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Detection of Arrhythmia using Single-Lead ECG and Deep Neural Network

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Abstract*: Cardiac arrhythmia is a frequent condition in to- day's society. If the detection is made early on, it can be crucial. Early detection might aid in a quick and painless recovery. Using EKG (ECG), a heart specialist discovered an arrhythmia during the medical history. The disadvantage is that detection calls for skilled professionals. Automatic detection is now necessary due to the demand for professionals in every detection. However, these antiquated methods require expert data and are unable to model a wide variety of cardiac illness. Machine learning techniques have recently offered ways to take action on widespread heart disease identification. We have an 8500 single lead ECG recordings dataset for training that contains Around 10–60 seconds. To monitor a live ECG signal, we have also created single-led ECG measuring device utilizing an Arduino and an ECG module. Three categories—Normal, Atrial Fibrillation Rhythm, and Other Rhythms—are used to categorize the dataset. To train our model for the classification of ECG arrhythmia, we used deep neural networks. With the use of a single lead ECG data set used for training and testing, the model has been taught to identify three different forms of arrhythmia. To train our model to categorize the Single lead data obtained via an ECG module and an Arduino, we utilized a 34-layer DNN architecture into three groups. With this method, the Arrhythmia classification can be simply accessible and inexpensive. For a single lead data set, our model's accuracy of roughly 82 percent is extremely impressive*

Problem Statement: Arrhythmia detection is a very time- and money-consuming process when done with a 12-lead ECG. The objective of a portable and straightforward system is to detect arrhythmia using a single lead portable ECG module using deep learning and Arduino

Keywords: Deep learning, CNN, ECG, arrhythmia, single lead

I. INTRODUCTION

Due to changes in lifestyle, diseases of the respiratory systemor heart have been on the rise. There is a broad number of cardiac conditions that, if caught early, can be properly treated. Cardiac arrhythmia is the condition that is most frequently produced. Cardiac arrhythmia is a collection of abnormal rhythms that fall under many categories of arrhythmias. While some cardiac conditions are particularly life-threatening, others that appear to be unimportant can raise the risk of cardiomyopathy and stroke. For a big population, a system that can detect arrhythmia at minimal cost and with reasonable ease of access could be very helpful. using a single lead data set to train a deep learning model that can be evaluated with data obtained from Arduino-based low-cost

ECG modules can be quite useful. Using a single lead ECG for the same purpose can be very helpful because 12 lead ECG equipment is expensive and bulky. Compared to the ECG with 12 leads, the single lead is significantly less expensive andsmaller. Finding the dataset for the single lead ECG to train thedeep learning model was difficult because there isn't much information online about these ECGs. We have located about 8500 different recordings, each lasting between 10 and 60 seconds, that have been divided into three categories: normal rhythm, rhythm associated with atrial fibrillation, otherrhythms, and noisy signal.

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II. LITERATURE SURVEY

Deep learning has been utilized in recent years to addressa number of issues in a variety of applications, including speechrecognition, several medical sectors, and other visual applications. Most significantly, feature extraction has improved. Numerous studies have been conducted and methods for detecting various types of arrhythmias utilizing ECGs withvarious Leads have been devised.

[1] In this study, the ECG was divided into various categories using the SVM classifier technique. SVM typically constructs a Hyper plane between the derived classes using the MIT- BIH dataset, which can display data points between the plane.

[2] The research suggests using a 2D CNN module to categorize the ECG into various Classes. They achieved nearly 99 percent accuracy by using a set of MIT-BIH arrhythmia data.

[3] The authors explained the recent Deep learning methods applied to ECG signal for classification while focusing on CNN model.

[4] In order to categorize the five micro-classes of heartbeat types in the MIT-BIH Arrhythmia database, this research suggests a reliable and effective 12-layer deep one-dimensional convolutional neural network.

[5] This research paper discusses about visualizing the saliency of CNN model to classify arrhythmia.

[6] The author of this research uses machine learning to offer an ECG arrhythmia classifier that has a low-demanding feature processing. They have used data from the MIT BH data set and have nearly attained an accuracy of 92 percent for a technique that only needs a single lead ECG.

III. SYSTEM ARCHITECTURE

The hardware portion of the project and the deep learning portion are separated. Module 1: Hardware an Arduino Uno, an ECG sensor, and an SD card module make up the hardwarecomponent. This hardware component assists in remotely collecting ECG data and storing it on a memory card for later classification. We have employed the AD8232, a tiny chip that is used to gauge the heart's activity. Many types of heart disorders can be detected using ECG readings. The AD8232 helps to reduce the noise in ECG signals so that the PR andQT signals are more clearly audible.

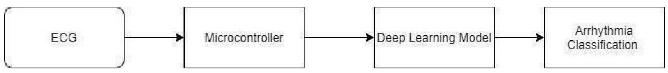

Fig. 1. System Architecture

3.1 Deep Neural Network

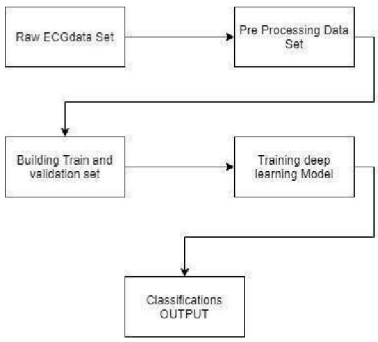

Fig. 2. DNN Process

We used a single lead data set from the Physionet Challenge to train a deep neural network model. We have 8500 recordingsthat have been blessed by technicians across four different classifications. A convolution DNN is proposed in this paper tobe used to detect arrhythmia. It receives an input of an ECG signal from a raw ECG sampled at 300 Hz and classifies the various types of the model was trained using TensorFlow andKear's for 20 epochs, and the results are as follows.

A mathematical model, part D Let S be the total system, where S = I, P, D, and O. I = Input data from Online News. Process = P data set Step 1: Logging into the system Putting thedata into frames for processing in step two. Data preprocessing is step 3. Step 4: Extracting and choosing features. Dataset for training and testing in step 5. Classification is step six. Step 7: The optimized classifier's final output and its performance metric. the output (Online News Predicted class label)

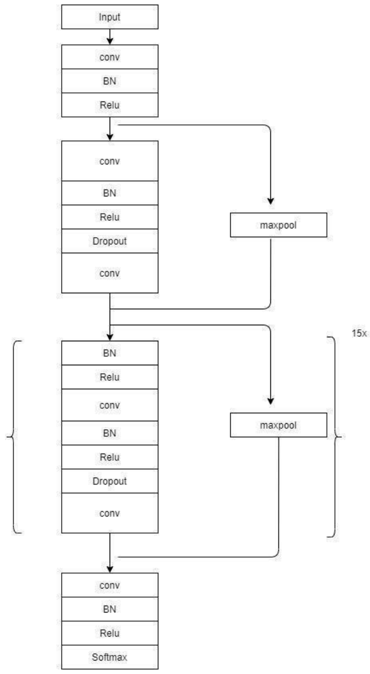

Fig. 3. Proposed DNN Architecture

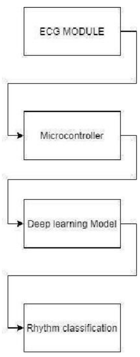

Fig. 4. Flow diagram

3.2 Used Database

ECG recordings from the Physionet Challenge make up the entire data set. ECG recordings were sampled using a bandpassfilter at 300 Hz, as is typical for ECG recordings.

	recording	Time			
		mean	max	median	min
Normal	5154	31.9	61	30	9
AF	771	31.6	60	30	10
Other rhythm	2557	34.1	60.9	30	9.1
Noisy	46	27.1	60	30	10.2
Total	8528	32.5	61	30	9

Fig. 5. Data Set Content

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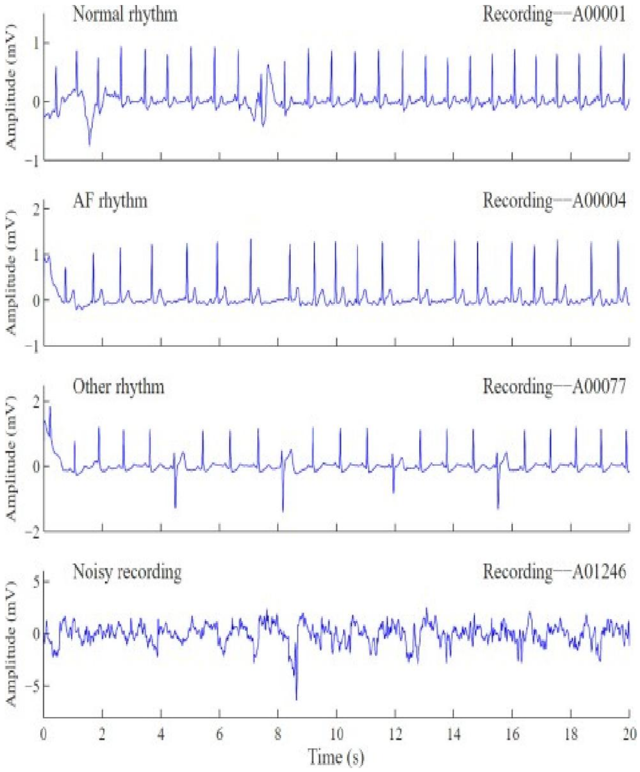

Fig. 6. Data Set Example

IV. RESULTS AND PREDICTION

The test results for the Model are listed below. After testingand all, we were able to average an F1 score of roughly 0.87 across all Classifications. A more precise dataset and more conditions would have increased the accuracy.

Test Results

	Precision	Recall	f1-score
A	0.859	0.912	0.885
N	0.914	0.923	0.919
O	0.803	0.785	0.794
~	0.731	0.613	0.667
avg/total	0.872	0.873	0.872

Reference Classification	Predicted Classification					
		Normal	AF	Others	Noisy	Total
	Normal	143	0	7	0	150
	AF	1	44	5	0	50
	Others	15	0	55	0	70
	Noisy	1	0	0	29	30
	Total	160	44	67	•	

Fig 8. Classification 1

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Reference Classification	Predicted Classification				
	Normal	AF	Others	Noisy	Total
Normal	702	1	65	0	768
AF	2	92	8	0	102
Others	73	4	326	0	423
Noisy	1	0	0	6	7
Total	778	97	399	6	

Fig. 9. Classification 2

When we calculate the F1 score of models on the Validationset provided by 2017 PhysioNet/CinC Challenge on their website ,we obtain the F1 score of 93.61%, F1o score of 80.29% and F1p score of 98.30%. These values are derived from values in TableII by formulas provided in the scoring of 2017 PhysioNet/CinC Challeneg. Then,using the methods provided in the scoring 2017 PhysioNet/CinC Challenge,we calculated the F1 score on the testing set, or 15% of the data set. We obtained theF1 score of 89.22%, along with F1n scores of 90.81%, F1a scores of 94.46%, F1o scores of 81.29%, and F1p scores of 92.30%.

Sr no.	Person name	No. of readings taken	Result from readings	Normal/Total readings	Accuracy
1.	Srushti	10	Normal-9 Other- 1	9/10	90%
2.	Vaishnavi	10	Normal - 8 Noisy - 1 Other - 1	8/10	80%
3.	Sarish	10	Normal - 9 Noisy - 1	9/10	90%
4.	Amos	10	Normal - 8 Noisy - 1 Other - 1	8/10	70%
5.	XYZ	10	Arrhythmia-8 Noisy-1 Other-1	8/10	80%

Average Accuracy = (Normal/Total readings) * 100
= (42/50) * 100
= 84%

V. CONCLUSION

We believe that single lead Classification with a better collection of data sets can give more accurate Results that can point to better results as the hardware is cheap and better data that is annotated. We have Derived Three Types of ECG Classification Using A single lead signal that can be cheap and easy to access for people.

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