Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 44 (2023), No. 3, pp. 575–584
DOI : 10.47974/JIOS-1416

Predicting stock prices with LSTM: A hybrid machine learning model for financial forecasting

Gargi Pant Shukla [§]
Doon Business School
Dehradun 248001
Uttarakhand
India

Nitin Balwani [†]
School of Business Management
NMIMS University
Mumbai 400056
Maharashtra
India

Santosh Kumar [*]
Jaipuria Institute of Management
Jaipur 302033
Rajasthan
India

Abstract

This article discusses the challenges of accurately predicting the direction of the stock market and proposes a new approach using machine learning and manual forecasting. The article explores the use of technical analysis and machine learning to predict current stock market indices' values by training on historical data. The authors demonstrate how these methods can be used to influence investor judgments at different levels of consideration, including unrestricted, near, medium, high, and volumic. The article also explores the use of social media platforms like Twitter and the correlation between stock prices and local weather patterns to improve forecasting accuracy. The authors present their research in three phases, demonstrating the potential of machine learning and technical analysis to provide

[§] *E-mail:* **gargipant87@gmail.com**
[†] *E-mail:* **Nbalwani@gmail.com**
[*] *E-mail:* **talksant@gmail.com (Corresponding Author)**

accurate and reliable predictions for investors seeking to protect themselves from market volatility.

Subject Classification: *Primary 93A30, Secondary 49K15.*

Keywords: *Mathematical modeling, Ordinary differential equations, A duopoly economy, Market share.*

1. Introduction

LSTM (Long Short-Term Memory) is a type of recurrent neural network that can be used for time series forecasting, including stock market forecasting. LSTM is well-suited for modeling sequences of data that have long-term dependencies, making it useful for predicting stock prices that are influenced by a range of factors over time.

When using LSTM for stock market forecasting, it is important to gather relevant data and preprocess it appropriately. This may involve selecting specific stock indices or individual stocks, gathering historical data for these securities, and performing feature engineering to extract meaningful features that can be used to train the LSTM model.Time series prediction is one of the numerous applications of machine learning. The stock market is one of the most intriguing (and lucrative) time series to try and predict in the future. Both buyers and brokers stand to gain greatly from an accurate stock projection. Machine learning is a powerful tool for predicting the future of financial markets by analysing the past. In order to increase accuracy, it predicts a stock valuation that is similar to the actual value [1]. This project has been broken into three stages. Listed below are the details:

Phase 1 – During this step, we identified all of the variables that affect the stock market. We used a variety of machine learning models, such as LSTM and ARIMA, to forecast whether a stock's price will rise or fall in light of the available data.

Phase 2 – Sentimental analysis was employed in this stage's foundational work. We will use sentiment analysis on the data obtained by twitter to examine the impact of many unpredictable occurrences on the stock market, such as any space research success or failure, war conditions in that area, holidays, any debates, etc. As a large number of individuals use Twitter to express or debate the present situation. We'll focus on the basic aspects of the stocks at this stage.

Phase 3 - Furthermore, in the third phase, we'll discuss how the stock market's effects extend beyond the information technology industry. A sector's stock may be more affected by certain key features than others based on its relationship to those features. Companies in the agro-based industry would be more affected by weather conditions than those in the IT sector. We're working to find a solution now.

2. Literature Review

A paper titled "Machine Learning Stock Market Prediction" was presented at the ICSCCC conference (Lee et al., 2019). LSTM and machine-based regression are used in this article to forecast stock prices. These factors are taken into consideration when determining how much of an impact each size may have. The value of a company's financial stock may rise in the future. The LSTM strategy was used in order to better estimate stock value using machine learning approaches than before possible.

"Prediction of the Indian Stock market Index by using ANN [3]" involves the preparation and testing of the model CNX S&P Nifty 50. The accuracy of neural network output is linked to sample performance assessments. Over the course of four years, 29.65 percent of the network's accuracy in forecasting index closing value has an average accuracy of 69.72 percent. Using ARIMA with tan sigmoid and linear transfer functions, the model has 10 input neurons, a hidden layer of 5, and one output neuron.

Application Journal of Expert Systems, No. 206, presented a paper entitled "CNNpred [4]: CNN-based stock market prediction utilising various parameters." This article uses a CNN-based platform to collect data from various sources, spanning a variety of sectors, in order to build criteria for estimating the future of these markets. Predicting F-measurement efficiency was improved by 3-11% using this approach.

At a work presented in the 2005 ICCIDS, "NSE Stock Market Forecasts Using Deep-Learning Models [5]," There are four alternative deep learning architectures discussed in this article. RRN, LSTM, and CNN neural networks have been used to forecast the market price of a company based on historical data, such as a company's stock price. Each day's closing prices for Indian government bonds on the NSE and New York stock exchanges (NYSE). Competitors aren't keeping up with CNN. For this reason, the Network predicted that the stock markets have some internal features. Neural networks outperform the linear model in terms of performance (ARIMA).

Many elements, such as geographic, geographical, climatic, and social-emotional aspects affect the value of the stock market [6]. In order to accurately anticipate the stock market's movement, shareholders' shares and stocks, and the supply and demand of stock must all be taken into account while creating a machine learning model. “Exploiting investors social network for stock prediction in China” was published in ELSEVIER, 2017 [7]. Xueqiu, a popular Chinese Twitter-like social network dedicated to investors, is utilized to anticipate stock price variations using nonlinear models. Financial news, according to the journal, may have a significant impact on stock prices. The results show that the predicting performance may be improved by the use of emotion and the perception of stock relatedness.

3. Proposed Work

3.1 *Artificial Neural Network*

It is possible to build computers that imitate the workings of genuine neurons using neural networks. It is well-known in the field of statistics that ANNs are non-linear when used to uncover and generalize an underlying pattern in a dataset. Analytical neural networks (ANNs) can highlight the dynamic link between the outputs and inputs. When other approaches fall short, ANN thrives because it can recognize underlying data patterns (Wen et al., 2019). In general, ANN has three layers: a “input,” “secret,” and “output.” Only the input layer of concealed output layers uses linear activation functions. Next, there is an output layer that follows the input layer.

$$A = (xiwi) + b$$

Net sum A and threshold b are defined in this manner: This activation function F is applied to the net sum to produce the output (A). Supervised learning methods like backpropagation may be used to train an artificial neural network with several hidden layers between the input and output layers. As a first step, an error or disparity between the projected and actual output is calculated. By recalculating the weights of neural network edges, the total error has been reduced.

3.2 *Recurrent Neural Network*

For an artificial neural network with several hidden layers, backpropagation can be used to train it. Running a Forward pass is the initial step in determining the difference between planned and actual output. Errors in neural network edges have been decreased by recalculating their weights. The activation function F receives a net sum treatment (FA).

3.3 *Long short-term memory*

An RNN type known as LSTM stands out. Long-term dependencies might be considered in these networks. It was introduced by Hochreiter and Schmidhuber in 697. The purpose of these networks is to prevent the problem of long-term dependence, yet their inherent behavior is to retain information for a long period. In Figure 3, the LSTM cell is depicted. In comparison to other neural networks, LSTM has a unique structure. Instead of a single neural network layer, LSTM is composed of memory, Figure 1, as opposed to the more traditional RNN's extremely particular neural network with a feedback loop. There are three doors in every cell or block, and the cell state is used to regulate the flow of data [9].

3.4 *Deep Extreme Learning Machine*

Deep Extreme Learning Machine is used to synthesize deep neural networks using Extreme Learning Machine. It is a stack of supervised auto-encoders. It is an efficient method to reduce network traffic, training time, and memory usage. It increases the performance as one hidden layer of DELM is equivalent to many hidden layers in ordinary ELM. It has huge applications where there are constraints on hardware implementation.

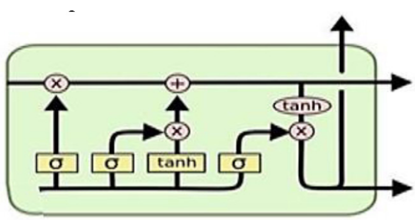

Figure 1

Long Short-Term Memory

This is an effective and fastest way of classification. It has an edge over convolutional neural networks since the optimization and feature learning stages are omitted in this deep learning technique.

3.5 *Factors consider by Analysts for stock prediction*

In order to forecast stock prices, analytical analysts use thousands of various mathematical indicators. In this section we will introduce you to some of the most common, but first here are some keywords that you should know:

a) Supporting level: The level the professional analyst assumes would not be smaller than the inventory price (also called a floor sometimes)
b) Resistance Level: The level where the technical analyst thinks the stock price will not reach the opposite of support level.
c) Breakout: when a stock reaches or falls below the resistance threshold, it is considered a "breakout."
d) Advance Decline Line: Overall progressing problems smaller than the total number of decreasing problems added to a combined total.

3.6 *Variables considered by analysts for stock prediction*

Moving averages: Moving average data is used to draw up charts indicating whether or not the price of a commodity is up or down. They can be used to map trends every day, weekly or monthly. The average number is added per new day (or week or month) and the oldest number is dropped; hence the average number of "moves" over time.

I. Relative Control: The relative strength of a stock is measured with a percentage shift in stock values over a defined time and a 1 to 100 scale rating against all stocks on the market.
II. Maps: Charts: Diagramming is the key technique technicians use to compile their data and forecast costs. For testing purposes, technical analysts can use many types of charts, including line charts, bar charts and candlestick charts.
III. Volume: Volume is essentially the number of stock shares that are exchanged for a given time (e.g., 1 day or 30 days). Any professional

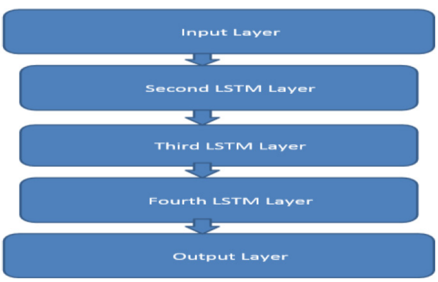

Figure 2

General Architecture of LSTM Used

researcher's measure moving volume averages just as others calculate values is the amount it is relevant because it demonstrates how the stock was active for a certain time, which in turn will impact the stock price.

All of the relevant libraries and data must first be imported into the system. First and foremost, all of the RNN and LSTM libraries, as shown in Figure 2, have been imported. Once the RNN has been begun, one input layer, three hidden levels, and one output layer are all added to it, and the process is repeated. In order to obtain the findings, the RNN must first be constructed, and then the data must be put into the RNN. Finally, matplotlib is used to construct a visual depiction of the changes in stock prices over time in order to have a better understanding of the process. If you are using a basic RNN to analyse long-term correlation time series, the goal is to avoid or minimise the vanishing gradient problem. With the aid of the LSTM, the RNN obtains output, input, and forget gates, among other things. In order to prevent the gradient from being erased, all three gates in Figure 3 have been replaced with new ones. LSTM is used to resolve a long-term dependence problem. The information required by the LSTM in order to maintain its state is stored in memory neurons that have been specially designed for this purpose. In addition, the activation function of each gate is shared by all of them. This function performs a trade-off or nonlinear data change on the input data set. The forget gate,f-t, can be used to filter out part of the information about the current state of the system. The LSTM neural network equations (6-6) fd6 are contained inside this section. The forget gate is made up of memory cells, input gates, and output gates, among other things.

$$
\begin{aligned}
f_t &= \sigma(W1_f \cdot (h0_{t1-1} \| x_{1t}) + b1_f), \\
i_t &= \sigma(W1_i \cdot (h0_{t1-1} \| x1_{t1}) + b_i), \\
\tilde{C}_t &= \tanh(W1_C \cdot (h0_{t1-1} \| x_{t1}) + b_C), \\
C_t &= f_{t1} \times C1_{t1-1} + i_{t1} \times \tilde{C}_{t1}, \\
o_t &= \sigma(W_o \cdot (h1_{t-1} \| x_{t1}) + b_o), \\
h_t &= o_t \times \tanh(C_{t1}).
\end{aligned}
$$

4. Experimental Results & Analysis

The suggested method is educated and validated using the Google Inc. dataset. It is separated into training and test sets, respectively, and

Table 1

Computed value of the LSTM model for the Stock market

LSTM	RMSE	0.051196	30.2462	306.448	0.65447	0.13452
	MAE	0.052214	19.1464	224.245	0.50446	0.10466
	R2	0.99286	0.94971	0.98043	0.96428	0.93412
Proposed Model	RMSE	0.03225	76.5462	78.4848	0.4044	0.06462
	MAE	0.02262	47.3417	71.0463	0.21477	0.04456
	R2	0.99296	0.98455	0.98746	0.94794	0.94962

outcomes are obtained when the various models are passed. The projection is shown with red line and the real pattern is shown in blue. The proximity of both lines shows the efficiency of the LSTM model.

The projection approximates actual patterns when there is a significant amount of time. The train score was 0.00106 MSE (0.03 RMSE) and the exam score was 0.00275 MSE (0.09 RMSE).

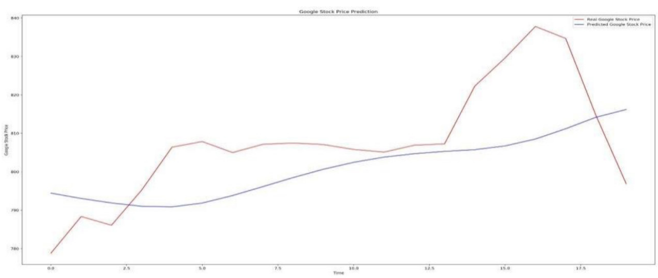

Figure 3

Result by ARIMA modelling

The projection is shown by red line in figure 4 and the real pattern is shown by blue.

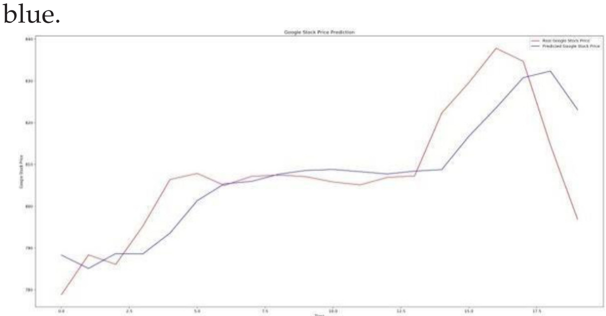

Figure 4

Result by LSTM modeling

The proximity of both lines shows the efficiency of the LSTM model. The projection approximates actual patterns when there is a significant amount of time. The train score was 0.00106 MSE (0.03 RMSE) and the exam score was 0.00275 MSE (0.09 RMSE).

With more training time and data gathering, it becomes easier to achieve higher precision in the machine's output. The LSTM model outperformed the regression model in terms of precision and accuracy. The greater the amount of time the machine has been taught and the greater the amount of data collected, the greater the precision. The LSTM model outperformed the regression model in terms of accuracy.

5. Conclusion and Future Work

Precision and efficiency are improved when we utilise Machine Learning to analyse the possible inventory pricing of a firm. Our preliminary investigation finds a statistically significant relationship between the various input parameters. For the purpose of feeding the RNN, we employ the LSTM model to assess inventory values as hidden layers in the RNN. When it comes to long-term performance, LSTM outperforms ARIMA. The findings are convincing, pointing to the notion that machine learning techniques may be used to anticipate the financial market more successfully and efficiently. These improvements will be implemented in the near future. The precision of the stock market forecast approach may be further improved by employing a sample substantially larger than the one utilised in the original study. Various other variables, such as Twitter data scraping and stock market weather dependence, might be incorporated to capture public opinion on a product or service. ARIMA and LSTM are implemented individually using moving averages. For upcoming projects, intraday pricing may also be used to compare values and better understand how stock, crude oil, and gold prices fluctuate. The data on stock sales and purchases may also be used to analyse how changes in stock prices and other external variables have impacted the purchasing and selling patterns. This will aid in making a prediction that is more accurate. The models may also be enhanced to offer real-time, interactive forecasts depending on input from the user, and they can then be applied to other forecasting issues including weather, illness, and housing price forecasting, among others.

References

[1] Alsubaie, Y., Hindi, K. E., and Alsalman, H. 'Cost- Sensitive Prediction of Stock Price Direction: Selection of Technical Indicators'. *IEEE Access*, Vol 7, pp. 146876–146892 (2019).

[2] Bouktif, S., Fiaz, A., and Awad, M. 'Augmented Textual Features-Based Stock Market Prediction'. *IEEE Access*, Vol 8, pp. 40269–40282 (2020).

[3] Bousono-Calzon, C., Bustarviejo-Munoz, J., Aceituno- Aceituno, P., and Escudero-Garzas, J. J. 'On the Economic Significance of Stock Market Prediction and the No Free Lunch Theorem'. *IEEE Access*, Vol 7, pp. 75177– 75188 (2019).

[4] Bousono-Calzon, C., Molina-Bulla, H., Escudero-Garzas, J., and Herrera-Galvez, F. J. 'Expert Selection in Prediction Markets with Homological Invariants'. *IEEE Access*, Vol 6, pp. 32226–32239 (2018).

[5] Jui-Jung Tsai, Yang-Chao Wang & Peng-Cheng Ren. How do government policies impact dynamic linkages between China's stock and real estate markets?, *Journal of Discrete Mathematical Sciences and Cryptography*, 21:2, 445-450 (2018). DOI: 10.1080/09720529.2018.1449326.

[6] Jui-Ching Huang & Wen-Tsao Pan. Performing stock closing price prediction through the use of principle component regression in association with general regression neural network, *Journal of Discrete Mathematical Sciences and Cryptography*, 12:6, 717-728 (2009). DOI: 10.1080/09720529.2009.10698267.

[7] Baidaa Saleh Mahdi, Jalal Hatem Hussein Al-Bayati & Amer J. Al-Mahdawi. Minimum spanning tree application in Covid-19 network structure analysis in the countries of the Middle East, *Journal of Discrete Mathematical Sciences and Cryptography*, 25:8, 2723-2728 (2022), DOI: 10.1080/09720529.2022.2060923.

[8] Vinita Malik & Sukhdip Singh. Artificial intelligent environments: Risk management and quality assurance implementation, *Journal of Discrete Mathematical Sciences and Cryptography*, 23:1, 187-195 (2020). DOI: 10.1080/09720529.2020.1721883.

[9] Zhi-Guo Li, Dong-Ming Wei & Piotr Kowalski. Transmission and influence of International oil price on China's macroeconomic –based SVAR model, *Journal of Discrete Mathematical Sciences and Cryptography*, 19:3, 535-548 (2016). DOI: 10.1080/09720529.2016.1177961.