



e-ISSN: 2319-8753 | p-ISSN: 2320-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 10, Issue 7, July 2021

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.569

9940 572 462

6381 907 438

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www.ijirset.com



Stock Market Prediction Using LSTM Recurrent Neural Network

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ABSTRACT : It has never been easy to invest in a set of assets. The abnormality of the financial market does not allow simple models to predict future asset values with higher accuracy. Machine learning, which consists of making computers perform tasks that usually require human intelligence, is currently the dominant trend in scientific research. Recurrent Neural Networks (RNN) and especially Long-Short Term Memory model (LSTM) to predict future stock market values. The main objective of this paper is to see in which precision a Machine learning algorithm can anticipate and how much the epochs can improve our model. This article aims to build a using these models.

KEYWORDS: Stock prediction. LSTM algorithm, Algorithmic trading, Recurrent neural network.

I. INTRODUCTION

Several studies have been the subject of using machine learning in the quantitative financial, predicting prices of managing and constricting entire portfolio of assets and investment process, and machine learning algorithms can cover many other operations. In general, machine learning is a term used for all algorithm's methods using computers to reveal patterns based only on data and not using any programming instructions. For quantitative finance and especially assets selections, several models supply a large number of methods that can be used with machine learning to forecast future assets value. This type of models offers a mechanism that combines weak sources of information and makes it a strange tool that can be used efficiently. The combination of statistics and learning models has recently polished several machine learning algorithms, such as acritical neural networks, gradient boosted regression trees, support vector machines, and random forecast. These algorithms can reveal complex patterns characterized by non-linearity and some relations that are difficult to detect with linear algorithms. These algorithms also prove more effective and multicollinearity than the linear regressions ones. A large number of studies is currently active on the subject of machine learning methods used in finance; some studies used tree-based models to predict portfolio returns [4], others used deep learning in the production of future values of financial assets [9] [1]. Also, some authors overviewed the forecasting of returns using of AdaBoost algorithm [10].

Others proceed to forecast stock returns using a unique decision-making model for day trading investments on the stock market. The model developed by the authors uses the support vector machine (SVM) method and the mean-variance (MV) method for portfolio selection [6]. Another paper conversed deep learning models for intelligent indexing [3]. Also, some study has covered many trends and Applications of Machine Learning in Quantitative Finance [2]. The literature review covered by this paper consists of return forecasting portfolio construction, ethics, fraud detection, decision making, language processing, and sentiment analysis. These models do not depend on one long term memory (passed sequences of data); in this regard, a class of machine learning algorithms based on Recurrent Neural Network prove to be very useful in financial market price prediction and forecasting. A paper has the accuracy of autoregressive integrated moving average ARIMA and LSTM as illustrative techniques when forecasting time series data. These techniques were executed on a set of financial data, and the results showed that LSTM was far more superior to ARIMA [8]. Our paper aims to use an ML algorithm based on LSTM RNN to forecast the adjusted closing prices for a portfolio of assets; the main objective here is to obtain the most accurate trained algorithm to predict future values for our portfolio.

II. RELATED WORK

There are many related types of research on the stock price prediction. Support vector machines were applied to build a regression model of historical stock data and predict trends [1]. This type is used optimization algorithm is used to optimize the parameters of the support vector machine, which can predict the stock value robustly [2]. This study improves the support vector machine method, but the particle swarm optimization algorithm requires a long time to calculate. LSTM was combined with the naive Bayesian method to extract market emotion factors to improve

prediction performance [3]. This method can be used to predict financial markets in completely different time scales with other variables. The emotional analysis model integrated with the LSTM time series learning model to obtain a robust time series model for predicting the opening price of stocks, and the results showed that this model could improve the accuracy of prediction [11]. Jia [12] discussed the effectiveness of LSTM for predicting stock price, and the study showed that LSTM is an effective method to predict stock profits. Real-time wavelet denoising was combined with the LSTM network to predict the east Asian stock index, which corrected some logic defects in previous studies [13]. Compared with the original LSTM, this combination model is greatly improved with high prediction accuracy and small regression error.

Bagging method was used to combine multiple neural network method to predict the Chinese stock index (including the Shanghai composite index and Shenzhen component index) [4], each neural network was trained by backpropagation method and Adam optimization algorithm, the results show that the method has different accuracy for the prediction of the different stock index, but the prediction on close is unsatisfactory. The evolutionary method was applied to predict the changing trend of stock prices [5]. The deep belief network with inherent plasticity was used to predict the stock price time series [6]. The convolutional neural network was applied to predict the trend of stock price [7]. A forward multi-layer neural network model was created for future stock price prediction using a hybrid method combining technical analysis variables and essential analysis variables of stock market indicators and BP algorithm [8]. The results show that this method has higher accuracy in predicting daily stock prices than the technical analysis method. Effective soft computing technology was designed for Dhaka Stock Exchange (DSE) to predict the closing price of DSE [9]. The comparison experiment with artificial neural networks and adaptive neural fuzzy reasoning systems shows that this method is more effective.

Artificial bee colony algorithm was combined with wavelet transforms and recurrent neural network for stock price forecasting. Many international stock indices were simulated for evaluation, including the Dow Jones industrial average (DJIA), London FTSE 100 index (FTSE), Tokyo Nikkei-225 index (Nikkei), and the Taiwan stock exchange Capitalization Weighted Stock Index (TAIEX). The simulation results show that the system has good prediction performance and can be applied to a real-time trading system of stock prediction. A multi-output speaker model based on RNN-LSTM was used in the field of speech recognition [14]. The experimental results show that the model is better than a single speaker model and fine-tuning under the infrastructure when adding new output branches. Obtaining a new output model not only reduces memory usage but also better than training a new speaker model. A multi-input multi-output convolutional neural network model (MIMO-Net) was designed for cell segmentation of fluorescence microscope images [15]. The experimental results show that this method is superior to the most state-of-the-art deep learning-based segmentation method. Inspired by the above research, considering that some parameters and indicators of stock are associated with one another, it is necessary to design a multi-value associated neural network model that can handle multiple associated prices of the same stock and output these parameters and indicators at the same time. For this purpose, it is proposed an associated neural network model based on LSTM deep recurrent network, which is established by historical data and for predicting the opening price, lowest price and highest price of the stock on the next day.

III. RECURRENT NEURAL NETWORK (RNN) AND LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) is one of many types of Recurrent Neural Network RNN; it is also capable of catching data from past stages and use it for future predictions [7]. In general, an Artificial Neural Network (ANN) consists of three layers:

- 1) input layer,
- 2) Hidden layers,
- 3) output layer.

In a NN that only contains one hidden layer, the number of nodes in the input layer always depends on the dimension of the data; the nodes of the input layer connect to the hidden layer via links called 'synapses'. The relation between every two nodes (input to the hidden layer) has a coefficient called weight, which is the decision-maker for signals. The process of learning is naturally a continuous adjustment of weights; after completing the learning process, the Artificial NN will have optimal weights for each synapse.

The hidden layer nodes apply a sigmoid or tangent hyperbolic (tanh) function on the sum of weights coming from the input layer called the activation function; this transformation will generate values with a minimized error rate between the train and test data using the SoftMax function.

The values obtained after this transformation constitute the output layer of our NN, these value may not be the best output, in this case, a backpropagation process will be applied to target the optimal value of error, the backpropagation process connects the output layer to the hidden layer, sending a signal conforming the best weight with the optimal error for the number of epochs decided. This process will be repeated, trying to improve our predictions and minimize the prediction error.

After completing this process, the model will be trained. The classes of NN that predict future value base on the passed sequence of observations is called Recurrent Neural Network (RNN); this type of NN make use of earlier stages to learn of data and forecast futures trends.

The earlier stages of data should be remembered to predict and guess future values; in this case, the hidden layer act like a stock for the past information from the sequential data. The term recurrent is used to describe the process of using elements of earlier sequences to forecast future data.

RNN cannot store long time memory, so using the Long Short-Term Memory (LSTM) based on "memory line" proved to be very useful in forecasting cases with long time data. In an LSTM, the memorization of earlier stages can be performed through gates along memory lines.

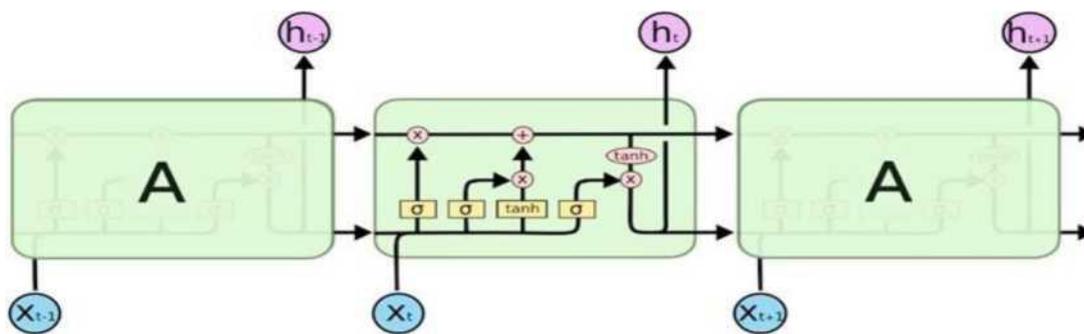


Fig. 1 Describe the composition of LSTM nodes.

The ability to memorize the sequence of data makes the LSTM a special kind of RNNs. Every LSTM node must be consisting of a set of cells responsible for storing passed data streams, the upper line in each cell links the models as a transport line handing over data from the past to the present ones, the independence of cells helps the model dispose filter of add values of a cell to another. In the end, the sigmoidal neural network layer composing the gates drive the cell to an optimal value by disposing or letting data pass through. Each sigmoid layer has a binary value (0 or 1) with

0 "let nothing pass through"; and 1 "let everything pass through." The goal here is to control the state of each cell; the gates are controlled as follow:

- Forget Gate outputs a number between 0 and 1, where one illustration "completely keep this"; whereas 0 indicates "completely ignore this."

- Memory Gate chooses which new data will be stored in the cell. First, a sigmoid layer, the "input door layer," chooses which values will be changed. Next, a tenth layer makes a vector of new candidate values that could be added to the state.

- Output Gate decides what will be the output of each cell. The output value will be based on the cell state along with the filtered and freshest added data.

IV. PROPOSED SYSTEM

As represented in the previous section getting the historical data from the market is a mandatory step. Then there is a need to extract the feature which is required for data analysis, then divide it as testing and training data, training the algorithm to predict the price, and the final step is to visualize the data. Fig. 1 represents the architecture of the proposed system.

The typical LSTM unit consists of a cell, an info door, an entrance door and a door with a view. The cell collects values over discretionary time intervals, and the three inputs manage the progress of data into and out of the cell. The main advantage of the LSTM is its ability to learn context-specific temporal dependence. Each LSTM unit collects

information for either a long or short period (hence the name) without explicitly using the activation function within the recurrent components. A significant certainty to note is that any cell state is uniquely increased by the output of the overlooked entryway, which changes somewhere in the range of 0 and 1. In other words, the overhead door in the LSTM cell is responsible for both the loads and the capacity to initiate the cell state. Subsequently, data from a past cell state can pass through a cell unaltered rather than expanding or decreasing exponentially at each time-step or layer, and loads can meet their ideal quality in a reasonable measure of time. This allows LSTM's to take care of the evaporating slope issue - as the value put away in the memory cell is not iteratively adjusted, The inclination does not disappear when prepared with back engendering, where markets such as NSE and BSE are considered to be Indian trading entities for our analyzes.

V.A STOCK PRICE PREDICTOR USING LSTM

The proposed framework learns online, anticipating the relative costs of the stock with the assistance of Long Short Term Memory (LSTM). The Long Short Term Memory (LSTM) is a counterfeit intermittent neural system (RNN) design[1] used in the field of deep learning; unlike standard feed-forward neural systems, LSTM has input associations. Not only does the procedure not focus on single information (e.g. pictures) but also on full information arrangements, (For example, a speech or a video). For example, LSTM is material for undertakings, such as unpartitioned, associated penmanship recognition, speech recognition and recognition of peculiarities in arranged traffic or IDS (interruption location frameworks).

Algorithm 1: Stock prediction using LSTM Input:

Historical stock data Output: Predicting the stock price using price variation

Step 1: Start.

Step 2: Data Preprocessing after getting the historical data from the market for a particular share.

Step 3: Import the dataset to the data structure and read the open price.

Step 4: do a feature scaling on the data so that the data values will vary from 0 and 1.

Step 5: Creating a data structure with 60 timestamps and one output.

Step 6: Building the RNN (Recurrent neural network) for

Step 5 data set and initializing the RNN using sequential repressor.

Step 7: Adding the first LSTM layer and some Dropout regularization for removing unwanted values.

Step 8: Adding the output layer.

Step 9: Compiling the RNN by adding adam optimization and the loss as mean_squared_error.

Step 10: Making the predictions and visualizing the results using plotting techniques.

Before processing the data, an important step is to collect the information from the market. Information assortment is the primary step in our proposed framework importing information from advertising clearing organizations like BSE (Bombay Stock Exchange) and NSE (National Stock Exchange). The dataset that will be utilized in the market expectation must be separated depending on different perspectives. Information assortment additionally supplements to upgrade the dataset by including more information that is outside. Our information, for the most part, comprises of the earlier year stock costs. For python, the available packages for retrieving the data from NSE is NSEpy.

The next step is to preprocess the data; in this step, the Information Pre-Processing is a significant advance in information mining; here, the change in crude information into a basic configuration is required. The information which is retrieved from the source will be conflicting, fragmented and it will contain mistakes. The preprocessing step will purify the information; toward the end, there is a need to perform highlights scaling, restricting the factors.

The preparation of the model incorporates cross-approval, which is a very well-founded, projected execution of the model using the preparation information. The purpose of the tuning models is to tune the calculation training explicitly is to add information to the calculation itself. The test sets are immaculate, as a model ought not to be decided dependent on concealed information. Scale up the information to the actual offer costs. The final step is to draw the data using a visualization technique that helps to show the variation of data in the outcome of our algorithm.

VI.METHODOLOGY

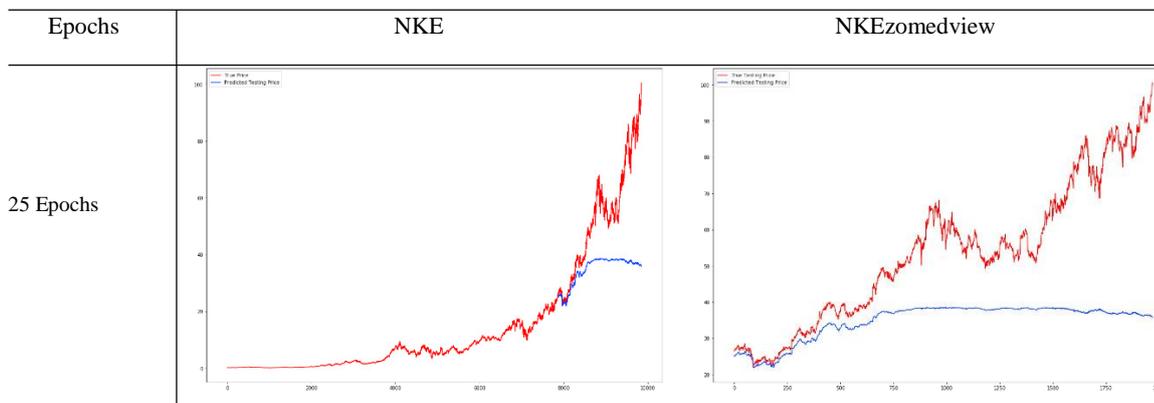
The project's objective is to provide a third-party investment tool to investors with democratized machine learning technologies. The project's success is primarily determined by two factors, namely, whether the investment tool provides useful, accurate stock price predictions to investors and whether investors can use and understand the



predictive information provided by the machine learning technologies. The first factor is evaluated by the model scores described in 2.2.7. However, the evaluation of the second factor is based on user experience. Therefore, external users have to be involved in the evaluation. For this purpose, hallway testing is used. Hallway testing involves allowing users who have not been involved in developing the project to test the application and give constructive feedback about users feel about the application. In addition, users participating in the tests are asked a set of questions about the usability and whether they understand the information presented by the mobile application. This would give indications about whether the democratization of machine learning technologies succeeds.

VII.RESULT AND DISCUSSION

After training our NN the result of our testing has shown different results, the number of epochs as well as the length of the data have both significant impact on the result of testing. For example, if we changed the dataset for NKE giving it a time set going from 12/2/1980 to 12/19/2019 the results will appear as follow:



In fig. 2 Result of training for the NKE stocks with different dataset time.

After observing our data, we can see that the data was less volatile and have lower values at first. Actual market value in the Figure, the red lines represent the actual market value, and the blue lines represent the predicted price value; after the NKE starts peaking more significant values, the asset becomes more volatile than this asset's nature changed. In our case is better to avoid this type of change. Our model has lost trace of opening prices around 600 to 700 days of testing, which conform to the change in data nature.

The result for our dataset for a different number of epochs is giving by the following Figure:

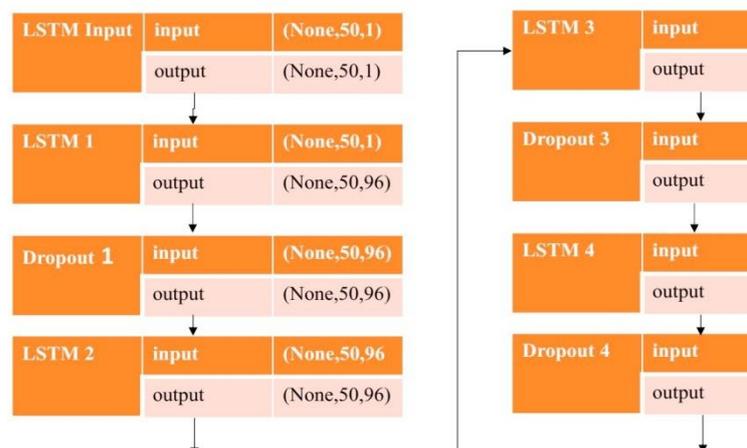


Figure 3: the LSTM model structure

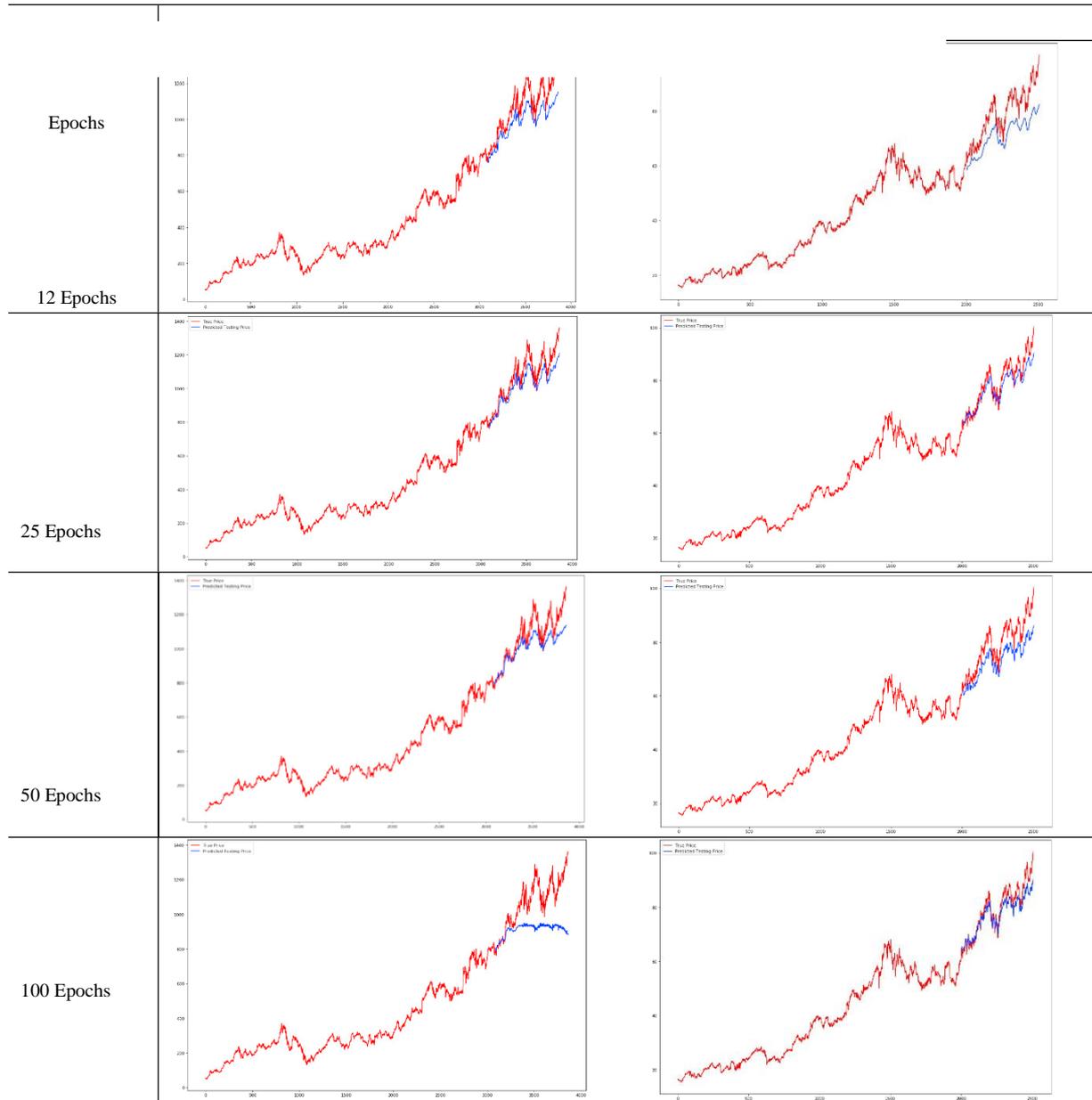


Figure 4: Result of training for NKE and GOOGL stocks with different number of epochs

For a different data set, we can observe that training with fewer data and more epochs can improve our testing result and at the same time allow us to have better forecasting and prediction values. For example, the following table shows our training and testing precision for all the epochs for both NKE and GOOGL asset prices.



Table 2: the value of loss for GOOGL and NKE for deferrent number of epochs

	GOOGL		NKE	
	processing Time / sec	Loss	processing Time / sec	Loss
12 epochs	264	0.0011	132	0.0019
25 epochs	550	0.001	275	0.0016
50 epochs	1100	6.57E-04	550	0.001
100 epochs	2200	4.97E-04	1100	8.74E-04

The table 2 above confirms that the precision of our forecasting increases if we add more epochs of training for our model

VIII.CONCLUSION

This paper RNN based on LSTM built to forecast future values for both GOOGL and NKE assets; the result of our model has shown some promising results. The testing result confirms that our model can trace the evolution of opening prices for both assets. For our future work, we will try to find the best sets for bout data length, and the number of training epochs that better suit our assets and maximize the accuracy of our predictions. The study of the share is carried out in this paper, and it can be carried out for several shares in the future. The prediction could be more reliable if the model trains a more significant number of data sets using higher computing capacities, an increased number of layers, and LSTM modules.

In future enhancement, the inclusion of sentiment analysis from social media to understand what the market thinks about the price variation for a particular share and it can implement this by adding Twitter and Facebook API to our program as Facebook is a leading social media which has lots of market trend information posted by users.

The testing result confirms that our model can trace the evolution of opening price for any assets. We will try to find the best sets for bout data length and several training epochs that better suit our assets and maximize the accuracy of our predictions for our future work. This paper proposes RNN based on LSTM built to forecast future values. The result of our model has shown some promising result.

REFERENCES

- [1] [1] A. V. Devadoss and T. A. A. Ligori, "Forecasting of stock prices using multi layer perceptron," *Int J Comput Algorithm*, vol. 2, pp. 440-449, 2013.
- [2] [2] J. G. De Gooijer and R. J. Hyndman, "25 years of time series forecasting," *International journal of forecasting*, vol. 22, no. 3, pp. 443-473, 2006.
- [3] [3] V. K. Menon, N. C. Vasireddy, S. A. Jami, V. T. N. Pedomallu, V. Sureshkumar, and K. Soman, "Bulk price forecasting using spark over nse data set," in *International Conference on Data Mining and Big Data*. Springer, 2016, pp. 137-146.
- [4] [4] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time series analysis: forecasting and control*. John Wiley & Sons, 2015
- [5] [5] Olah, C. (2015). Understanding lstm networks-colah's blog. Colah. github. io.
- [6] [6] Paiva, F. D., Cardoso, R. T. N., Hanaoka, G. P., & Duarte, W. M. (2018). *Decision-Making for Financial Trading: A Fusion Approach of Machine Learning and Portfolio Selection*. *Expert Systems with Applications*.
- [7] [7] Patterson J., 2017. *Deep Learning: A Practitioner's Approach*, O'Reilly Media.
- [8] [8] Siami-Namini, S., & Namin, A. S. (2018). *Forecasting economics and financial time series: Arima vs. lstm*. arXiv preprint arXiv:1803.06386. [
- [9] [9] Takeuchi, L., & Lee, Y. Y. A. (2013). *Applying deep learning to enhance momentum trading strategies in stocks*. In *Technical Report*. Stanford University. [10] Wang, S., and Y. Luo. 2012. "Signal Processing: The Rise of the Machines." *Deutsche Bank Quantitative Strategy* (5 June).



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