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Automated Detection of Cardiac Arrhythmia Using Recurrent Neural Network

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Abstract: Cardiac arrhythmia is a medical condition characterized by an irregular heartbeat, which may be too fast, too slow, or inconsistent. It can lead to severe complications if not diagnosed and treated in a timely manner. Electrocardiogram (ECG) signals play a crucial role in detecting and analyzing cardiac arrhythmia. The goal of this paper is to apply deep learning techniques to the diagnosis of cardiac arrhythmia using ECG signals while minimizing the amount of data preprocessing required.. However, deep learning techniques provide a more automated and data-driven approach by directly learning from raw ECG signals. Our results demonstrate that the CNN-LSTM hybrid model achieves a five-fold cross-validation accuracy of 0.834 in distinguishing normal and abnormal ECG signals associated with cardiac arrhythmia. This indicates that combining CNNs with LSTMs enhances the model's ability to capture both spatial and temporal dependencies in ECG signals. Furthermore, the accuracy obtained by other hybrid architectures, such as CNN-GRU and CNN-RNN, is comparable to that of the CNN-LSTM model, suggesting that deep learning-based approaches are highly effective in identifying cardiac arrhythmia. In conclusion, this study highlights the potential of deep learning techniques in automating the diagnosis of cardiac arrhythmia with minimal data preprocessing. The results suggest that hybrid architectures, particularly CNN-LSTM, offer promising accuracy and can serve as reliable diagnostic tools. CNN with an accuracy of 95.22%. An accuracy of 84.54% was achieved in the detection of inferior MI in ECG using CNN.

I. 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. The deaths due to cardiovascular diseases are more than due to all types of cancer and chronic lower respiratory diseases combined.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 as a result 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.Extensive research has been done in the area of arrhythmia detection. CNN with an accuracy of 95.22%. An accuracy of 84.54% was achieved in the detection of inferior MI in ECG using CNN. Four types of arrhythmia were classified with an accuracy of 99.38% with MIT BIH data set along with another dataset as input. Classification of MIT Arrhythmia database of ECG into normal and abnormal was conducted using artificial neural network (ANN) achieving an accuracy of 96.77

1.1 Objective

Cardiac arrhythmia is a condition where heart beat 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 convolutional neural network (CNN), recurrent structures such as recurrent neural network (RNN), long short-term memory (LSTM) and gated recurrent unit (GRU) and hybrid of CNN and recurrent structures to automatically detect the abnormality. Unlike the conventional analysis methods, deep learning algorithms don't have feature extraction based analysis methods. The optimal parameters for deep learning techniques are chosen by conducting various trails of experiments.

All trails of experiments are run for 1000 epochs with learning rate in the range . We obtain five-fold cross validation accuracy of 0.834 in distinguishing normal and abnormal (cardiac arrhythmia) ECG with CNN-LSTM. Moreover, the accuracy obtained by other hybrid architectures of deep learning algorithms is comparable to the CNN-LSTM.

II LITERATURE SURVEY

"A new pattern recognition method for detection and localization of myocardial infarction using T-wave integral and total integral as extracted features from one cycle of ECG signal."

In this paper we 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 infarction (MI) in left ventricle of heart. In our previous work we used some features of body surface potential map data for this aim. But we know the standard ECG is more popular, so we focused our detection and localization of MI on standard ECG. We use 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 we believe that the MI affects the morphology of the ECG signal which leads to total integral changes. We used some pattern recognition method such as Artificial Neural Network (ANN) to detect and localize the MI, because this method has very good accuracy for classification of normal signal and abnormal signal. We used one type of Radial Basis Function (RBF) that called Probabilistic Neural Network (PNN) because of its nonlinearity property, and used other classifier such as k-Nearest Neighbors (KNN), Multilayer Perceptron (MLP) and Naive Bayes Classification. We used PhysioNet database as our training and test data. We reached over 76% for accuracy in test data for localization and over 94% for detection of MI. Main advantages of our method are simplicity and its good accuracy. Also we 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 has good accuracy in MI localization.

Multiscale energy and eigenspace approach to detection and localization of myocardial infarction:

In this paper, a novel technique on a multiscale energy and eigenspace (MEES) approach is proposed for the detection and localization of myocardial infarction (MI) from multiload electrocardiogram (ECG). Wavelet decomposition of multilead ECG signals grossly segments the clinical components at different subbands. In MI, pathological characteristics such as hypercute T-wave, inversion of T-wave, changes in ST elevation, or pathological Q-wave are seen in ECG signals. This pathological information alters the covariance structures of multiscale multivariate matrices at different scales and the corresponding eigenvalues..

Automated detection and localization of myocardial infarction using electrocardiogram: A comparative study of different leads:

Identification and timely interpretation of changes occurring in the 12 electrocardiogram (ECG) leads is crucial to identify the types of myocardial infarction (MI). However, manual annotation of this complex nonlinear ECG signal is not only cumbersome and time consuming but also inaccurate. Hence, there is a need of computer aided techniques to be applied for the ECG signal analysis process. Going further, there is a need for incorporating this computerized software into the ECG equipment, so as to enable automated detection of MIs in clinics.The extracted features are then ranked based on the *t* value. locating inferior posterior infarction by using only lead 9 (V_3) ECG signal. Our proposed method can be used as an automated diagnostic tool for (i) the detection of different (10 types of) MI by using 12 lead ECG signal, and also (ii) to locate the MI by analyzing only one lead without the need to analyze other leads.

Thus, our proposed algorithm and computerized system software (incorporated into the ECG equipment) can aid the physicians and clinicians in accurate and faster location of MIs, and thereby providing adequate time available for the requisite treatment decision.

Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals.:

The electrocardiogram (ECG) is a useful diagnostic tool to diagnose various cardiovascular diseases (CVDs) such as myocardial infarction (MI). The ECG records the heart's electrical activity and these signals are able to reflect the abnormal activity of the heart. However, it is challenging to visually interpret the ECG signals due to its small amplitude and duration. Therefore, we propose a novel approach to automatically detect the MI using ECG signals. In this study, we implemented a convolutional neural network (CNN) algorithm for the automated detection of a normal and MI ECG beats (with noise and without noise). We achieved an average accuracy of 93.53% and 95.22% using ECG beats with noise and without noise removal respectively. Further, no feature extraction or selection is performed in this work. Hence, our proposed algorithm can accurately detect the unknown ECG signals even with noise. So, this system can be introduced in clinical settings to aid the clinicians in the diagnosis of MI.

Classification of arrhythmic ECG data using machine learning techniques:

In this paper we proposed a automated Artificial Neural Network (ANN) based classification system for cardiac arrhythmia using multi-channel ECG recordings. In this study, we are mainly interested in producing high confident arrhythmia classification results to be applicable in diagnostic decision support systems. Neural network model with back propagation algorithm is used to classify arrhythmia cases into normal and abnormal

classes. Networks models are trained and tested for MIT-BIH arrhythmia. The different structures of ANN have been trained by mixture of arrhythmic and non arrhythmic data patient. The classification performance is evaluated using measures; sensitivity, specificity, classification accuracy, mean squared error (MSE), receiver operating characteristics (ROC) and area under curve (AUC). Our experimental results gives 96.77% accuracy on MIT-BIH database and 96.21% on database prepared by including NSR database also.
detecting them in real-time is of paramount importance for early intervention. Traditional methods require long ECG traces and tedious preprocessing for accurate diagnosis. In this paper, we explore and employ deep learning methods such as RNN, LSTM and GRU to detect the Atrial Fibrillation (AF) faster in the given electrocardiogram traces

III. PROPOSED METHODOLOGY

3.1 Proposed System

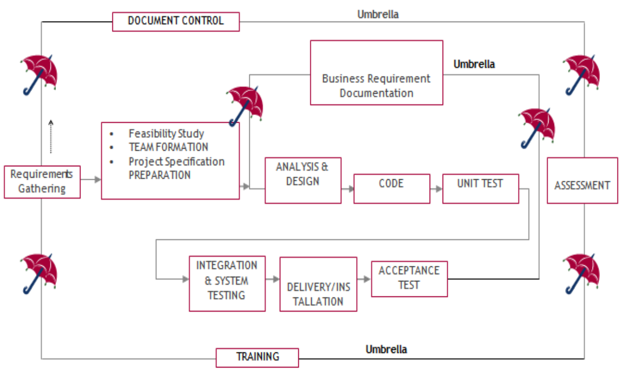
The proposed deep learning architecture for the classification of ECG recordings into either normal or arrhythmia is presented in Deep learning algorithms don't need explicit feature extraction and analysis like traditional machine learning based classifiers. It just passes raw input data to more than one hidden layer to obtain the optimal feature representation by itself. The newly formed feature representations are further passed as input to the fully connected layer (dense layer) which uses sigmoid activation function to produce output binary values 0 or 1 indicative of arrhythmia or normal ECG. It is an extension of feed forward network having feedback loops.This results in a cyclic graph. These loops are the short-term memory used to store and retrieve past information over time scales.

Advantages of Proposed System:

- High Accuracy

3.2. Procedure Model used with justification

The SDLC (Umbrella Model)



SDLC is nothing but Software Development Life Cycle. It is a standard which is used by software industry to develop good software.

Stages in SDLC:

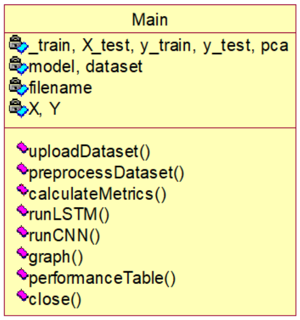
• Requirement Gathering, Analysis, Designing, Coding, Testing, Maintenance.

IV. SYSTEM DESIGN

UML Diagram:

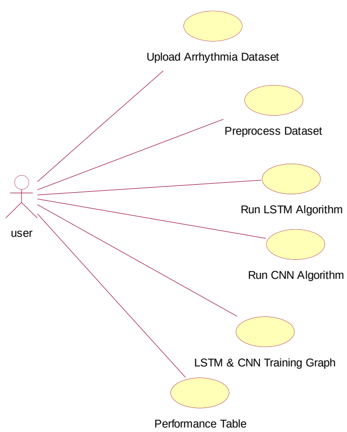
1. Class Diagram:

The class diagram is the main building block of object oriented modelling. It is used both for general conceptual modelling of the systematic of the application, and for detailed modelling translating the models into programming code. Class diagrams can also be used for data modelling. The classes in a class diagram represent both the main objects, interactions in the application and the classes to be programmed. In the diagram, classes are represented with boxes which contain three parts:



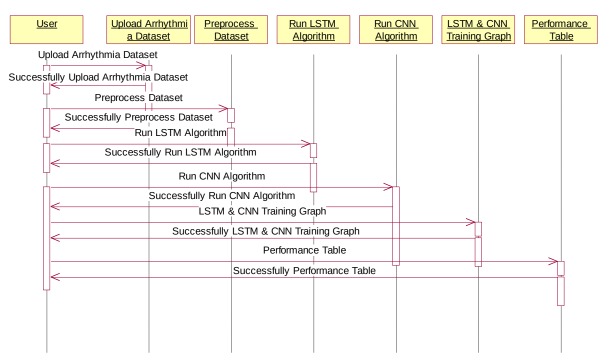
2. Use case Diagram:

A use case diagram at its simplest is a representation of a user's interaction with the system and depicting the specifications of a use case. A use case diagram can portray the different types of users of a system and the various ways that they interact with the system. This diagram is typically used in conjunction with the textual use case and will often be accompanied by other types of diagrams as well.



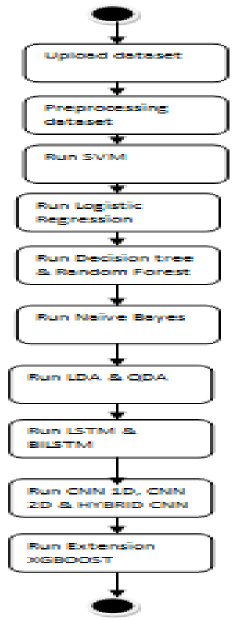
3. Sequence diagram:

A sequence diagram is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.



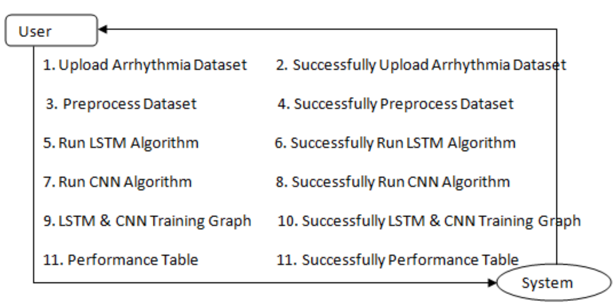
4. Activity Diagram:

Activity diagram is another important diagram in UML to describe dynamic aspects of the system. It is basically a flow chart to represent the flow form one activity to another activity. The activity can be described as an operation of the system. So the control flow is drawn from one operation to another. This flow can be sequential, branched or concurrent



5. Data Flow Diagram:

Data flow diagrams illustrate how data is processed by a system in terms of inputs and outputs. Data flow diagrams can be used to provide a clear representation of any business function. The technique starts with an overall picture of the business and continues by analyzing each of the functional areas of interestAs the name suggests, Data Flow Diagram (DFD) is an illustration that explicates the passage of information in a process.

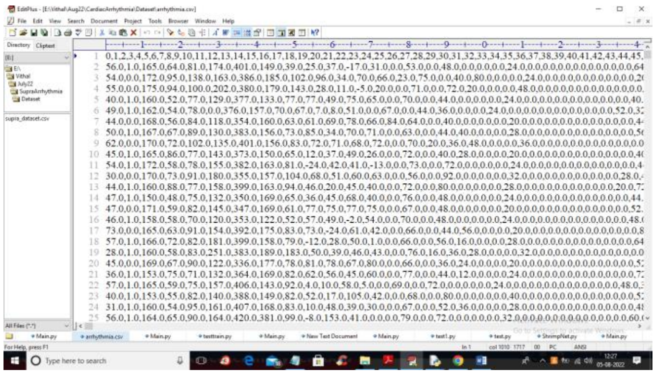


IV EXPERIMENTAL ANALYSIS

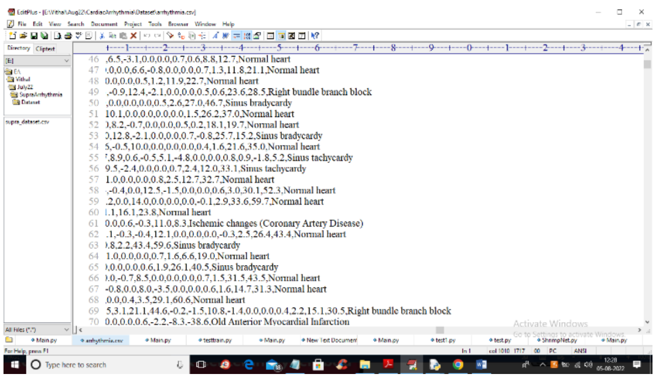
In this project you asked to design CNN and LSTM algorithm to predict Arrhythmia diseases with 7 different stages. To train both algorithm we have used MIT-BH dataset with 7 different disease stages.

You told to get 95% accuracy which is difficult to get with LSTM but with CNN we got 97% accuracy.

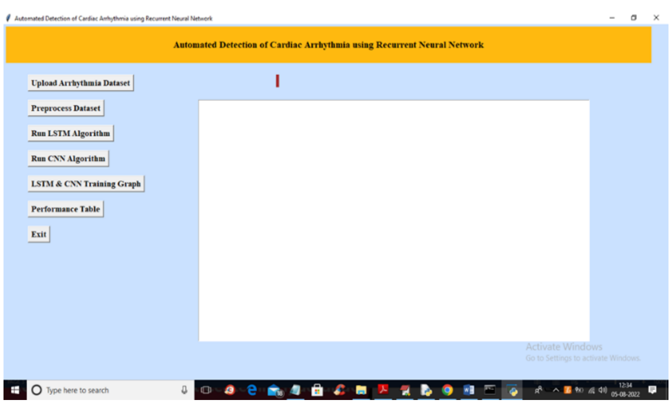
To train both algorithm we have used below dataset



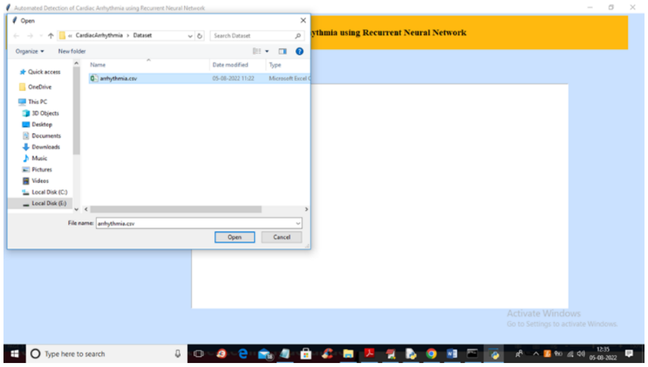
In above dataset screen first row contains column names and remaining rows contains dataset values and in last column we can see class label as disease name.



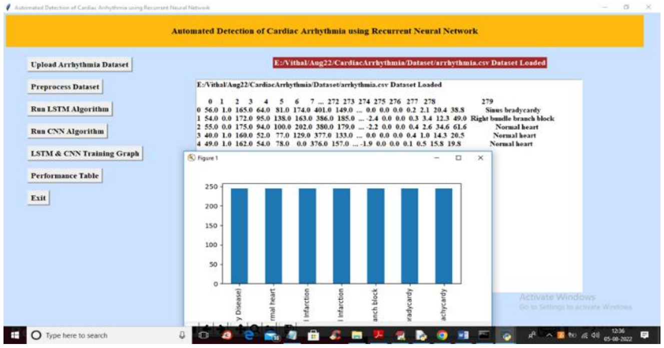
In above screen in last column we can see disease name and by using above dataset we are training both algorithms. To run project double click on ‘run.bat’ file to get below screen



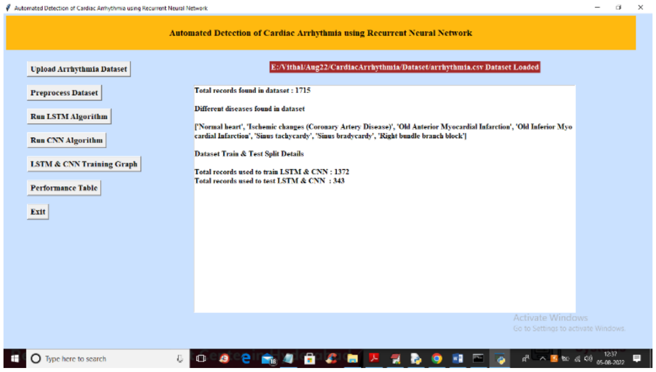
In above screen click on ‘Upload Arrhythmia Dataset’ button to upload dataset and get below output



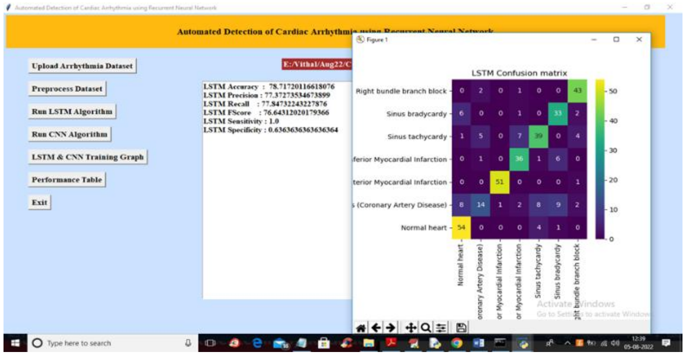
In above screen selecting and uploading ‘Arrhythmia’ dataset and then click on ‘Open’ button to load dataset and get below output



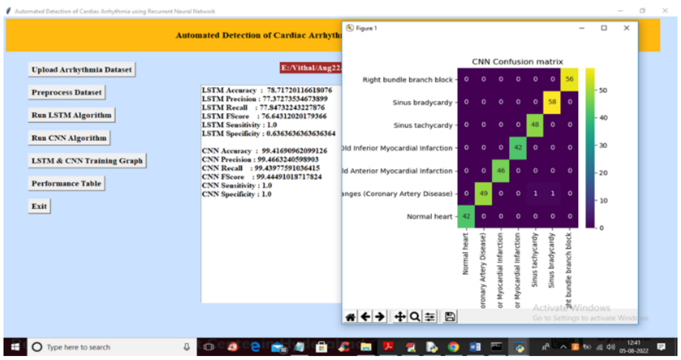
In above screen we can see dataset loaded and in graph x-axis represents 7 different disease stages and y-axis represents number of records found for that disease in dataset.



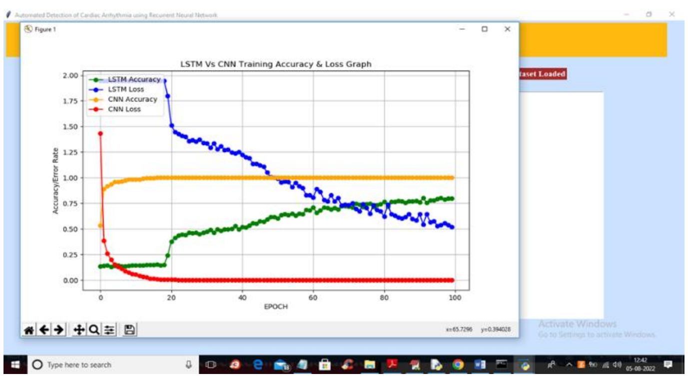
In above screen all dataset converted to numeric format and we can see total dataset size with train and test split details and displaying names of disease and now click on ‘Run LSTM Algorithm’ button to train LSTM with above process dataset and get below output



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 and now close above graph and then click on ‘Run CNN Algorithm’ button to train CNN and get below output

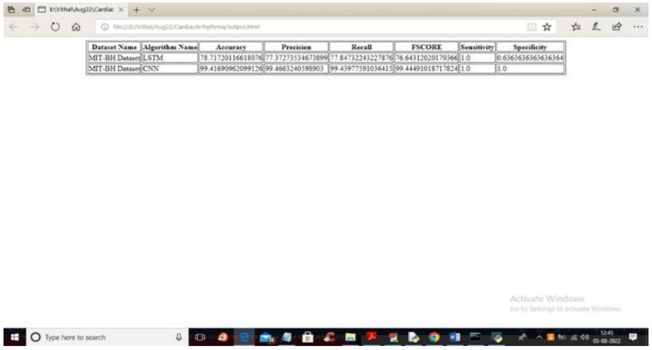


In above screen with CNN we got 99% accuracy and in confusion matrix graph only 2 counts in blue colour boxes are wrong prediction and rest are correct prediction. Now click on ‘LSTM & CNN Training Graph’ button to get below graph.



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.

In above graph we can see both algorithms accuracy got increase in every epoch and loss get decrease and now close above graph and then click on “Performance Table’ button to get below output.



Dataset Name	Algorithm Name	Accuracy	Precision	Recall	FSCORE	Sensitivity	Specificity
MIT-BH Dataset	LSTM	78.71720116618076	77.37273534673899	77.84732243227876	76.64312020179366	1.0	0.6363636363636364
MIT-BH Dataset	CNN	99.41690962099126	99.4663240598903	99.43977591036415	99.44491018717824	1.0	1.0

In above screen we can see output metrics of both algorithms in tabular format

V. CONCLUSION

Cardiac arrhythmia is basically 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 very 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 publically available MIT-BIH arrhythmia database. We compared the performance using a variety of deep learning architectures of CNN, CNN-RNN, CNN-LSTM and CNN-GRU and obtained an accuracy of 0.834. 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 CNN and recurrent structures in the task of arrhythmia classification. 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. 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 re modeling 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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