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AUTOMATED DETECTION OF CARDIAC ARRHYTHMIA USING RECURRENT NEURAL NETWORK

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ABSTRACT

Cardiac arrhythmia is a condition where irregular heart rhythms occur. According to World Health Organization (WHO), about 17 million people in the world die every year due to cardiovascular diseases. This is about 31% of the total deaths globally. According to the statistics of American Heart Association (AHA), one out of every three deaths in US is related to cardiovascular diseases. The deaths due to cardiovascular diseases are more than due to all types of cancer and chronic lower respiratory diseases combined. A 2014 study indicates that approximately 2 to 3% of the people in North American and European countries are affected by atrial fibrillation. A heart rate which is high (above 100 beats per minute in adults) is called tachycardia and a heart rate that is slow (below 60 beats per minute) is called bradycardia. If the beat is too early, then it is called premature contraction. Irregular beat is called fibrillation or flutter. Other than the criteria of heart rate, there are a number of other classifications for cardiac arrhythmia depending upon different types of criteria. Another type of classification is in terms of the site of origin of the irregular heart rate. Cardiac arrhythmia is a condition where heartbeat is irregular. The goal of this paper is to apply deep learning techniques in the diagnosis of cardiac arrhythmia using ECG signals with minimal possible data pre-processing. We employ one-dimension convolutional neural network (1D-CNN), and long short-term memory (LSTM) to automatically detect the abnormality. This work is focused on the design of CNN and LSTM algorithms to predict Arrhythmia diseases with 7 different stages. To train both algorithms, the MIT-BH dataset is used with 7 different disease stages. Further, existing LSTM resulted in low accuracy. So, this work adopted the CNN model for training and testing Arrhythmia disease.

Keywords: Cardiac arrhythmia, deep learning, ECG signals.

1. INTRODUCTION

Cardiac arrhythmia is a condition where irregular heart rhythms occur. According to World Health Organization (WHO), about 17 million people in the world die every year due to cardiovascular diseases. This is about 31% of the total deaths globally. According to the statistics of American Heart Association (AHA), one out of every three deaths in US is related to cardiovascular diseases. The deaths due to cardiovascular diseases are more than due to all types of cancer and chronic lower respiratory diseases combined. A 2014 study indicates that approximately 2 to 3% of the people in North American and European countries are affected by atrial fibrillation. A heart rate which is high (above 100 beats per minute in adults) is called tachycardia and a heart rate that is slow (below 60 beats per minute) is called bradycardia.

If the beat is too early, then it is called premature contraction. Irregular beat is called fibrillation or flutter. Other than the criteria of heart rate, there are several other classifications for cardiac arrhythmia depending upon different types of criteria. Another type of classification is in terms of the site of origin of the irregular heart rate. Atrial arrhythmias originate in the atrioventricular (AV) node. The AV node is positioned between the atria (each of the two upper cavities of the heart from which blood is passed to the ventricles is referred to as atria) and the ventricles. Atrial fibrillation (AF), atrial

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flutter, atrial tachycardia, premature atrial contractions, and sinus bradycardia are some examples of atrial arrhythmias. Atrial fibrillation and atrial flutter are examples of arrhythmia which may lead to serious consequences.

In AF, the atrium is contracted in a very fast and irregular manner with the heart's electrical signals originating from a different part of the atria or in the adjacent pulmonary veins instead of sino-atrial (SA) node. The walls of the atria fibrillate (quiver very fast) instead of beating in a normal way, making atria unable to pump blood properly into the ventricles. Stroke and heart failure are two complications to which atrial fibrillation can lead to. Conditions like high blood pressure, overactive thyroid gland, coronary and rheumatic heart diseases can lead to AF. Atrial flutter has similar symptoms and complications as AF. But in atrial flutter, the advancement of electrical signals of the heart through the atria happens in a fast and regular manner instead of the irregular way it happens in AF.

Ventricular arrhythmias are premature rhythms occurring in an ectopic ventricular focus. Ventricular fibrillation, ventricular tachycardia, premature ventricular contractions are some examples of ventricular arrhythmias. Some arrhythmias are symptomless and not at all life threatening. But some symptomless arrhythmias can even lead to serious complications like blood clotting, stroke, heart failure and sudden cardiac death. Arrhythmias occur when the electrical signals to the heart that co-ordinate heartbeat are not working properly. The first step in the diagnosis of this abnormality is the analysis of electrocardiogram (ECG) and the confirmation that the ECG is not indicative of cardiac arrhythmia.

ECG is a bio signal representing the activity of the autonomous nervous system (ANS) controlling heart rhythm. Thus, the electrical activity of the heart is recorded in ECG. It is a non-invasive and efficient tool to study cardiac rhythms and diagnose arrhythmias. The ECG signal is generated because of the following processes. The heartbeat is originated as an electric pulse from the SA node situated in the right atrium of the heart. After contracting both atria, this electric pulse, then activates atrioventricular (AV) node that connects electrically the atria and the ventricles. This is followed by the activation of both ventricles. The complete heart activity is represented in the ECG waveform. Abnormalities in the morphology of ECG waveforms are indicators of cardiac arrhythmias. ECG waveform is analysed to ascertain the risk associated with any type of arrhythmia.

2. LITERATURE SURVEY

Jafarnia et al. used two new features i.e., T-wave integral and total integral as extracted feature from one cycle of normal and patient ECG signals to detection and localization of myocardial in-fraction (MI) in left ventricle of heart. And used the T-wave integral because this feature is important impression of T-wave in MI. The second feature in this research is total integral of one ECG cycle, because that the MI affects the morphology of the ECG signal which leads to total integral changes. Also, this work can improve the accuracy of classification by adding more features in this method. A simple method based on using only two features which were extracted from standard ECG is presented and had good accuracy in MI localization.

Sharma et al. studied the multiscale wavelet energies and eigenvalues of multiscale covariance matrices are used as diagnostic features. Support vector machines (SVMs) with both linear and radial basis function (RBF) kernel and K-nearest neighbor are used as classifiers. Datasets, which include healthy control, and various types of MI, such as anterior, anteriolateral, anterioseptal, inferior, inferiolateral, and inferioposterio-lateral, from the PTB diagnostic ECG database are used for evaluation. The results showed that the proposed technique can successfully detect the MI pathologies.

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Acharya et al. proposed a novel method of automated detection and localization of MI by using ECG signal analysis. In this study, a total of 200 twelve lead ECG subjects (52 normal and 148 with MI) involving 611,405 beats (125,652 normal beats and 485,753 beats of MI ECG) are segmented from the 12 lead ECG signals. Firstly, ECG signal obtained from 12 ECG leads are subjected to discrete wavelet transform (DWT) up to four levels of decomposition. Then, 12 nonlinear features are extracted from these DWT coefficients. The extracted features are then ranked based on the t value. This proposed method has achieved the highest average accuracy of 98.80%, sensitivity of 99.45% and specificity of 96.27% in classifying normal and MI ECG (two classes), by using 47 features obtained from lead 11 (V5).

Mohammadzadeh and Setarehdan used a neural network classifier to automatic classification of cardiac arrhythmias into five classes. HRV signal is used as the basic signal and linear and nonlinear parameters extracted from it are used to train a neural network classifier. The proposed approach is tested using the MIT-BIH arrhythmia database and satisfactory results were obtained with an accuracy level of 99.38%.

Vishwa et al. proposed an automated Artificial Neural Network (ANN) based classification system for cardiac arrhythmia using multi-channel ECG recordings. In this study, producing high confident arrhythmia classification results to be applicable in diagnostic decision support systems. The classification performance is evaluated using measures; sensitivity, specificity, classification accuracy, mean squared error (MSE), receiver operating characteristics (ROC) and area under curve (AUC). Experimental results give 96.77% accuracy on MIT-BIH database and 96.21% on database prepared by including NSR database also.

Swapna et al. discussed the characteristics and different methods (and their measures) of analyting the heart rate variability (HRV) signal, derived from the ECG waveform. The HRV signals are characterised in terms of these measures, then fed into classifiers for grouping into categories (for normal subjects and for disorders such as cardiac disorders and diabetes) for carrying out diagnosis.

Sujadevi et al. explored and employed a deep learning method such as RNN, LSTM and GRU to detect the Atrial Fibrillation (AF) faster in the given electrocardiogram traces. This study used one of the well-known publicly available MIT-BIH Physionet datasets. This is the first time Deep learning has been employed to detect the Atrial Fibrillation in real-time. Based on this work experiments RNN, LSTM and GRU offer the accuracy of 0.950, 1.000 and 1.000 respectively. This methodology does not require any de-noising, other filtering, and preprocessing methods. Results are encouraging enough to begin clinical trials for the real-time detection of AF that will be highly beneficial in the scenarios of ambulatory, intensive care units and for real-time detection of AF for life saving implantable defibrillators.

Pathinarupothi et al. applied a deep learning technique called LSTM-RNN (long short-term memory recurrent neural network) for identification of sleep apnea and its severity based only on instantaneous heart rates. This tested this model on multiple sleep apnea datasets and obtained perfect accuracy. Furthermore, this work has also tested its robustness on an arrhythmia dataset (that is highly probable in mimicking sleep apnea heart rate variability) and found that the model is highly accurate in distinguishing between the two.

Goldberger et al. of cardiovascular and other complex biomedical signals. The resource has 3 interdependent components. PhysioBank is a large and growing archive of well-characterized digital recordings of physiological signals and related data for use by the biomedical research community. It currently includes databases of multiparameter cardiopulmonary, neural, and other biomedical signals from healthy subjects and from patients with a variety of conditions with major public health

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implications, including life-threatening arrhythmias, congestive heart failure, sleep apnea, neurological disorders, and aging. PhysioToolkit is a library of open-source software for physiological signal processing and analysis, the detection of physiologically significant events using both classic techniques and novel methods based on statistical physics and nonlinear dynamics, the interactive display and characterization of signals, the creation of new databases, the simulation of physiological and other signals, the quantitative evaluation and comparison of analysis methods, and the analysis of nonstationary processes. PhysioNet is an on-line forum for the dissemination and exchange of recorded biomedical signals and open-source software for analyzing them. It provided facilities for the cooperative analysis of data and the evaluation of proposed new algorithms.

Gers et al. reviewed an illustrative benchmark problem on which standard LSTM outperforms other RNN algorithms. All algorithms (including LSTM) fail to solve a continual version of that problem. LSTM with forget gates, however, easily solves it in an elegant way.

3. PROPOSED METHOD

Cardiac arrhythmia is a condition where irregular heart rhythms occur. According to World Health Organization (WHO), about 17 million people in the world die every year due to cardiovascular diseases. This is about 31% of the total deaths globally. According to the statistics of American Heart Association (AHA), one out of every three deaths in US is related to cardiovascular diseases. The deaths due to cardiovascular diseases are more than due to all types of cancer and chronic lower respiratory diseases combined. A 2014 study indicates that approximately 2 to 3% of the people in North American and European countries are affected by atrial fibrillation. A heart rate which is high (above 100 beats per minute in adults) is called tachycardia and a heart rate that is slow (below 60 beats per minute) is called bradycardia. If the beat is too early, then it is called premature contraction. Irregular beat is called fibrillation or flutter. Other than the criteria of heart rate, there are a number of other classifications for cardiac arrhythmia depending upon different types of criteria. Another type of classification is in terms of the site of origin of the irregular heart rate.

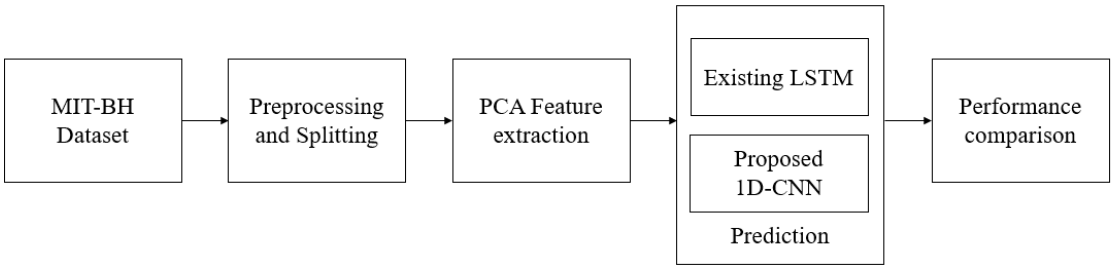

Fig. 1: Proposed block diagram.

Cardiac arrhythmia is a condition where heartbeat is irregular. The goal of this paper is to apply deep learning techniques in the diagnosis of cardiac arrhythmia using ECG signals with minimal possible data pre-processing. We employ deep learning convolutional neural network (1D-CNN), and long short-term memory (LSTM) to automatically detect the abnormality. This work is focused on the design of CNN and LSTM algorithms to predict Arrhythmia diseases with 7 different stages. To train both algorithms, the MIT-BH dataset is used with 7 different disease stages. Further, existing LSTM resulted in low accuracy. So, this work adopted the CNN model for training and testing Arrhythmia disease.

Fig. 1 shows the block diagram of proposed. Here, MIT-BH dataset is considered for evaluating the performance of overall system. Initially, the dataset is splitted into 80% for training and 20% for

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testing. Then, the entire operations are going to be perform on both training and testing datasets. Further, pre-processing operation is carried out to remove the missing symbols and unknown characters, special characters. The pre-processing operation also normalizes the number of rows and columns presented in the dataset. Further, both LSTM and 1D-CNN models are applied to evaluate the prediction of MITBH dataset. So, through this prediction it is going to identify the cardiac arrhythmia presented in overall dataset. Finally, performance comparison is takes place between both LSTM and 1D-CNN models.

3.1 MIT-BH Dataset

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10-mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database. This directory contains the entire MIT-BIH Arrhythmia Database. About half (25 of 48 complete records, and reference annotation files for all 48 records) of this database has been freely available here since PhysioNet's inception in September 1999.

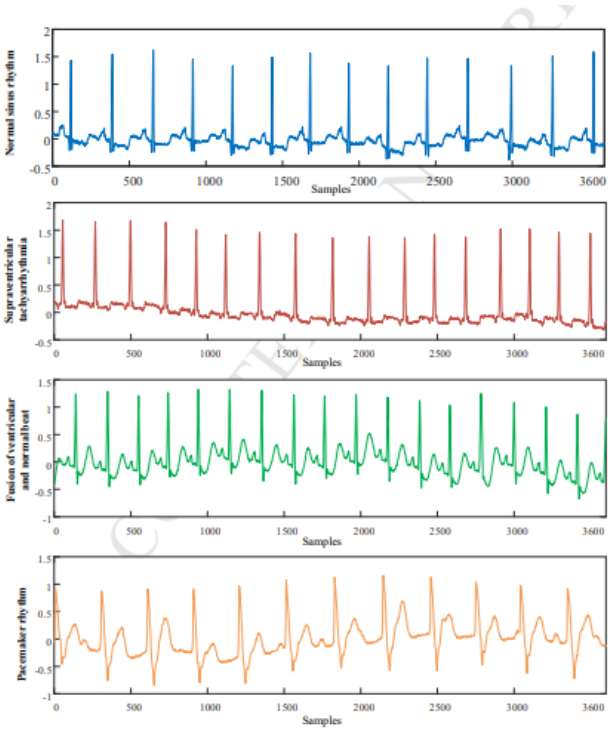

Fig. 2: Typical signal samples of different classes.

Finally, the dataset contains ‘Normal heart', 'Ischemic changes (coronary artery disease)', 'Old Anterior Myocardial Infarction', 'Old Inferior Myocardial Infarction', 'Sinus tachycardy', 'Sinus bradycardy', 'Right bundle branch block' as disease classes.

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4. RESULTS AND DISCUSSION

Modules

To implement this project to designed following modules.

1) Upload Arrhythmia Dataset: using this module will upload dataset to application. Finally, the dataset contains ‘Normal heart', 'Ischemic changes (coronary artery disease)', 'Old Anterior Myocardial Infarction', 'Old Inferior Myocardial Infarction', 'Sinus tachycardy', 'Sinus bradycardy', 'Right bundle branch block' as disease classes.

2) Pre-process Dataset: this module will read all dataset values and then replace missing values with MEAN and then normalize training values and then selected important features from dataset by applying PCA algorithm. Dataset contains more than 270 columns and all these columns are not required so PCA selected relevant features from dataset. After features selection dataset splitted into train and test where application using 80% dataset for training and 20% for testing.

3) Run LSTM Algorithm: the 80% training data is applied input to LSTM to trained a model and then model will be applied on 20% test data to perform prediction and then calculate accuracy.

4) Run CNN Algorithm: the 80% training data is applied input to CNN to trained a model and then model will be applied on 20% test data to perform prediction and then calculate accuracy.

5) LSTM & CNN Training Graph: this module plots CNN and LSTM training graph

6) Performance Table: this module displays both algorithms performance in tabular format.

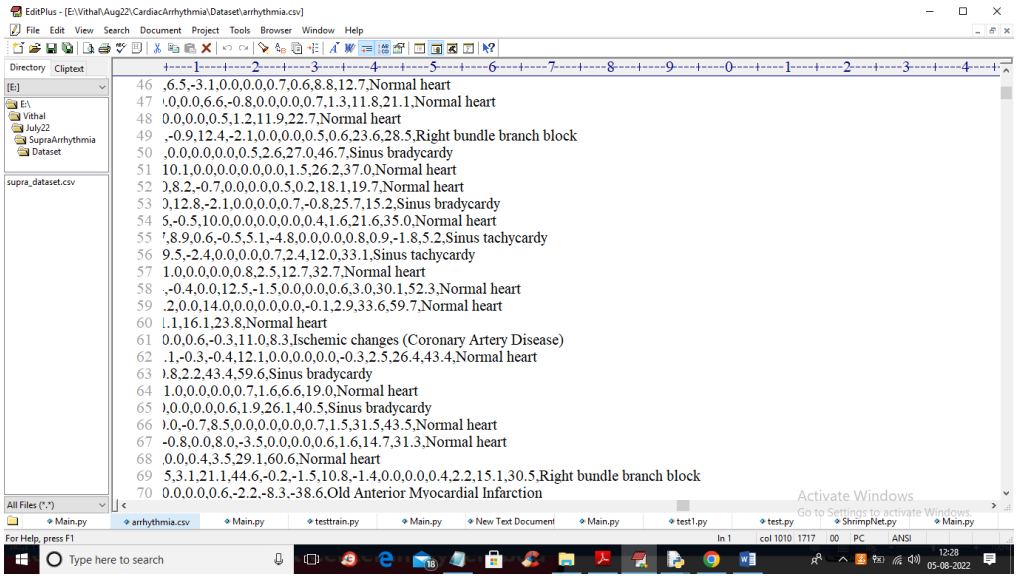

Fig. 3: Sample dataset.

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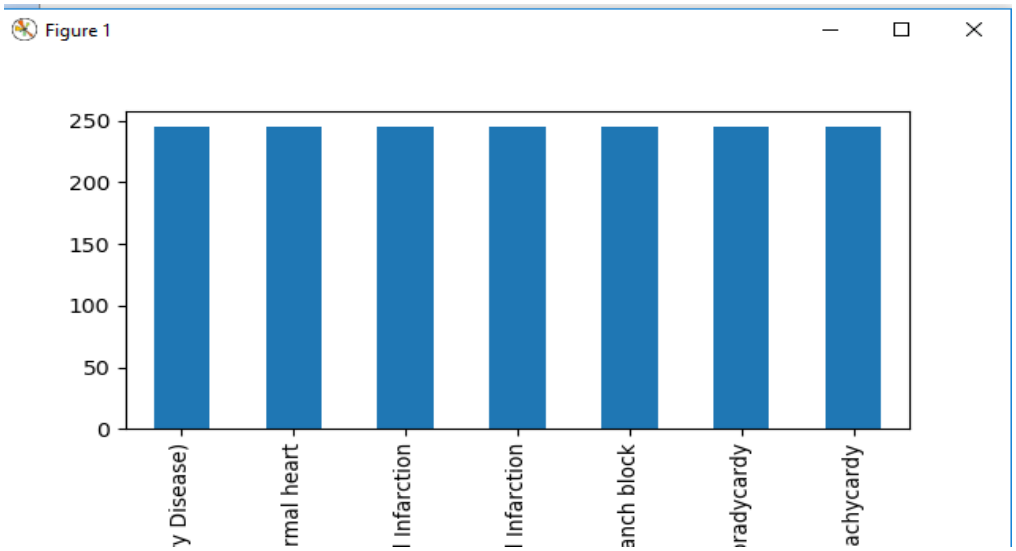

Fig. 4: Records found for each class.

In Fig 4, we can see dataset loaded and in graph x-axis represents 7 different disease stages and y-axis represents number of records found for that disease in dataset.

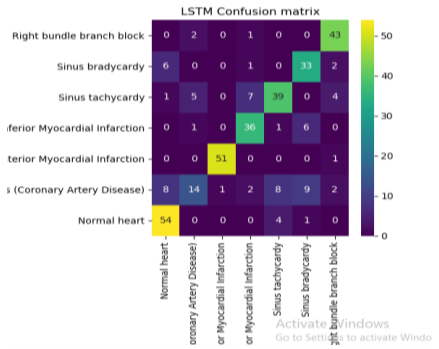

Fig. 5: Confusion Matrix of LSTM.

In above screen with LSTM, we got 78% accuracy and in confusion matrix graph x-axis represents Predicted classes and y-axis represents TRUE classes and all blue colour boxes count are wrong prediction and different colour boxes count are correct prediction and we can see LSTM predicted so many wrong classes.

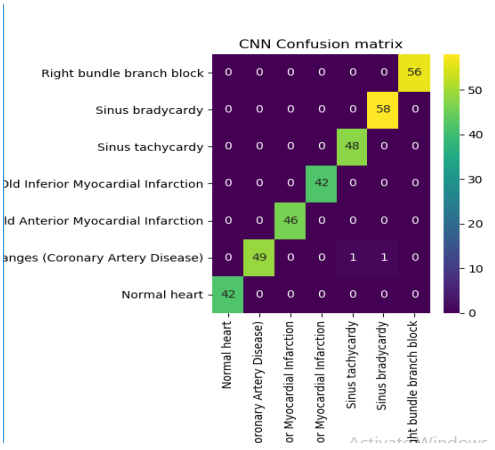

Fig. 6: 1D-CNN Confusion matrix.

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In above screen with CNN, we got 99% accuracy and in confusion matrix graph only 2 counts in blue colour boxes are wrong prediction and rest are correct prediction.

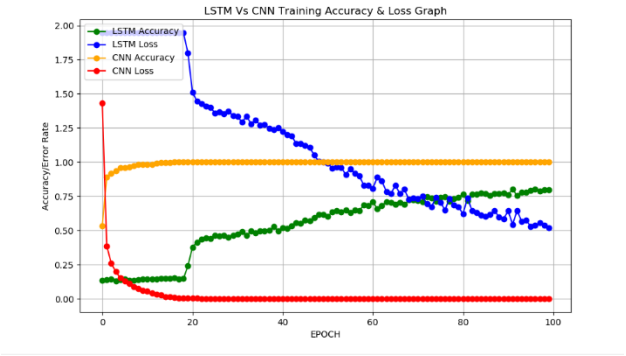

Fig. 7: Accuracy and Loss performance graph.

In above graph x-axis represents training epoch and y-axis represents training accuracy and loss values and green colour line represents LSTM accuracy and orange colour line represents CNN accuracy and red colour line represents CNN loss and blue line represents LSTM loss and in above graph we can see both algorithms accuracy got increase in every epoch and loss get decrease.

Table 1. Performance comparison.

Metric	Existing LSTM	Proposed 1D-CNN
Accuracy	83.38	99.54
Precision	83.075	99.24
Recall	83.0074	99.56
F-Score	82.32	99.24
Sensitivity	100	100
Specificity	91.66	97.28

5. CONCLUSION

Cardiac arrhythmia is an irregularity in heart rhythm. Some types of cardiac arrhythmia can lead to complications like stroke, heart attack and may even lead to sudden cardiac death. So, timely detection and diagnosis of arrhythmia is especially important. Once arrhythmia is detected, next stage of identification of category of arrhythmia can be done. We developed an automated non-invasive system based on deep learning networks to perform the basic classification of a given ECG data as belonging to normal ECG or abnormal (having arrhythmia) ECG using the most popular public ally available MIT-BIH arrhythmia database.

We compared the performance using a variety of deep learning architectures of LSTM, 1D-CNN. With concern on computational cost, we are not able to train more complex architecture. The reported results can be further improved by using more complex deep learning architecture. The complex network architectures can be trained by using advanced hardware and following distributed approach in training that we are incompetent to try.

We have discussed the role of deep learning techniques such as 1D-CNN in the task of arrhythmia classification. The highlight of the proposed method is that it does not need any noise filtering and

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feature engineering mechanisms. The results obtained prove that the performance of our method is better than other published results in effectively classifying ECG as belonging to normal or arrhythmia class.

Future scope

Though deep learning networks produces excellent results, the disadvantage lies in the insufficient understanding of the complex inner mechanisms of the deep learning networks. This could be overcome by remodelling the nonlinear deep networks to a linear form by computing eigenvalues and eigenvectors in different time steps. The future work can be the collection of real-world datasets from hospitals having cardiac care units and the application of the same methodologies to the real datasets.

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