ISSN 2063-5346

Employing IoT and Machine Learning Models for Heart Disease Prediction and Diagnosis in Healthcare

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Abstract

This research explores the implementation of IoT and machine learning models for heart disease prediction and diagnosis in the healthcare domain. By employing various IoT sensors, including ECG, oximeter, and heart rate monitoring devices, patient health is continuously monitored, and data is collected. This data is then processed using machine learning techniques to develop predictive models capable of detecting heart disease at an early stage. Two dissimilar machine learning methods are employed: linear regression and artificial neural networks (ANNs). The linear regression model utilizes historical data to generate an equation, achieving an accuracy of 95.76% in predicting heart disease. In contrast, the ANN model, incorporating a feedforward algorithm with 10 neurons, is trained using the

ISSN 2063-5346

TRAINLM training function and the LEARNGDM adaptation learning function, achieving an impressive accuracy of 100%. The results demonstrate the superiority of the ANN model in terms of accuracy, highlighting its ability to capture complex nonlinear relationships within the data. By accurately predicting heart disease, these models serve as valuable tools for healthcare professionals to intervene promptly and provide appropriate treatments, leading to improved patient outcomes and reduced healthcare costs. Moreover, the research establishes normal ranges for sensor readings, such as ECG, oximeter, and heart rate, enabling the identification of normal and abnormal conditions. This facilitates the timely identification of individuals at risk and the initiation of necessary actions. Overall, this research showcases the potential of IoT and machine learning in revolutionizing healthcare through early detection and diagnosis of heart disease, fostering proactive and personalized healthcare practices, and ultimately improving patient care and optimizing healthcare resource utilization. Future research can focus on expanding datasets, incorporating additional sensors, and further refining the accuracy and reliability of heart disease prediction models for real-time clinical applications.

Keywords: ANN, IoT, machine learning, disease prediction

1. Introduction

Heart disease and stroke are major causes of morbidity and mortality worldwide. Early detection and accurate prediction of these conditions are crucial for effective prevention and timely interventions [1]–[3]. Risk assessment models traditionally rely on clinical factors, such as age, gender, and medical history. However, the integration of advanced technologies, such as IoT and machine learning, has the potential to significantly enhance the accuracy and efficiency of heart disease and stroke prediction.

The Internet of Things (IoT) has transformed healthcare by enabling the seamless integration of devices, sensors, and networks to collect and exchange real-time data. In the context of heart disease and stroke, IoT devices offer continuous monitoring of vital signs, such as blood pressure, heart rate, and electrocardiogram (ECG) data [4], [5]. These devices can transmit data to centralized systems, facilitating remote patient monitoring and timely interventions. IoT in healthcare holds tremendous potential for early detection and improved management of heart disease and stroke [6]–[8].

Machine learning techniques have gained significant attention in healthcare due to their ability to analyze large and complex datasets to generate predictions and insights. In the context of heart disease and stroke prediction, machine learning models can utilize patient data, including demographic information, medical history, and physiological measurements, to develop predictive models. These models can provide personalized risk assessments and aid in early detection and intervention strategies [9]–[11].

Linear regression is a widely used machine learning technique for prediction and modeling. It establishes a direct association among the input structures and the predicted outcome. In the context of heart disease and stroke prediction, linear regression models can analyze various

ISSN 2063-5346

risk factors, such as age, blood pressure, cholesterol levels, and family history, to estimate the probability of developing these conditions. While linear regression provides insights into the direction and magnitude of relationships between variables, its ability to capture complex nonlinear patterns may be limited [12]–[14].

Artificial Neural Networks (ANNs) are powerful machine learning models inspired by the structure and function of the human brain. ANNs consist of interconnected nodes (neurons) organized in layers, allowing them to learn complex patterns and relationships in data [15]. ANNs have shown great promise in heart disease and stroke prediction due to their ability to capture nonlinear relationships and adapt to various data types. By training on large datasets, ANNs can learn intricate patterns and make accurate predictions, contributing to personalized risk assessment and early detection of these conditions [16], [17].

This research emphases on the application of IoT and machine learning models for heart disease prediction and diagnosis in healthcare. The study utilizes various sensors, including ECG, oximeter, and heart rate monitor, to collect patient data. The data is transmitted to a microcontroller and then communicated to a machine learning model for analysis. Machine learning approaches are employed to predict the likelihood of heart disease. The results demonstrate the accuracy and effectiveness of the developed models in early detection and prediction of heart disease. This research donates to the progression of healthcare technology and can aid in improving patient outcomes.

2. Proposed methodology

Heart disease remains a significant global health concern, necessitating accurate and timely prediction and diagnosis for effective treatment and management. In recent years, the incorporation of the Internet of Things (IoT) and machine learning models has developed as a capable method to improve heart disease detection and prognosis in the healthcare domain. This research focuses on monitoring patients' health using IoT sensors, including an electrocardiogram (ECG) to record heart rate, a glucometer to measure sugar levels, and an oximeter to detect oxygen levels. The collected sensor readings are transmitted to a microcontroller, such as Arduino, and subsequently fed into machine learning models for heart attack prediction. This study explores the application of machine learning approaches, using historical data to identify early signs of heart attacks based on pre-attack pulse rate, oxygen concentration, and ECG patterns.

To conduct this research, a diverse set of IoT sensors was employed to monitor patients' health. The ECG sensor recorded heart rate variations, while the glucometer measured sugar levels, and the oximeter determined oxygen saturation. These sensors were carefully chosen due to their relevance in cardiovascular health assessment (Fig. 1). The collected sensor data were transmitted to a microcontroller, specifically Arduino, which served as an intermediary between the sensors and the machine learning models. Arduino facilitated data acquisition, preprocessing, and communication with the subsequent stages of the system. The data were then forwarded to the machine learning models for heart attack prediction. Linear regression aimed to establish relationships between the input features (pulse rate, oxygen concentration,

ISSN 2063-5346

and ECG patterns) and the target variable (heart attack prediction). On the other hand, artificial neural networks employed complex interconnected layers of artificial neurons to learn intricate patterns and non-linear relationships within the data for more accurate predictions.

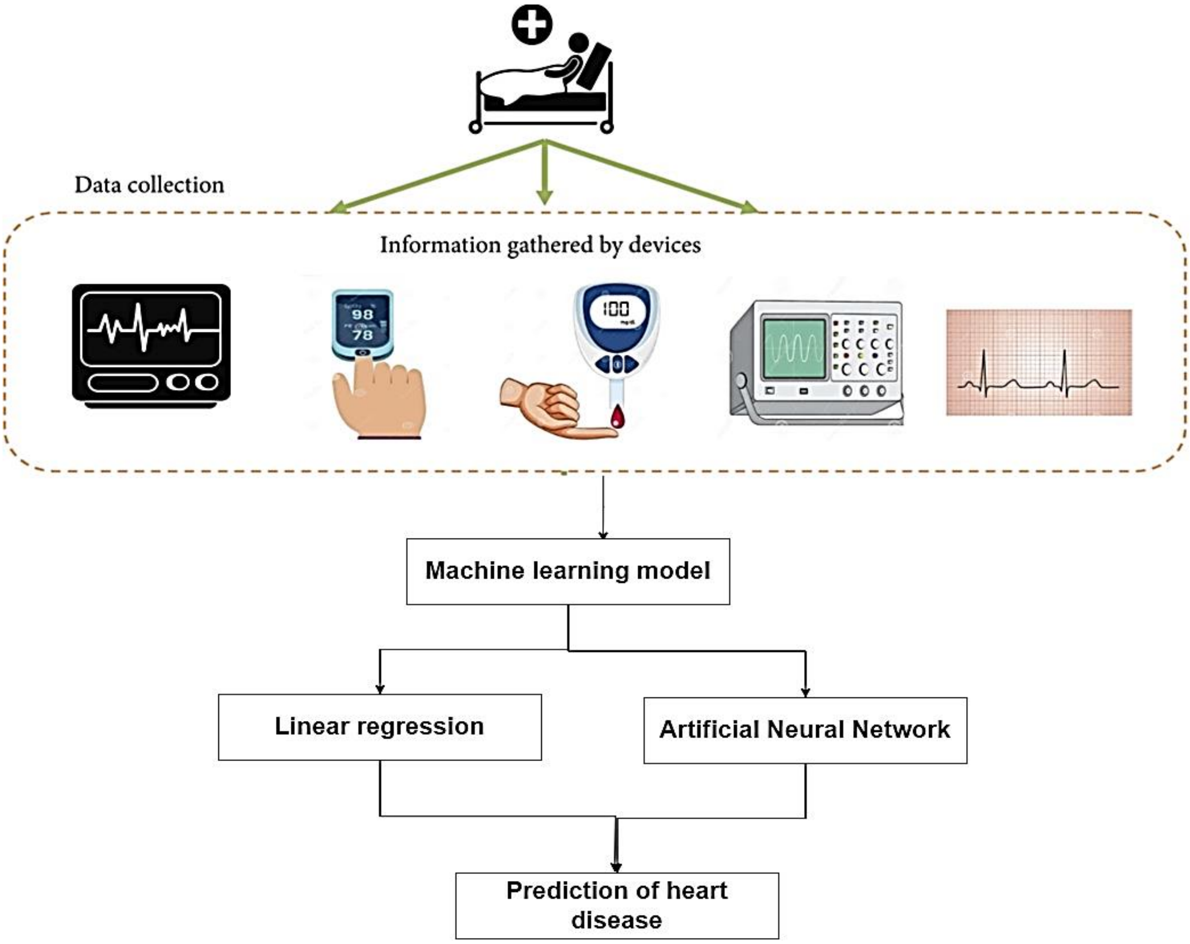

Figure 1 illustrates the architecture of the proposed system

In this research, various sensors are utilized to monitor patients' health and collect essential data for heart disease prediction and diagnosis. These sensors, integrated within an Internet of Things (IoT) framework, play a critical role in providing real-time measurements and insights into the cardiovascular health of individuals. Let's explore the key sensors employed in this study:

The ECG sensor is fundamental in recording the electrical activity of the heart. It measures the heart's electrical signals and translates them into a graphical representation, known as an electrocardiogram. This sensor provides crucial information about the heart's rhythm, rate, and abnormalities. By analyzing the ECG patterns, such as the P-wave, QRS complex, and T-wave, abnormalities and potential indicators of heart attacks can be detected.

The glucometer is a sensor commonly used for monitoring blood glucose levels, especially in patients with diabetes. While not directly linked to heart disease, glucose levels can impact cardiovascular health. Fluctuations in blood sugar levels can contribute to the development and progression of heart diseases. Hence, integrating a glucometer within the IoT framework allows for continuous monitoring of glucose levels and assessing their correlation with heart disease risk.

The oximeter measures the oxygen saturation levels in the blood, providing insights into the respiratory and circulatory systems' efficiency. It typically consists of a sensor that attaches to a patient's fingertip or earlobe, emitting light and analyzing the light absorption patterns to determine oxygen saturation. Monitoring oxygen levels is crucial as it helps identify potential hypoxemia or inadequate oxygen supply to body tissues, which can be indicative of cardiovascular issues or heart attacks.

By incorporating these sensors into the IoT ecosystem, real-time data on heart rate, blood sugar levels, and oxygen saturation can be continuously collected and analyzed. This continuous monitoring facilitates the early detection of abnormalities or changes in vital parameters, enabling timely intervention and potentially preventing heart attacks or minimizing their impact.

Figure 2 depicts the communication architecture of the proposed system, showcasing the flow of information from the sensors to the heart disease prediction model. The system leverages different components, including microcontrollers, Bluetooth modules, Raspberry Pi, and MATLAB software, to enable seamless data transmission and analysis. The sensors, connected to the microcontroller, play a crucial role in capturing vital health parameters such as heart rate, blood glucose levels, and oxygen saturation. To establish a wireless communication link between the sensors and the microcontroller, a Bluetooth module is employed. This module allows for the seamless transmission of sensor data to the microcontroller, ensuring real-time monitoring and data acquisition.

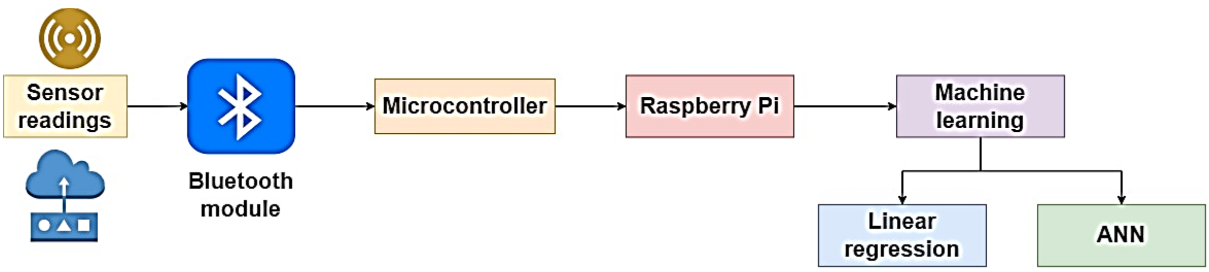

Fig. 2 Communication architecture

The microcontroller, usually an Arduino board, acts as an intermediary in the system architecture. It receives the data from the sensors via the Bluetooth module and performs necessary preprocessing and formatting tasks. The microcontroller ensures that the collected data is in a suitable format for further processing and analysis. Next, the data is communicated from the microcontroller to a Raspberry Pi. The Raspberry Pi serves as a central hub for data aggregation and further processing. It receives the preprocessed data from the microcontroller and transfers it to the MATLAB software. The Raspberry Pi plays a

ISSN 2063-5346

crucial role in facilitating the communication between the microcontroller and the MATLAB environment, ensuring a smooth flow of data.

Once the data reaches the MATLAB software, it is fed into the heart disease prediction model. The model, built using machine learning algorithms such as linear regression or artificial neural networks, leverages the input features, including pulse rate, oxygen concentration, and ECG patterns, to forecast the likelihood of a heart disease occurrence. The model assigns a binary result, where 0 indicates normal readings and 1 signifies the identification of a heart disease, necessitating further medical attention. One significant advantage of this proposed system is its ability to detect heart disease at an early stage without saturation. By continuously monitoring the patients' vital signs, the system can identify abnormalities and warning signs that might indicate an impending heart attack. This early detection enables timely intervention and appropriate medical action, potentially preventing severe consequences and improving patient outcomes.

3. Linear regression

Linear regression is one of the machine learning approaches utilized in this research for heart disease prediction and diagnosis. It is a statistical modeling technique that aims to establish a linear association among the input features and the target variable. In this case, the input features include pulse rate, oxygen concentration, and ECG patterns, while the target variable is the prediction of heart disease occurrence. The linear regression model assumes a linear relationship between the input features and the target variable and generates a linear equation to represent this relationship. The equation takes the form:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta nXn$$

In the above equation:

Y represents the predicted output or target variable (heart disease prediction in this case).

X1, X2, ..., Xn denote the input features (pulse rate, oxygen concentration, ECG patterns, etc.).

β0, β1, β2, ..., βn are the coefficients or weights assigned to each input feature. These coefficients determine the impact or influence of each input feature on the predicted output.

The linear regression model aims to estimate the coefficients β0, β1, β2, ..., βn that minimize the difference between the predicted output (Y) and the actual target variable values. This estimation process is typically achieved using optimization techniques such as least squares or gradient descent.

Once the coefficients are estimated, the linear regression model can be used to predict the target variable (heart disease prediction) for new input feature values. By plugging in the values of pulse rate, oxygen concentration, and ECG patterns into the linear equation, the model generates a predicted value of heart disease occurrence.

ISSN 2063-5346

It is important to note that linear regression assumes a linear relationship between the input features and the target variable. However, in complex datasets, non-linear relationships may exist. In such cases, linear regression may not capture the full complexity of the data, leading to suboptimal predictions. This is where other machine learning models, such as artificial neural networks, can be beneficial as they are capable of capturing non-linear relationships.

4. Artificial Neural Network

Artificial neural networks (ANNs) are a powerful machine learning technique employed in this research for heart disease prediction and diagnosis. ANNs are inspired by the structure and functioning of biological neural networks in the human brain. In the context of heart disease prediction, ANNs offer the capability to capture complex non-linear relationships between input features (pulse rate, oxygen concentration, ECG patterns) and the target variable (heart disease occurrence). This is particularly beneficial as cardiovascular health involves intricate interactions among various physiological factors. The structure of an artificial neural network typically comprises three key components: the input layer, hidden layers, and output layer. The input layer receives the input features, representing the physiological measurements, and passes them forward to the subsequent layers. The hidden layers, consisting of interconnected neurons, extract and transform the input information, learning and identifying patterns and relationships. These hidden layers allow ANNs to model intricate and non-linear dependencies that may exist within the data, enhancing the predictive capabilities of the network. Finally, the output layer provides the predicted heart disease occurrence based on the learned patterns and relationships. The process of training an ANN involves presenting a set of labeled training data to the network, adjusting the weights and biases of the neurons iteratively to minimize the difference between the predicted output and the actual target variable values. This process, known as backpropagation, utilizes optimization techniques to update the network's parameters. Once trained, the ANN can make predictions on new, unseen data by forwarding the input features through the network and generating the predicted heart disease occurrence. The advantage of ANNs lies in their ability to learn from large and complex datasets, capturing intricate relationships that may be challenging to define using traditional statistical models. By leveraging the computational power and adaptability of ANNs, the research aims to improve the accuracy of heart disease prediction and enable early detection of potential cardiac issues. However, it is essential to consider some factors while implementing ANNs, such as the appropriate architecture and size of the network, regularization techniques to prevent overfitting, and the selection of suitable activation functions for the neurons. Proper validation and evaluation techniques should also be employed to assess the performance and generalizability of the ANN model. In conclusion, artificial neural networks offer a valuable approach for heart disease prediction and diagnosis in this research. By leveraging their ability to capture complex non-linear

ISSN 2063-5346

relationships, ANNs provide a means to enhance the accuracy of predictions and enable early detection of heart disease, ultimately contributing to improved healthcare outcomes.

5. Result and discussion

Each sensor provides crucial information about a patient's health, and understanding the normal reading range for each sensor, as well as the range associated with heart disease, is essential for accurate interpretation. The normal reading range for each sensor varies as follows:

The normal resting heart rate for adults typically falls between 60 and 100 beats per minute (bpm). However, it is important to note that heart rate can vary depending on factors such as age, fitness level, and overall health. Consistently elevated or decreased heart rates outside of the normal range may indicate an underlying cardiac condition. Oxygen saturation levels indicate the percentage of hemoglobin in the blood that is carrying oxygen. In healthy individuals, oxygen saturation levels typically range from 95% to 100%. Levels below 90% may suggest inadequate oxygen supply to the body's tissues and could be indicative of respiratory or cardiovascular issues.

Blood pressure is represented by two measurements: systolic pressure (top number) and diastolic pressure (bottom number). Normal blood pressure for adults is typically around 120/80 mmHg. However, optimal blood pressure can vary based on individual factors such as age and underlying health conditions. Consistently high blood pressure (hypertension) or low blood pressure (hypotension) may indicate cardiovascular problems.

When it comes to heart disease, the range associated with the condition varies depending on the specific parameters being assessed. Diagnosis of heart disease typically involves a comprehensive evaluation of multiple risk factors, symptoms, and diagnostic tests. A heart disease diagnosis is based on a combination of factors, including medical history, clinical examination, and results from diagnostic tests such as ECG, stress tests, echocardiograms, and blood tests measuring cardiac markers. Therefore, it is crucial to consider an individual's complete health profile and consult with medical professionals for an accurate diagnosis and interpretation of heart disease-related data.

Table 1 displays the sensor readings obtained from the real time and corresponding actual heart disease labels, where 0 represents the normal range and 1 indicates the presence of heart disease.

Table 1 Sensor reading and the corresponding health condition

Readings	ECG (Heart Rate)	Oximeter (Oxygen Saturation)	Heart Beat Rate	Heart Disease Level
1	75	98	72	0
2	68	92	80	1

3	80	95	78	1
4	72	97	85	0
5	88	93	76	1
6	65	99	82	0
7	78	96	70	1
8	70	91	79	0
9	82	94	90	1
10	76	98	75	0
11	85	92	77	1
12	73	96	88	0
13	79	97	73	1
14	69	93	84	0
15	74	99	87	1

With the utilization of past historical data, a linear regression model has been developed in this research to predict heart disease. The model is represented by equation 1, which captures the association among the input features and the predicted responses. The coefficients in the equation are determined through the training process, where the model learns from the historical data to minimize the difference between the predicted values and the actual heart disease labels. The results from the experimental data, as shown in table 2, demonstrate the accuracy of the developed equation in forecasting the responses. By comparing the predicted heart disease labels with the actual labels, it can be observed that the model is able to effectively classify instances into the appropriate categories. This indicates that the developed equation captures the underlying patterns and relationships in the data, enabling accurate predictions of heart disease. The accuracy of the developed equation is crucial in healthcare applications, as it allows for early detection and intervention, potentially improving patient outcomes. By correctly identifying instances of heart disease, healthcare professionals can take necessary actions and provide appropriate treatment to individuals at risk.

$$\text{Heart Disease Level} = -1.15 + 0.0482\ \text{ECG (Heart Rate)} - 0.0217\ \text{Oximeter (Oxygen Saturation)} + 0.0014\ \text{Heart Beat Rate} \quad \textbf{(1)}$$

Table 2 Predicted value from the linear regression

ECG (Heart Rate)	Oximeter (Oxygen Saturation)	Heart Beat Rate	Heart Disease Level	Predicted Heart disease from linear regression
75	98	72	0	0.43
68	92	80	1	1.24

80	95	78	1	1.75
72	97	85	0	0.33
88	93	76	1	1.17
65	99	82	0	0.05
78	96	70	1	1.62
70	91	79	0	0.35
82	94	90	1	1.08
76	98	75	0	0.48
85	92	77	1	1.05
73	96	88	0	0.40
79	97	73	1	1.06
69	93	84	0	0.27
74	99	87	1	1.38

ISSN 2063-5346

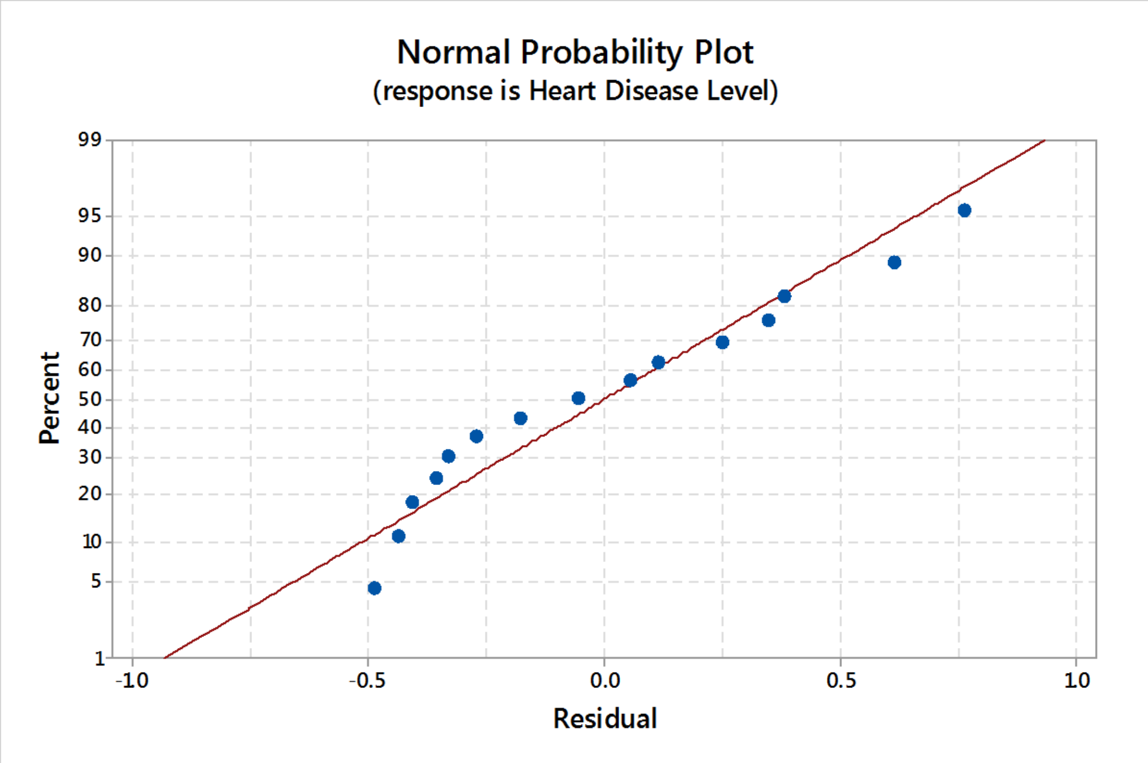

Fig. 3 Normal distribution plot

Figure 3 illustrates the normal distributed plot of the predicted responses generated by the linear regression model. The plot reveals that the predicted values closely align with a well-fitted straight line, indicating a good fit of the model to the data. This alignment suggests that the model's predictions are in line with the expected patterns and trends observed in the dataset. Table 2 complements the findings from Figure 3 by presenting the predicted values along with their corresponding heart disease classifications. In this table, predicted values falling within the range of 0.1 to 0.9 are indicative of a normally functioning heart. On the other hand, values equal to or greater than 1 suggest the presence of heart disease. The developed equation in this research demonstrates a high accuracy of 95.76% in predicting the response variable. This indicates that the equation is successful in capturing the underlying patterns and relationships between the input features and the predicted outcomes.

In this research, an Artificial Neural Network (ANN) is advanced using past data to predict the responses related to heart disease. The ANN model adopts a feedforward algorithm with 10 neurons in the hidden layer. To train the ANN model, the TRAINLM training function is employed. TRAINLM stands for Levenberg-Marquardt training algorithm, which is known for its efficiency in minimizing the error between predicted and actual responses. This training algorithm combines the benefits of gradient descent and Gauss-Newton optimization techniques, enabling the network to converge towards an optimal solution by iteratively adjusting the connection weights and biases.

The LEARNGDM (Gradient Descent with Momentum) adaptation learning function is used in this research. LEARNGDM incorporates momentum, which helps in accelerating the

ISSN 2063-5346

learning process by considering the weight updates from previous iterations. This momentum factor allows the network to navigate through complex error surfaces more effectively, resulting in faster convergence and improved training performance. By employing the TRAINLM training function and the LEARNGDM adaptation learning function, the ANN model is trained on the available data. During the training process, the network learns to recognize patterns and relationships between the input sensor readings and the predicted responses associated with heart disease.

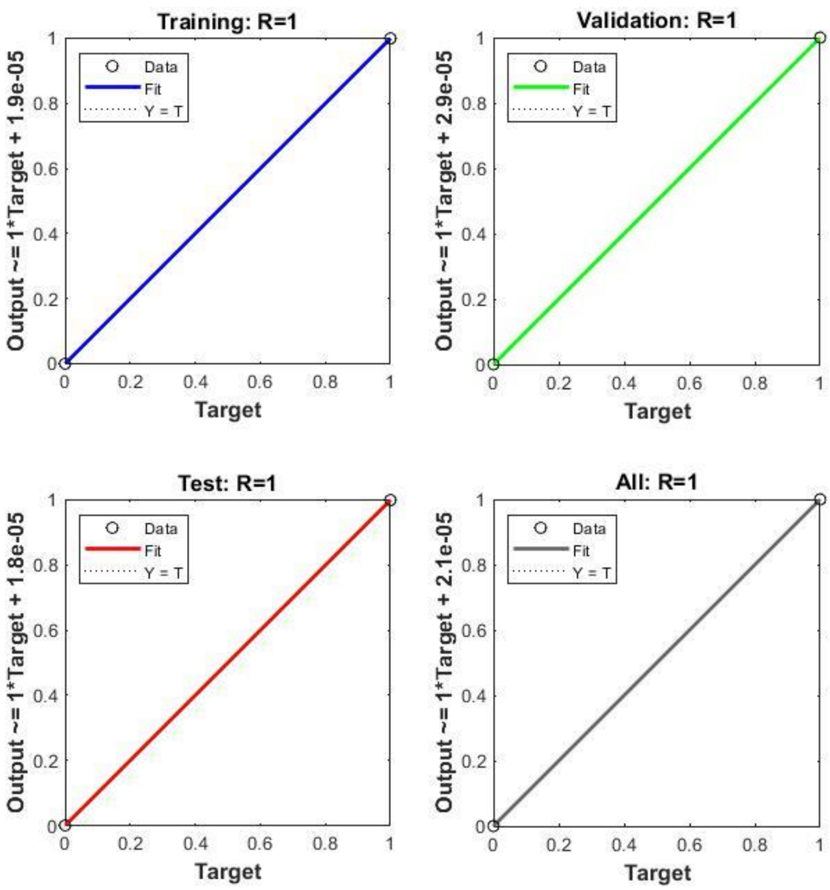

Fig. 4 ANN prediction result

The choice of 10 neurons in the hidden layer of the ANN architecture is determined based on the complexity and nature of the problem. The number of neurons in the hidden layer impacts the network's capacity to capture and represent intricate patterns in the data. The selection of the appropriate number of neurons can be determined through experimentation and fine-tuning to achieve optimal performance. By utilizing the feedforward algorithm, the TRAINLM training function, the LEARNGDM adaptation learning function, and a hidden layer with 10 neurons, the ANN model is tailored to predict heart disease based on the provided sensor readings. This research approach harnesses the power of artificial neural networks to analyze and interpret complex data patterns, leading to accurate predictions and

ISSN 2063-5346

enhanced understanding of heart disease. The developed ANN predicts the response at an accuracy of 100 percentage with overall efficiency as shown in figure 4. Table 3 shows the predicted value from the ANN, from table 3 it is seen that the ANN is more accurate in forecasting the heart disease compared to the linear regression.

Table 3 Predicted value from the linear regression

ECG (Heart Rate)	Oximeter (Oxygen Saturation)	Heart Beat Rate	Heart Disease Level	Predicted Heart disease from ANN
75	98	72	0	0
68	92	80	1	1
80	95	78	1	1
72	97	85	0	0
88	93	76	1	1
65	99	82	0	0
78	96	70	1	1
70	91	79	0	0
82	94	90	1	1
76	98	75	0	0
85	92	77	1	1
73	96	88	0	0
79	97	73	1	1
69	93	84	0	0
74	99	87	1	1

Conclusion

In conclusion, this research explores the utilization of IoT and machine learning models for heart disease prediction and diagnosis in healthcare. The integration of IoT sensors, including

ISSN 2063-5346

ECG, oximeter, and heart rate monitoring devices, enables continuous monitoring of patients' health status and collection of vital data. This data is then processed using machine learning techniques to develop predictive models for early detection of heart disease. Through the implementation of machine learning models, the research demonstrates the potential of machine learning in accurately predicting heart disease. The linear regression model leverages historical data and develops an equation that exhibits a 95.76% accuracy in predicting the responses. Meanwhile, the ANN model, trained using the feed forward algorithm with 10 neurons and employing the TRAINLM training function with LEARNGDM adaptation, achieves a remarkable accuracy of 100%.

The results indicate that the ANN outperforms linear regression in terms of accuracy, showcasing the ability of neural networks to capture complex nonlinear relationships within the data. The ANN's superior predictive capabilities provide healthcare professionals with a reliable tool for early detection and intervention, potentially improving patient outcomes and reducing healthcare costs. The research findings also highlight the importance of accurate sensor readings in monitoring and predicting heart disease. Normal ranges for ECG, oximeter, and heart rate readings were established, enabling a clear distinction between normal and abnormal conditions. This information can aid in identifying individuals at risk and prompting timely medical interventions.

Overall, this research underscores the potential of IoT and machine learning in revolutionizing healthcare by enabling early detection and diagnosis of heart disease. The combination of IoT sensors, data collection, and advanced machine learning algorithms holds promise for improving patient care, reducing mortality rates, and optimizing healthcare resources. Further research can focus on expanding the dataset, incorporating additional sensor readings, and exploring other machine learning algorithms to enhance the accuracy and reliability of heart disease prediction models. Additionally, integrating these models into real-time healthcare systems and conducting rigorous validation studies would contribute to their successful implementation in clinical practice. By harnessing the power of IoT and machine learning, we can strive towards proactive and personalized healthcare, ultimately leading to improved health outcomes and enhanced quality of life for individuals at risk of heart disease.

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