Hybrid Approach For Cardiac Arrythmia Using IoT

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Abstract- *Compared to the single-lead approach, the 12-lead electrocardiogram (ECG) method can diagnose more cardiovascular diseases; however, because multiple electrodes need to be attached to the body, it is challenging to utilise in daily life. Electrocardiography is being more widely used in daily life as an ageing society draws near, even reaching the level of passenger automobile heart disease monitoring systems. In order to classify the driver's heart health status, this study suggests implementing a machine learning model with a single-lead ECG measuring system in the steering wheel of the car. Together with the measurement hardware, an algorithm is proposed for the ECG measuring system in order to get stable ECG readings. The ECG signal's range and interval are utilised to assess stability in noisy environments brought on by car vibration and the driving movement. A two-stage machine learning structure is presented to classify four kinds of cardiac diseases: noise, other rhythms, atrial fibrillation, and normal. 188 features were selected in order to provide the machine learning models with an ideal feature subset. retrieved from the single-lead ECG dataset, and a feature selection process akin to a sequential wrapper was carried out. The suggested two-stage classification structure thus yielded the best score F1NAO = 0.7898 and real-time classification performances (0.86 seconds on average) when the naïve Bayes model using 10 features was located in the first step and the support vector machine using 13 features in the second step.*

Keywords- Atrial fibrillation, EKG, feature selection, machine learning, healthcare, and two-stage classification.

I. INTRODUCTION

This paper presents a thorough description of cardiac arrhythmia, including an in-depth analysis of its various presentations, signs, and consequences, including heart failure and stroke. It explores the causes, which include thyroid hyperthyroidism and alcohol addiction, emphasising the need of keeping a good resting heart rate. When talking about the differential diagnosis, it clarifies bradycardias, tachycardias, and normal electrical activity in addition to congenital heart disorders such Long QT syndrome and Wolff-Parkinson-White syndrome, which can result in lethal arrhythmias. It further clarifies the role of the re-entry process in potentially fatal arrhythmias, emphasising the autowave vortices of excitation in the heart as the main culprit. The discourse's motivation highlights the necessity of accurate arrhythmia detection, criticising human methods for their inadequacy and promoting the use of deep learning techniques, namely convolutional neural networks (CNNs), to improve diagnostic precision. The issue statement suggests creating a system specifically designed to recognise and categorise arrhythmias, meeting the urgent demand for trustworthy diagnostic instruments in clinical settings. In the meanwhile, the goals are to build a strong method for classifying electrocardiogram (ECG) traces in order to give doctors useful information that they may use to make well-informed treatment decisions. In the end, the chapter promotes the use of artificial intelligence and machine learning, particularly CNNs, as critical instruments for enhancing arrhythmia diagnostic and treatment effectiveness. The goal of utilising these cutting-edge technologies is to improve patient care and outcomes in the field of cardiovascular health by optimising diagnostic procedures and reducing any risks related to issues related to arrhythmias. In tackling complicated cardiovascular problems, this multidisciplinary approach highlights the synergy between medical skill and technological innovation, ultimately leading to improved patient outcomes and quality of life.

II. EXISTING SYSTEM

Traditional electrocardiogram (ECG) monitoring techniques, which entail placing electrodes on the patient's skin to record electrical activity, are the mainstay of the current system for cardiac arrhythmia identification. This method has limits in terms of real-time detection and ongoing monitoring, notwithstanding its effectiveness. Moreover, the integration of IoT sensors with standard ECG devices is limited, hence limiting the acquisition of crucial information like age, sex, height, and weight. This results in a limited perspective on the patient's physiological condition. Furthermore, the current system's data pre-treatment methods might not be able to effectively use the potential of cutting-edge machine learning models. Thus, there is potential for enhanced precision and efficacy in the identification of arrhythmias. This emphasises the need for a more complete and timely solution that uses cutting-edge machine learning algorithms to accurately classify cardiac arrhythmias and combines IoT devices for improved data collecting.

III. PROPOSED SYSTEM

For this research, a system that uses Internet of Things (IoT) sensors to identify cardiac arrhythmias in real time is proposed. In order to record vital physiological information such as age, sex, height, weight, QRS duration, QT interval, and T wave morphology, these sensors will be placed in strategic locations. To guarantee its quality and appropriateness for machine learning analysis, the gathered data will go through a thorough pre- treatment procedure. The next step will be to create a cutting- edge multi-class classification model that accurately classifies arrhythmias into thirteen different categories by utilising deep learning architectures and sophisticated algorithms. Using the pre-processed data, this model will be trained and refined to enable it to discover complex patterns and correlations linked to various arrhythmic disorders. The technology has the potential to completely transform cardiac health monitoring by processing data from a variety of sources in real-time and provide precise and timely insights for early intervention and individualised treatment plans. In addition, the suggested system will undergo a thorough assessment utilising recognised performance measures to guarantee its dependability and efficiency in clinical environments, eventually leading to better patient results in the field of cardiac care.

IV. REQUIREMENT SPECIFICATIONS

Software requirements:

1. Arduino IDE
2. Embedded C
3. Thingspeak

Ardunio IDE: Arduino IDE: Arduino's main business is producing open-source computer hardware and software. The Arduino Community is the project and user group in charge of developing and making use of microcontroller-based development boards. These development boards are the open-source prototype platforms called Arduino Modules. The simplified microcontroller board comes with a number of distinct development board bundles.The most common way to programme is to utilise the Arduino IDE, which uses the C programming language. Because of the open-source community, this gives you access to a huge library of Arduino projects that is always growing. Get the Arduino Integrated Design Environment (IDE) latest version from https://www.arduino.cc/en/Main/Software. This is how the Arduino IDE appears when it is opened. A blank sketch displays as it opens, allowing you to start programming straight away. We need to set up the board and port settings before we can enable code uploading. After using a USB cable to connect your Arduino board to the PC, configure the board and COM port settings.

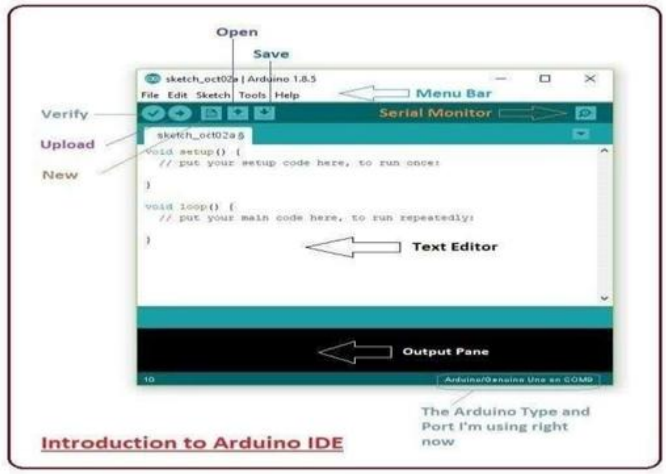


Fig.1. Arduino IDE

Embedded C: Embedded C is a version of the C programming language that is intended primarily for embedded systems in industrial automation, consumer electronics, automotive, and aerospace. It maximises efficiency by allowing low-level access to hardware peripherals required for system operations. Its real- time features allow it to respond swiftly to external events and meet tight scheduling limitations. Code is portable and can be reused across multiple microcontroller architectures. Embedded C uses specialised Integrated Development Environments (IDEs) to make code development, compilation, debugging, and deployment easier for embedded system projects. Overall, it is a useful tool for designing firmware and low-level software, promoting creativity in a range of industries.

ThinkSpeak: ThingSpeak, MathWorks' open-source Internet of Things (IoT) platform, allows users to effortlessly gather, analyse, and visualise data from linked devices or sensors. ThingSpeak's user-friendly, web-based, The interface makes it simple to manage Internet of Things projects and incorporate data into analytics workflows or applications. ThingSpeak's RESTful API allows devices to instantly send real-time data using a variety of protocols, including MQTT and HTTP POST requests. ThingSpeak also includes integrated tools that allow users to view data trends through editable graphs, charts, and maps, giving them a better understanding of how sensor data patterns develop over time. Furthermore, ThingSpeak's support for advanced data analysis with MATLAB enables customers to apply complex methods for machine learning and signal processing directly within the platform. ThingSpeak distinguishes out as a versatile solution for a wide range of IoT applications, from industrial automation and healthcare to environmental monitoring, thanks to its seamless integration and vibrant community.

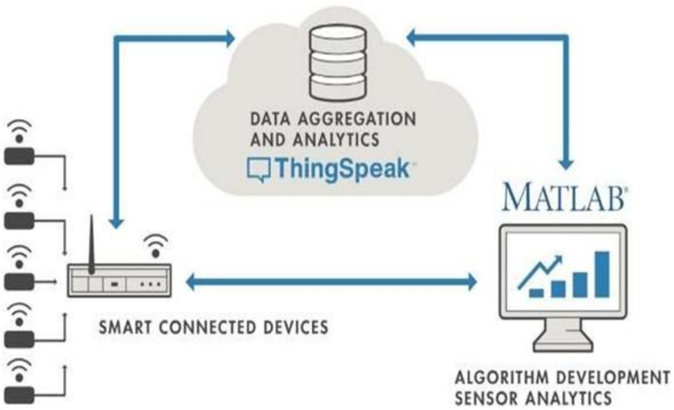


Fig.2. Thinkspeak process

Hardware Requirements:

- ESP32
- Heart Rate Sensor
- LCD Display
- 1-wire Temperature Sensor
- ECG Sensor

ESP32: ESP32 is a low-cost System on Chip (SoC) Microcontroller developed by Espressif Systems, the same company that created the well-known ESP8266 SoC. It is the successor to the ESP8266 SoC and comes in both single-core and dual-core versions of Tensilica's 32-bit Xtensa LX6 Microprocessor, which includes Wi-Fi and Bluetooth. The advantage of ESP32, like ESP8266, is that it includes integrated RF components such as a power amplifier, a low-noise receive amplifier, an antenna switch, filters, and an RF balun. This makes creating hardware around the ESP32 very simple because it requires relatively few external components. ESP32 has many more functionalities than ESP8266, making it difficult to cover all of them in our Getting Started with ESP32 article. So I compiled a list of some of the most significant ESP32 specifications here. However, for a complete set of specifications, I strongly advise you to go to the Datasheet.Single or dual-core 32-bit LX6 microprocessor with clock speeds of up to 240 MHz.520 KB of SRAM, 448 KB of ROM, and 16 KB of RTC SRAM.Wi-Fi connectivity is 802.11 b/g/n compatible, with speeds of up to 150 Mbps.Supports both Classic Bluetooth v4.2 and BLE standards.There are 34 programmable GPIOs.

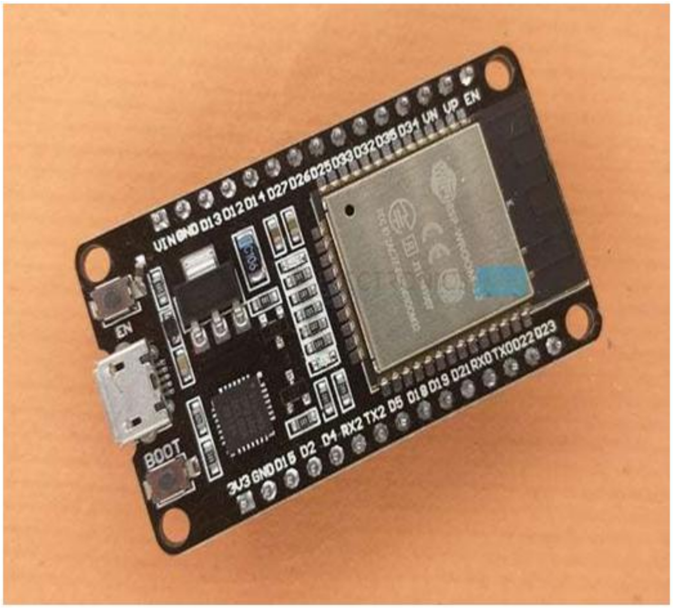


Fig.3. ESP32

Heart Rate Sensor: Monitoring heart rate is critical for athletes and patients since it indicates the status of the heart. There are several ways to assess heart rate and the most precise one is using an electrocardiogram.The more convenient way to measure heart rate is to utilise a Heartbeat Sensor. It comes in a variety of shapes and sizes and provides an immediate way to assess the heartbeat.The Heartbeat Sensor works on the Photoplethysmograph concept. According to this theory, changes in the volume of blood in an organ are measured by changes in the intensity of light passing through it. A heartbeat sensor's light source is often an IR LED, with the detector being any Photo Detector such as a Photo Diode, an LDR (Light Dependent Resistor), or a Photo Transistor.We can organise these two components, a light source and a detector, in two different ways: Two types of sensors: transmissive and reflective. In a Transmissive Sensor, the light source and detector are facing one other, and the person's finger must be placed between the transmitter and the receiver. Reflective Sensors, on the other hand, have the light source and detector adjacent to each other, and the user's finger must be put in front of the sensor. A basic Heartbeat Sensor has a sensor and a control circuit. The Heartbeat Sensor's sensor comprises of an IR LED and a Photo Diode mounted on a clip.The Control Circuit is made up of an Op-Amp IC and a few more components that help to link the signal to a microcontroller. A circuit schematic will help us understand how the Heartbeat Sensor works.The circuit shown above depicts a finger-type heartbeat sensor that detects pulses. Every heartbeat alters the volume of blood in the finger, as does the light from the IR LED that passes through the finger and is detected by the Photo Diode.

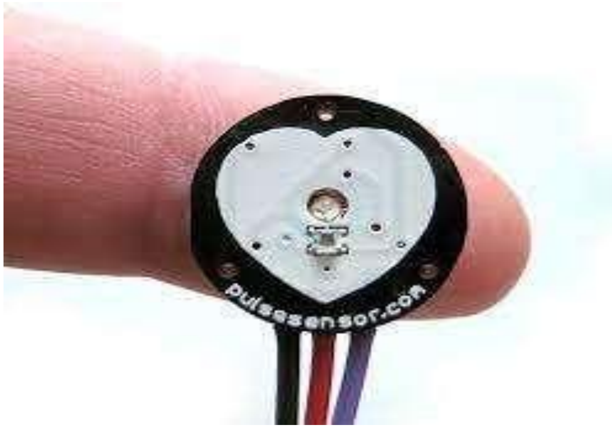


Fig.4. Heart Rate Sensor

LCD Display: A 16x2 LCD display, a veteran in the domain of alphanumeric output modules, consists of a matrix of 16 character locations across two rows, providing a canvas for the representation of up to 32 characters in total. These displays, which operate normally via parallel connections, are ideal for seamless integration into a wide range of electronic settings, making them indispensable in the repertoire of embedded systems design. These LCDs are often used to transmit ASCII-encoded information, which includes letters, digits, and various symbols. They are typically driven by a nominal 5-volt DC source and include an inbuilt contrast adjustment mechanism, allowing for precise visual quality control. When combined with LED backlights, their efficacy is increased, making them indispensable in applications that require visibility in a variety of ambient lighting conditions. These adaptable displays are widely used in the field of digital instrumentation, including areas as diverse as real-time clocks, instrumentation panels, and embedded user interfaces, with their prowess supported by the dexterous orchestration of microcontroller systems. Dynamic libraries and thorough documentation strengthen developers' arsenals, making it easier to interact with these displays and realise their full potential in the digital environment.

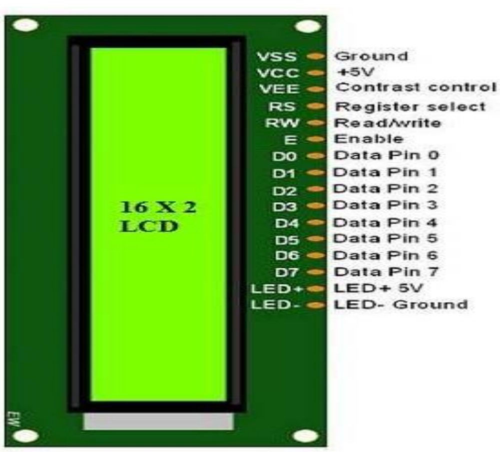


Fig.5. LCD Display

1-wire Temperature Sensor: The pre-wired and waterproof DS18B20 sensor provides accurate temperature measurement in a wide range of situations, with an operational temperature range of-55 to 125°C (-67°F to +257°F). It uses a 1-Wire interface with adjustable resolutions of 9 to 12 bits and requires only one digital pin for communication. Each chip has a unique 64-bit ID burned into it for simple differentiation when many sensors use the same pin. Its ±0.5°C precision from -10°C to +85°C, along with a temperature-limit alert mechanism, ensures exact monitoring. The sensor's stainless steel tube and PVC jacketed cable are durable, however the PVC limits the operating temperature to less than 100°C. Furthermore, its compatibility with 3.0V to 5.5V power/data makes it suitable for a variety of systems. Although the Dallas 1-Wire protocol necessitates complex code parsing, the sensor's digital nature ensures no signal deterioration even over long distances, making it an excellent choice for distant or wet environments. The DS18B20 sensor is highly precise, achieving a temperature accuracy of ±0.5°C across its operational range (- 10°C to +85°C). This level of precision makes it appropriate for a variety of applications, including environmental monitoring, industrial operations, and HVAC systems. The sensor's 1-Wire interface simplifies connectivity by requiring only one digital pin for communication. This feature facilitates integration with microcontrollers and other devices, and because numerous sensors can share a single pin, it enables the building of multi-sensor networks for comprehensive temperature monitoring.

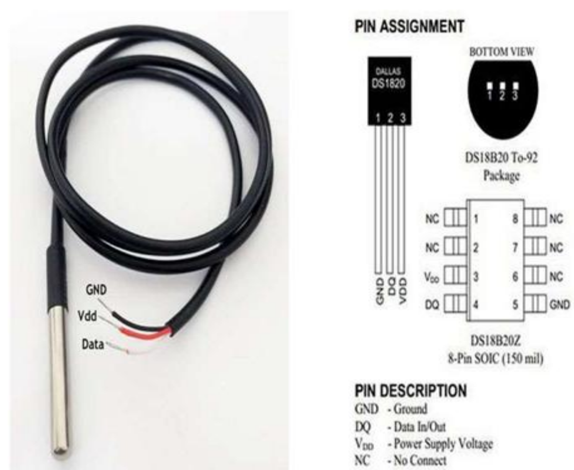


Fig.6. 1-wire Temperature Sensor

ECG Sensor: An ECG (Electrocardiogram) sensor is an essential equipment that monitors the electrical activity of the heart, usually through electrodes put on the skin. These sensors detect and record electrical impulses in the heart, which are then translated into a graphical depiction known as an electrocardiogram (ECG). ECG sensors, which are widely used in medical diagnostics to identify arrhythmias, heart attacks, and other cardiac disorders, are highly accurate and precise in catching small variations in heart rhythm. They are also integrated into wearable fitness trackers and medical monitoring devices, delivering real-time heart rate data and allowing for continuous monitoring outside of clinical settings. With wireless connectivity options and user-friendly interfaces, ECG sensors provide for quick and accessible heart health monitoring for both healthcare professionals and consumers, helping to early identification and intervention in cardiac diseases. ECG sensors monitor the electrical impulses produced by the heart during contraction and relaxation, also known as depolarization and repolarization. These impulses go throughout the body and can be measured using electrodes carefully placed on the skin's surface. Modern ECG sensors frequently use complex signal processing techniques to filter out noise and artefacts, resulting in accurate readings even in tough conditions. Furthermore, some ECG sensors include multi-lead setups, which provide extra information about the heart's electrical activity from various perspectives. This enables for a more thorough cardiac examination, particularly for identifying complex illnesses like myocardial infarction or conduction anomalies.

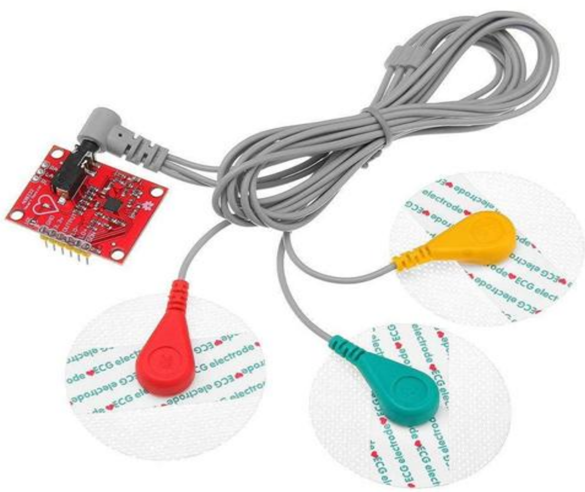
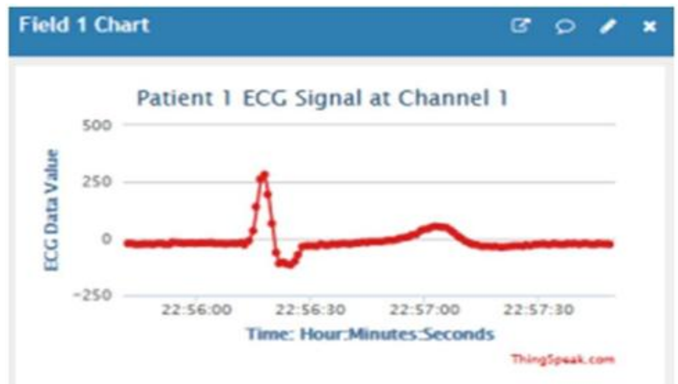


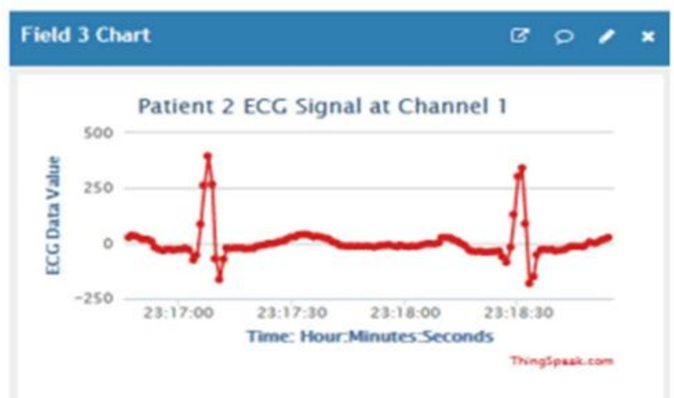
Fig.7. ECG Sensor

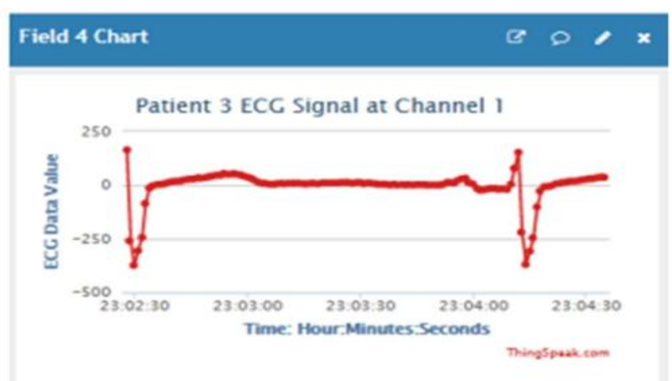
V. IMPLEMENTATION

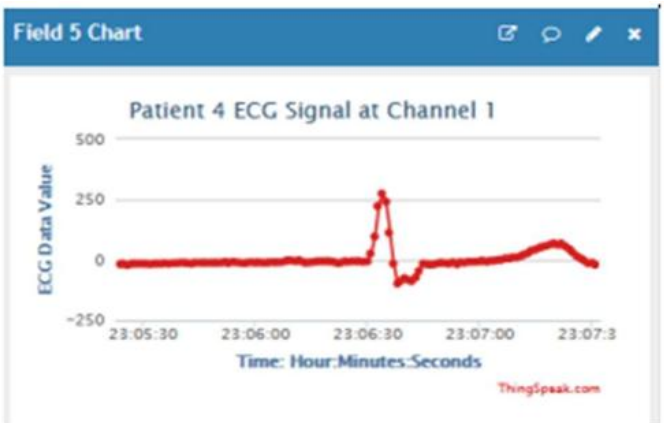
Working: The Internet of Things-based hybrid approach for cardiac arrythmia The implementation process includes several stages that are necessary for effective Machine Learning (ML) analysis. Beginning with library importation, major modules such as 'numpy' for scientific computing, 'pandas' for data manipulation,'matplotlib.pyplot', and'seaborn' for data visualisation are used. Data pre-processing is the cleaning and transformation of raw data in preparation for analysis, including the handling of missing values (NaNs) using techniques such as removal, forward/backward fill, or mean substitution. Data analysis then dissects, changes, and models the data to extract useful information, whereas feature extraction transforms raw data into numerical traits to improve model performance. Splitting the dataset into training and testing subsets makes model evaluation easier, with accuracy assessments used to estimate prediction performance. Algorithms such as Random Forest, K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, Weighted KNN, and Decision Tree are evaluated for accuracy in predicting outcomes based on the provided dataset. Weighted KNN, SVM, and Decision Tree show the highest accuracies, highlighting their efficacy.

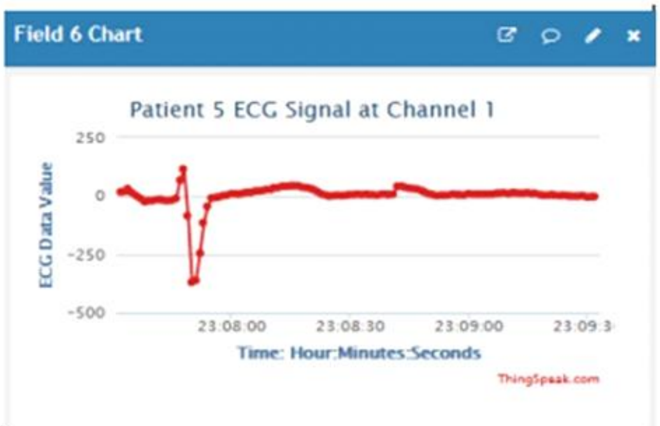
VI. RESULTS

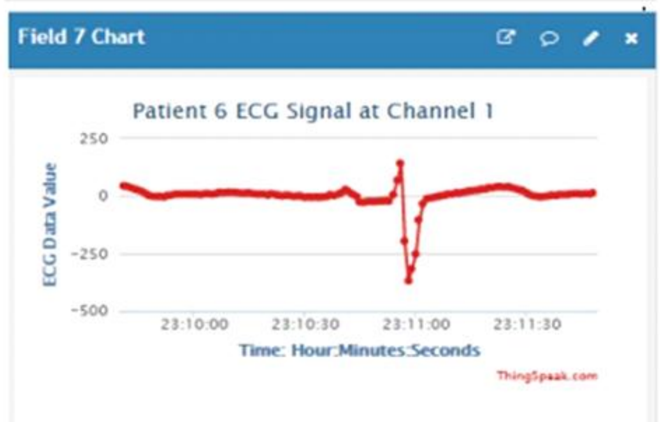












VII. CONCLUSION

The results clearly indicate that machine learning can aid in the diagnosis of cardiac arrhythmias. It aids in the diagnosis and prediction of cardiac arrhythmias. The capacity to detect cardiac arrhythmias at an early stage would enable timely intervention. Furthermore, the findings highlight machine learning's potential to dramatically improve the early detection and prediction of cardiac arrhythmias, allowing for timely medical interventions. Healthcare practitioners can improve patient care and outcomes by employing algorithms like Random Forest, Support Vector Machine (SVM), and Decision Tree, all of which shown high accuracies in this study. Furthermore, the ability to detect cardiac arrhythmias early on not only allows for rapid medical attention, but it also opens the door to personalised treatment plans customised to the needs of each patient. As a result, incorporating machine learning technology into clinical practice has the potential to revolutionise cardiovascular health management, leading to better patient outcomes and lower healthcare costs.

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