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Parallelism: Deep Neural Network Based Arrhythmia Classification Using Single Lead Ecg And Microcontroller

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Abstract—**Cardiac Arrhythmia can be found common in most people these days. It can be vital if the detection is done at early stages. Early detection can help people recover fast and easily. During the medical History the Arrhythmia has been detected using EKG (ECG) by a heart specialist. The drawback is it requires trained professionals for detection. The need of professionals for every detection has raised a need for automatic detection. and However, these ancient strategies need professional data and area units unable to model a good range of heart disease. In recent years Machine Learning strategies have provided solutions to acting on heart disease identification at scale. We have a dataset for training that contains around 8500 single lead ECG recordings that contain Around 10 to 60 secs. We have also designed a Single led ECG measuring system using Arduino and ECG module to measure live ECG Signal. The data set is divided into three classes that are Normal, Atrial fibrillation Rhythm and Other Rhythms. We have used Deep Neural network To Train Our model for the classification of the ECG Arrhythmia. The Model has been trained to classify three types of Arrhythmia using a data set of Single lead ECG for training and taction. We have used a 34-layer DNN architecture to train our model to classify the Single lead data collected using ECG module and Arduino into three classes. This approach can make the Arrhythmia classification easily available at low cost. Our model has shown an accuracy of almost 82 percent which is quite high for a single lead data set**

I. INTRODUCTION

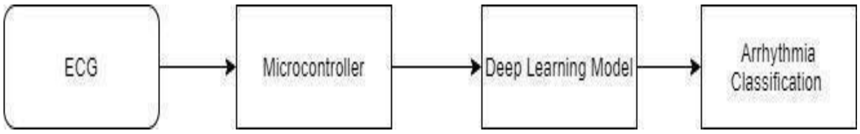
Respiratory or Cardiac diseases have been increasing day by day due to the Lifestyle changes. There is a long list of cardiac diseases which if detected earlier can be treated Properly. The most common condition that is caused is the Cardiac arrhythmia. Cardiac arrhythmia square measures a bunch of irregular rhythms that can be classified into different types of arrhythmias. While certain forms of heart disease are also critical, other seemingly innocuous heart disease will increase the chance of stroke and cardiomyopathy. A system that can detect Arrhythmia at cheap cost and fairly easily accessible at low cost can prove quite handy for a large 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. As the 12 lead ECG equipment is costly and Bulky using a Single lead ECG for the same can be very useful. The single lead is much cheaper and small in size as compared to the 12 lead ECG. Finding the Dataset for the single lead ECG for training the Deep learning Model was a task as not a lot of data for the single lead ECG is available on the internet. We have found around 8500 different recordings of 10 to 60 secs that have been labeled by technician for 3 classes that are normal rhythm, Atrial fibrillation Rhythm, other rhythms and Noisy Signal

II. LITERATURE SURVEY

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. Mostly it has improved in a Feature extraction. Many papers have been published and techniques have been developed in detection of different Types of Arrhythmia using ECG with different Leads. [1] In this paper they have used a SVM classifier algorithm to classify the ECG in different types Using the MIT-BIH dataset, SVM usually creates a Hyper plane in between the derived classes which can visualize data points in between the plane 91 % accuracy was achieved during this. [2] A novel @D Convolution Neural Network has been proposed in this paper for classification of five different types of Arrhythmias. Here the ECG is converted into heart beat and each heartbeat is processed in grey scale, images for the input of CNN. The model was trained on a MIT BIH data set which had almost 97 percent accuracy. [3] In this paper the author has presented an ECG arrhythmia classifier using a machine learning approach Echo state it has a low demanding feature processing that only requires a single lead ECG, they have used data set from the MIT BH data set and have almost obtained an accuracy of 92 percent. [4] The paper has proposed a 2D CNN module to Classify the ECG into different Classes They have used a MIT-BIH arrhythmia data set which has got them almost 99 percent accuracy. [5] This paper has implemented ECG classification using Wavelet transform and multiple Recurrent neural networks. The algorithm is lightweight and can be used for wearable devices; the

MIT BIH data set has been used to test the results. [4] have proposed Combination of CNN and LSTM to capture the Spatial and temporal options In the Domain of images there has been significant progress has been made to supply interoperability of CNN models. Majority of the systems developed have used Multiple Lead ECG data set ECG classification using Single Lead data set can be very cheap and easy to use if the accuracy acquired is high through which it can be used in low-cost systems for continuous ECG and remote ECG monitoring

III. SYSTEM ARCHITECTURE



A. PROBLEM STATEMENT-

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 Single lead Portable ECG Module using Deep learning and Arduino is the goal for a portable and simple system.

B. OBJECTIVE –

Design a System to detect different Types of Arrhythmia using Single Lead ECG and deep Neural Network. To design a Portable ECG measuring System and detection of cardiac diseases. Rhythms. The Architecture had 32 Layers to reduce the Complication the network consisted of 16 residuals with 2 convolution blocks with each block. We have applied Batch normalization before every convolution layer and a rectified linear activation. There is a dropout layer between the convolution layer and the activation layer.

C.SYSTEM ARCHITECTURE-

The Project is Divided into two parts: The hardware side and the deep learning part. 1.Hardware Module: The Hardware part consists of an Arduino Uno, ECG sensor and a Sd card module. This hardware module helps collect the ECG data remotely and store it in the memory card that can be used for classification after words. We have used AD8232, which is a small chip that is used to measure the heart activity of the heart. ECG signals Are used to detect many heart diseases. Generally, ECG signals are very noisy; the AD8232 helps reduce the noise for a clearer signal from PR and QT.

1. Deep neural Network:

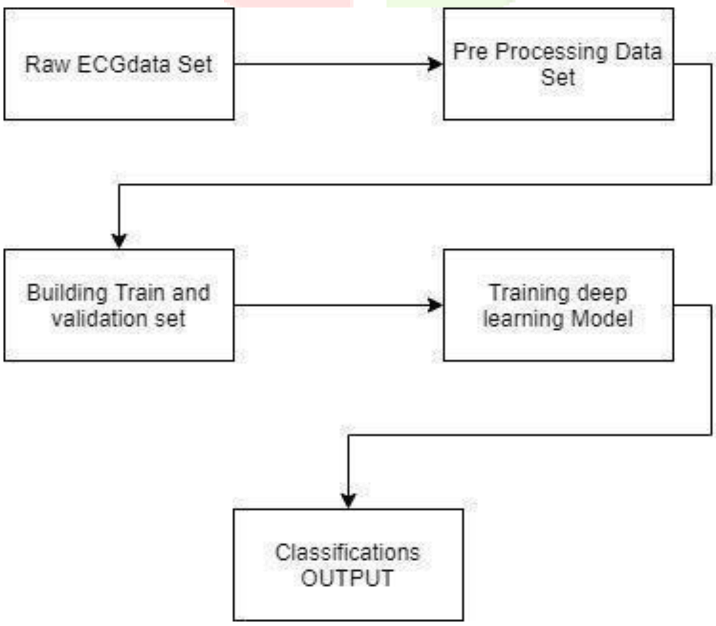


Fig.1 DNN process

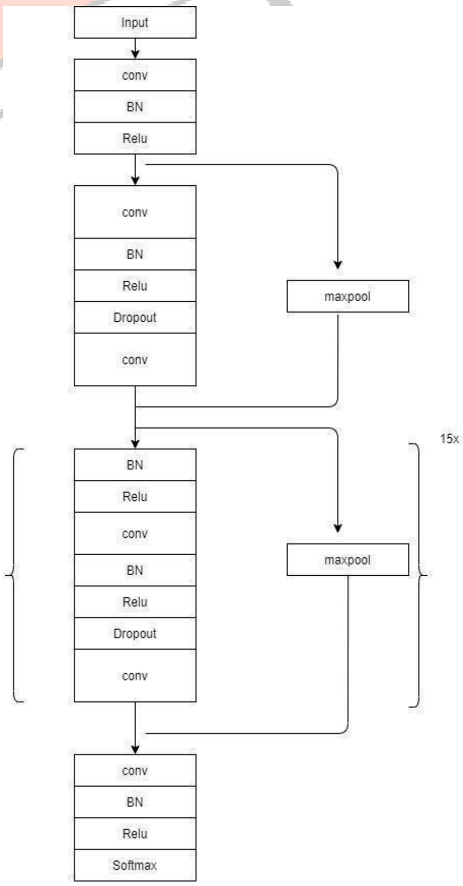


Figure 2: Proposed DNN architecture

we have trained a model using deep neural networks using a single lead data set prided by Physio net challenge. We havearound 8500 recordings anointed by technicians in 4 differentclasses. In this paper there is a convolution DNN that isproposed that is used to detect arrhythmia which takes input of ECG signal from raw ECG sampled at 300 Hz and classifies the different We have trained the model using TensorFlow andKear's for 20 Epoch with following results.

Loss	Accuracy	ValidationLoss	ValidationAccuracy
0.396935	0.86106	0.597745	0.8155

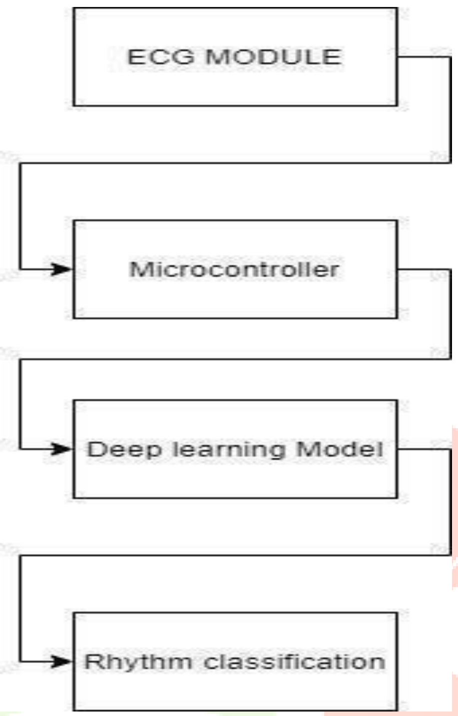


Fig 3: Flow Diagram

B. MATHEMATICAL MODEL

Let S is the Whole System Consist of

S= {I, P,D, O}

I = Input Online News data.P = Process:

D = Dataset

Step1: Entering The system

Step2: Converting the data into frames for processing.

Step3: Data Preprocessing.

Step4: Feature extraction and feature selection.

Step5:Training and Testing dataset.

Step6: Classification.

Step7: Final output optimized classifier and its performanceindicator.

O= Output (Online News Predicted class label)

C. DATASET USED

The data set contains a total of ECG recordings, collected from thePhysio net Challenge. ECG recordings were sampled as ECG recordings are sampled at 300 Hz with a bandpass filter.

Parameters	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**

Table 2: Data set content

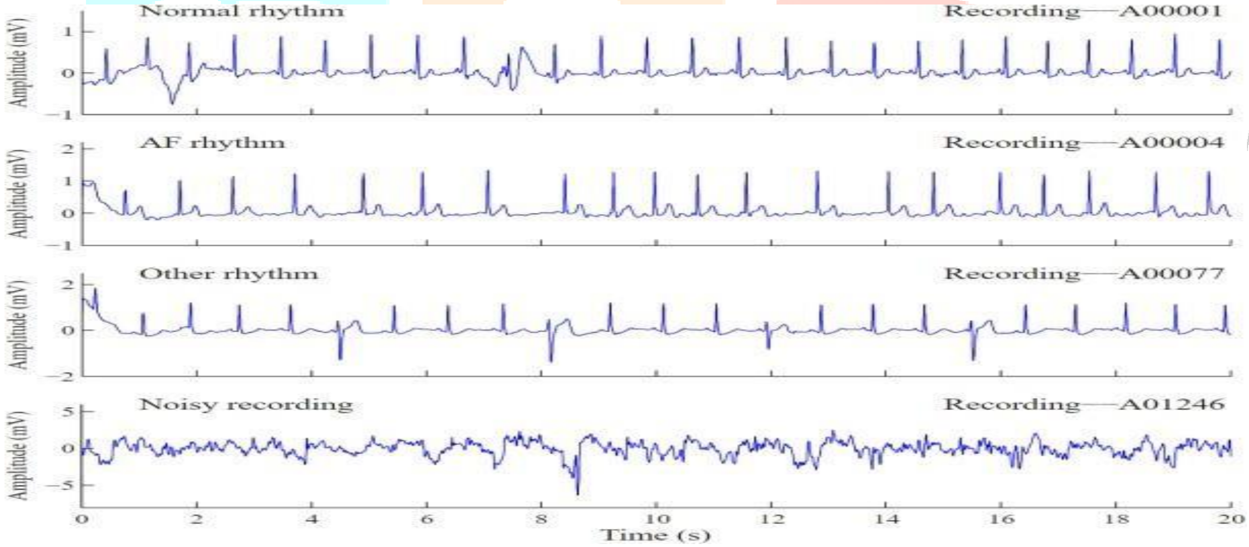


Fig 4: Data set Example

IV. RESULT AND DISCUSSION

Following are the test scores of the Model after testing and all where we have achieved a F1 score of around 0.87 on an average for all the Classifications. The Accuracy could have been improved with a more accurate dataset and more conditions.

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

Table 3: Test results

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	29	

Table 4: Predicted Classification table 1

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	

Table 5: Predicted Classification Table 2

By using 85% data for training and 15% accuracy for testing we get 86.49% testing accuracy then we calculate F1 scoreof models on Validation set given by 2017 Physio Net / Cin C Challenge on their website we got F_1 score 91.11% with F_{1n} score 92.25%, F_{1a} score 93.61%, F_{1o} score 80.29% and F_{1p} score 98.30%,these values are calculated from values in Table II by formulas given in scoring of 2017 Physio Net/Cin C Challenge. Then we calculate F1 score on testing set i.e., 15% of data set then we got F_1score 89.22% with F_{1n} score 90.81%, F_{1a} score 94.46%, F_{1o} score 81.29% and F_{1p} score 92.30% these values are calculated from values in Table III by formulas given in scoring 2017 Physio Net/Cin C Challenge.

V. CONCLUSION

We believe that single lead Classification with a better collection of data sets can give more accurate Results that can point to betterresults 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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