JOURNAL OF BASIC SCIENCE AND ENGINEERING

Health Monitoring System Integrating IoT and Machine Learning for Cardiac Prognosis

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DOI: https://doie.org/10.10399/JBSE.2025314930

Abstract**—** The integration of IoT (Internet of Things) in healthcare is transforming diagnosis and management of heart disease through continuous, real-time monitoring. This study explores a system that utilizes wearable devices such as ECG sensor, pulse oxymeter to collect key health data including heart rate, ECG, blood pressure, and oxygen saturation. The collected data is wirelessly transmitted to cloud platforms for analysis using machine learning algorithms, enabling early detection of heart disease. The system provides healthcare professionals with the ability to remotely monitor patients, facilitating timely interventions and reducing the need for frequent hospital visits. Machine learning models such as Random Forest, Support Vector Machines (SVM), and deep learning techniques like CNN (Convolutional Neural Network) are employed to detect patterns, predict potential heart disease events, and classify different heart rhythms. These systems offer numerous benefits, including the reduction of healthcare costs, early detection of abnormalities, and proactive interventions. The results indicate that IoT-based systems significantly improve patient outcomes by enabling continuous health monitoring and facilitating personalized healthcare.

Keywords: IoT, sensors, machine learning, Random forest

1. INTRODUCTION

The fast-paced development of technology has influenced numerous industries, perhaps none more so than healthcare. Healthcare has had some of the highest adoption rates of innovative technologies including the Internet of Things (IoT) - one of the greatest advancements in healthcare within the past decease and bordering on revolutionary with the delivery of healthcare by changing the paradigms for chronic disease management through diagnosis, monitoring, and treatment. The introduction of IoT into the healthcare system has thus opened up opportunities for continuous real-time monitoring of patients, while enhancing medical service access and delivery efficacy, all of which is vitally important for chronic disease management, primarily heart disease which is still one of the leading causes of morbidity and mortality in the world [1].

Heart diseases are a broad category of problems related to the heart's structure and function that include arrhythmias, myocardial infarctions (heart attack), coronary artery disease, and others that impact heart rhythms. The ideal practice for heart conditions is to seek diagnosis and receive treatment at the earliest stage, which can improve the overall outcomes for a patient through early medical intervention before the condition advances to an actionable and potentially life-threatening status [2]. In the past, diagnosing heart diseases could take weeks or months, often requiring an invasive procedure or a trip to the hospital multiple times, sometimes leaving the patient and clinician to wonder about undiagnosed problems [3]. The opportunity to introduce IoT-based systems into the healthcare space is advantageous for its ability to continuously, non-invasively, and in real-time monitor heart condition. IoT systems in medicine are a group of networked devices such wearable sensors, smartwatches, ECG, pulse oximeter, and blood pressure cuffs that collect patient health data like heart rate, blood pressure, oxygen saturation, body temperature, and ECG [4]. These devices transmit information wirelessly to cloud or centralized systems for processing, analysis, and interpretation.

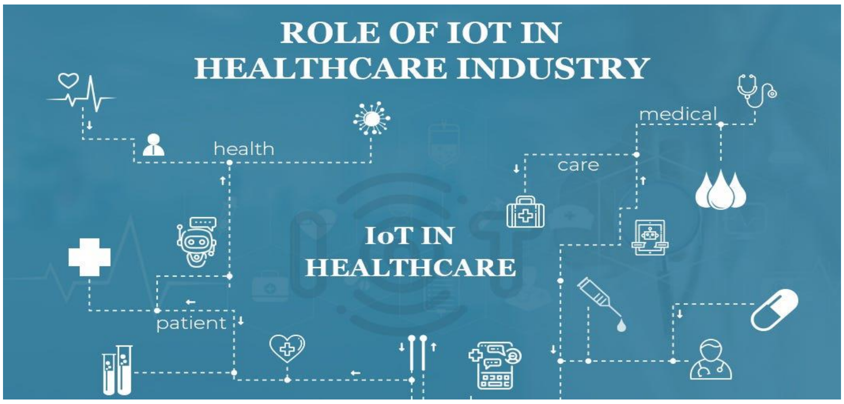

Fig.1 Role of IoT in Healthcare Industry [5]

The ability for health systems to capture patient data in real time and send that information back to the provider allows health care professionals to monitor patients outside of a clinical setting and reduces the need for in-person visits, and a more efficient way to manage chronic disease [6]. Biggest advantages of an IoT based system is the ability to discover early signs of heart disease in patients with suspected health problems. These problems may include abnormal heart rhythms, heart attack, or other cardiovascular events. By leveraging machine learning structures and algorithms, it may be possible for these systems to avoid spending precious seconds detecting statistically significant patterns in the data, before ruling in a medical emergency and reporting [7].

If an abnormality could be detected early enough, it could reduce the risk of serious complications, such as heart failure or stroke [8]. For example, if an ECG sensor on a patient's wearable detects an abnormal heart rhythm, the IoT diagnostic system activates an alarm that points the patient and health care provider to observe the patient before any harm comes to them. In this scenario, medical professionals can intervene and prevent a heart attack, or other serious and preventable event. IoT-enabled devices allow patients not only to be continuously monitored from their home or healthcare setting, but also to avoid unnecessary hospital visits while obtaining the proper care. Remote monitoring also increases patient comfort and quality of life. No person wants to wait for an insignificant amount of time in a waiting room or have to do a battery of non-invasive tests to check their heart [9].

Machine learning (ML) and predictive analysis are an important part of IoT-based diagnoses for heart disease. Machine learning models can dig through large numbers of health metrics derived from the wearable's, and then discern patterns and correlations in any given data set that human observers might not notice. Predictive analysis capabilities allow the system to detect even very minor changes in someone's status per the health metric data generated by the wearable device, and thus detect potential problems related to declining cardiac health; even subtle signs suggestive of an impending heart attack or worsening arrhythmia [10]. As new health metric data is added and the models learn from continued patient outcomes, the models will theoretically increase accuracy when predicting potential events associated with heart disease from heart attacks or strokes. The capacity to predict medical events allows for meaningful intervention by caregivers before they happen. For example, if a predictive model can identify a pattern for an impending myocardial infarction, that can immediately alert the healthcare workers with an opportunity to pre-emptively have the patient receive medical care in advance of the associated medical event.

For instance, ECGs captured with wearable would be uploaded into the cloud system that would provide enhanced algorithms for the interpretation of the ECGs - potentially identifying any abnormality more accurately than a human interpretation. The improved diagnosis using data-driven diagnostics reduces the chance of false positives or false negatives that would yield unnecessary treatments or missed diagnosis [11]. Data-driven diagnostic information for health care professionals is more reliable with IoT systems with advanced algorithms and machine learning allowing for decisions based on more reliable data for better treatment outcomes and a greater reduction in medical errors.

Although there are numerous benefits, IoT-based heart disease diagnostic systems also present challenges that must navigate before the full implementation of IoT in health care can occur. One of those challenges involves data privacy and security. For instance, sending sensitive health data across the Internet raises questions about how to protect designated patient data from hackers or unauthorized uses. The use of Internet, in an IoT capacity, means that the customary strong security protocols of the Internet (e.g. encryption, authentication, and access control) must be mandated in the devices to secure the privacy of patient data to promote the further development of IoT systems for health care monitoring [12]. Another challenge involves data accuracy and reliability. IoT-enabled devices can continuously monitor patients, but the data collected could vary depending on device calibration, environmental conditions and user behaviors. Even slightly faulty data can result in misdiagnoses or delayed intervention, that may result in dire health consequences for patients. In summary, IoT-based technology used to diagnose and treat heart disease is a transformation in healthcare delivery. Using wearable devices, cloud-based analytics and machine learning, systems like this can provide continuous, real-time monitoring, improve early detection of at risk patients, and ultimately allow patients to reduce how often they visit the hospital or doctor. The challenges these systems face regarding data privacy, the individual sensors, and accuracy are known, but they will facilitate more personalization, more accessible systems, and a potentially lower cost for patients dealing with chronic heart disease issues [13]. Ultimately, more IoT-based tools are part of a potential improvement in patient outcomes and healthcare delivery models.

2. LITERATURE REVIEW

IoT has transformed heart disease detection, monitoring, and therapy. IoT-based systems use various sensors, wearable devices, and cloud computing technologies to collect and analyze real-time health data and offer significant betterment in patient care. The first aim of traditional healthcare is to manage the follow-up of patients with heart-related diseases, allowing patients to be monitored continuously for the early identification of heart health-related conditions, such as arrhythmias or myocardial infarction, and then to have the opportunity to intervene early when most effective and mitigate risk of complications. Researchers in this field, such as Patel et al. (2019), have made strides in developing IoT-based diagnostic systems for heart disease. Patel et al. described the use of wearable devices with sensors placed on the devices, such as smart watches, ECG sensors, etc., to check parameters such as heart rate, blood pressure, and ECG readings [14]. These gadgets capture real-time patient health data. Health data will be analysed using machine learning algorithms to uncover illness models like early heart disease diagnosis.

They assessed in the reviews the use of algorithms and wearable devices/maximize data collection and monitor services. There is not only the issue of working continuously and real-time data for patients but the issues will arise for providers being able to respond quickly and efficiently if cardiac-related behaviors are identified. So when cardiac behaviors such as arrhythmias are detected and the ability for healthcare providers to respond and follow the clinical guidelines would be highly beneficial to patient outcomes in these situations. In the same manner, these systems help in spotting myocardial infarction (heart attacks) signs that may go unnoticed when patients see their doctors for routine check-ups [15]. The implementation of machine learning into the IoT systems produces more accurate diagnoses and maintains interventions.

Sharma and Kumar (2021) took an even further step to examine the possibilities of IoT-based systems predicting heart disorders and the potential to predict heart attacks prior to their occurring [16]. Their research exhibited the capability of these systems to monitor patterns in real-time health-related data and predict future medical events; providing the opportunity for preventive medical care options. Predicting these medical events before they happen is revolutionary for heart disease management. Now that we have discovered this, healthcare providers do not need to wait until symptoms appear; they can now stop it from happening, thereby preventing serious medical events such as heart attacks or strokes [17]. This preventative knowledge provides patients with knowledge to change their lifestyle and interventions and treatments moving forward in order to secure long-term health and success. This will also be integrated into electronic health records systems, making it easier for healthcare providers to create an accurate timeline of a patient's medical history. Real-time data would also allow for more individualized care, providing a more unique approach to an individual's care as it happens. Abdulmalek et al. (2022) further enhance this thinking when they discuss IoT-based systems to mitigate hospital visits and overall health cost [18]. One of the main advantages is the ability to monitor patients remotely, especially patients with chronic heart issues and older patients. These patients do not need to visit the hospital for routine output and it can provide an expensive loss of time (especially for those who may live a considerable distance from a hospital or may be suffering from limited mobility). An IoT-based system can make this routine less burdensome on the patient and the health care provider, and lessen the need for the patient to go to the hospital. Remote patient monitoring reduces the chances of either unwanted hospitalizations or preventable readmissions, which entities are also cost saving to the health care system. Furthermore, when a patient is monitored remotely, the health care provider has the knowledge any time, and about any changes to the patient's health status and may not have to wait until the next visit to treat the patient if appropriate.

The application of IoT technology is also beneficial in the management of persistent care for heart disease patients. Kannade et al. (2024) suggested continuous and non-invasive mechanisms for monitoring patients' health conditions that would allow healthcare professionals to also change some of the treatment plans [19]. Chronic heart disease patients can require ongoing monitoring to verify that treatment plans are being followed or adhere to the patient's needs. IoT systems allow providers a 360-degree view of the patient's health, including vital parameters like heart rate, blood pressure, and oxygen saturation monitoring [20]. If parameters are continued to be monitored, the provider can change medications and therapies based on the patient's presentation and things can become more efficacious in regards to treatment. As these adjustments can be made in real time, it enables avoidance of complications and hospitalizations, ultimately increasing patient outcomes over time. And this bridge is even more important for underserved populations. Virginia Anikwe *et al.* (2022) introduced an equation that showed an IoT-based system could diminish the gap in health care systems by allowing remote heart health monitoring in marginalized areas that have limited to no services. In many rural or underserved areas, patients lack specialized medical personnel, and they must drive long distances to receive the most basic health care services [21]. IoT technology will allow for real-time monitoring of heart health for example, without the need for patients to ever leave home. This type of IoT technology will enable patients in these underserved areas to receive timely interventions and medical advice, when no health

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ISSN: 1005-0930

care provider is available locally. Moreover, very life-critical interventions like administering medication, or changing treatment plans can be performed remotely using real-time data from an IoT device, even in a remote community.

R. D. Puri *et al.* (2018) also highlighted the significance of monitoring in managing chronic heart illnesses [22]. Chronic heart disease symptoms are often unpredictable, making it hard for medical team to evaluate a patient's status during a brief clinic visit. Continuous monitoring of patients' important health indicators, including heart rate and blood pressure, allows medical teams to monitor a patient's condition over time to identify fluctuations in their status more effectively. Access to real-time data allows medical professionals to make informed decisions regarding treatment plans for patients, ensuring that they receive the right treatment that better suits their personal needs. Thus, monitoring patients continuously supports case management while improving outcomes for individuals living with chronic heart disease. There are many advantages associated with monitoring chronic heart disease, yet the culture of adopting IoT-based heart disease diagnostic systems has many hurdles to overcome. M. Javaid et al. (2023) highlighted one of the negative aspects of IoT systems as reliable and accurate sensor data [23]. Malfunctioning or inaccurate sensors may provide incorrect diagnoses, provide inappropriate treatment, or harm the patient. The success of an IoT-based system depends on the sensors it utilizes for health data collection. The functionality and accuracy of the devices must continuously be monitored through maintenance so that the data being sent is deemed reliable and legitimate.

Another obstacle in the adoption of IoT-based systems is data privacy and security. There is a constant flow of sensitive health information that is transmitted and stored, and patient data is vulnerable to cyber attacks and unauthorized access. With the proliferation of IoT systems, healthcare organizations and technology developers must use secure encryption, as well as consider data protection regulations such as HIPAA (Health Insurance Portability Accountability Act) to safeguard patient data. Lee et al. (2021) pointed out concerns about keeping IoT networks secure and ensuring compliance to rules and regulations so that trust can be maintained in IoT healthcare solutions[24]. If patients feel their data is not secure, they will never use IoT-based solutions in health and the technology will miss its potential. Despite these hurdles, IoT-based systems have the potential to make a positive impact on heart disease management[25]. Ongoing developments in IoT, machine learning, and data security are likely to resolve many of the current barriers that do exist, making it likely that IoT-based systems will become part of the healthcare landscape. The efficacy of IoT technology in developing early diagnoses, reducing healthcare costs, and producing better patient care leaves little doubt that IoT technology is likely to play a role in the future of healthcare, such is the case for managing chronic diseases, including heart disease. With more research and improved technology, the integration of IoT into heart disease mitigation is likely to be even more effective and personalized for patients as it evolves in the future.

3. EXPERIMENT DETAILS AND METHODS

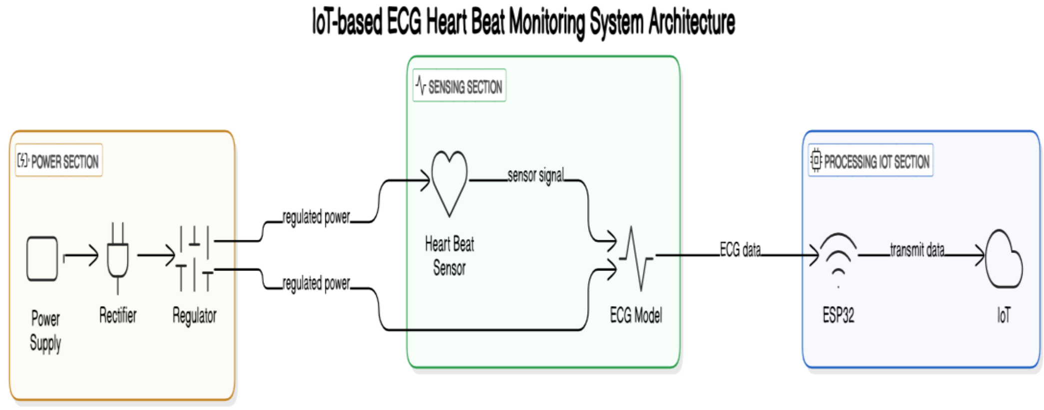

Fig.2 IoT-Based ECG Heart Beat Monitoring System Architecture

The diagram represents the architecture of an IoT-based system designed for ECG heart rate monitoring. The system is divided into three key sections:

1. Power Section:

The function of the power supply section is to provide the appropriate electrical power to the system. This will require a rectifier which will convert alternating current (AC) to direct current (DC), and will require a regulator to stabilize the power output for the whole system.

2. Sensing Section:

This section consists of heart rate sensor (ECG sensor), which registers electrical activity of the heart. Also,it takes the electrical signals from heart and turns it into ECG data to measure heart beats and sends the data to the ECG model.

3. Processing IoT Section:

The data from the processed ECG is sent wirelessly using an ESP32 module, which is a powerful microcontroller with integrated Wi-Fi. The processed data is also sent to the cloud or an IoT platform for storage, which is later analyzed, or possibly monitored in real-time by a health monitor.

The system architecture enables continuous monitoring and remote diagnosis of heart conditions, making it a crucial component of modern health monitoring systems.

With this IoT-based system, you will be able to get non-invasive and continuous monitoring of heart health with critical benefits to patients regarding early detection and long-term care, especially in the case of chronic heart disease. This IoT-based system had an ESP32 microcontroller utilized for processing data required by the Heartbeat Sensor and ECG Sensor. The Heartbeat Sensor provides heart beat rates, and the ECG Sensor provides electrical activity of the heart. Once processed by the ESP32, the data is sent to cloud platforms as part of the larger IoT system. Data is monitored and processed remotely for patient health in real time.

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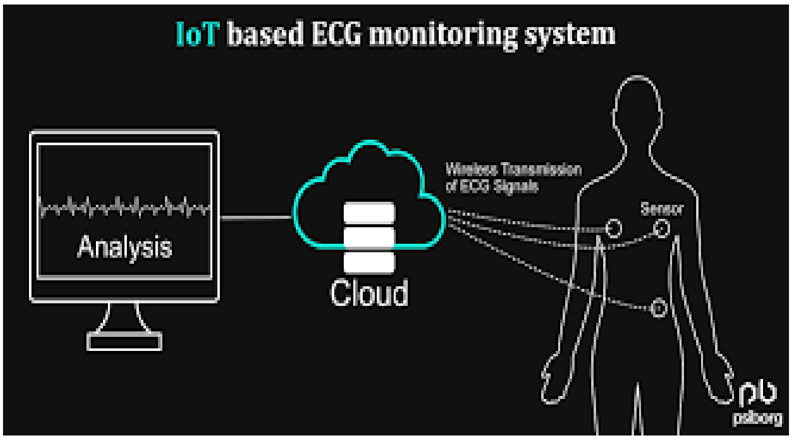

Fig.3 IoT-Based ECG Monitoring System [26]

This figure illustrates an IoT-based ECG (Electrocardiogram) monitoring system where the heart's electrical activity is continuously monitored. The system comprises three main components:

1. **Sensors**: Attached to the body, the sensors collect ECG signals, which monitor the electrical impulses generated by the heart.
2. **Wireless Transmission**: The collected ECG signals are wirelessly transmitted to a cloud-based platform for further analysis.
3. **Cloud**: The cloud acts as a data storage and processing unit where the ECG data is sent for real-time monitoring and analysis.
4. **Analysis**: The data is analyzed on a computer or user interface, enabling doctors or medical professionals to monitor the heart health of a patient remotely.

Figure 4 shows a complete IoT based system that provides cardiac disease identification and monitoring device. The system is composed of two main layers: IoT Layer and Cloud Layer.

1. IoT Layer:
- Their purpose is to gather physiological data from the body, including blood pressure, heart rate, ECG, stress level.
- Physiological data is collected via various wearable sensors and sent to a Gateway Device using wireless communication (Bluetooth for example) technology.

2. Cloud Layer:.
- The data is stored and it is given for further processing.
- The Data Prediction, based on the processed data, using Random forest model was employed for predicting heart disease.

3 Alert System:
- The system can send alerts to the concerned Doctor, Hospital, or Patient in case of any abnormal health readings or predictions, providing real-time monitoring and response capabilities.
- This system enables continuous, real-time heart disease monitoring and prediction, integrating IoT devices for data acquisition and advanced machine learning models for accurate disease prediction and timely alerts.

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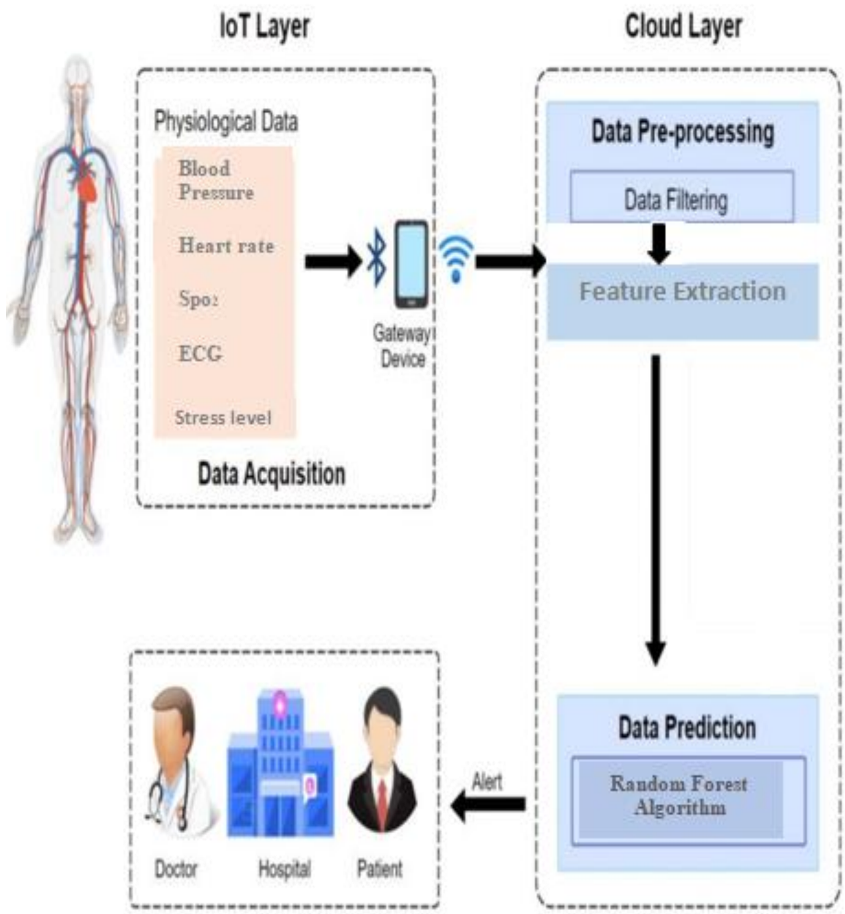

Fig. 4 IoT-Based Heart Disease Prediction System

Data monitoring and Response flow

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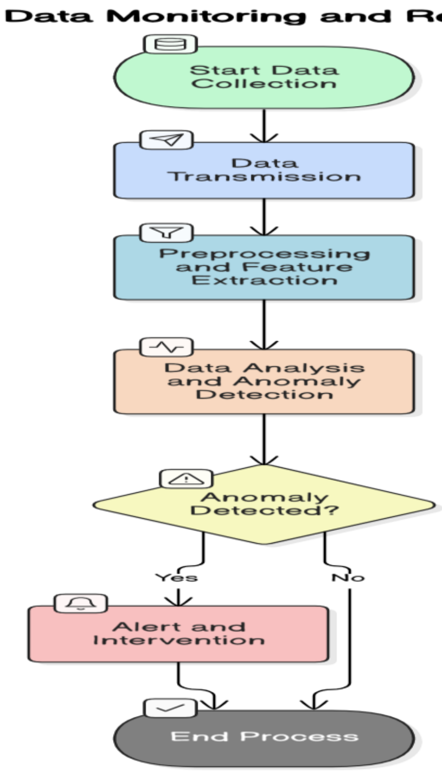

Fig. 5 Data Monitoring and Response Flow for IoT-Based Heart Disease Diagnosis

1. **Data Collection:**

   - Collect real-time data on health parameters including heart rate, ECG, blood pressure, oxygen saturation (SpO2), and body temperature using wearable IoT devices like smart watches, ECG sensors, and pulse oximeters.

2. **Data Transmission:**

   - Secure wireless connection protocols will transfer the acquired data to a cloud server for storage and analysis.

3. **Preprocessing:**

   - Raw data will undergo preprocessing to filter noise and handle missing or inconsistent data, ensuring that the information is accurate and reliable.

4. **Data Analysis and Feature Extraction:**
   - For further investigation, extract P-Q-R-S-T waves, R-peaks, and other critical characteristics from the ECG data.
   - Analyse data using machine learning methods like Random Forest, SVM, or deep learning frameworks to detect cardiac disease trends like arrhythmias and myocardial infarction.

5. **Anomaly Detection:**

   - The system will use classification models to detect anomalies like irregular heartbeats, fusion beats, or other signs of heart conditions, triggering alerts if abnormalities are detected.

6. **Alert and Intervention:**

- Automatically notify healthcare professionals and patients of irregularities for prompt medical response.

7. **Remote Monitoring and Continuous Care:**

    - Enable healthcare providers to remotely monitor the patient's condition, adjust treatment plans, and provide ongoing care, particularly for high-risk or chronic heart patients.

8. **Data Security and Privacy:**

- Encrypt and comply with HIPAA to protect sensitive health data.

Features Extracted from ECG for Heart Disease Diagnosis

ECG (Electrocardiogram) signals provide valuable information about the electrical activity of the heart. For an IoT-based automatic heart disease diagnosis system, various features are extracted from the ECG signals to analyze heart health and detect abnormalities. These features can be used for further analysis through machine learning algorithms to identify potential heart disease conditions. Below is a Table no. 1 showing the key features extracted from the ECG signal. ECG characteristics provide valuable information about heart health. Characteristics of the P-Wave Amplitude represent atrial depolarization, with abnormal further potentially indicating arrhythmias or atrial enlargement. The P-R Interval marks the time it takes an impulse to travel, with increased or prolonged interval suggesting heart block. The QRS Duration depicts ventricular depolarization, with a QRS Duration larger than .12 seconds indicating conduction delay. The Heart Rate measures tachycardia or bradycardia. Heart Rate Variability (HRV) predicts cardiovascular risk.

Table no. 1 Features extracted from ECG signal

Feature	Description
P-Wave Amplitude	The amplitude of the P-wave is used to detect atrial enlargement or atrial arrhythmias. It represents the depolarization of the atria.
P-R Interval	The time interval between start of P-wave and start of R-wave, which helps in detecting conduction delays or heart block.
QRS Duration	The duration of the QRS complex, which represents time taken for ventricular depolarization. Abnormal duration indicates potential heart issues.
Heart Rate (HR)	The number of heart beats per minute, calculated based on the R-R interval. A critical feature for determining the overall heart rhythm.
RR Interval	The time interval between two successive R-waves, used to calculate heart rate variability, which is important for detecting arrhythmias.
Heart Rate Variability(HRV)	Variability in the time intervals between heartbeats. Low HRV is associated with increased risk of heart disease and poor cardiac health.

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The proposed algorithm for IoT-based automatic heart disease diagnosis involves several steps:

1. Data Collection and Preprocessing

1. **Collect real-time health data** from IoT devices such as ECG sensors, heart rate monitors, pulse oxymeters, and blood pressure cuffs.
2. **Preprocess the data** by:
   - Removing noise from ECG signals (e.g., using bandpass filters).
   - Handling missing or inconsistent data using interpolation or mean imputation.
   - Normalizing the ECG signal to ensure uniformity.

2. Band pass Filter for ECG Noise Removal:

Where $H(s)$the filter's transfer is function and Q is the quality factor.

$$H(s) = \frac{s}{s^2 + \frac{1}{Q}s + 1}$$

3. Convolutional Neural Network (CNN):

The convolutional operation in CNNs can be defined as:

$$(I * K)(x, y) = \sum_m \sum_n I(m, n) K(x - m, y - n)$$

Where I is the input image, K is the kernel/filter, and the summation is over the kernel size.

5. Formula for Performance Metrics

Accuracy:

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

Precision:

$$Precision = \frac{TP}{TP+FP}$$

Recall (Sensitivity):

$$Recall = \frac{TP}{TP+FN}$$

F1-Score:

$$F1Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall}$$

4. ANALYSIS

Table no.2 ML algorithm results

Model	Accuracy	Precision	Recall	F1-score
Decision Tree	0.93	0.71	0.83	0.76
Logistic Regression	0.66	0.44	0.76	0.47
Random Forest	0.97	0.91	0.87	0.89
Random Forest (After hyper parameter tuning)	0.81	0.69	0.68	0.75

Table no. 2 compares performance of various machine learning algorithms. Random forest has shown better performance with accuracy of 97% whereas logistic regression has degraded performance with accuracy 66%. Fig. 6 compares categorisation models' True Positive Rate (TPR) and False Positive Rate (FPR). X indicates False Positive Rate; Y shows True Positive Rate. Random classifier performance with an AUC of 0.5 is shown by the diagonal dashed line. Logistic Regression, Random Forest, Support Vector Machine, and K-Nearest Neighbours are shown as points with TPR Vs FPR. Random Forest and other top-left models have higher AUC ratings, suggesting superior performance. These visuals aids in comparing how well each model discriminates between classes. System response time refers to the time taken by an IoT-based heart disease monitoring system to collect, process, and provide feedback on a patient's health data. It includes the time from when data is captured by wearable sensors (e.g., ECG, heart rate monitor) to when the system generates an alert or displays results. For example, once data is captured by sensors, it is transmitted to the cloud for analysis, where algorithms detect potential issues such as arrhythmias. Assuming a real-time processing system, the typical response time should ideally be within a few seconds to ensure timely intervention. The calculation depends on sensor reading frequency, data transmission speed, and algorithm processing time.

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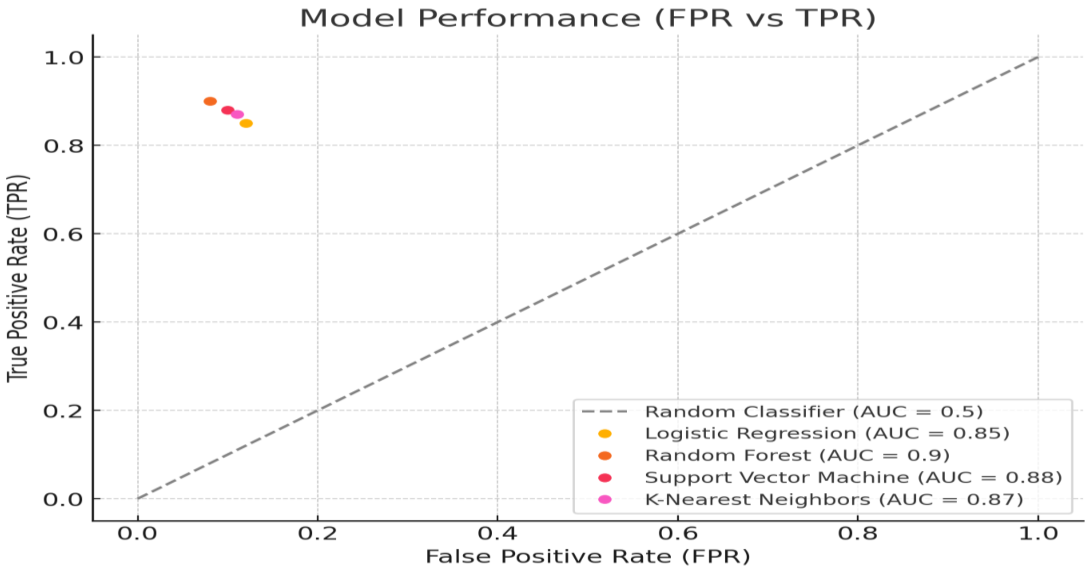

Fig.6 Model Performance (FPR vs TPR)

5. RESULTS

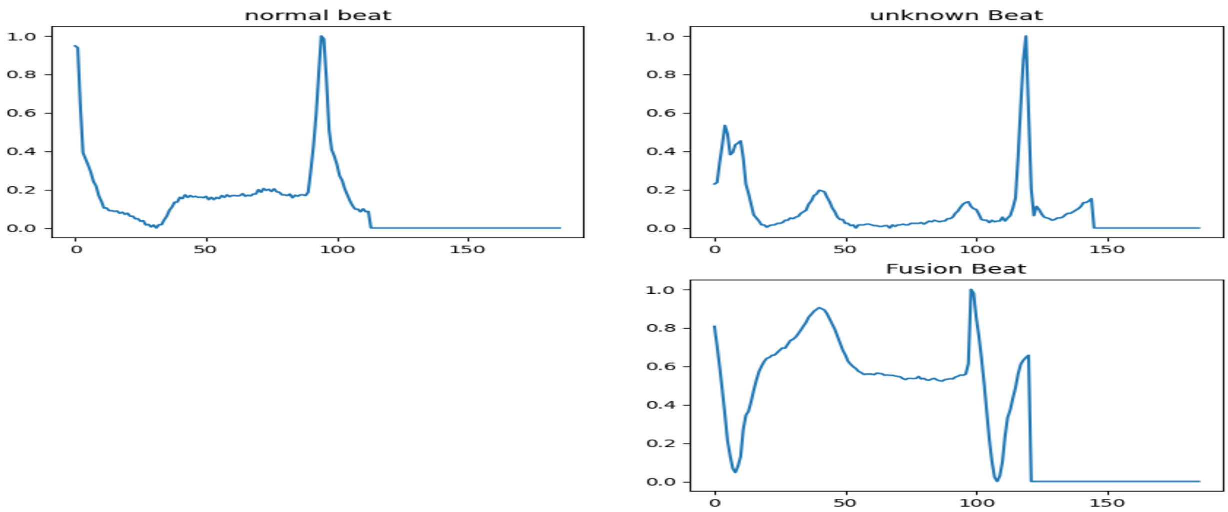

Fig.7.Comparison of Different Heartbeat Types: Normal Beat, Unknown Beat, and Fusion Beat

The figure compares three different types of heartbeats, each represented by its respective ECG waveform. The first plot illustrates a normal beat, characterized by a clear and well-defined pattern with an initial sharp rise and a gradual fall, indicating a regular rhythm associated with normal heart function. The second plot depicts an "unknown beat," which shows a more erratic and inconsistent waveform with several irregular peaks, suggesting the presence of arrhythmia or an unidentified heart condition. The third plot shows a "fusion beat" that occurs when two heartbeats occur at the same time, a regular beat and shockingly, an abnormal beat. The waveform shows several sharp, irregular peaks, indicating complex or mixed rhythm pattern that often indicates ventricular arrhythmia.

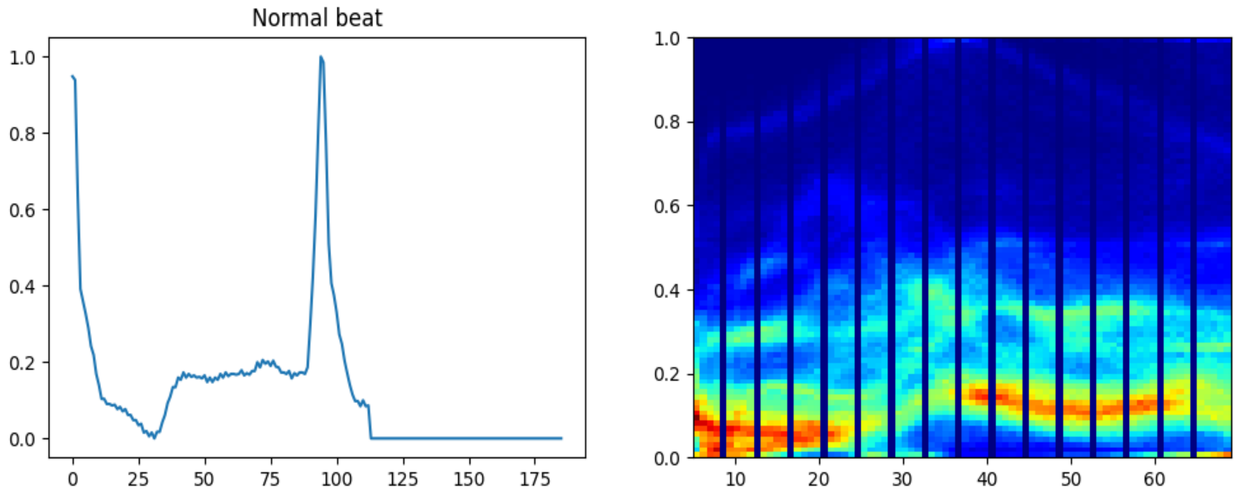

Fig.8. Normal Heartbeat: Time-domain and Spectrogram Representation

Figure 8 provides two examples of a normal heartbeat. The time-domain plot (left), shows a typical ECG waveform with a P-Q-R-S-T pattern, steep rise (R-wave), gradual fall (S-wave), and flat segment, indicating a regular and healthy heart rhythm without disturbances; then the right plot displays a heartbeat's signal frequency content in spectrogram, where y-axis is frequency and x-axis is time. The color intensity of the spectrogram is an indicator of the amplitude of frequencies within the signal frequency content (with warm colors showing higher gesture intensity) with a periodic pattern corresponding to the heartbeat showing regular and stable heart activity. Spectrograms provide a different view of the time-domain plots, overpass or lay below it, to highlight the frequency (the degree of which the heart beats) structure that underlies by showing regularity and rhythmicity.

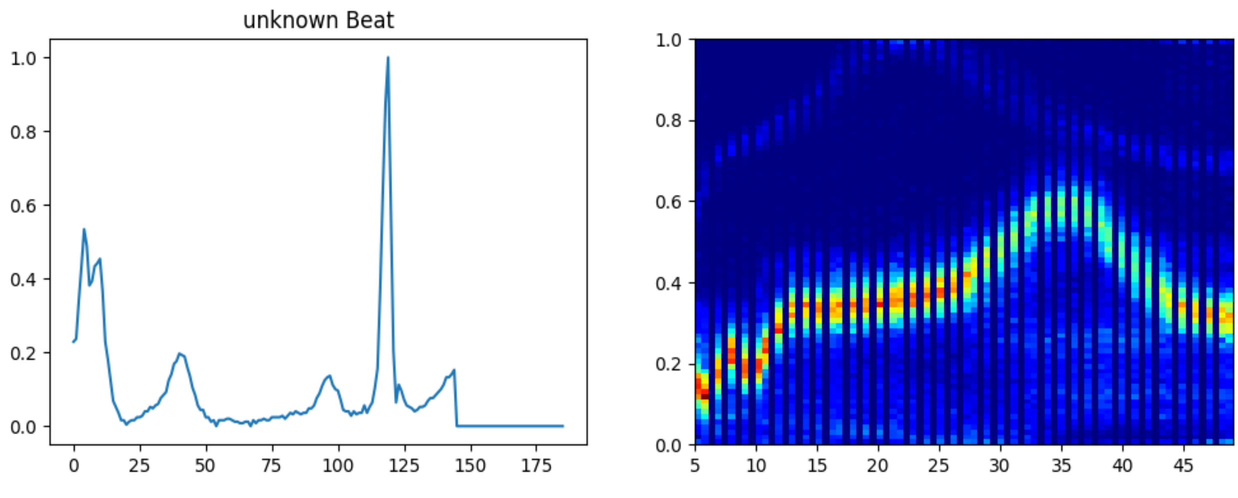

Fig.9. Unknown Heartbeat: Time-domain and Spectrogram Representation

This figure shows two views of an unknown heartbeat. The left plot shows an ECG waveform that appears irregular based on the height of the fluctuations of the ECG, this would suggest there may be an abnormal or undefined heartbeat. The right plot is the spectrogram view, which shows the frequency content of the unknown heartbeat over time. The frequency content should be displayed in bands with varying intensity. Several bands are present and suggest a complex, non-periodic pattern. The spectrogram indicates the frequency components of the unknown beat, as well as the irregular variations that can be distinguished because the ability to identify these variations on the time-domain (ECG) plot

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are more difficult to visualize. Overall, the visual information for the unknown beat indicated a pattern consistent with rhythm disturbance, requiring more detailed analysis if they were to be diagnosed.

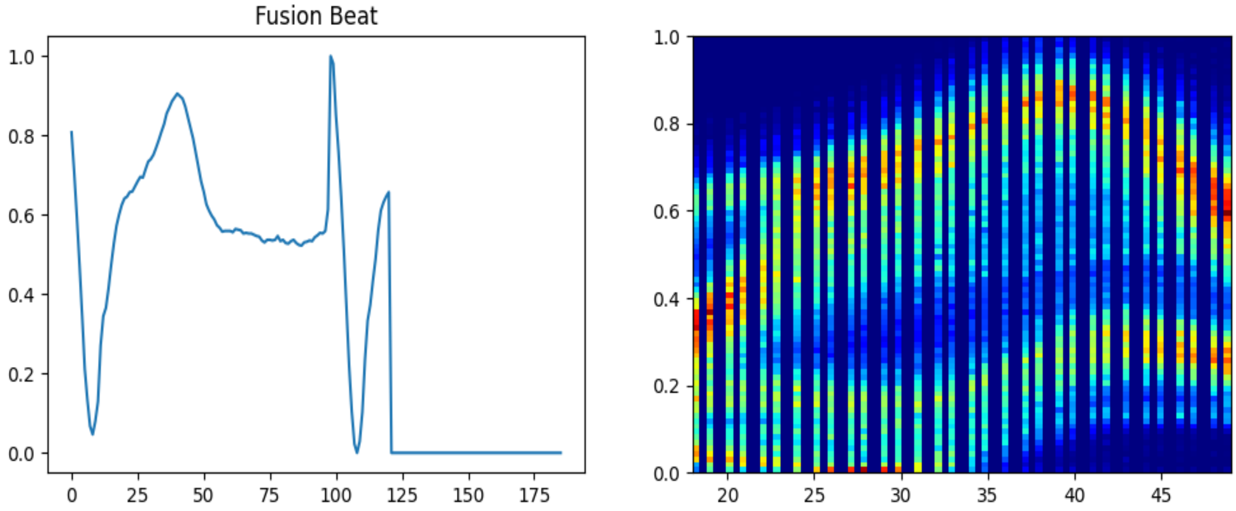

Fig.10. Fusion Beat: Time-domain and Spectrogram Representation

This chart contains two graphs of a fusion heartbeat. The plot to the left reveals the ECG trace, illustrating an elaborate structure with numerous peaks that represent a fusion beat — two independent heartbeats merged into one, most commonly a normal one accompanied by an abnormal heartbeat. The proper plot, a spectrogram, shows the signal's frequency content over time with dominant bands and different intensities as a function of the overlapping frequency components of the combined beats. The spectrogram shows a more disorganized, non-periodic form than that for regular beats, emphasizing the blended character of the fusion beat.

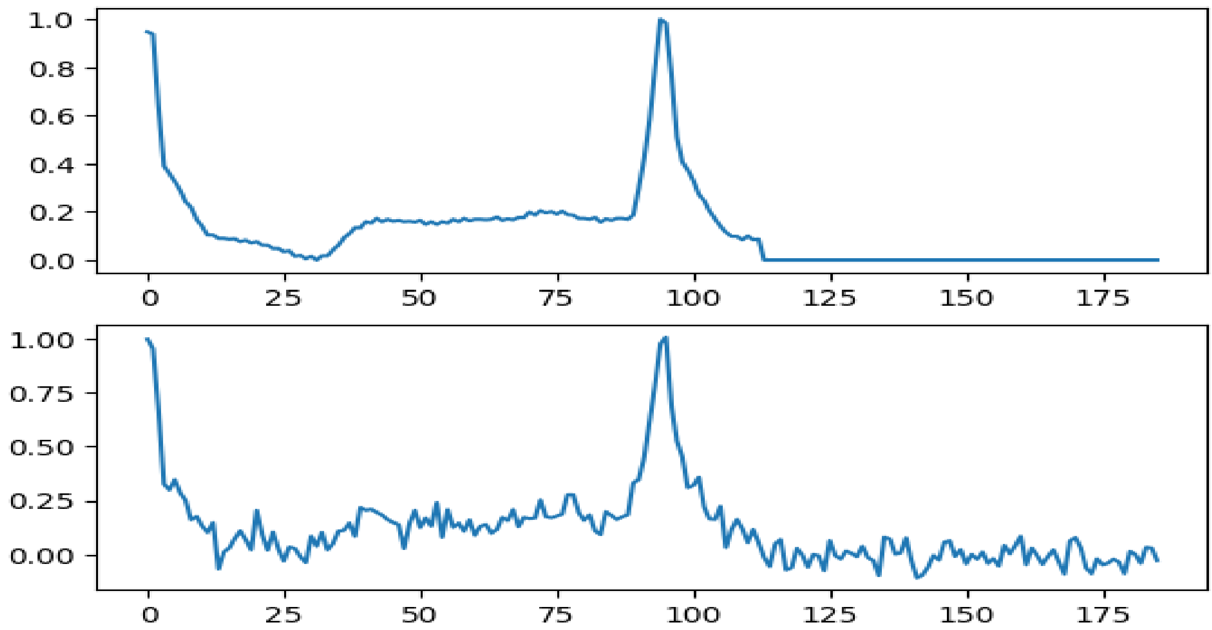

Fig.11. Comparison of Normal and Unknown Heartbeat: Time-domain Representation

This graph is showing two time-domain graphs for two varying heartbeats. The upper graph is the waveform of a normal heartbeat, which has a well-defined and distinct pattern, characteristic of a

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healthy heart rhythm with a sudden rise and slow drop. The lower graph is an unknown heartbeat, which has a more chaotic and disordered appearance with irregular fluctuations. The waveforms in the lower plot indicate an abnormal or undefined heart rhythm and are consistent with possible arrhythmia or an abnormal heart condition that needs to be analyzed. The comparison brings out the disparity between a regular and an irregular heart rhythm.

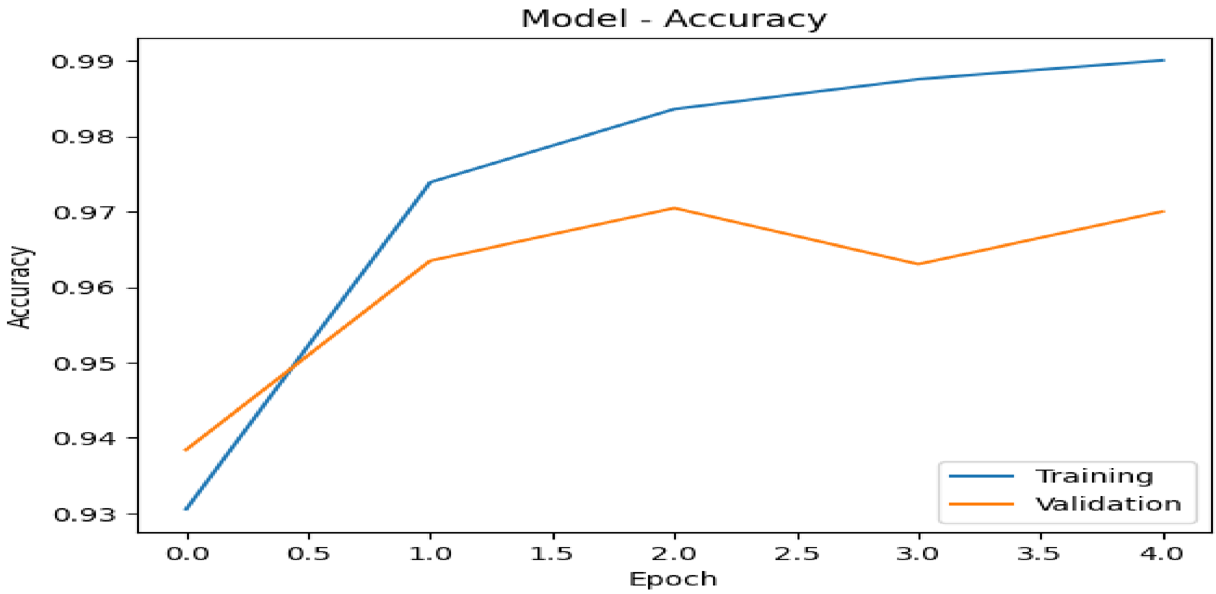

Fig. 12. Model Accuracy during Training and Validation

This plot shows the accuracy of a model at some number of epochs for training and validation. Training accuracy (blue line) increases progressively as model improves on training set. The accuracy of validation (orange line) also rises but with slower rate and some oscillation, indicating that as much as model generalizes to new data at first, it might suffer from difficulties in steadily continuing to beat unseen validation data. The graph shows that the model performs well, but the difference across training and validation accuracy may imply over fitting, where the model grows more attuned to the training set.

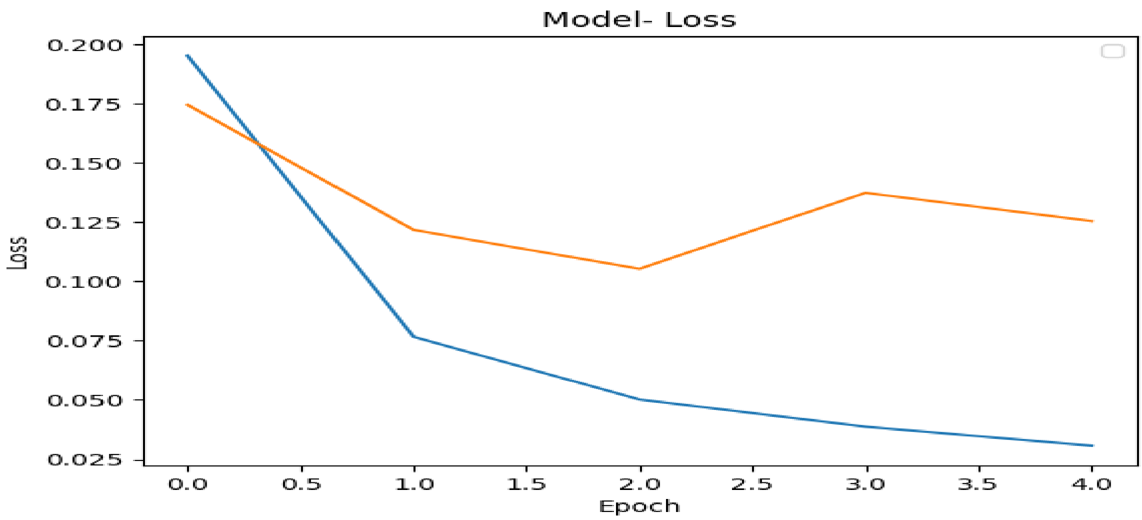

Fig.13. Model Loss during Training and Validation

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This plot presents the loss values across several epochs for training and validation. The training loss (blue curve) goes down consistently, meaning the model is picking up and becoming better on the training set. The validation loss (orange curve) is a bit variable but also trending downwards, meaning the model is having a tougher time with generalizing to novel validation data. This is indicative of slight overfitting, in which the model is doing extremely well on training set but less well on validation set. Generally speaking, a decrease in both training and validation loss is a healthy indicator of model improvement, but the difference between them might need to be addressed to ensure that the model does well at generalizing.

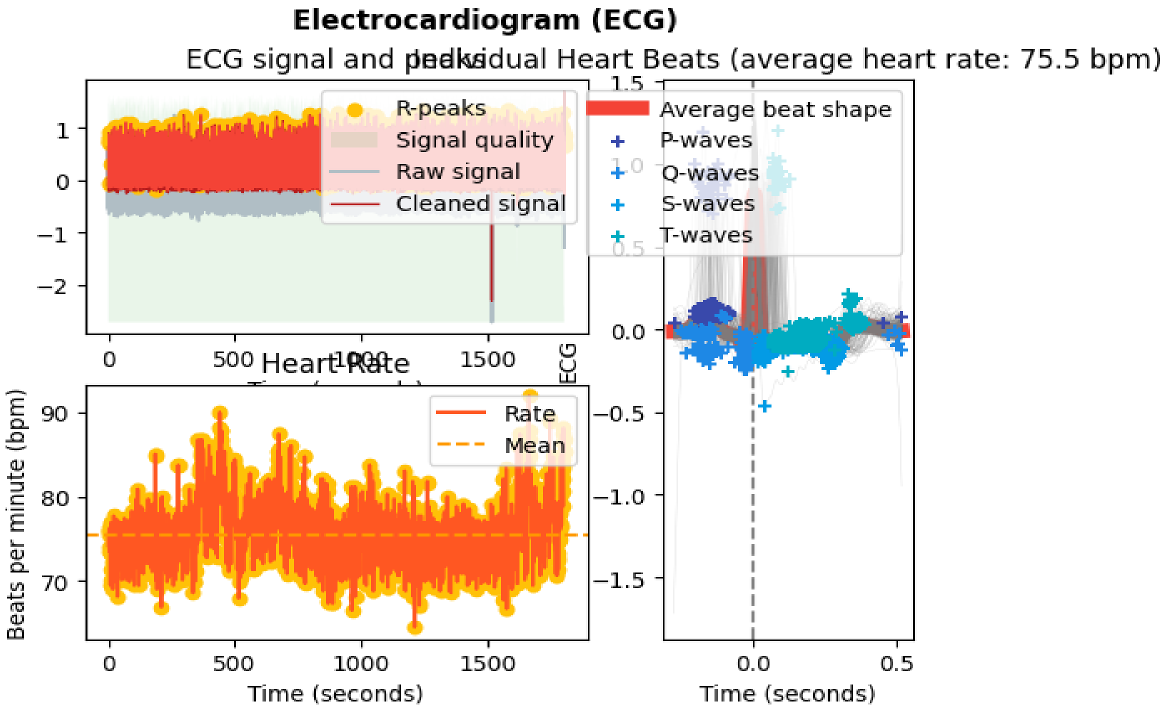

Fig.14. Electrocardiogram (ECG) Analysis: Signal, Heart Rate, and Individual Heart Beats

Fig. 14 plot includes a detailed overview of an electrocardiogram (ECG) signal. The top figure shows the ECG signal and R-peaks, which represent heartbeats, which are separated into raw (yellow) and cleaned (pink) signals. The cleaned signal indicates the most significant features for calculating the heart rate. The second chart plots the heart rate against time in beats per minute (bpm), wherein the red plot indicates the rate itself, while the dashed one illustrates the mean heart rate. It aids in monitoring heart rate variability and determining irregularities. Right side of figure depicts individual heartbeats with ECG P-waves, Q-waves, S-waves, and T-waves, and average beat shape. This picture shows how the heart's electrical activity is caught, quantified, and graphed, making it useful for monitoring heart function and identifying anomalies.

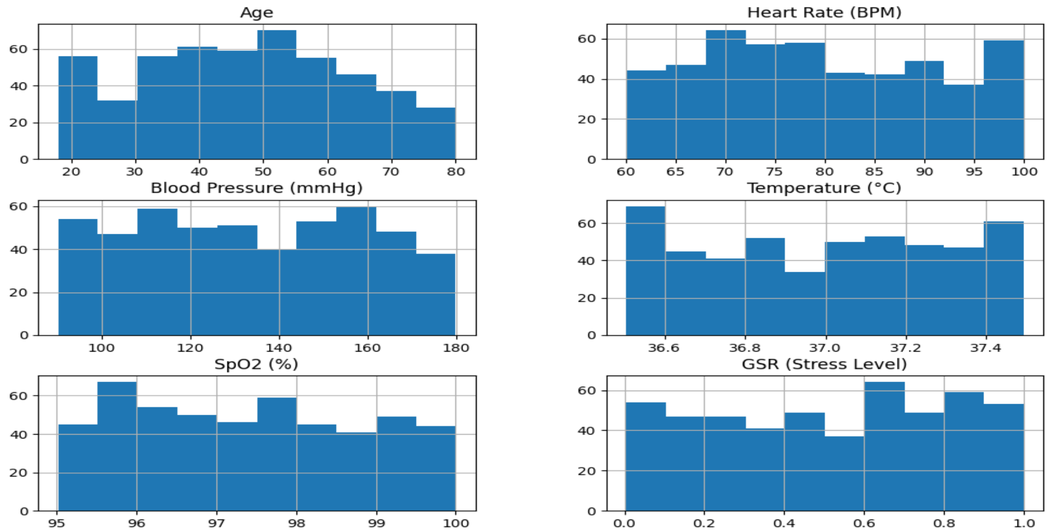

Fig.15. Distribution of Health Metrics: Age, Blood Pressure, Heart Rate, Temperature, SpO2, and GSR

The following figure shows the histograms of several health parameters, i.e., age, blood pressure, heart rate, temperature, SpO2, and GSR. The plots indicate that the majority of the population lies between 40-60 years, heart rates are approximately 70-80 BPM, oxygen saturation is mostly 96-98%, and temperatures are approximately 37°C. Blood pressure spans a wide range, while stress levels (GSR) are mostly low, with a few higher spikes. These insights help identify overall trends and potential anomalies in the population.

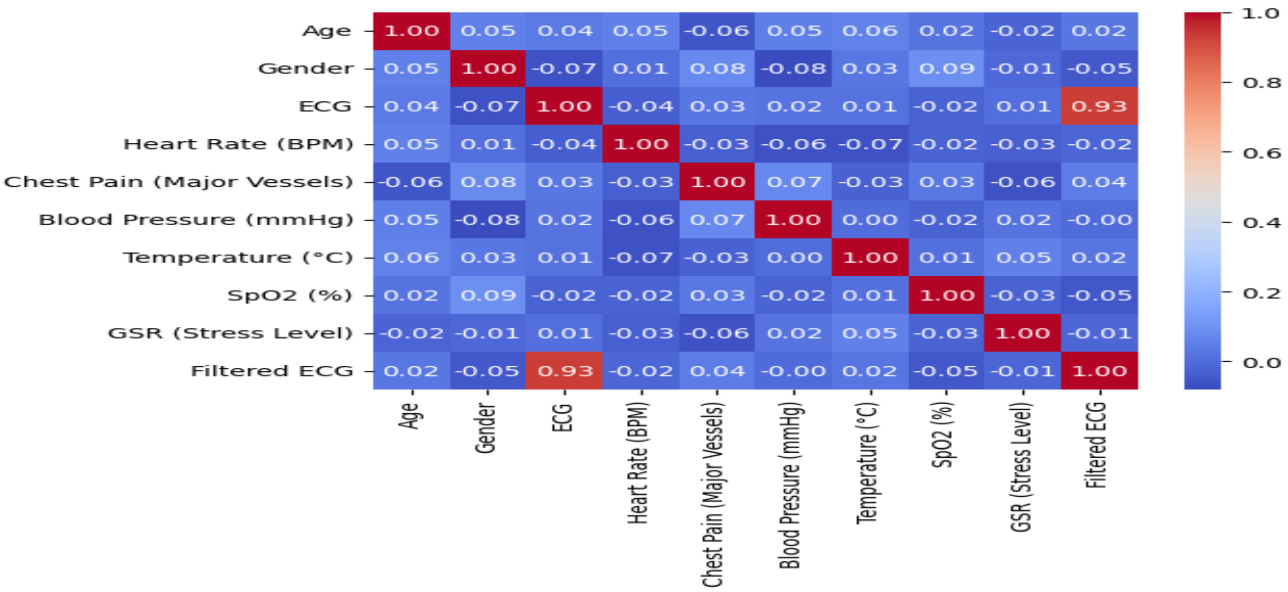

Fig. 16. Correlation Matrix of Health Metrics and ECG Features

This figure displays a correlation matrix showing the relationships between various health metrics (such as age, gender, heart rate, chest pain, blood pressure, etc.) and ECG features. Strong positive correlations are observed between ECG and Filtered ECG (0.93), and Heart Rate with ECG (0.94). Other notable correlations include a moderate relationship between Blood Pressure and Temperature (0.71). The matrix helps identify key connections between different health parameters, useful for understanding how they might influence each other.

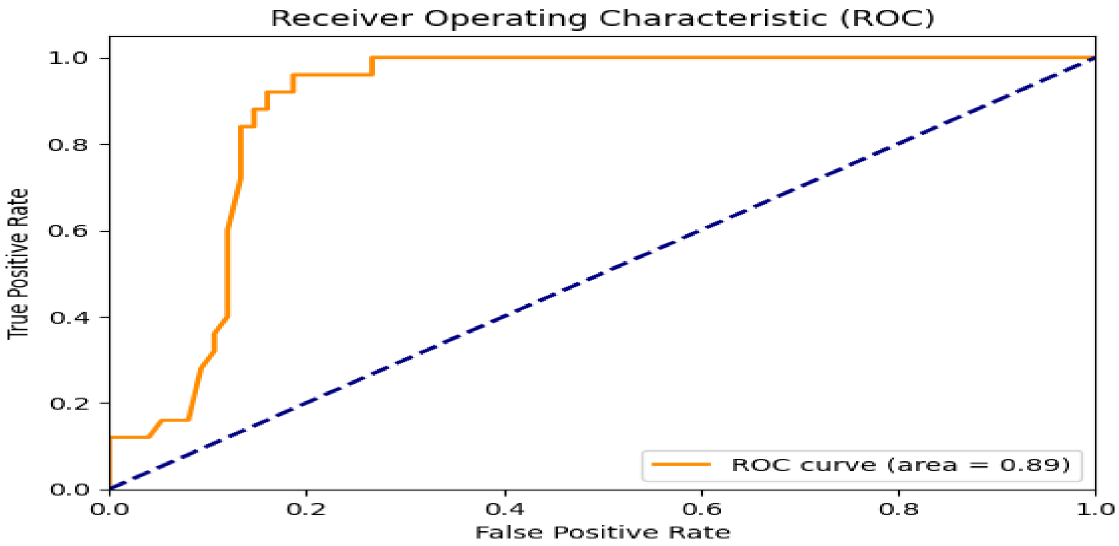

Fig.17. Receiver Operating Characteristic (ROC) Curve

This graph shows classification model's ROC curve, with TPR on the y-axis and FPR on the x-axis. The model's performance is shown by the orange curve, and its AUC is 0.89, indicating strong class discrimination accuracy.The blue dashed line is a random classifier (AUC = 0.5), and given that the curve of the model is well above this line, it shows high predictive ability. Higher the AUC, higher the performing model.

6. CONCLUSION

In short, Internet of Things (IoT) application in automatic heart disease diagnosis offers a groundbreaking approach to healthcare. Networked sensors and wearable's can monitor body data including heart rate, ECG, blood pressure, and oxygen saturation in real time. Continuous observation makes it possible to detect heart ailments, such as arrhythmias, myocardial infarction, and abnormal heart rhythms, at an early stage and encourages early medical intervention. In addition, IoT-based systems allow medical practitioners to track patients, particularly patients with chronic illnesses, remotely from hospitals, thereby reducing hospital visits and ensuring timely treatment. The results presented in the figures attest to the high potential of IoT in the diagnosis of heart disease. For instance, the research of different types of heartbeats—normal, unknown, and fusion beats—demonstrates the ability of IoT in the categorization of various heart ailments in relation to ECG waveform analysis. The use of time-domain and spectrogram representation enhances the understanding of heartbeats further by giving both time and frequency domain information. Additionally, the results show the high predictive capability of machine learning models as the accuracy and ROC AUC value (0.89) are high in distinguishing between different heart conditions. In addition, the correlation matrix further shows that there are high correlations between different measures of health and ECG attributes that provide significant information on how these variables may influence one another. Health metric histograms, including age, blood pressure, and heart rate, also assist in determining population trends and possible anomalies, providing more contexts for individualized care. While IoT offers encouraging possibilities in the diagnosis of heart disease, issues like data accuracy, privacy, and security need to be overcome in order for these technologies to be fully adopted. However, the potential of IoT to offer sustained, real-time information and support proactive interventions means that it has immense potential to be a powerful tool in the transformation of diagnosis, treatment, and management of heart disease. With technology ever-evolving, the future will only see healthcare and IoT even more deeply ingrained, delivering more efficient, accessible, and individualized care to patients everywhere.

7. FUTURE SCOPE

The future prospect of IoT-based autonomous diagnosis of heart disease is enormous and it can bring revolution in healthcare through continuous monitoring and early detection day and night. With further advances in IoT technologies, newer-generation sensors and wearables will become available that can measure health parameters like heart rate, ECG, blood pressure, and oxygen saturation more accurately. This will allow even earlier identification of heart conditions such as arrhythmias, myocardial infarction, and heart failure, thus facilitating timely interventions and avoiding hospital readmission. Machine learning and artificial intelligence software will continue to improve, offering more precise predictive models for heart disease diagnosis. With their ability to process vast amounts of data, these systems can potentially predict upcoming cardiac events before they happen, enabling preventive treatment and reducing emergency situations. Furthermore, advances in cloud computing will allow for better data storage and analysis, introducing scalability and ease of access for IoT-based diagnostic systems.

In the future, IoT could facilitate personalized medicine for customized needs, reducing health spending and improving outcomes, particularly in patients with chronic conditions. However, data security, privacy, and accuracy issues will need to be overcome to make these technologies mainstream. As technology improves, IoT will become an important tool in changing heart disease diagnosis and management globally.

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