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AUTOMATED DETECTION OF CARDIAC ARRHYTHMIA USING RECURRENT NEURAL NETWORK

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Abstract: 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 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 trials 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.

Keywords: : Automated face recognition, Convolutional neural networks(CNN),Image or video frame, machine learning(ML).

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. 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. 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 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 manner in which it happens in AF.

I. EXISTING SYSTEM

This database has a major issue when applied to deep learning networks in the original format. It is due to the fact that these 48 sequences largely consist of two types of data (either related to normal or abnormal heartbeats). Due to this, beat-to-beat dependence is very much possible in the data sequences. Another issue is the difference in baseline voltages of different sequences. In order to tackle both these issues, we extracted individual heartbeats from continuous sequences of database. These extracted heartbeats are used to train our deep learning networks. LSTM introduced memory blocks instead of conventional simple RNN units to handle the problem of vanishing and exploding gradient. LSTMs can handle long term dependencies much better than the traditional RNNs whereby LSTMs can remember and connect previous information that really lags back so much in time compared to the present.

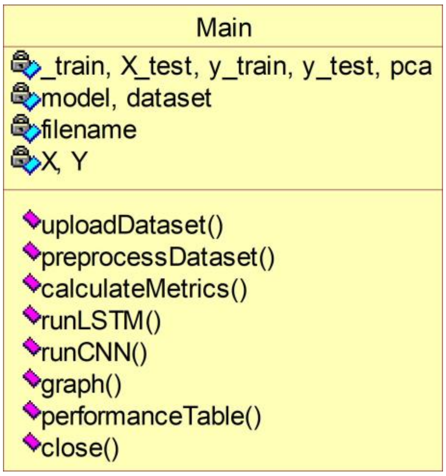
II. PROPOSED SYSTEM

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. Temporal tasks can be executed very effectively with this improvement. Unlike multilayer perceptrons (MLPs), RNNs can handle temporal sequences of arbitrary length. RNN can also share its parameters across time-steps to avoid not being generalized on dealing with the unseen sequence of arbitrary length. In short, RNNs are models that can effectively learn dynamic temporal behaviours for input-output sequences of any arbitrary length. RNN is used extensively, especially for long standing AI tasks in the field of machine translation, language modelling and speech recognition. The objective of this work is to develop an automated method for the diagnosis of cardiac arrhythmia. We perform a two class classification of the given ECG signal, whether cardiac arrhythmia is present or not. We use ECG recordings from the publically available MIT-BIH arrhythmia database in Physionet. The MIT-BIH arrhythmia database is the first generally available dataset which is widely used for ascertaining the efficiency of cardiac arrhythmia detection algorithms.

III. SYSTEM DESIGN

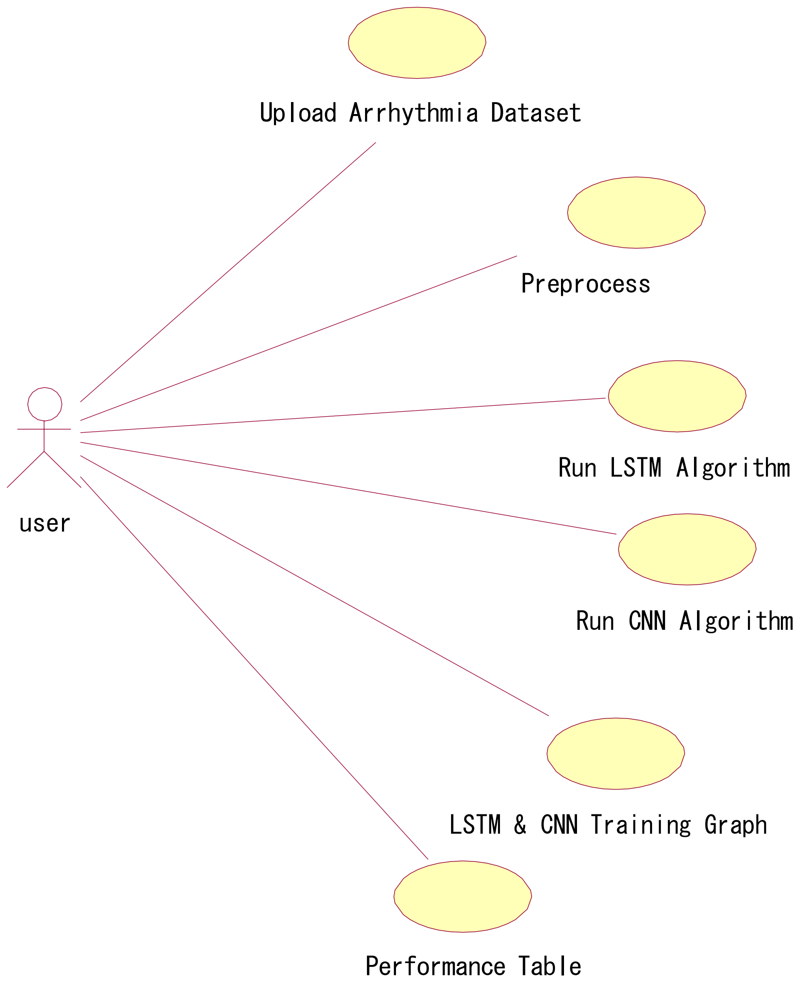
The class diagram is the main building block of object oriented modeling. It is used both for general conceptual modeling of the systematic of the application, and for detailed modeling translating the models into programming code. Class diagrams can also be used for data modeling. The classes in a class 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:

- The upper part holds the name of the class
- The middle part contains the attributes of the class
- The bottom part gives the methods or operations the class can take or undertake



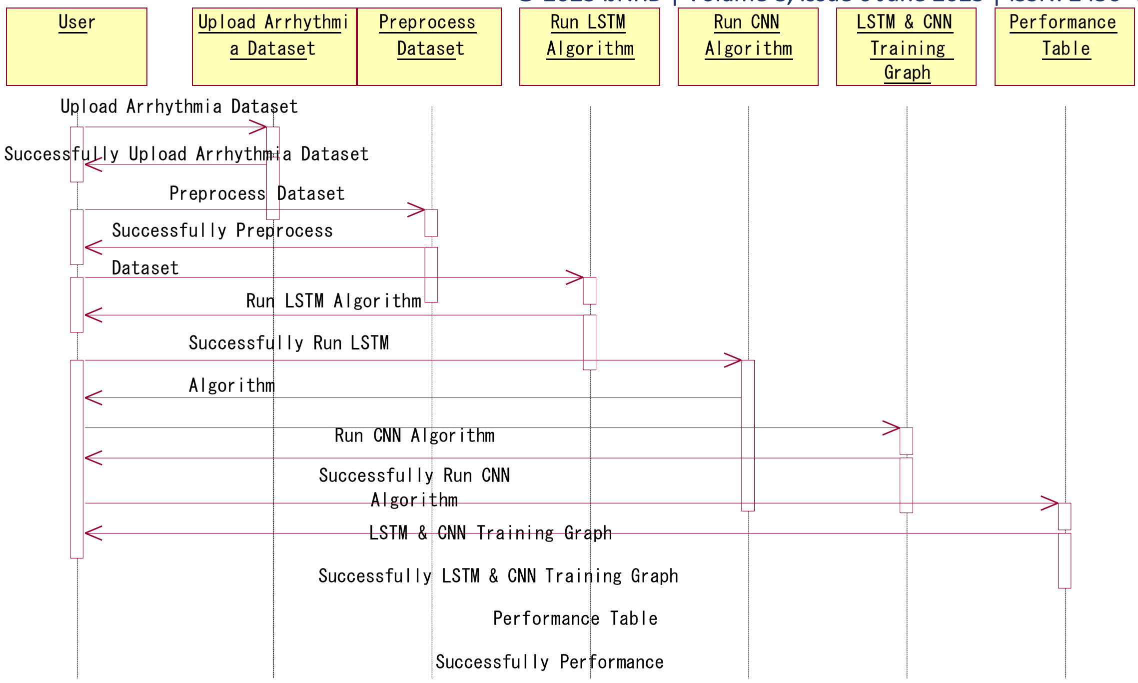
5.1.2 USECASE DIAGRAM:

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 type of diagram is typically used in conjunction with the textual use case and will often be accompanied by other types of diagrams as we



5.1.3 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.



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 per form 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 highlight of the proposed method is that it doesn't need any noise filtering and 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. 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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