LSTM -RNN Model to Predict Future Stock Prices using an Efficient Optimizer

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Abstract - *Stock price prediction is the process of ascertaining the future value of a company stock to make captivating profits by devising proper decisions. Predicting stock prices successfully may lead to attractive profits by making proper decisions. But it poses several challenges due to dynamically changing and disorganized data, making prediction a difficult task among the investors to make the right choice in investing to reap high gains. This Paper proposes a deep learning model called Long Short-Term Memory (LSTM), a kind of recurrent neural network (RNN) to predict the day to day stock prices of a particular company. In comparison to the conventional machine learning and artificial neural network models, recurrent neural networks are able to accept and consider the order of sequential input data which helps in data persistence and prove to be a good choice for time series data like stock data. In this paper LSTM model is tested with different combination of optimizers like adam, adamax, SGD, RMSprop, number of epochs and number of LSTM layers to decide on the appropriate choice of hyperparameters which ultimately leads to a better performing prediction model.*

Key Words: **Recurrent Neural Network, LSTM, adam, mean squared loss, stock price, prediction**

1. INTRODUCTION

Stock price prediction [11] has gained popularity among the research community. To aid the investors in making right choices and decisions about stock market investments they need to know the future value of any company stocks. Predicting company stock prices is a challenging task as it is influenced by the ever changing dynamic and disorganized nature of stock data. Many researchers in the past have used machine learning and artificial neural networks to predict the stock prices. In comparison to the conventional machine learning [12] and artificial neural network [10] models, recurrent neural networks are able to accept and consider the order of sequential input data which helps in data persistence and prove to be a good choice for time series data like stock data. Recurrent Neural Networks [9] are a kind of artificial neural network configured to work with sequential data by identifying patterns in sequential input, such as text, genomes, stock prices, handwritten or spoken words and sensor data to predict the next sequential output. They use feedback loops to loop information back to the network. This way the inputs are linked to each other and this allows the information to persist. RNN's have a gradient vanishing problem because of which RNN cannot remember long distance sequence. This makes training RNN difficult and hyper parameter tuning at earlier stages utilizes more time and expensive in terms of computation. Long Short-Term Memory (LSTM) solves the problem of standard RNN by using short term and long-term memory cells to organize the data. Memory cell is a unit of computation that replaces traditional artificial neurons in the hidden layer of the network. This helps LSTM to efficiently link memories and input remote in time, hence is appropriate to capture the nature of dynamic data over time with higher prediction capability.

In this paper, LSTM [9] model is trained on Google daily stock prices dataset of consecutive five years to develop a prediction model to predict the daily forecast of the next year in sequence with higher accuracy. The model is tested with combination of LSTM layers, epochs, and optimizers like adam, adamx, sgd and RMSprop to create a model to provide better prediction. The resulting model is assessed in terms of performance parameters such as mean squared error and accuracy.

2. RELATED WORKS

A. Jayanth Balaji et. al [1], has used fourteen different deep learning models based on Extreme Learning Machines, Lon Short-Term Memory, Convolutional Neural Network and Gated Recurring unit to evaluate stocks S&P BSE BANKEX index. Performance parameters like root mean squared error, directional accuracy and median absolute error were used. The experimental results showed that deep learning models performed better achieving higher accuracy. Roger Achkar et. al [2], considered two different techniques- BPA-MLP and LSTM-RNN- for stock price prediction and applied on different data sets, such as Facebook TM stocks, Bitcoin,Google stocks. They achieved a best-case accuracy of 97% for MLP algorithm, and 99.5% for LSTM algorithm. Xiongwen Pang et. al [3], proposed a deep long-short layer to predict the stock market. Embedded layer was used to term memory neural network (LSMN) with embedded layer to vectorize the data, to foretell the stock prices. The experimental results show that the accuracy of this model is 57.2% for the Shanghai A-shares composite index. Sefa Tekim et. Al [4], examined data of 25 leading companies of Borsa Instanbul and applied several estimation algorithms. The experimental outcomes indicate that Random Forest Algorithm gave the best result with an accuracy of 57.37

percent. V Kranthi Sai Reddy [5] used predicted daily and minute wise stock prices applying Support Vector Machine (SVM), a machine learning technique on small and large capitalization in the three different markets. The experiment was conducted on weka and yale data mining tools and outcomes show that SVM performed well with good accuracy. K. Hiba et. al [6], used ensemble based random forest algorithm on the sample dataset chosen after preprocessing of the raw dataset which proved to be showing better results of prediction. Kamran Raza [7] performed prediction task on stock prices using various versions of artificial neural networks like single layer perceptron, deep belief network, multilayer perceptron, radial basis function and machine learning algorithms like naive bayes, support vector machine and decision tree. The experimental outcome suggests that multilayer perceptron performed better with an accuracy of 77 percent. Poonam Somani, et. al [8], found out that conventional models like support vector machine and neural networks used in stock price prediction failed in incorporating stock market fluctuations and did not perform well. So, they proposed an alternative prediction model built on hidden markov model to predict with better accuracy.

3. METHODOLOGY

3.1 System Design

The raw dataset has attributes like Date, Open, High, Close, Volume and Dividend. This data set is prepossessed to contain only those attributes that are necessary for prediction task. Next step the final training set is applied to the customized LSTM-RNN Model to build a prediction Model. Test data is then applied to this model which predicts the future value of stock prices of a company based on the historical stock data it was trained with. Fig-1 shows the overall system design.

3.2 Construction of LSTM-RNN Model

The First step in the construction of Long Short Term-Memory-Recurrent Neural Network (LSTM-RNN) is to initialise the sequential RNN. Next, the first layer of LSTM, followed by hidden layers of LSTM with some dropout regularization and 50 units is added. Then the final output layer is added with just one output unit. Model is then compiled with selected optimizers like Adam, Adamax, Stochastic gradient descent (Sgd) and RMSprop to build the final LSTM-RNN Model. Fig-2 shows the construction process of LSTM.

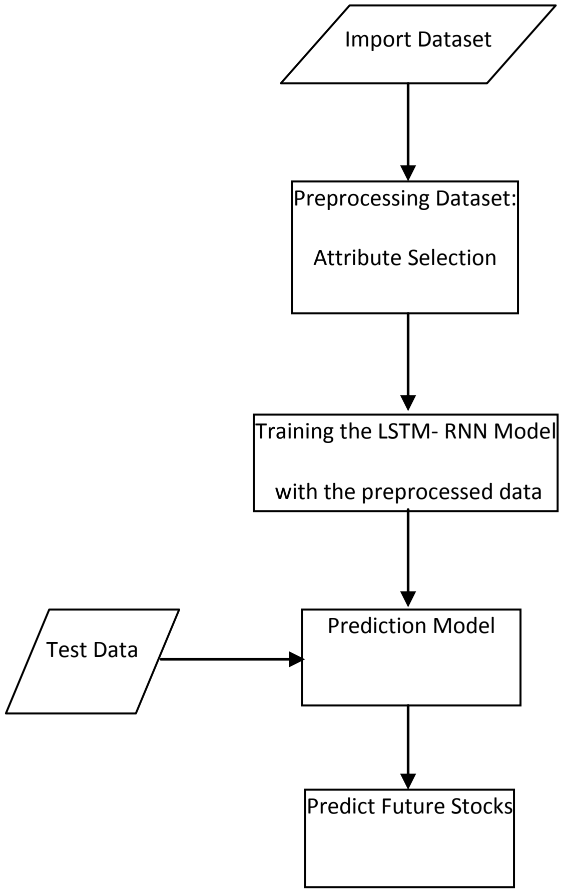

Fig -1: System Design

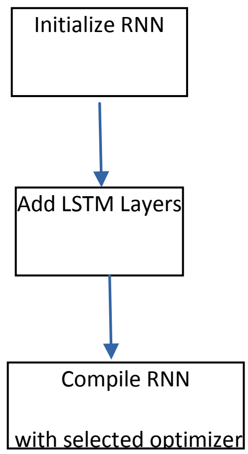

Fig -2: Construction of LSTM

3.3 Optimizers

Optimizers are targeted at increasing the efficiency of learning algorithms by increasing their accuracy at prediction tasks. From this, it is evident that good choice of an optimizer is vital to the success of the prediction model.

Stochastic Gradient Descent (SGD) [13] uses only a single sample from the whole dataset for each iteration. During every iteration, sample is selected after it is randomly shuffled. It avoids redundant computations on the large dataset to update a parameter because it processes single updation at a time.

RMSprop [16], called as Root Mean Square propagation, is an optimization technique based on gradient descent with momentum. It facilitates algorithm to proceed in horizontal direction taking bigger steps and enhancing the rate of learning. It restricts the vertically proceeding oscillations. It adjusts the learning rate dynamically by choosing different rates for different parameters.

Adam [14], is an optimization algorithm calculates adaptive learning rates of individual parameters using only first order gradients. It combines the capabilities of optimization algorithms like RMSprop and AdaGrad. It works well with sparse gradients, a feature acquired from AdaGrad and works well with mobile and online environment, a feature acquired from RMSprop. Adamax [15] is a variant of Adam optimization technique. It has proved to be stable in the infinity order form which distinguishes it from other optimizers. It is an adaptive form of SGD and is better than SGD in terms of its insensitivity towards the choice of parameters.

4. EXPERIMENTAL SETUP

The experiment was conducted on intel processor core i5 with Nvidia GEFORCE GTX and Windows 10 Operating System. The project was implemented on Keras version 1.0.8 on top of Tensorflow 14.0.1 using python 3.6 version. The Google stock data set has been used in this experiment. Training set including day wise data of consecutive five years. The entire training set comprised of 1258 instances with attributes namely "Date" ,"Open" ,"High" ,"Low" ,"Volume". The Test data set comprised of 840-day wise instances.

5. RESULTS AND DISCUSSION

5.1 Model with 4 LSTM layers and 100 Epochs

Chart -3: Future Stock Prediction using Adam Optimizer

Chart -3 shows the experimental results of predicting Google's Future Stocks using Adam Optimizer. The mean squared error incurred in this experiment is 0.0014.

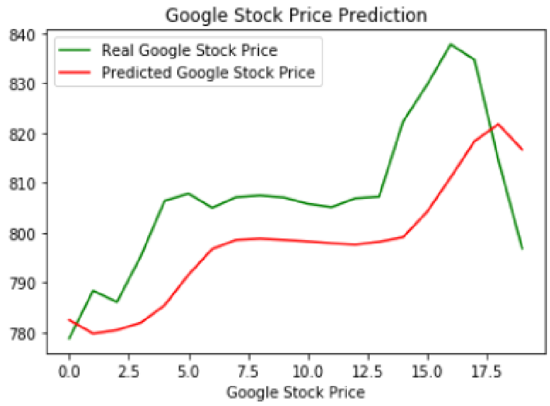

Chart -4: Future Stock Prediction using SGD Optimizer

Chart -4 shows the experimental results of predicting Google's Future Stocks using SGD Optimizer. The mean squared error incurred in this experiment is 0.0038.

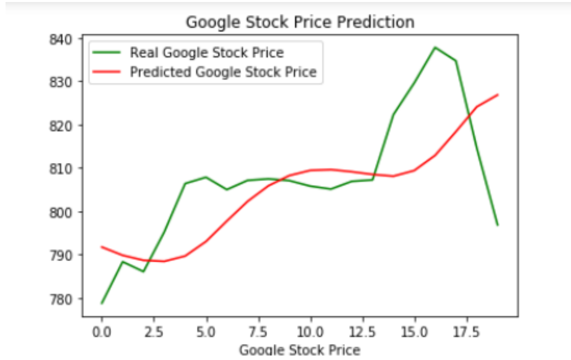

Chart -5: Future Stock Prediction using Adamax Optimizer

Chart -5 shows the experimental results of predicting Google's Future Stocks using Adamax Optimizer. The mean squared error incurred in this experiment is 0.0017.

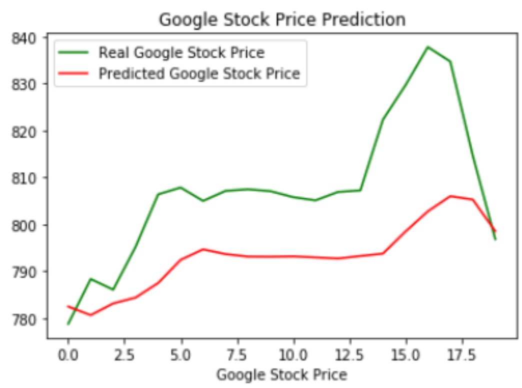

Chart -6: Future Stock Prediction using RMSprop Optimizer

Chart -6 shows the experimental results of predicting Google's Future Stocks using RMSprop Optimizer. The mean squared error incurred in this experiment is 0.0016.

5.2 Model with 4 LSTM layers and 50 Epochs

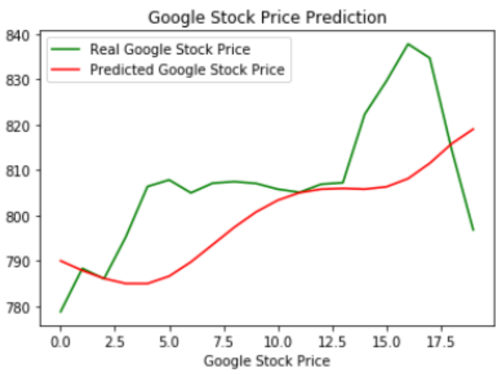

Chart -7: Stock Prediction with Adam Optimizer

Chart - 7 shows the experimental results of predicting Google's Future Stocks using Adam Optimizer. The mean squared error incurred in this experiment is 0.0022.

Chart -8: Stock Prediction with SGD Optimizer

Chart -8 shows the experimental results of predicting Google's Future Stocks using SGD Optimizer. The mean squared error incurred in this experiment is 0.0042.

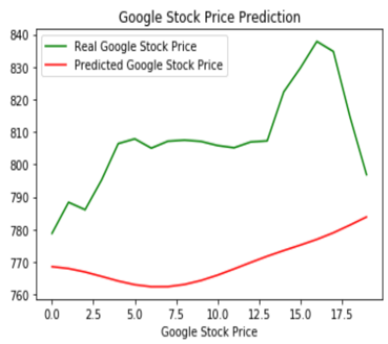

Chart -9: Stock Prediction with Adamax Optimizer

Chart -9 shows the experimental results of predicting Google's Future Stocks using Adamax Optimizer. The mean squared error incurred in this experiment is 0.0030.

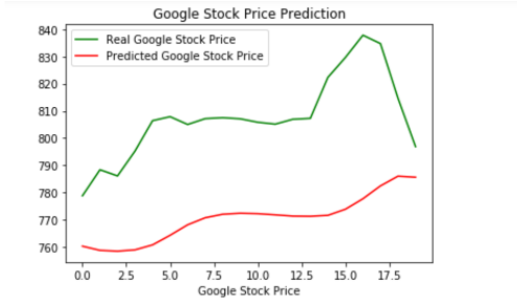

Chart -10: Stock Prediction with RMSprop Optimizer

Chart -10 shows the experimental results of predicting Google's Future Stocks using RMSprop Optimizer. The mean squared error incurred in this experiment is 0.0024.

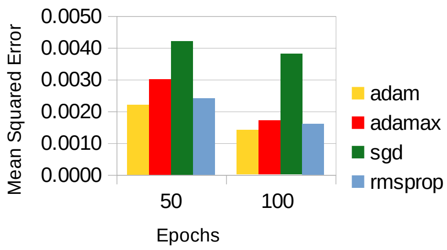

Chart -11: Comparison of Optimizers (4 LSTM layers)

Chart 11 shows the comparison of optimizers in terms of mean-squared error performance parameter. Experiments were conducted using 4 LSTM layers and epochs of 100 and 50. It shown in the above figure that Adam optimizer produces lower mean squared error compared to the other optimizers in both settings of 100 epochs and 50 epochs.

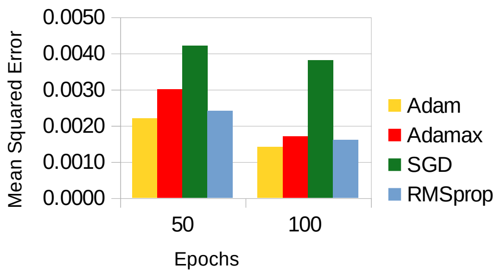

Chart -12: Comparison of Optimizers (5 LSTM layers)

Chart 12 shows the results of prediction of various optimizers like Adam, Adamax, SGD, RMSprop with LSTM layered RNN model based on the performance parameter Mean Squared Error. From the graph shown above it is evident that Adam performs better under both conditions of

50 epochs and 100 epochs with mean squared error of 0.0022 and 0.0014, respectively.

5.3 Adam Optimizer with variant LSTM layers and Epochs

Chart -13: Stock Prediction with 100 epochs and 5 LSTM Layers

Chart -13 shows the real and predicted Google Stock prices using RNN model with 5 LSTM layers and Adam optimizer with Epochs set to 100.The model incurred mean squared error loss of 0.0017.

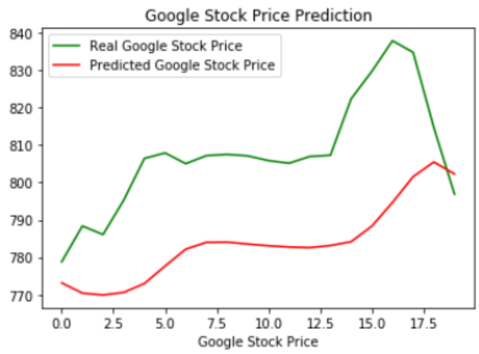

Chart -14: Stock Prediction with 100 epochs and 6 LSTM layers

Chart -14 shows the real and predicted Google Stock prices using RNN model with 6 LSTM layers and Adam optimizer with Epochs set to 100.The model incurred mean squared error loss of 0.0018.

Chart -15: Stock Prediction with 50 epochs and 5 LSTM layers

Chart -15 shows the real and predicted Google Stock prices using RNN model with 5 LSTM layers and Adam optimizer with Epochs set to 50.The model incurred mean squared error loss of 0.0027.

Chart -16: Stock Prediction with 50 epochs and 6 LSTM layers

Chart -16 shows the real and predicted Google Stock prices using RNN model with 6 LSTM layers and Adam optimizer with Epochs set to 50. The model incurred mean squared error loss of 0.0029.

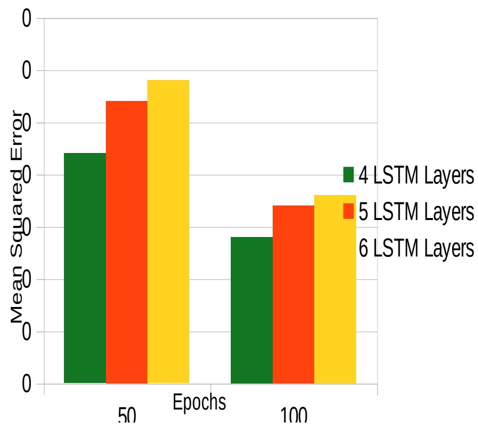

Chart -17: Performance of Adam Optimizer

Chart -17 highlights the performance of Adam Optimizer in terms of Mean Squared Error. From the graph it is evident that the Adam optimizer performed better under 100 epochs and 4 LSTM layer Model with Mean Squared Error of 0.0014.

6. CONCLUSIONS

Stock Market Investors can reap high gains by making right choices of investment if they are able to predict the expected future price stocks of a particular company. Hence Stock market Prediction models are in great demand in today's world. This paper is focused on implementation of one such model using RNN-LSTM Model. The model was tested with Google stock price dataset using Keras, TensorFlow and Python Libraries. The model was tested with different combinations of LSTM layers, number of epochs and optimizers. The experimental results show that the model performed better in terms of mean squared error with 4

LSTM layers, 100 epochs and Adam optimizer. In future this model's performance can be tested against parameters like accuracy and prediction time.

REFERENCES

[1] A. Jayanth Balaji, D. S. Harish Ram, Binoy B. Nair,"Applicability of Deep Learning Models for Stock Price Forecasting An Empirical study on BANKEX Data",8th International Conference on Advances in Computing and Communication (ICACC-2018),Procedia Computer Science 143 (2018) 947–953,Science Direct, Elsevier.

[2] Roger Achkar , Fady Elias Sleiman, Hasan Ezzidine,Nourhane Haida,"Comparison of BPA-MLP and LSTM-RNN for Stocks Prediction",2018 6th International Symposium on Computational and Business Intelligence (ISCBI),DOI:10.1109/ISCBL2018.0019, Electronic ISBN: 978-1-5386-9450-3.

[3] Xiongwen Pang, Yanqiang Zhou, Pan Wang, Weiwei Lin and Victor Chang,"Stock Market Prediction based on Deep Long Short Term Memory Neural Network ",In Proceedings of the 3rd International Conference on Complexity, Future Information Systems and Risk (COMPLEXIS 2018), pages 102-108 ISBN: 978-989-758-297-4 .

[4] Sefa Tekim,Ethem Canakoglu,"Prediction of Stock Returns in Instanbul Stock Exchange using Machine Learning Methods",2018 26th Signal Processing & Communications Applications Conference (SIU),IEEE,DOI:10.1109/SIU.2018.84004607,E-ISBN: 978-1-5386-1501-0.

[5] V Kranthi Sai Reddy,"Stock Market Prediction Using Machine Learning ", International Research Journal of Engineering and Technology (IRJET), Volume: 05 Issue: 10 , Oct 2018 , e-ISSN: 2395-0056 .

[6] K. Hiba Sadia, Aditya Sharma, Adarrsh Paul, SarmisthaPadhi, Saurav Sanyal , "Stock Market Prediction Using Machine Learning Algorithms ",International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-8 Issue-4, April 2019 .

[7] Kamran Raza,"Prediction of Stock Market Performance by using Machine Learning Techniques",2017 International Conference on Innovations in Engineering and Computational Techniques,IEEE,DOI:10.1109/ICIEECT.2017.7916583,e-ISBN:978-1-5090-3310-2.

[8] Poonam Somani,Shreyas Talele,Suraj Sawant,"Stock Msrket Prediction using Hidden Markov Model",2014 IEEE 7th Joint Interaction Information Technology and Artificial Intelligence Conference,DOI:10.1109/ITAC.2014.7065011,Electronic ISBN:978-1-4799-4419-4.

[9] Bo-Sheng Lin ; Wei-Tao Chu ; Chuin-Mu Wang,"Application of Stock Analysis Using Deep Learning" ,IEEE 2018 7th International Congress on Advanced Applied Informatics (IIAI-AAI),DOI: 10.1109/IIAI-AAI.2018.001288 Electronic ISBN: 978-1-5386-7447-5.

[10] Mohammad Talebi Motlagh ; Hamid Khaloozadeh,"A new architecture for modeling and prediction of dynamic systems using neural networks: Application in Tehran stock exchange",IEEE,,2016 4th International Conference on Control, Instrumentation, and Automation (ICCIA),DOI: 10.1109/ICCIAutom.20167483.160 , Electronic ISBN: 978-1-4673-8704-0.

[11] Aakanksha Sharaff; Meenakshi Choudharyy,"Comparative Analysis of Various Stock Prediction Techniques",IEEE,2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI),DOI: 10..1109/ICOEL2018.8553825,Electronic ISBN: 978-1-5386-3570-4 .

[12] Poonam Pandey, Radhika Prabhakar "An Analysis of Machine Learning Techniques (J48 & AdaBoost) -for Classification", IEEE 2016 1st India International Conference on Information Processing (IICIP) ,12-14 August,2016.

[13] Ersan YAZAN; M. Fatih Talu,"Comparison of the stochastic gradient descent based optimization techniques",2017 International Artificial Intelligence and Data Processing Symposium (IDAP),DOI: 10.1109/IDAP.2017.8090299,Electronic ISBN: 978-1-5386-1880-6.

[14] Zihan Chang,Yang Zhang,Wenbo Chen,"Effective Adam-Optimized LSTM Neurral Network for Electricity Price Forecasting",IEEE 2018, 9th International Conference on Software Engineering and Service Science.

[15] Aini Hanifa, Saiful Akbar,"Detection of unstable approaches in flight track with recurrent neural network", IEEE, 2018 International Conference on Information and Communications Technology, DOI:10.1109/ICOIACT.2018.8350754.

[16] S. Vani,T.V. Madhusudhana Rao, "An Experimental Approach towards the performance assessment of various Optimizers on Convolutional Neural Network", 2 019 IEEE 3rd International Conference on Trends in Electronics and Informatics (ICOEI), DOI:10.1109/ ICOEI.2019.8862686

BIOGRAPHIES

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