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Arrhythmia classification on ECG using Deep Learning

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***Abstract*—In this paper, an intellectual based electrocardiogram (ECG) signal classification approach utilizing Deep Learning(DL) is being developed. 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 arrhythmia 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.**

***Index Terms*—ECG, Arrhythmia, CNN, MIT-BIH Database**

I. Introduction

As indicated by the World Health Organization (WHO) studies [1], cardiovascular disease(CVD) are the fundamental reasons which cause death world broadly. An ECG is a nonlinear and non-stationary diagnostic signal that is important for analyzing cardiac disorders [2]. It is difficult to assess a cardiovascular disorder using ECG because of long processes that require a control in detail and rare arrhythmias. In order to overcome these difficulties, the computer-assisted analysis of biomedical signals has become an essential method in recent years. Arrhythmia and many cardiac disorders usually need to use long-term ECG in inspection controls [3]. Therefore, computer-based assessment and diagnosis systems provide major simplicity and reliability in the diagnosis and treatment of the cardiovascular diseases by the cardiologists. The electrical activity of heart is measured using ECG electrode. It is a bipolar weak signal with low-frequency. The normal frequency range of the signal is 0.05-100Hz [1] and from 10uV to 5mV is the amplitude range, whose normal value is 1mV. Several heart related diseases are analyzed using ECG signal.
Using this typical ECG waveform as in Fig.1, we can diagnose

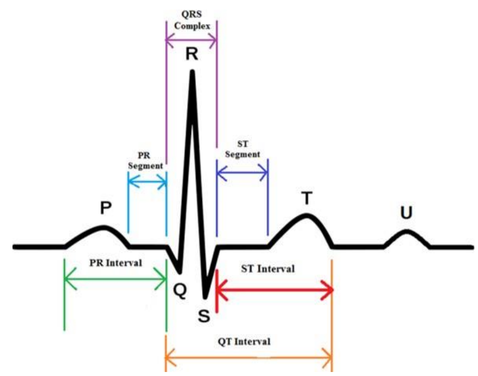

Fig. 1. A Typical ECG Waveform

various abnormalities in our heart. Any variation in the waveform such as increase or decrease in values of amplitude& time period, the absence of any characteristic waves allows the physician to conclude that there is a presence of an abnormality in the heart [27]. Arrhythmias are problem related to the abnormal rhythmic activity and rate of heartbeats [4]. The heart beat can be too fast, too slowly, or inconsistently in different types of arrhythmias, which may feel like antagonism affection or fluttering. Arrhythmia can be classified by Heart rate, mechanism (automaticity, re-entry, triggered) or duration of the heartbeats. Several types of arrhythmia are harmless, but some of them refer to cardiac disorders that may lead to death if not diagnosed & treated. The ECG is a popular diagnosis tool which is of the primary importance for cardiologists [26]. Arrhythmia occurs due to three reasons in general: psychiatric reasons, primarily due to physical and emotional stress and are cardiac causes [9]. Arrhythmias can be classified hazardous and non-dangerous arrhythmias. Many analyzes have been made to investigate the hazardous arrhythmias. Recordings of long-term ECG are required for classification of heartbeat and diagnosis of hazardous arrhythmias which is time-consuming & impossible, automatic arrhythmia classification algorithms reveal a great support. Subsequently, the automatic heartbeat classifications of the latter arrhythmias are imperative be examined and researched for sparing existence of the people. ECG reveals the conduction system, rhythmic activity of the heart which is an significant non- invasive medical tool for

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diagnosing various heart diseases by cardiologists [6]. In order to overcome these challenges, the computer-assisted analysis of biomedical signals has become an essential method in recent years. The computer assisted diagnosis and analysis systems achieve rapid and advanced assessments in long, and hard to identify processes. Arrhythmia and many cardiac disorders usually need to use long-term ECG in inspection controls. Subsequently, computer-based methods and diagnosis systems provide major simplicity and reliability in the diagnosis and treatment of the diseases for cardiologists [5]. This arrhythmia on ECG measurements spontaneously appear as observed deformations and irregularities in the form of waves [9].

Data are collected from the MIT-BIH database are utilized in this investigation reason, which incorporates recordings of many normal and hazardous arrhythmias along with normal sinus rhythm samples. The database includes 48 recordings, each recording contains 2 thirty-minute data from ECG electrode (denoted lead 1 and 2). In 45 recordings, modified-lead II electrode is denoted by lead1 & for the other three is lead V5. Lead V1 is denoted by lead 2 for 40 recordings and for other recordings it is either lead II, V2, V4, or V5. 23 recordings are proposed to provide delegate sample of regular clinical recordings & 25 recordings contain supraventricular and complex ventricular junction arrhythmias. The data are sampled at the frequency range of 360 Hz and band pass filtered at range of 0.1100 Hz. There are more than 109000 ventricular beats from 15 diverse types heartbeats are labelled. The largest class of Normal beat (NOR) with over 75000 beats & the smallest class has 2 beats of Supraventricular premature beat (SP) . The recordings are being separated into two datasets, each dataset containing 48 recordings by means of beat types with similar approximate proportion. Each dataset contains approximately 50000 heartbeats & have a combination of the practice and multifaceted recordings of arrhythmias. For training the execution of system using classifiers, the first dataset (DS1) was utilized and for a final performance assessment of the arrhythmia classification the second dataset (DS2) was utilized. The AAMI endorsed practice were utilized to join the MIT-BIH arrhythmia types into 7 arrhythmia classes which were utilized in all subsequent processing. Each class incorporates arrhythmias of one or more types, class 1 includes beats originating in sinus node (normal beat), class 2 includes premature ventricular contraction(PVC), class 3 includes paced beats(PAB), class 4 includes right bundle block(RBB), class 5 includes left bundle block(LBB), class 6 includes premature atrial contraction(PAC), class 7 includes ventricular fluttering wave(VFW) and class 8 includes ventricular ectopic beats(VEB) [3] [22].

II. Related works

Mohamed Limam et al, proposed a framework to classify ECG signal into AF, N, Alternative rhythm, or noisy signal using 6 layers of CRNN including 2 independent CNNs, to remove related patterns, one from heart rate & other from ECG, which are combined into RNN classifier for representing the progression of the removed patterns. The final result is accessed using a Support Vector Machine (SVM) obtained with an accuracy of 77% [8].

Pourbabaee et al, proposed 5 layer CNN as feature extractor, and by merging the features learned with other classifiers such as KNN, SVM, MLP which had enhanced the execution of patient screening framework as compared to classifier of CNN. It is inferred that KNN classifier gives better result with higher RC, CCR, DOR values [9].

Juyoung Park et al, proposed a framework for detection & heartbeat classification. The framework recognizes heartbeats in the course of rhythmic features and using a k-nearest neighbor(k-NN) algorithm they were classified. Features such as P wave & QRS complex were used and an adaptation of locally weighted regression which is a distance metric algorithm used as the classifier, and Classified 17 types of arrhythmia with an accuracy of 96% [10].

Shalin Savalia et al, proposed a framework with CNN and MLP were the MLP(MultiLayer Perceptron) algorithm uses 4 hidden layers & the CNN uses 4 convolution layers. And classified 7 types of arrhythmia using CNN and MLP, compared their outcome and reasoned that MLP is better with 88.7%. because in CNN 2 diseases, ventricular bigeminy & first degree AV block (FAV) have mispredicted [11].

Serkan Kiranyaz et al, proposed 1D CNN a dedicated CNN model which is trained for specific patient, it is used to distinguish long term ECG data stream in an accurate manner. It is trained using comparatively common & patient-specific training data, Due to its simple and standard parameter nature, the proposed system is highly nonspecific. They classified VEB and SVEB arrhythmia with an accuracy of 99% [12].

Tae Joon Jun et al, proposed 2D CNN with 11 layers to classify 7 arrhythmias. Each ECG beat is distorted into 2D grayscale image & given as an input for classifier of CNN. The evaluation was performed using ten-fold cross-validation which involves each ECG recording as test data and as a result accuracy of 99% were obtained [13].

Pranav Rajpurkar et al, trained a 34-layer CNN which maps a sequence of rhythm classes by ECG models. Their model go beyond the performance of cardiologist in identifying a heart arrhythmias in wide range from single-lead records of ECG and classified 14 types of arrhythmia with an accuracy of 80%. They have not detected Ventricular Flutter or Fibrillation which is an arrhythmia related to Cardiac arrest [14].

III. Proposed System

Based on the exciting method, classifying ECG signal in Time series analyzes, using Machine Learning. Deep Learning gives the best outcomes which is the emerging trend in medical field analyzes which concerns more consideration in biomedical signal processing.The existing method requires preprocessing stage (Denoising, Feature Extraction) and classification (classify signal).

Here we use CNN a Deep Learning algorithm to classify the ECG signal because of its high performance in pattern recognition. The main feature of DL is that it doesnt requires any preprocessing stage, raw data is given as input to CNN and it automatically preprocess and extract the features and produce the output.

It is the primary methodology of DL, where various leveled layers are train vigorously using stochastic gradient decent (SGD) algorithm. It is a supervised feature learning mechanism and also a prominent technique for feature extraction and classification of raw time-series data [15].The SGD strategy works more rapidly and effectively than batch learning strategies,incredibly when it is connected to a enormous data set. It is a vigorous learning technique with respect to displacements, interpretations, unwanted effects and distortions on the input signal [9]. A multichannel CNN is utilized for both feature extraction and classification assignments that is applied to various time-series data [16].

Here we propose a intellectual based screening framework which substitutes the manual features. Utilizing the CNN the system learns automatically from the raw ECG time-series signals. The well-built feature learning potential of CNN makes them an superlative & appropriate decision for multidimensional signal processing applications. It learns a discriminative representation of raw ECG time-series signals as input in the time domain.

Our system designed is used to classify following arrhythmia Premature Ventricular Contraction, Left Bundle Block, Ventricular Flutter Wave, Premature Atrial Contraction, Right Bundle Block and Ventricular Ectopic Beat, Paced Beat including Normal Beat (N) as in TABLE II. These cardiac conditions are important in diagnosing the Cardiac function so it is important to classify these arrhythmia as early as possible. The raw ECG signals are given through a CNN and passes to other layer of the model as in Fig.2 [23] [24].

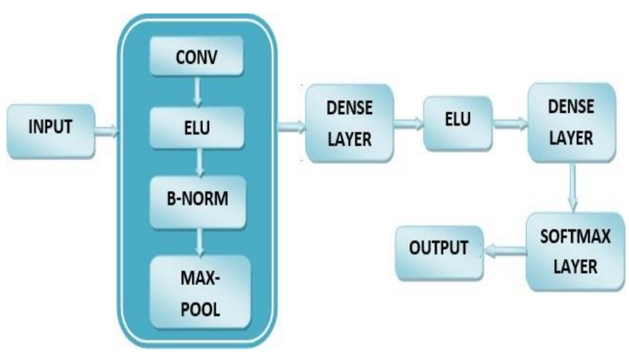


Fig. 2. Proposed Block Diagram

A. Data augmentation

Data augmentation can efficiently reduce over fitting and preserve distribution in balance manner between classes. This benefit is mainly important in clinical analysis of data on the grounds that most clinical information are typical& only some data are unusual. In this sort, owed to the gradient descent learning, the normal loss equivalent to a majority of classes in the set is uniquely diminished. In our paper it is an arrhythmia, is similarly overlooked.

B. Kernel initialization

In CNN, kernels are represented as weights (or filters) & single convolution layer contains a group of kernels. Intellectual weight initialization is essential to achieve convergence. Our proposed model of CNN uses Xavier initialization and this initialize stabilize the scale of gradients irregularly similar in all type of kernels [13].

C. Activation function

In the model, the output value of kernels are defined using the activation function. In recent models of CNN, nonlinear activation is comprehensively utilized, comprising rectified linear units (ReLU), exponential linear units (ELU) [18] & leakage rectified linear units (LReLU) [17] . Despite the fact that ReLU is the most extensively utilized activation function in CNN. A small negative value is configured in ELU & LReLU where as ReLU interpret entire negative values to zero, which results in few nodes never again contribute in learning.

$$ReLU(x) = max(0, x) \tag{1}$$

$$ELU(x) = \begin{cases} x, & \text{if } x \geq 0. \\ \gamma(exp(x) - 1), & \text{if } x < 0. \end{cases} \tag{2}$$

$$LReLU(x) = max(0, x) + amin(0, x) \tag{3}$$

D. Regularization

Regularization (normalization), is a technique to diminish the over fitting in training phase of the system. Typical normalization strategies are L1 & L2 normalization, regardless, for the most part to apply batch normalization and dropout in current models of deep CNN. Batch normalization has been developed to lessen the internal covariate shift, where the mean and variance are calculated for input batches followed by normalization, scaling and shifting. The placement of batch normalization is generally applied before the activation function & after the convolution layer.

Dropout is a way to deal with abstain from overfitting with diminishing the reliance between layers by contributing nodes of the comparative layer probabilistically [13]. Convolutional layers don't have some free-parameters and co-adaptation between nodes so dropout is not applied immediately next to convolutional blocks which could diminish the over fitting.

E. Cost and optimizer function

The effectiveness of training neural network is defined using cost function which represents the ratio of training sample & the obtained output. The cost function is constrained by utilizing optimizer function. There are diverse sorts of cost functions, however we use cross-entropy function for loss measurement. To limit the cost function, along with the learning rate a gradient descent-based optimizer function is utilized.

$$C = -\frac{1}{n} \sum [y \ln a + (1 - y) \ln(1 - a)] \tag{4}$$

Loss function is the fundamental parameter in ML, DL which is utilized to investigate the execution of our proposed system in classifying (or) differentiating the parameters. Here we utilized Cross Entropy a Cost function to improve our system. We can expand our system execution by limit the value of Loss function using Cross Entropy. Few optimizer functions such as Adadelta [21], Adagrad [20] and Adam [19] are used.

F. Validation set

The validation set is utilized to decide if a trained system has accomplished adequate accuracy with given trained set. Without the validation strategy, the model is presumably to fall over fitting. For the most part, the loss value is the validation criterion for CNN.
The archietecture of the proposed system is shown in TABLE I.

TABLE I
CNN ARCHIETECTURE OF PROPOSED SYSTEM

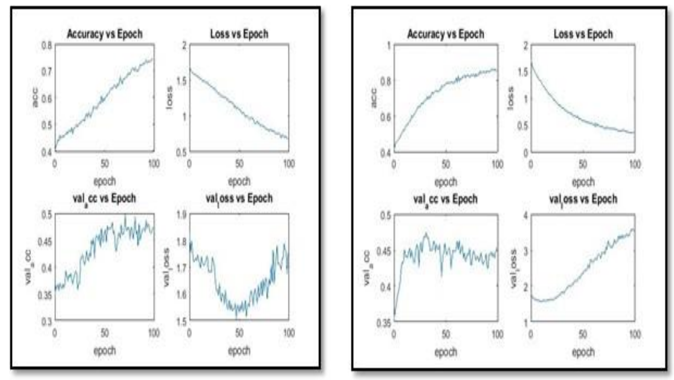
Layers	Type	Filter size	Stride	Kernel
L1	Conv1D	3x3	1	128
L2	Conv1D	3x3	1	128
L3	pool	2x2	2	-
L4	full	-	-	520
L5	out	-	-	8

TABLE II
DATASET DSECRIPTION

Types	Dataset	No.of beats
Normal	100,101,103,105,108,112, 113,114,115,11,121,122, 123,202,205,219,230,234	75052
PVC	106,116,119,200,201,203, 208,210,213,215,221,228,233	7090
APC	209,220,222,223,232	2456
RBB	118,124,212,231	7319
PAB	102,104,107,217	7055
LBB	109,111,207,214	8065
VEB	207	106
VFW	207	473

IV. RESULTS & DISCUSSIONS

In this paper, we proposed a intelligent based ECG Arrhythmia Classification system, where the raw time series data is given as input, and the output is obtained from softmax layer.The signal are preprocessed, feature are extracted and the output is obrained from softmax layer.The proposed system for classifying 7 types of arrhythmia is compared by varying the Activation function and Number of Epochs.
Here we have classified the arrhythmias with greater accuracy which will help the cardiologist to diagnose the cardiac conditions. We have classified Premature Ventricular Contraction , Paced Beat , Left Bundle Block , Ventricular Flutter Wave , Premature Atrial Contraction, Right Bundle Block and Ventricular Ectopic Beat including Normal Beat with an accuracy of 93.6% and with an loss of 0.22.



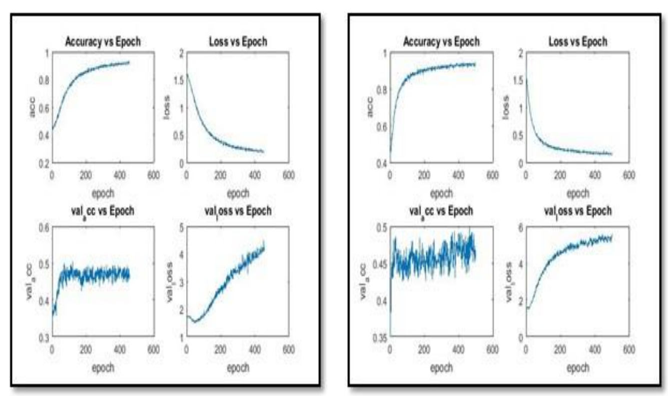
ELU 100 **RELU 100**

Fig. 3. ELU 100 vs RELU 100

A. ELU 100 vs RELU 100

Here, we compared the result between ELU and RELU activation function for 100 epoch, it is known that ELU gives better result with good accuracy, and less loss function mentioned in Fig.3.

B. ELU 500 vs RELU 500



ELU 500 **RELU 500**

Fig. 4. ELU 500 vs RELU 500

Here we increased the epoch to 500 and analyzed the system for 2 activation function, It is known that ELU gives better performance. The accuracy has been increased from 77% to 93.6% while increasing the number of epoch shown in Fig.4.The minimal loss function defines the effectiveness of the proposed system, we obtained an loss function about 0.22. The loss obtained in our system is very less when compared to the exciting methods, this show the effectiveness of our proposed system in classifying the arrhythmia.
From the analyzes it is known that ELU activation function gives better result and we classified arrhythmia with an accuracy of 93.6%.

V. Conclusion

In this paper, we designed an system were we give raw ECG data as input, the datas are preprocessed and features are extracted and we obtain the output from the softmax layer. The output is analyzed and compared for different activation function. We conclude that the system designed for classifying 7 arrhythmia gives better result while using ELU activation function with an accuracy of 93.6%.

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