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Deep Learning Based Arrhythmia Classification using Single lead ECG

Shreya S. Burhade, Aakanksha S. Kapadnis, Minal V. Gade

Department of Electronics & Telecommunication Engineering, Sandip Institute of Technology & Research Centre, Nashik, India

ABSTRACT: Cardiac Arrhythmia can be found common in most people these days. Atrial fibrillation (AF) is an irregular and often rapid heart rhythm (arrhythmia) that will result in blood clots within the heart. These respiratory/cardiac diseases have been increasing due to lifestyle changes. It has more than 1 million cases per year it may cause coronary artery diseases heart attacks high blood pressure lung diseases and so on.In recent years Machine Learning methods have provided solutions to functioning on heart disease identification at scale. Manually detecting cardiac arrhythmia can be time-consuming, therefore Using Arduino and an ECG module to measure live ECG signals, a single-lead ECG measurement device has been designed at a low cost. We classified data into three categories Normal, Atrial Fibrillation Rhythm, and Other Rhythms.For the classification of ECG Arrhythmia, Deep Neural has been used in the Network to Train Our model. This method could make the classification of arrhythmias more accessible and affordable.

KEYWORDS: Arrhythmia, Rhythm, Deep Learning, ECG.

I INTRODUCTION

Because of lifestyle changes, respiratory and cardiac diseases are on the rise. There's a protracted list of internal organ diseases that can be treated properly if diagnosed early. A system that will discover cardiac arrhythmia at the lowest price and is simply accessible at a low cost can prove quite handy for a big population. Training a deep learning model on a single lead data set that can be tested on data acquired from a Low-cost ECG module using Arduino can be quite helpful.[1]

Since the 12 lead ECG is expensive and Bulky employing a Single lead ECG for the same can be exceptionally valuable. The single lead is much cheaper and has little estimate compared to the 12 lead ECG. Finding the Dataset for the single-lead ECG for preparing the Profound learning Demonstrate was an errand as not a part of the information for the single-lead ECG is accessible on the web. We discovered over 8500 recordings ranging in length from 10 to 60 seconds that were classified into three categories by professional: normal rhythm, atrial fibrillation rhythm, other rhythms, and noisy signal

Detection of Arrhythmia is a very tedious process if we are using a 12-lead ECG it isn't cost and time-efficient. Detection of arrhythmia using a Single lead three-electrode Portable ECG Module using Deep learning and a Microcontroller is the goal of a portable and simple system. Which can reduce the cost and remove the immobile disadvantage that the bulkier systems possess

An ECG record the electrical signals from the heart. electrodes are attached to the chest to record electrical signals of the heart. an arrhythmia occurs when there is a problem with the electrical system of the heart. In arrhythmia, heartbeats can be too fast or too slow. A Deep Neural Network (DNN) is used for the automatic interpretation of ECG signals to identify abnormalities in a patient's heart. Single-lead ECG is used for basic heart monitoring.

Cardiac arrhythmia may lead to stroke, sudden death, and heart failure. heart arrhythmias are grouped by their speed a) tachycardia and b) bradycardia.

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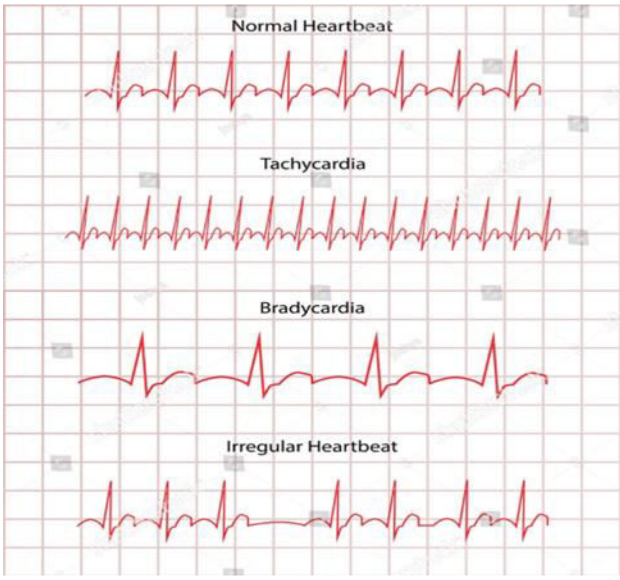

Fig.1. Types of Arrhythmias [2]

Symptoms of arrhythmia consist of fluttering inside the chest, a racing heartbeat (tachycardia), a slow heartbeat (bradycardia), chest pain, shortness of breath, etc. Therefore, our goal is to design a portable ECG measuring system and Arrhythmia classification for Cardiac diseases using a single Lead ECG and a Deep Neural Network.

II.RELATED WORK

In the past few years deep learning has been used to solve many problems around various applications like speech recognition, in Various medical fields and other Visual Applications. For the most part it has further developed in a Feature extraction. Many papers have been published and techniques have been developed in detection of different Types of Arrhythmias using ECG with different Leads.

Sricharan et al.[3] this method of diagnosis is hampered by the lack of accessibility to expert cardiologists. For quite some time, signal processing methods had been used to automate arrhythmia diagnosis. However, these traditional methods require expert knowledge and are unable to model a wide range of arrhythmia. Recently, Deep Learning methods have provided solutions to performing arrhythmia diagnosis at scale. However, the black-box nature of these models prohibits clinical interpretation of cardiac arrhythmia. There is a dire need to correlate the obtained model outputs to the corresponding segments of the ECG. To this end, two methods are proposed to provide interpretability to the models.

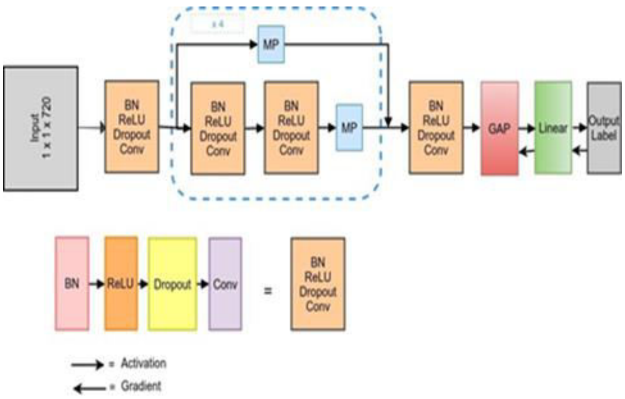

Fig. 2. Schematic of CNN Visualization [3]

The first method is a novel application of Gradient-weighted Class Activation Map (Grad-CAM) for visualising the saliency of the CNN model. In the second approach, saliency is derived by learning the input deletion

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mask for the LSTM model. The visualisations are provided on a model whose competence is established by comparisons against baselines. The results of model saliency not only provide insight into the prediction capability of the model but also aligns with the medical literature for the classification of cardiac arrhythmia.

Dhwaj et al. [4] they developed a Deep Learning (DL) model with a combination of Convolutional Neural Net and Long Short-term Memory assisted by Oversampling technique which classifies the 2017 PhysioNet/CinC Challenge dataset into four classes, i.e., normal sinus rhythm, atrial fibrillation, others and noisy classes with an accuracy better than present techniques. We can integrate this Algorithm to CPS-heart to find abnormalities in the human heart.

Rajkumar et al. [5] studied an intellectual based electrocardiogram (ECG) signal classification approach utilizing Deep Learning (DL) is being developed.

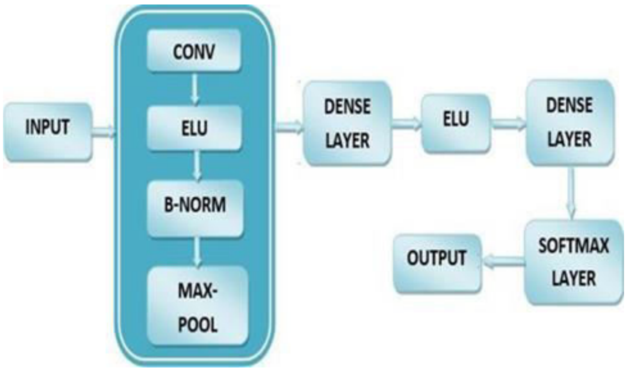

Fig.3. Proposed Block Diagram [5]

ECG plays important role in diagnosing various Cardiac ailments. The ECG signal with irregular rhythm is known as Arrhythmia such as Atrial Fibrillation, Ventricular Tachycardia, Ventricular Fibrillation, and so on. The main aspire of this task is to screen and distinguish the patient with various cardio vascular arrhythmia. This examination encourages us to recognize diverse kinds of arrhythmia utilizing Deep Learning algorithm. Here we use Convolutional Neural Network (CNN) a DL algorithm which is efficient in classifying signals. Utilizing CNN, features are learned Automatically from the time domain ECG signals which are acquired from MIT-BIH Database from Physiobank.com. The feature adapted specifically replaces manually extracted features and this analysis will help the Cardiologists in screening the patient with Cardiac illness effectively. The CNN is trained, tested using ECG Dataset obtained from MIT-BIH Database and from the signal 7 types of arrhythmias were classified. The proposed system is compared for Various Activation function by varying the number of epochs. From the result obtained we came to know that ELU activation function gives better result with an accuracy of 93.6% and with a loss of 0.2.

Halil et al. [6] presented that the ECG uses some methods to diagnose these cardiac arrhythmias and tries to correct the diagnosis. ECG signals are characterised by a collection of waves such as P, Q, R, S, T. These five waves are preformed, wave transformed, and classified. In the current literature, the P, Q, R, S, T waves in ECG signals are classified using some machine learning techniques. In the work to be done, MLP (Multi-Layer Perceptron) and SVM (Support Vector Machine) classification techniques which are not compared with each other using these signals will be compared. Is study, BP (Back Propagation) algorithm with MLP classifier and KA (Kernel-Adatron) algorithm with SVM classifier were used. In addition, the use of these methods is new in the field of ECG classification. It will try to find a more effective method with new uses in the study and the literature will contribute to this area. In addition, wave transformation techniques such as DWT, DCT, and CWT will be used to increase the success of the classification used in the study. This will lead to the most effective classification method in the existing data set. In the work to be done, it is aimed to bring improvements to the classification methods used in existing studies. It is aimed to develop a method to improve the calculation time and standard classification performance of MLP and SVM, and it is aimed to contribute to the informed consciousness of this work.

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Outcome:

Proposed a novel adaptation of visualization techniques of CNN and LSTM for ECG signals. The visualization was observed to line up with the clinical literature in ECG interpretation [3]

Deep Learning (DL) model with a combination of Convolutional Neural Net and Long Short-term Memory assisted by Oversampling technique. It Can integrate this Algorithm to CPS-heart to find abnormalities in the human heart. [4]

Based on the exciting method, classifying ECG signal in Time series analyzes, using Machine Learning.System designed for classifying 7 arrhythmia gives better result while using ELU activation function [5]

Data set will be used in the classification of ECG arrhythmia and in the analysis of diseases in MATLAB application. [6]

We designed a system which gives four types of Classification such as normal, arrhythmia, other, noisy. The hardware we used is cheaper than others (Arduino nano and AD8232 ECG sensor).

Advantages over all the above methods:

- We have a low-cost single lead sensor.
- The Deep learning architecture provide high accuracy results.
- Single lead ECGs are easily accessible.

III.PROPOSED SYSTEM

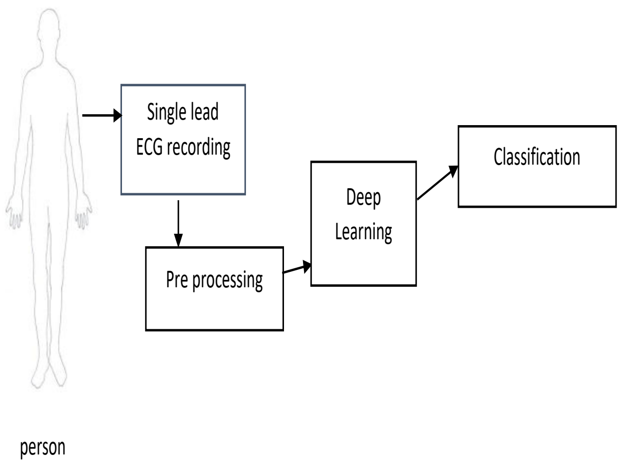

Fig. 4 Schematic View of the Proposed System

AD8232 ECG sensor will record electrical signals of heart by applying the electrodes on body. The placements of electrodes on body are in the fig. 4. These signals are recorded for 30-60 secs.

The AD8232 is an integrated front end for signal conditioning of cardiac biopotentials for heart rate monitoring. It consists of a specialized instrumentation amplifier (IA), an operational amplifier, a right leg drive amplifier, and a mid supply reference buffer. In addition, the AD8232 consists of leads off detection circuitry and an automated fast repair circuit that brings again the signal rapidly after leads are reconnected.

The AD8232 includes a specialized instrumentation amplifier that amplifies the ECG signal at the same time as rejecting the electrode half-cell capability at the identical stage. This is possible with an indirect current feedback architecture, which reduces length and power as compared with conventional implementations.

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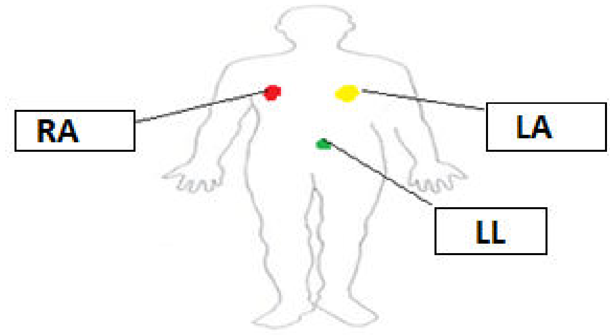

Fig. 5 electrodes placement

Arduino nano is a microcontroller, this will convert ECG recordings into text file. The Arduino Nano is a small, intact, and breadboard-friendly board grounded on the ATmega328P introduced in 2008. It gives the equal connectivity and specifications of the Arduino Uno board in a lower form factor.

The Arduino Nano is equipped with 30 male I/ O heads, in a DIP30-like configuration, which can be programmed using the Arduino Software integrated development environment (IDE), which is common to all Arduino boards and running both online and offline. The board can be powered via a type- B mini-USB cord or from a 9 V battery.

IV.SYSTEM DEVELOPMENT

The dataset we are using is from PhysioNet Challenge 2017, it consists of 8528 sample data of single ECG which is sampled at 300 Hz and ranges in 30sec to 60sec in duration.

The dataset contains four types of ECG signal with different numbers of samples i.e., i) 5154 signals of normal rhythm. ii) 771 signals of atrial fibrillation iii) 2557 signals of others and iv) 46 are noisy.

We trim the raw ECG data from 1-25 secs. After trimming deep learning model will now no longer face any issues for training.

After trimming process ECG is normalized between 0 and 1. Because of normalized data training speed of model is increased.

If the data is highly imbalanced deep learning model will not process on it. That’s why we over sampled data using the technique SMOTE (synthetic minority over sampling technique). This process will increase the accuracy and it also expands deep learning decision making capacity.

Deep learning will perform classification task. As per the recordings deep learning classifies normal, Arrhythmia, Other and noisy rhythm.

The Model has been trained using deep neural networks using a single lead data set provided by PhysioNet challenge. Data sets consist around 8500 recordings annotated by technicians in 4 different classes. In this paper there is a convolution DNN is proposed to detect arrhythmia which takes input of ECG signal from raw ECG sampled at 300 Hz and classifies.

A DNN architecture which accepts an ECG raw signal of 200 samples per second. The architecture takes input of only Raw ECG data. A 34-layer architecture out of which 16 are residual blocks which have two convolution layers.

The Architecture has 32 Layers to lessen the Complication the network consisted of sixteen residuals with two convolution blocks with every block. We have applied Batch normalization before every convolution layer and a rectified linear activation. It has a dropout layer between the convolution layer and the activation layer.

The Convolutions layers includes Filter width of 16 and 32*2k filters where k is the hyper parameter which for every fourth residual block will be incremented by 1 starting from 0(zero). A batch Normalization is used before every Convolution layer and a relu activation adopting a pre activation. Finally, the fully connected SoftMax layer

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produces distribution over four output classes. The model has been trained the use of Tensor Flow and Keras for 20 Epoch.

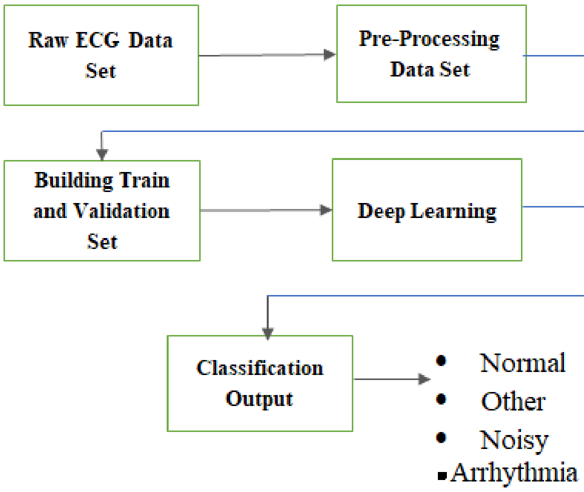

Fig. 6 System development [1]

V.RESULTS & DISCUSSION

AD8232 ECG sensor reads heart signals with electrodes attached to the body after that Arduino nano coverts the recorded data into text file with the help of ECG code as shown in fig. 7.

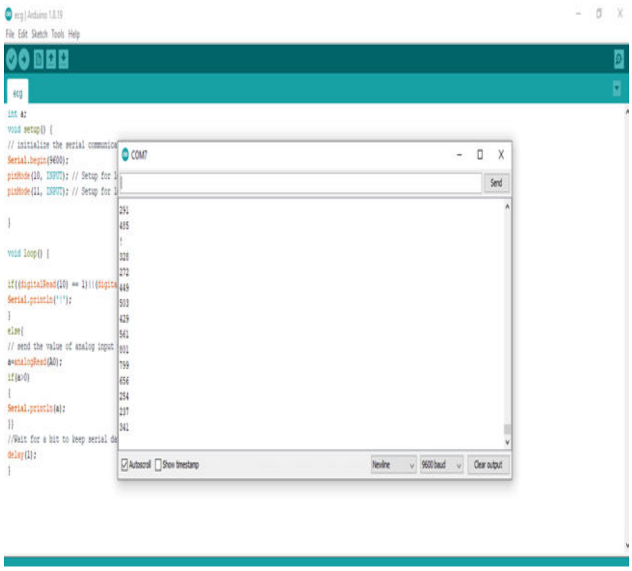

Fig. 7 Arduino code

for prediction it requires mat file so this text file is converted into mat file with the help of text to mat code as shown in fig. 8.

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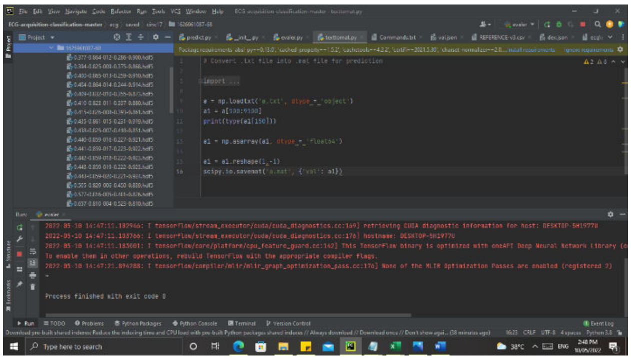

Fig. 8 text to mat code

For output this mat file is run in the evalver code. Our system gives four type of ECG classification such as normal, arrhythmia, other, noisy.

Following are the results:

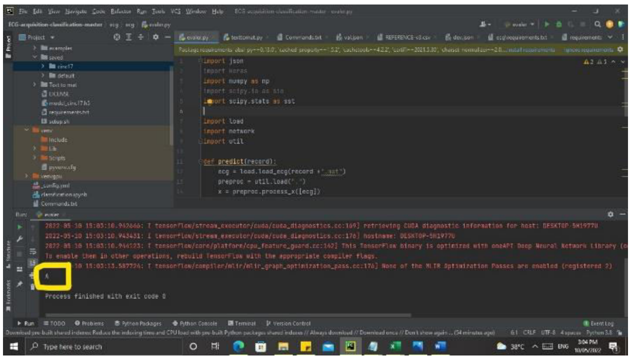

Fig. 9 Arrhythmia (A)

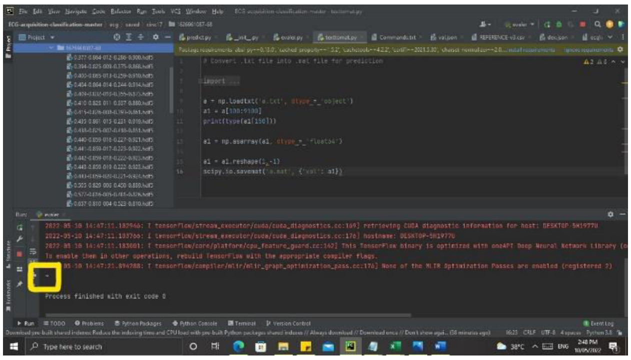

Fig. 10 Noisy (~)

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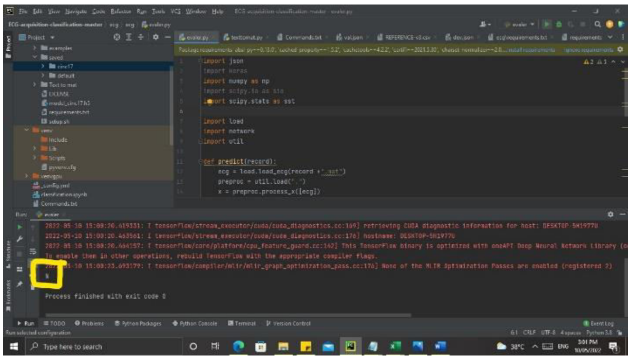

Fig. 9 Normal (N)

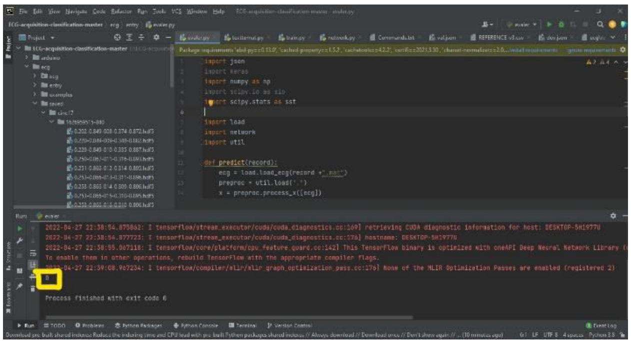

Fig. 11 Other (O)

VI. CONCLUSION

In this paper, using deep learning, we're looking to resolve the arrhythmia detection problem. The hardware is low price and the records is well-annotated, we expect that single-lead classification with a bigger data set can produce extra correct findings. We have derived Four types of ECG Classification (Atrial fibrillation, Normal, Noisy, Other) using a single lead three electrode signal that can be cheap and easy to handle as well as easy to access for people.

VII. FUTURE SCOPE

A. Advantages

- The system does not required power to operate so, it has a long life.
- Easy to operate.
- The Device is portable.
- User friendly and cost effective.
- Quick Diagnosis.

B. Limitations

- Accuracy can be low.

C. Future scope

Depending on the quickly evolving mobile technology, we can create ECG arrhythmia detection in mobile devices. Applications related to creating an arrhythmia pre-announcement system can be done in future research. In future research may develop systems that continuously monitor ECG measurements and intervene as needed.

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