ARPN Journal of Engineering and Applied Sciences

PERFORMANCE ANALYSIS OF LSTM NETWORK IN DIAGNOSIS OF ATRIAL FIBRILLATION CLASS OF ARRHYTHMIA

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ABSTRACT

The abnormality in the rhythm of the heartbeat is known as Arrhythmia. This abnormal rhythm can be fast or slow from the normal rhythm of the heartbeat. Certain abnormalities in the heart can be cured if the diagnosis is done at the earliest. The conventional method of recording and analyzing these rhythms are done using Electrocardiogram. This analysis is done manually which needs the expertise to identify the kind of heart disorder. An alternate solution for this problem is to implement the computer-assisted analysis. Machine learning methods are becoming more popular in various domains which makes a milestone every day through research and development. This paper discusses the results achieved with the implementation of a machine learning algorithm for the diagnosis of atrial fibrillation. The methodology used for the study is Long Short-Term Memory (LSTM) network to classify the signals used for the study into a normal and abnormal rhythm.

Keywords: deep learning, LSTM, atrial fibrillation, machine learning.

1. INTRODUCTION

Cardiovascular diseases (CVDs) are the foremost cause of human death, with over 17 million people losing their lives every year. The common other symptoms of cardiovascular diseases are weakness, dizziness, fainting, and severe pain in the chest and left part of the shoulder. These heart diseases are happening due to the imbalance of electrolytes in the blood which is passing in through the heart to the whole body. An arrhythmia is a heart disease that is the condition of irregular heartbeat. These irregularities can be caused by genetics or by injury. An arrhythmia is not only meant for a too-fast or slow heartbeat, but also for an irregular heartbeat or heart rhythm. It could mean that the heart is beating too fast-tachycardia (more than 100 beats per minute (bpm)), slow-bradycardia (less than 60 bpm), skipping a beat, or in extreme cases, cardiac arrest. The other types of abnormal heart rhythms or arrhythmia are Atrial fibrillation, Atrial flutter, and ventricular fibrillation. Atrial fibrillation is the most common type of arrhythmia which affects humans frequently (AF), Atrial fibrillation causes an irregular and fast heartbeat. Atrial fibrillation is an irregular and often rapid heart rate that leads to heart stroke and severe heart failure. This may lead to death. The result is a fast and irregular heart rhythm. The heart rate in Atrial fibrillation may range from 100 to 175 beats a minute whereas the normal heart rate is 60 to 100 per minute. The heart is made up of four chambers-two upper chambers (atrial) and two lower chambers (ventricles). In normal cases, the signal travels through the two upper heart chambers and through a connecting path between the upper and lower chambers. This is called an atrioventricular node. But in the case of Atrial fibrillation the signals in the upper chambers are chaotic. The Electrocardiogram (ECG) is the common method to detect arrhythmia which records the rhythm of heartbeat and heart rate. ECG records the electrical signal from the heart over a period of time. This signal is captured in the form of a sinusoidal waveform also known as the 'PQRST' wave.

The main function of the heart is to collect impure blood from other parts of the body and purify the blood and distribute it among the other organs of the human body like the brain, kidney, lungs, etc., an electrical impulse is generated due to this purification process. When this process is affected, then the rhythm of the heart is affected.

General factors such as age, gender, chest pain type (CPT), history of smoking, and alcohol consumption are considered for the prediction of heart diseases. Similarly, the clinical factors are fasting blood sugar, Resting ECG, Slope (SL) of the Peak exercise (ST), Oldpeak i.e. ST depression Induced by Exercise Relative to rest, Thallium Scan, Serum Cholesterol, Thalach, Resting Blood Pressure (RBP), Number of major vessels (0-3) colored by fluoroscopy(Vcf), Obesity or Body Mass Index (BMI) [1]

Early detection of heart disease through big data analytics was proposed [2] where the authors proposed a constant coronary illness forecast framework dependent on apache Sparkle for streaming data events against AI through in-memory calculations. This framework comprised information stockpiling, streaming processing, and visualization. For data storage and streaming, Sparkle MLlib with Spark streaming was utilized to visualize the coronary illness classification model on data events. Aapache Cassandra was applied to store the gigantic volume of datasets for visualization. To identify cardiac diseases ensemble classification technique was presented [3] whereas noise and fault data were cleaned as an initial procedure to improve the quality of the signal. The author applied various filtering techniques such as median filter, high pass filter, and bandpass Butterworth filter to remove different interferences. 169 features were extracted using the WFDB software tool. Multi- Label classification by ensemble classifier was performed by combining multi label binary relevance, multi label kNN, multi label

VOL. 18, NO. 3, FEBRUARY 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

hierarchical adaptive resonance associative map (HARAM), multi-label twin support vector machine (MLTSVM), classifier chain, label powerset, sklearn embedder, and embedding classifier. They achieved an overall classification accuracy of 75.2 %. Similarly, an ensemble (Subspace K-NN) classifier was applied in [4] and the authors were able to achieve a classification accuracy of 82.9%. They utilized entropy and the Hjorth descriptor technique for the classification of arrhythmia. Savitzky-Golay filter was used for preprocessing and discrete wavelet transform for feature extraction.

Generalized Linear Model (GLM) with convex penalties was applied [5] for the identification of heart diseases. The penalty models were Lasso, Ridge, and Elastic net. The misclassification error criterion was utilized for ten-fold cross-validation. The authors could achieve a prediction accuracy of 72 % without including the laboratory-based data. The heart disease (statlog) dataset at UTI with binary variables was utilized in [6]. In this paper, Sparse Discriminant Analysis (SDA) was performed for the identification of a coronary illness. An extremely randomized Tree was applied for obtaining the significant features to avoid underfitting and overfitting on the classification. From the results, it was concluded that Thal, Vcf, CPT, maximum heart rate, old peak, and age are the significant features. They achieved a prediction accuracy of 96 % for SDA than the other methods such as Linear Discriminant Analysis (LDA), Random forest, and Bootstrap Aggregating. UCI repository Cleveland heart disease dataset was utilized in [7] that contains 303 instances of 76 attributes. The authors used WEKA TOOL for the classification. The performance analysis for the classifiers J48, KNN, RBF, and NAIVE BAYES was done and it is observed that J48 provides a better accuracy with 87.12%. The authors applied python programming for developing classifiers such as Decision Trees, KNN, and SVM. Using Python coding, the Decision tree provided better results with 93.4% accuracy.

In recent years deep learning networks play a significant role in the classification and prediction of CVD. Various combinations of a deep learning network for cardiac arrhythmia detection were applied in [8]. The Convolution Neural Network (CNN) is combined with Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU). They were able to achieve an accuracy of 83.4 %. Similarly, an LSTM network was implemented [9] for identifying different ECG beat types such as Left bundle branch block, Right bundle branch block, Atrial premature contraction, etc., They tried the network with different batch sizes and were able to get a maximum accuracy of 99.26 % for the batch size of 128.

MIT- BIH ECG arrhythmia dataset was utilized by many researchers [10-12]. Baseline correction and normalization were performed on the ECG data [10] as a first step. Then, Discrete Wavelet Transform (DWT) was applied for denoising with 3, 5, and 8 levels of decomposition. The 5th level denoised signal was subtracted from the 3rd level denoised signal for extracting the QRS complex from the signal. In addition, P and T's waves were obtained from windowing. Using DWT, morphological features of the signal such as QRS duration, R peak, R-R, and P-R interval were extracted. Overall classification accuracy of 87.01 % was achieved using Levenberg- Marquardt (LM) back propagation methodology. Support Vector Machine (SVM) was implemented [11] to classify premature ventricular contraction (PVC) and atrial premature contraction (APC) from ECG signals. For denoising, the authors preferred the moving average filter over the median filter and notch filter. Discrete wavelet transform (DWT) is mainly used for the feature extraction of the ECG signal. SVM produced a classification accuracy rate of 95% for the PVC and APC classifications. The authors [12] implemented various types of RNN cell types such as simple RNN, LSTM, and LSTM with a peephole that has an extra connections from the internal state vector to the forget input and output gates. They have also performed real-time testing with a personal wearable device. The authors extracted features using wavelet transform and fed them to the algorithm. They observed that the results were better with wavelet features than without wavelets.

Since a large dataset is required for the effective identification of the different type of CVD deep learning networks is generally preferred for such medical applications. Therefore in recent years, deep learning algorithms are gaining popularity in CVD identification. MIT BIH arrhythmia database could be easily trained when RNN architecture with memory is applied. Hence, in this paper, the LSTM network is explored for the identification of Atrial fibrillation.

2. METHODOLOGY

The MIT BIH arrhythmia dataset from physionet is extracted and as a first process data cleaning is performed. Based on the labeling in the dataset, the normal and Atrial fibrillation signals are considered for the study. Figure 1 shows the typical normal and Atrial fibrillation signal from the dataset. The dataset is formatted to suit the training of the LSTM network. The dataset is randomly divided for training and testing data.

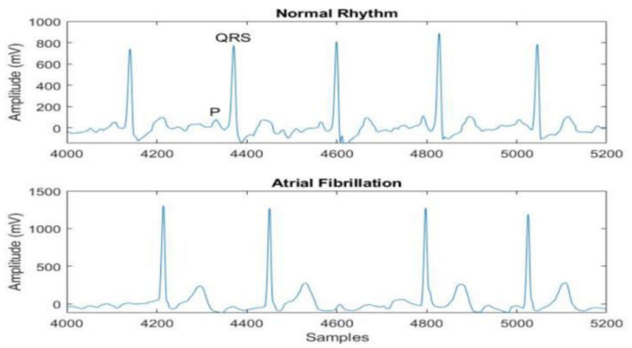

Figure-1. Normal and Atrial fibrillation signal from MIT BIH arrhythmia dataset.

ARPN Journal of Engineering and Applied Sciences

2.1 Long short term memory (LSTM)

Though Recurrent Neural Network (RNN) has memory, it cannot have long-term dependencies. Long Short-Term Memory (LSTM) network can address this issue, by remembering information for a long duration. The figure shows the architecture of the LSTM network. Based on the previous state (St-1) and the forget gate (ft) that decides on which relevant information to be remembered and which information to be discarded, the current state St is computed. LSTM performs a selective write, selective read and selective forget so that only important information is retained to compute the current state. Figure-2 shows the architecture of an LSTM network.

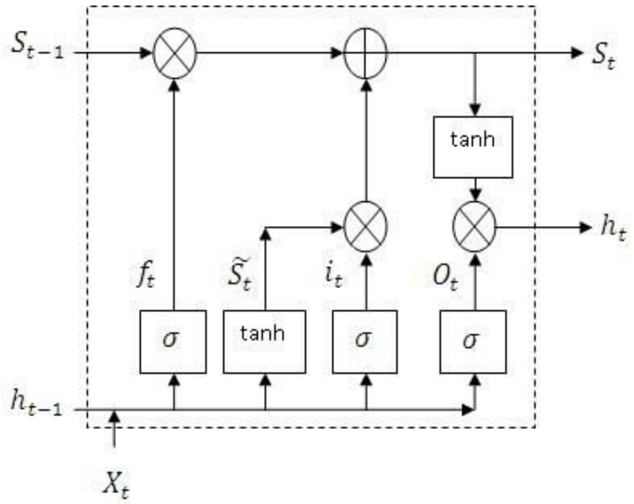

Figure-2. Architecture of LSTM network.

X_t	- Current Input Vector
f_t	- Forget gate
O_t	- Output gate
i_t	- Input gate
S_t	- Current State
S_{t-1}	- Previous State
$\tilde{S}_t$	- Temporary State
h_t	- Output of Current Block
h_{t-1}	- Information from previous Block
σ	- Sigmoid activation function
tanh	- Hyperbolic tan activation function

The LSTM architecture has 3 gates, such as input gate, an output gate and forget gate. The input gate (it) decides how much selective read has to be performed as per equation (1), and the Output gate (Ot) decides how much selective write has to be done for the next time step as per equation (2) and the forget gate performs selective forget such that only necessary information is passed on to the next state as per equation (3)

$$i_t = \sigma(W_i h_{t-1} + U_i X_t + b_i) \quad (1)$$

Where Wi,Ui and bi are the parameters to be learned which connect each state, input to the state, and bias respectively with respect to the input gate

$$O_t = \sigma(W_o h_{t-1} + U_o X_t + b_o) \quad (2)$$

Where Wo, Uo, and bo are the parameters to be learned which connect each state, input to the state, and bias respectively with respect to the output gate

$$f_t = \sigma(W_f h_{t-1} + U_f X_t + b_f) \quad (3)$$

Where Wf, Uf, and bf are the parameters to be learned which connect each state, input to the state, and bias respectively with respect to the forget gate

There are three states in the LSTM architecture such as temporary state, previous state, and current state.

$\tilde{S}_t$ is a temporary state which is computed based on equation (4),

$$\tilde{S}_t = W h_{t-1} + U X_t + b \quad (4)$$

Where W, U and b are the learning parameters

St is the current state that is computed based on equation (5),

$$S_t = f_t \cdot S_{t-1} + i_t \cdot \tilde{S}_t \quad (5)$$

Output of the current block ht is computed based on equation (6),

$$h_t = O_t \cdot \tanh(S_t) \quad (6)$$

In equations (5) and (6) the product is element-wise multiplication and in equation (5) the summation is element-wise addition.

The training dataset is split as subsets (mini-batch) and various trials were performed by varying the Learning rates and a number of epochs heuristically. The algorithm is trained for various combinations. The results of the training and testing are discussed in the next section.

VOL. 18, NO. 3, FEBRUARY 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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Table-1. Algorithm for CVD identification.

Training Phase Steps
Step 1 - Process
Step 2 - Data Cleaning
Step 3 - Identify the signals with Normal (N) and Atrial Fibrillation(A) labels in the dataset
Step 4 - Load and format the dataset for LSTM training
Step 5 - Split the dataset for training and testing
Step 6 - Setup the layers (input layer, LSTM layer, Fully Connected, Softmax and Classification layer 5 layers) of a network for Training
Step 7 - Train the network for classification till convergence
Testing Phase
Step 1 - Test the dataset with testing data and estimate performance metrics

The algorithm for the classification of the signal under analysis into normal and Atrial fibrillation is discussed in Table-1. The entire network is designed with five layers. The input layer is the sequence layer that supports and process sequential input dataset. The LSTM layer processes the input from the sequence layer at every time step. LSTM provides current output by considering the current input and the previous time step output. The fully connected layer multiplies the input by a weight matrix and then adds a bias vector. The softmax layer acts as the activation layer, which computes the output based on the softmax function as given in equation (7). A classification layer computes the cross-entropy loss for classification and weighted classification tasks with mutually exclusive classes. From the classification layer, the signal under study is classified into binary either as normal or abnormal rhythm. The various layers of the proposed network are shown in figure 3.

$$\sigma(\vec{Z})_j = \frac{e^{Z_j}}{\sum_{i=1}^{k} e^{Z_i}} \qquad (7)$$

Where,

σ - softmax
$\vec{Z}$ - Input vector
e^{Z_j} - Standard exponential function for input vector
k - number of input classes in the multiclass classifier
e^{Z_i} - Standard exponential function for output vector

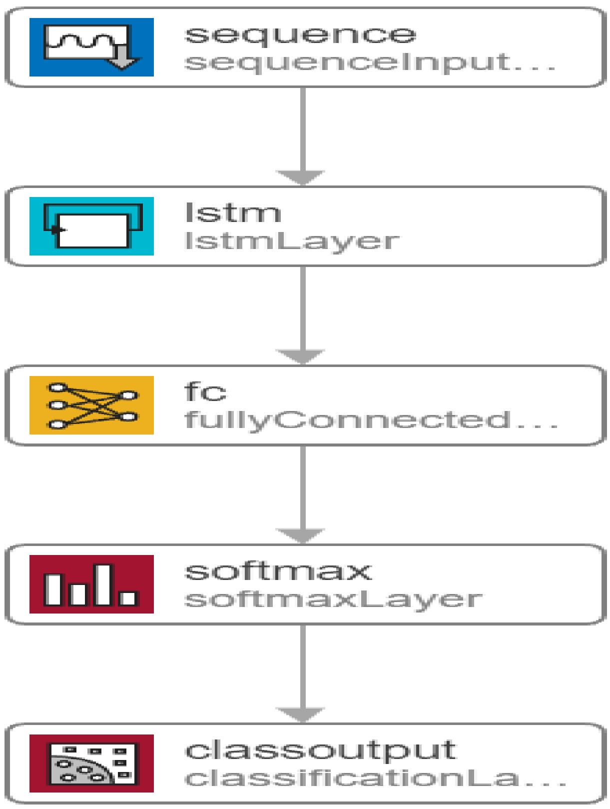

Figure-3. Various layers and connections of proposed network.

3. RESULT AND DISCUSSIONS

The dataset is trained using the LSTM network, initially for various learning rates (LR). The learning rate is varied with values less than or equal to 0.1. After several trails, an average of 50 % of accuracy is achieved for learning rates close to 0.01. The performance of various trails is listed in Table-2. Variation in mini-batch size for the learning rates 0.1, 0.01, and 0.001 does not have any significant change in accuracy. Hence further variation of learning rates is done and an average accuracy of 68 % is achieved with 0.007 learning rates. LR lesser than 0.007, does not influence the performance much.

VOL. 18, NO. 3, FEBRUARY 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Hence after several trials of LR (Max 30 trials, few have been recorded as shown in the table), an optimized value of 0.007 is fixed for the algorithm. The network training has converged with 10 -30 epochs. Hence a maximum of 30 epochs has been used for training. As the size of the mini-batch training dataset is increased, it is observed that the training accuracy also improved. The confusion matrix for training and testing LSTM is given in Figures 4 and 5. Performance metrics are estimated using a confusion matrix and the same has been recorded in Table-3.

Table-2. Performance of various trials of LSTM algorithm.

Trials	Learning Rate	MiniBatch size	Epochs	Training Accuracy	Testing Accuracy
1	0.1	16	10	50.00	50.00
2	0.01	16	10	51.5	52.95
3	0.01	50	10	53.6	54.08
4	0.1	16	30	50.32	50.84
5	0.01	16	30	52.9	53.54
6	0.01	50	30	53.92	54.12
7	0.007	50	10	61.466	58.26
8	0.007	90	30	68.20	67.44

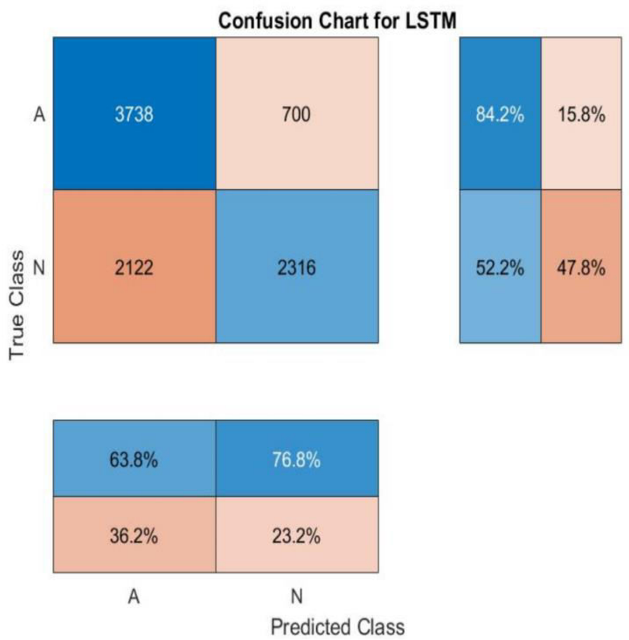

Figure-4. Confusion chart for training LSTM.

True Positive (TP): Correctly identifying the Normal subject

True Negative (TN): Correctly identifying the Abnormal subject

False Positive (FP): Wrongly identifying the Normal subject

False Negative (FN): Wrongly identifying the Abnormal subject

The performance metrics of the algorithm can be given by equation (8) - (13)

Accuracy = TP+TN / (TP+TN+FP+FN) (8)

Sensitivity = TP/ (TP+FN) (9)

Specificity = TN/ (TN+FP) (10)

Precision = TP/ (TP+FP) (11)

False Positive Rate = FP/ (TN+FP) (12)

Classification error = (FP+FN)/ (TP+TN+FP+FN) (13)

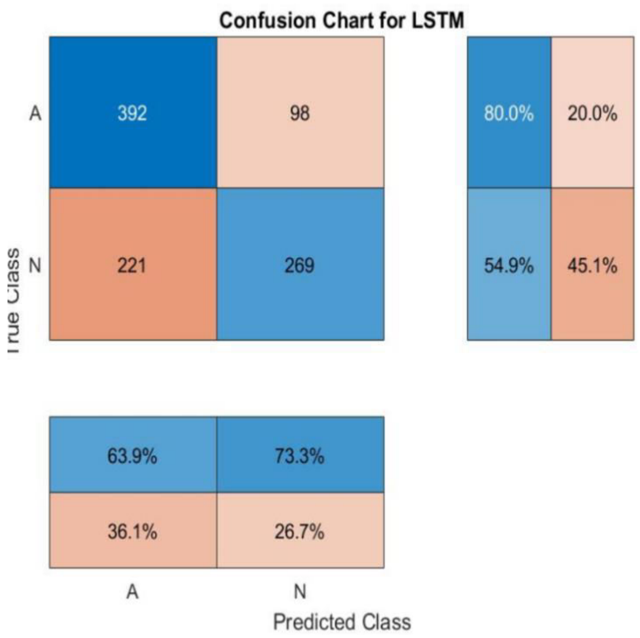

Figure-5. Confusion chart for testing LSTM.

Table-3. Performance analysis for training and testing LSTM.

Performance metrics	Training (%)	Testing (%)
sensitivity	76.76	73.29
Specificity	63.78	63.9
Precision	52.2	54.9
False Positive Rate	36.21	36.05
Classification error	31.8	32.55

From the results, it is observed that the number of Epochs has less impact on the performance of the algorithm. Also, Mini Batch size requires a sufficient dataset for providing better training accuracy and better performance is observed for learning rates less than 0.01.

4. CONCLUSIONS

The study attempted to implement an LSTM network for the identification of Atrial Fibrillation from ECG signals. With 4438 samples used for the study, the classification accuracy of 68.2% for training, and with 490 samples, an accuracy of 67.44 % is achieved for testing. The speed of convergence of the training progress is influenced by the hardware constraint of the machine. The machine used in this study is an i5 processor @ 2.4 GHz with 16 GB RAM that could support only up to a minibatch size of 90 for this architecture. The performance of the algorithm could be enhanced further by utilizing higher-end GPUs. In addition, the integration of LSTM with other deep learning networks can be explored for better performance.

ACKNOWLEDGEMENT: Not Applicable

Funding Statement: Not Applicable

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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