Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7766116

STOCK MARKET PREDICTION USING LSTM

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Abstract
The stock market is viewed as an unpredictable, volatile, and competitive market. The prediction of stock prices has been a challenging task for many years. The stock market is one of the most complex, difficult to predict yet lucrative ways to earn money. While investing, the focus is always on getting higher benefits. Investing in the stock market may demand the need to study various associated factors and extract useful information for reliable forecasting. The papers presented before having their prime focus on either different machine learning algorithms or the use of historical data to provide forecasts. This paper focuses on the use of LSTM (Long-Short Term Memory) to predict future trends of Sensex, Nifty and HUL stock prices. These analysis led us to identify the impact of feature selection process on prediction quality is used in the prediction of stock market performance and prices. This system will provide accurate outcomes in comparison to currently available stock price predictor algorithms. The network is trained and evaluated with various sizes of input data to urge the graphical outcomes.

Keywords: Machine Learning, Stock Price Prediction, Long Short Term Memory, Stock Market.

1.Introduction

Stock market trading has gained enormous popularity globally and for many people, it is a part of the everyday routine to make gains. But forecasting the movement of stock prices is a challenge due to the complexity of stock market data. Forecasting can be defined as the prediction of some future events by analysing the historical data. It spans many areas including industry, business, economics, and finance. However, as the technology is advancing, there is an improvement in the opportunity to gain a steady fortune from the stock market and it also helps experts find the most useful indicators to make much better forecasting. Many of the forecasting problems involve the analysis of time. Time-series data analysis helps to recognize patterns, trends and phases or cycles that are present in the data. In the case of the stock market, early knowledge of bullish or bearish mode serves to wisely invest capital.

The study of trends also helps to recognize the best performing companies over a given period. This makes analysis and forecasting of the time series a significant research field. Deep learning is a framework for training and modelling neural networks that in many learning tasks, have recently exceeded all traditional methods. The paper that we have presented modelled and predicted the stock prices of Sensex, Nifty and HUL. Furthermore, we focus architecture LSTM to predict future trends of stock prices as well as the financial time series based on historical data.

2. Objectives

Many researchers and investors are interested in the finance market. Thus, they need guidance and reliable predictions to invest wisely. Recently, stock market forecasting has gained more interest because investors may be better informed if the market path is accurately predicted. Many businesses already use the concept of deep learning and machine learning to make profits. Investment and trading profitability in the stock market is largely dependent on predictability. If any system that can reliably predict the volatile stock market movements was created, the system's owner would become wealthy. More about the expected market trends will help market regulators take corrective measures. We tried to gain insight into market behavior over time with an effective stock prediction model. The main objectives of the research are as follows:

1. To identify the impact of the feature selection process and hyper-parameter optimization on prediction quality and metrics used in the prediction of stock market performance and prices.
2. To analyze historical data of Sensex, Nifty, and HUL and used it for training and validation purposes.
3. The use of deep learning models to forecast the Price of the above indexes.
4. To examine the results and analyze the efficiency of the model evaluation metrics, features and epochs.

3. Literature Survey

There were three important indicators in the literature for stock price forecasting. They are fundamental, technical and sentiment analyses. These were used to analyse the stock market. They also demonstrate that the relationship between minimum daily returns and future stock returns is dynamic and quantile dependent by using quantile regression. By analyzing the historical data, forecasts can be described as predictions of any future events. Many of the issues of forecasting include time analysis. Time-series data analysis helps to recognize patterns, trends and phases or cycles that are present in the data. The early understanding of bullish or bearish mode helps to spend capital wisely in the case of the stock market. The pattern analysis also helps to classify the highest performing companies over a given period of time. This makes analysis and forecasting of time series an important research area. The existing stock price forecasting approaches can be listed as follows:

(1) Fundamental Analysis and Technical Analysis
(2) Machine Learning Models
(3) Neural Network Models

4. Stock market

Most of the trading in the Indian stock market takes place on its two stock exchanges: the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). The BSE has been in existence since 1875 The NSE, on the other hand, was founded in 1992 and started trading in 1994 However, both exchanges follow the same trading mechanism, trading hours, and settlement process. As of June 2022, there are 1,300+ stocks listed on National Stock Exchange(NSE). As of June 2022, there are 5,000+ stocks listed on the Bombay Stock Exchange(BSE). In 2022 over NSE and BSE 7462 companies are listed. Per day stocks trading volume is 2,54,602 crores. So 1,78000 Lakhs transactions are done per day over NSE and BSE.

National stock markets have emerged as the major channel for the financial integration of emerging market economies amid globalization, deregulation and advances in information technology. Among the factors contributing to growing financial integration are a rapid increase in the cross-border mobility of private capital inflows due to investors seeking portfolio diversification and better yields, a growing reliance of nations on the savings of other nations, and a shift in the leverage preference of companies from debt to equity finance. It is generally perceived that financial integration can be associated with several benefits, including the development of markets and institutions and effective price discovery, leading to higher savings, investment and economic progress. Researching stocks can give you a long-term advantage as an investor.

Analyzing stocks helps investors find the best investment opportunities. By using analytical methods when researching stocks, we can attempt to find stocks trading for a discount to their true value. To gain better returns from the stock market and avoid losing money, one must research thoroughly before investing. This research would help the investor to decide where and how to invest, so as to get good returns. It gives investors an insight into the company's standing in the market, which helps them to decide whether investing in a particular company is viable or not. Unfortunately, investors often don't get the data on time, which traps them into buying an overvalued stock.

Consequently, one can say that the stock price is regulated by supply and demand [8]. The total amount of shares available in a company corresponds to the supply while many different factors affect the demand which may in turn have varying predictability. There are often several different prices to consider when analyzing a specific stock but in this thesis, the closing price is the only one user which is the price of the last transaction just before the stock exchange closes for the day. Sensex and Nifty are the two prominent Indian Market Indexes. Since the prices in the stock market are dynamic, the stock market prediction is complicated. Accurate prediction of stock market returns is a very challenging task due to the volatile and non-linear nature of the financial stock markets. With the introduction of artificial intelligence and increased computational capabilities, programmed methods of prediction have proved to be more efficient in predicting stock prices.

5. Methodology

Long Short Term Memory has been utilized for predicting the next day's closing price for Sensex, Nifty and HUL. The financial data: Date, Open, High, Low, Price Earning Ratio, Price Book Ratio, Dividend Yield, Volume, Volume Average Moving Price, Yearly High and Yearly Low, total Ten factors of stock are used as inputs to the model. The baseline LSTM model was subjected to both a training phase and a testing phase from the available data. The data used to test the tool was the daily closing price of individual stocks traded over a ten-year period, from 2011 to 2021. The initial baseline model used 70:30 training and testing data ratios as guided by the formulae 2N+1 as a best practice. 70% of training data was from the period from January 1, 2010, to December 31, 2021.

6. Need of LSTM:

- LSTMs are particularly powerful because **they can learn long-term dependencies in data**, making them very effective for tasks such as language modeling and machine translation.

- It helps preserve the error that can be backpropagated through time and layers. By maintaining a more constant error, they allow recurrent nets to continue to learn over many time steps.
- It contain information outside the normal flow of the recurrent network in a gated cell.
- It leads to many more successful runs, and learns much faster.
- LSTM also solves complex, articial long time lag tasks that have never been solved by previous recurrent network algorithms.

7. Long Short-Term Memory

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) capable of addressing linear problems. LSTM is a deep learning technique. Long-term Memory (LSTM) Units are enforced to learn very long sequences. This is a more general version of the gated recurrent system. LSTM is more benign than other deep learning methods like RNN or traditional feed-forward because LSTMs tackle the evanescent gradient issue possessed. LSTM is one of the most successful RNN architectures. Such networks are specifically designed to avoid the issue of long-term dependence but their normal behavior is to retain knowledge for a long-time period back. This is because LSTMs store their information in memory similar to a computer's memory since this network can read, write and remove information from its memory.

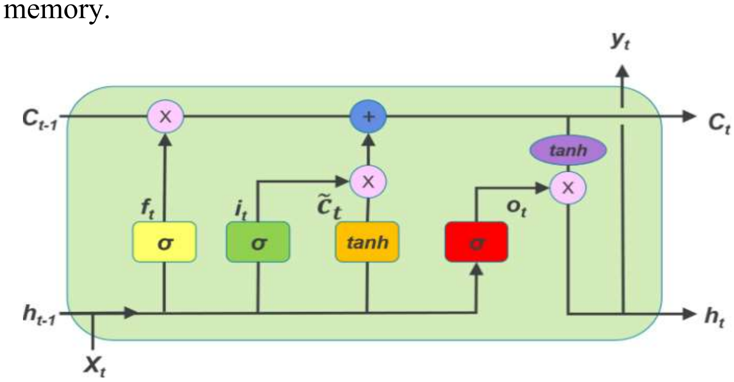

Figure 1. Structure of LSTM

The LSTM model comprises a specific set of memory cells that replace the RNN's hidden layer of neurons and its key is memory cell status. This model extracts information via the gate structure to retain and update the memory cell state. LSTM structure includes three gates: input, forget and output gate. Also, each memory cell has three layers of sigmoid and one layer of tanh. These gates decide whether to let new input into (input gate) or not, remove the information (i.e input) because it is not necessary (forget gate) or allow it to affect the output at the current time stage (output gate). In other words, the gates are used to manage and control the interaction of memory cells among themselves and neighbors. An illustration of the structure of LSTM memory cells with its three gates is shown in Figure 1.

The equations for the gates in LSTM are:

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)$$
$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$
$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o)$$

Equation of Gates

$$\begin{aligned}
i_t &\rightarrow represents\ input\ gate.\\
f_t &\rightarrow represents\ forget\ gate.\\
o_t &\rightarrow represents\ output\ gate.\\
\sigma &\rightarrow represents\ sigmoid\ function.\\
w_x &\rightarrow weight\ for\ the\ respective\ gate(x)\ neurons.\\
h_{t-1} &\rightarrow output\ of\ the\ previous\ lstm\ block(at\ timestamp\ t-1).\\
x_t &\rightarrow input\ at\ current\ timestamp.\\
b_x &\rightarrow biases\ for\ the\ respective\ gates(x).
\end{aligned}$$

The equations for the cell state, candidate cell state and the final output:

$$\tilde{c}_t = tanh(w_c[h_{t-1}, x_t] + b_c)$$
$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t$$
$$h_t = o_t * tanh(c^t)$$

Ct --- Cell state (memory), Ct --- represents candidates for the cell state.
To get the memory vector for the current timestamp (c_{t}) the candidate is calculated.

8. Proposed Model

The proposed model built three different deep-learning algorithms to predict the stock returns of the Sensex, Nifty and HUL indexes using LSTM. For sequential data tasks, this approach is quite popular and displays superior results to those of traditional deep learning techniques. Our goal is to forecast the stock price of the above sample indexes through time series prediction models based only on historical data. To design the suggested neural network models we need to follow some basic steps, namely,

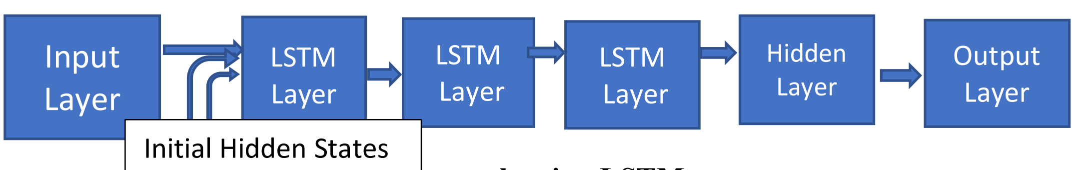

Figure 2: Model Framework using LSTM

Data Collection and Pre-processing, feature extraction, model building and training. Finally, output generation and analysis are based on different evaluation metrics. Our methodology consists of several stages which are as follows:

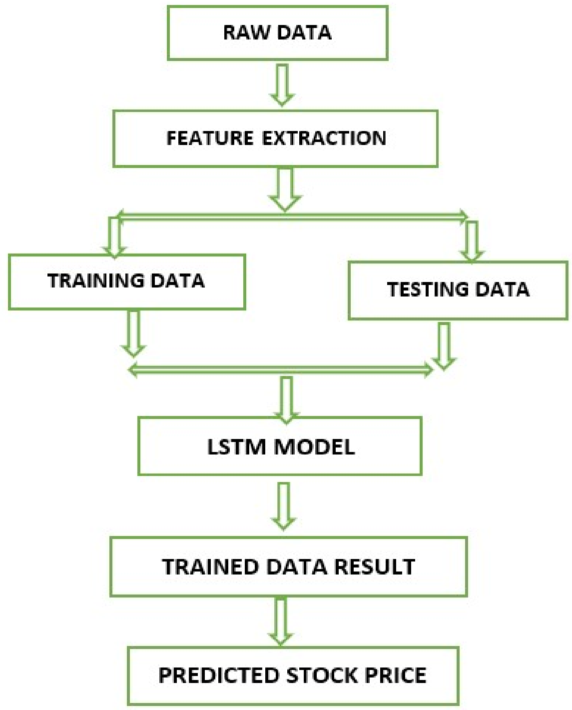

Figure 3, Block diagram of LSTM training and prediction process.

8.1 Data collection (raw data): This study attempts to predict stock returns of the Sensex, Nifty and HUL indexes concerning the stock's previous value. It requires historical data on the stock market to create the prediction model. Therefore, it is essential to have a reliable source with data relevant and appropriate for the prediction. The historical numeric data of stock price is collected from Investing.com. The dataset contains the daily price of each stock, daily open, high, low, Price Earning Ratio, Price Book Ratio, Dividend Yield, Volume, Volume Average Moving Price, Yearly High and Yearly Low. There are ten variables in the basic transaction dataset. This historical data is used for the prediction of future stock prices.

Date	Open	High	Low	Price	PE RATIO	PB RATIO	DIV YIELD	Volume	VAMP	YH	YL
03-01-2011	20621.61	20664.8	20531	20561.05	23.59	3.85	1.02	12000	20585.62	20664.8	15135.86
04-01-2011	20617.38	20651.21	20449.01	20498.72	23.53	3.84	1.02	15200	20532.98	20664.8	15135.86
05-01-2011	20509.95	20509.95	20243.95	20301.1	23.33	3.81	1.03	14400	20351.67	20664.8	15135.86
06-01-2011	20395.5	20425.85	20107.17	20184.74	23.19	3.78	1.04	16600	20239.25	20664.8	15135.86
07-01-2011	20163.85	20210.62	19629.22	19691.81	22.65	3.7	1.06	15800	19843.88	20664.8	15135.86
10-01-2011	19714.42	19720.43	19158.43	19224.12	22.12	3.61	1.09	17200	19367.66	20664.8	15135.86

Table 1. Sensex sample Data set

The attribute of the dataset used in this paper is Date, Open, High, Low and Close. Over the period of time in the Price of a financial instrument, an open-high-low-close is used to illustrate the movement.

Date : This attribute represents the corresponding date of the event. The date is used per day of the week to represent the attribute of the date.

Open : This attribute represent the opening stock trade during the day.
High: This attribute represents the highest stock trade price during the day.
Low: This attribute represents the Lowest price of the stock trade during the day.
Close: This attribute represents the closing price of the stock trade during the day, This is the average price of trading that occurred in the last 15 minutes. It is the reference point that is used by investors to compare the performance of the stock over a time period.

Price Earning Ratio: PER for the last 12 months of the company. This is different from the full year PER reported by the company in the previous audited financial year.
Price Book Ratio: It represents the relationship between the total value of an organisation's outstanding shares and the book value of its equity.
Dividend Yield: A good dividend yield is high enough to meet your current income needs. But low enough to suggest a company's dividend is not at risk. Dividend yields that meet these requirements will typically fall between 2% and 5%. Since a stock with a yield of less than 2% may not provide the investor with enough current income.
Volume: volume patterns over time can help get a sense of the strength of conviction behind advances and declines in specific stocks and entire markets.

Volume Average Moving Price: It starts when the markets open and ends when the markets close for the day. Since it is done every day, the calculation uses intraday data.

Yearly High and Yearly Low: The 52-week high/low is **the highest and lowest price at which a security has traded during the time period that equates to one year** and is viewed as a technical indicator. The 52-week high/low is based on the daily closing price for the security.
8.2 Data pre-processing: It is a very significant step toward getting some information from the dataset to help us make the prediction. This step involves a**) Data discretization:** The data discretization replaces the raw values of the numeric attribute with interval levels. b) **Data transformation:** Data normalization is conducted before the start of the training process because non-linear activation functions tend to squash the node output either in (0, 1). To normalize or scale the data, to used the Standard Scaler class from the sklearn pre-processing library to scale our data between −1 and 1. This scaler allows us to standardize the feature by subtracting the mean and then scaling to unit variance. The mathematical formula of Standard Scaler is as follows:

$$X_{scaled} = \frac{X - U}{S}$$

With U = mean of X feature S = Standard deviation of X feature
The standardized values are shown below
[0.683 0.677 0.682 -0.486 -0.484 -0.487 1.034 1.017 0.931 0.644 0.449]
[-0.650 -0.611 -0.637 0.181 0.167 0.168 2.118 2.103 2.11 1.081 1.078]
[1.102 -1.189 -1.199 -1.192 -1.236 -1.214 -1.219 0.683 0.677 0.682 0.543]
[-0.486 -0.482 -0.487 1.034 1.017 0.931 0.432 -0.986 -0.231 0.678 0.921]

c) **Data cleaning:** This step involves filling in missing values and deleting duplicated data. d**)** **Data splitting:** After the dataset is transformed into a clean dataset, it is divided into training and testing sets to evaluate our models. The dataset is split into 70% for training and 30% for testing.

8.3 Feature selection: In this step, just the attributes that need to be fed to the neural network models are selected. In this research, choose Date, Open, High, Low, Close, Price Earning Ratio, Price Book Ratio, Dividend Yield, Volume, Volume Average Moving Price, Yearly High and Yearly Low. Each time take a different combination of features for both the training and testing sets of each model. Since our work aims to analyze stock indexes using historical stock data, which consists of attributes. Each one of them gives useful data or information that will help to forecast the stock index. So, instead of picking one feature such as close price. Wanted to try many sets of features, then we attempted to find out the best-extracted set of features that has the lowest error percentage using different DL techniques. This step will help to predict the stock index prices and choose the best model with high accuracy.

8.4 Train the neural network models: Sequential deep neural network models are developed by providing the data set for the training. Modeling is initiated using biases and random weights and those models are trained on daily stock price data. Our RNN model is composed of 2 Simple RNN layers each with a dropout layer, followed by a dense layer and an output dense layer for making predictions. The LSTM model contains two LSTM layers each layer followed by a dropout layer and two dense layers. Besides, one of the choices we need to make in the process of building a neural network is what activation function to use in the network's layers. Therefore, we will examine three activation functions Sigmoid, ReLU, and Softmax are used in deep learning models. The choice of the activation function is most important for the output layer of each model as it will define the format that predictions will take. The main purpose is to convert an input signal of a node in our neural networks to an output signal.

9. Performance

Evaluation metrics are attached to the tasks of machine learning and since try to predict future stock prices using deep learning approaches we need to use multiple evaluation metrics to examine and determine the model's performance and behavior. We established a set of the most commonly used metrics which are (1) Accuracy, (2) the root mean square error (RMSE), (3) mean absolute error (MAE), (4) the mean square error (MSE) and (5) coefficient of determination (R2) for comparing and optimizing the prediction models. These criteria are preferred to be smaller since they indicate the prediction error of the models.

• **Root Mean Square Error**: It is the most commonly used evaluation metric for regression tasks. It supports the premise that error is unbiased. This is known as the square root between both the actual score and the expected score of the average squared distance and N represents the total number of the data point. It is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} (Y_t - \hat{y}_t)}{N}}$$

The formula represents the distance between the real scores vector and the predicted scores vector, averaged by $\sqrt{N}$.. Y_t indicates the t ^{t} h data point's true score, and $\bar{Y}_t$ signifies the predicted value. N represents the total number of data points. So, we choose RMSE because the power of ' square root ' allows this metric to reveal large variations in numbers. this metric helps us to deliver more robust results that prevent the positive and negative error values from being canceled.

• **Mean Absolute Error**: It is the average difference between both the true values and the values predicted. It provides us a measure of how far the forecasts from the actual output have come. In other words, this gives us an idea of how the forecasts were incorrect. This error metric is defined as follows:

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |Y_t - \hat{y}_t|$$

• **Mean Square Error**: It is an estimator that calculates the average of squares of the errors. The term error in this metric describes the difference between the estimated value and the actual value. MSE is much like the MAE since the only distinction is that MSE uses the square average of the difference between the true values and the expected values. The equation below describes the mathematical formula used to measure the MSE.

$$MSE = \frac{1}{N}\sum_{t=1}^{N} (Y_t - \hat{y}_t)^2$$

In the equation above, y_t is the vector of the true values and $\bar{Y}_t$ is the vector of the values predicted. MSE is usually used when we have continuous-value vectors. The advantage of MSE is that the gradient is calculated more easily. We used this measure to compare the results of our models.

• **Coefficient of determination (R2):** The R-Squared metric shows the fit consistency of a series of predictions to the real values. It can show us how efficient our model of regression is compared to a very simple model that only predicts the average target value from the train set as forecasts. The R2 equation is as follows:

$$R^2 = 1 - \frac{\sum_{t=1}^{N} (Y_t - \hat{y}_t)^2}{\sum_{t=1}^{N} (\bar{Y}_t - \hat{y}_t)^2}$$

with $\bar{Y}_t$ is the empirical mean of Y feature. We choose five different metrics to evaluate our models as well as to decide which model is the best that meets our target performance. Overall, these metrics try to measure not just the predictive power of our models but also their trade-ability, which is critically important for us because we intend to use our models in the real world.

The closer the value of MAE and RMSE to 0, the smaller the error between the predicted value and the real value, and the higher the forecasting accuracy. The closer R^2 is to 1, the better the fitting degree of the model is.

Stock Name	Mean Absolute Error	Mean Square Error	Root Mean Square Error	R^2 Score
Sensex	102.56	186.28	13.65	0.9943
Nifty	29.36	16.17	4.02	0.9956
HUL	13.06	33.30	5.77	0.9942

Table 2. The error between predicted and real value

Accuracy: 99.76 %.

10. Output generation: Our neural networks generate their predictions in the form of a set of real values. Each output value is generated by one of the neurons in the output layer. The final part of our neural network is the output layer that produces the predicted value. The output value generated by the neural networks outputs layer is compared with the target value in this layer. Our neural network models need to use the backpropagation algorithm to carry out iterative backward passes that aim to find the optimum perceptron weight values and generate the most accurate prediction. When the training is completed the neural network models are used to obtain the predictions on the test set. Then, those models are evaluated based on the outcomes from the prediction. So to analyze the efficiency of the models we used different evaluation metrics.

	SENSEX		NIFTY		HUL	
Date	**Actual**	**Predicted**	**Actual**	**Predicted**	**Actual**	**Predicted**
01-01-2015	27507.54	27605.46	5950.85	6107.62	530.60	528.39
01-01-2016	26160.90	26587.71	6301.65	6301.65	758.45	758.54
01-01-2019	36254.57	36277.19	10435.55	10435.55	269.65	279.20
01-01-2020	41306.02	41135.44	12182.50	12182.50	384.75	376.99

Table 3. Comparison of Actual and Prediction Price

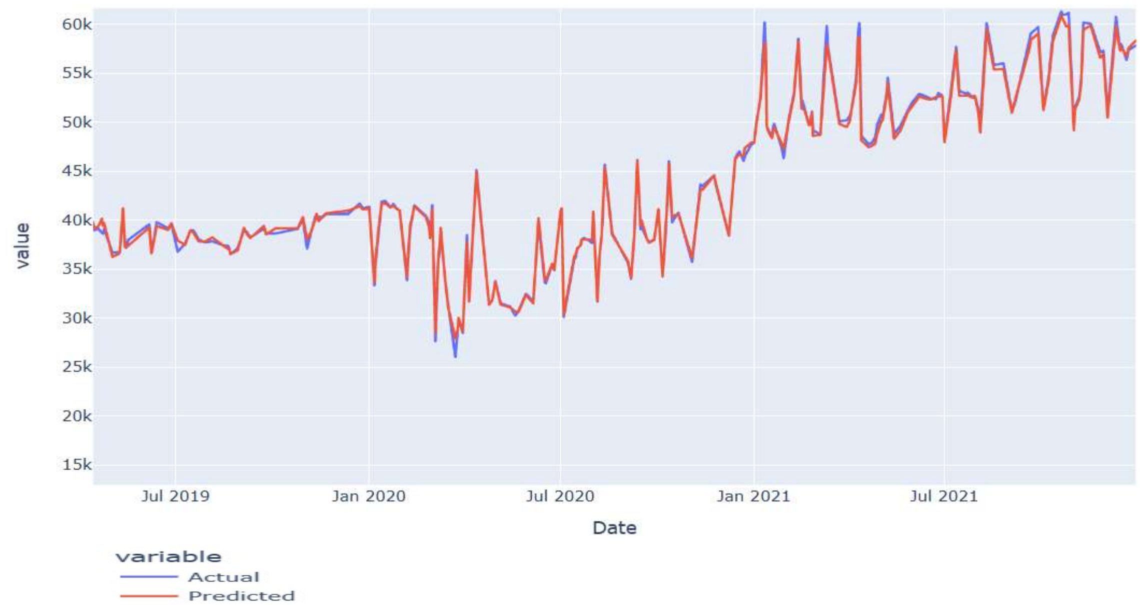

Figure 4. Comparison of the predicted value and the real value for Sensex

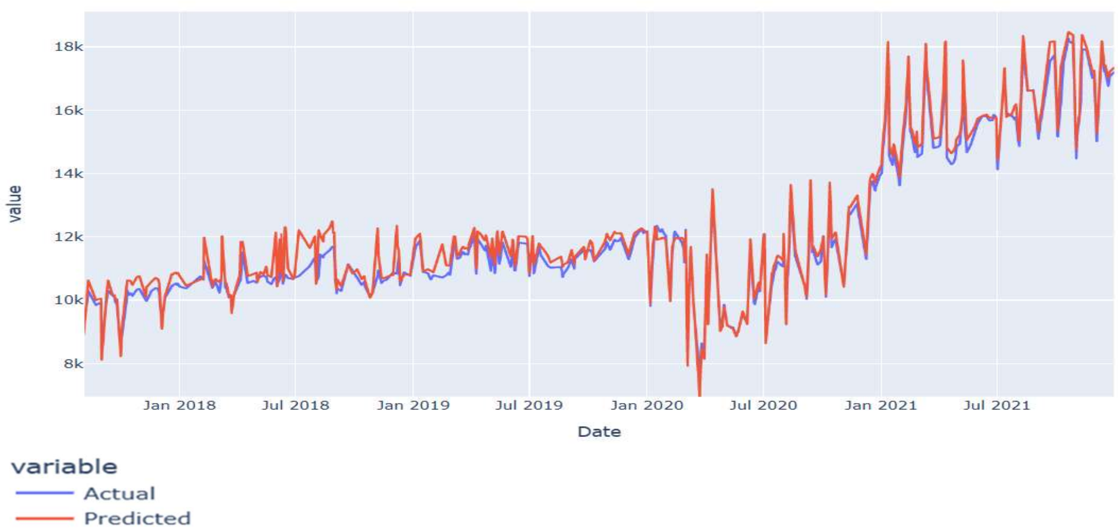

Figure 5. Comparison of the predicted value and the real value for Nifty

Figure 6. Comparison of the predicted value and the real value for HUL.

After using the processed training set data to train the LSTM model completed by training is u sed to predict the test set data, and the real value is compared with the predicted value as s hown in Figure 4 to 6, it predicts the value is very close to what the actual value is supposed t o be.

Exchange/ stock	Buying Date	Actual	Prediction	Selling Date	Actual	Prediction
Sensex	2016-02-16	23191.97	23084.53	2021-10-20	61259.96	61383.15
Nifty	2020-03-23	7610.25	6951.97	2021-10-20	18266.6	18478.69
HUL	2016-01-27	767.9	778.65	2021-03-09	2766.7	2756.73

Table 4. **prediction of bull and bear month for Sensex, Nifty and HUL**

LSTM is suitable for the forecasting of stock prices and can provide a relevant reference for investors to maximize investment returns. LSTM also provides the proposal of practica l experience for people's research on financial time series data. The method that we have used gives very high accuracy, that is, it predicts the value very close to what the actual value is supposed to be. As can be seen by the observations the accuracy of the model is very high which shows that there is a huge scope for using Long Short Term Memory for predicting future stock market trends in the future. Lastly and most importantly, the progress of this approach opens the way for the creation of better-suited market indicators.

11. Conclusion and Future Works

In this research, the neural network approach LSTM has been applied to the forecasting of stock market price movements. This study discusses the use of neural networks to predict future stock price patterns focused on historical prices. This model focused on the importance of choosing the correct input features, along with their pre-processing, for the specific learning models and predicting trends on the basis of data from the past 10 years. To measure the error percentage that exists in the training and testing dataset. Then, compare the obtained results using various sets of features with a specific number of epochs. After conducting several experiments with different features and epochs, to found that LSTM is the best model. As this model has established through the work that deep learning can stably predict the stock price movement, to think there is more scope to work on making the investment more dynamic and intelligently responsive to the market. In the future, it could be possible to combine the multiagent system and our deep learning methods to enhance predicting the exact price value.

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