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An IOT framework for detecting cardiac arrhythmias in real-time using deep learning resnet model

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ABSTRACT

A cardiac arrhythmia poses a serious health risk to patients and can have serious consequences for their health. A clinical assessment of arrhythmia disorders could save a person's life. The Internet of Things (IoT) will revolutionize the healthcare sector by continuously monitoring cardiac arrhythmia diseases remotely and minimally invasively. We propose a frame-work that will facilitate the development of a practical diagnostic tool for the identification of cardiac arrhythmias in real-time in this work. An Electrocardiogram (ECG) signal is processed using the Pan Tompkins QRS (Quantum Resonance System) detection method in order to extract the dynamic properties of the signal. The inter beat (RR) intervals are derived from an ECG signal in order to determine the characteristics of heart rate variability. The electrocardiogram is primarily used to identify irregular heartbeats (cardiac arrhythmias). Therefore, in our study, we evaluated other factors such as the heartbeat of the individual. As part of our IoT deployment, we are storing and analyzing data collected by the Pulse Sensor on the Thing-Speak IoT platform. The designed circuit's real-time collection of heartbeat and beats per minute values was uploaded to Thingspeak. Over the course of more than a week, we collected a variety of heart data. We propose Multi Channel Residual Network (MCHResNet) a deep-learning based solution that relies on multi-channel convolutions to detect both spatial and frequency features from electrocardiograms to facilitate the classification process. Based on the well-known Massachusetts Institute of Technology-Beth Israel Hospital Arrhythmia (MIT-BIH-AR) database, we evaluate the proposed framework against MCH ResNet. Our IoT-based framework has been shown to be effective based on the results reported in this paper.

1. Introduction

Cardiac arrhythmia, also known as an irregular heartbeat, is a condition in which the heart beats at an abnormal rhythm. This can include both too fast (tachycardia) or too slow (bradycardia) heart rates. Cardiac arrhythmias can be caused by a variety of factors, including heart disease, genetics, and certain medications [1,2]. Symptoms of cardiac arrhythmia can include palpitations, shortness of breath, light headedness, and fainting [3]. Symptoms of cardiac arrhythmia can include palpitations, shortness of breath, light headedness, and fainting [4,5]. Other more serious symptoms can include chest pain, dizziness, and fatigue. In some cases, cardiac arrhythmia can cause an irregular heartbeat that lasts for an extended period of time. In extreme cases, it can lead to cardiac arrest, which can be fatal. In some cases, arrhythmias can be harmless and do not require treatment, but in other cases they may be serious and require medical intervention. Diagnosis and treatment of arrhythmias typically involve an Electrocardiogram (ECG) and may include medications, lifestyle changes, or procedures such as ablation or pacemaker implantation [6,7].

The Internet of Things (IoT) has the potential to revolutionize the way we detect and manage cardiovascular conditions, including cardiac arrhythmia. A cardiac arrhythmia is a condition in which the heart beats with an irregular rhythm, which can be either too fast or too slow. This can lead to reduced blood flow, increased risk of stroke, and even death. IoT-based solutions for identifying and managing cardiac arrhythmia often involve wearable devices, such as smartwatches or patch monitors,

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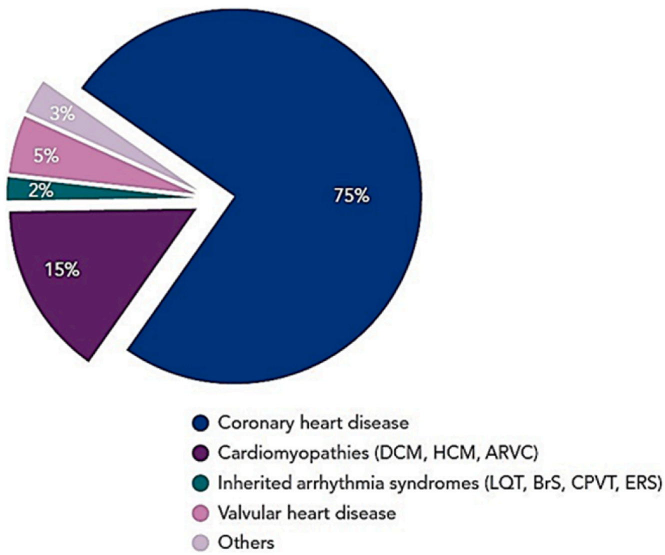

Fig. 1. Causes of arrhythmia and sudden cardiac death.

that can continuously monitor the wearer's heart rate and rhythm [8]. The data collected by these devices can then be transmitted to a healthcare provider for analysis and follow-up care. For example, a smartwatch equipped with an ECG (Electrocardiogram) sensor can detect arrhythmias and alert the wearer to seek medical attention. The ECG data can also be stored in the cloud for analysis by a physician, who can use this information to make a diagnosis and recommend a course of treatment. In addition to wearable devices, IoT-based solutions may also incorporate machine learning algorithms to detect patterns in heart rate and rhythm data that could indicate an arrhythmia [9,10]. These algorithms can also help to improve the accuracy of arrhythmia detection over time by continuously learning from new data. Overall, the integration of IoT technology in the healthcare industry holds great promise for improving the detection and management of cardiovascular conditions, including cardiac arrhythmias.

In Fig. 1, Arrhythmia and Sudden Cardiac Death (SCD) account for a sizable portion of fatalities globally, raising serious public health concerns. Early defibrillation and CPR are essential for survival, but access to these services and public defibrillators is frequently restricted, leading to low patient survival rates [11]. The use of intelligent technology could offer a remedy to this issue. SCD and arrhythmia are most frequently caused by coronary artery disease, but it's essential to look for other potential causes when making a diagnosis. This can help with family member detection and managing arrhythmia recurrence. However, the majority of SCD cases involve people who don't typically have traditional arrhythmia risk factors, emphasizing the need for better large-scale screening tools to more accurately predict risk in the general population.

Analyzing the correct data improve the condition of patients, and to make sure that the disease is diagnosed as soon as possible so that the patient can start medication and recovery process [12]. With correct data, doctors also get a better under-standing of the treatments that work well and the treatments that don't work as well. This allows them to provide the best possible care for their patients.

To build a Cardiac Arrhythmia detection model using IoT sensors, it is important to first collect data from patients wearing IoT sensors [13, 14]. The data should be collected over a long period of time in order to provide a comprehensive view of the patient's heart rate, breathing pattern, and other vital signs. This data can then be analyzed to identify any irregularities in the patient's heart rhythm that may indicate the presence of an arrhythmia. Once the data has been collected and analyzed, machine learning algorithms can be used to create a model that can accurately detect arrhythmias from the data. This model can then be tested on real-world data and refined if necessary [15]. Once the model is deemed accurate, it can be deployed on the IoT sensors in order to monitor the patient's heart rate and alert medical personnel if an arrhythmia is detected.

2. Literature review

A predictive analytics framework was suggested in the paper by Rosario Morello et al. (2021) titled "An IoT-based ECG system to diagnose cardiac pathologies for healthcare applications in smart cities." The paper claims that a smart ECG device has been constructed. The system can collect the ECG data using a set of three leads and then process it by computing particular parameters [16–18]. Diagnoses for heartbeat, bradycardia, ischemia, and infarction can be made. Through a collection of four leds, the user is shown the diagnosis. Data is also remotely accessible using an IP address and a standard web browser in an IoT method. The authors of this study [19–21] use the typical ECG signal of a healthy middle-aged woman. The data is collected using the ECG system mentioned in the paper. The data is stored in a web server using IoT. The data is accessed using the appropriate IP addresses. The acquired data is processed using the DSP analyzers and the ECG signal is obtained and can be used by the physicians to diagnose the disease. This paper mentions Telemedicine. Telemedicine and homecare services are today an important alternative to hospital admission [22]. Using IoT the real-time ECG data can be accessed by cardiologists and people from remote areas might be able to access good healthcare facilities.

Pool M.D. Oudkerk in the paper titled "Deep Learning-Based Data-Point Precise R-Peak Detection in Single-Lead Electro-cardiograms" has discussed about wearable devices to record ECG signals. They are primarily utilised for atrial fibrillation screening and other cardiac arrhythmias. The majority of arrhythmias are characterized by variations in the RR-interval, hence R-peak detection may be used in automatic arrhythmia diagnosis systems [23–25]. Rpeak detection techniques currently in use are reasonably accurate but lack sufficient precision [26, 27]. We provide a technique that makes use of a fully convolutional dilated neural network in order to enable data-point precise detection of R-peaks. Using manually annotated R-peaks in a heterogeneous sample of ECGs that include a variety of heart rhythms and acquisition noise, the network is trained and tested. 700 ECGs from the PhysioNet/CinC challenge 2017 were picked at random, with 500 being used for training, 100 for validation, and 100 for testing. The network achieves a precision of 0.910, recall of 0.926, and an F1-score of 0.918 on the test set. De Santana J. R. G in the paper titled "A New Approach to Classify Cardiac Arrythmias Using 2D Convolutional Neural Networks" describes a new methodology of arrhythmia detection by employing 2D convolutional neural networks. The utilization of 15 x 15-pixel gray-level images carrying the values of an ECG signal heartbeat is the primary feature of the suggested methodology. This research seeks to identify 17 arrhythmias. The MIT-BIH database, the primary benchmark database described in the literature, was used to validate and evaluate the suggested methodology.

When compared to other results that have already been published, the precision that was reached, 92.31%, is considered to be cutting edge. Chumrit Nutwara in the paper titles as "ECG-based Arrhythmia Detection Using Average Energy and Zero-crossing Features with Support Vector Machine" has presented a method in which average energy and zerocrossing quantities are used from the ECG records to create the method for arrhythmia detection from the ECG signal. The suggested system consists of feature extraction, arrhythmia identification, and ECG signal preprocessing. The ECG signals utilised in this investigation came from the MIT-BIH QT, normal sinus rhythm, and arrhythmia databases. We use a support vector machine (SVM) as a classifier to distinguish between the normal and abnormal (arrhythmia) ECG signals. The performance of the suggested system is assessed and validated using the K-fold cross validation technique. With the use of accuracy, sensitivity, specificity, and precision, we evaluate the system's performance.

Jinyuan He et al. (2020), in the paper titled "A framework for cardiac arrhythmia detection from IoT-based ECGs". The rise of the Internet of Things has resulted in novel methods of cardiac monitoring, but it has also posed new obstacles for manual arrhythmia identification.

To assist physicians, an automated solution is widely desired. Current attempts at automated arrhythmia identification may be classified into two categories: feature-engineering-based approaches and deep-learning-based methods. The majority of feature engineering-based approaches suffer from using a single classifier and fixed features to categorize all five kinds of heartbeats. This makes identifying abnormal heartbeats more challenging and decreases overall classification performance. This particular paper proposes two methods to classify the heartbeat using Multi-channel Heartbeat Convolution Neural Network with Dynamic Heartbeat Classification with Ad-justed Features (DHCAF) (MCHCNN). DHCAF is a feature-engineering-based strategy in which the author introduced the DES technique and create a result regulator to improve classi-fication performance. MCHCNN is a deep-learning-based sys-tem that captures both temporal and frequency patterns from heartbeats to aid categorization. On the well-known MIT-BIH- AR database, we assess the proposed framework with DHCAF and MCHCNN, respectively. The results of this study show the effectiveness of our system. In their article named "Machine learning and IoT-based cardiac arrhythmia diagnosis using statistical and dynamic features of ECG," R. Lakshmi Devi et al. Arrhythmia diseases that are quickly diagnosed can help save lives. By offering constant, remote, and noninvasive tracking of cardiac arrhythmia conditions, the Internet of Things (IoT) has the potential to advance the healthcare industry.

In order to record the ECG signal, analyse the ECG data, and alert the doctor in case of an emergency, an IoT platform for cardiovascular illness prediction uses an IoT-enabled ECG telemetry system. Early and thorough examination of the cardiac condition by the doctor is advantageous. We are developing an IoT-enabled ECG monitoring device to analyse the ECG signal. The raw ECG signal's statistical characteristics are calculated. The Pan Tompkins QRS detection technique is used to analyse the ECG signal in order to ascertain its dynamic properties. Classification and study of cardiac arrhythmia based on incremental support vector regression on IOT platform, S.T. Sanamdikar et al., 2021. The full ECG beat may be classified into five types of beat arrhythmias (N, S, V, F, U). Rapid and exact diagnosis of arrhythmias is crucial for diagnosing the cardiac condition and providing the patient with the appropriate therapy. Five different kinds of beat arrhythmias can be categorised based on the full ECG beat. (N, S, V, F, U). Arrhythmias must be accurately and quickly diagnosed in order to diagnose the patient's cardiac state and administer the proper therapy. In this study, ECG signals were analyzed and determined using Discrete Wavelet Transform and Higher Order Statistics methods, and then applied on an IOT-based platform. There are three sections to this system: In the first approach, the ECG data must be entered; in the second method, the ECG beats and their amplitudes must be extracted from the baseline. The wavelet transform function and higher order statistics are used to filter out noise and unwanted signal components before extracting ECG features. In our suggested IOT-based approach, the tiny Raspberry Pi is used with high specifications. It has a quad-core, 32-bit CPU with 40 pins that operates at 900 MHz. It has four USB ports, one gigabyte of memory (RAM), an Ethernet connection, a micro-SD port for storing the operating system and other files, and a low-power 5 V, 2 A power supply.

3. Working principle of the system

The pulse data is collected using the Pulse sensor using the Pulse sensor libraries in the Arduino IDE. The analog pulse values and the BPM data are collected from the pulse sensor and this data is collected and sent through Arduino Uno to the NodeMCU by using serial communication protocols. The NodeMCU is connected to the ThingSpeak platform and the data points are uploaded to the respective fields in a particular channel.

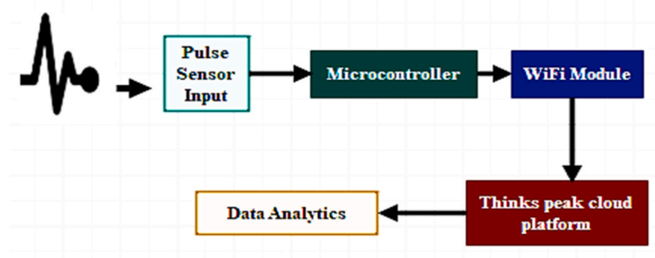

Fig. 2. System block diagram.

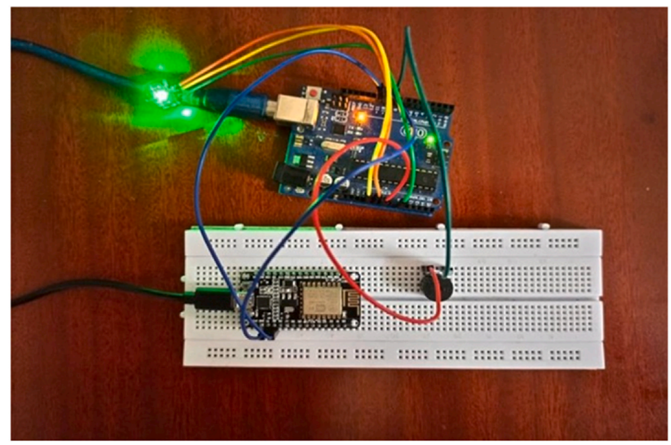

Fig. 3. Low-cost System design for identifying cardiac arrhythmia.

In Fig. 2, system diagram: The pulse sensor's analog pin is connected to the analog input A0 of Arduino Uno. And the VCC and GND of the pulse sensor is connected to the respective inputs on the Arduino Uno. NodeMCU.

3.1. System design

The given model and circuit in Fig. 3, can be used together to detect Cardiac Arrhythmia. The data is exported to the Thingspeak website using IoT Our research involves usage of Pulse sensor. Pulse Sensor is integrated with the buzzer. When the bpm (bulse per minute) of an individual is higher than the normal acceptable limits it indicates the user by buzzing thereby alerting the individual to slow down or take rest. The model and circuit are as follows:

- The Pulse Sensor is connected to the Arduino Uno board.
- The Pulse Sensor is used to measure the heart rate of the individual.

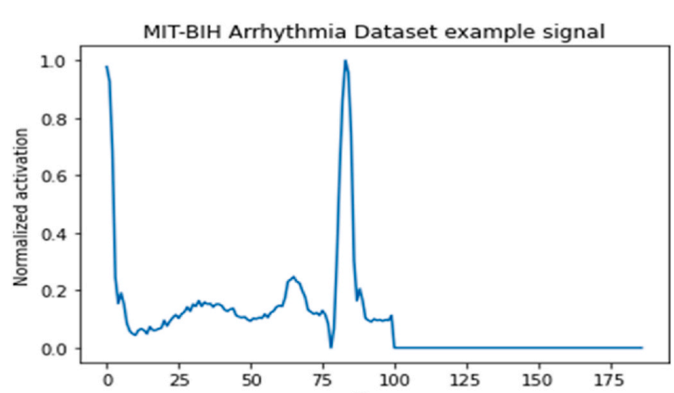

Fig. 4. A sample signal of MIT-BIH arrhythmia dataset.

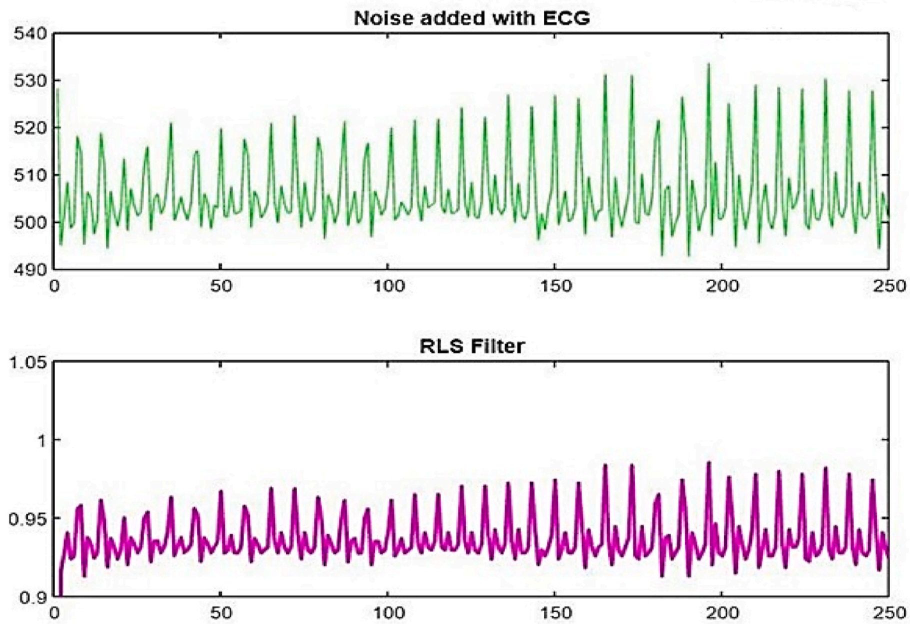

Fig. 5. The Noise Added ECG Signal and the Filtered ECG signal using RLS filter.

- The Arduino Uno board is used to analyse the data from the Pulse Sensor and detect Cardiac Arrhythmia.
- The Arduino Uno board is connected to the Thingspeak website, which is used to store the data from the Pulse Sensor and plot it in a graph.
- The Arduino Uno board is also connected to a buzzer, which is used to alert the individual if the bpm is higher than the normal acceptable limits.

3.2. Data sets

The MIT-BIH Arrhythmia database is a widely used database for evaluating algorithms for ECG analysis and classification. In Fig. 4, contains ECG recordings from two institutions: the Beth Israel Hospital (BIH) in Boston, Massachusetts and the Massachusetts Institute of Technology (MIT). The database consists of 48 half-hour recordings of two-channel ECG signals, with a total of approximately 5 min of annotated ECG waveform data. The recordings were taken from patients with a variety of heart conditions, including arrhythmias, and the database is commonly used for research in ECG signal analysis, arrhythmia detection, and classification. The database is publicly available for non-commercial use and is widely used as a benchmark for evaluating the performance of ECG analysis algorithms.

3.2. System functioning

The pulse sensor's data was successfully gathered. Using an ESP8266 module, we collected data for our research project over the course of more than a week, and the acquired data was shown on a serial monitor. The data was then uploaded to thingspeak, where it was visualized as follows using more than 2000 points of data (ECG and BPM signal across several weeks). Processing is done with MATLAB in the final step. The read API key and channel ID are available in the Thingspeak channel "Health monitoring," which is where we collected our data. Using RR-peaks and RR intervals, we can use MATLAB to detect whether a person has an arrhythmia and what kind of arrhythmia they have. We use the filtering concept of signal processing since real-time data collection will result in noise-filled data. We are using an adaptive filter algorithm called the RLS filter. Because adaptive filters are self-adjusting, they provide an optimum result based on the input. Whether the subject has an arrhythmia or not is determined by the RR interval, heart rate, and bpm. The finalized information is then further separated into subsystems so that we can identify the patient's type of cardiac disorder.

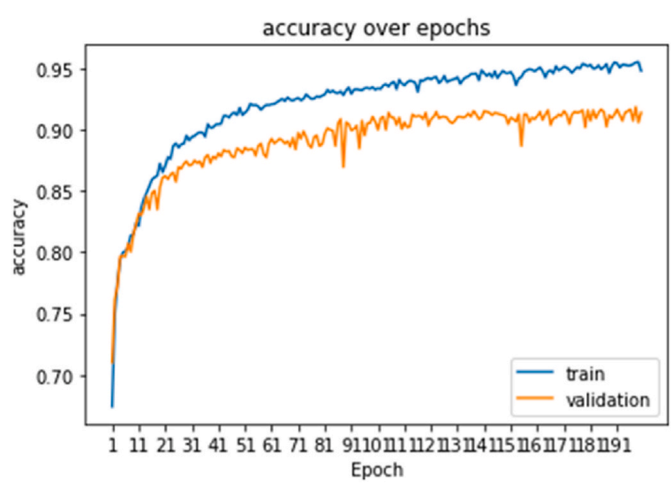

Fig. 6. Accuracy of the Modified ResNet architecture for the ECG Dataset.

4. Results

The circuit has been constructed and simulated, followed by real-time data collection, which is then uploaded to Things-peak. The Noise Added ECG Signal and the Filtered ECG signal using RLS filter is presented in Fig. 5. By using the channel ID and Read API Keys from the MATLAB code, the acquired ECG data is extracted from the Health Monitoring Channel. To detect Cardiac Arrhythmia, the RR intervals are identified via Wavelet Transformation, based on the RR interval of the subject. As a result, no Cardiac Arrhythmia is detected. Therefore, the presented circuit and MATLAB code serve as a reliable Diagnostic tool for Cardiac Arrhythmia.

4.1. Results of the IOT based framework

The accuracy of the Modified ResNet architecture for the ECG

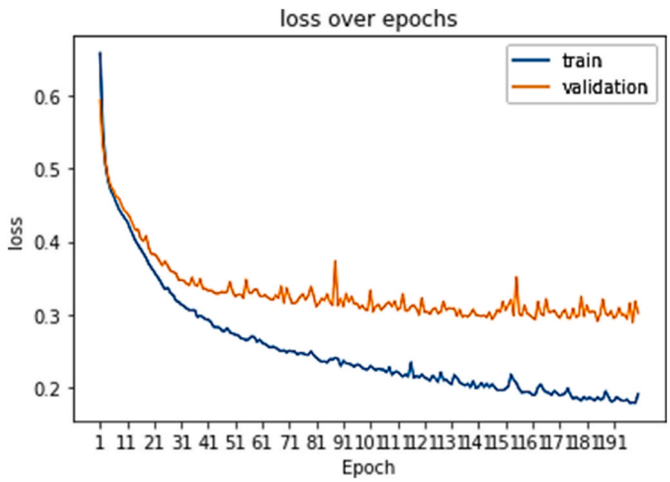

Fig. 7. Loss of the Modified ResNet architecture for the ECG Dataset.

Dataset is shown in Fig. 6. The performance of a ResNet model on the MIT-BIH Arrhythmia database for ECG analysis and classification is implemented by different techniques. However, this modified, ResNet based deep learning models such as ResNet have been shown to achieve good performance on ECG classification tasks.

In this work the modified Multiclassification based ResNet models have been applied to ECG signal classification using the MIT-BIH Arrhythmia database and have achieved promis-ing results with accuracy of 99.2% on test data in the PTB dataset (Shown in Fig. 7). This modified ResNet model was trained on ECG signals from the MIT-BIH Arrhythmia database and achieved an overall accuracy of 98.2% for the classification of five classes of ECG signals (normal, supraventricular premature beats, ventricular premature beats, paced beats, and fusion of ventricular and normal beats). The Data visualizationin Thing speak is shown in Fig. 8 and Matlab analysis of thinspeak data collected is shown in Fig. 9. This modified ResNet model was used for ECG arrhythmia classification, and the model achieved an accuracy of 95.5% on the validation dataset for the classification of six classes of ECG signals (normal sinus rhythm, atrial premature beat, ventricular premature beat, ventricular flutter/fibrillation, and pair of ventricular beats).

5. Conclusion

In conclusion, the designed circuit proved to be a successful tool for monitoring cardiac data in real-time. The data collected via Thingspeak's "Health-monitoring" channel was then successfully processed in MATLAB, with the RLS filter removing noise from the dataset. The MATLAB output then provided a reliable indication of any cardiac

Fig. 8. Data visualizationin Thing speak.

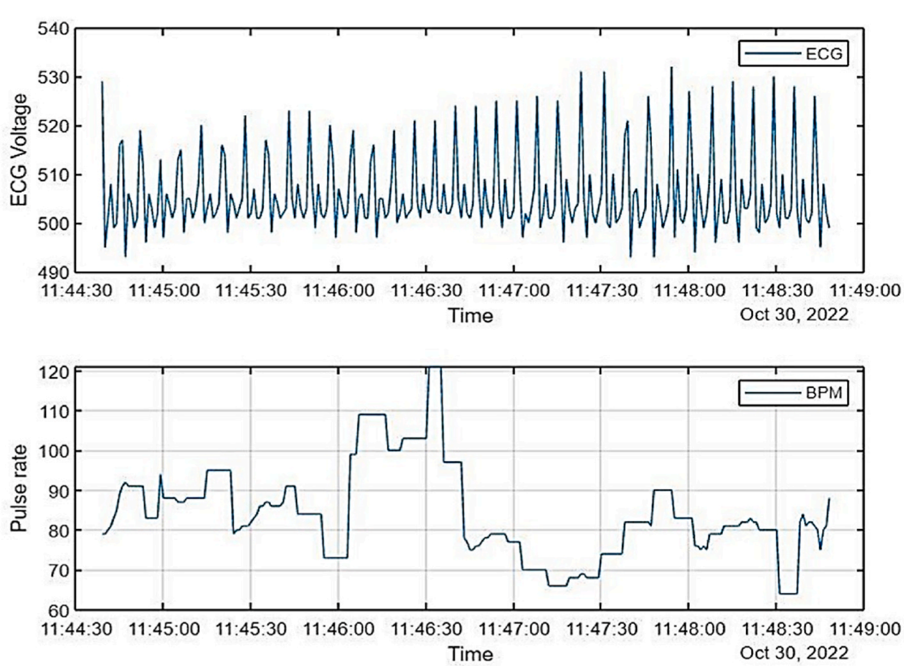

Fig. 9. Matlab analysis of thinspeak data collected.

arrhythmias present. Additionally, the circuit utilised a buzzer that warned of any heart rate readings above the normal range. Overall, this project was able to successfully collect and analyses more than 2000 data points over the course of days, and provided us with a valuable insight into cardiac health. It's worth noting that these results may not be directly applicable to other ECG datasets or in different scenarios, as the performance of a deep learning model can be affected by many factors such as the size and diversity of the training dataset, the choice of evaluation metrics, and the presence of domain-specific challenges.

In the future we intend to apply Machine Learning Algorithms on the collected data such as XG Boost, KNN, Random Forest, Naïve Byes to mention a few. Currently Arduino and Node MCU as the primary Microcontrollers in the project. The future scope would be to integrate the Pulse Sensor with complex hard wares and make use of other Complex hard wares such as CC3200, STM32 Development kit etc. The IoT implementation is done using the ThingSpeak channel the future of the IoT implementation is to upload the data to the leading cloud computing platforms such as Microsoft Azure or AWS and also making use of different application and Communication layer protocols.

CRediT authorship contribution statement

S. Sai Kumar: Writing – original draft, Formal analysis, Conceptualization, design of study. **Dhruva R. Rinku:** Writing – original draft, Formal analysis. **A. Pradeep Kumar:** revising the manuscript critically for important intellectual content, Data curation. **Rekharani Maddula:** Approval of the version of the manuscript to be published, Data curation. **C. Anna palagan:** revising the manuscript critically for important intellectual content.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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