Automated Detection of Atrial Fibrillation using Deep Learning Techniques

Saikishor Jangiti, Hariraj Venkatesan, Praveen Kumar C, Shankar Sriram V S

Abstract: Cardiac arrhythmia occurs when electric impulses co-ordinating the heart beat malfunction. In atrial fibrillation (AF), heart beats irregularly, which increases the risk of stroke and heart diseases. In this paper, the authors apply deep learning techniques to categorize ECG to classes of normal, AF or others. They utilize convolutional neural network (CNN) and hybrid of CNN and other deep learning architectures of long short-term memory (LSTM), gated recurrent unit (GRU) and recurrent neural network (RNN) to automatically detect AF. No feature extraction/selection is required. A number of trials of experiments were run (1000 epochs) to arrive at the optimum value of parameters. Learning rate was fixed in the range [0.01-0.5]. A high accuracy of 83.5% is obtained using separate training and testing datasets in classifying the input ECG as belonging to normal, abnormal (atrial fibrillation) and others with CNN-LSTM. This is the first work to perform classification mainly to detect AF using ECG recordings of very small duration (average 30s) with high accuracy employing deep learning techniques.

Keywords: atrial fibrillation; CNN; deep learning; ECG; LSTM.

I.INTRODUCTION

Cardiac arrhythmia is the situation in which heartbeats are not proper. Heartbeats are either fast (the condition of tachycardia with heartbeat per minute greater than 100) or slow (the condition of bradycardia with heartbeat per minute less than 60) or heart can beat in an irregular fashion. Irregular heartbeat is called fibrillation or flutter.

Cardiac arrhythmia can be classified in a different manner based on the location point of the heart rate. Two main classes under this category are atrial arrhythmias and ventricular arrhythmias. AF belongs to atrial arrhythmia class. Atrium (plural is atria) is the upper chamber of the heart where blood enters the heart.

Revised Manuscript Received on April 10, 2019

Swapna G, Center for Computational Engineering and Networking (CEN), Amrita School of Engineering,Coimbator, Amrita VishwaVidyapeetham, India.

Soman KP, Center for Computational Engineering and Networking (CEN), Amrita School of Engineering,Coimbator, Amrita VishwaVidyapeetham, India.

Vinayakumar R, Center for Computational Engineering and Networking (CEN), Amrita School of Engineering,Coimbator, Amrita VishwaVidyapeetham, India.

There are 2 atria which further passes the blood to the ventricles. In atrial arrhythmia, the source of heartbeat is the atrioventricular (AV) node positioned between the atria and the ventricles. Other than AF, arrhythmias of premature atrial contraction, supraventricular tachycardia, sinus bradycardia, atrial flutter and atrial tachycardia also belong to the class of atrial arrhythmias. AF and atrial flutter are the serious arrhythmia among these examples.In this paper, authors are concentrating on the condition of atrial fibrillation which is one of the serious type of arrhythmia. AF is the characterised by the fast fibrillation of the atrium. In AF, the electrical signals of the heart are originated from pulmonary veins instead of normal originating site of sino-atrial (SA) node. Fast and irregular atrium contraction happens and walls of the atria fibrillate leading to improper blood pumping into the ventricles. The condition of AF disrupts the effective movement of blood to ventricles and a clot may occur. If the clot breaks off, floats in the bloodstream and fits into an artery, which leads to the brain, then a stroke results. The possible symptoms of AF are light-headedness, shortness of breath, heart palpitations, chest pain or fainting. AF is associated with stroke, dementia, heart failure and other heart-related complications. Cardiovascular diseases are the prime cause of deaths globally according to World Health Organisation (WHO). According to the latest statistics from Centers for Disease Control and Prevention (CDC), approximately 2 percent of people younger than 65 years old are affected by atrial fibrillation, while it is approximately 9 percent in people of age more than 65. The estimated number of people with AF globally in 2010 was 33.5 million. AF associated mortality was observed to be higher in women. Mortality increased by two-fold in men and 1.9-fold in women from 1990 to 2010. In the next 30 to 50 years, AF affected people are likely to triple [Naccarelli et al 2009]. It is observed that as age increases, the probability of incidence of AF also increases. AF is a drain on country's economy since studies have shown that about 16 to 26 billion dollars of annual expenses in United States and about 1% of the National Health Service related budget in the United Kingdom are spent in managing AF [Chugh et al 2013]. Atrial fibrillation, if left untreated, is associated with a 5-fold increased risk for stroke. It also doubles the risk of cardiac related deaths. Therefore, proper prevention and control mechanism has to be developed to handle the increasing prevalence of AF. The first step towards this goal is to detect AF timely so that it can be managed well.AF diagnosis starts with electrocardiogram (ECG) analysis. ECG is checked for possible indications of arrhythmia. If arrhythmia is present, next is the task of finding out if the arrhythmia present is AF. ECG is a record

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

of the electrical activity of the heart. The non-invasive method of ECG analysis can be used to check cardiac rhythm and diagnose arrhythmia. Deviation of the ECG morphology from normal are mainly studied to find out arrhythmia and its type. Cardiac rhythm irregularity is due to malfunctioning of the heart. These leads to anatomical changes in the internal structure of the heart like Cardiac arrhythmia is the situation in which heartbeats are not proper. Heartbeats are either fast (the condition of tachycardia with heartbeat per minute greater than 100) or slow (the condition of bradycardia with heartbeat per minute less than 60) or heart can beat in an irregular fashion. Irregular heartbeat is called fibrillation or flutter. Cardiac arrhythmia can be classified in a different manner based on the location point of the heart rate. Two main classes under this category are atrial arrhythmias and ventricular arrhythmias. AF belongs to atrial arrhythmia class. Atrium (plural is atria) is the upper chamber of the heart where blood enters the heart. There are 2 atria which further passes the blood to the ventricles. In atrial arrhythmia, the source of heartbeat is the atrioventricular (AV) node positioned between the atria and the ventricles. Other than AF, arrhythmias of premature atrial contraction, supraventricular tachycardia, sinus bradycardia, atrial flutter and atrial tachycardia also belong to the class of atrial arrhythmias. AF and atrial flutter are the serious arrhythmia among these examples. In this paper, authors are concentrating on the condition of atrial fibrillation which is one of the serious type of arrhythmia. AF is the characterised by the fast fibrillation of the atrium. In AF, the electrical signals of the heart are originated from pulmonary veins instead of normal originating site of sino-atrial (SA) node. Fast and irregular atrium contraction happens and walls of the atria fibrillate leading to improper blood pumping into the ventricles. The condition of AF disrupts the effective movement of blood to ventricles and a clot may occur. If the clot breaks off, floats in the bloodstream and fits into an artery, which leads to the brain, then a stroke results. The possible symptoms of AF are light-headedness, shortness of breath, heart palpitations, chest pain or fainting. AF is associated with stroke, dementia, heart failure and other heart-related complications. Cardiovascular diseases are the prime cause of deaths globally according to World Health Organisation (WHO). According to the latest statistics from Centers for Disease Control and Prevention (CDC), approximately 2 percent of people younger than 65 years old are affected by atrial fibrillation, while it is approximately 9 percent in people of age more than 65. The estimated number of people with AF globally in 2010 was 33.5 million. AF associated mortality was observed to be higher in women. Mortality increased by two-fold in men and 1.9-fold in women from 1990 to 2010. In the next 30 to 50 years, AF affected people are likely to triple [Naccarelli et al 2009]. It is observed that as age increases, the probability of incidence of AF also increases. AF is a drain on country's economy since studies have shown that about 16 to 26 billion dollars of annual expenses in United States and about 1% of the National Health Service related budget in the United Kingdom are spent in managing AF [Chugh et al 2013]. Atrial fibrillation, if left untreated, is associated with a 5-fold increased risk for stroke. It also doubles the risk of cardiac related deaths. Therefore, proper prevention and control mechanism has to be developed to handle the increasing prevalence of AF. The first step towards this goal is to detect AF timely so that it can be managed well. AF diagnosis starts with electrocardiogram (ECG) analysis. ECG is checked for possible indications of arrhythmia. If arrhythmia is present, next is the task of finding out if the arrhythmia present is AF. ECG is a record of the electrical activity of the heart. The non-invasive method of ECG analysis can be used to check cardiac atria and ventricles, further leading to changes in the signals and waveforms generated by its functioning. Due to all these changes, normal shape of the ECG waveform is changed. The type of arrhythmia decides the unique ECG signal morphology [Swapna et al 2012]. AF brings about changes in the ECG morphology. The ECG is characterized by the absence of P waves and irregularity observed in RR interval. The baseline is also fluctuated irregularly. Instead of the normal rate of 60-100 beats per minute, the heart rate in the case of AF is 100-175 beats per minute. High blood pressure, atherosclerotic diseases, hyperthyroidism, rheumatic disease and pericarditis may cause AF [Swapna et al 2012] [Acharya et al 2013]. Only subtle difference will be there in the rhythms caused by some types of arrhythmia. For example, supraventricular tachycardia (SVT) and atrial flutter are often confused for AF. Note that all three fall under the category of atrial arrhythmia. Hence, exact detection of AF is extremely difficult. However, it is very important to exactly understand the type of arrhythmia since that information is very critical for treatment. Lot of research has happened in the topic of arrhythmia diagnosis, especially in the diagnosis of atrial fibrillation. There were works extracting features representing morphological changes happening in ECG taken from people with AF. There were also traditional machine learning based works in detecting AF. Now deep learning methods are being employed in AF diagnosis. The details of the previous researches in AF diagnosis are given in Discussion section. In this paper, the authors present an automated binary grouping method to diagnose atrial fibrillation. The online ECG data (freely available) 2017 PhysioNet/Computing in Cardiology Challenge database is made use in this research. The analysis method employed is deep learning using CNN, CNN-RNN, CNN-LSTM, CNN-GRU. Cardiologists can use our automated tool to confirm their findings in AF detection. The paper is organised in the following way: Section 2 describes the methods. Section 3 presents the data. Section 4 presents the experiments and network architecture. Section 5 presents the results obtained. Section 6 contains a discussion on the results. The paper concludes in section 7.

II.METHODS

A. Recurent Neural Network(RNN)

RNN is an improvement on feedforward network. RNN contain feedback loops [Elman 1990] which serve as short-term memory using which past information (in time scale) can be stored and retrieved. Temporal tasks can be adeptly executed by this modernization.

There is no constraint on the permitted length of temporal sequences in RNN, unlike multilayer perceptron (MLP). Parameters can also be shared across time-steps in RNN. In brief, the storage of RNN is replaced by another network or graph that contains time delays or has feedback loops and these controlled states are referred to as gated state or gated memory. These gated memory forms a crucial part of LSTM and GRU. RNN is widely used in the areas of speech recognition, language modeling and machine translation.

RNN is mathematically described as follows:

Error! Reference source not found.Error! Reference source not found. Error! Reference source not found. (1)

Error! Reference source not found.(2)

Error! Reference source not found. Error! Reference source not found.

x_t is the input vector, o_t is the output vector. $\boldsymbol{w_{xh}}$, $\boldsymbol{w_{hh}}$, $\boldsymbol{w_{hot}}$ represent weight matrices. f is the activation function (nonlinear) contained in the hidden layer. The commonly used one is the *sigmoid function* (σ) which is applied in element wise manner. The short- term memory to the RNN's network is represented by *H*.

In our case, RNN can intake input data series $\boldsymbol{x} = (x_1, x_2,....,x_{T-1}, x_T)$ (where $x_t \in R^d$) and maps them to hidden input series $h = (h_1, h_2,...h_{T-1},h_T)$ and output sequences $o = (ot_1, ot_2,......ot_{T-1}, ot_T)$ of duration T (corresponding to the hidden layers of the network) . h_0=0 is the initial step. h_0 is also the input in next step represented by $h_1=H(x_1,h_0)$. The recursive nature of hidden layer is represented compactly by the equation $h_T=H(x_T, h_{T-1})$.The current h_T value is given to the next layer with the objective of making available the previous state information h_{T-1}. Thus, the RNN's model can learn the hierarchical feature representation through the internal hidden layers of h_T.

The hidden layers have an affine transformation followed by non-linear activation function. Further, this h_T can be given as input to other stacked recurrent layer or to a final layer where the layer has nonlinear activation function, namely *softmax* function (*sf*).

Error! Reference source not found. (3)

The cyclic connections present in RNN architecture makes it difficult to understand the working of RNNs in entirety. For better understanding and analysis purpose, RNN's intricate network structures can be cleverly transformed to FFNs structure by unfolding or unrolling over time steps. The newly transformed structure consists of simple FFNs that can be analyzed easily.

B. Long Short_Term Memory(LSTM)

LSTM [Hocreiter et al 1997] is an improved version of RNN architecture, developed in order to model long-range dependencies of temporal sequences more accurately than conventional RNNs. LSTM contains memory blocks in place of traditional RNN units (Fig. 1). LSTM can manage long-term dependencies in an effective manner compared to conventional RNN. This property of LSTM made it of wide use in the area of natural language processing (NLP), language modeling and hand written recognition. Generally, it is of wide use in areas where long time-series data analysis is required. Memory block in LSTM can be considered as a complex processing centre built of memory cells. The input and output gates are multiplicative gates which can permit or block the flow of cell activation through the memory block to the subsequent nodes. The entire processes happening in the memory block is managed by a set of adaptive multiplicative gates.Forget gate [Gers et al 1999] and peephole connections [Gers et al 2002] are the new additions to the LSTM architecture as research progressed. The forget gate can be used in place of CEC (constant error carousel). Peephole connections are included in memory cell and gates for the purpose of understanding the exact time related information of the outputs.

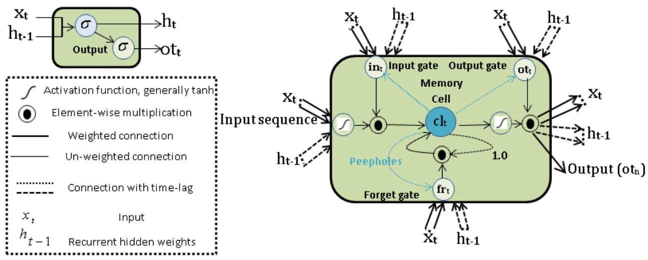

Fig. 1: Memory block of RNN (left) and LSTM (right)

The functioning of the LSTM is briefly summarized as given below. $x = (x_1, x_2,....,x_{T-1}, x_T)$ represents input data sequence of arbitrary length fed to the LSTM architecture. $o = (ot_1, ot_2,......ot_{T-1}, ot_T)$ is the output data sequence. The input (*in*), output (*ot*) and forget gate (*fr*) are the three multiplicative units that perform the continuous write, read and reset functions on memory cell (*cl*) in an iterative manner from t = 1 to *T* in LSTM's recurrent hidden layer. The three multiplicative gating units assist the memory cell to store wide range of temporal information. The operations in LSTM happening at time step *T* is briefly represented by the below equations.

Error! Reference source not found.(4)

Error! Reference source not found.(5)

Error! Reference source not found. (6)

Error! Reference source not found.(7)

Error! Reference source not found. (8)

C. Gated Recurent Unit(GRU)

GRU is an improved form of LSTM with reduced number of variables [Cho et al 2014]. GRU can capture dependencies of different time scales adaptively. GRU has gating units that modulate the flow of information inside its memory. Unlike LSTM, GRU doesn't have separate memory cells. The memory consumption and computational cost of GRU is much smaller than that of LSTM.

The operations happening in GRU can be explained using the following equations:

Error! Reference source not found.(9)

Error! Reference source not found.(10)

Error! Reference source not found.(11)

Error! Reference source not found.(12)

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Here equations 9, 10, 11 and 12 represents update gate, forget (reset) gate, current memory and updated memory respectively. *FM* represents the output features obtained from CNN. GRU is a second part of CNN-GRU and the output of the CNN is given as input to GRU.

D. Convolutional Neural Network (CNN)

CNN is an improvised MLP. CNN use the convolution operation as one of its layers.

CNNs and neural networks have certain similarities. Both are comprised of neurons along with weights and biases whose values should be learned by the network. Each neuron is fed with some inputs. Scalar product operation is then performed, followed by a nonlinearity function block which is optional. A loss function like *softmax* is incorporated on the last fully connected layer of CNN. The CNN normally also includes a non-linear activation function such as *RELU*. CNN is primarily made up of convolutional (CONV), pooling (POOL) and fully connected (FC) layers which are of 1D (one-dimensional) when used for the analysis of one-dimensional signals. The input data to CNN, in one-dimensional case is arranged in time instants which are ordered sequentially. The most important layer of CNN is the convolutional layer.

The CNN is sequenced as INPUT-CONV-RELU-POOL-FC. $x = (x_1, x_2,....,x_{n-1}, x_n, cl)$ is the input ECG data (one-dimensional) vector. Here $x_n \in R^d$ denotes features (normal and anomalous (here AF data) and $cl \in R$ represents the class label (normal or anomalous). Convolutional1D forms a feature map *fm* by subjecting the input data to the operation of convolution using a filter $w \in R^{fd}$. The inherent features in the input data are represented by *f*. A new set of features is produced at its output which is given as input to the subsequent block.

fm is the new feature map obtained from *f* in the following manner.

Output vector to the next block is a function of (**Error! Reference source not found.** + b). *w* is the weights, *b* is the bias and **Error! Reference source not found.** is the input vector.

For example, in **Error! Reference source not found.**, the filter *hl* is applied to feature set *f* contained in the input data $(x_{1:f}, x_{2:f+1}, \ldots\ldots, x_{n-f+1})$ and a feature map $hl = (hl_1, hl_2, \ldots\ldots hl_{n-f+1})$ is generated.

Here $b \in R$ is the bias term and $hl \in R^{n-f+1}$.

The following equation represents the basic convolution operation:

Error! Reference source not found.(13)

Here *x* is the input vector, *f* is the function (filter operation), *y* is the output vector.

Convolutional layer's output is given to the *RELU* layer where an activation function such as $max(0,x)$ is applied to input *x*. Downsampling is done by the next POOL layer through max pooling operation represented by**Error! Reference source not found.** in order to obtain the most significant features. These features having highest values are passed on to the fully connected layer. The *softmax* function contained in it, produces the probability distribution of each class as CNN's final output.

E. Hybrid networks

In the case of hybrid networks like CNN-RNN etc, CNN is made up of convolutional1D and max pooling1D layers only. The max pooling layer's output is fed as input to the subsequent network layer.

Error! Reference source not found.

(14)

x_i is the input and **Error! Reference source not found.**is the output of the CNN. Each data type of**Error! Reference source not found.** has an associated class label. **Error! Reference source not found.**is the output of the maxpooling layer in CNN. **Error! Reference source not found.**is given to the input to the deep learning network employed subsequent to CNN.

III.DATA ACQUISITION

The 2017 PhysioNet/CinC Challenge database consists of single short ECG recordings consisting of classes belonging to normal sinus rhythm, AF and others (others can be alternative rhythms or high noise affected rhythms). A total of 12,186 ECG recordings (provided by AliveCor for this Challenge) are present in the database. The training set and test set consists of 8,528 recordings and 3,658 recordings respectively. The recordings in both training and test sets are of similar durations ranging from 9s to 61s with similar distributions. Since the test set is presently unavailable in public domain, we split the publically available training set of 8528 recordings into 2 sets (training 5968 and testing 2560). The details of the recordings are as described below. Each recording was done with single-channel ECG device with a recording duration of average of 30s. The recorded data is then transmitted to a smartphone or tablet acoustically into the microphone using a carrier frequency of 19 kHz and a modulation index of 200 Hz/mV. The data were then digitized in real time at 44.1 kHz and 24-bit resolution and finally stored as 300 Hz, 16-bit files with a bandwidth of 0.5-40 Hz and a dynamic range of ± 5 mV [Clifford et al 2017] [Goldberger et al 2000].

Table 1: Description of data set used for our research work

Type	Training	Testing
Normal	3608	1546
AF	540	231
Other rhythm	1790	767
Noisy	30	16
Total	5968	2560

IV.EXPERIMENTS

The most recent software framework TensorFlow (Google's open source data flow engine) were used to experiment our deep learning networks we tried [Abadi et al 2016]. It is an open source artificial intelligence library. It makes use of data flow graphs for modeling purpose. Using TensorFlow, researchers can create large-scale neural networks containing a number of layers. TensorFlow is mainly used for various tasks like classification and prediction.

TensorFlow also allows programmers to work on diversified platforms, for example, a number of CPUs, GPU, mobile devices etc. We run all our experiments are run in single NVidia GK110BGL Tesla k40 using GPU enabled TensorFlow.

E. Identifying topologies

Next are maxpooling1D block, flatten, dropout value of 0.4, then a fully connected layer with *softmax* non-linear activation function. The connection between neurons starting from the input layer to the output layer via the hidden layers is made fully-connected. Normalization is applied to the input data set's values in order to make their values fall in the range 0-1. Three trails of experiments are conducted choosing initially filter size parameter value as 32, further tried with value 64, and finally with 128. All experiments are run for 500 epochs keeping batch size as 32. The optimizer and loss function chosen are *ADAM* and binary cross entropy respectively. It was observed that the filter size value of 64 filters gave the best performance. Further increase in value did not better the accuracy of AF detection. Hence, for all the remaining experiments, filter size value was fixed at the optimum value of 64. In a similar manner, optimal learning rate value was fixed at 0.001.

F. Network architectures

Several topologies of CNN 1, 3, 5, 7 layers, CNN 1 layer with RNN/LSTM/GRU, CNN 3 layer with RNN/LSTM/GRU, CNN 5 layer with RNN/LSTM/GRU and CNN 7 layer with RNN/LSTM/GRU were experimented to determine an optimal CNN network structure for training.
When we used 3, 5, 7 CNN layers (more than 1 layer cases), filter size was 128 (double of 64) instead of earlier value of 64. Two trails of experiments were conducted for all the above mentioned network topologies with each experiment running for 500 epochs (again with learning rate 0.001). It was observed that as the complexity of the network topology increased, number of epochs needed to attain the required performance in AF detection was higher than 500 epochs. It was also found that performance of complex networks was superior to that of the simple deep learning networks. In fact, it was not possible to run simple CNN networks for more than 500 epochs due to the problem of overfitting. Overfitting refers to modeling the training data too perfectly to the extent that detail as well as noise are learned. Overfitting negatively impacts the performance of the model on new input data.

G. Proposed architecture

In contrast to conventional machine learning classifiers, deep learning algorithm based networks do not extract features explicitly, instead they learn the optimal feature representation by itself implicitly as the data passes from input to the output layer of the network. 18000 neurons make up the input layer, while 7 convolution layers built up the hidden layer. The number of filters is chosen as 64, 128, 256, 512, 1024, 1536 and 2024 for each of these 7 layers. Next is the max pooling1D layer with the pool length as 2 for reducing the dimensionality. The max pooling layer output features, learnt by CNN network are passed to the subsequent RNN/LSTM/GRU layer. The RNN/LSTM/GRU layer contains 50 units/memory blocks. RNN/LSTM/GRU network further extracts finer details contained in the sequences and these details are then passed to the next fully connected layer via a dropout layer with value as 0.2. Dropout parameter mitigates the undesirable issue of overfitting. The FC layer containing *softmax* function, outputs probability values for normal, AF, others. Categorical cross entropy is selected as loss function. To minimize the loss of categorical cross entropy, we used *ADAM* optimizer via backpropagation.

V.RESULTS

The accuracy details of the test data are listed in the Table 2.

Table 2: Results of AF detection accuracy

Architecture	Accuracy	Recall	Precision	F1-score
CNN7 layer	0.637	0.637	0.726	0.575
CNN7layer with LSTM	**0.835**	0.835	0.845	0.829

Generally, the LSTM network passes the inputs to more than one layer for the purpose of capturing the hidden patterns present in the time domain of the data. The activation in each layer facilitates towards the final objective of distinguishing classes of the input data. To visualize and understand how this objective of class identification is achieved, activation values of the last layer of the LSTM networks are given as input to t-SNE [Maaten et al 2008] instead of feed forward network (FFN). t-SNE does the transformation of the high dimensional feature vectors into two dimensional feature vectors. The newly transformed feature vectors are displayed in Figure 2.

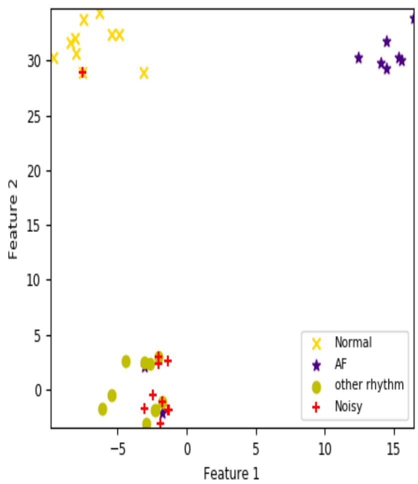

Fig. 2: Two-dimensional linear projection (PCA) of the ECG samples and their activation values of the penultimate layer neurons.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

It can be observed from Figure 2 that samples with similar activation values fall in a cluster. It is also observed that ECG data of normal, AF, other rhythm and noisy classes are not exactly falling in different clusters. The inference is that complete learning of the ECG data has not happened. It may be because of the fact that the size of our input ECG data is insufficient and larger sized data has to be fed into as input to deep learning networks to get better accuracy values. That is our future research objective for improving the accuracy of the network in distinguishing AF.

VI.DISCUSSIONS

A lot of research has been done in the topic of arrhythmia diagnosis. The below are the summary of important latest previous works in the diagnosis of atrial fibrillation. Early researchers used morphological feature extraction and analysis for AF detection. AF was detected based on the average number of f waves in TQ interval in ECG with an accuracy of 93.67% [Du et al 2014]. Detection of AF was done on the basis of identification of a single P wave during a cardiac cycle. 97.8% of the total AF duration and 99.3% of the normal duration were correctly identified [Pürerfellner et al 2014]. Many researches on AF detection were done using machine learning techniques, but most of them did a multiclass (3 and more categories) classification. Recent ones were by [Acharya et al 2016] [Desai et al 2016]. 13 nonlinear features of shannon entropy, fuzzy entropy, tsallis entropy, approximate entropy, permutation entropy, modified multiscale entropy, wavelet entropy, sample entropy, renyi entropy, signal energy, fractal dimension, kolmogorovsinai entropy and largest lyapunov exponent were extracted from tachycardia ECG beats to classify normal, AF, atrial flutter, ventricular fibrillation (VF) with an accuracy of 96.3% using KNN and decision tree (DT) classifiers [Acharya et al 2016]. The same 4 class classification as above was conducted with recurrence quantification analysis (RQA) along with rotation forest classifier achieving accuracy value of 98.37% [Desai et al 2016]. Deep learning algorithms are presently widely used in the detection of several anomalies like diabetes detection [Swapna et al 2018a][Swapna et al 2018c],sleep apnea [Rahul et al 2017a][Rahul et al 2017b], area of arrhythmia diagnosis [Swapna et al 2018b] and heart related signal analysis [Sujadevi et al 2017a] [Sujadevi et al 2017b][Sujadevi et al 2018]. CNN was used for the automated detection of the same 4 classes (normal, AF, atrial flutter and VF) and a maximum accuracy of 94.9% was achieved [Acharya et al 2017].

In our proposed work, a binary classification of ECG input as belonging to normal and AF category is done with a good accuracy of 83.5% using ECG recordings of very small duration (average 30s). Though the accuracy value is slightly less than previous works, it is important considering that detection of AF in a person is ascertained from a very short duration ECG (average duration 30 seconds).

VII.CONCLUSION AND FUTURE WORK

Atrial Fibrillation (AF) is an arrhythmia leading to serious complications. Therefore, a reliable and automated non-invasive system is needed for the timely detection of AF. We develop a model, which has a very high accuracy in distinguishing AF from single lead ECG records, which are the latest available in public domain. The high performance is due to the deployment of deep and hybrid deep learning networks. Our system can aid physicians to diagnose AF with great accuracy. Future research can explore ways to enhance the accuracy value to still higher heights by trying different deep learning architectures

REFERENCES

1. Abadi M, Barham P, Chen J, Chen Z, Davis A, Dean J, Devin M, et al. (2016), TensorFlow: A system for large-scale machine learning, In OSDI, 16: 265-283.
2. Acharya UR, Faust O, Ghista DN, VinithaSree S, Alvin APC, Chattopadhyay S, Lim T, Ng EY, Yu W(2013), A systems approach to cardiac health diagnosis, Journal of Medical Imaging and Health Informatics, 3 (2): 261–267.
3. Acharya UR, Fujita H, Adam M, Oh SL, Tan JH, Sudarshan VK, Koh JEW (2016), Automated characterization of arrhythmias using nonlinear features from tachycardia ECG beats, In IEEE International Conference on Systems, Man, and Cybernetics, DOI: 10.1109/SMC.2016.7844294.
4. Acharya UR, Fujita H, Oh SL, Hagiwara Y, Tan JH, Adam M (2017),Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network, Information Sciences, 405.
5. Cho K, Merrienboer B, Gulcehre C, Bahdanau D, Bougares F, Schwenk H, Bengio Y (2014), Learning phrase representations using RNN encoder-decoder for statistical machine translation, arXiv preprint arXiv : 1406.1078.
6. Chugh SS, Havmoeller R, Narayanan K, Singh D, Rienstra M, Benjamin EJ, Gillum RF, Kim YH, McAnulty JH, Zheng ZJ et al. (2013), Worldwide epidemiology of atrial fibrillation: a global burden of disease 2010 study, American Journal of Cardiology, 129 (8): 837–847.
7. Clifford G, Liu C, Moody B, Lehman L, Silva I, Li Q, Johnson A, Mark R (2017), AF classification from a short single lead ECG recording: The Physionet computing in cardiology challenge 2017, Computing in Cardiology, 44.
8. Desai U, Martis RJ, Acharya UR, Nayak CG, Seshikala G, Shetty KR (2016), Diagnosis of multiclass tachycardia beats using recurrence quantification analysis and ensemble classifiers, Journal of Mechanics in Medicine and Biology, 16 (1): 1640005.
9. Du X, Rao N, Qian M, Liu D, Li J, Feng W, Yin L, Chen X (2014), A novel method for real-time atrial fibrillation detection in electrocardiograms using multiple parameters, Ann Noninvasive Electrocardiol, 19 (3): 217–225.
10. Elman JL (1990), Finding structure in time, Cognitive Science, 14 (2): 179-211.
11. Gers FA, Schmidhuber J, Cummins F (1999), Learning to forget: continual prediction with LSTM, Neural Computation, 12 (10): 2451 – 2471.
12. Gers FA, Schraudolph NN, Schmidhuber J (2002), Learning precise timing with LSTM recurrent networks, The Journal of Machine Learning Research, 3 (Aug): 115 –143.
13. Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE (2000), PhysioBank, PhysioToolkit, and PhysioNe, Circulation, 101 (23): 215-220.
14. Hochreiter S & Schmidhuber J (1997), Long short-term memory, Neural Computation, 9 (8): 1735-1780.
15. Maaten L & Hinton G (2008), Visualizing data using t-SNE, Journal of machine learning research, 9(Nov), 2579-2605.
16. Naccarelli GV, Varker H, Lin J, Schulman KL (2009), Increasing prevalence of atrial fibrillation and flutter in the United States, American Journal of Cardiology, 104 (11): 1534–1539.
17. Pürerfellner H, Pokushalov E, Sarkar S, Koehler J, Zhou R, Urban L, Hindricks G (2014), P-wave evidence as a method for improving algorithm to detect atrial fibrillation in insertable cardiac monitors, Heart Rhythm, 11 (9): 1575–1583.
18. Rahul KP, Vinayakumar R, Ekanath R, Gopalakrishnan EA, Soman KP (2017a), Instantaneous heart rate as a robust feature for sleep apnea severity detection using deep learning, In IEEE EMBS International Conference on Biomedical & Health Informatics.

19. Rahul KP, Dhara PJ, Ekanath R, Gopalakrishnan EA, Vinayakumar R (2017b), Single sensor techniques for sleep apnea diagnosis using deep learning, In IEEE International Conference on Healthcare Informatics (ICHI).
20. Sujadevi VG, Soman KP, Vinayakumar R (2017a), Real-Time detection of atrial fibrillation from short time single lead ECG traces using recurrent neural networks, In The International Symposium on Intelligent Systems Technologies and Applications, Springer, September, 212-221.
21. Sujadevi VG, Soman KP, Vinayakumar R, Sankar AP (2017b), Deep models for phonocardiography (PCG) classification, In IEEE International Conference on Intelligent Communication and Computational Techniques (ICCT), December, 211-216.
22. Sujadevi VG, Soman KP, Vinayakumar R, Sankar AP (2018), Anomaly detection in phonocardiogram employing deep learning, Computational Intelligence in Data Mining, pp 525-534.
23. Swapna G, Ghista DN, Martis RJ, Ang APC, VinithaSree S (2012), ECG signal generation and heart rate variability signal extraction: signal processing, feature detection, and their correlation with cardiac diseases, Journal of Mechanics in Medicine and Biology, 12 (4): 1240012.
24. Swapna G, Soman KP, Vinayakumar R (2018a), Automated detection of diabetes using CNN and CNN-LSTM network and heart rate signals, Procedia Computer
25. Science, 132, 1253-1262.
26. Swapna G, Soman KP, Vinayakumar R (2018b), Automated detection of cardiac arrhythmia using deep learning techniques, Procedia Computer Science, 132, 1192-1201.
27. Swapna G, Vinayakumar R, Soman KP (2018c), Diabetes detection using deep learning algorithms, ICT Express, 4, 243-246.