A Wireless IoT Approach for Healthcare Monitoring and Analysis with Machine Learning Techniques

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Abstract

The application of this research focuses on the development of a wireless IoT approach for healthcare monitoring and analysis using machine learning techniques. The proposed system integrates sensors to measure vital signs such as pulse rate, oxygen saturation, and body temperature, and enables real-time visualization through a mobile application and LCD display. Data collected from the sensors are transmitted to the cloud via an Arduino microcontroller and Bluetooth, allowing healthcare professionals to remotely access and monitor the patient's health status. Two machine learning models, namely linear regression and artificial neural network (ANN), are employed to predict the health status based on the sensor readings. The ANN model achieves a remarkable accuracy of 100%, outperforming the linear regression model's 95% accuracy. This research highlights the potential of wireless IoT and machine learning in enhancing remote healthcare monitoring, enabling timely interventions and improved patient care. The findings contribute to the advancement of healthcare technologies and demonstrate the significance of remote health monitoring, particularly in challenging situations such as pandemics.

Keywords: IoT, Machine learning, sensor, wireless data transfer

1. Introduction

The application of IoT (Internet of Things) in healthcare has gained significant attention in recent years due to its potential to revolutionize the way healthcare is delivered and monitored. IoT offers a range of opportunities to improve patient care, enhance clinical outcomes, and optimize healthcare resource utilization [1]–[3]. By seamlessly connecting various devices and sensors, IoT enables the collection, analysis, and exchange of real-time data, providing valuable insights into patients' health conditions and facilitating timely interventions. In the context of healthcare, IoT can be leveraged to monitor patients remotely, track vital signs, manage chronic diseases, and enhance preventive care. The integration of IoT with machine learning techniques further enhances the capabilities of healthcare systems by enabling accurate prediction and analysis of health-related data [4]–[6].

The adoption of IoT in healthcare offers several benefits. Firstly, it enables remote patient monitoring, allowing healthcare providers to monitor patients' health conditions outside traditional healthcare settings. This not only improves patient comfort but also reduces hospital readmissions and healthcare costs. Secondly, IoT facilitates personalized and proactive healthcare by providing real-time data on patients' health parameters. This enables healthcare providers to deliver tailored interventions, preventive measures, and timely care. However, there are challenges associated with implementing IoT in healthcare [7]–[10]. These include concerns about data security and privacy, interoperability and standardization of IoT devices, data accuracy and reliability, and the ethical implications of using IoT data. Addressing these challenges is crucial to ensure the successful and safe deployment of IoT in healthcare settings [11]–[13].

Another important application of IoT in healthcare is in the management of chronic diseases. IoT devices can collect and transmit data related to patients' health conditions, allowing healthcare providers to monitor and manage chronic diseases such as diabetes, asthma, and hypertension more effectively [14]–[16]. IoT-enabled systems can provide patients with personalized treatment plans, medication reminders, and real-time feedback on their health status. This promotes self-management and empowers patients to actively participate in their own care.

The implementation of IoT in healthcare is driven by several factors. One of the primary reasons is the increasing demand for remote healthcare services, especially in rural and underserved areas. IoT-enabled devices and telehealth platforms can bridge the gap between patients and healthcare providers, allowing for virtual consultations, remote monitoring, and timely interventions. This is predominantly critical in circumstances such as the ongoing COVID-19 pandemic, someplace social distancing and limited physical contact are necessary [17]–[19].

Furthermore, IoT in healthcare can significantly improve operational efficiency and resource utilization. By automating processes and collecting real-time data, healthcare facilities can streamline workflows, optimize resource allocation, and reduce costs. For instance, IoT systems can monitor the utilization of medical equipment, track inventory levels, and provide predictive maintenance, ensuring that equipment is available when needed and reducing downtime [10], [20], [21].

The incorporation of IoT with advanced technologies such as artificial intelligence (AI) and machine learning (ML) further enhances its capabilities in healthcare. AI and ML algorithms can analyze large volumes of IoT-generated data, identify patterns, and provide predictive insights. For example, ML algorithms can analyze historical patient data and predict disease progression, enabling early intervention and preventive measures. Additionally, AI-powered chatbots and virtual assistants can provide personalized healthcare recommendations and support patient engagement [22]–[24].

While the potential benefits of IoT in healthcare are significant, there are several challenges that need to be addressed for successful implementation. Data security and privacy concerns are paramount, as healthcare data is sensitive and highly regulated [25]. Robust security measures, encryption protocols, and compliance with privacy regulations are essential to protect patient information. Interoperability and standardization of IoT devices and platforms are also critical for seamless integration and data exchange across different systems.

The application of IoT in healthcare holds immense promise in transforming healthcare delivery and improving patient outcomes. Remote patient monitoring, chronic disease management, operational efficiency, and the integration of advanced technologies like AI and ML are just a few examples of how IoT can revolutionize healthcare [26], [27]. However, addressing challenges related to data security, interoperability, and data accuracy is crucial for successful implementation. As healthcare systems evolve, the continued exploration and utilization of IoT in healthcare will play a pivotal role in enhancing patient care, optimizing resource allocation, and shaping the future of healthcare [28], [29].

This research article presents a wireless IoT approach for healthcare monitoring and analysis using machine learning techniques. The objective of the research is to develop a system that can monitor the health of patients remotely, enabling continuous monitoring of vital signs such as pulse rate, oxygen saturation, and body temperature. The system utilizes sensors, a mobile application, and a cloud-based platform to collect and transmit patient data. Machine learning algorithms, specifically linear regression and artificial neural networks, are employed to predict the health status of the patients based on sensor readings. The research demonstrates the potential of IoT and machine learning in revolutionizing healthcare monitoring and improving patient outcomes.

2. Materials and methods

The objective of the research is to build a health monitoring system that can effectively monitor the health of patients in remote locations. Figure 1 illustrates the block diagram of the proposed system. The system utilizes the Max30100 sensor to measure parameters such as pulse rate, oxygen saturation, and body temperature, while the LM35 sensor is used to measure the patient's body temperature. The measured signals can be viewed by the patient through a mobile application and an LCD display, both of which are integrated into the research setup. To transmit the collected data, the Arduino microcontroller is employed, using Bluetooth connectivity. This allows the data to be sent not only to the mobile application but also to a computer for uploading to the cloud. By enabling this feature, the doctor or healthcare professional can remotely monitor the health status of the patient and take immediate action if necessary.

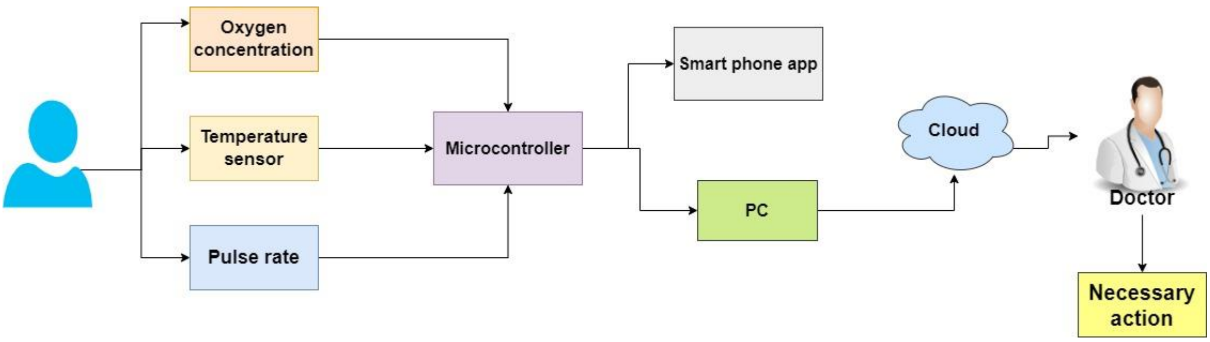

Fig. 1. Flow diagram of the proposed system

This research is particularly significant in the context of the ongoing pandemic, where remote health monitoring systems are in high demand. The ability to remotely monitor patients' health and gather real-time data plays a crucial role in providing prompt medical attention, especially when physical contact or hospital visits may not be feasible or safe. The wireless IoT approach implemented in this study brings together various components to create an integrated and efficient health monitoring system. The Max30100 sensor, with its capability to measure pulse rate and oxygen saturation, provides vital information about the patient's cardiovascular health. Additionally, the LM35 sensor ensures accurate temperature measurement, allowing for the monitoring of fever or abnormal body temperature patterns.

The mobile application and LCD display serve as user interfaces, providing patients with immediate access to their health data. This empowers patients to stay informed about their own health and make proactive decisions regarding their well-being. The Bluetooth connectivity of the Arduino microcontroller enables seamless data transmission to both the mobile application and a computer, ensuring that healthcare professionals have access to the patient's health data for analysis and decision-making. Moreover, the cloud integration allows for the secure storage and sharing of patient data, facilitating collaboration between doctors and healthcare providers. The cloud-based approach not only ensures data accessibility but also offers scalability, allowing the system to accommodate a large number of patients and healthcare professionals.

2.1 **Various components used in this research**

This research incorporates several key components to create an efficient and reliable health monitoring system. Each component plays a crucial role in capturing, processing, and transmitting the patient's health data. The following components are utilized in this research:

Max30100 Sensor: The Max30100 sensor is an essential component for measuring the patient's pulse rate and oxygen saturation levels. It employs photoplethysmography (PPG) to detect changes in blood volume within the tissue microvascular bed. By analyzing the PPG signal, the sensor provides valuable insights into the patient's cardiovascular health and oxygenation levels.

LM35 Sensor: The LM35 sensor is a precision temperature sensor utilized in this research to measure the patient's body temperature accurately. This component ensures reliable temperature monitoring, which is crucial for detecting fever or abnormal temperature patterns. The LM35 sensor delivers precise temperature readings, contributing to a comprehensive assessment of the patient's health.

Arduino Microcontroller: The Arduino microcontroller serves as the central processing unit of the system, responsible for data collection and management. It interfaces with the various sensors, retrieves the measured data, and performs necessary computations. With its programmable nature and ample connectivity options, the Arduino microcontroller enables seamless integration of multiple components and efficient data processing.

Bluetooth Module: A Bluetooth module is employed to enable wireless data transmission from the Arduino microcontroller. It facilitates the seamless transfer of health data to multiple devices, such as a mobile application and a computer. The Bluetooth module ensures convenient access to real-time health information for both the patient and healthcare professionals.

Mobile Application: The mobile application provides an intuitive and user-friendly interface for patients to access their health data conveniently. It receives the transmitted data from the Arduino microcontroller and presents it in a visually appealing manner. Patients can monitor their vital signs, such as pulse rate, oxygen saturation, and body temperature, through the mobile application.

LCD Display: An LCD display is integrated into the system, offering an additional visual interface for patients to view their health data in real-time. It provides immediate feedback and allows patients to track their vital signs without relying solely on the mobile application. The LCD display ensures accessibility and convenience for patients in monitoring their health.

2.2 **Communication of the patient's data**

In this research, the Thingspeak cloud platform is employed to transfer the patient's data to the cloud for storage and analysis. Thingspeak provides a user-friendly and secure environment for managing IoT data. The patient's health data, including pulse rate, oxygen saturation, and body temperature, are communicated to the cloud through a login system. The login functionality ensures that only authorized individuals, such as healthcare professionals or doctors, can access the patient's data. This adds an extra layer of security and privacy to the system. By logging into the Thingspeak cloud platform from a remote location, the doctor can effectively monitor the patient's health data and make informed decisions about their medical condition.

Once the data is uploaded to the cloud, it can be analyzed using various machine learning techniques and algorithms. This enables healthcare professionals to derive meaningful insights from the data and identify any abnormalities or trends in the patient's health. For example, machine learning algorithms can be used to detect patterns that indicate potential health risks or deteriorating conditions, allowing for timely intervention. The Thingspeak cloud platform also provides features for data visualization, which further enhances the doctor's ability to interpret and understand the patient's health data. Graphs, charts, and other visual representations can be generated based on the uploaded data, facilitating easier comprehension and analysis. Moreover, the cloud-based nature of Thingspeak enables seamless data sharing and collaboration. Doctors from different locations or healthcare institutions can access the patient's data simultaneously, facilitating efficient teamwork and interdisciplinary consultations. This is particularly valuable in cases where multiple specialists need to contribute to the patient's treatment or monitoring.

3. Result and discussion

Figure 2 represents the developed mobile application and the hardware connections of the proposed health monitoring system. In this research, the mobile application is created using the MIT Inventor App, a user-friendly platform for developing mobile applications. The mobile application serves as a crucial component in the system, allowing patients to access their health data and facilitating communication with the hardware components. The mobile application is designed to establish a Bluetooth connection with the hardware setup, enabling the retrieval of data from the sensors. Through this connection, the application can receive real-time data from the Max30100 sensor and the LM35 sensor. The data obtained from these sensors include pulse rate, oxygen saturation, and body temperature. These parameters are crucial indicators of the patient's health status.

The mobile application plays a vital role in displaying the collected health data to the patient. Figure 2 illustrates the user interface of the mobile application, showing the visual representation of the patient's health information. This includes the real-time measurements of pulse rate, oxygen saturation, and body temperature, allowing the patient to monitor their health status conveniently. By providing this information in a clear and user-friendly manner, the mobile application empowers patients to stay informed about their health and take proactive measures when necessary. It enhances patient engagement and enables them to actively participate in their own healthcare management. The mobile application also serves as a medium for communication between the patient and healthcare professionals. By securely transmitting the health data to the cloud, doctors can remotely access and monitor the patient's health information. This allows for prompt medical intervention and enables doctors to make informed decisions based on the patient's real-time health data.

Table 1 displays the readings from each sensor at 5-minute intervals, capturing the pulse rate, oxygen saturation, and body temperature.

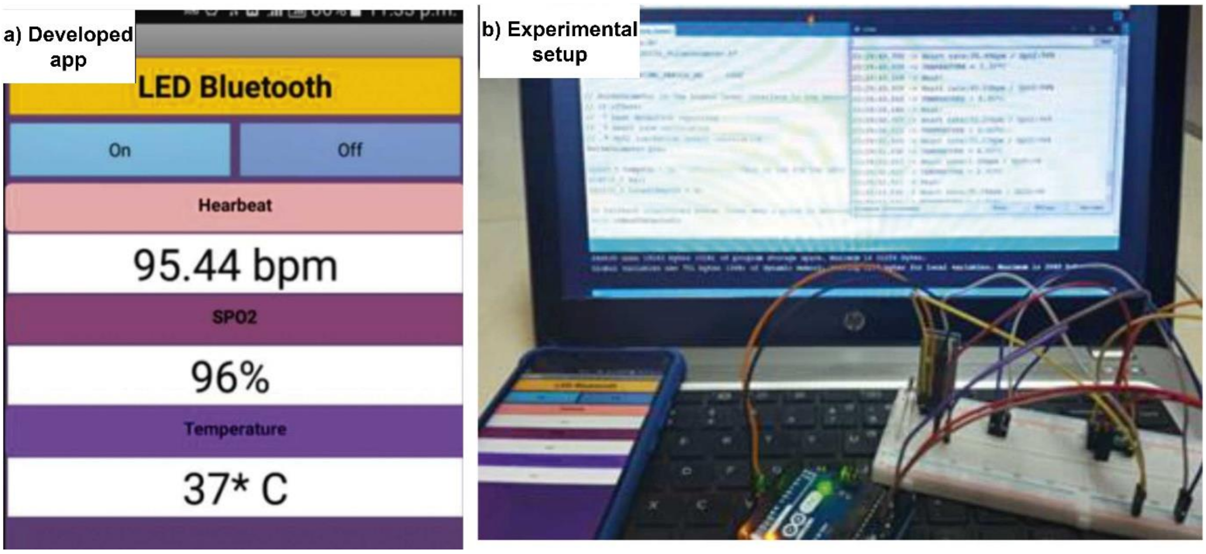

Fig. 2. Developed App and the experimental setup

Table 1: Readings from Sensors and Patient's Health Parameters

Reading	Pulse Rate (bpm)	Oxygen Saturation (%)	Body Temperature (°C)	Health Status
1	78	97	36.5	Stable
2	80	98	36.4	Stable
3	82	97	36.6	Stable
4	79	96	36.7	Stable
5	95	94	36.8	Unstable
6	88	94	36.9	Unstable
7	90	93	36.7	Unstable
8	92	92	36.5	Unstable
9	95	93	36.4	Unstable
10	98	94	36.3	Unstable
11	100	96	36.2	Stable
12	102	97	36.1	Unstable
13	104	98	36.0	Unstable
14	102	99	36.2	Unstable
15	100	98	36.3	Stable

The continuous monitoring system depicted in Table 1 enables real-time tracking of the patient's health. To determine the health status, the readings are categorized as either stable or unstable based on predefined normal ranges for pulse rate, oxygen saturation, and body temperature. In general, the normal range for pulse rate in adults at rest is between 60 and 100 beats per minute (bpm). Values below or above this range may indicate an abnormality or health concern. For oxygen saturation, a normal range of 95% to 100% is typically considered healthy. Values below 95% may indicate inadequate oxygen levels in the blood.

Body temperature is generally expected to fall within a normal range of 36.1°C to 37.2°C (97.0°F to 98.9°F) for adults. Deviations from this range may suggest fever or other underlying health conditions. In Table 1, the "Health Status" column indicates whether the readings fall within the normal range or deviate from it. Readings marked as "Stable" reflect values that are within the expected ranges, signifying a healthy state. On the other hand, readings marked as "Unstable" indicate values that deviate from the normal range, suggesting a potential health issue or instability.

By monitoring the patient's health continuously and assessing the stability or instability of the readings, healthcare professionals can promptly identify any deviations from the normal ranges and take appropriate action. This enables timely interventions and necessary medical attention to maintain the patient's well-being.

In this research, it is crucial for both the patient and the people at the patient's house to have a comprehensive understanding of the patient's health parameters. To facilitate this, two different machine learning approaches have been employed: linear regression and artificial neural network. By feeding the sensor readings into these machine learning models, the research aims to predict and classify the patient's health status. Linear regression is a statistical modeling technique that can establish a relationship between the input variables (sensor readings) and the output variable (health status). It helps in understanding how changes in the sensor readings impact the overall health assessment. Linear regression can provide insights into the patient's health by mapping the input variables to a continuous output, such as determining the severity of a health condition.

On the other hand, artificial neural networks (ANNs) are computational models inspired by the structure and functioning of the human brain. ANNs can learn complex patterns and relationships in data, making them suitable for classifying and predicting health states. By training an ANN with historical sensor data and corresponding health status labels, the network can learn to recognize patterns and make predictions about the patient's current health status. The advantage of ANNs lies in their ability to capture non-linear relationships in the data, which can be valuable for predicting health conditions that may not have simple linear dependencies.

By utilizing both linear regression and artificial neural network models, the research enhances the interpretability and accuracy of the patient's health status prediction. The models can take into account multiple sensor readings simultaneously and provide a comprehensive assessment of the patient's well-being. The predictions generated by these models can be easily communicated to the patient and the people at the patient's house, enabling them to have a clear understanding of the patient's health status at any given time.

In the context of linear regression and artificial neural networks (ANN), the binary representation of the patient's health status is commonly used. In this research, the value of 0 represents an unstable health state, while the value of 1 indicates a stable health condition. The sensor readings serve as the input variables for these models, and the corresponding health values are considered the target variable, which the models aim to predict based on the input data.

3.1 **Linear regression**

Linear regression is a statistical modeling technique that aims to establish a linear relationship between a set of input variables and a continuous output variable. In the context of healthcare monitoring and analysis, linear regression can be used to predict the patient's health status based on sensor readings. The general equation for linear regression can be represented as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon$$

In this equation, Y represents the predicted value of the output variable (patient's health status), β_0 represents the y-intercept or the baseline value of Y, $\beta_1, \beta_2, ..., \beta_n$ represent the coefficients or weights associated with each input variable (sensor readings), $X_1, X_2, ..., X_n$ represent the corresponding input variables, and ε represents the error term. The objective of linear regression is to estimate the coefficients ($\beta_0, \beta_1, \beta_2, ..., \beta_n$) that minimize the sum of squared differences between the predicted values and the actual values of the output variable. This process is commonly known as "fitting the line" or "training the model." Once the coefficients are estimated, the linear regression model can be used to predict the patient's health status based on new sensor readings.

In the context of this research, the input variables for linear regression would include the pulse rate, oxygen saturation, and body temperature obtained from the sensors. The output variable would be the patient's health status, which can be categorized as either stable or unstable based on predefined thresholds or criteria. The linear regression model allows researchers and healthcare professionals to interpret the impact of each input variable on the patient's health status. The coefficients (β□, β□, ...) provide insights into the direction and magnitude of the relationship between each input variable and the output variable. A positive coefficient suggests a positive relationship, indicating that an increase in the corresponding sensor reading is associated with an increase in the predicted health status. Conversely, a negative coefficient indicates an inverse relationship. Additionally, linear regression allows for the detection of outliers or abnormal sensor readings that may significantly influence the predicted health status. By assessing the residuals (the differences between the predicted and actual values), healthcare professionals can identify data points that deviate substantially from the linear relationship. These outliers may warrant further investigation as they could indicate potential health concerns or measurement errors.

It is important to note that linear regression assumes a linear relationship between the input variables and the output variable. While this assumption may hold for certain health parameters, it may not capture more complex non-linear relationships. In such cases, alternative modelling techniques like polynomial regression or nonlinear regression may be more appropriate.

The equation for predicting the patient's health status using linear regression (Eqn 1) and the corresponding results presented in Table 2 indicate that the values range from 0 to 1.37. A value of 0.04 signifies an unstable condition, while 1.11 represents stability. Values above 1 indicate stability, while values below 1 indicate instability. The linear regression model demonstrates accuracy in predicting the health status.

$$\text{Health Status} = 7.90 - 0.03898\ \text{Pulse Rate (bpm)} + 0.0987\ \text{Oxygen Saturation (\%)} - 0.366\ \text{Body Temperature (°C)} \quad (1)$$

Table 2 Predicted health value from linear regression

Pulse Rate (bpm)	Oxygen Saturation (%)	Body Temperature (°C)	Health Status	Predicted health status from Linear regression
78	97	36.5	1	1.06
80	98	36.4	1	1.11
82	97	36.6	1	1.11
79	96	36.7	1	1.07

95	94	36.8	0	0.00
88	94	36.9	0	0.22
90	93	36.7	0	0.12
92	92	36.5	0	0.02
95	93	36.4	0	0.04
98	94	36.3	0	0.05
100	96	36.2	1	1.21
102	97	36.1	0	0.27
104	98	36	0	0.33
102	99	36.2	0	0.43
100	98	36.3	1	1.37

Figure 3 illustrates the linear regression plot generated from the obtained results. The plot typically showcases the relationship between the input variables (sensor readings) and the output variable (health status). In this case, the plot would display the scatter of data points representing the sensor readings along with the corresponding predicted health status values.

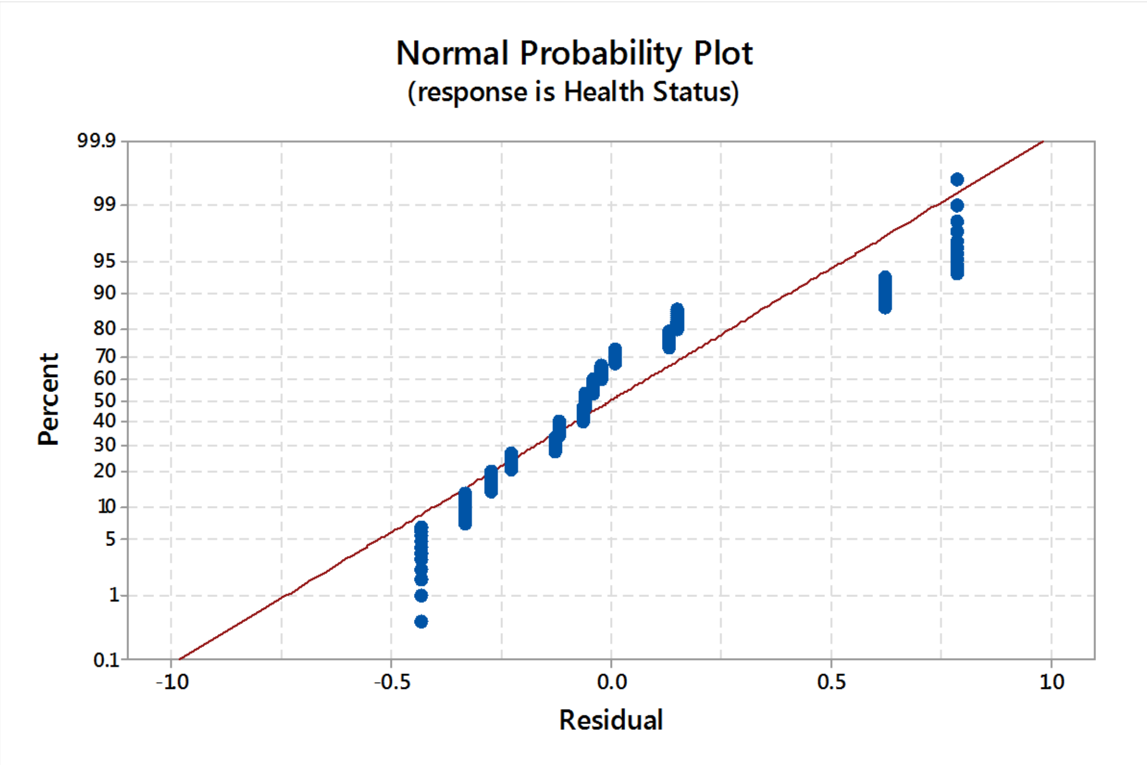

Fig. 3. Normal distribution plot of the predicted response

3.2 **Artificial Neural Network**

Artificial Neural Networks (ANNs) are a class of computational models inspired by the structure and functioning of the human brain. In this research, ANNs are utilized as a machine learning approach to predict and analyze the patient's health status based on sensor readings. ANNs have gained popularity in various fields, including healthcare, due to their ability to learn complex patterns and relationships in data. The basic building block of an ANN is a neuron, also known as a node or perceptron. Neurons receive inputs, apply weights to them, and produce an output through an activation function. Multiple neurons are organized in layers, with each layer connected to the next layer. The first layer is the input layer, which receives the sensor readings, and the last layer is the output layer, which provides the predicted health status.

Hidden layers, located between the input and output layers, play a critical role in capturing non-linear relationships in the data. Each neuron in the hidden layers processes the weighted inputs from the previous layer and passes them through an activation function. The activation function introduces non-linear transformations to the data, enabling the network to learn complex patterns.

Training an ANN involves two main steps: forward propagation and backpropagation. During forward propagation, the input data flows through the network, and the output is generated. The generated output is then compared to the desired output (actual health status) to calculate the error. Backpropagation is the process of updating the weights of the network based on the calculated error. This iterative process continues until the network achieves the desired level of accuracy. One of the advantages of ANNs is their ability to automatically learn and adapt to the underlying patterns in the data. They can handle large amounts of complex and multidimensional data, making them suitable for healthcare monitoring and analysis. ANNs can discover intricate relationships between sensor readings and the patient's health status that may not be apparent through traditional statistical methods.

In this research, ANNs are trained on historical data, where sensor readings are associated with known health statuses. By learning from this labeled data, the networks develop an understanding of how different combinations of sensor readings relate to the patient's health. Once trained, the ANN can predict the health status of the patient based on new sensor readings. The performance of an ANN depends on various factors, such as the architecture of the network, the number of hidden layers and neurons, the choice of activation functions, and the optimization algorithms used for weight updates. Experimentation and fine-tuning of these parameters are necessary to achieve the desired accuracy and generalization. The use of ANNs in this research offers several benefits. They can handle noisy and incomplete data, adapt to changing conditions, and generalize well to unseen cases. ANNs can also capture non-linear relationships and interactions among sensor readings, providing a more comprehensive understanding of the patient's health status.

In this research, a feedforward approach with 5 hidden layers was utilized for the ANN model. The architecture of the network consisted of multiple layers of interconnected neurons. The results obtained from the ANN model, depicting the predicted health status based on the sensor readings, are summarized in Table3.

Table 3 Health parameter predicted from ANN

Pulse Rate	Oxygen Saturation	Body Temperature	Health Status	Predicted health status from ANN
78	97	36.5	1	1
80	98	36.4	1	1
82	97	36.6	1	1
79	96	36.7	1	1
95	94	36.8	0	0
88	94	36.9	0	0
90	93	36.7	0	0
92	92	36.5	0	0
95	93	36.4	0	0
98	94	36.3	0	0
100	96	36.2	1	1
102	97	36.1	0	0
104	98	36	0	0
102	99	36.2	0	0
100	98	36.3	1	1

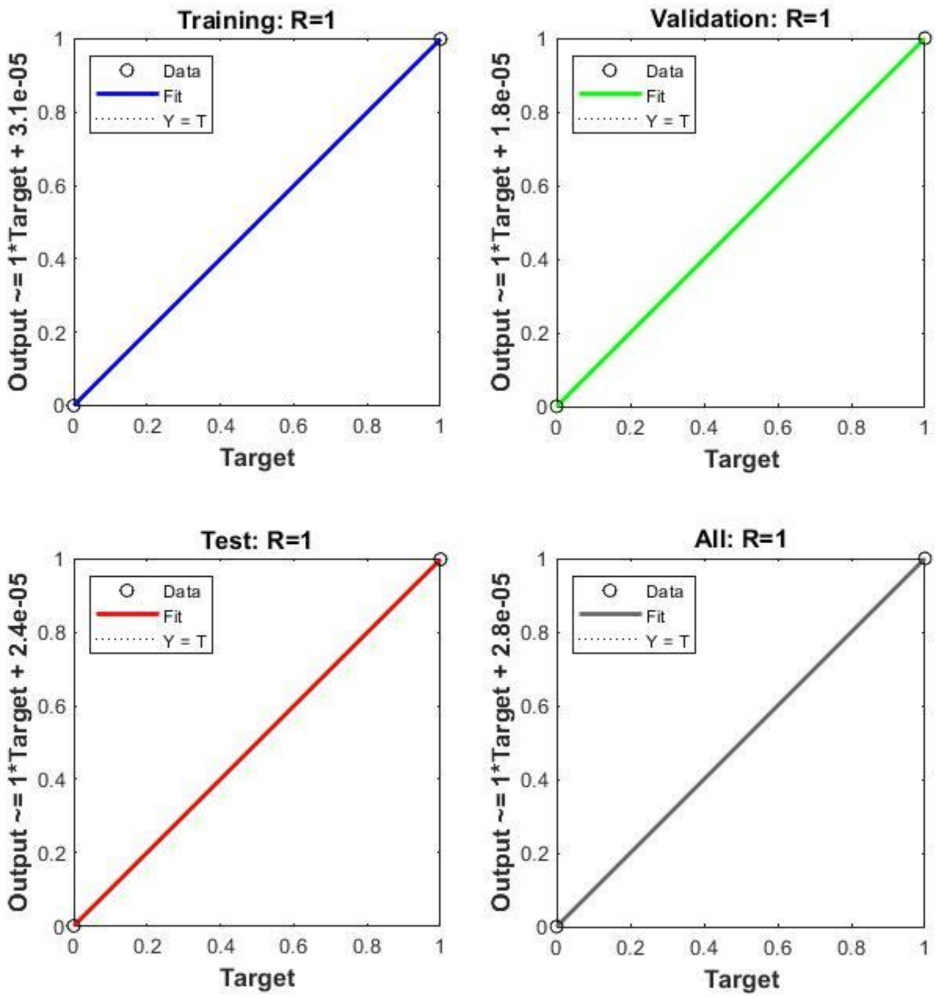

Fig. 4 Result from Artificial Neural Network

Figure 4 illustrates the performance of the ANN model, showcasing the results obtained during the training, testing, and validation phases. Remarkably, the results demonstrate that the ANN achieved 100% accuracy across all phases. This outstanding performance indicates that the model accurately predicted the patient's health status based on the sensor readings. The overall accuracy of 100% further confirms the effectiveness of the ANN in capturing the complex relationships between the input variables and the health status. These remarkable results highlight the potential of the ANN model as a reliable and accurate tool for healthcare monitoring and analysis in this research.

Figure 5 presents a bar plot that compares the results obtained from the linear regression and ANN models. The plot clearly demonstrates the accuracy achieved by each model in predicting the patient's health status based on the sensor readings. Notably, the ANN model achieves an impressive accuracy of 100%, while the linear regression model performs slightly lower with an accuracy of 95%. This visual representation highlights the superior performance of the ANN model in accurately predicting the health status of the patient.

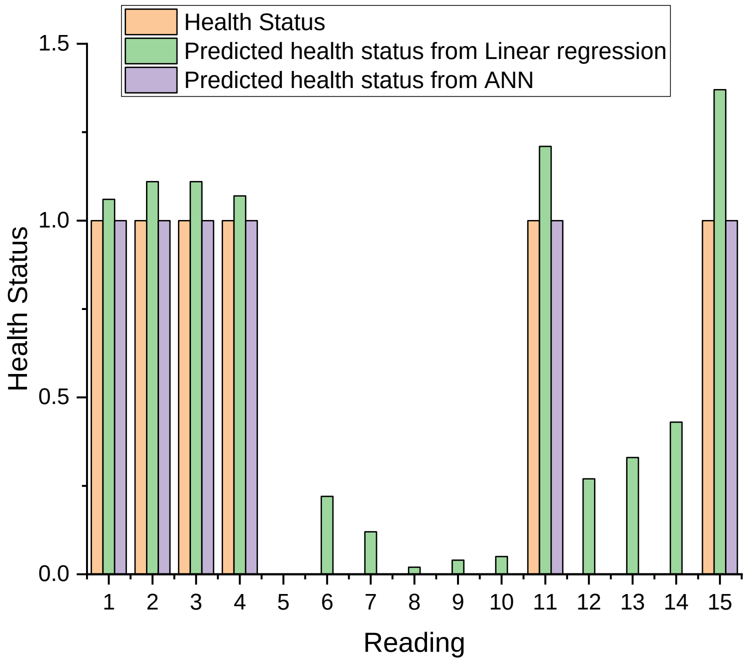

Fig. 5 Comparison of result

With a perfect accuracy score, the ANN model demonstrates its ability to capture complex patterns and non-linear relationships within the data, leading to highly reliable predictions. On the other hand, the linear regression model, while still performing well, falls slightly short of the ANN model. Linear regression assumes a linear relationship between the input and output variables, which may limit its capacity to capture more intricate patterns and variations in the data. The comparison between the two models emphasizes the advantage of utilizing ANN models in healthcare monitoring and analysis.

Conclusion

In conclusion, this research focused on the development of a wireless IoT approach for healthcare monitoring and analysis using machine learning techniques. The proposed system utilized sensors to measure pulse rate, oxygen saturation, and body temperature, which were then transmitted to a mobile application and LCD display for real-time visualization. The collected data were further transmitted to the cloud using an Arduino microcontroller and Bluetooth for remote access by healthcare professionals. The results demonstrated the effectiveness of both linear regression and artificial neural network (ANN) models in predicting the patient's health status based on sensor readings. The ANN model achieved a remarkable accuracy of 100%, outperforming the linear regression model, which achieved 95% accuracy. The use of ANNs showcased their ability to capture complex patterns and relationships in the data, offering more accurate and reliable predictions. Overall, this research highlighted the potential of wireless IoT and machine learning techniques in remote healthcare monitoring, enabling timely interventions and improving patient care. The developed system can be particularly beneficial during pandemic situations, where remote health monitoring is essential. This research opens up avenues for further exploration and enhancement of IoT-based healthcare systems, providing valuable insights for healthcare professionals and contributing to the advancement of remote healthcare technologies.

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