Prediction of Cardiac Arrhythmia using Machine Learning

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***Abstract* - Cardiac arrhythmia is an irregular heartbeat that might be excessively fast, too slow, or unstable. Electrocardiography (ECG) is a test that identifies heart arrhythmia. It uses electrodes placed to the chest to record the neural signals of a patient's heart across a long period. Doctors often examine ECG signals to identify cardiac arrhythmias because they reflect the physiological state of the heart. A crucial medical skill specialist is the ability to recognize harmful types of heart arrhythmias from ECG data. However, a doctor's manual interpretation of ECG waveforms is tedious and time-consuming. As a result, developing automatic approaches to identify abnormal circumstances from routinely collected ECG data is critical. Furthermore, if cardiac problems can be diagnosed automatically through health monitoring, prompt first aid procedures can be applied quickly. Machine learning algorithms are used inside by the equipment. In this case, machine learning will be crucial. While increasing cardiovascular disease (CVD) risk factors are linked to an increased likelihood of developing heart issues in humans, CVD is caused by ECG fluctuation signals and certain clinical situations. The algorithm Random Forest (RF) is implemented in the proposed work and obtained an accuracy of 98%.**

Keywords:- Electrocardiograph), Cardiovascular Disease (CVD), Random Forest (RF) ,Machine Learning algorithm.

I. INTRODUCTION

Cardiac arrhythmia is a phrase used to refer a range of cardiac arrhythmia problems for which the heartbeat is irregular, rapid, or slow. Arrhythmias come in a variety of forms, some of which have no symptoms. When symptoms do occur, tremors or a sense of a pause in heartbeats may be noticeable. In more extreme situations, light-headedness, fainting, chest tightness, or chest pain may develop. indicate an underlying heart condition or disease, such as heart disease or cardiomyopathy. Therefore, it is important to consult a healthcare professional if you suspect you have an arrhythmia or if you experience symptoms such as palpitations, chest pain, shortness of breath, or fainting. Depending on the type and severity of the arrhythmia, treatment options may include medication, lifestyle changes, or procedures such as ablation or implantation of a pacemaker or defibrillator. In some cases, surgery may be necessary to correct the underlying problem.

Approximately 80% of due to heart deaths are caused by ventricular arrhythmias. Arrhythmias can strike anyone at any age, but they are more common in the elderly. Arrhythmia is triggered by a disturbance in heart rate abnormalities, but certain conditions such as hypothyroidism, anemia, or chronic obstructive pulmonary disease (COPD) can cause a slower heart rate (bradycardia). On the other hand, conditions such as hyperthyroidism, caffeine or alcohol consumption, and certain medications can cause a faster heart rate (tachycardia). A heart rate that is consistently above or below the normal range may be a sign of an underlying health problem and should be evaluated by a healthcare professional. Arrhythmia until there is an exogenous trigger, such as drug abuse or an electric shock. Pulses may not be able to flow through the heart adequately if there is a root problem, increasing the risk of arrhythmia. This means that the electrical impulses that control the heartbeat originate from the sinoatrial (SA) node, which is located in the right atrium of the heart, and are conducted in a regular pattern through the atria and ventricles. A normal sinus rhythm is typically associated with a heart rate of sixty to one hundred beats per minute and is considered a sign of a healthy heart..

A cardiac arrhythmia (abnormal heart rhythm) is one of the most frequent heart illnesses. It occurs when your pulse is too rapid, too slow, or beats in an irregular rhythm. In fact, most people experience heart arrhythmias on a regular basis. The electrical activity in the heartbeat follows the normal pattern in a normal heart rhythm (normal sinus rhythm).

- The cluster and the pulse can both be continuous (about 50 to 100 beats per minute).
- Tachycardia is characterised by a fast heartbeat (greater than 100 beats per minute)
- A sluggish heartbeat is known as bradycardia (less than 60 beats per minute)

II. HISTORICAL PERSPECTIVES AND CURRENT TRENDS

The machine learning network has made significant progress in recent years in using ECG signals to help diagnose heart diseases [1-6]. With the advancement of technology for artificial intelligence (AI), numerous techniques from the field of machine learning are utilized in the process of feature detection of the electrocardiogram (ECG) signal to address issues related to a large number of signal features and the challenging task of manual intervention. Past two years there is research proposed by researches and they find the optimization-based deep learning approach to classify five distinct heartbeats.

The following machine learning algorithms are used to classify arrhythmias: Support vector machines (SVMs) (11–15), artificial neural networks (16–19), optimal path forests (20), and Independent Component Correlation (ICA) Algorithm [21]. Recurrent neural networks (RNN) or long

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short term memory (LSTM) h ave recently been considered the preferred method by researchers [22–23]. Deep learning methods have also been used to classify ECG signals [24, 25] The block-based neural network, or BbNN, that was designed to classify ECG signals. The internal configuration of the A collection of two-dimensional modular networks make up BbNN. and an adaptable structure The Hermite function is introduced as a feature extraction method and they also use higher-order statistics (HOS) to get better extract features in the SVM classifier method. The Hermite transform coefficient is used as the input of BbNN along with and the duration among neighboring two R peaks. This paper introduces the optimal path forest classifier OPF). Using this method, the results of six distance metrics, six feature extraction algorithms, and three classifiers are compared in two variations of the same data set. In terms of calculation speed during the training and testing phases, OPF is more effective than SVM. data set. In terms of calculation speed during the training and testing phases, OPF is more effective than SVM..These algorithms generally do not involve QRS detection, definite signal pre-processing or feature extraction. These techniques are required larger training datasets which can be challenging as the data of arrhythmia diseases are relatively infrequent in comparison to healthy cases.

Arrhythmia prediction

The prediction of cardiac events or arrhythmias before their occurrences is more challenging application of machine learning in this context. It is very crucial, since a reliable prediction system could alert patients and clinicians both for the cardiac event, thereby facilitating timely involvement in the matter and the prediction of arrhythmic events before their occurrence is still an open problem for researchers [26].

III. APPROACHES

Traditionally, researchers have utilized a variety of heartbeat classification algorithms that typically necessitate a lot of stages of pre-processing, like manually extracting features and noise, among other things. We will examine the flaws because our focus is lightweight arrhythmia monitoring. of the current system for monitoring ECGs and arrhythmias, as well as the challenges of migrating the existing analytics to ultra-edge IoT.the steps needed to use ML algorithms to classify traditional heartbeats. Traditional applications for feature extraction and classification make extensive use of DWT, DDEs, and machine learning techniques. Despite the fact that these ECG analytics methods alleviate many of the drawbacks of manual ECG monitoring, logic-in-sensors cannot be used in conjunction with them due to the significant computational steps involved. When these models are combined with cutting-edge logic-in-sensor IoT devices, the traditional ECG monitoring systems' reliance on multi-lead ECG signals and the need for numerous preliminary procedures (such as noise filtering) present a significant obstacle.

$$f\left(a_i, x_{r_j}\right) =$$
$$a_1 x_{r_1} + a_2 x_{r_2} + a_3 x_{r_3} + \ldots.. + a_{i-1} x_{r_s} + a_i x_{r_1} x_{r_1} + a_{i+1} x_{r_1} x_{r_2} + a_i\, 2 x_{r_1} x_{r_3} + \ldots + a_{j-1} x^2{}_{r_m} + a_j x^3{}_{r_1} + a_j\, 2 x_{r_2}$$

In this situation, $x_j = x(t_j)$, where n, t, m, and j denote the number of delays, time, degree of nonlinearity, and time delays, respectively. It is crucial to use appropriate time-delays and monomials while creating a DDE-based classification system. A typical ECG monitoring system's requirement for internet connectivity in order to connect to cloud servers for ECG studies is another drawback, in addition to the high processing costs, of the system. Because of this, a lot of users eat up a lot of network capacity. Additionally, because data is constantly being transmitted, cloud-based analytics may seriously compromise user privacy. Because of this, obtaining ECG analytics for the purpose of identifying arrhythmias may become more challenging using this method. We are developing a compact solution that would allow for the deployment of a localised automated system with intelligence together with sensor-based logic for cutting-edge IoT analytics. We envisioned a lightweight ECG/arrhythmia monitoring system that could recognise heartbeats from unprocessed single-lead ECG data with the help of AI.

IV. DATA PREPARATION

We used the Physio-Sudden Net's Cardiac Death Holter Database, the St. Petersburg Arrhythmia MIT-BIH Supraventricular Arrhythmia Database, the MIT-BIH Arrhythmia Database[27] to discover arrhythmia. Arrhythmia Database with 12 Leads (INCART). The datasets include recordings of a variety of common and potentially fatal arrhythmias, as well as examples of a healthy cardiac rhythm. Numerous researchers have utilised these files in a variety of ECG-based investigations. The datasets are made up of a text header file, a binary file, and a binary annotation file.

From the annotation files in each dataset, we created four distinct heartbeat The American Association for Medical Instrumentation (AAMI) EC57 standard defines heartbeat types. The datasets used assess for the generalization of the proposed model.

V. PROPOSED SYSTEM ARCHITECTURE

A conceptual model representation of a system that is set up to make it easier to understand the structures and behaviours of the system. System components and planned sub-systems that will cooperate to complete the overall system might make up a system architecture. Languages for expressing system architecture, often known as architecture description languages, have undergone efforts to be codified (ADLs).

A system's basic structure as seen in its components, their interactions with one another and the environment, and the guiding principles guiding its creation and growth may all be characterized. A set of visual representations of a real or hypothetical system is called a statement of work.. These representations begin with an elevated, broad description of a functional structure and evolve through time to become increasingly specific and the architecture diagram for the

Proposed System shown below in Figure. 1

Figure. 1: Architecture Diagram for the Proposed System

a) Data Extraction: The algebraic and formatted dataset was extracted from the ECG. Sexe, age, height, heart rate, and the number of deflections are all taken into consideration. The database for this project is from the UCI Machine Learning Repository. After that, the data are saved as a csv file.

b) Preprocessing: Due to missing values and inconsistent data, the dataset is not ready to be processed in the classification process. Several values were eliminated because each patient had the same value. The variance or standard deviation value is used to check invariant properties. The remaining missing values are filled in with average values.

c) Feature Selection: This is accomplished using two methods: Principal Component Analysis (PCA) and Random Forest. The preprocessed data comprises a lot of features, and the categorization method we chose is a lengthy procedure. To save time and retrieve the most important features that are most closely related to the output class, feature selection is required.

d)The features are selected are then used as input for the five classifications that follow.

e)Each algorithm's accuracy is assessed and displayed.

VI. VI. Different Arrhythmia Diagnoses

VII. A.NormalElectrical Activity

An electrical impulse from the sinus node, also known as the Sino-atrial node or SA node, a small area of tissue in the right atrium of the heart, initiates each heartbeat. Before the atrioventricular (AV) node is activated. Both atria contract as a result of the impulse (main pumping chambers). Humans have a pulse and an average 60-90 beats per minute of heart rate. The average heart rate for humans is between sixty and ninety beats per minute.The resting heart rates of children are significantly greater. Athlete, on the other side, can have a heartbeat of 40 bpm and yet be deemed healthy. When people breathe in and out, their heart rhythms vary among mild acceleration and slowing, which is known as sinus arrhythmia. In children, it is usually very apparent and disappears with time. These can happen during meditation breathing techniques like deep inhalation and breath holding.

B. Bradycardias

Regular P waves, indicating proper sinus node function, are followed by a momentary lack of heartbeats and a pause in supraventricular activity, as depicted. solid black lines. In contrast to the preceding (regular) P-wave, each Pr interval that crosses the pause (represented by the dotted line) begins from a distinct atrial region, indicating an escape rhythm.

A condition known as bradycardia results in a heartbeat that is sluggish (less than 60 beats per minute). Sinus bradycardia, a delayed sinus node signal, sinus arrests, or an This could be caused by an obstruction of the electrical impulse as it moves from the atria to the ventricles (AV block, also known as a heart block).There are three types of heart block: mild, moderate, and severe. Transient AV node poison (drugs that block conduction) may be the cause.or permanent node destruction. Bradycardias can be found inside the hearts of normal-functioning distance runners and other extremely active people. Different types of seizures can cause sinus arrhythmia.

C. Tachycardia's

a heart rate that is higher than one hundred beats per minute at rest minute is considered to be tachycardia in adults and children over the age of 15. Although tachycardia can cause palpitation, it is not always an arrhythmia. An increase in pulse rate can be affected by physical action or emotive stress. Sinus tachycardia is caused by the the action of the central nervous system on the sinus node. When taken or injected, stimulants like coffee or amphetamines, as well as a hypothyroidism gland (t4 and triiodothyronine) or anemic, all stimulate parasympathetic activity in the heart.

VII. HEART DEFECTS

Heart defects that are present at birth and can be seen are known as congenital heart defects. Even if the illness is unrelated to one's overall health, anyone can be affected. Arrhythmias can be extremely rapid or even fatal if the nerve pathway is disrupted. An electrical muscle-filled extra channel in the heart is what causes Wolff–Parkinson–White syndrome. The tissue makes it possible for the heart's electrical impulse to travel at breakneck speed. In adults who are otherwise healthy, intraventricular The most prevalent type of ventricular tachycardia is known as outflow tract tachycardia.This problem is characterized by an abnormal nodal in the heart valve just before the pulmonary artery. The patient experiences ventricular tachycardia when the node is triggered, which prevents the heart from refilling with blood before it begins pounding. Long QT disorder is a serious heart condition linked with an increased incidence of death. Cardiac ablations, medications, and lifestyle changes to reduce stress and enhance movement are one of the treatments offered.

Re-entry

The heart should not stop moving from one end to the other of the body, when an electrical impulse travels recursively inside the heart in a tightly packed circle, this is referred to as a recursive journey. re-entrant arrhythmias occur.Every heart cell has the potential to send excitation impulses in any direction, but only once every few seconds. Normally, the action potential impulse travels quickly enough across the heart that each cell responds only once. Because The impulse will arrive late because the myocardial units are unwilling to activate the rapid sodium channel, and it may be regarded as a fresh impulse if the demand changes in the resistant phase or if transmission is extremely sluggish in certain locations (such as after a heart attack). Autowave vortices, which are vortices of excitement in the myocardium, are thought to be the primary cause of the life-threatening irregular heartbeats that occur as a form of re-entry.] Atrial flutter is caused by the autowave reverberator, which is common in the sidewalls of the atria. Re-entry is responsible for dangerous ventricular tachycardia and Supraventricular tachycardia with the greatest paroxysm.. WPW syndromes, which use aberrant conduction pathways, are not the same as these forms of re-entry circuits.

Fibrillation

Fibrillation happens when the heart's chambers are linked together in a series of micro-reentry circuits, resulting in uncontrolled electrical impulses. The atria, or upper chambers of the heart, are affected by atrial flutter. The atrium (afib) or the ventricular (ventricular fibrillation) can both be affected by fibrillation. with pericardial effusion being the most dangerous.

Atrial fibrillation can be caused by severe health physical illnesses, therefore it's important to have it checked out by a doctor. It isn't usually considered a medical emergency.

Ventricular fibrillation is a medical emergency that happens in the heart's ventricles (lower chambers). Ventricular fibrillation (VF, or V-fib) can progress without treatment. harm you in minutes. When a heart stops pumping blood effectively, it is said to be in V-fib. V-fib is regarded as a form of cardiac arrest. CPR can save a person's life if they don't have a normal pulse, but cardioversion is the only way to get a good heart rhythm back. The technique of providing an electricity to the heart, essentially resets the mitochondria and lets the heart is beating properly again, is known as defibrillation.

Triggered beats

When ion channels in individual heart cells malfunction, improper electrical activity propagation occurs, which can lead to a prolonged irregular rhythm. Anti-arrhythmic medicine can cause them, which is why they are quite infrequent.

VIII. ALGORITHMS

KNN Classifier with RF:

RF- Random Forest – Random Forest is a main algorithm in Machine Learning. It helps to combine the output of multiple decision trees and produce a final output.

The k-nearest neighbour's algorithm, which is also known as KNN or k-NN, is a supervised learning classifier. uses proximity to classify or predict a single data point's grouping. Because it is based on finding adjacent points that are similar to one another, it can be used to solve problems with classification or regression.it is most usually used as a classification tool. We mainly use this algorithm in combination with Random Forest in order to classify the diseased and healthy values (ECG)[27]. Euclidian distance is the major formula used to find the nearest points. K-NN's operation can be described using the algorithm. The first step is to select the Kth neighbor, the second step Determine the Euclidean distance that K neighbors in are from one another. Choose the K closest neighbors based on the Euclidean distance. Count the number of data "z" points in each category among these k neighbors in the short term. The group with the most neighbors should contain the brand-new data points.

SVM Classifier with RF:

Support Vector Machine (SVM), one of the most popular supervised learning algorithms, is utilized to deal with regression and classification issues. However, the majority of its applications lie in classification problems involving machine learning [28, 29]. In order to quickly identify new data points in the future, the SVM method seeks to construct the ideal line or decision boundary that can divide n-dimensional space into classes. A hyperplane is the name given to this boundary of optimal choice. The extreme vectors and points that make up the hyperplane are chosen with SVM. Because of these exceptional circumstances, the procedure is known as a "support vector machine." This method is primarily used in conjunction with Random Forest to distincategorizeguish between the sick and healthy.

Logistic Regression:

One of the most widely used supervised learning machine learning algorithms is logistic regression, which is used to predict a categorical dependent variable using a predefined set of independent factors. For categorical dependent variables, and logistic regression is used to predict the output. As a result, the outcomes need to be discrete or categorical. It provides probabilistic values between 0 and 1, which can be true or false, yes or no, 0 or 1, and so on, as opposed to exact values between 0 and 1.

Except for their application, Linear regression and logistic regression share a lot of similarities. Logistic regression is used to address classification difficulties, whereas linear regression is used to solve regression issues. Use this method to distinguish between ill and healthy numbers (ECG).

These are the procedures: Preparing the data, fitting logistic regression to the training set, and predicting the test result are the first three steps. Finally, the test accuracy is processed by creating a confusion matrix and visualising the test set result.

Naïve Bayes' Classification

It is a simple classification technique that is based on the Bayes theorem. It is based on a strong (naive) independence of attributes. An algorithm [28]that is supervised is the Bayes classifier. A mathematical model-related idea known as the Bayes theorem can be used to calculate probability. The probability of the samples are calculated using following formula

$$\mathbf{Prob(X \mid Y)=(Prob(Y \mid X)*Prob(X))/Prob(Y)}$$

probability. the class (c, target) given predictor's posterior probability is as (X|Y). The prior probability of the class is probability(X). The probability of a given class's predictor is represented by probability (Y|X). The predictor's prior probability is probability(Y).

IX. PERFORMANCE INDICATORS

We combined three measurement indicators to examine the classification results, weighted F1 score, accuracy, and weighted precision The ability of a test to correctly differentiate between the three scenarios determines its correctness. When C is the number of samples in the ith class, TPi instances is the number of instances correctly assigned to the ith class, and length(yi) is the classification task's number of classes (Y is the total number of samples in all classes)..

$$\text{Accuracy} = \frac{\sum_{i=1}^{C}(TP_i instances)}{length(Y)}$$

To assess how exact the model is among those expected to be in the ith class and how many really are, the value of weighted accuracy is multiplied by the weight of the ith class in the following manner.

Weighted precision =

$$\sum_{i=1}^{C}\left(\frac{length\,(y_i)}{length(Y)} \times 2\,\frac{TP_i instances}{TP_i instances + FP_{iinstances}}\right)$$

In this scenario, the number of cases incorrectly classified as belonging to the eighth class is represented by FPi. The total of recall and precision is the weighted F1 score. Therefore, even though we did not directly use recall as a performance indicator, it is implicitly used due to the use of the F1 result. The following is how the weighted F1 score is calculated:

$$\text{Weighted\_F1\_score} = \sum_{i=1}^{C}\left(\frac{length\,(Yi)}{length(Y)} \times 2\,\frac{P_i \times R_i}{P_i + R_i}\right)$$

In the equation above, Pi and Ri represent the I th class's recall and precision, respectively. TPi/(TPi + FPi) is the formula for Pi, and TPi/(TPi + FNi) is the formula for Ri. FNi is the number of examples that have been incorrectly assigned to a class other than the ith class

The number of classes in the classification job under consideration, length(yi) is the number of samples in the ith class, Tpi instances is the number of instances properly recognised as belonging to the ith class, and length (Y),According to the results of the experiments, the best performance for the three convolution layers is achieved with 98% accuracy, precision, and F1_score at 0.9801, 0.9701, and, respectively.

X. RESULTS AND DISCUSSION

The comparative study of different algorithms are shown in Figure 2.

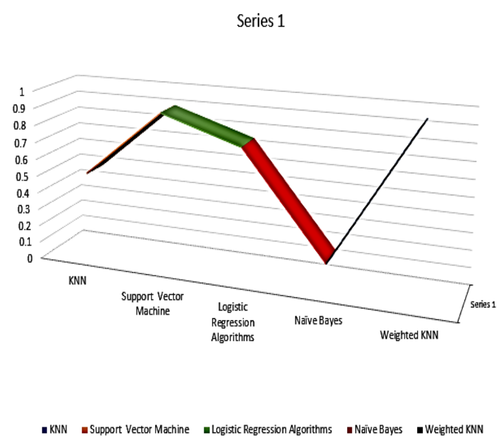

Figure 2. Comparative result of classification algorithm

The screen shots of the reults monitored are shown below. Figure 3. shows the Hardware Components used in project which consist of ECG paddle, ECG Sensor, Arduino board, Wi-fi module, LED display

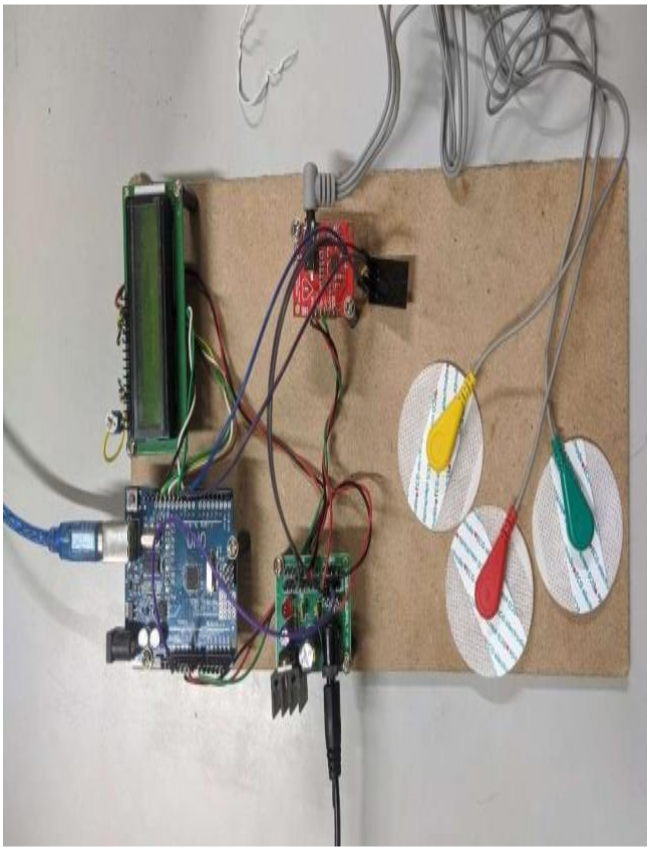

Figure 3: Hardware Components

Figure 4, shows the hardware components in ON state and displaying Cardiac Arrest Monitoring System in LCD display

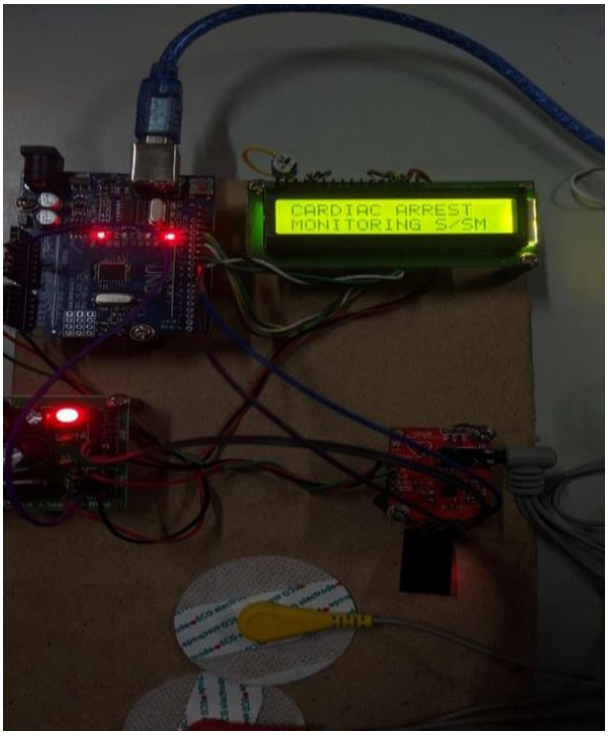

Figure 4:Cardiac Arrest Monitoring System

Figure.5 shows LCD Displaying ECG Value:654 using ECG Paddles,

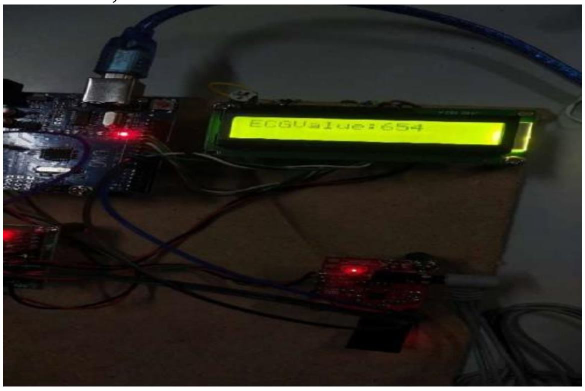

Figure 5: LCD Displaying ECG Value:654 using ECG Paddles

Figure 6 shows the Software Interface ,the entries of the attributes age, sex, height, weight, p-r interval, QRS value.The real values are taken from Hardware Component.

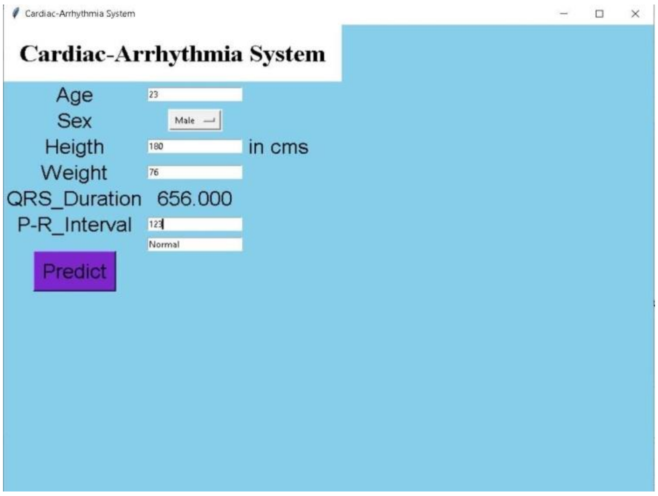

Figure 7: Software Interface

The test cases displays the real-timee result, with the attribute names which shows different status if values between110-125 is normal ,if it is less than, the variations in the heart are represented in status show as the analysis in Table 1

Table 1: Real time test case data

SL NO.	Age	Sex	Height	Weight	QRS duration	PR interval	Status
1	15	Male	150	38	652	125	Normal
2	17	Female	143	34	650	121	Normal
3	22	Male	158	55	658	128	Normal
4	30	Female	155	50	656	126	Normal
5	75	Female	160	73	529	105	Right Bundle Branch block
6	52	Male	163	72	657	123	Normal
7	64	Female	158	68	650	121	Normal
8	66	Male	175	87	890	156	Coronary Artery
9	78	Male	168	80	652	125	Normal
10	63	Female	165	71	655	120	Normal
11	23	Male	70	54	590	115	Sinus tachycardia

VIII. CONCLUSION

The proposed deep learning method has been tested using four different datasets and has shown positive results in its ability to improve the current ECG monitoring system through the proposed method utlizes Smart IoT sensors augtoment the present ECG monitoring method with ultra-edge computing. This research work also utilizes the possibility for integrating intelligence into IoT devices and the promise for lower manufacturing costs for these intelligent sensors. Utilising intelligent IoT sensors for cutting-edge computing.This work serves as an example of the potential for embedding intelligence into IoT devices and could lead to decreased costs for mass manufacturing intelligent sensors.

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