

e-ISSN: 2319-8753 | p-ISSN: 2347-6710

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International Journal of Innovative Research in SCIENCE | ENGINEERING | TECHNOLOGY

# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 11, Issue 6, June 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

# Impact Factor: 8.118

9940 572 462

6381 907 438

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| e-ISSN: 2319-8753, p-ISSN: 2320-6710| <u>www.ijirset.com</u> | Impact Factor: 8.118|

Volume 11, Issue 6, June 2022

| DOI:10.15680/IJIRSET.2022.1106172 |

# DNN Based Arrhythmia Detection Using Low Cost Single Lead ECG

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**ABSTRACT:** Cardiac Arrhythmia can be found common in most people these days. It can be vital if the detection is doneat early stages. Early detection can help people recoverfast 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 onheart 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. Single led ECG measuring system using Arduino and ECG module to measure live ECG Signal has been designed at very cheap cost.. The data set is divided into three classes that are Normal, Atrial fibrillation Rhythm andOther Rhythms. Deep Neural has been used in the 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 action. using ECG module and Arduino

# KEYWORDS: ECG, DNN, Arrhythmia

# 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 measure a bunch of conditions which will be characterized by irregularities within the cardiac rhythm. While certain forms of heart disease are also critical, other seemingly innocuous heart disease will increase thechance of stroke and cardiomyopathy. the foremostcommon tool accustomed Diagnose arrhythmia is the ECG (ECG). The graph may be an easy and noninvasive procedure to assess the electrical activity of the guts. However, identification of heart disease employing a commonplace twelve lead resting graph is difficult by the fact that bound arrhythmic beats will occur occasionally. standard approach has been to perform an offline process of the graph signals obtained from an internet information victimization signal process algorithms that highlight potential anomaly sections for associate graphtechnician.

#### **II LITERATURE SURVEY**

[1] In last Few years deep learning models are used to solve a good vary of issues in vision and speech, showing important a big major improvement in performance compared to feature extraction based mostly approaches. For cardiac arrhythmia classification, Hannun et al.

[2] planned a thirty four layer CNN design that has been shown to be adept in classifying cardiac arrhythmia victimization thirty second single-lead cardiogram rhythms. Zihlmann et al. [3] applied spectrograph rework to the cardiogram Associate in Nursing provided it as an input to a convolutional recurrent neural network (CRNN). Murugesan et al.

[4] proposed combining each CNN and LSTM so as to capture spatial and temporal options. Whereas the recording equipment approach of deciliter models may well be adequate in several usecases, there is a necessity for explicable models in sensitive domains such as medication to know model competence and potential failure cases. Within the domain of imaging, significant progress has been created to supply inter pretability to CNN models by understanding the strikingness of models through works like category Activation Map [5] and Grad-CAM [6]. In addition, a technique to see predictions of a Long Short Term Memory network (LSTM) on Associate in Nursing cardiogram was planned by Westhuizen et al.

[7] through learning Associate in Nursing input deletion mask. However, the analysis is restricted to a single beat that fails within the case of syncopated cardiac arrhythmia like Premature chamber Contraction (PAC).

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# **III. PROPOSED SYSTEM**

# **3.1 PROBLEM STATEMENT**

Detection of Arrhythmia is a very tedious process if we are using a 12 lead ECG ti isnt cost and time efficient. Detection of arrhythmia using Single lead Portable ECG Module using Deep learning and arduino is the goal for aportable and simple system.

# **3.2 OBJECTIVE**

- Design a System to detect different Typesof Arrhythmia using Single Lead ECG and deep Neural Network.
- To design a Portable ECG measuring System AND DETECTION OF Cardiac Diseases.

# **3.3 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.

#### 2 Deep Neural Network:



### Fig 1 : DNN process

We have trained a model using deep neural networksusing a single lead data set provided by Physionet challenge. We have around 8500 recordings anointedby technicians in 4 different classes.

In this paper there is a convolution DNN that is proposed that is used to detect arrhythmia whichtakes input of ECG signal from raw ECg sampled at 300 hz and classifies the different 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 andthe activation layer.

The Convolutions layers consist of 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 Zero. A batch Normalization is used before every Convolution layer and a relu activation adopting a pre activation. Finally the fully connected softmax layer istribution over 4 output classes. The model has been trained using TensorFlow and Keras for 20 Epoch with following results in Table 1.

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# Figure 2: Proposed DNN architecture

We have trained the model using tensorflow andKeras for 20 Epoch with following results.



LossAccuracyValidation<br/>LossValidation<br/>Accuracy0.3969350.861060.5977450.8155

Table 1 : Training Results

Fig 3: Flow Diagram

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# 3.4 MATHEMATICAL MODEL

Let S is the Whole System Consist ofS=

 $\{I, P, D, O\}$ 

I = Input Online Newsdata.P

= Process: D = Dataset Step1: Entering The system Step2: Converting the datainto frames for processing.

Step3: Data Preprocessing.

Step4: Feature extraction and feature selection.

Step5: Training and Testingdataset.

Step6: Classification.

Step7: Final output optimized classifierand itsperformance indicator.

O= Output (Online News Predicted class label)

# **3.5 DATASET USED**

The data set contains a total of ECG recordings, collected from the Physionet Challenge. ECG recordings were sampled as ECG recordings are sampled at 300 Hz with abandpass filter.

Туре	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



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# IV. RESULTS AND DISCUSSION

Following are the test scores of the Model after testing andall 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	Fl-Score
Α	0.859	0.912	0.885
Ν	0.914	0.923	0.919
0	0.803	0.785	0.794
~	0.731	0.613	0.667
Avg/Total	0.872	0.873	0.872

#### Table 3 : Test results

# V. CONCLUSIONS

We believe that single lead Classification with abetter 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.

# VI. ACKNOWLEDGMENTS

I wish to express my profound thanks to all who helped us directly or indirectly in making this paper. Finally I wish to thank all our friends and well- wishers who supported us in completing this paper successfully. I am especially grateful to my guide forhis time to time support, very much needed, valuable guidance. Without the full support and cheerful encouragement of my guide, the paper would not have been completed on time

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Impact Factor: 8.118





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