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A Deep Learning Based Cardiac Arrhythmia Detection System

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ABSTRACT:

For modern medicine, electrocardiogram (ECG) is a key diagnostic evaluation tool of cardiac arrhythmias detections. A deep-learning based classification technique has been proposed in this work to detect the cardiac arrhythmias. This proposed scheme is using deep-learning based network that has been trained previously on a standard ECG data set to do automatic ECG arrhythmia assessments by classifying acceptable ECGs into related cardiac contexts.In simulation result having Confusion Matrix Graph (N, A, O, E it representing four diseases), Confusion Matrix Table to identify accuracy about disease. In Training Performance Graph proved deep learning testing accuracy around 94.26%. In Layered architecture classify different layers used in application of deep neural network convolution.ECG (Electro-cardio-gram) having an important place in medical industries and medical science. But there are many machine based learning to identify diseases using ECG data. The main problem present in Machine learning report is analyzed by doctors it may be possibility prediction or analysis about disease not sure

Keywords— Deep Leatning, ECG classification, convolution neural networks, cardiac arrhythmia, transfer learning

1. INTRODUCTION

In twentieth century Electrocardiogram (ECG) analysis has been developing for the core of heart related disease. In ECG signals shows heart activities with the help of electrical. There are so many diseases can be identifying using ECG like rhythm disorder, cardio vascular problem like arrhythmias. Such kind of diagnosis done with the help of electrodes (six electrodes in chest and four electrodes in limbs.

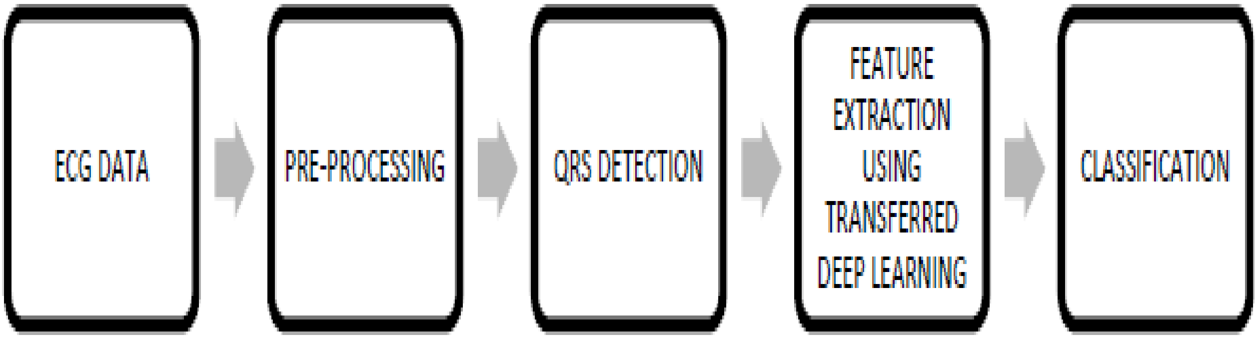

Fig 1: Block diagram of Deep Learning based arrithemmia detection.

To cure heart related diseases firstly importance is diagnosis, monitoring more than 24 hrs using electrical electrodes. There are so many computer based diagnosis method and open access free source available for ECG databases.

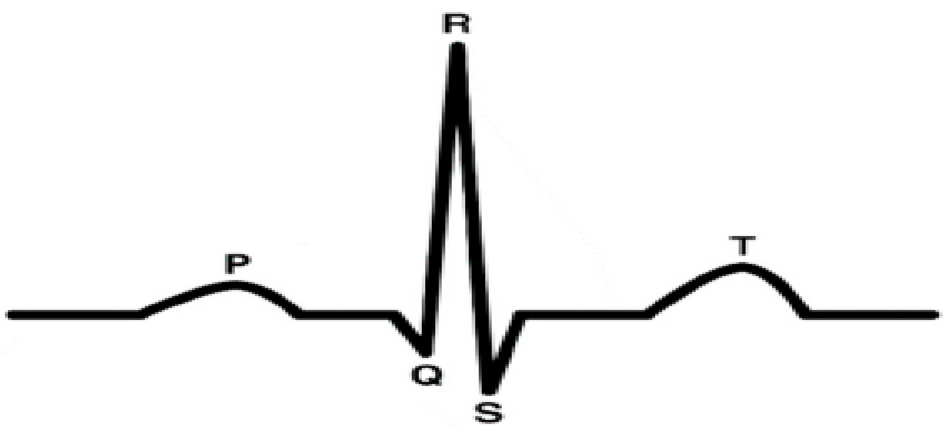

Fig 2: A Conventional ECG Wave form

II RELATED WORK

The basic stages of the ECG processing technique are as follows: (a) Preprocessing (b) Heart rhythm recognition (c) Feature withdrawal and selection (d) Classifier building [3]. For arrhythmia detection, many authors have proposed different types of solutions. The presentedschemes are composed of basic to complicated and advance algorithms also such as linear discriminant (LD) [6–7] or decision trees [5–7] and more complicated ones like deep learning methods [13, 20–22].Additionally, many researchers have concentrated on selecting the best subset (dimensionality decline) for arrhythmia detection, sometimes even using more complex signal processing methods [23].On the one hand, morphological extracted features from the time domain [3, 14, 15, 24], and higher order statistics (HOS) [4, 6, 7, 9] are particularly popular as input features.Feature variety methods, on the other hand, have been used, namely independent constituent analysis (ICA) [18, 26], principal component analysis (PCA) [18], particle swarm optimization (PSO) [16], and the genetic algorithm—back propagation neural network (GA-BPNN) [23]. The proposed heartbeat arrangement method was tested employing two globally renowned ECG databases: the MIT-BIH arrhythmia (MIT-BIH AR) [14] and the AHA [15].

III.PROPOSED WORK

This work proposes an intelligent ECG based Arrhythmia Classification system using untreated EEG data as input and softmax layer as output. In this first the preprocessing of signal is performed, after preprocessing feature extraction is performed and then these features are sent for classification, and the softmax layer output is presented as final output. A deep learning (DL) based signal classification network is the signal processing unit in this work. This DL based network is a 8 layer deep neural network in which we have used first four layers as 1D convolution networks of kernel size 1x55, 1x25, 1x10 and 1x5 respectively with 512, 256, 128 and 64 convolution filters respectively. After each convolution operation the output features are regularized using Batch Normalization and then the output signal is fed to four consecutive Fully Connected layers of neuron size 256, 128, 64 and 4 respectively. Since here we have to classify the signals into four different arithemia classes that's why we have used Softmax layer as output layers. This Softmax layer provides probability of a signal to be belonged to a particular arithemia disease class.

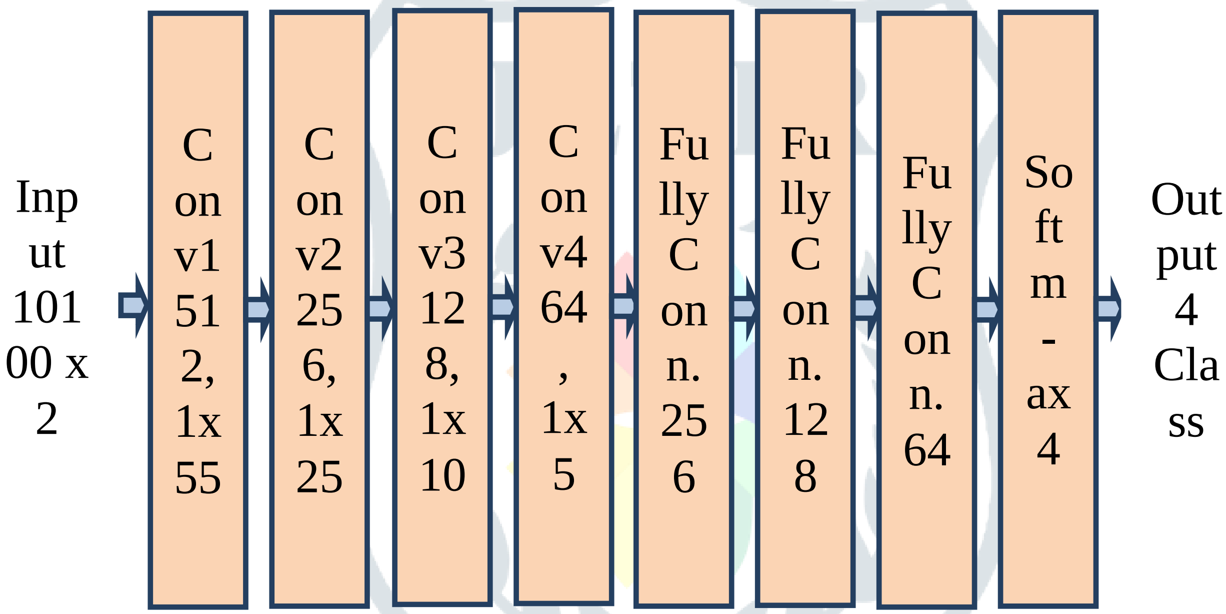

Fig 3: Model Sequential of layers

By using variable Epochs and hyper parameters, the planned system for categorizing four types of arrhythmia is evaluated. We have identified arrhythmias with great accuracy here, makes it much easier for doctors to diagnose cardiac conditions.

Table 1: Different types of layers with output shapes and parameters

S.No	Layer (Type)	Output Shape	Parameter
1	conv1d_1 (Conv1D)	(None, 10046, 512)	28672
2	max_pooling1d_1 (MaxPooling1)	(None, 1004, 512)	0
3	dropout_1 (Dropout)	(None, 1004, 512)	0
4	conv1d_2 (Conv1D)	(None, 980, 256)	3277056
5	max_pooling1d_2 (MaxPooling1)	(None, 196, 256)	0
6	dropout_2 (Dropout)	(None, 196, 256)	0
7	conv1d_3 (Conv1D)	(None, 187, 128)	3277056
8	max_pooling1d_3 (MaxPooling1)	(None, 37, 128)	0
9	dropout_3 (Dropout)	(None, 37, 128)	0
10	conv1d_4 (Conv1D)	(None, 33, 64)	0

11	global_average_pooling1d_1	(None, 64)	0
12	dense_1 (Dense)	(None, 256)	16640
13	dropout_4 (Dropout)	(None, 256)	0
14	dense_2 (Dense)	(None, 128)	32896
15	dropout_5 (Dropout)	(None, 128)	0
16	dense_3 (Dense)	(None, 64)	8256
17	dropout_6 (Dropout)	(None, 64)	0
18	dense_4 (Dense)	(None, 4)	260

Total params: 3,732,612

Trainable params: 3,732,612

Non-trainable params: 0

IV. SIMULATION RESULT

For implementing this network and software simulation, Python and Keras with Tensorflow backend are used. After successful implementation of the DL network, training has been done on a publically available dataset. The training was done on a computer having Intel I7 CPU with no GPU that took 7 hours 17 minutes 11 seconds. After successful training, the proposed network is tested on the test dataset in which we have analyzed 4 types of arrhythmia whose name (N ,A ,O ,E) are Ventricular Flutter Wave,Premature Ventricular Contraction, Left Bundle Block, impulsive Atrial Contraction,Paced Beat, Right Bundle Block as well as Ventricular Ectopic Beat together withNormal Beat with an accurateness of 94.26% and with a loss of 0.22.

Figure 4 represents the confusion matrix of the classification result. In this figure the Y axis represents the true label and the x-axis represents predicted label. From this confusion matrix, we infer that majority of times the proposed classifier detects the true class (arithemia disease) and the average classification accuracy we got is 94.26%. Figure 5 represents the training performance of the proposed DL based disease detector on the training and validation data for 100 epochs. The confusion matrix in numeric form is being represented in table 2. From this table, we infer that the proposed DL based network provides maximum classification accuracy for ‘N’ class that is 98% while it provides minimum classification accuracy 86.80% for ‘O’ class.

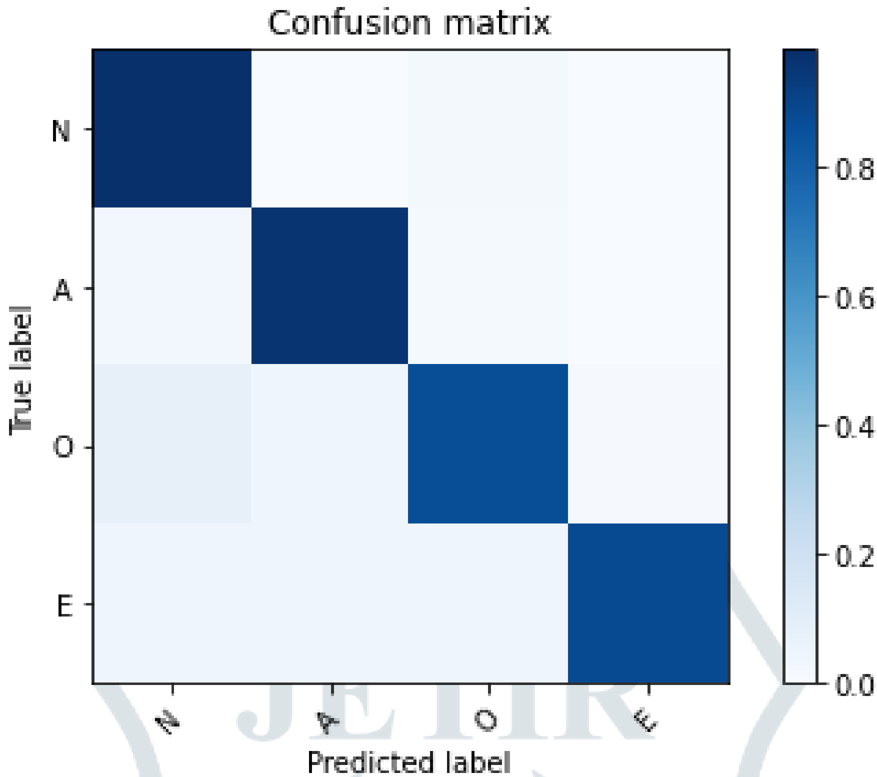

Fig 4: Confusion Matrix graph of 4 types of arrhythmia

Table 2: Confusion Matrix of 4 types of arrhythmia disease

	N	**A**	**O**	**E**	**Accuracy Percentage**
N	490	0	10	0	**98%**
A	2	75	1	0	**96.15%**
O	20	11	217	2	**86.80%**
E	1	1	1	22	**88%**

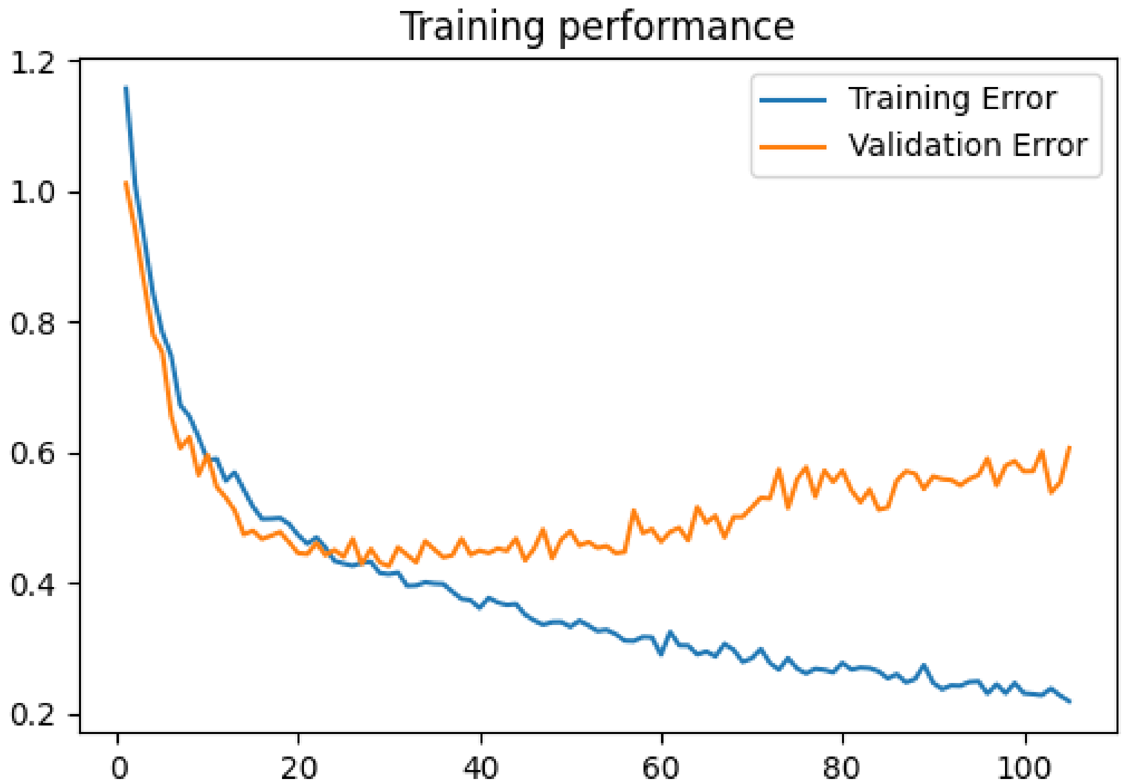

Fig 5: Graph of Training Performance

V. CONCLUSION

This paper proposes a scheme which accepts raw electroencephalogram data as an input, preprocesses it, identifies and extracts features, and delivers through the softmax layer. For every activation function, the output is analyzed and compared. Here we can say that the designed system for detecting different types of arrhythmia works better with an effectiveness of 88.04 % while using the RELU activation function.With an accuracy of 88.04 % and a loss of 0.22, we classified Premature Atrial Contraction, Premature Ventricular Contraction, Paced Beat, Left Bundle Block, Right Bundle Block, Ventricular Flutter Wave, and Ventricular Ectopic Beat, including Normal Beat.

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