Research Article

Deep Learning-Based Diagnosis Of Schizophrenia

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Abstract: People from different age groups suffer from a variety of mental health disorders but most of these come without a cause and are very difficult to cure. One such disorder is Schizophrenia. More than 20 million people around the world suffer from this disorder. In order to get a better understanding of such mental health disorders and to help in the study of the cure, here the EEG of the affected and normal patients are studied and classified. The intelligence of Neural Networks is deployed in the classification of the EEG signals as they provide a wide variety of algorithms to extract the features and to classify the data which in turn helps in the process of identification of abnormalities present in the EEG signal of the schizophrenic subjects when compared to normal subjects. Here, the LSTM algorithm which is a type of RNN architecture is deployed to classify the EEG of schizophrenic subjects and normal subjects. Further, the EEG signal is pre-processed using various techniques and the data is cleaned to study the major brain waves of the EEG signal and the absolute and relative power of each of the brain waves is calculated and graphically observed to understand the behaviour of the EEG of Schizophrenic subjects and to propose therapeutic guidance to relieve such patients from stress.

Keywords:

1. Introduction

People across the world suffer from diverse cognitive disorders viz. stress, depression, Alzheimer's disease, Schizophrenia. Most of these disorders come without a pre- dominant cause and often lack a set of defined therapeutic procedures. It is of great importance that the activity of the brain is comprehended enough to propose a solution for the same. The most commonly used technique to study the electrical activity of the brain is the Electro Encephalograph

(EEG) signals [2]. The EEG measurement is an electrophysiological process of monitoring the electrical activity of the brain which represent the responses of the brain under certain situations [3]. The EEG ranges from 1- 60Hz and this band contains the five major brain waves, viz., delta(1-3Hz), theta(4-7Hz), alpha(8-12Hz), beta(13-38Hz), and gamma (39-42Hz) [5-7][11]. The EEG is usually measured by placing electrodes on the human scalp following the 10/20 electrode system. Here the FP1 and the FP2 locations were preferred as it promotes ease of extraction of the EEG signal and also gives a fair amount of information [8]. By analysing the data obtained from the EEG signals and by comparing certain parameters like the relative power, the classification of EEG signals can be achieved.

Schizophrenia is a condition wherein the patient usually becomes delusional and often begins to hallucinate. The patient finds it difficult to differentiate real-life events from illusionary events. Usually, the EEG signals of the schizophrenic patients throw aberrations in the frequency spectrums, which when identified aids in classifying the affected and healthy patients [4]. Repeated analysis and monitoring of the brain wave data is required in order to identify such abnormalities.

Deep learning-based deployment of neural networks helps immensely in the classification of the EEG data by studying the abnormalities in the EEG signal of the schizophrenic subjects when compared to the normal subjects [6]. In this work, the Layered Long Short-Term Memory (LLSTM) algorithm is proposed for higher accuracy of classification between EEG signals of Schizophrenic subjects from the Normal subjects [7]. The Long Short-Term Memory networks are a special type of Recurrent Neural Networks which are very powerful, when finding and classifying features of a dataset that is large. By choosing the right pre-processing techniques, the number of inputs, hidden and output layers, nodes in each layer, the scaling factor (α), and the appropriate cross-validation framework, a very high percentage of classification accuracy was achieved in classifying EEG signals [16].

This work includes assessment through classification of the EEG signals corresponding to the healthy and schizophrenic patients

2. Proposed Method for Assessment of Schizophrenia

A layered LSTM based deep learning model was constructed for binary classification to identify schizophrenic patients by means of the EEG signal taken from the patient’s FP1 and FP2, where the FP1 and FP2 represent the locations (frontoparietal) in the scalp which follows the 10/20 electrode system to extract the EEG signals from the brain [9-10].

function. The ‘sparse categorical cross entropy’ loss function was opted as categorical values can be passed to measure the losses.

Optimizers change and update the parameters constantly depending on the estimated losses. Different parameters such as accuracy, precision, loss, recall value, F1 score for the proposed Layered LSTM using different optimizers were compared and studied. The optimizers Adadelta, Adagrad, Adam, Nadam, RMSprop, SGD were used for classification [1]. A batch size of 10 was chosen to process for each epoch before updating the model hyper parameters.25 epochs were fixed to define the number of

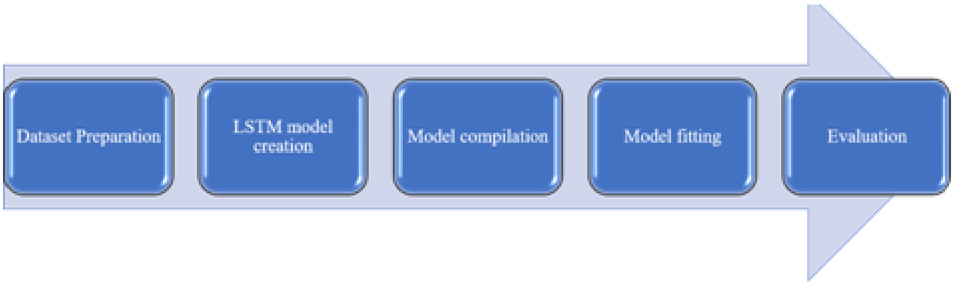

Figure 1 Block Diagram of Schizophrenic classifier based on LSTM

Dataset Preparation

Data collection and pre-processing are key steps prior to training the deep learning model, for better accuracy of classification with reduced error. The dataset of 25 healthy subjects [26] and 15 Schizophrenic individuals [27] were taken from fp1 and fp2 of a 10/20 electrode system; fp1 and fp2 signals were drawn out of the dataset as they are vital for feature extraction than the rest of the 10/20 electrode system. The data was accumulated, labelled appropriately and stored. The features were normalized between 0 and 1 to avoid data inconsistency. The structured data was then imported using the Pandas library in Python for suitable analysis and interpretation.

Proposed Model Construction

The selection of appropriate models is important for obtaining a good classification rate. The layered LSTM is proposed with lookback mechanism for better reiteration as it minimizes the vanishing gradient problem caused by other recurrent algorithms. Vanishing gradient problem is basically caused by backpropagation mechanism in recurrent algorithms by which weights get updated based on the model loss. This mechanism in turn minimizes the gradient and at one point it might become indistinguishably small and LSTM solves the aforementioned problem. The Layered LSTM model (LLSTM) was implemented using the Keras library. The proposed model architecture has 128 neurons in each progressive layer and was constructed initially as a single layered architecture and then extended to 2 layered architecture. SoftMax activation function is introduced to converge the result to a value between 0 to 1 for all the probabilities of the two classes of classifier ensuring that the total probability sums up to 1. Dropout was added to the model in order to minimize overfitting problems which is caused by the outliers in the dataset. In the proposed architecture, the weights are updated constantly by means of error values computed by the loss

iterations of the model prior to testing. The model was then validated by stratified k-fold cross validation which ensures that the model is able to observe all different formats of patterns.

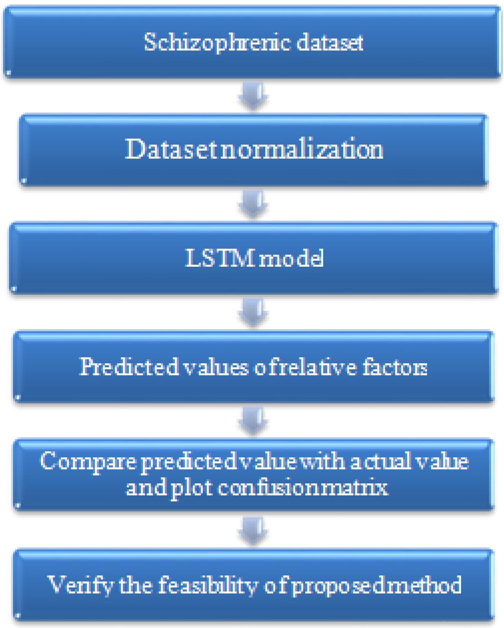

Figure 2 Flowchart of classification Procedure

3. Results and Discussion

3.1. Classification

Layered LSTM was proposed to classify individuals into healthy and schizophrenics. The single and double layered LSTMs were experimented with different optimizers to assess their accuracy in classification. This evaluation is plotted in the form of 5 different graphs as shown in figure 3,4,5,6,7.

Statistical Parameters-based Model Evaluation

The proposed two- layered architecture of LSTM with Adam optimizer generates better results with accuracy of 87% as shown in Figure 3 and thus obtains higher accuracy for schizophrenia classification based on EEG signal. The high precision and recall statistical measures that display the rate of rue positive detection and are projected in Figures 4 and 5 respectively. The proposed LLSTM with 'Adam' or 'Nadam' optimizers produces good precision and Adam is found to work slightly better than 'Nadam' for LLSTM with a precision value of 88% and recall value of 86% and 87% of f1- score in classifying schizophrenic individuals based on EEG.

Model Loss

Model loss is one of the negative parameters for a deep learning model. Lesser the value of loss better the model works. Loss is a kind of parameter which is proportional to the wrong predictions that are being made based on the loss model applied for classification. Based on the graph in Figure 7 it can be realized that the proposed Layered LSTM architecture with 'Nadam' optimizer gives better results with a model loss of 22.45%.

Optimizers	**1-Layered LSTM**	**2-Layered LSTM**
Adadelta	0.5	0.6444
Adagrad	0.5224	0.5778
Adam	0.83667	0.87
Nadam	0.8	0.8556
RMSprop	0.7667	0.7
sgd	0.5889	0.6556

Table 1 Accuracy analysis with different optimizers

Optimizers	**1-Layered LSTM**	**2-Layered LSTM**

Adadelta	0.46	0.59
Adagrad	0.25	0.29
Adam	0.82	0.88
Nadam	0.81	0.86
RMSprop	0.77	0.7
sgd	0.32	0.31

Table 2 Precision analysis with different Optimizers

Optimizers	**1-Layered LSTM**	**2-Layered LSTM**
Adadelta	0.5	0.55
Adagrad	0.5	0.58
Adam	0.82	0.86
Nadam	0.79	0.85
RMSprop	0.76	0.66
sgd	0.54	0.56

Table 3 Recall Value analysis with different Optimizers

Optimizers	**1-Layered LSTM**	**2-Layered LSTM**
Adadelta	0.445	0.53
Adagrad	0.33	0.42
Adam	0.83	0.87
Nadam	0.8	0.86
RMSprop	0.76	0.62
sgd	0.59	0.4

Table 4 F1-score analysis with different optimizers

Optimizers	**1-Layered LSTM**	**2-Layered LSTM**
Adadelta	0.6932	0.6919
Adagrad	0.694	0.6861
Adam	0.17389	0.2389
Nadam	0.4897	0.2245
RMSprop	0.3391	0.37
sgd	0.6823	0.5867

Table 5 Model Loss Analysis with different optimizers

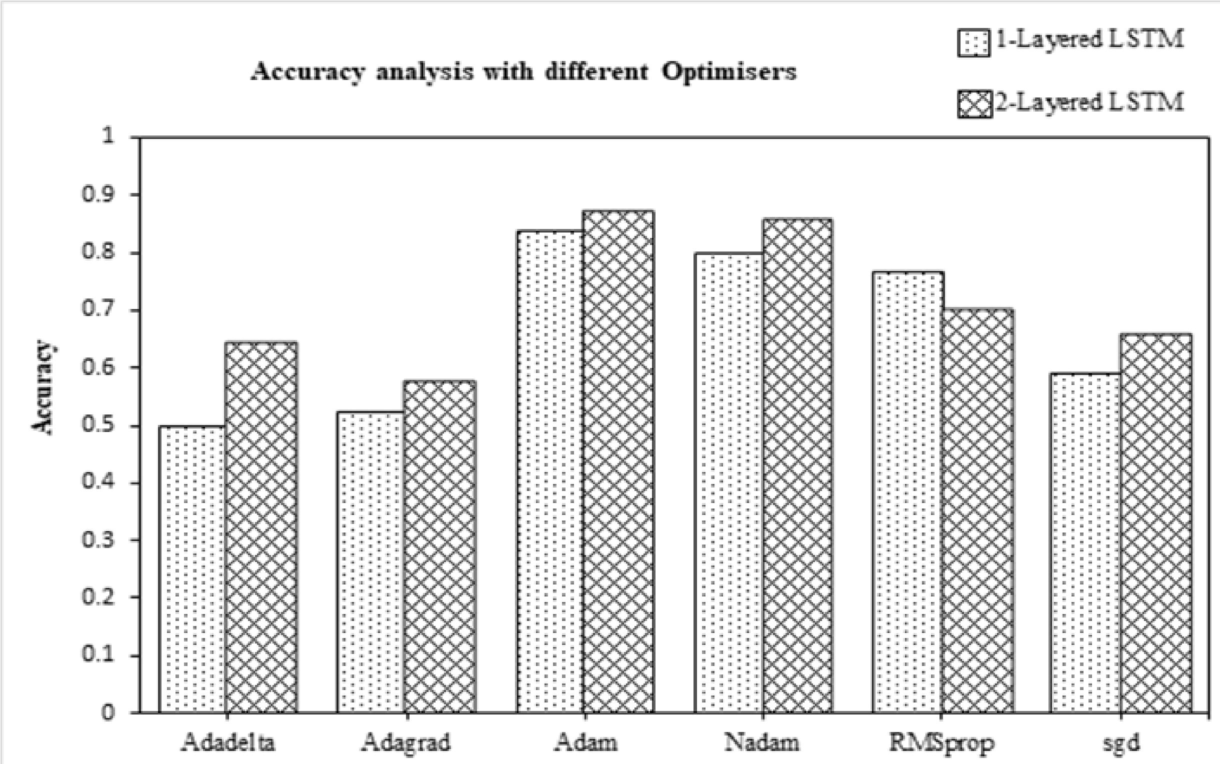

Figure 3 Accuracy analysis with different optimizers

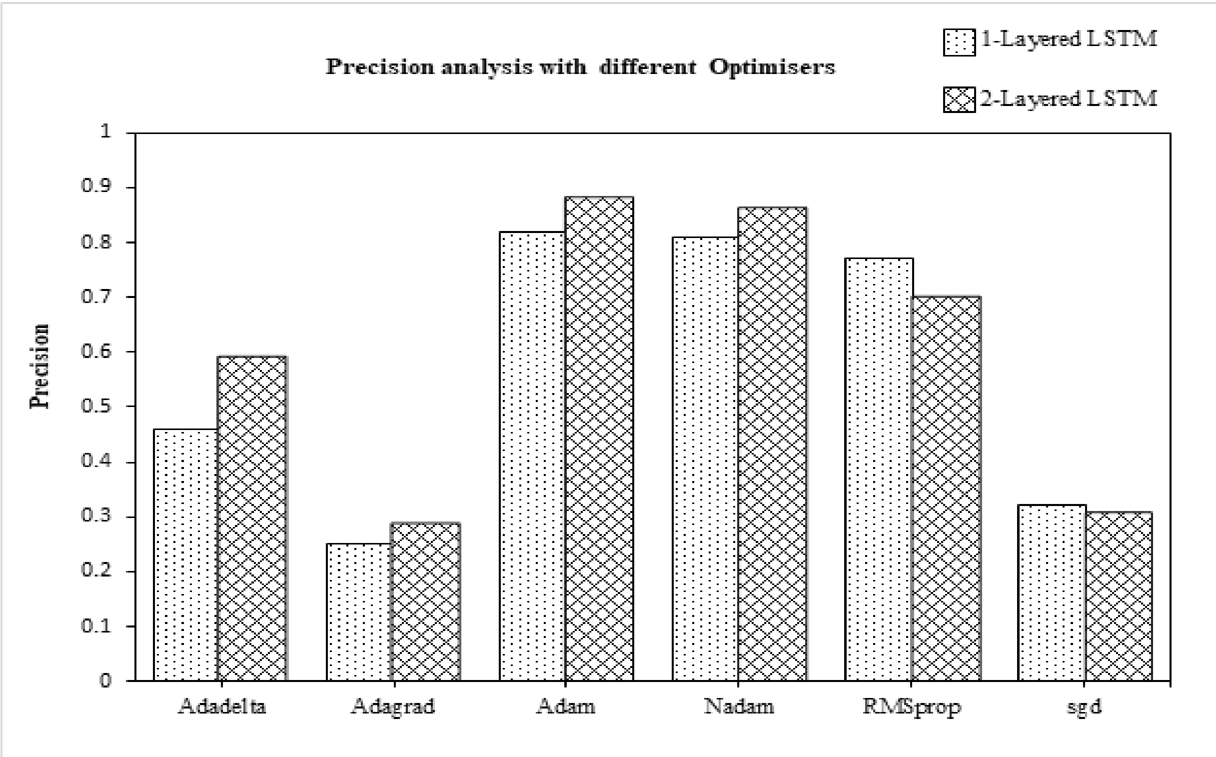

Figure 4 Precision analysis with different optimizers

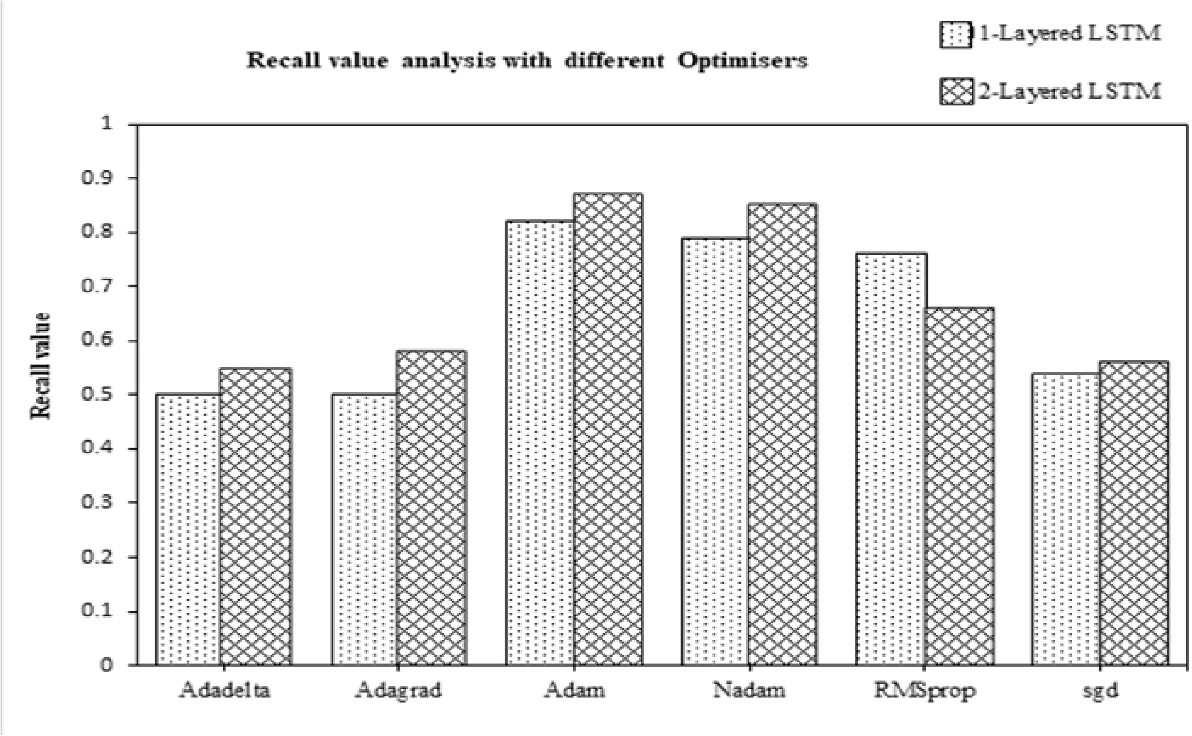

Figure 5 Recall Value analysis with different optimizers

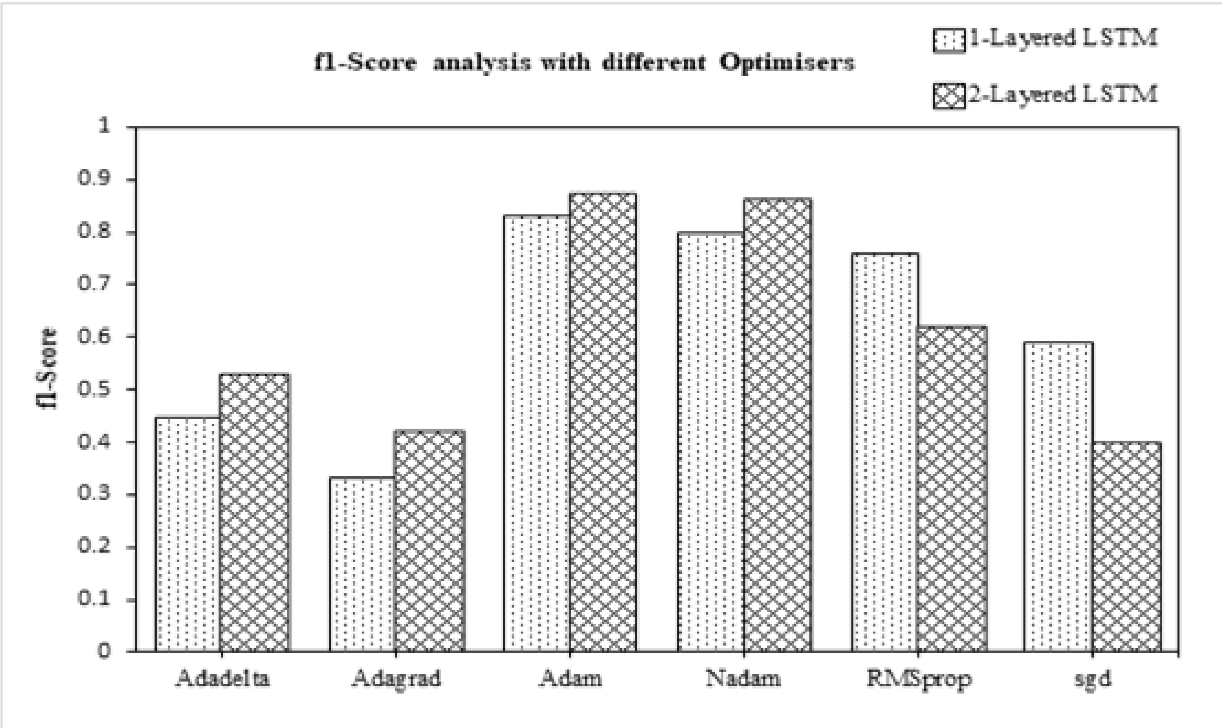

Figure 6 f1-Score analysis with different optimizers

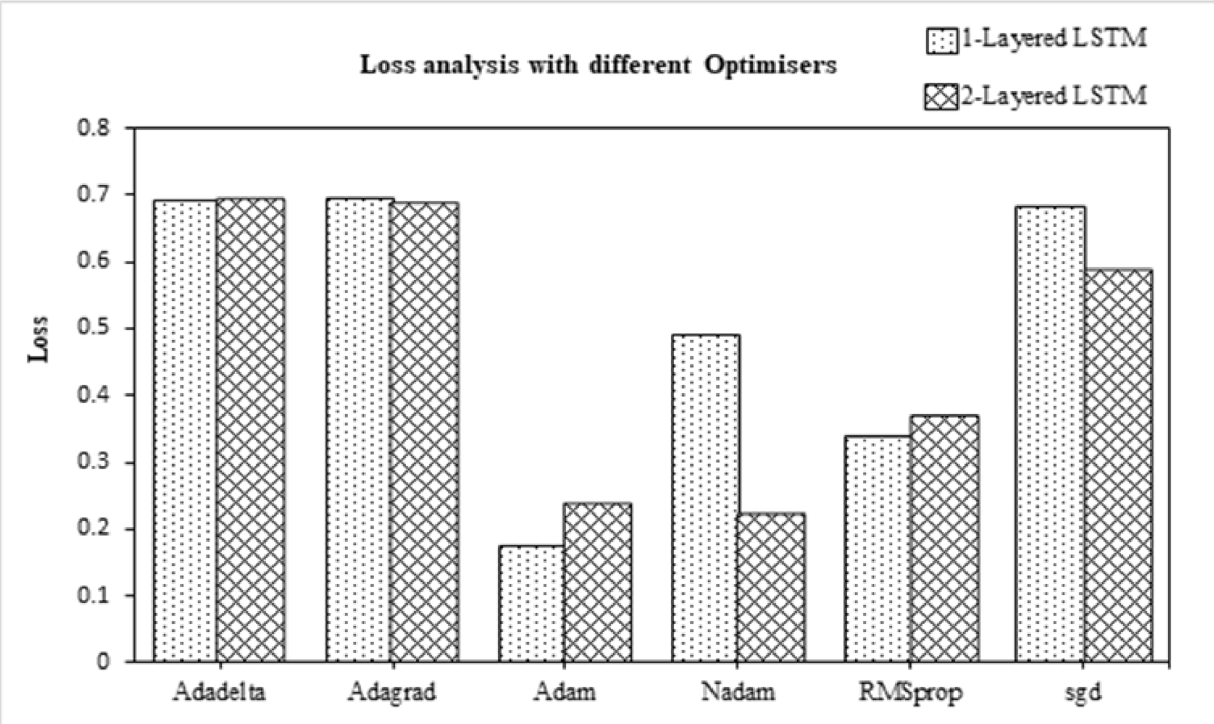

Figure 7 Loss analysis with different optimizers

4. Conclusion And Future Work

In this paper, the Layered LSTM model is proposed to identify schizophrenic cases based on EEG signals. The proposed model was experimented with various optimizers to identify the best suitable classification architecture for schizophrenic assessment. Experimentally, it was concluded that the two-layered LSTM with Adam optimizer generates highest accuracy of 87%. As we have growing cases of cognitive disorders, standardizing the treatment procedures through therapeutic sessions would certainly help such patients to a great extent. This could be further extended for analyzing and comparing the activity of the major brainwaves such as alpha, beta, theta, delta of normal and schizophrenic patients. The alpha activity depicts the state of calmness and relaxation, where the brain transforms to a state awaiting commands and to perform actions. The beta waves are faster and usually represent the state of alertness of the brain and finally the theta waves represent the brain waves observed during sleep. In accordance with this finding, music therapy which is known to improve the alpha activity of the brain, is suggested as the possible neuro-bio feedback to potentially improve the alpha, beta and theta activities of brain which could improve the condition of schizophrenic patients to a great extent..

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