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CLASSIFICATION OF NORMAL AND ATRIAL FIBRILLATION ECG SIGNAL USING LONG SHORT TERM MEMORY NETWORK IN DEEP LEARNING

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ABSTRACT

Atrial fibrillation is a cardiac disorder usually identified by rapid heart rhythm and irregular beating of a heart which leads to an increased risk of heart failure and cardiac stroke. In this paper, we propose the classification of normal and abnormal ECG signals using a Recurrent Neural Network and Long Short-Term Memory Network in Deep Learning. PhysioNet Challenge 2017 dataset is used for training and testing Neural Network. We train signals by applying various filters to attain high prediction accuracy. The total accuracy achieved by the method we used is 91% which is greater than the previous research/methods used to classify Atrial fibrillation signals.

Keywords: Atrial Fibrillation, Electrocardiogram, Recurrent Neural Network, Deep Learning, Long Short Term Memory.

I. INTRODUCTION

This Atrial fibrillation (AF) is one of the most prevalent cardiac arrhythmias, and it is expected to become more common in the future. In adults over the age of 40, the lifetime chance of getting AF is estimated to be 25% [1]. Atrial fibrillation is a heart ailment in which the heart's rhythm is disrupted by the erratic firing of impulses from the sinoatrial node. Other random electrical impulses in the atria normally override the node. Fibrillation is a word that defines the partial contraction of the cardiac muscles at a high rate, approximately 400 times a minute. Fibrillation emerges as a result of the irregular propagation of impulses from the sinoatrial node. This means that it's hard for a human with AF to predict their heart rate or when their heart muscles will contract and relax, implying that their heart rate is exceedingly unpredictable [2]. An ECG is still required to establish the diagnosis of AF, even if an erratic pulse points to it. Because AF can be paroxysmal, a negative ECG does not rule out a pulse-based diagnosis of AF. A single lead rhythm strip or 12 lead ECG capturing 30s of AF should be used to diagnose patients with suspected AF [3]. Here we are using the data from Physionet Challenge 2017 dataset and an effective AF detection method based on a bi-directional double-layer LSTM architecture.

II. PROBLEM IDENTIFICATION

There is a method in deep learning using Convolution Neural Network (CNN) in which the ECG signal is categorized into normal and abnormal signals. CNN can use only in the spatial data input and can only process in the feed-forward neural method and it only considers the current input [12]. So to overcome this problem we have designed a Recurrent Neural Network in the same deep learning model to categorize the ECG signal into normal and abnormal signals.

III. EXPERIMENTAL METHOD

Atrial fibrillation signal is classified by using a type of Recurrent Neural Network (RNN) called the Long Short Term Memory (LSTM) network. Pre-processed and feature extracted signal is used to train the LSTM network. Recurrent neural networks (RNNs) are dynamic systems with an internal state at each classification time step. Circular connections between higher layer and lower layer neurons, as well as self-feedback connections, are optional [4]

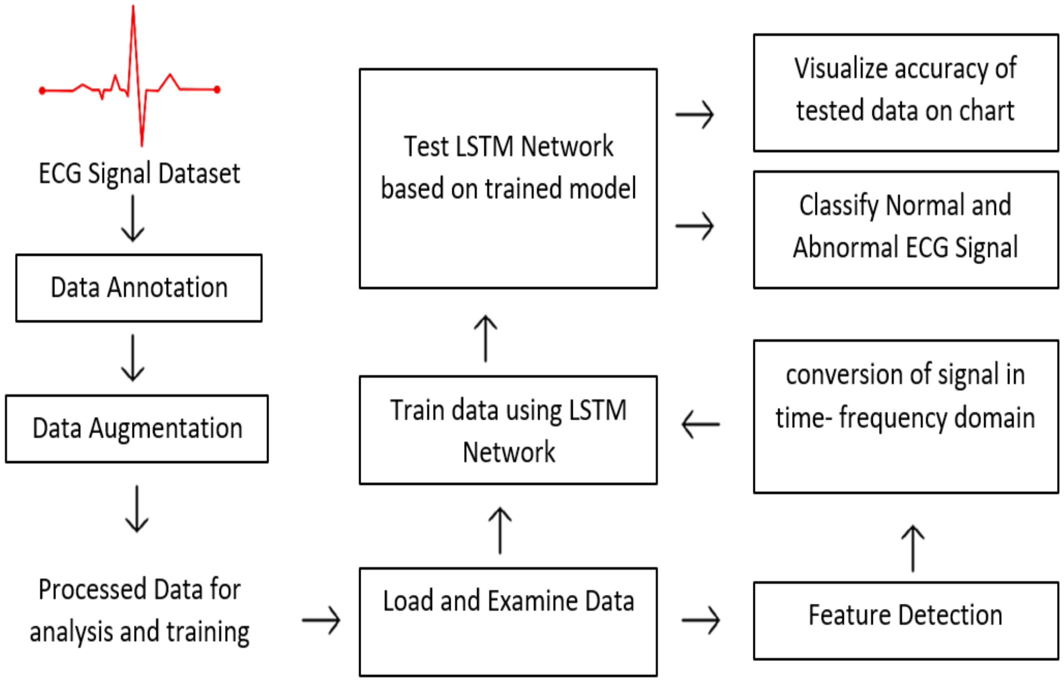

Figure 1: Block Diagram of Experimental Method.

A. ECG Signal Dataset

The PhysioNet 2017 Challenge dataset is used for testing our algorithm. These data mainly consist of single short lead ECG recording ranging from 30 seconds to 30 seconds in length. A normal sinus rhythm, alternative rhythm, atrial fibrillation, and noise signal are included with that data. The dataset contains 8528 single lead recordings of ECG signals in various lengths [5].

B. Data Annotation

Data annotation is a process in which a human data annotator adds categories, labels, and other contextual aspects to a raw data set so that machines can interpret and act on the information [6]. Here raw data used in Deep Learning (DL) consists of ECG signaling data. Using algorithm in MATLAB, unlabeled ECG data is labeled as normal (N) and atrial fibrillation (A) signal which is later used for further processing.

C. Data Augmentation

Data augmentation is a set of techniques for producing additional data points from current data to artificially increase the amount of data available. Making modest adjustments to data or utilizing deep learning models to produce additional data points [7]. We use an augmentation procedure known as oversampling to tackle the issue of an uneven distribution of obtained classes [8]. By duplicating the existing signals in the smaller class until the number of signals in the larger class equals the number of signals in the smaller class.

D. LSTM Network Architecture

Bidirectional LSTM networks are widely accepted by researchers, because of their superior features [9]. It solves the problem of vanishing gradient by feedback connection [10]. The proposed architecture othe f LSTM network consists of a two-dimensional input layer connected with bidirectional LSTM cells. The recurrent layer handles both the output of the layer and its signals from one backward step along all dimensions at each step in the data sequence [9].

E. Feature Extraction

Training accuracies of classifiers can be improved by extracting features from the data as like testing accuracy. After the conversion of the signal into the frequency domain, the spectrograms' information is extracted using time-frequency (TF) moments. Each instant can be input to the LSTM as a one-dimensional feature. Z-scoring is a popular approach to improving RNN performance. Since the mean of instantaneous frequency and spectral entropy is high, training of the network consumes much time.

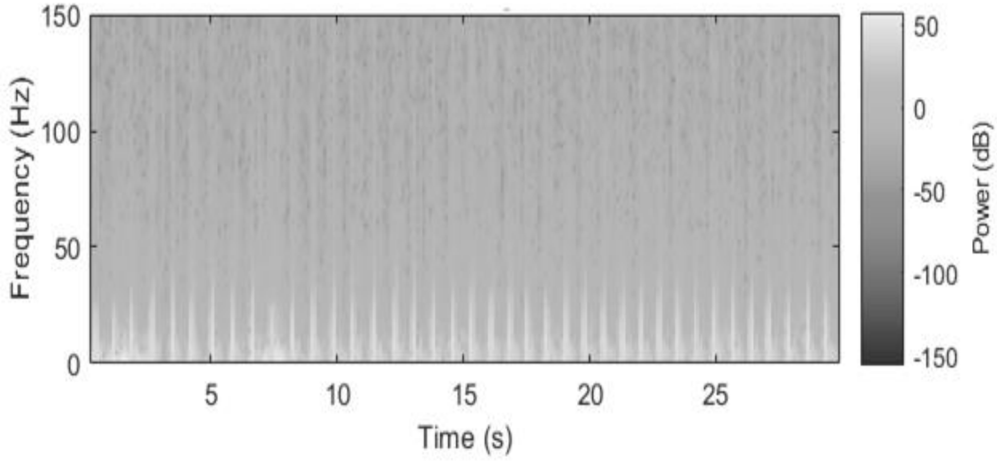

Figure 2: Visualizing Spectrogram of Signal.

Spectrogram of signal provide hidden details in time domain signal and helps to improve training and testing accuracy.

F. Time-frequency Domain Conversion

The Short-Time Fourier Transform (STFT) is often used to transform signals from the time domain to a time-frequency representation.[11]. Here we use Short Time Fourier Transform to compute the exact time-frequency moment (TF) and spectrograms. The resultant signal is used to train the neural network and also for testing. Instantaneous frequency and spectral entropy of time frequency domain ECG signal is used in our experimental method.

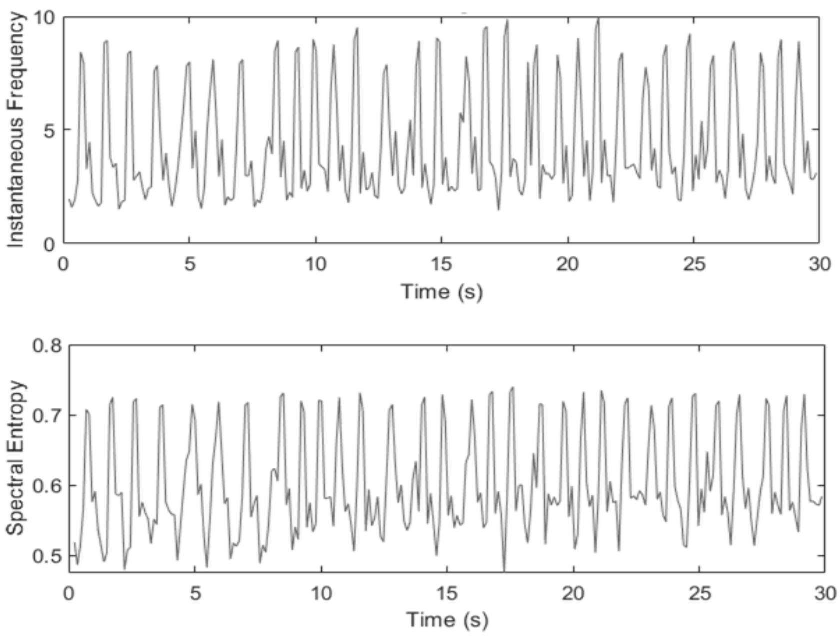

Figure 3: Visualizing Instantaneous Frequency and Spectral Entropy of ECG Signal.

IV. RESULTS AND DISCUSSION

In this experimental work, by using the 2017 PhysioNet Challenge dataset [5] which contains recordings of a single lead ECG with a sampling rate of 300 Hz, a 2-dimension input layer with a bidirectional LSTM network with 100 hidden units is trained and tested. After data augmentation, 8876 samples are used for training and 980 samples are used for testing. By not considering the batch size and time window, we achieved an accuracy of 91% in classifying the Atrial fibrillation signal. This can be further increased if altering the batch size and window time. Figure 3 represent training of ECG signal is LSTM model and visualize accuracy of model on graph in each iteration. From that graph, we obtained 91% of accuracy.

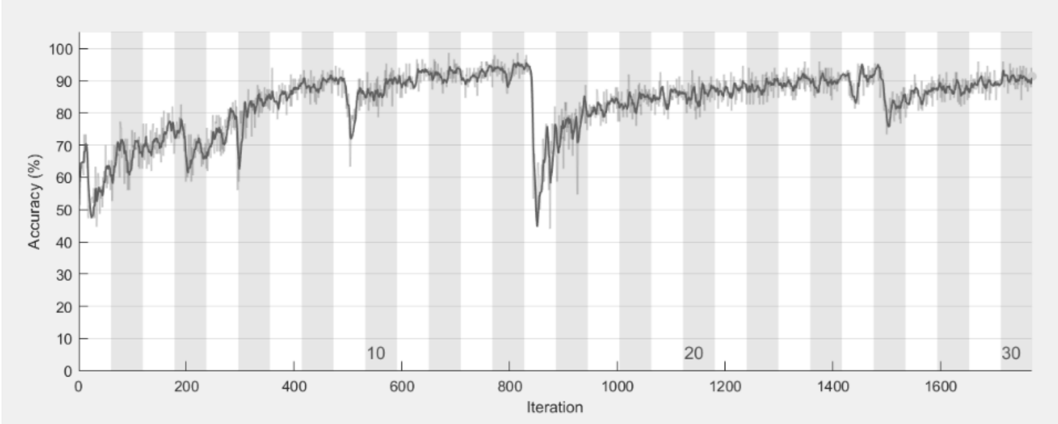

Figure 4: Training Chart of LSTM Network

V. CONCLUSION

In this paper, we have proposed an effective system to detect atrial fibrillation and classify ECG signals using the LSTM algorithm in the recurrent neural network of deep learning. The sensitivity and specificity of automated ECG diagnosis will improve with the development of optimization methods for processing the huge volumes of data being accumulated. The deep learning ECG diagnosis method we created looks to be reliable enough in medical evaluation. It has the potential to reduce misdiagnosed and missed diagnoses in healthcare settings while potentially conserving large general hospitals' resources on personnel.

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