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Healthcare based financial decision making system usingartificial intelligence

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***Abstract*---**Artificial Intelligence is providing immense areas to work with and areas like Deep Learning and Machine Learning is taking over many research areas nowadays. The analysis and prediction of time series with machine and deep learning techniques are providing very promising results in the field of healthcare. The future values can be predicted with the help of time series. Therefore, the prediction of time series in healthcare based financial management provides organization with the useful information that supports in decision making. In this paper, the time series prediction on healthcare financial data is done by implementing Long Short Term Memory approach of Neural Networks for prediction of output for the time series datato predict business capabilities. Temporal characteristics of healthcare financial data are analyzed for time series forecasting. From the results, it is evident that this model is highly feasible to analyze the data with high precision and accuracy.

***Keywords*---**artificial intelligence, healthcare, neural network, LSTM approach, decision system.

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Introduction

The most emerging techniques in Artificial Intelligence based data analysis are Machine Learning and Deep Learning which are taking the process of analysis to exploring levels. The models based on these techniques are usually data driven instead of model driven. Taking into consideration, it can be said that the Convolutional Neural Network Models are best suited for areas like image processing and recognition and the Recurrent Neural Networks suits best for model based problems like Analysis and time series predictions. The different Recurrent Neural Network models differentiate on the basis of their capability to remember the data given as input. Usually, the RNN's Vanilla form is not capable to remember the previous data. These models are feed forward Learning methods in context of Deep Learning technique. The one of the Recurrent Neural Network Model is LSTM i.e. Long Short Term Memory Network which helps to model the relationship between input and output. LSTM and its subtypes with hybrid models are highly used for financial timeseries forecasting. These types of models are feedback Network models which keeps the capability to learning from its previous data [17]. The architecture of these models is designed in the way so that they can remember the previous data and then builds the novel models on the basis of previous and present data. The performance, effectiveness and accuracy of the analysis on time series data can be highly affected because of data type with the context and the techniques uses to analyze it. The prediction in the time series data can also get affected by some features like unexpected events, changes, shocks and seasonality.

Studying and analyzing time series data helps in several areas to lead towards effective decision making. The scientist who is working on data of earthquake for prediction of the future earthquakes or the healthcare officials who are analyzing patient waiting time for betterment of staff, it is important and helpful to work with time series prediction. [18] The Time Series is a concept of sequential data points in sequence of chronology which are often collected at regular intervals. The analysis of Time Series is applicable to any data which varies with time.

There are basically two things to be considered which makes time series different from a simpleregression area which are as follows:

- Time Dependency: Unlike simple regression model, it doesn't imply restriction on observations to be independent.
- Seasonality: The most Time series models along with the trend of increase or decrease carries some seasonality which considers variations with respect to the one time frame. For example, the warm clothes will have comparatively high sales in winter season [1].

The traditional analysis of time series data usually uses regression for fitting and then finding average for the purpose of prediction. [21] The ARIMA i.e. Auto Regressive Integrated Moving Average model played very good role in the field and several variations in the same has come into existence like Seasonal ARIMA, ARIMAX with Explanatory Variable which works very well with forecasts of short terms but crashes out for predictions of long terms. RNN networks are one of the most powerful networks to model sequential data. The model presented in this work can be applicable to different problems varying from forecast of sales to consumption of energy forecast. Figure 1 represents basic working technique of Recurrent Neural Networks [2].

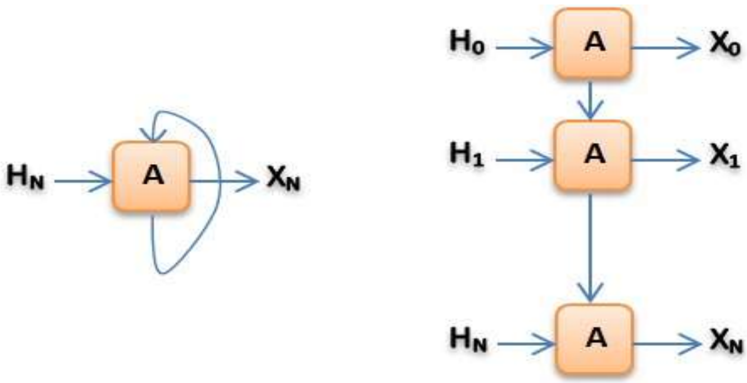

Fig. 1. Recurrent Neural Network

The LSTM networks of Recurrent Neural Network perform well in extraction of pattern in an input feature space based on long sequences. The model of Long Short Term Memory having ability for manipulation of its state of memory, these type of problems are well suited. The LSTM networks are very good in learning Long term dependencies. Figure 2 shows generalized structure network of Long Short Term Memory Network. These networks work gloriously on different variations of problems and they are widely in use now days.

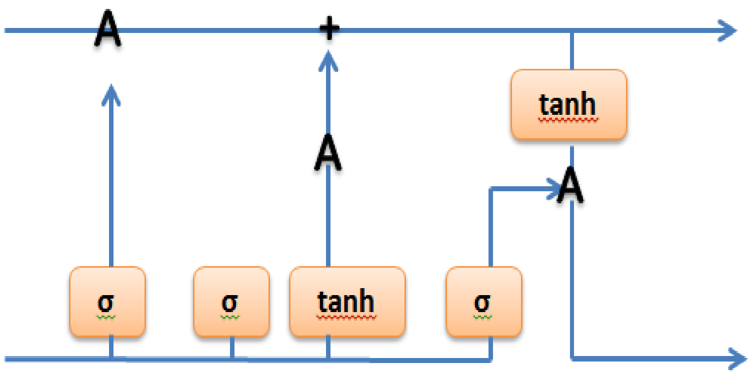

Fig. 2. The Long Short Term Memory (LSTM) Structure

Long Short Term Memory Networks are specifically modeled to handle long term dependency problems. It is being the default behavior of LSTM Networks to remember information [2]. It is able to handle the problem of long term dependency for which RNN is not able to find out the word in long term memory. RNN proved to be not given good performance in case the length of gap increases. This network can keep the information for a long time and it is utilized for prediction, processing and classification based on data of time series.

The manipulations of memory are being done by the gates and the cells are used to keep the information. There are three gates in LSTM structure on which it works.

- Forget Gate is used to remove the unused information of the cells.
- Input Gate is utilized to add useful information to the cells.
- Output Gate is utilized to present the information as an output that is extracted from thecurrent cell.

The objectives of the presented work are:

- Performing Data Pre-processing on the given time-series data set and feature engineering.
- Performing Exploratory Data Analysis (EDA) using Python's Matplotlib and Seabornlibraries.
- Modeling a Deep Neural Network (LSTMs) for a Time series data.
- Splitting the data into Training and Testing Data.
- Training the LSTM model on Training data.
- Optimizing the LSTM model for more accurate predictions.

The rest of the paper is classified into five sections, Section 2 discusses the state of art methods and comparison between various algorithms. The proposed methodology is presented in section 3 followed by result discussion in section 4. Section 5 concludes the outcomes of the paper.

Literature Review

The simple and earliest approach for analysis of time series are majorly based on ARIMA i.e.Autoregressive Integrated Moving Average Model and its different forms like SARIMA and ARIMAX [3]. The approaches of Deep learning and Machine learning have set a new path for analyzing data of time series. Different forms of forecast models like gradient boosted trees, deep learning and random forest for modeling S&P 500 constitutes [4]. It has also been reported that training of neural network models and along with the same, the deep learning based algorithms was proved to be very difficult. An RNN based approach for prediction of stock returns has been introduced which contains an idea to build up a model by adjustment of the threshold return levels by RNN internal layers [5]. A same type of work has also been performed on domain of financial data. "Time series analysis and possible applications" by Mirjana Ivanović and Vladimir Kurbalija [6], time series based data presented and the applications and analysis has become gradually important in different domains. In this work, the important activities, problems, models related to the time series analysis have been discussed and also discussion about practical applicability of the models and applications has been done for the same. "Trend time series modeling and forecasting with neural networks" by Min Qi [7], presented an important view towards time series that there is no general idea present to model the time series data trends in spite of its well importance in the field. The Neural Network architectures have shown promising results in forecasting of time series as compared to the traditional approaches. In this paper, the analysis to model out best for time series has been done by utilizing Neural Network Architectures. The different strategies based on detrending, differencing, raw data and raw data with time index have been utilized for modeling different trend patterns like stochastic, deterministic, breaking trend, linear and non-linear.

“Deep Learning for Time-Series Analysis” by John Cristian Borges Gamboa [8], the time series comprises of temporal dependencies which leads to two identical time points belonging to different classes which makes it difficult to do analysis. The already existing techniques are often dependent on features which are expensively created and have requirement of skilled knowledge. The new models based on unsupervised learning for analysis of time series have been developed with the invention of deep learning. These new developments are being covered in this paper which are based on the deep learning techniques and applications of time series analysis. “Financial Time-Series Data Analysis Using Deep Convolutional Neural Networks” by Jou-Fan Chen et. al. [9], this paper mainly contributes for the optimization of algorithmic trade framework with the Convolutional Neural Networks and Planar representation methods. This paper has presented a system implementation on the dataset of Taiwan Stock Index futures. The results presented in this paper shows that techniques of deep learning worked effectively in trading simulation application and it may have big role in modeling noisy financial data and also complex problems.

“Long Short-Term Memory Networks for Anomaly Detection in Time Series” by Pankaj Malhotra et. al. [10]. Long Short Term Memory Network is being demonstrated to be proven to be very useful for sequence of learning which contains longer patterns of unknown length because of the ability of them to keep long term memory. The involvement of recurrent hidden layers in these networks also helps the temporal feature learning at higher level for fast learning. In this work, Stack based Long Short Term Memory Networks for detection of faults in time series has been done. The training of network on non-anomalous data has been done on time series and the result of prediction errors are being modeled as Gaussian distribution on multi- variation which was being utilized to predict the probability of anomalous behavior. The efficiency of the approach presented on different datasets of Space Shuttle, power demand, multi-sensor engine dataset and ECG.

In the literature study, there are numerous studies present which shows comparison of different classifiers like AR model, ARIMA, or BPANN, SVM, Back Propagation etc. to choose the most suitable one for time-series prediction. The machine learning classifiers have been analyzed to show better performance as compared to simple AR models. Different classifiers are used by the researchers in this domain and a comparison is also presented in this section.

Table 1 Comparison of Different Classifiers

Approach	Advantages	Limitations
LSTM	Extra Gates in LSTM helps tohandle error values in back propagation. Utilization of BPTT in LSTMsolved the problem of back propagation.	Unstable with utilization ofReLU activation function. It can stick up into deepmodels.
SVM	Good in handling gradient Decent. Good with High Dimensional Data.It	Not good for Large Datasets.

	is memory Efficient.	Doesn't perform well whendata contains noise.
Random Forest	Good in handling Missing Valuesand also non-linear parameters efficiently. Can be utilized to with both Classification and Regression.	Consumes more time in data training. It increases complexity.

Different classifiers have been studied, compared to analyze their strengths and weaknesses [11]. The approach of Gated Recurring Units consists of update and resets gate. The approach of Long Short Term Memory consists of input gate, output gate and forget gate. The GRU classifier utilized less number of parameters for training which leads to utilization of less memory. The LSTM, on other hand provides more accurate results as compared to GRU. LSTM approach work very well for large sequences or in the cases where accuracy is very critical parameter. In a research work [12] where authors performed analysis for 4 stock market value prediction utilizing ARMA, BP and GARCH models. The performance of ARMA and BPmodels came better as compared to ARMA model for the criteria of deviation performance and ARMA model suits better for performance parameters of direction (and also weighted direction). Another comparison [13] has been done between Artificial Neural Network and Support Vector Machine model on stock market data.

The research work has shown by plugging in the data into both models for prediction of stock market and results shown that Artificial Neural Network provided better results as compared to Support Vector Machine. The researcher in this work worked on prediction of stock market with random forest classifier and researchers compared different classifiers like Artificial Neural Network, Support Vector Machines, Random Forest and Naïve Bayes model which showed that ANN, SVM and Random forest model showed better performance with discrete values. The work done [14] by researchers worked on comparison of Long Short Term Memory and Support Vector Machines for prediction of stock's price utilizing the data of SSE 50 Index and the results shown in this work presents that LSTM provides better as compared to SVM. The comparison of different classifiers which has been studied and analyzed is presented in Table 1. The study and analysis of strength and weaknesses of different classifiers helped to choose the best suited model for the work.

Methodology

The methodology based on Agile Model comprises functionalities of both iterative and incremental models. This methodology along with adaptability of process is uses with the help of which project is divided into small incremental parts as iterations. One iteration is of 2-3 weeks.

LSTM based work flow

The LSTM model has been developed for testing the dataset. The steps of methodology for the present work comprises of following steps:

- Requirement Analysis
- Gathering Data Set (Time Series Data)
- Performing necessary EDA (Exploratory Data Analysis), Plotting Graphs
- Building LSTM Neural Network using Google's TensorFlow library.
- Training the LSTM model on the dataset
- Evaluating our LSTM model by plotting Training and Testing Curve.
- Plotting final output using Matplotlib or Seaborn.
- Debugging

The stock prediction utilizing LSTM approach performs to predict corresponding value given a set of input values. Firstly, important libraries and dataset is to be imported, then normalization of data is performed and training data is converted into right shape. Secondly, Training the model with LSTM has been done for the dataset collected which comprises of model training, creation of dense layer, creation of LSTM and dropout layers. Later, testing of LSTM trained model is done and evaluation of results occurs.

The LSTM model training and testing results finally are plotted and shown in graphs.

Figure 3 shows the block diagram explaining methodology of the work.

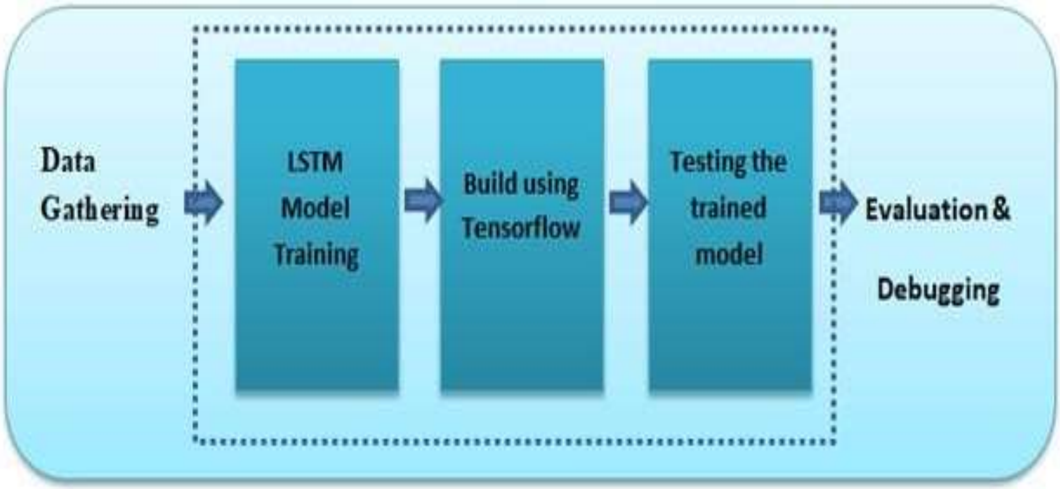

Fig. 3. Flow of the proposed Methodology The equations for LSTM model are shown as equation 1, 2, and 3 as follows:

$$i_m = \sigma(w_i[h_{m-1}, x_m] + b_i) \quad (1)$$
$$f_m = \sigma(w_f[h_{m-1}, x_m] + b_f) \quad (2)$$
$$o_m = \sigma(w_o[h_{m-1}, x_m] + b_o) \quad (3)$$

where, i_m = input gate, f_m = forget gate, o_m = output gate, σ = sigmoid function, w_i, w_f w_o = weight for respective gates, $h_m - 1$ = output of last block, x_m = input at current time and b_i b_f b_o

= bias.

The novel algorithm developed for the work is presented below and figure 4 shows LSTM training. The equations for state of cell, cell state of candidate and final output is shown in equation 4, 5, and 6.

$$c_m = \tanh(w_c[h_{m-1}, x_m] + b_c) \quad (4)$$
$$s_m = (f_m \times c_{m-1}) + (i_m \times c_m) \quad (5)$$
$$h_m = x_m \times \tanh(c_m) \quad (6)$$

where, s_m = state of cell, c_m = candidate for cell state at particular time t.

Algorithm: Time Series Prediction Using LSTM Approach
Input: Financial Health (Stock Market) dataset"
Output: Price (USD) v/s Days

1. Time_Series_Data() Input File
2. Exploratory Data Analysis
3. **while** not the end of file **do**
4. **for** each value in file **do**
5. Perform LSTM Training and Testing.
6. **if** Expected Result **then**
7. Evaluate LSTM Model
8. ***else***
9. Optimize the LSTM Model
10. ***End***
11. **End**
12. Calculate RMSE as sqrt $\{1/(\Sigma i=1 \text{ to } N\ (d_i - z_i)^2)\}$
13. Plot in form of Graph
14. ***end***

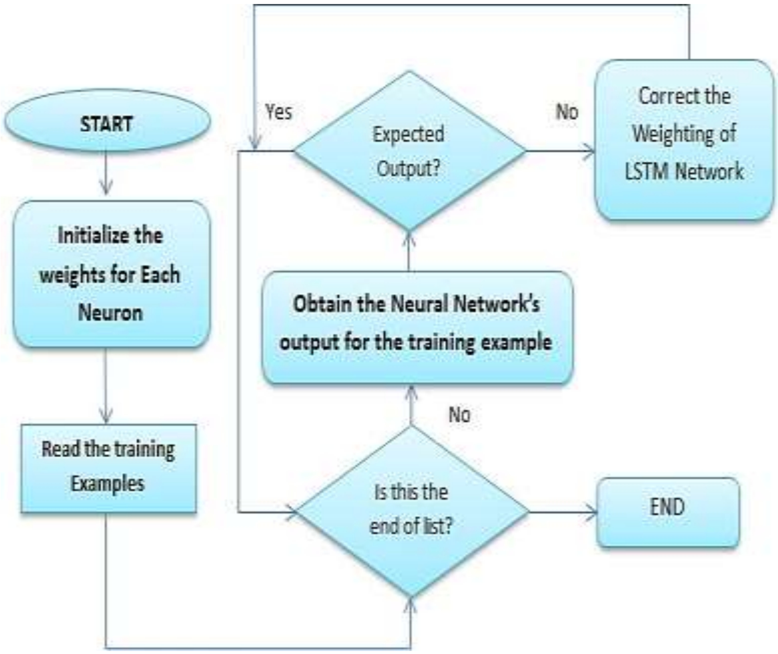

Fig 4. Flowchart for performing LSTM Training

Results

Predicted future values for test dataset using Deep Learning, we used healthcare (Stock Market) dataset for testing our model. Figure 5 shows the result on Training Dataset with comparison of Price and Days while Figure 6 shows Variation in **a**djacent close values and **v**olume of data. It is visible that as the time is passing it is showing that price is increasing which is presented as Initial Data Plot (Before testing).

Fig. 5. Actual Dataset (Price (USD) v/s Days)

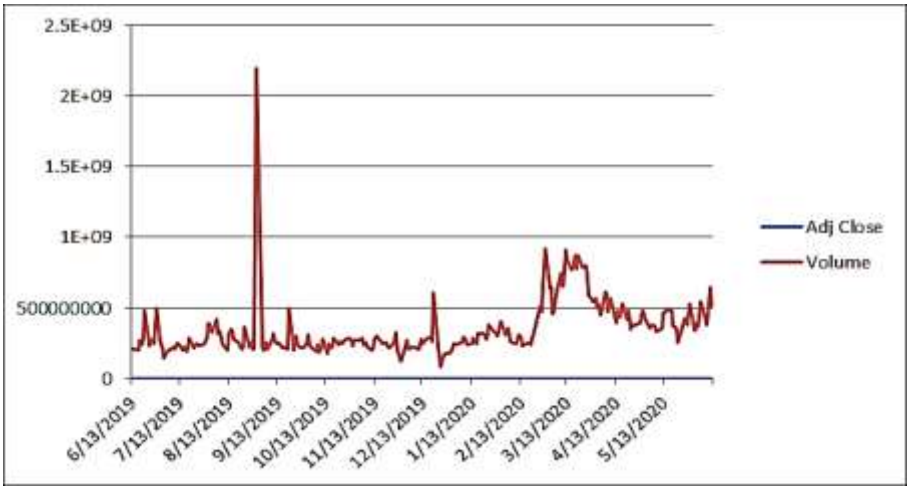

Fig 6. Variation in adjacent close values and volume of data

Figure 7 show results after Training the data. The model has been testing on TestingData. The Blue Line indicates Actual Dataset (Training Data), Orange Line indicates TestDataset (Test Data) and Green Line indicates Predicted reading. The Root Mean Square Error has been identified between predicted and actual values, utilizing values of N. The formula forRMSE is as equation 4:

$$RMSE = sqrt \{ ^{1}/_{n} \sum_{i=1} (\hat{z}_i - z_i)^2 \} \qquad (4)$$

Here, in this work the value of N is taken as 2 because it provides lowest Root Mean Square Error. Figure 8 shows are Error identified in the work. The work done in past [15] with different classifiers for calculation of RMSE for financial services is being compared with this work and same has shown in Figure 9.

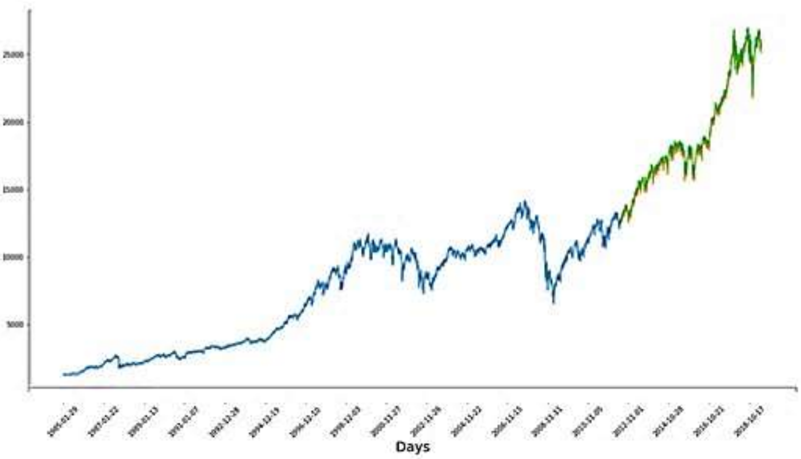

Fig. 7. Output (Price (USD) v/s Days)

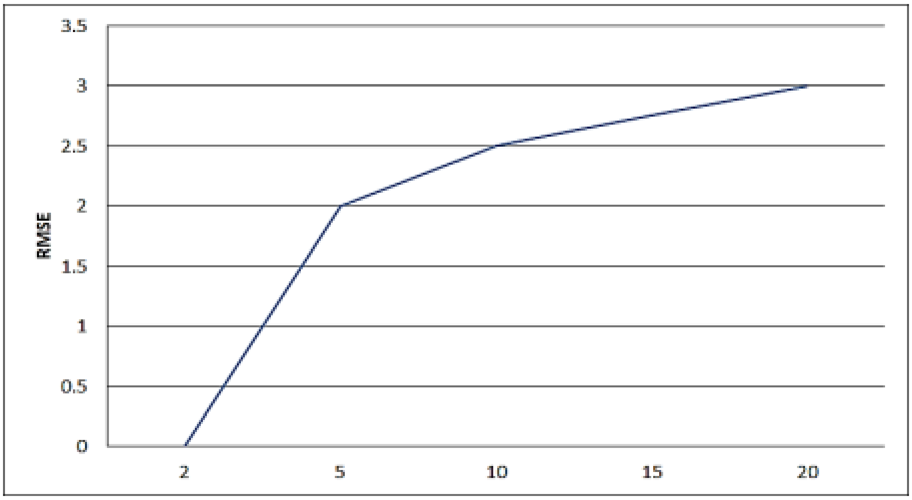

Fig 8. RMSE between predicted and actual values

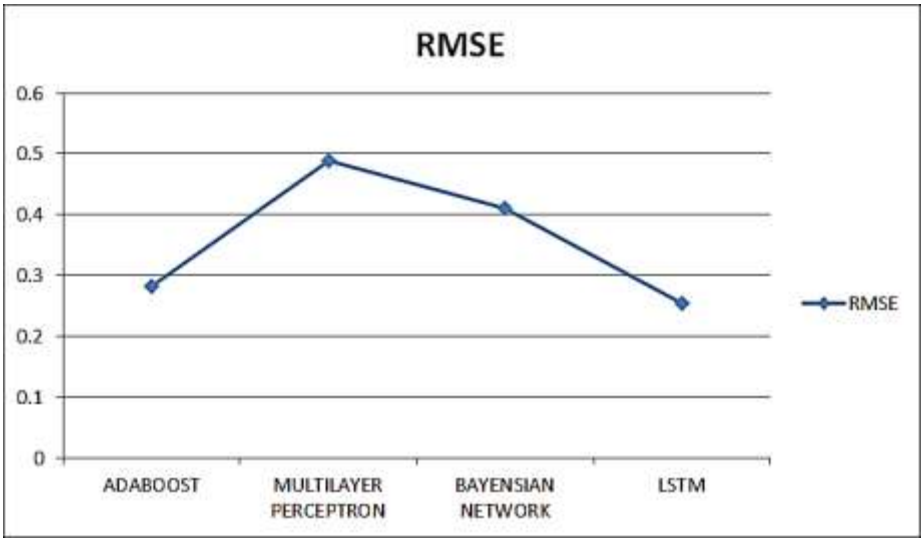

Fig. 9. Comparison of Classifiers on the basis of RMSE calculation

It is visible that the predicted reading overlaps the test dataset. Our model was able to predict the output (actual dataset) with a better accuracy and error is less compare to other machine learning models.

Conclusion and Future Scope

LSTMs when introduced were a big step in what can be accomplished with RNNs. LSTMs are explicitly designed to avoid the long-term dependency problem. We used healthcare related financial dataset (Time Series dataset) which had raw data values with date for each record for implementing and deducing if LSTMs can be used for Time Dependent datasets. The implemented model shows promising results with good accuracy. Even the Stock Market is a volatile market, no matter which technique we use, we can never be hundred percent sure that the prediction is accurate or not. But can be sure on sample datasets it performed. The results for time series prediction are good compare to other ML methods. In future, we are planning to extend the work on different domains and the utilization of a hybrid approach with LSTM is being thought of to be implemented.

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