic transformation. [9]. The Internet of Things paves the way for the collection of vast amounts of physiological data via sensors and wearable devices, including heart rate, temperature, blood oxygen levels, and electrocardiogram (ECG) signals. [10–12]. The collected data is then transmitted to another server distant from the user where complex algorithms with the use of artificial intelligence are used to analyse patterns that relate to different health conditions. ANNs, which are part of deep learning algorithms, can work with large amounts of information and independently learn the data to reveal the important characteristics that correspond to certain health conditions [13,14]. This helps to eliminate the need for having to extract features by hand, this being a time-consuming process and prone to some errors. Another way to enhance deep learning algorithms is to add attention layers to upgrade the inputs that the system is drawn to the most informative ones. This improvement works well with the model by improving its performance. Operators in deep learning models make it possible to attend to the relevant features of data input about the specific classification goal at hand [15]. Because of this, it is possible to use it in settings with limited resources, like home healthcare systems, without sacrificing accuracy or computing complexity. [16]. There are several potential benefits to home medical systems that combine IoT and deep learning, such as early intervention, regular checkups without hospitalization, and real-time monitoring. Better health and an improved patient experience are other benefits of integrating this technology. [17,18]. Telemonitoring applications can provide appellate recommendations to the patient and enable them to take responsibility for their treatment process. IoT in connection with deep learning as a tool for enhancing the medical systems for home use can be a major change in the healthcare business. Such an integration enables the healthcare providers to provide very individualized care to the patients; at the same time, it can help reduce national health costs and improve health results [19].

It is important to point out that this paper is related to many ideas regarding the IoT and WSNs. We bring out a framework that capitalizes on the application of IoT and WSNs. Explaining the concept of a developed system for the collection and sorting of data concerning COVID-19 patients, the usage of this system in a real-time environment is also depicted. The main contributions of this research can be outlined as follows:

- ✓ Development of a home healthcare system that uses the Internet of Things (IoT) and deep learning to track vital signs like temperature, pulse rate, oxygen saturation, and arrhythmia.
- ✓ 5G Communication for High-Speed Monitoring to support real-time monitoring of vital signs such as blood pressure, heart rate, oxygen levels, and temperature. This improves responsiveness and reliability in healthcare monitoring.
- ✓ Introduces an Artificial Neural Network (ANN)-based system for intelligent health monitoring. This system uses IoT technology to process data from wearable devices and achieve accurate monitoring of various health parameters.
- ✓ Proving that the suggested deep learning model is quite accurate and performs well, with a precision of 0.9870.

✓ Investigating the possibility of combining IoT-5G and deep learning technologies in home medical systems to offer real-time tracking, prompt intervention, enhanced patient care, and decreased healthcare expenses and hospital visits.

The rest of this paper is organized as follows: Section 2 discusses related work. Section 3 presents the use case of our system while Section 4 presents the proposed system/framework. Section 5 discusses the results observed. Finally, section 6 concludes the paper and gives avenues for further work.

2. Related Work

Many researchers have used smart healthcare IoT to carry out their work in health prediction. An overview of the applications of health monitoring with sensor devices and 5G monitoring systems that have been published is provided in this section.

Ghazal et al. [20] used IoT-based machine-learning approaches to develop smart cities. They discussed the concept of a Smart City which utilizes wireless networking, broadcast networking, Internet mesh networking, telecommunication network, and the end-to-end sensor network, with the IoT as the core. Gulati et al. [21] considered wireless networking techniques for energy preservation and data aggregation in IoT-WSN systems. The importance of energy-effective data aggregation techniques is to increase the lifespan of WSN nodes, which are small and battery-driven machines. The authors provided an overview of various approaches and algorithms for energy-efficient data aggregation in IoT-WSN systems. They discussed the critical and non-critical applications of IoT and WSN, emphasizing their impact on various sectors of everyday life. Yu et al. [22] highlighted the importance of 5G networks for the continuous growth of IoT and the challenges faced in reducing network latency and increasing throughput without sacrificing reliability. They proposed the use of Cognitive Radio Networks (CRNs) as a feasible alternative to address these challenges and enable the coexistence of IoT, WSN, 5G, and beyond 5G works. Yildirim et al. [23] Present a new advanced technique based on deep learning to identify and classify 17 different forms of cardiac arrhythmias by analyzing long-duration electrocardiography (ECG) signals. Preventing cardiovascular disease is of utmost importance, given that over 50 million individuals globally are susceptible to it. The existing automated ECG analysis techniques are insufficient. The objective of the study is to create a novel deep-learning method for accurately and rapidly categorizing arrhythmias. The study utilizes 1000 ECG signal fragments extracted from the MIT-BIH Arrhythmia database. The focus is on 10-second fragments rather than individual QRS complexes, resulting in a 13-fold reduction in the required number of analyses. An end-to-end processing system was developed using a 1D-Convolutional Neural Network (1D-CNN), which integrates feature extraction, selection, and classification into a single phase. It was established that the suggested method is rather fast and allows to the classification of data in real-time. This fact distinguishes it as simple and user-friendly because it does not entail complex processes. For the one-dimensional convolutional neural network (1D-CNN) we achieved a maximum accuracy value is 91. 33% in classifiers for 17 different classifications of arrhythmia. The time required to classify each of the samples was 0. 015 seconds. There has been a plethora of developments up to this chapter a few of which are flowing; These can be applied to Mobile and Cloud computing Devices.

Hammad et al. [24] present electrocardiograph (ECG) is used to diagnose cardiovascular diseases (CVDs), however, the analysis of a large ECG data is complex. The following work is to present a new DNN approach for enhancing the diagnosis of CVD based on ECG. The strategy includes the learning stage that contributes to accurate classification of the acquired data by providing powerful tools for feature extraction, the next step where the genetic algorithm is used to select the best feature extraction and classification. Interestingly, the proposed technique gives better results in comparison to the present methods and the accuracy is raised on an average to 0. 94, precision of 0.93 and an F1 score of 0. 953. Therefore, the findings imply that the proposed model can appropriately inform users and doctors to identify forms of irregularities.

Qasim et al. [25] proposed a secure house system on IoT using Arduino and Raspberry Pi microcontrollers for sensing and detecting activities including gas, Humidity, body temperature and movement. Developing an Android prototype which will enable the human interface to warn the house owner about Any suspicious activities in the house. It is proposed to use LM35 and Infrared (IR) sensors for gas cylinders and electronic devices respectively to sense different sorts of signals. The sensed information is transferred to a neural network architecture to estimate possible risks. Lai et al. [26] suggested a sub-WSN in an IoT system to overcome the problems of few channel bands and high-power consumption in the conventional art, which included a sub-gateway and a plurality of sub-sensor nodes. There is a rather complex connection between the sub-gateway and the sensor node; the Sub-sensor nodes are involved in the sensing of the environment and wireless transmission of data to the sub-gateway through an RF signal. The sub-WSN design focused on optimizing ultra-low power consumption, thus, it is suitable for energy-sensitive IoT applications. Thus, the sub-WSN can contribute to the IoT system, augmenting the channel capacity and decreasing the overall power consumption level. Islam et al. [27] Introduce an IoT that allows for real-time diagnosis of clinical conditions for home-based health care. There are three different kinds of sensors used by the system: an infrared thermometer (MLX90614), an electrocardiogram (ECG) sensor (AD8232), and a blood oxygen saturation level and heart rate detector (MAX30100). Data transmission to a server is accomplished through MQTT. A convolutional neural network enhanced with an attention layer is used to classify probable health conditions in the deep-learning model that is sent to the server for examination. In the case of heartbeat, the system can differentiate five classes of heartbeat using Electrocardiogram (ECG) signal data also for fever whether one is having it or not the system will determine by checking body temperature. Also, it gives an account of the present rate of pulse plus the oxygen status as well. In case of detection of severe uncertain anomalies, the system will provide the connection of the user with the closest physician for further examination.

. Landaluce et al. [28] introduced RFID and WSN were reviewed by the authors of [4]. They also deliberated on the issues involved in the conversion of RFID systems to sensing and computational elements and on how one should decide on the architecture of wirelessly linked networks of sensors. It also pointed out that RFID can either be a WSN on its own or can be implemented and incorporated into another WSN to enrich the features of the overall systems. They also addressed the obstacles and challenges that need to be overcome in developing novel IoT applications such as energy harvesting efficiency, communication interference, fault tolerance, data processing capacity, cost feasibility, and integration of these factors. Additionally, they reviewed two emerging trends in IoT:

- The combination of RFID and WSN exploits their advantages and complements their limitations.
- The use of wearable sensors for new promising IoT applications.

Saleh et al. [29] presented the integration of WSNs with IoT networks, focusing on exchanging information, applying security, and configuration. It highlighted the challenges in network construction, such as authentication, confidentiality, availability, integrity, and network development. This sheds light on the potential integration challenges imposed by the integration of WSN for IoT, particularly regarding differences in traffic features. Martinez et al. [30] analyzed the development of distributed monitoring applications derived from cooperative sensor networks by determining the present state of networked object adoption of low-power, multi-hop wireless technology. Subsequently, they evaluated how this technology has changed as a result of being integrated into the IoT. Ferrero Martín [31] classified existing IoT sensors to manage various available sensors. He defined the main characteristics of sensors, for selecting the most suitable sensors for IoT applications. He offered examples of commercial sensors that are particularly suitable for IoT applications, providing practical guidance for implementation.

Prakash et al. [32] designed an IoT-enabled wearable medical device for physiological data acquisition; specifically, stress, heart rate, and activity levels were tracked. Sensor, end-point, and relay nodes are successfully deployed in the study's interior settings, creating a collaborative wireless network enabled by IoT architecture using radio frequency (RF), Wi-Fi, Bluetooth, and other hybrid wireless protocols. The performance characteristics of the WSN are analyzed, demonstrating that the efficiency of the existing network can be improved through the integration of IoT architecture. Wu et al. [33] proposed an IoT healthcare management platform for personal wearable devices that uses deep learning (DL) to monitor input devices and modify a mobile app or intelligent classroom platform. The operating process included gathering sensor data, optimizing it using deep learning models, and connecting it with the IoT platform. It emphasized the importance of optimizing the data by eliminating noise data from human factors and re-evaluating the profound learning results to remove data with known errors and add more accurate data. This optimized dataset can be used to construct a higher accuracy model and integrate it into the IoT platform. This demonstrates that the IoT platform, combined with the deep learning (DL) model, can analyze outputs and identify the current status of each device, which is beneficial for users of healthcare applications systems. Raviprasad et al. [34] showed experimental investigations using a considered database confirm that the performance of the proposed system is capable and within the range of acceptance compared to existing methods. Balaji and Karthik [35] proposed an improved version of the Harris Hawks Optimization model combined with the Harris Hawks Optimization with the Deep Learning-based Energy Consumption Prediction algorithm (IHHODL-ECP)for predicting integrated energy consumption in IoT settings. The authors introduced a preprocessing step to make raw electrical data compatible with the subsequent processing in the IHHODL-ECP model. They combined three deep learning models (DNN, GRU, and DBN) for energy consumption prediction. They employed the IHHO algorithm for adjusting hyperparameters in the prediction technique. Experimental results showed that the IHHODL-ECP model outperforms other present approaches, such as LR, LSTM, and CNN-LSTM models, in terms of accuracy, with a lower MAPE (mean absolute percentage error) value of 33.85%.

The impact of WLAN on WSN, with IEEE802.25.4 ZigBee sensors, and the coexistence that results when both run on the same channel were assessed by Nourildean et al. [36]. This study explores how WLAN integration affects WSN, specifically IEEE802.15.4 ZigBee sensors. Since Wi-Fi and ZigBee share a channel, the study examines their coexistence. The inquiry used the Riverbed Modeler Academic edition in several simulated situations. The results show that Wi-Fi networks reduce ZigBee throughput, latency, and data loss. File transfer, web browsing, and database access exhibit this effect.

The main benefit of the introduced approach, which is based on the use of deep learning models, is that such models can learn from large volumes of data and as a result, create highly accurate categorization models. Moreover, an application of transfer learning and data augmentation techniques has been used to increase the effectiveness of deep learning models, especially in cases where the data volume is limited. Making use of IoT devices and cloud technology innovations, deep learning models have the potential to change the face of health care since patients can be monitored remotely while diagnoses can be done with high accuracy.

The literature reviews offer real research papers in this field that contain useful information on the if and how IoT and deep learning technologies may be deployed in personal health systems. Consequently, the conclusions made in this work could represent sensible claims, and the further development of advanced remote medical monitoring systems is deemed highly relevant in this regard.

3. Materials and Methods

The IoT-based patient monitoring system supported by the Deep Learning system was created by an integrated approach of hardware and software. The patients' data collected were in real-time, through the application of IoT devices such as wearable sensors and smart CH devices. It is noteworthy that Data analysis was precise and fast utilizing Deep Learning techniques. The model was trained using many datasets and health factors. Data was preprocessed, convolutional and recurrent neural networks were trained, and real-time performance was optimized. Deep Learning may change patient monitoring and healthcare results, as shown by thorough testing of the system's stability and security in real-world healthcare settings.

3.1 Use Case: In-home support equipment during the COVID-19 pandemic

In this paper, we outline a home-care monitoring system for people who need remote assistance but only have access to the Internet. This setup may be utilized for remote patient monitoring and diagnosis. We presented a hybrid model platform with varying aggregation, fixed, and mobility node phases. There is a progression from essential, data-assisted emergency nodes to coordinated, communicated with predetermined hospital assistance centers. Real-time sensors like smartphones and wearable devices may be preferred for identifying and diagnosing COVID-19 patients. The primary advantage of IoT technology is the ability to maintain up-to-date patient information safely [37].

Additionally, the reward messages are automatically delivered to the doctor and update the database during any emergency phase or from any system. Using WSN, researchers can gather crucial network metrics (statistics) and information on difficulties plaguing healthcare facilities due to radio noise and interference. We propose a system based on the IoT and WSN that may be used to improve healthcare.

3.2 Challenges of WSN and IoT Integration

The challenges of WSN and IoT Integration can be summarized as follows:

- **Security:** Incorporating the "IP address to the field" capability into sensor nodes, with their conventional sensing functions.
- **Quality of Service:** Gateways translate protocols/repeaters, sensor nodes must maximize resources to provide quality services, and the IoT will use all kinds of gadgets. By pooling resources, like cooperative labor, we can guarantee a higher quality of service for resource-intensive security measures.
- **Configuration:** Sensor nodes in WSNs require configuration for network scalability, architecture, and self-healing tasks. Users are expected to install software and recover from system problems.
- Node compromise is a vulnerability due to the large number of nodes and physical attacks.
- Unauthorized data access can lead to incorrect data volumes, especially with the proliferation of illegal nodes on the Internet.
- Denial of Service (DoS) attacks can disrupt the network when not adequately managed.

- Data privacy is a concern, requiring protection against corrupted information passing through multiple layers.

4. Proposed Model

The proposed model consists of a raspberry that obtains information about the patient through wearable sensors such as a body temperature sensor, blood pressure, oxygen meter, and heart rate sensor. Machine learning algorithms based on an ANN have been used for making a decision. These decisions can encompass a wide range of outcomes, including identifying abnormal health patterns such as abnormal heart rate or increasing or decreasing the oxygen in the blood, predicting potential medical issues, alerting healthcare professionals or patients in case of emergencies, and recommending appropriate interventions or treatments. Using a 5G network antenna, the data and decisions are transmitted to the Cloud for cloud storage. Web applications get the information from the Cloud once received. The decision obtained by the Raspberry Pi is received by the web application with an appointment to the critical cases that require medical assistance or an ambulance, as shown in Figure 1.

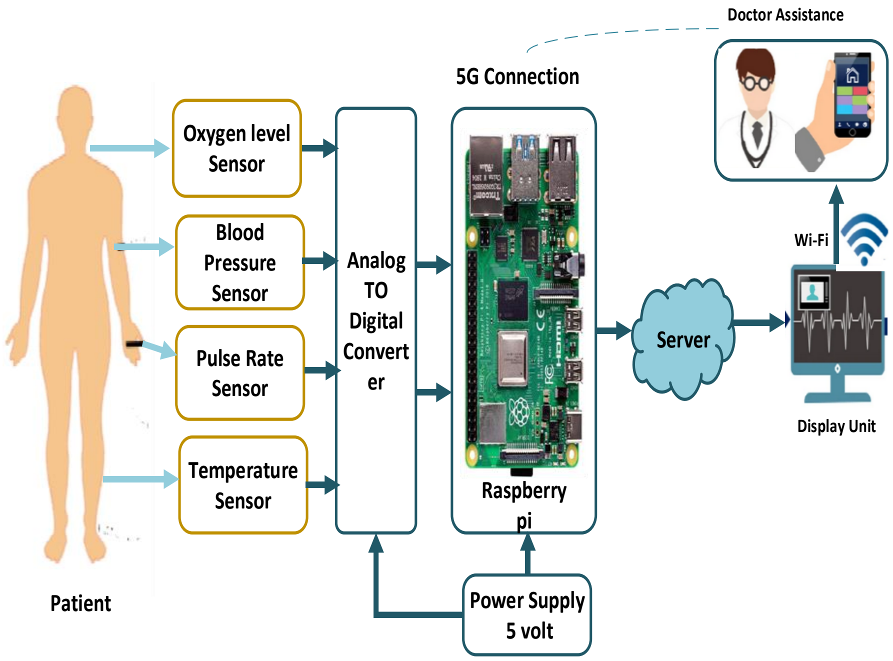

Figure 1. The proposed framework of 5G communications integration of WSN and IoT for patient monitoring.

4.1 Hardware configurations

Raspberry 4 and other components have been installed as follows:

4.1.1 Sensors

The patient's body is connected to specific kinds of sensors to retrieve the information from the patient. These sensors are Fingertip Pulse Oximeter SpO2, Contactless Temperature Sensor Module GY-906, Digital Wrist

Blood Pressure Heart Rate Monitor, ECG (Measurement Pulse Heart) Monitoring Sensor Module Kit, and the MAX30102 Pulse Oximeter SpO2& Heart-Rate Module.

- *Fingertip Pulse Oximeter SPO2, and PR*: The MAX30100 sensor combines a pulse oximeter and a heart rate monitor. It can detect heart rate and SpO2, has two LEDs, precise optics, low-noise analog processing, and a voltage. This sensor operates at a high sample rate and will be compared to a commercial oximeter in this paper.
- *Contactless Temperature Sensor Module GY-906*: The GY-906 non-contact infrared sensor is used for temperature detection in this project. It captures an image of the forehead, identifies the best spot for accurate temperature reading, and proceeds if the temperature is average. If not, a buzzer sounds, and authorities are notified.
- *Digital Wrist Blood Pressure Heart Rate Monitor*: Blood pressure is the force of blood on artery walls as the heart pumps it through the body. It has two values: systolic (when the heart beats) and diastolic (between beats). A sphygmomanometer measures it.
- *Electrocardiogram/ECG (Measurement Pulse Heart) Monitoring Sensor Module Kit:* The AD8232 is used for ECG measurements. It extracts, amplifies, and filters bio-signals, eliminating noise and motion artifacts. It boasts an impressive Common Mode Rejection Ratio of 80 dB.
- *MAX30102 Pulse Oximeter SPO2& Heart-Rate Module:* The MAX30102 module measures heart rate and pulse oximetry with noise-reduction features and LED rejection. It's designed for portable devices, powered at 1.8V, with separate 3.3V for LEDs. It uses I2C for communication and can be turned off with no standby current.

It is noteworthy that RM500U-CN 5G HAT (viz, a 5G antenna) has been used to transfer information from the Raspberry Pi 4 to the station where the server is found.

4.2 Methodology

The proposed system has been executed by establishing a connection between the sensors and the Raspberry Pi 4 to obtain the essential sensor data from the patient. The sensors gather diverse physiological data, including heart rate, blood pressure, temperature, and other essential indicators. The raw sensor data is preprocessed by normalizing it to the minimum and maximum allowable values. This step ensures consistency and eliminates any potential biases caused by different sensor ranges. Method for extracting features:

1. Data collection:

- Sensors: The patient's attached sensors collect real-time physiological data. Each sensor is tasked with monitoring distinct data, such as a heart rate monitor for detecting heart rate and a thermometer for measuring body temperature, among others.
- Collected Patient Data: Along with real-time sensor data, static patient information including patient identity, age, gender, chronic disease status, and other pertinent characteristics are gathered. The fixed data is essential for providing context to the sensor data and enhancing the precision of any subsequent analysis.

2. Data normalization

• which entails converting the data gathered from the sensors into a common scale often a scale of zero to 1 or 0 to 255. This stage ensures that data collected from different sensors can be synchronized such that it can be integrated. Calibration is useful in endeavouring to minimize the impact of differences in the range of sensors and their units of measurement.

3. Data Integration:

• Raw sensor data that has been normalized is integrated with the patient demographics and other steady-state features. This integration creates a full dataset for each patient, one containing only the measurement data from the point at which it is retrieved and the other containing the birth date, sexual, religion, and ethnicity data, as well as marital status, which should not change and therefore can be assumed to remain constant for the duration of the study.
• Data Fusion: From the various sensors the feature vector at each time stamp is obtained as follows. This vector defines the patient at the time of his complaint and is a synthesis of various aspects of his physiology and demography.

4. Feature Extraction:

• Temporal Features: In this paper, the analysis will rely on finding and becoming acquainted with the temporal structure and characteristics of the Sensor Data. For instance, it could calculate moving averages, identify high points, or low points and come up with any changes over some time.
• Statistical characteristics which describe the shift and variability of data are calculated from the collected data of a sensor. Such type of information includes measures of central tendency which are mean, median, standard deviation and variance.
• Specialized characteristics related to a specific domain: Other substrates that may be derived revolve around the domain of usage and might also be explored. In a cardiovascular monitoring system, some of the parameters might be heart rate variability (HRV) or blood pressure variability (BPV).

5. Data Transmission:

This data with these many features is then passed into the Raspberry Pi 4 and away it goes. The Raspberry Pi 4 acts as a processing unit which collects the data, performs some of the primary preprocessing of the data and puts it in a format for further analysis or transmits the data to another location server or cloud for further analysis and storage.

6. Visualization and Analysis:

   The processed data is utilized to provide visual representations and analytical assessments, furnishing healthcare providers with practical and implementable understandings. These visualizations can aid in the surveillance of patient well-being, identification of irregularities, and facilitation of well-informed choices.

   Figure 2 displays the flowchart of the proposed system, which outlines the complete sequence of steps from data collection to analysis and visualization.

Figure 2. Flowchart of the proposed system

4.2.1 Dataset

This dataset comprises anonymized data from Hospital Sírio-Libanês, São Paulo, in Brasilia [38]. The dataset in question is widely regarded as the first of its kind, providing researchers with comprehensive information on COVID-19 patients. This dataset is particularly valuable as it offers specific metrics that may aid in the assessment of intensive care unit (ICU) requirements. The information is presented in a window-based format and elucidated by the staff at the Sírio-Libanês hospital, as shown in Figure 3. The most effective and widely recommended procedures worldwide made all the data anonymous. The data have been cleaned up and normalized column per column using the Min-Max Scaler to fall somewhere between -1 and 1.

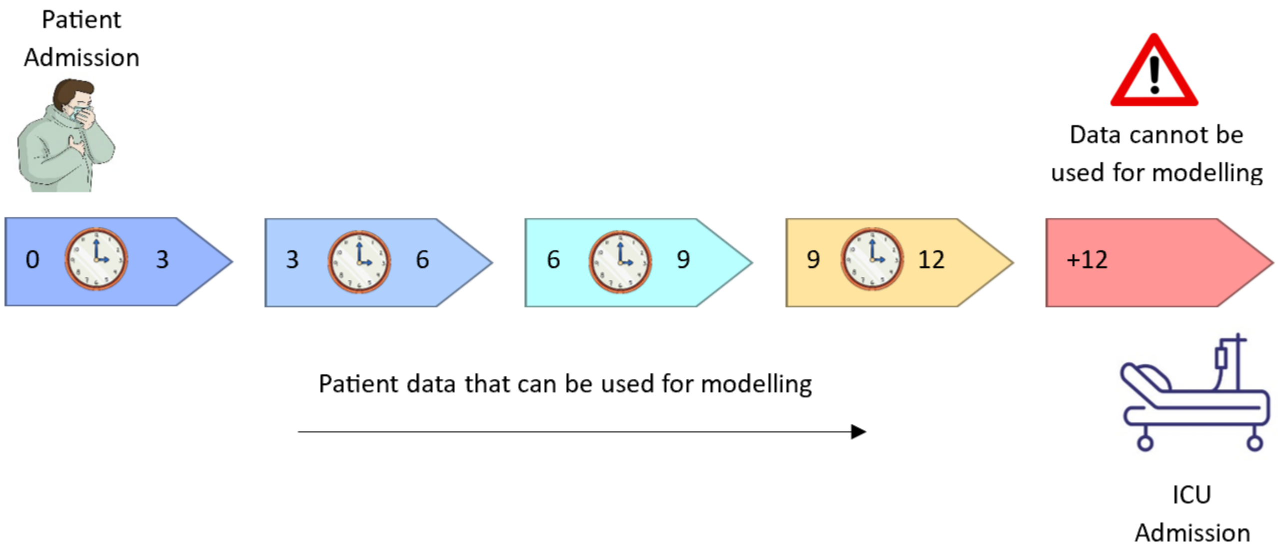

Figure 3. The data of patients are aggregated by time windows.

The dataset features in the dataset are (a) patient demographic information (03); (b) patient previously grouped diseases (09); (c) blood results (36); and (d) vital signs (06).

Preprocessing

The preprocessing stage is critical to fill in missing values and move the features into one scope of values. The preprocessing is done as follows:

- **Remove unused features sensor:** The dataset consists of more sensor data than the sensors used in this research. In addition to the sensors of this research, other data, either information about patient diseases or unused sensor data, are also available. This requires removing the unused sensor data to prevent using unnecessary data in making a decision.
- **Missing values:** It is essential to have a strategy for dealing with missing values since they occur often. A missing value in your data may represent a wide range of potential meanings. It's possible that the event never took place or that the necessary data is unavailable. It is possible that the data entry clerk just made a mistake or needed more information. Different data mining methods deal with missing data in different ways. Typically, they ignore or remove records with missing values, substitute a mean value for the omitted data, or extrapolate missing values based on the ones there.

- **Missing Values Replacement Policies:** There are five such policies:

  (1) Ignore any records that are lacking their associated values.

  (2) Change them to a global constant, such as "?" (the question mark).

  (3) Manually fill in missing values depending on your prior experience with the domain.

  (4) Replace them with the variable’s mean (if it is numerical) or the value that occurs most frequently (if categorical).

  (5) Modeling strategies such as nearest neighbors, the Bayes rule, decision trees, and the EM algorithm can be utilized.

In this research, the adopted policy replaces the missing values using the data mean.

- **Normalization**: Normalization makes -1.0 to 1.0 or 0.0 to 1.0 more understandable. Classify several scenarios using it. Multi-dimensional features sometimes need normalization since one attribute's values on a larger scale may dilute another's on a smaller one. Normalizing compares traits with various precisions. Data mining models with several characteristics may be insufficient. Property values are scaled. Normalizing attributes enables scaled measurement.
- **Methods of Data Normalization:**
  1) Decimal Scaling
  2) Min-Max Normalization
  3) Z-Score Normalization (zero-mean Normalization)

In this research, the Min-max normalization technique was used for data normalization. This technique performs a linear transformation on the original data. Minimum and maximum value from data is fetched, and each value is replaced according to the formula (1).

$$v' = \frac{v - \min(A)}{\max(A) - \min(A)}(new\max(A) - new\min(A)) + new\min(A) \qquad (1)$$

ANN

The results of the classifier in the suggested model are shown in Figure 4. Classifiers like Deep Neural Networks (DNNs), Long Short-Term Memories (LSTMs), Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), and Random Forests (RFs) are compared against one another to determine which is the most effective. One hundred people performed ten distinct actions and movements for 60 seconds each to create the testing and training set. Compared to the other models, ANN is shown to have better accuracy performance. The success of the model's performance in the updated setting depends on timely updates. Increasing the number of training examples improves generalization. However, regular data gathering is arduous and time-consuming.

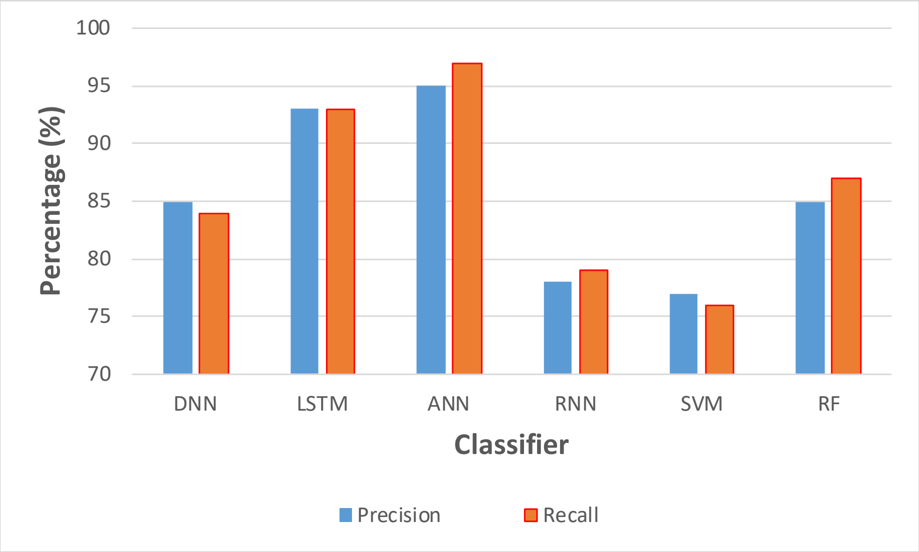

Figure 4. Comparison of the impact of various classifiers.

5. Results

6. Implementing the suggested approach to the dataset required utilizing both the sensor data and patient information as test data following the model's training. The model underwent 500 epochs of training, resulting in an accuracy of 0.9870 and a loss of 0.0377. The model's durability and usefulness in predicting outcomes based on the integrated sensor and patient data are demonstrated by its high degree of accuracy and minimal loss. Figures 5 and 6 depict the training process. The model employed in this study is a sophisticated deep-learning framework specifically engineered to process both time-series data from sensors and static demographic data. The architecture incorporates specialized layers, such as LSTM or GRU layers, designed to extract features from sequential input. The Adam optimizer was selected due to its efficiency and ability to adaptively adjust the learning rate, resulting in speedier convergence. The learning rate was initially set to 0.001. Learning rate decay was implemented to systematically decrease the learning rate as the training advanced, aiding the model in refining its weights with greater precision.
7. Figures 5 and 6 depict the evolution of the loss and accuracy metrics during the 500 epochs. These graphs illustrate the progressive enhancement of the model's performance over time and its eventual convergence to a stable state.

```
Epoch 484/500
52/52 [==============================] - 0s 2ms/step - loss: 0.1130 - accuracy: 0.9578
Epoch 485/500
52/52 [==============================] - 0s 3ms/step - loss: 0.1269 - accuracy: 0.9675
Epoch 486/500
52/52 [==============================] - 0s 2ms/step - loss: 0.0515 - accuracy: 0.9870
Epoch 487/500
52/52 [==============================] - 0s 3ms/step - loss: 0.0538 - accuracy: 0.9708
Epoch 488/500
52/52 [==============================] - 0s 2ms/step - loss: 0.0505 - accuracy: 0.9773
Epoch 489/500
52/52 [==============================] - 0s 3ms/step - loss: 0.0619 - accuracy: 0.9740
Epoch 490/500
52/52 [==============================] - 0s 3ms/step - loss: 0.2078 - accuracy: 0.9253
Epoch 491/500
52/52 [==============================] - 0s 3ms/step - loss: 0.0999 - accuracy: 0.9513
Epoch 492/500
52/52 [==============================] - 0s 3ms/step - loss: 0.0996 - accuracy: 0.9610
Epoch 493/500
52/52 [==============================] - 0s 3ms/step - loss: 0.1141 - accuracy: 0.9675
Epoch 494/500
52/52 [==============================] - 0s 3ms/step - loss: 0.1681 - accuracy: 0.9351
Epoch 495/500
52/52 [==============================] - 0s 6ms/step - loss: 0.1047 - accuracy: 0.9578
Epoch 496/500
52/52 [==============================] - 0s 8ms/step - loss: 0.1018 - accuracy: 0.9578
Epoch 497/500
52/52 [==============================] - 0s 5ms/step - loss: 0.0913 - accuracy: 0.9675
Epoch 498/500
52/52 [==============================] - 0s 3ms/step - loss: 0.0613 - accuracy: 0.9773
Epoch 499/500
52/52 [==============================] - 0s 3ms/step - loss: 0.0496 - accuracy: 0.9805
Epoch 500/500
52/52 [==============================] - 0s 2ms/step - loss: 0.0377 - accuracy: 0.9870
<keras.callbacks.History at 0x7fde94220490>
```

Figure5. Training process

The epoch 500 shows an accuracy of 0.9870 with a loss of 0.0377.

The training and validation loss curves are depicted in Figure 5. The training loss exhibits a steady decrease, suggesting that the model is proficiently acquiring the patterns present in the data. The validation loss exhibits a comparable pattern, indicating that the model effectively generalizes to new data without suffering from overfitting. After the 500 epochs, the training loss decreased to 0.0377. The validation loss remained in proximity to this value, suggesting minimal overfitting.

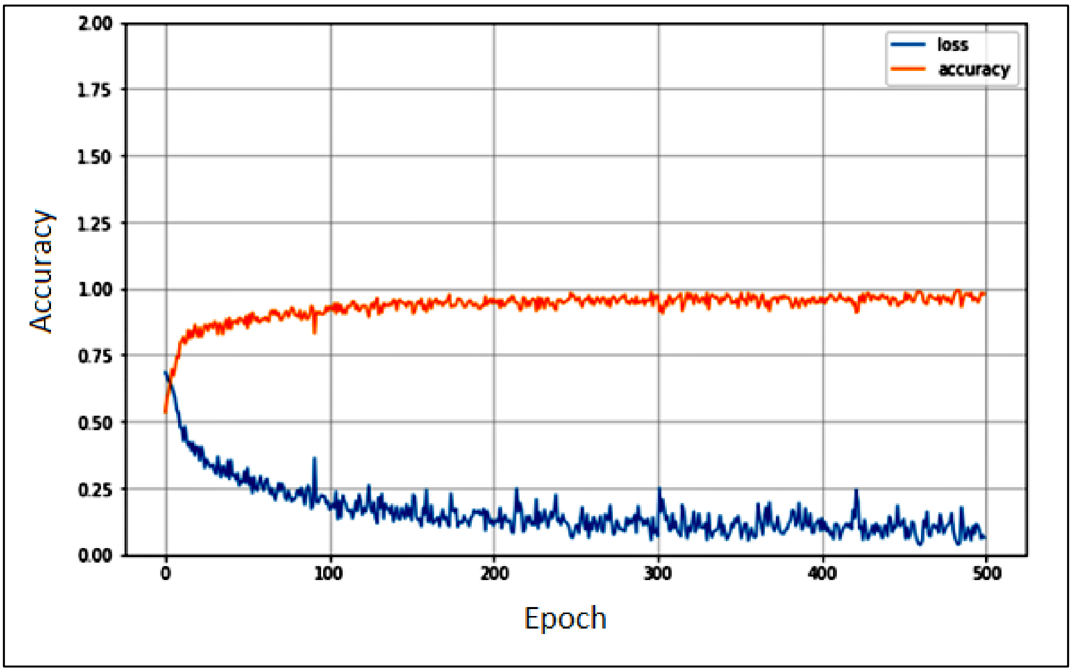

Figure 6. Losses and accuracy in the training process.

Figure 6 displays the accuracy numbers for both the training and validation sets. The training accuracy consistently improves, ultimately achieving a value of 0.9870 after the training period. The validation accuracy also exhibits a commensurate enhancement, showcasing the model's resilience and dependability. The model's high accuracy value of 0.9870 suggests that it can accurately anticipate outcomes for most of the test scenarios.

A prototype of the health monitoring system has been meticulously crafted and is present during rigorous testing involving a diverse group of patients or subjects. The primary objective of this testing phase is to thoroughly assess and scrutinize the system's performance under various real-world scenarios.

A comprehensive examination of four pivotal patient parameters has been initiated to achieve the following metrics: such vital signs as heart rate, body temperature, blood pressure, and levels of oxygen saturation (SpO2). These aspects are closely measured to determine how well the system would be able to obtain and analyze fundamental health information. Further on, the comparative analysis helps to identify the efficiency and rather high degree of reliability of the system. This involves comparing the measurement data collected from the system’s sensors with that collected from the available commercial sensors. Thus, carrying out such a comparative analysis, we would like to reveal the accuracy and effectiveness of the system for providing valid health-related information. Such a systematic evaluation helps to identify requisites for the health monitoring system to be optimally effective and precise for the improvement of patients’ conditions and the convenience of the providers.

Table 1. Heart rate sensor data compared with the data from a commercial sensor.

Number of Patient samples	**Measured bpm (our sensor)**	**Observed bpm (commercial sensor)**	**Relative error**
P1	95	97	2.105
P2	94	95	1.064
P3	91	93	2.198
P4	93	92	1.075
P5	92	92	0.000
P6	91	92	1.099
P7	98	99	1.020
P8	97	98	1.031

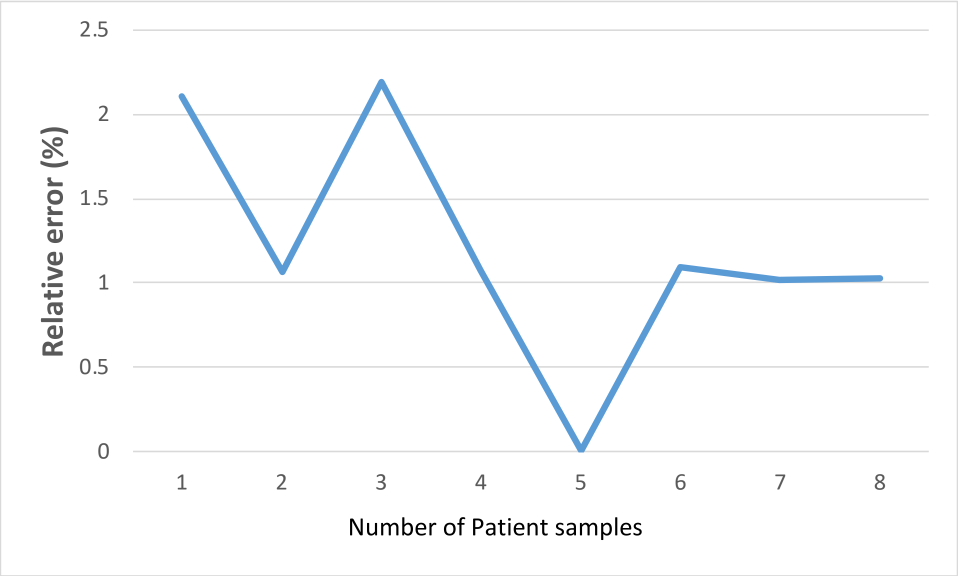

Figure 7. Relative error of Heart rate between our sensor and the commercial sensor for eight patients.

Heart rate data was acquired and compared to data from a commercial sensor (see Table 1). Results showed a relative inaccuracy ranging between 0.00 and 2.2. The relationship between the sample size and the relative error is seen in Fig.7.

Table 2. Analysis of GY-906 temperature sensor-collected body temperatures vs. those from a commercially available, non-contact thermometer

Number of Patient samples	Temperature of room	The patient's Body temperature was measured	The patient's Body temperature observed	Relative error (%εr)
S1	35°C	35°C	36°C	2.857
S2	35°C	36°C	37°C	2.778
S3	34°C	36°C	36°C	0.000
S4	36°C	35°C	36°C	2.857
S5	36°C	35°C	37°C	2.857
S6	[illegible]	[illegible]	[illegible]	2.941
[illegible]	[illegible]	[illegible]	[illegible]	.857
[illegible]	[illegible]	[illegible]	[illegible]	.778

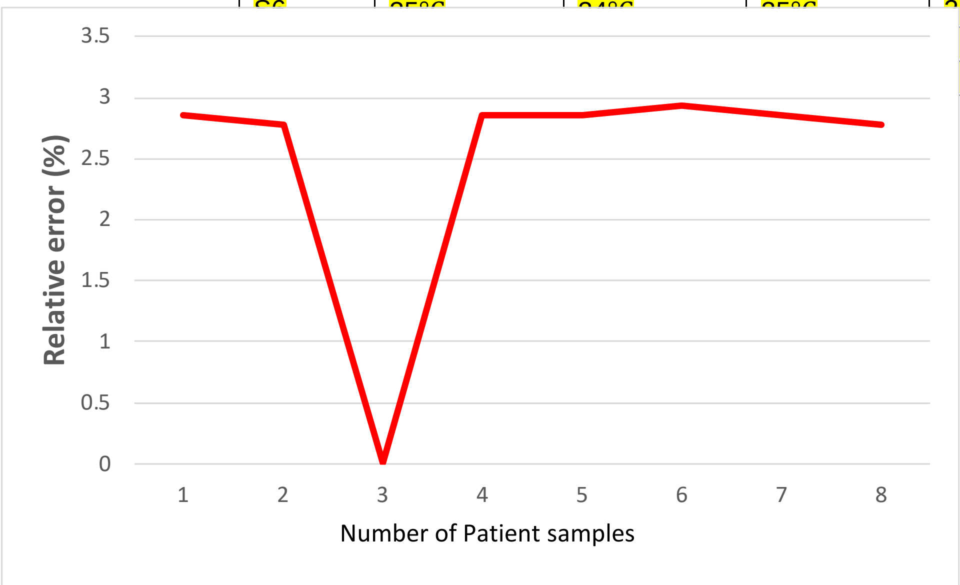

Figure 8. Relative error vs. Number of patient samples in body temperature measurement

The GY-906 sensor was used to take the patient's temperature, and the results were compared to those of a commercially available, non-contact sensor, as shown in Table 2. The maximum relative error was calculated to be 2.9, and its value is contingent on multiple factors like humidity, room temperature, and proper sensor location, so the relative error is about 0 – 3, as shown in Figure 8. Table 3 shows the results of using the developed handcuff system to measure blood pressure. The measurement of blood pressure is divided into two main factors, namely, systolic blood pressure and diastolic blood pressure. In this research, both factors were measured, and a relative error table was compared with a commercial blood pressure monitor. Figure 9 illustrates the highest relative error which was determined to be 2.9 in diastolic blood pressure and 3.4 for systolic blood pressure between our sensor and the commercial sensor.

Table 3. Systolic and diastolic blood pressures were measured by our sensor and the relative error between the measured and commercial sensor.

Number of Patient samples	systolic blood pressure measured	Systolic blood pressure observed	Relative error	diastolic blood pressure measured	diastolic blood pressure observed	Relative error
P1	115	118	2.609	75	77	2.667
P2	120	121	0.833	72	73	1.389
P3	112	115	2.679	70	72	2.857
P4	117	121	3.419	77	79	2.597
P5	109	110	0.917	80	82	2.500
P6	122	120	1.639	74	72	2.703
P7	107	110	2.804	69	71	2.899
P8	126	125	0.794	79	80	1.266

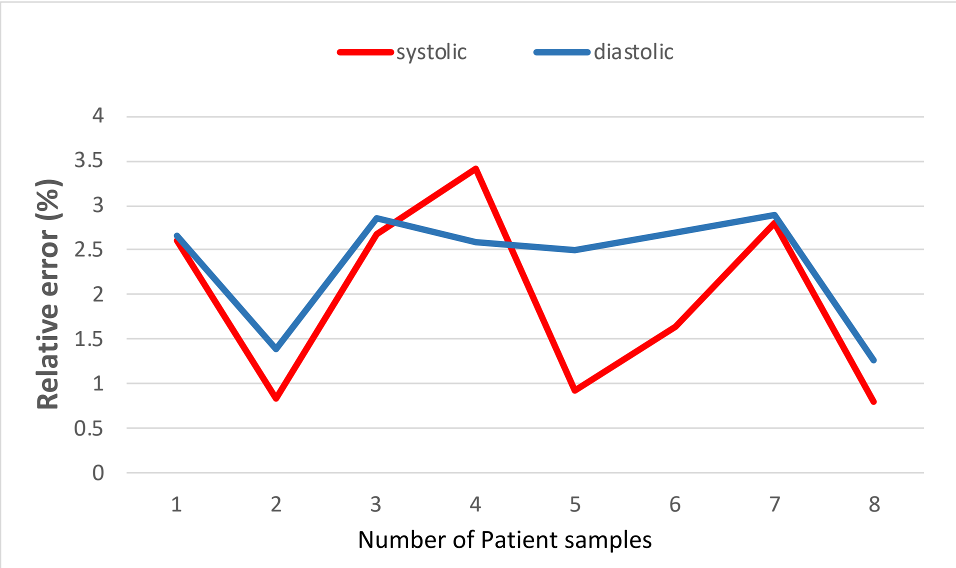

Figure 9. Explain the relative error between the measured sensor and commercial sensor for both the systolic and diastolic blood pressure.

The oxygen level in patients is tracked using a standalone SpO2 sensor in the designed system (Table 4). Obtaining a maximum relative error of 1.053 indicates that the O2 measuring equipment is very accurate. The plot comparing relative error vs. number of patient samples is shown in Figure 10.

Table 4. Comparison of measured SpO2 system with commercial oximeter.

Number of Patient samples	Measured SpO2 (our sensor) (in %)	Observed SpO2 (commercial sensor) (in %)	Relative error (%ϵr)
P1	99	99	0.000
P2	98	98	0.000
P3	96	97	1.042
P4	97	98	1.031
P5	99	99	0.000
P6	98	99	1.020
P7	95	96	1.053
P8	97	98	1.031

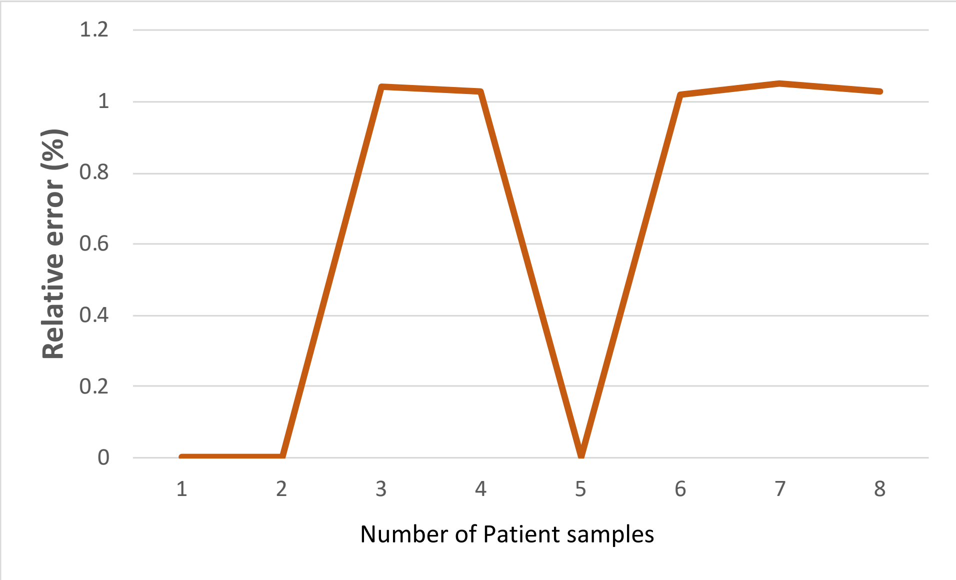

Figure 10. Explain the relative error between the measured SPO2 and commercial oximeter.

The data is captured, saved, and delivered to the Cloud in real-time, as shown in Figure 11. Doctors and other medical professionals may get patient information through the cloud service application. The nurse or doctor should be given a connection to an internet access point. This URL is accessible from any device with an internet browser. When admitted to a medical facility for observation and treatment, they are assigned a unique identification number. Let us suppose all a patient's vitals are within normal ranges. Such a system would help the doctor decide how to treat a patient. Security is also an issue with this approach since information might be forged. To ensure maximum security, it may be necessary to use a dedicated cloud service that employs robust encryption protocols. It would be encrypted before sending any information to a doctor. The digital ID associated with the patient's health card or national identity might one day be connected to the patient's prescription. Each patient's bed will have biomedical sensors installed to monitor their health. Its greatest strengths are this system's inexpensive price and flexibility in treating patients with other COVID strains. This advanced technology may lessen pressure on medical facilities and staff, which benefits patient diagnosis and treatment in the long run. People from poor socioeconomic backgrounds rely heavily on public hospital care, and since this method is very inexpensive to implement, it might be widely used to help those in need.

Figure 11. Real-time heart rate and SpO2 measurement using Raspberry and MAX30100 sensors.

Table 5. Comparison of our proposed method with previous studies

Ref	method	accuracy
[23]	Deep CNN	0.913
[24]	DNN + GA + KNN	0.980
[27]	CNN with attention laye	0.982
Proposed method	ANN	0.987

8. Conclusion

In this paper, healthcare transformation is obtained through the convergence of IoT and WSN within a high-speed 5G communication framework. We propose a model that comprises a Raspberry Pi device that acquires patient information through wearable sensors such as a body temperature sensor, blood pressure sensor, oxygen meter, and heart rate sensor. In our framework/model, ANNs are used as machine learning algorithms for decision-making. The data and decisions are sent to the Cloud using the 5G network antenna, while the data and related decisions are kept in a cloud-based storage system. Web applications retrieve data from the Cloud upon receipt. The Raspberry Pi successfully implements a decision-making system, which is integrated into a web application. Relying on ANNs to extract the basic features, the accuracy reached (96%). Maximum relative errors are heart rate (2.19), body temperature (2.94), systolic blood pressure (3.4), diastolic blood pressure (2.89), and SpO2 (1.05). The proposed system is designed to prioritize significant instances that need immediate medical treatment or emergency services. In the future, we aim to enhance disease classification by using the CNN and SVM models while also leveraging 6G communications to augment the velocity of data transmission.

For future work, several enhancements and expansions are planned to further improve the system:

• Enhanced Disease Classification: It is planned to use Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) in the model to improve the performance and minimize the errors in disease classification. CNNs are well suited for spatial data and could help enhance feature learning from large medical data sets. SVMs can ensure good classification performance, particularly in higher dimensional space.

• Leveraging 6G Communications: Therefore, when 6G technology appears in the future, we will change the communication structure to 6G. It will enhance the system throughput rate by elevating the speeds at which data is transmitted, bringing down the system latency and hence making the system more efficient. Improved convergence will allow for the surveillance of important medical conditions in real-time and timely intervention.

• Integration of Additional Sensors: Wearable sensors that include glucose monitors, motion sensors and many others that are special to the medical field will give an overall picture of the health of the patients. This will help the system in the sense that it will be potentially able to oversee more characteristics related to health and therefore identify more diseases.

• Advanced Data Analytics and Predictive Modeling: Engaging the higher levels of analytics, predictive modelling, and decision support systems can help the system in the early identification of the patient's health complication before reaching critical levels. This means that the application of machine learning will have the ability to analyze historical data to identify possible trends in health that are likely to occur in future hence providing better early interventions.

• Enhanced User Interface and Experience: Enhancing the web application's look and feel will make it easier to use by healthcare practitioners and patients respectively. Additionally, like 'My Dashboard',” 'Alerts' and 'Health reports' can increase the engagement and usage of the application.

Abbreviations

ANNs	Artificial Neural Network
CRN	Cognitive Radio Network
DL	Deep Learning
DNN	Deep Neural Networks
ICU	Intensive Care Unit
IEEE	Institute of Electrical and Electronics Engineers
IHHODL-ECP	Harris Hawks Optimization with Deep Learning-based Energy Consumption Prediction
IoT	Internet of Things
IR	Infrared
LSTMs	Long Short-Term Memories
RFs	Random Forests
RFID	Radio Frequency Identification
RNN	Recurrent Neural Network
SVMs	Support Vector Machines
WSN	Wireless Sensor Network
QoS	Quality of Service

CONFLICT OF INTEREST

The authors declare no potential conflict of interests

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