LSTM based Comparative Analysis on Irregular Heart Rate Classification from a Short Single Lead ECG.

Prepared by: MD RAKIBUL AHASAN

Subject Name: ECE526 Biomedical Signal Analysis and Machine Learning

Abstract

The heart is considered an important organ for the human body, it beats around 3.5 billion times/per lifetime and ensures the momentum of blood in the inner vessel. Any failure in the heart will lead to a serious abnormality and humans might undergo serious surgery or permanent medication like a blood thinner. So regular diagnosis must be done and one of the popular methods is electrocardiogram (ECG) signal analysis of the heart. An ECG works by capturing the electrical activity of the heart to provide heartbeats rhythm analysis, an indication of preliminary blockage, or any arrhythmia of the heart. As the same sound, the ECG went through a couple of steps to reach analysis, like appropriately capturing the heart signal, understanding its content, and removing unwanted signals, feature analysis, transformation, and classification as applicable. Another aspect of ECG is, it is very cheap and readily available in all the diagnosis centers of the world as well as it can provide instant analysis too. Hence the accuracy ECG analysis must be accurate enough so that the next decision is appropriate. In this project, I am working on the physionet 2017 challenge data set and using a type of recurrent neural network LSTM for normal ECG signal and atrial fibrillation ECG signal. I used three types of LSTM networks among those Deep LSTM machine learning with Adam optimizer provides the best performance with accuracy close to 88 percent and a recall value of 91 percent.

Evolution of ECG and Its mechanism

Many electrical activities are running in a heart and the first capture is done in May 1887 by Augustus Waller using a mercury electrometer [1]. The mechanism was to place two electrodes in the human body mercury and acid attach to it and the mercury expands and contracts according to the potential difference. But this method has some distortions and while studying it Willem Einthoven (Leiden, The Netherlands) was able to improve it and he is known as the father of modern ECG. He improved the ECG by using a string galvanometer. The galvanometer is coated with a thin layer of silver-coated quartz filament and attached to a strong magnetic field. When the current pass through the quartz material it provides a movement and with considerable magnification this movement is similar to the mercury electrometer. Moreover, it is possible to calibrate the string by tightening and loosening it to capture the signal more accurately [2].

However, the modern ECG is based on a 12-lead system placed like three bipolar limbs, three augmented unipolar limbs, and six precordial leads. The mechanism of its first ten electrodes is placed in the patient's limbs and chest surface. And then it starts capturing the magnitude of the heart signal at 12 angles and the duration of each capture time is 10 seconds. It not only captures the magnitude, but it also captures the electrical depolarization direction of the heart [3].

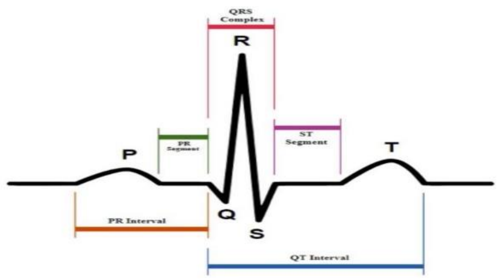


Figure 1: PQRST wave

About fig 1, there are three components of ECG those are P wave, QRS complex, and T wave. Each of these signals contains much important information and it's a must to know the properties of those signals. The P wave captures the depolarization of the left and right atrium however the magnitude of the P wave is quite low around 2.5 mm tall and last only 0.11 seconds. The QRS complex consists of three successive wave Q wave, R wave, and S wave. Altogether those provide the depolarization of ventricles. The notation of these waves is Q wave has a negative magnitude, and after that, the R wave occurs which has a positive magnitude, and again the S wave with a negative magnitude. The duration of QRS did not last more for an adult and usually lies between 0.06 to 0.10 seconds. The junction points or the J-point is the point where the QRS complex and ST segments meet. It is also known as the starting point of the ST segment and is important to the diagnosis of elevation myocardial infarction. Lastly, the T wave provides ventricular polarization. It has a high peak at the start and gradually ends. However, if it occurs in the opposite, it means some sort of cardiac pathology.

Application of ECG

The main benefit of ECG is that it is very cheap, and the result comes as accurately as possible. The ECG is asked by a doctor when a patient encounter shortness of breath, dizziness, or chest pain. An ECG can detect the rhythm of the heart it is beating fast or slow known as arrhythmias. It can also give an initial understanding of whether the blood running through the heart vessel is blocked or not. It can also accurately diagnose whether a patient encounters a heart attack. Another important thing it detects the thickness of the heart wall or enlarged. In another way, it can be said ECG gives a preliminary analysis of a heart and saves millions of lives with proper treatment initiation [4].

The base procedure of ECG is plugging electrodes over the skin of the human body and the position of electrodes is important for accurate measure of PQRST wave. There are mainly three types of ECG, if the ECG is performed while the patient is in a resting position then it is called the resting ECG, while if the patient is running or doing exercise, and ECG that time known as stress or exercise ECG. Moreover, there are some portable ECG machine or watch which attach to your body and can monitor your heart rate at any time.

Project In High Level:

The importance of ECG is very vast, and it can do early detection of heart diseases and can save a million of life. Hence the accuracy measurement of ECG must be high and here machine learning will play a key role. Keep that in mind I want to explore the pre-processing steps of multiple ECG signals, I will also want to perform feature selection extraction, and normalization and use machine learning to achieve as highest accuracy possible. Inspired by recent advancements I want to use deep learning [6] for ECG signal analysis. The basic methodology is in below fig 2.

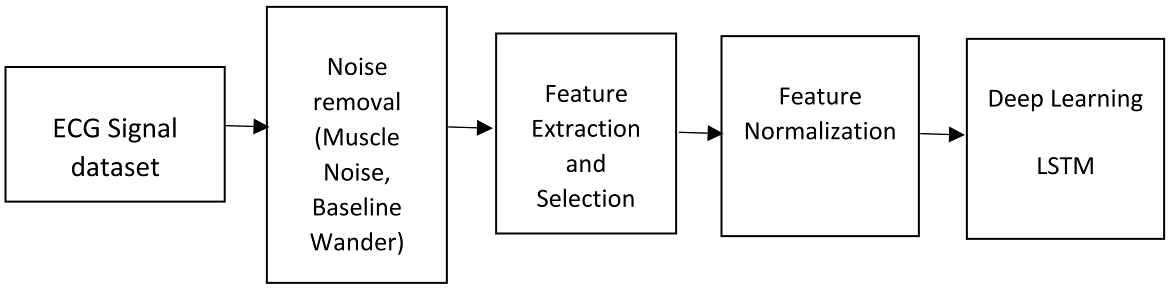


Figure 2: Deep Learning Analysis of ECG

Objective from the Dataset and Its details:

The most popular online database for biomedical research is the physionet website and it regularly publishes large-scale biomedical data. I will be using the 2017 physionet challenge data set [7] as my base ECG signal data set. The purpose of this data set is to classify from a single short ECG lead recording to normal sinus rhythm (NSR), alternate rhythm, atrial fibrillation (AF), or unable to classify. I will be focusing on AF classification; AF generally means irregular heart bit and the heart rate is usually high during that time. However, the heart rate is also within the acceptable limit if AF continues. It is said the root cause of AF is not always certain, but the common cause is damage to the heart. Early identification of AF prevents the risk of death, coronary heart disease, stroke, etc. AF is often associated with age; between 40-50 age the AF is 0.5 percent and it will rise to 5-15 percent if the age is more than 80 [8].

The AF detector roughly depends on analysis based on atrial activity or based on ventricular response. The absence of P wave or fibrillatory f wave presence in the TQ interval is fundamental to atrial activity AF detection. On the other hand, the prediction of RR interval in the QRS complex is the basis of the ventricular response method. Some study also conducted where both atrial activity and ventricular response methods were taken into a consideration for AF detection. And more research includes that if we introducing machine learning base feature extraction and proper training from a dataset has enhanced the AF detection much more accurately.

Previous AF detection challenges focused on the limited number of patients or carefully selected clean data as we focus only on normal and AF classification. However, this challenging dataset from physionet combines many non-AF signals and is considered under a single class and classified as Normal sinus rhythm, AF, Other rhythms, or Too noisy to classify.

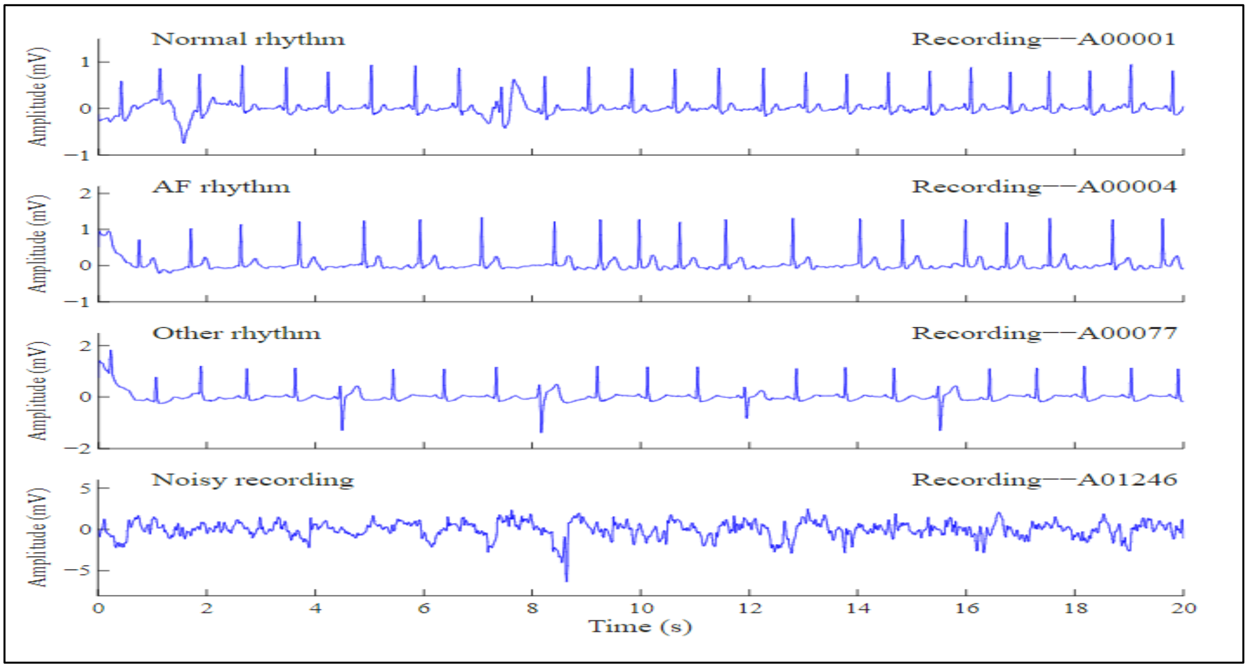
The dataset contains 8528 single lead ECG recording duration from 9s to 60s. A details is in Table 1. The ECG recording the sampled as 300 Hz and filtered by a band pas filter of AliveCor device. The dataset format is MATLAB V4 WFDB-compliant format has a .mat file containing the ECG and .hea file which contains the waveform information. This file contains all type of signal normal signal, AF, other rhythms and too much noisy signal. A demonstration of that is in figure 3.

From the table 1 it is seen the ration of AF signal w.r.t normal signal and other rhythm signal is quite low and my project objective of use machine learning to classify to AF signal as accurately as possible.

Table 1: Data profiling of the ECG dataset.

Type	# recording	Time length (s)				
		Mean	SD	Max	Median	Min
Normal	5154	31.9	10	61	30	9
AF	771	31.6	13	60	30	10
Other rhythm	2557	34.1	12	60.9	30	9.1
Noisy	46	27.1	9	60	30	10
Total	**8528**	**32.5**	**11**	**61**	**30**	**9**

Figure 3: Various signal visualization in present is the dataset.



Comparative Analysis Approach using Machine Learning:

I will use deep learning techniques for the classification of AF signals. The deep learning technique is LSTM. The LSTM stands for long – short-term memory and it has a feedback connection. It has the capability of processing the entire sequence of data and it's a special kind of recurrent neural network. The high-level workflow from the dataset is shown below figure 4. Apart from a regular LSTM-based classification, I will also explore a combination of neural networks for example

LSTM and DeepLSTM just to see what challenges I would get and how to resolve those challenges.

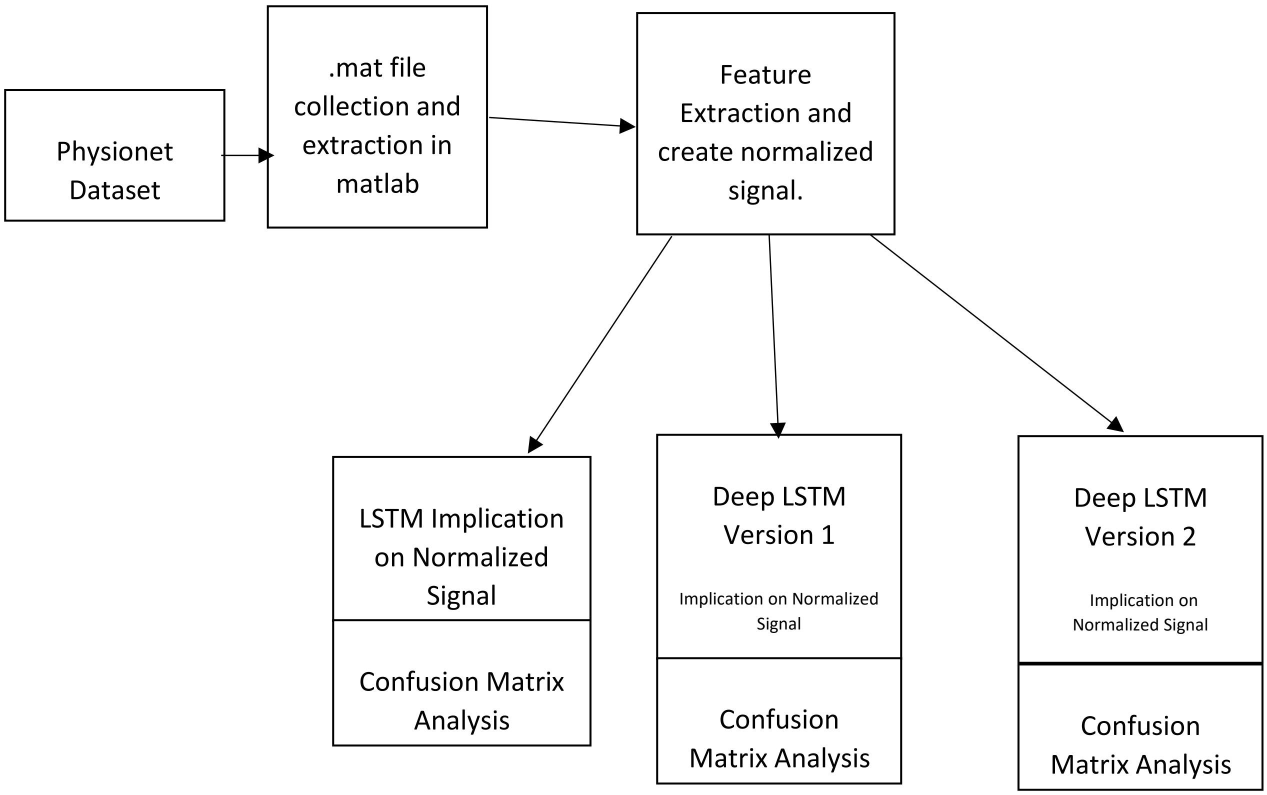


Figure 4: Deep Learning workflow for AF classification.

Project Plan:

The high-level project plan is Table 2.

Table 2: Project plan

Sl. No	Task	Week 1	Week 2	Week 3	Week 4
1	Data Collection				
2	Data Preprocessing				
3	Feature extraction and Normalized data				
4	LSTM analysis on Raw signal data				
5	LSTM in Normalized Data				
6	Deep LSTM in Normalized Data				
7	Confusion matrix analysis				
8	Final report Preparation.				

Data Preprocessing:

Below are the steps considered for the data preparation[10] of classification by LSTM or Deep LSTM.

1. Input the ECG signal.
2. Convert the ECG signal to having a finite sample length *of m*. If the signal sample length is < *m* discard or equal to *m* keep the signal or if it's a multiple of sample length *m* divide into a multiple of sample length m and the rest is discarded.
3. Divide the data set into training and testing data set with a ratio of training 0.8 and testing 0.2.
4. Evenly balance the data set so that the number of training data for normal and AF classes are equal and vice versa for testing data for normal and AF classes.
5. Calculate the instant frequency and spectral density of the ECG signal considering sample frequency =200 Hz.
6. Calculate the mean and standard deviation of the training data set and standardize the training and testing data set.
7. Feed the data set into the various LSTM network.

LSTM in Short:

LSTM stands for (Long Short-Term Memory) and it's an improved version of recurrent neural network (RNN). Fig 5 has a typical architecture of an RNN here in the first stage the input will pass through the computational box and provide an output however in the second stage with new input there will another feed which is the output of the first stage. In this way, each input stage has information from the preceding stage and with that information, RNN can provide a better understanding of the information and can-do better classification or prediction. But there is an issue, the output from the preceding stage keeps increasing because there is no memory management and thus RNN sometime fails to do proper classification [9].

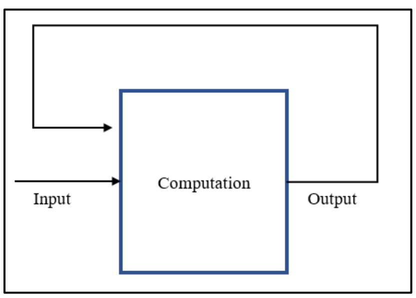


Figure 5: A typical RNN architecture.

To solve the memory management issue of RNN, LSTM came into the picture. LSTM came up with a function call state which is tagged with the computation box and provides input to the computation whenever required. This state stores important information of previous states thus improving the classification or prediction. The state is also known as LSTM cell and divided into three parts, forget cell, add cell, and output cell. Forget cell refers to forger information, add cell refers to the information store in the state and the output cell refers to the output to the computation box. All those boxes has a decision matrix of [0,1] if 0 all forget or 1 for all not forget for forget cell box and similar to add cell and output cell.

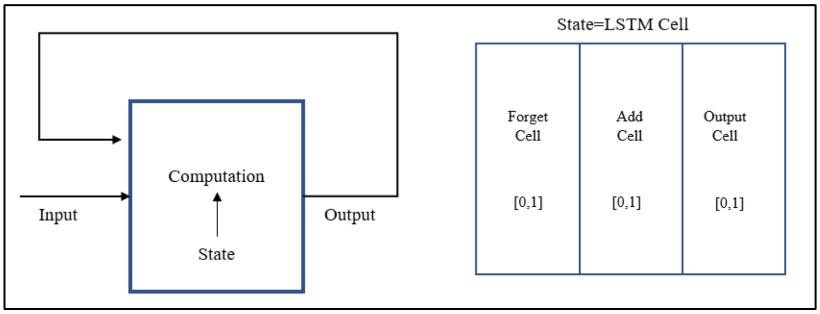


Figure 6: A typical LSTM architecture

In this project I will be using a different type of LSTM network and the parameters are listed in the table below.

Table 3: Types of LSTM layer

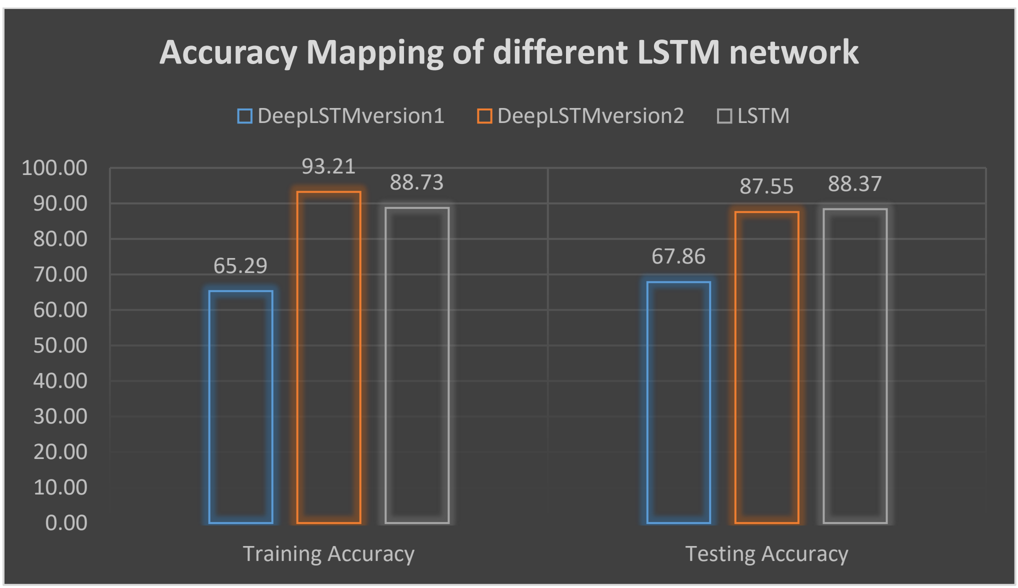
Type	**LSTM**	**DeepLSTMversion1**	**DeepLSTMversion2**
layers	sequenceInputLayer(2) bilstmLayer(100,'OutputMode','last') fullyConnectedLayer(2) softmaxLayer classificationLayer	sequenceInputLayer(2) lstmLayer(125,'OutputMode','sequence') dropoutLayer(0.2) lstmLayer(100,'OutputMode','last') dropoutLayer(0.2) fullyConnectedLayer(2) softmaxLayer classificationLayer	sequenceInputLayer(2) lstmLayer(125,'OutputMode','sequence') dropoutLayer(0.2) lstmLayer(100,'OutputMode','last') dropoutLayer(0.2) fullyConnectedLayer(2) softmaxLayer classificationLayer
Optimization Solver	adam	sgdm	adam
MaxEpochs	15	30	30
MiniBatchSize	150	150	150
LearnRateSchedule	piecewise	piecewise	piecewise
InitialLearnRate	0.01	0.01	0.01
GradientThreshold	1	1	1
ExecutionEnvironment	Auto	Auto	Auto
Verbose	TRUE	TRUE	TRUE

In all types of LSTM, the basic layers are sequenceInputLayer, fully connected layer, softmax layer, and classification layer. In the sequentiallayer the LSTM will take the input of sequential ECG data, in our case there are two types of sequential data AF(atrial fibrillation and N) data. After processing those sequential data through the LSTM layer that data will be fed into the fullyConnectedLayer. The fullyConnectedLayer basically takes the output from the LSTM layer, linearly transforms them, and applies the necessary activation function to produce the output. That output will pass through the softmax layer and classification layer to fine-tune the data. Now let's have a detail for the different variants of the LSTM layer I have used in this project. Refer to Table 3 in the "LSTM" the main core content of the LSTM layer is defined as bilstmLayer(100, 'OutputMode', 'last') which means it will process the sequential ECG in a forward and backward direction with 100 hidden layers and 'last' as output mode means it will take the last output from the sequence and fed to fullyconnectedlayer. The terms "DeepLSTM" consist of more hidden layers, different output modes, and finally a dropout layer to overcome the overfitting. I have used a similar structure for DeepLSTM part. The first layer is lstmLayer(125, 'OutputMode', 'sequence') which contains 125 hidden layers with the ''OutputMode'' sequence means it will take input of ECG sequential data and produce another sequential data of vector size 125. After that, a dropout layer with 20 percent is considered to avoid overfitting. The second layer is lstmLayer(120, 'OutputMode', last) which contains 100 hidden layers with ''OutputMode'' last to produce the last output from the sequential data processing and fed to the fully connected layer.

Result Analysis:

As mentioned above the overall ECG dataset is divided into an 80:20 ratio for the training and testing set. The accuracy of all three models will be evaluated first. Accuracy refers to how accurately one can classify the ECG signals with respect to the overall data set. Figure 7 has all the details of this accuracy analysis.

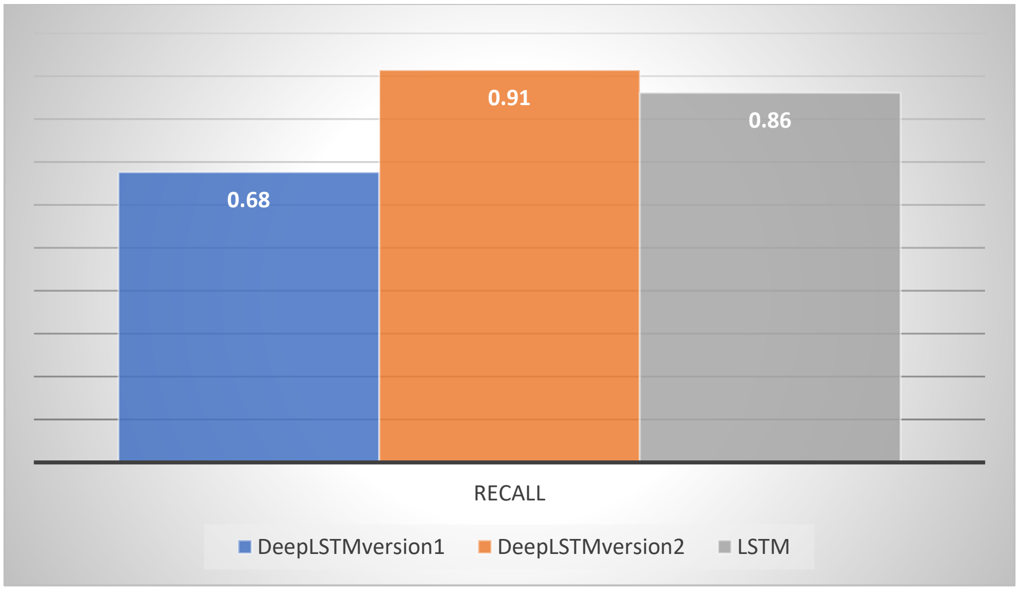
Figure 7: Accuracy mapping of different LSTM network



I observed out of 3 LSTM classification models "DeepLSTMversion1" is the worst one with an accuracy of 65.29 and 67.86 for both training and testing. The reason was that I used sgdm optimizer which gives less accurate results. Learning from that scenario I changed to "adam" optimizer for "DeepLSTMversion2" and "LSTM" model. And upon using that I got a significant improvement of almost 40 percent in both training and testing data. Though in the training data set "DeepLSTMversion2" provide better performance than "LSTM" in the test data set both machine learning model DeepLSTMversion2 and LSTM perform almost similarly. Hence from there, I cannot conclude which machine learning model to choose for ECG classification.

To conclude which machine learning model to use I took another parameter "recall". This is a very important parameter in machine learning because it tells us in the original dataset the classification of atrial fibrillation is classified correctly by our developed machine learning model. Figure 8 has a view of recall understanding of all the machine learning model I used. The "DeepLSTMversion1" is worse as expected with value 0.68, and surprisingly "DeepLSTMversion2" provides a considerable better performance than "LSTM" network. DeepLSTMversion2 has the recall value of 0.91 whereas the LSTM value is 0.86.

Figure 8: Recall mapping of different LSTM network in testing data



In the appendix I have added all the confusion matrix of training and testing data along with the training progress of all three-machine learning models.

Conclusion:

ECG is an important part of the biomedical signal analysis where we can detect heart diseases very fast, moreover, it is readily available in many diagnosis centers. With limited hardware and ECG analysis is performed and instant diagnosis is possible by a lab technician or by a doctor. To do that understanding of the signal system, and the probability is required which is absent in the medical area. This gap could be minimized if we use a machine learning-based decision model which can understand the pattern of an ECG signal and efficiently classify the important waves of an ECG and provide a diagnosis. In this project, I have tested multiple types of recurrent neural network-based ECG classification model which can accurately classify the atrial fibrillation ECG signal from the normal signal. I have also observed accuracy is not always the right matrix for a classification decision hence I consider the recall value to evaluate the machine learning performance. Considering the accuracy and recall value a DeepLSTMversion2 with adam optimizer provide the superior performance in all aspects of atrial fibrillation ECG classification from Normal ECG signal.

References

[1] https://www.ncbi.nlm.nih.gov/pmc/articles/pmc6881865/.

[2] Wilhelm Einthoven,THE DIFFERENT FORMS OF THE HUMAN ELECTROCARDIOGRAM AND THEIR SIGNIFICATION.,The Lancet, Volume 179, Issue 4622,1912,Pages 853-861,ISSN 0140-6736.

[3] https://en.wikipedia.org/wiki/Electrocardiography

[4] https://www.nhs.uk/conditions/electrocardiogram

[5] A survey on ECG analysis, Biomedical Signal Processing and Control, Volume 43, 2018, Pages 216-235, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2018.03.003.

[6] Xinwen Liu, Huan Wang, Zongjin Li, Lang Qin, Deep learning in ECG diagnosis: A review, Knowledge-Based Systems, Volume 227, 2021, 107187, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2021.107187.

[7] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.

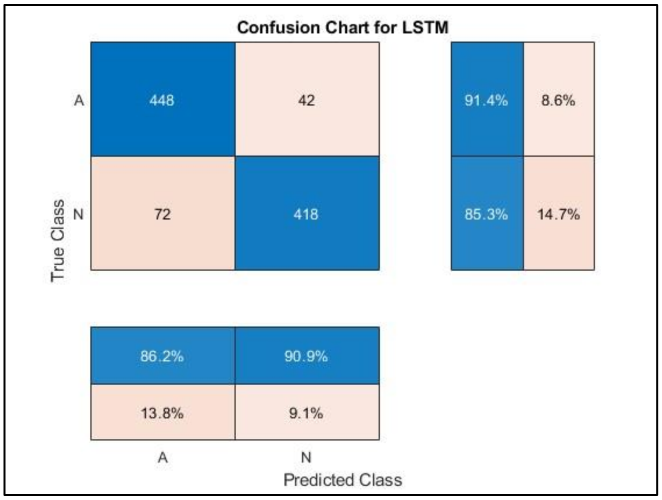
[8] G.V. Naccarelli, H. Varker, J. Lin, K.L. Schulman, Increasing prevalence of atrial fibrillation and flutter in the United States, Am J Cardiol 104 (11) (2009) 1534–1539.

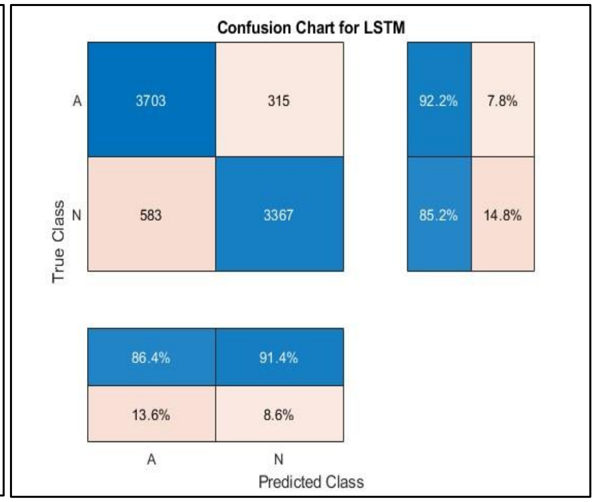
[9] https://en.wikipedia.org/wiki/Long_short-term_memory

[10]https://www.mathworks.com/help/signal/ug/classify-ecg-signals-using-long-short-term-memory-networks.html

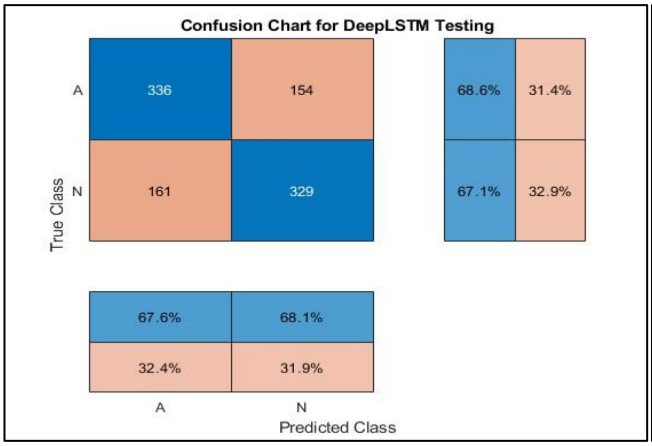
Appendix:

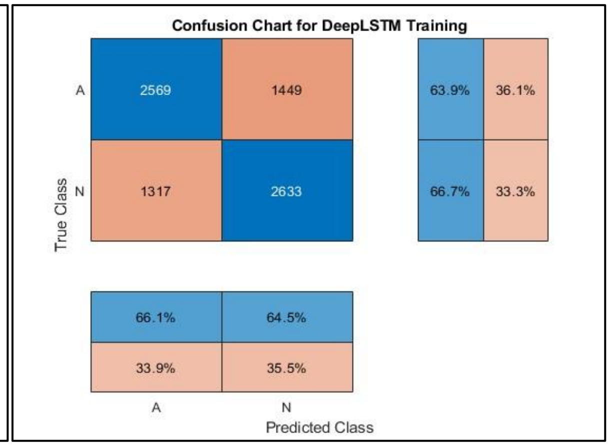
Training progress, Training and Testing data confusion matrix for LSTM.

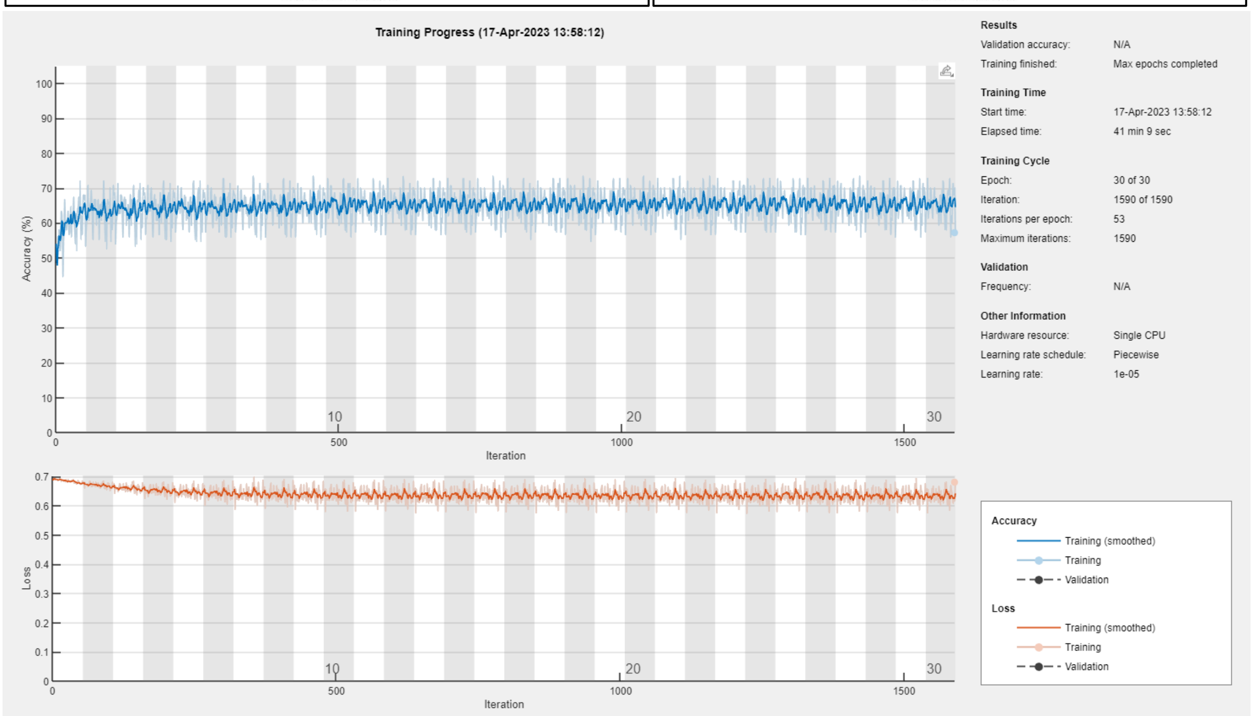




Training progress, Training and Testing data confusion matrix for Deep LSTM version 1.







Training progress, Training and Testing data confusion matrix for Deep LSTM version 2.