



Optimization Analysis of Multivariate Stock Price Prediction **using LSTM Deep Learning Networks**

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Abstract

Stock market price prediction is a challenging task because financial time-series data are highly nonlinear, dynamic, noisy, and influenced by multiple interacting market factors. Traditional forecasting approaches may have limitations in capturing complex temporal dependencies among different financial variables. To address this challenge, this research proposes an “Optimization Analysis of Multivariate Stock Price Prediction using LSTM Deep Learning Networks.” The proposed approach utilizes a multivariate dataset containing important stock-market parameters such as Open, High, Low, Close, Trading Volume, and selected technical indicators. Data preprocessing techniques, including missing-value handling, normalization, feature preparation, and time-series sequence generation, are applied before model training. A Long Short-Term Memory (LSTM) deep learning network is developed to learn both short-term and long-term temporal dependencies within the multivariate stock-market data. Unlike conventional neural networks, LSTM uses memory cells and gating mechanisms to retain relevant historical information and reduce the difficulty of learning long-term dependencies. To improve forecasting performance, the proposed methodology incorporates model optimization through appropriate hyperparameter selection, including the number of LSTM layers, hidden units, learning rate, batch size, sequence length, and dropout rate. Different configurations can be systematically analyzed to identify an effective LSTM architecture for stock-price prediction. The proposed research aims to develop an accurate and optimized deep learning framework capable of forecasting future stock prices from historical multivariate financial data. The resulting model can provide useful analytical information for stock-market trend analysis, financial forecasting, and data-driven investment research. Future extensions may incorporate attention mechanisms, Transformer architectures, sentiment data, macroeconomic indicators, and metaheuristic optimization techniques to further investigate the robustness and generalization of stock-price forecasting models.

Keywords: - Stock Market, Long Short Term Memory (LSTM), Deep Learning (DL)

1. INTRODUCTION

In addition, stock price volatility prediction is a recent research area in time series, and it plays a vital role in decreasing investment threat. Although, stock price tendency not only relies on historical trend but also its correlated social characteristics. Moreover, world's



economy is hugely dependent on the stock markets of every country since billions of dollars are traded each day. The stock market has non-linear and highly variable time series data, estimated based on time to obtain different activity status [1]. Generally, the stock market is referred to as a complex financial system, which involves various company stocks, and also changes in price are varying upon time for each company [2, 3].

Nowadays, stock markets play economic operations stock market index is a significant one to several stakeholders in the market. The stock market price imitates total present information based on the Efficient Market Hypothesis (EMH). Eventually, various sources are generally separated as quantitative data and qualitative description. The quantitative data includes turnover rate, historical prices and so on, and qualitative descriptions have social media posts, annual reports, news, announcements and so on. Generally, qualitative data is shapeless, and hence extraction of required signals from them is insignificant. Therefore, dealing with qualitative data is a challenging one [4].

Even though, the stock market prediction is considered a difficult and undecided issue because of different characteristics, namely noise, irregularities, daily market trends, political influence and insecurities present in the stock market. Alternatively, traders and investors rely upon trading analysis, past and present stock data. The stock market is considered as a dynamic financial system as it includes several elements or stocks and the price changes heavily depends on time [5].

Basically, stock market prediction includes exposure of market trends based on the time. Every stock market investor's plan is to improve the profit from their investments and decrease the correlated risks. Even though various factors, like political events, investor's sentiment, economic limitations and so on affect forecasting of the stock market index is highly significant for several stockholders in the market.

Besides, the overall economic development is majorly dependent on stock market, thus the analysis of behaviours and future prediction is very useful for attaining economic targets. Consequently, the core ingredient of stock market prediction is a trading system, which includes various elements for prediction, trading policy and risk analysis. The main purpose of trading element is to generate a collection of stocks, which increases overall return with regards to the risk of stocks in a group [6, 7].

2. STOCK MARKET PREDICTION

In basic, forecasting behaviors are separated into three levels, such as short, medium and long. Furthermore, stock market movements are influenced by various macroeconomical aspects, like bank exchange rate, commodity price index, investors' expectations, bank rate, general economic conditions, investor's psychology, firms' policies, institutional investors' choices, political events and so on [8, 9]. Additionally, stock value indices are computed using higher market capitalization stocks, whereas several technical parameters are also employed to obtain statistical information about stock price values [10]. In the stock market, there are two assumptions for predicting stock price value. The first one is EMH stating at any time, stock price completely confines all identified information about stock where all identified



information's are utilized through market participants and also random price variations obtains new random information's.

Therefore, stock prices execute a random walk, that is every future price does not follow any patterns or trends. This assumption deduces fluctuations, so incomplete or delayed information controls the stock market prices. In addition, an exterior incident influences successive stock market prices, although the precise prediction of a stock price is complex. From the prediction perception, it can be categorized into two types, namely stock price trend and stock price forecast. The stock price trend is also named as classification, and stock price forecast is also termed as regression [11]. Basically, the time duration for stock price trend prediction is highly related with previously selected features [7].

Because of the identification of suitable movement of stock price decreases the risk of future trend calculation. The industry, economy and other correlated features are considered to compute the intrinsic value of a company, which helps to forecast stock prices from fundamental analysis method. Stock market decision-making technique is a very complex and significant job because of unstable and complex nature of the stock market. It is necessary to discover a huge quantity of valuable information created through the stock market. In addition, every investor has an imminent requirement for identifying future behaviours of stock prices.

Although, it helps the investors to achieve the best profit by identifying the best moment to sell or buy stocks. Normally, trading in stock market can be performed electronically or physically. The investor becomes the owner or partnership of a particular company, while an investor obtains a particular company share. Furthermore, financial data of the stock market is very complex in nature, so for predicting stock market behaviour is also complex. The stock market prediction helps the investors to take investment decisions by offering strong insights regarding stock market behaviour for reducing investment risks.

3. PROPOSED METHODOLOGY

Long-term dependencies can lead to explosions or disappearing gradients, which can be solved with the help of the LSTM model, a recurrent neural system developed to deal with these issues. Memory blocks, the building blocks of the LSTM architecture are a collection of recurrently linked sub-networks. Nonlinear gating units are used to preserve the memory block's state over time and to control the flow of information through it. The cell can recall values for arbitrary periods of time, and the cell's three gates are responsible for regulating the flow of information connected with it. The stock market is where shares of stock are traded, exchanged, and circulated. Although it's a legal and sensible way to move money, issuing stock also gives companies an opportunity to collect a big quantity of idle cash. The organic composition of business capital can be improved, and the growth of the economy can be considerably aided by such efficient capital accumulation. As a result of this, the collection of capital and the accumulation of capital are effectively fostered by the movement of stock. Deep learning using neural networks has gotten a lot of interest from researchers. A

complicated nonlinear dynamic system like a neural network could be the only way to cope with the poor efficiency of a complex nonlinear system [11].

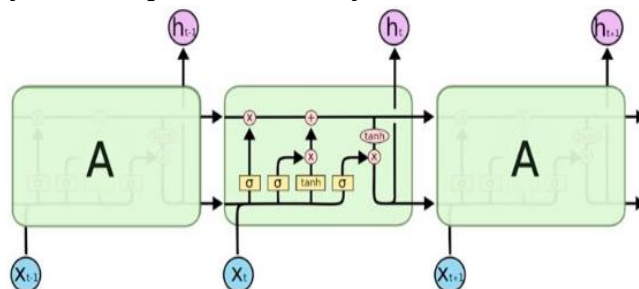


Fig. 1: The internal structure of an LSTM

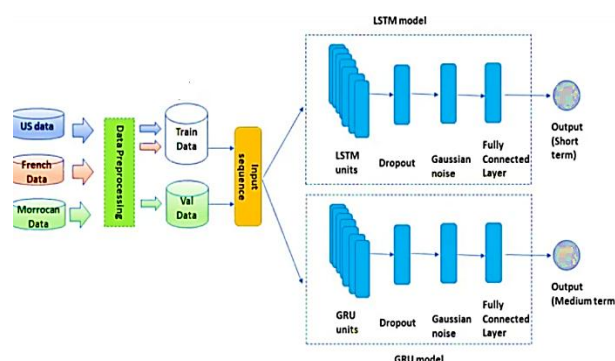


Fig. 2: Flow Chart of Proposed Methodology

The ability of LSTM architectures with multiple hidden layers is to represent sequential data at a higher level and hence perform more efficiently and accurately. The model's hidden layer output is sent straight into the input of the next hidden layer in its architecture, which consists of numerous stacked LSTM layers. A series of values is provided instead of the usual multilayer LSTM design in which each layer outputs a single value to the following layer. LSTM networks operate exceptionally well with sequence data and long-term dependencies because of its robust learning and memory processes. Those were able to increase memory capacity and exert control over memory cells by inserting gates. The output gate is the only gate responsible for reading data from the cell. In addition to the output gate, another gate is required to determine when data should be read into the cell [12].

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \quad (1)$$

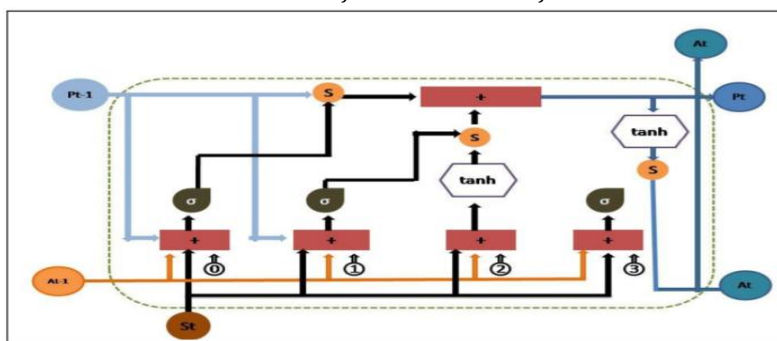


Fig. 3: Working of LSTM

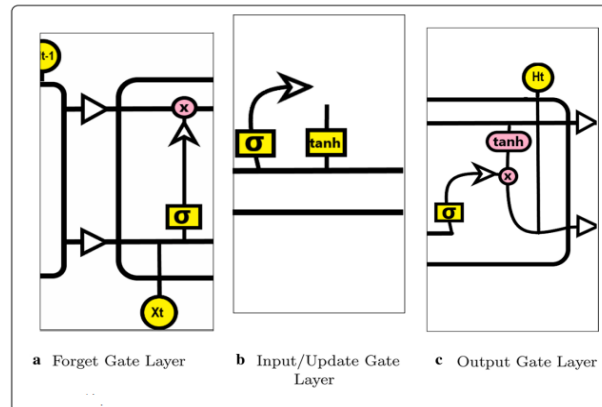


Fig. 4: LSTM Layer

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (2)$$

and

$$C_t = \tanh(w_c[h_{t-1}, x_t] + b_c) \quad (3)$$

Stock index values and the index's daily direction of movement were studied in a series of experiments. ANN cannot be capable of learning data patterns consistently and can operate inconsistently and unpredictably when using complicated financial data. Neuronal structures and the brain's internal workings are mirrored in ANN. Multiple layers of parallel processing use a slew of basic, coupled linear and nonlinear computing units.

$$O_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (4)$$

and

$$h_t = O_t \times \tanh(C_t) \quad (5)$$

Update gate:

$$z_t = \sigma(W_z * [h_{t-1}, x_t])$$

Reset gate:

$$r_t = \sigma(W_r * [h_{t-1}, x_t])$$

A constraint on LSTM ability to learn data patterns has been established in various applications. Researcher can exhibit erratic and unexpected behavior because of the intricate nature of the financial data. Learning patterns cannot operate in situations when the amount of data is too great [13].

4. SIMULATION RESULTS

Stock prices are extremely unpredictable; this complexity is a major draw for researchers and statisticians looking for a technique to anticipate them. Despite the numerous study articles and techniques in this area, many people believe that stock markets cannot be predicted. This is primarily due to the large number of factors that influence stock values, many of which are dependent on other potentially unknown factors.

The figure 5 represents the historical closing price trend of a stock over approximately 3000 observations. The x-axis indicates the observation or time index, while the y-axis represents the closing price. At the beginning, the closing price is around 2 and shows a strong upward movement, reaching approximately 6–7 in the early part of the series. After this initial

increase, the stock experiences several fluctuations, including a noticeable decline around observations 600–1000, where the price falls to nearly 3.5–4. The price then recovers significantly between approximately 1000 and 1300, reaching around 6–7. During the middle portion, the series remains relatively stable but continues to show short-term fluctuations between approximately 5 and 6.5. A further decline occurs around observations 2500–2700, with the closing price reaching its lowest level of approximately 2.5–3. Subsequently, the stock shows a strong recovery toward the end of the dataset, increasing to around 6.5–7. Overall, the graph demonstrates high volatility, repeated upward and downward trends, and significant changes in closing prices, indicating that the stock price series may contain complex temporal patterns that can be analyzed using machine learning and deep learning forecasting models such as LSTM, GRU, or other neural-network-based techniques.

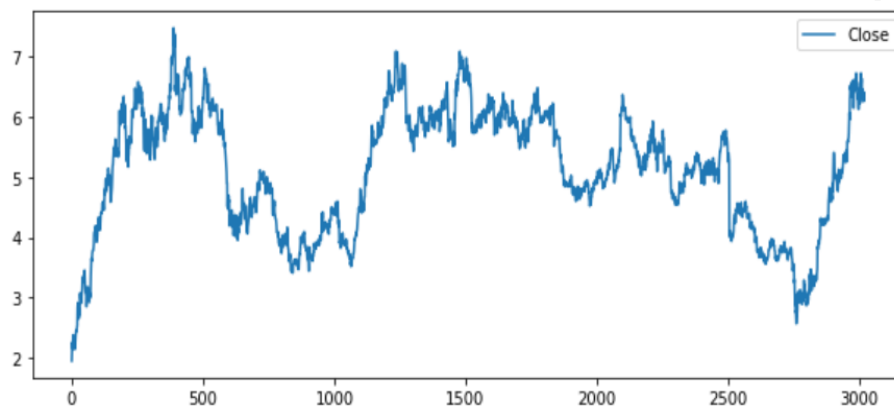


Fig. 5: Closing Price of Perform Exploratory Data Analysis

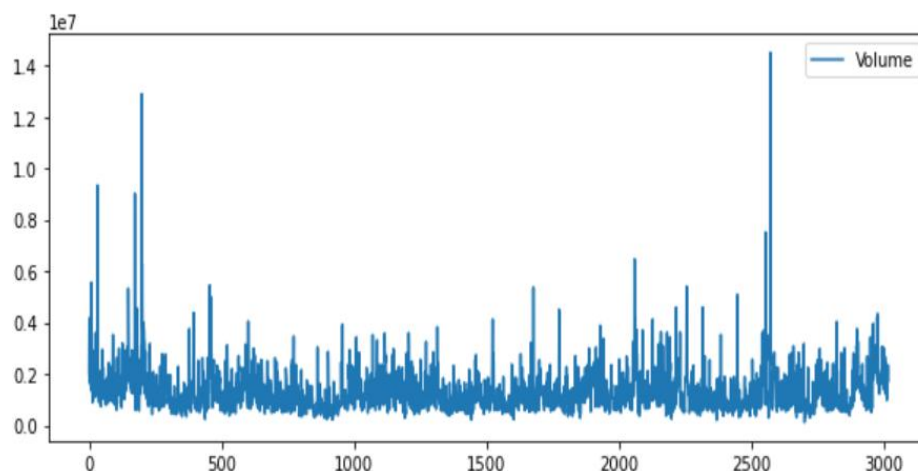


Fig. 6: Volume of Perform Exploratory Data Analysis



Fig. 7: Wipro Closing Price of Perform Exploratory Data Analysis



Fig. 8: Wipro Daily Return of Perform Exploratory Data Analysis

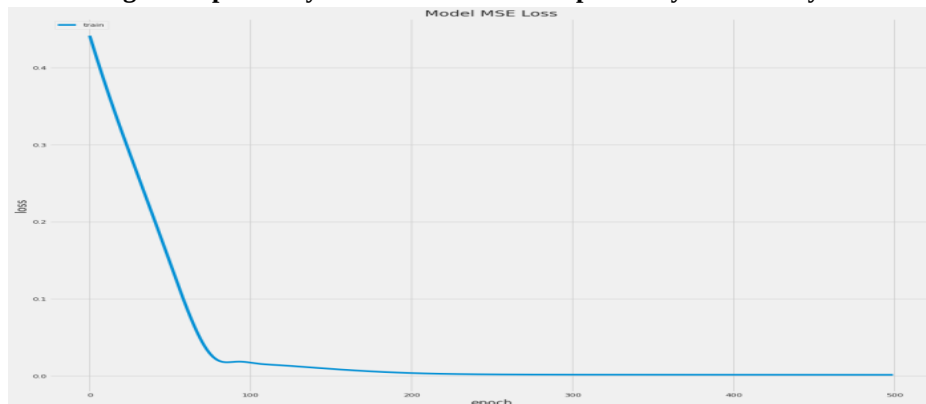


Fig. 9: Model Losses of Perform Exploratory Data Analysis

The Forecast Plot compares the actual stock closing prices with the values generated by the forecasting model. The gray line represents the true data, showing the actual fluctuations in the stock closing price throughout the complete dataset, while the black line represents the training-fit values, indicating how closely the model learned the historical price patterns during the training phase. The red line represents the testing forecast, which is generated by the trained model for the unseen testing period. From the graph, the black training line

follows the gray actual-data line relatively closely across most of the historical observations, indicating that the model has captured the major upward and downward trends in the training data. In the testing region near the end of the dataset, the red forecast initially shows some deviation from the actual values, particularly around the sharp decline and subsequent recovery, but it later follows the strong upward movement and reaches approximately 6.4–6.5, close to the actual closing price. Overall, the plot indicates that the forecasting model is able to capture the general trend and temporal movement of the stock price, although some differences between the actual and predicted values remain during periods of rapid price fluctuations.



Fig. 10: Prediction and Forecast of Perform Exploratory Data Analysis

5. CONCLUSION

The ability to predict stock prices is essential for making investments and financial decisions. However, because the stock market is so unpredictable, investing there carries a significant risk. With varied degrees of success, several studies have been carried out to forecast the market in order to make income. These studies used a number of approaches, including fundamental analysis, statistical analysis, and technical analysis. These approaches, however, do not provide the in-depth analysis required for accurate stock value prediction. Stock market value forecasting has never been easy. It is considered that the company's stock price is not significantly affected by the state of the economy in the country and is not correlated with regional or national economic growth. The training results show that the predicted values closely follow the actual historical prices, indicating that the model has effectively captured major upward and downward trends. During the testing phase, the forecast also follows the overall movement of the actual stock price, particularly the sharp recovery observed toward the end of the dataset. Although some deviations occur during periods of rapid price variation, the model provides a reasonably close representation of the actual trend. Therefore, the results indicate that deep learning-based time-series forecasting can be effectively applied for stock price prediction, while further optimization, additional financial features, and longer historical datasets could potentially improve forecasting accuracy and robustness.



REFERENCES

- [1] Y. Huang and C. Yang, "Enhancing stock price forecasting with a modular deep learning framework incorporating plug-and-play transformer variants," *Expert Systems with Applications*, vol. 315, Art. no. 131572, 2026.
- [2] P. K. Sahu, "A novel hybrid deep learning framework with volatility-weighted loss for high-fidelity stock price prediction," *Neural Processing Letters*, 2026.
- [3] S. Agal, "A hybrid deep learning framework for volatility prediction in financial markets," *Scientific Reports*, 2026.
- [4] G. Taneva-Angelova and D. Granchev, "Deep Learning and Transformer Architectures for Volatility Forecasting: Evidence from U.S. Equity Indices," *Journal of Risk and Financial Management*, vol. 18, no. 12, Art. no. 685, 2025.
- [5] M. Vo, "Stock Market Volatility Forecasting: Exploring the Power of Deep Learning," *FinTech*, vol. 4, no. 4, Art. no. 61, 2025.
- [6] Shravan Raviraj, Manohara Pai M M. and Krithika M Pai, "Share price prediction of Indian Stock Markets using time series data - A Deep Learning Approach", IEEE Mysore Sub Section International Conference (MysuruCon), IEEE 2021.
- [7] J. J. Duarte S. M. Gonzalez and J. C. Cruz "Predicting stock price falls using news data: Evidence from the brazilian market", *Computational Economics* vol. 57 no. 1, pp. 311-340, 2021.
- [8] Andrea Bucci, "Cholesky-ANN models for predicting multivariate realized volatility", *Journal of Forecasting*, vol. 39, no. 6, pp. 865-876, 2020.
- [9] Sarat Chandra Nayak and Bijan Bihari Misra, "Extreme learning with chemical reaction optimization for stock volatility prediction", *Financial Innovation*, vol. 6, no. 1, 2020,
- [10] Andrés Vidal and Werner Kristjanpoller, "Gold volatility prediction using a CNN-LSTM approach", *Expert Systems with Applications*, 157, 113481, 2020.
- [11] J Jia Zhai, Yi Cao, and Xiaoquan Liu, "A neural network enhanced volatility component model", *Quantitative Finance* vol. 20, no. 5, pp. 783-797, 2020.
- [12] Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu, "Financial time series forecasting with deep learning: A systematic literature review: 2005-2019", *Applied Soft Computing*, vol. 90, 106181, 2020.
- [13] G. Ding and L. Qin "Study on the prediction of stock price based on the associated network model of lstm" *International Journal of Machine Learning and Cybernetics* vol. 11 no. 6 pp. 1307-1317 2020.
- [14] S. T. Z. De Pauli M. Kleina and W. H. Bonat "Comparing artificial neural network architectures for brazilian stock market prediction" *Annals of Data Science* vol. 7 no. 4 pp. 613-628 2020.
- [15] Zhihao PENG, "Stocks Analysis and Prediction Using Big Data Analytics", *International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)*, IEEE 2019.
- [16] Eduardo Ramos-Pérez, Pablo J. Alonso-González, and José Javier Núñez-Velázquez, "Forecasting volatility with a stacked model based on a hybridized artificial neural network. *Expert Systems with Applications*", 129, pp. 1-9, 2019.
- [17] A. Site D. Birant and Z. Isik "Stock market forecasting using machine learning models", *Innovations in Intelligent Systems and Applications Conference (ASYU)* pp. 1-6, 2019.
- [18] Werner Kristjanpoller R. and Esteban Hernández P. "Volatility of main metals forecasted by a hybrid ANNARCH model with regressors", *Expert Systems with Applications* 84, pp. 290-300, 2017.