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Predicting Stock Price from Historical Data using LSTM Technique

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Abstract
The accurate prediction of stock prices in the financial domain has always been a challenging task. While the Efficient Market Hypothesis declared that it is impossible to predict stock prices accurately, research has shown that stock price changes may be predicted with some degree of certainty with predictive models if appropriate and suitable variables are chosen. This work presents a robust and accurate model using statistical and Long Short-Term Memory (LSTM) techniques. Daily stock price data of a particular company was collected from the Yahoo Finance database which served as the primary source for the analysis. The Long Short-Term Memory (LSTM) technique was mainly used to forecast the stock market closing price on a particular day. The accuracy of this model was evaluated through multiple matrices which included Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared, and Directional Accuracy. This provided a clear and comprehensive assessment of the accuracy and performance. This study not only predicted the stock price using the proposed LSMA model but also analysed its accuracy by comparing it with popular conventional methods such as Simple Moving Average (SMA) and Exponential Moving Average (EMA) providing insights into the effectiveness of the LSMA model.
Keywords: Directional accuracy; long short-term memory; recurrent neural network; simple moving average; stock price prediction.

1. Introduction

Much research work has been done to predict the stock prices and it is a popular and anticipated subject matter in the financial domain. Several researchers have attempted to utilise time-series data to predict future values, but the accuracy of these predictions has been relatively low [1], [2], [3] and [4]. Two sides argue debating the possibility of predicting the stock price. In fairness to the opposite side, it is difficult to predict stock values because they depend on a variety of variables, such as the political climate, world economy, corporate the decision making of a company and performance, etc. Therefore, utilising methods to anticipate stock values by examining patterns over the previous several years could prove to be highly beneficial in making informed stock market moves. Such methods could help maximise profits and minimise losses.

Research has demonstrated that predictive models, when utilising appropriate and relevant variables, can achieve reasonably accurate stock price predictions. Recent research has focused on variable selection, functional form specification, and forecasting methods to improve prediction accuracy. In their study, Sen and Datta Chaudhuri propose a novel time series decomposition approach to stock price forecasting [5] and [6]. The proposed approach involves decomposing the stock prices time series into seasonal, trend, and random components, allowing for a more comprehensive analysis of the underlying patterns and trends in the data. The results of the study show that the proposed method outperforms traditional forecasting methods such as ARIMA and Neural Networks in terms of prediction accuracy, indicating its potential usefulness in stock market prediction.

Kim and Han [7] developed a model for predicting the stock price index that combined artificial neural networks (ANN) and genetic algorithms (GAs) with the discretisation of features. Analysing technical indicators to identify the direction of price movements in the daily Korean stock price index was among the data used in their study (KOSPI). They gave their chosen features and formulas using data encompassing samples of 2928 trade days, spanning from January 1989 to December 1998. In addition, they used optimisation of feature discretisation, a method related to dimensionality reduction. Their use of GA to enhance the ANN is one of their work's strengths. First, they used 12 fixed observational inputs and processing components in the hidden layer. Another drawback is that the authors only paid attention to two aspects of optimisation during the learning phase of the ANN. Even yet, they continued to think that feature discretisation optimisation in GA has a lot of potentials.

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A technique to forecast the movement of the Japanese stock market using an enhanced artificial neural network model was also reported by Qiu and Song [8]. In this study, scientists create a hybrid GA-ANN model by combining genetic algorithms with artificial neural network-based models.

Many other research work has been done to predict the future movement of stock prices and it is a popular and anticipated subject matter in the financial domain [9]. Those literature argues for or against the efficient market hypothesis [10]. The main flaw in the stock price prediction theories currently proposed in the literature is their inability to forecast stock price trends over a brief period [11]. The current work tries to remedy this weakness by utilising deep neural networks LSTM modelling and prediction capabilities for stock price movement.

Örsel and Yamada [12] adopt a naive view and suggest that they tend to go up over a long period, but follow a random walk model in the short term. They tried to find out the effectiveness of machine learning algorithms, such as Kalman filtering and long-short term memory architectures. The authors found that the LSTM model was more effective than the Kalman filter in predicting future stock prices.

Predicting stock price using RNN or LSDM is much more effective because the neural network that learns sequence patterns through internal loops and their gate structure like RNN, and LSDM are robust and can store information for a long time, and unnecessary information was forgotten/discarded [13] and [14].

Wimmer and Rekabsaz [15] propose a new approach to predicting stock market movements using Vision-Language models, specifically CLIP, to extract features from stock data. Authors conduct experiments on the German share index and assess various models for stock price prediction using historical data. They find that their approach outperforms existing deep learning-based models and examine the potential for faster decision making.

In the global economy, the amount of money that can be invested in the stock market is limited. However, considering the interest of various participants in the financial market, such as individuals, domestic institutions, and foreign financial institutions, this limit is constantly being tested. According to our world economic, if a stock price is growing, some other stock prices should be declining in the very near future. The objective of this paper is to predict the closing price using Long short-term memory. Using LSTM, given the previous movement pattern of the stock, an investor will be able to anticipate the price of a stock in the upcoming time frame. The strategy incorporates metrics like acceleration, pivot points, and range, all of which are dependent on daily data close stock price.

The goal of statical analysis of stock prices, which is used to find patterns in stock movement and capitalise on them. In this work, two conventional moving average methods like Simple moving average (SMA), and Exponential Moving Average (EMA) are devised towards this end to compare between conventional and machine learning techniques. There are mainly four components used in this work. (1) A time-series data set of daily stock prices of a particular company, (2) a comprehensive feature selection or engineering, (3) a long short-term memory (LSTM) based deep learning model and (4) Evaluation. In this paper, Long Short-Term Memory to indicate stock price analysis and prediction was used. It is believed by us that this strategy will offer a variety of important information to stock market investors, particularly short-term investors.

2. Methodology

2.1. Selecting the data

The data used in this approach was collected from Yahoo Finance by choosing the name of a certain firm or company that is desired to be predicted. A list of daily stock data was seen by accessing the "Historical Data" portion of the website. After that, the CSV file can be downloaded and the time period that will be used for analysis can be filtered out using this method. Historical data for six different companies were collected using this method.

2.2. Description of the data

An example of the data and variables can be seen in Figure 1.

Date	Open	High	Low	Close*	Adj Close**	Volume
Dec 13, 2022	98.07	99.80	97.42	98.14	98.14	12,494,569
Dec 12, 2022	93.09	93.88	91.90	93.56	93.56	27,363,900
Dec 09, 2022	93.90	94.49	93.02	93.07	93.07	21,873,700

Figure 1: *Data sample columns*

The dataset comprises various details of the stock, including Date, High, Low, Open, Close, Adjacent close, and Volume. However, the sole focus of our prediction is to determine the closing price of the stock.

1. **Date:** The date column indicates the date following other additional information. Various dates are tracked by dates, so it is important not to shuffle the data because our model is mainly time series.
2. **Open:** Open refers to the initial price at which a stock commenced trading on the stock exchange at the start of the trading day.
3. **High and Low:** The 'high' and 'low' values of a stock are frequently included in financial magazines and websites. High represents the price at which a stock has traded at any given time. The low represents the time's most affordable pricing. The intraday high and low of a stock are frequently referred to as its daily high and low.
4. **Adj. Close:** It is the closing price after taking into account all applicable splits and dividend payouts is known as the 'adjusted close.'
5. **Close:** Close refers to the price at which a stock end trading for that day. Sometimes, overnight price changes in stocks might be caused by things like firm earnings reporting in after-hours trading.
6. **Volume:** Volume represents the total number of shares traded for a particular stock on a given day. The volume is a measure of market activity. Higher volume means there is more interest in the stock, while lower volume can indicate less interest or lower liquidity.

Importance of closing price: The closing price is the last trending price of the day. Any time frame's reference point is often thought of as the close price. It is the price that traders agreed upon following the day's activity. When analysing historical stock price data, financial institutions, regulators, and individual investors use the closing price as a benchmark indicator of the stock's value on a particular day. It is a fundamental measure of an asset performance over time as depicted in Figure 2.

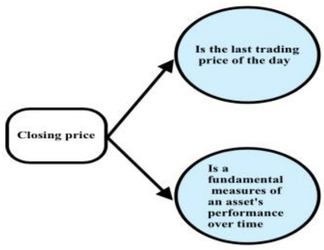

Figure 2: *Importance of closing price*

2.3. Used technique (Long Short-Term Memory)

In this work, LSTM (long short-term memory) is used. LSTM is commonly used in deep learning and artificial intelligence. Unlike conventional feed-forward neural networks, LSTM has feedback connections and can processe complete data sequences, in addition to individuale data points, making it a recurrente neural network.

The three gates, input, forget, and output, are represented by the letters I, f, and o in the formula Eqs. (1), (2), and (3). The learned data is preserved in the cell state C, as shown in the formula Eq. (5), which is then sent as the output h, as represented by the formula Eq. (6). Considering the information gathered from each timestamp, all these calculations are performed for every timestamp t (t-1).

In Eqs. (1)-(6), x_t represents the input at timestamp t, and *U* and *W* are weight matrices. The sigmoid function is denoted by *σ,* and the hyperbolic tangent function is denoted by *tanh*. Eq. (1) calculates the input gate, Eq. (2) calculates the forget gate, Eq. (3) calculates the output gate, Eq. (4) computes the temporary cell state, Eq. (5) updates the cell state, and Eq. (6) calculates the final output.

$$i_t = \sigma(x_t U^i + h_{t-1} W^i) \quad (1)$$

$$f_t = \sigma(x_t U^f + h_{t-1} W^f) \quad (2)$$

$$o_t = \sigma(x_t U^o + h_{t-1} W^o) \quad (3)$$

$$C'_t = tanh\,(x_t U^g + h_{t-1} W^g) \tag{4}$$

$$C_t = \sigma(f_t * C_{t-1} + i_t * C'_t) \tag{5}$$

$$h_t = hanh(C_t) * o_t \tag{6}$$

The function of the input gate is to decide what to include in the existing cell state, while the forget gate determines what information should be discarded from the current cell state and the amount of information to be discarded. The output gate, which is employed in the final equation, regulates how much output the first two gates compute. Such a recurrent neural network may process complete data sequences in addition to single data points. The architecture of long- and short-term memory is depicted in Figure 3.

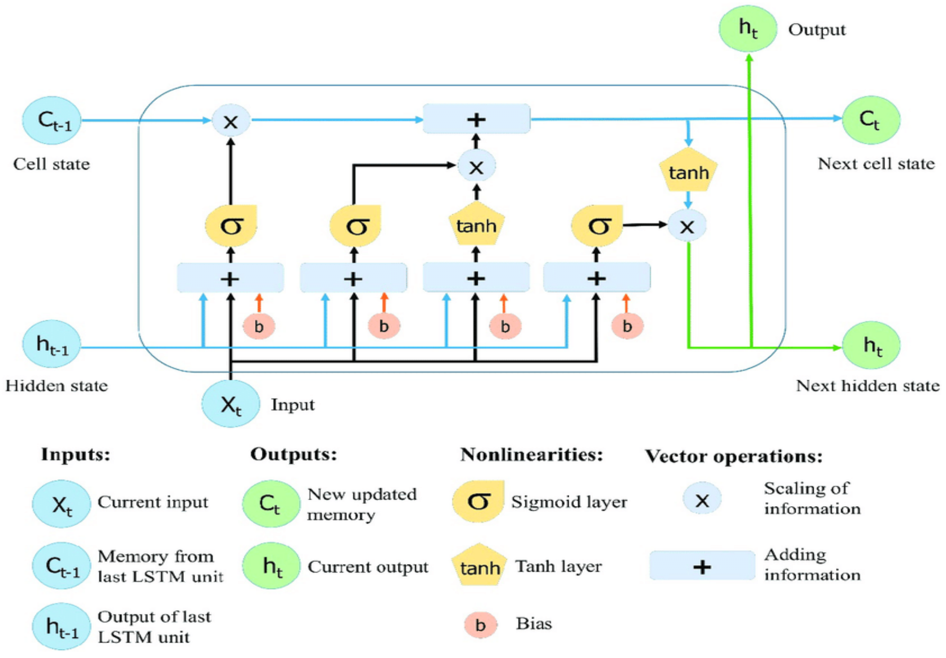

Figure 3: *Architecture of Long Short-term memory. Reproduced from Yan [16].*

LSTM has a wide range of applications including stock market prediction, rainfall-runoff modelling [17], fMRI data analysis, and anomaly detection [18]. While standard RNN is good at preserving information, it is not effective in learning long-term dependencies due to the vanishing gradient problem. LSTM overcomes this issue by using memory cells that run through the chain and allow information flow to remain unchanged. The gate mechanism of LSTM selectively passes information by using a sigmoid layer, hyperbolic tangent layer, and point-wise multiplication operation. The key component of LSTM is the cell state which interacts linearly with the gate mechanism.

2.4. Advantages and disadvantages of LSTM

The objective of this paper is to predict stock market movement/price using historical data. Based on that objective here are some advantages and disadvantages of using Long Short-Term Memory (LSTM) technique over other available techniques:

Advantages:

1. LSTM can handle long term dependences and it has the ability to remember past information for a very long time, which will benefit us because this paper is dealing with financial time series data.
2. LSTM can handle non-linear relationships between variables which is important for capturing the complex dynamics of the stock market.
3. LSTM can learn from data and can adapt new data, which is important for financial forecasting in an ever changing market.

Disadvantages:

4. LSTM can be a resource hungry especially when dealing with large amounts of data.

5. LSTM can overfit the training data, which may lead to poor results when it applied to real or new data.
6. LSTM requires a large amount of training data to achieve good accuracy or performance.

2.5. General block diagram of the system

The block diagram depicted in Figure 4 breaks down the major components of the selected modes and displays flow control. Moreover, it represents the complete architecture of the proposed technique.

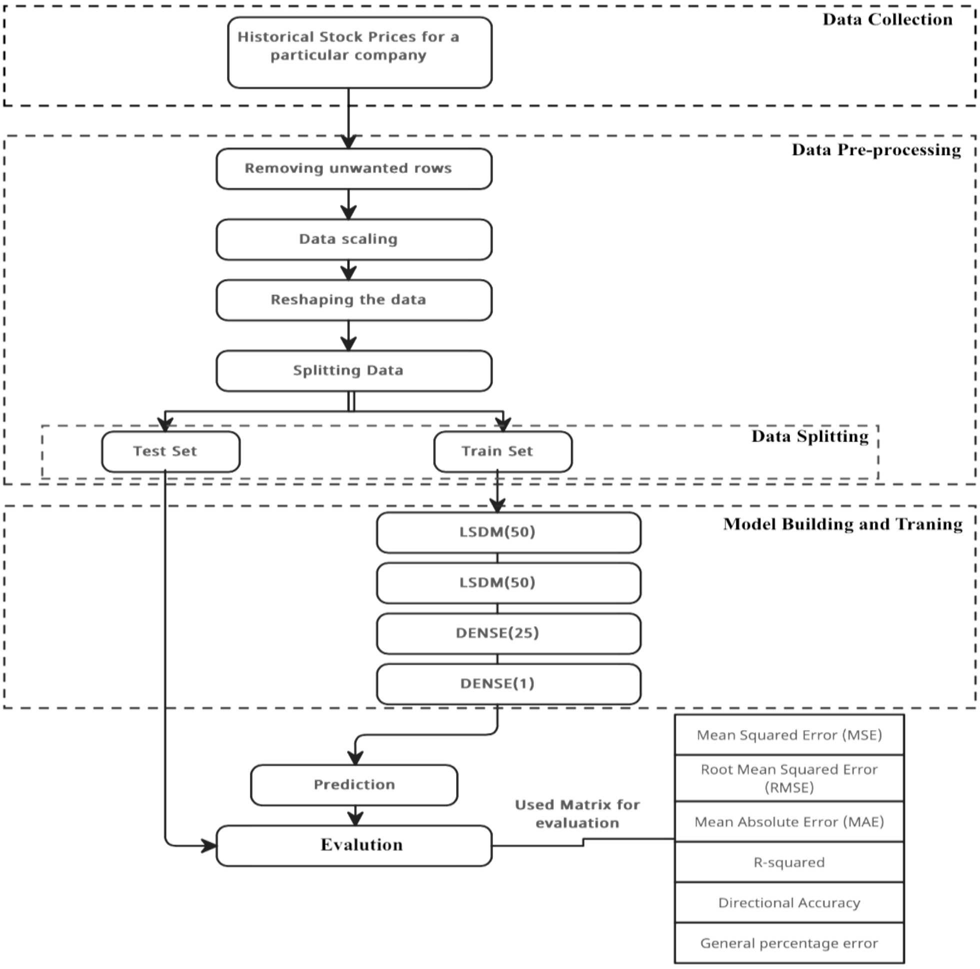

Figure 4: *General block diagram [Dotted border indicates major component/stage of the system. The top right corner of dotted border contains the name of the component/stage.]*

The selected system is detailed in Figure 4, which consists of four general stages which are Data collection, Data preprocessing, Model building and prediction and Evaluation. In data collection, historical data of a company is taken from Yahoo Finance. In the data preprocessing step, the collected data is subjected to several operations such as removing unwanted rows, scaling, reshaping, and splitting the data into train and test datasets. The reasoning behind this processes was elaborated in subsequent sections. In the model building and training step desired LSTM model was build and trained from train set data. Finally, in the evolution step the accuracy of the model is evaluated by various matrices which are detailed in the evolution section.

2.6. Data preprocessing

When working with real data, it is usually advisable to normalise or rescale the data within a set range, just like with any other machine learning model. This will help the model to rapid convergence by preventing characteristics with higher numeric values from unfairly interfering with and biasing the model. Selected model used the following techniques to preprocess selected data:

2.6.1. Removing wanted rows

Unwanted rows were removed from the dataset because those rows can negatively affect our model.

2.6.2. Data visualisation

Data visualisation helps us to understand how our data is moving. Understanding the kind of data being dealt with is important.

Figure 5: *Plotting data focusing on closing price history. For (AAPL) or Apple*

Figure 6: *Plotting data focusing on closing price history. For (AAPL) or Apple*

Figure 5 represents a graph where the closing price (in dollar) is represented on the y-axis and the x-axis represents the dates. This graph indicates a steady increase in closing prices. Figure 6 represents a graph where the closing price (in dollar) is represented on the y-axis and the y-axis represents the dates. Blue curve price indicates high, and orange indicates the low price of a stock in a day. This data shows High and Low price of a day is stable and is not vary much from one another.

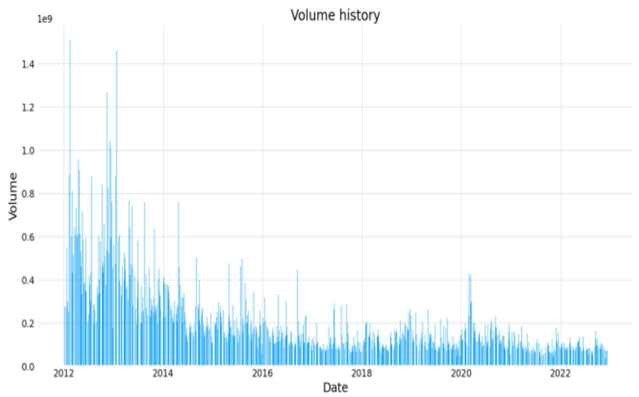

Figure 7: *Plotting data focusing on Volume history. For (AAPL) or Apple*

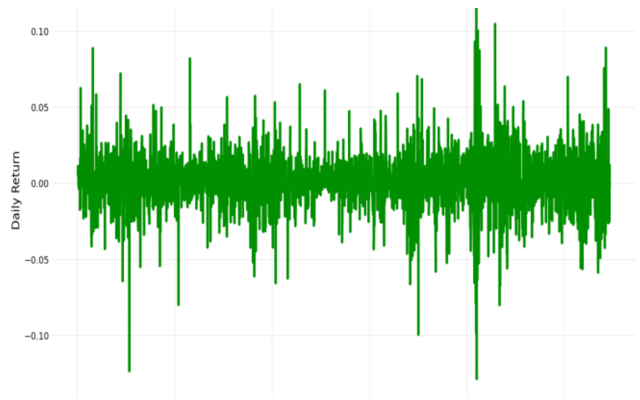

Figure 8: *Plotting data on daily return. For (AAPL) or Apple*

In Figure 7, the daily trading volume (in millions) is represented on the y-axis and the x-axis represents the dates. On the other hand, Figure 8 shows the daily return percentage of the stock, with the y-axis representing the daily return percentage and the x-axis representing the dates.

2.6.3. Creating data frame

In total, 12 years of historical data were collected. However, it was found that not all companies had data available for 12 years. The primary approach was to train the model using as much available data as possible.

2.6.4 Splitting data

Table 1 presents the data split into train and test datasets, comprising a total of 4380 rows. The split ratio used was 80-20, where 80% of the data was used to train the model and 20% was used to test the model.

Table 1. Splitting dataset

	Data set	***Training Dataset***	***Testing Dataset***
Time interval	01/01/2011 – 08/12/2022	01/06/2011 – 08/12/2019	01/06 / 2019 – 08/12/2022

2.6.5. Scaling the data

The data was scaled between 0 to 1 because scaling the data between 0 and 1 is advantageous before feeding it into a neural network.

2.6.6. Building LSTM model

In total 2 LSTM were added with 50 neural each. Two Dense layers were added with 25 and 1 neural, respectively, as illustrated in Figure 9.

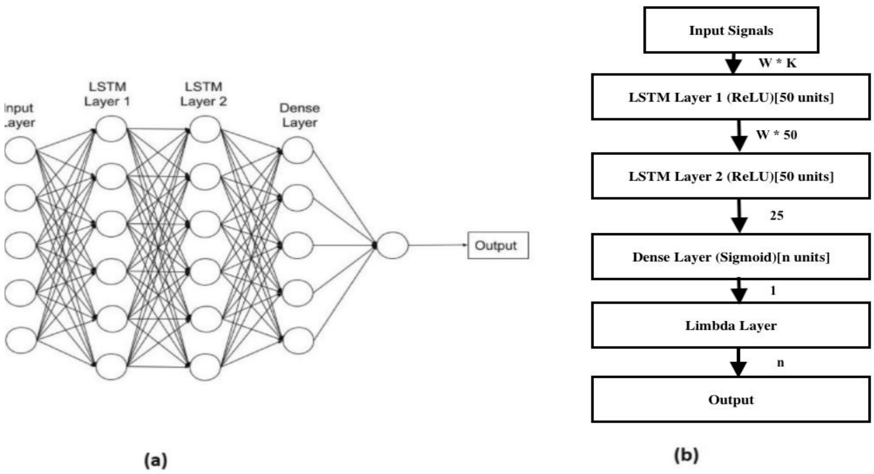

Figure 9: LSDM model with 2 LSTM layers and 2 dense layers. Figure (a), represent process through input to output. And, Figure (b), represent block diagram of LSTM with detailed information about each layer.

3. Result And Analysis

3.1. Plotting our findings

The closing stock price is obtained, and the comparison between the predicted and original closing price can be observed simultaneously in Figure 10 and Figure 11.

By analysing Figure 10, one can infer that the predicted and original closing prices of the stock are close, providing a comprehensive understanding. It also reveals that the prediction of stock prices for the next day, week, or month results in highly accurate outcomes. However, when forecasting beyond four months, the predictions tend to become less precise. A detailed discussion of the accuracy and evaluation is presented in a later section.

	Close	predictions
Date		
2021-01-05	87.045998	87.078453
2021-01-06	86.764503	86.988075
2021-01-07	89.362503	86.870628
2021-01-08	90.360497	87.168510
2021-01-11	88.335999	87.754349
...	...	...
2022-12-05	99.870003	98.471504
2022-12-06	97.309998	98.913086
2022-12-07	95.150002	98.754662
2022-12-08	93.949997	98.011292
2022-12-09	93.070000	96.930969

Figure 10: Close (actual price) and predicted values

Figure 11 represents a graph where the closing price (in dollars) is plotted on the y-axis, and the x-axis represents the dates. The blue curve indicates train data value and orange indicates predicted data values and red indicates the original price of a stock in a day. The overlapping curves in this graph indicate that the predicted price was quite accurate.

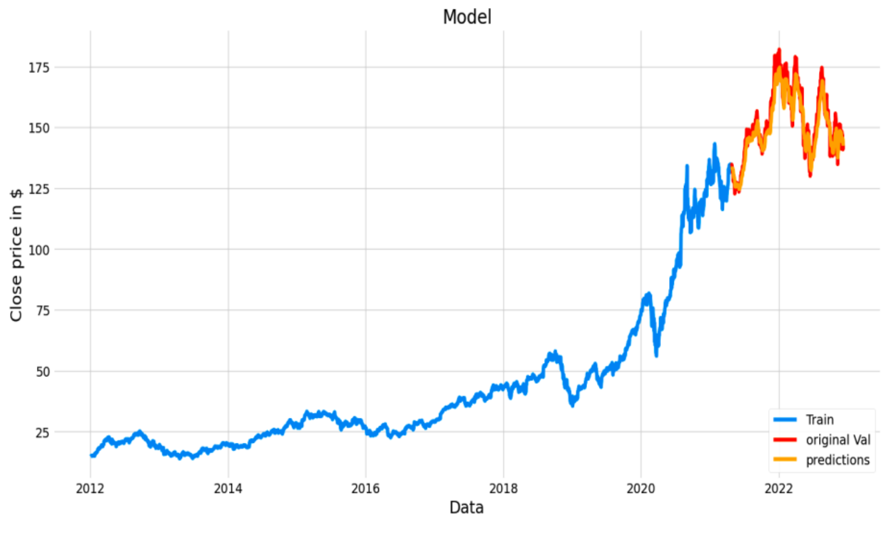

Figure 11: *Train, original values and predicted values (For AAPL or Apple)*

3.2. Accuracy

3.2.1. Finding

Our dataset ranges from 01/01/2011 – 08/12/2022. To determine the accuracy of the model, the team made a prediction for the closing price of AAPL for November 9th, 2022, which was previously unknown to the model. The predicted value was 142.81 dollars, while the actual closing price on that day was 144.49 dollars. By calculating the percentage of error, a 98% accuracy rate was achieved for AAPL.

3.2.2. Finding average accuracy for our selected six companies

Six of our selected companies are Google, Netflix, Goldman Sachs, Apple, Nasdaq and JPMorgan Chase & Co.

Table 2. Finding average accuracy.

	Predicted price($)	***Real Price ($)***	***Accuracy(%)***
Google (GOOG)	95.72	93.559	97.74
Netflix (NFLX)	321.862	315.179	97.923
Goldman Sachs (GS)	353.48	363.179	97.33
Apple (AAPL)	142.81	144.49	98.84
Nasdaq (GILD)	80.58	88.54	91
JPMorgan (JPM)	131.34	134.21	97.86
		In Average	96.78

Table 2 presents the average accuracy of our selected six companies, which is 96.47%. But merely relying on the accuracy metric is insufficient to assess the performance of a model. Therefore, the subsequent section elaborates on and evaluates the model using various other evaluation metrics.

3.2.3. Evaluating our model based on different metrics

Following evolution metrics are used to determine the true accuracy of the model. Several metrics were used to evaluate our model. These metrics are listed below:

1. Mean Squared Error (MSE)
2. Root Mean Squared Error (RMSE)
3. Mean Absolute Error (MAE)
4. Directional Accuracy
5. R-squared

Mean Squared Error (MSE): MSE is used as evaluation metric in machine learning for regression problems. It measures the average squared difference between the estimated values and the actual values. In Eq. (7), N is the number of data points, y is the actual value, and ŷ is the predicted value.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2 \tag{7}$$

The MSE value typically ranges from 0 to infinity. A lower MSE indicates better accuracy, as it means the predicted values are closer to the real or actual values. An MSE of 0 indicates a perfect match between the predicted and actual values, which is rarely achievable in real-world scenarios. As the MSE value increases, it indicates a larger average difference between predicted and actual values, signifying a less accurate model.

Table 3. Mean Squared Error (MSE) for different companies

	MSE Value
Google (GOOG)	24
Netflix (NFLX)	160
Goldman Sachs (GS)	136.72
Apple (AAPL)	16
Nasdaq (GILD)	1.30
JPMorgan (JPM)	14.71
In Average	58.78

Table 3 represents the Mean Squared Error (MSE) values, which indicate the accuracy of the model's predictions. The majority of the companies exhibit low MSE error values, while NTFX and GS displayed moderate accuracy, resulting in a relatively high average MSE value.

Root Mean Squared Error (RMSE): This metric is used to evaluate stock prices and their corresponding actual values. Careful examination of the RMSE formula Eq. (8) reveals that it allows us to obtain an absolute measure of error by taking into account the discrepancy (or error) between the real or actual (At) and predicted or anticipated (Ft) price values for all N timestamps.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2} \tag{8}$$

The RMSE value typically ranges from 0 to infinity. A lower RMSE indicates better accuracy, as it means the predicted values are closer to the real or actual values. An RMSE of 0 indicates a perfect match between the predicted and actual values, which is rarely achievable in real-world scenarios. As the RMSE value increases, it indicates a larger average difference between predicted and actual values, signifying a less accurate model.

Table 4. Mean Squared Error (RMSE) for different companies

	RMSE Value
Google (GOOG)	4.91
Netflix (NFLX)	12
Goldman Sachs (GS)	11
Apple (AAPL)	4.40
Nasdaq (GILD)	1.14
JPMorgan (JPM)	3.83
In Average	6.21

Table 4 indicates, predicted prices are very accurate. Less than 10 RMSE value indicates that the model is predicting very close to the real price.

Mean Absolute Error (MAE): Measures the average absolute difference between the predicted and actual values. Eq. (9) is calculated as the average of the absolute differences between the predicted and actual values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i\right| \tag{9}$$

MAE value range between 0 to infinity. Lower MAE indicates more accurate results.

Table 5: Mean Absolute Error (MAE) for different companies

	MAE Value
Google (GOOG)	4.18
Netflix (NFLX)	9
Goldman Sachs (GS)	10
Apple (AAPL)	3.46
Nasdaq (GILD)	0.81
JPMorgan (JPM)	3.18
In Average	5.1

Table 5 indicates, predicted prices are very accurate. Less than 10 MAE value indicates that the model is predicting very close to the real price.

Directional Accuracy: This is a metric used to measure the percentage of predictions made by a model that correctly predicts the direction of the true value. Following Eq. (10):

$$DA = \frac{\sum_{i=1}^{n} sign(y_i - y_i) = sign(y_{i-1} - y_{i-1})}{n-1} \tag{10}$$

A correct directional prediction occurs when the predicted value has the same sign (positive or negative) as the actual value. A value above 0.5 would indicate that the model is performing well.

Table 6: Directional accuracy (DA)for different companies

	DA Value
Google (GOOG)	0.52
Netflix (NFLX)	0.51
Goldman Sachs (GS)	0.89
Apple (AAPL)	0.45
Nasdaq (GILD)	0.51
JPMorgan (JPM)	0.52
In Average	0.57

Table 6 indicates, predicted prices direction are moderately accurate. The model's predicted direction of the stock price movement (whether it will go up or down) has been accurate about 57% of the time.

R Squared: It is a statistical measure that represents the proportion of the variance for a dependent variable. Eq. (11) measures the goodness of fit of a linear regression model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - yi)^2}{\sum i = 1^n (y_i - \bar{y})^2} \tag{11}$$

R Squared value ranges from 0 to 1, with a higher value indicating a better fit of the regression model to the data.

Table 7: R Squred error for different companies

	R2 Value
Google (GOOG)	0.91
Netflix (NFLX)	0.98
Goldman Sachs (GS)	0.55
Apple (AAPL)	0.90
Nasdaq (GILD)	0.96
JPMorgan (JPM)	0.96
In Average	0.877

Table 7 indicates, a value of 0.877 means that 87.7% of the variability in the dependent variable (y) can be explained by the independent variable(s) (x) in the regression model. A higher R-squared value indicates a better fit of the model to the data.

3.2.4. Comparing with other methods:

Comparing LSTM accuracy with 30-day Simple Moving Average and Exponential Moving Average. This comparison will help us to understand the finding. SMA can calculated by following equation Eq. (12).

$$SMA = \frac{\sum_{i=n-k+1}^{n} p_i}{k} \tag{12}$$

A simple moving average can be used to find the unweighted mean of the past K data points. The smoother the curve is, the higher the value of K, however increasing K reduces accuracy. The simple moving average is calculated if the data points are p1, p2,..., pn.

The weighted average of the preceding K data points is revealed by the Exponential Moving Average (EMA). The most recent data points are given more weight and significance by EMA. The equation Eq. (13) provides the formula to compute the EMA during the time period t.

$$EMA_t = \{ \begin{matrix} price_1 & t = 1 \\ alphapricet + (1-\alpha)EMAt - 1 & t > 1 \end{matrix} \tag{13}$$

Using Simple and exponential Moving Average method, stock price was predicted for a single day. The accuracy is compared with Long Short-Term Memory and shown in Table 8.

Table 8: Comparison between LSTM vs SMA vs EMA

	LSTM	***SMA***	***EMA***
Accuracy	96.646%	91.17%	94.85%

Table 8 clearly indicates that LSTM is more accurate than SMA and EMA. While SMA and EMA exhibit comparable performance, they are significantly outperformed by LSTMs

4. Conclusion And Future Work

This study has demonstrated the effectiveness of using LSTM for stock price prediction. For the benefit of shareholders and short-term investors, this paper offers a system for predicting stock price value utilising long short-term memory. The main objective in employing such a prediction method is to maximise profit from the stock. By employing comprehensive feature engineering and selecting appropriate input features, this model was able to achieve a high accuracy rate of 96%. By increasing the size of the training data, the system can achieve higher accuracy and a lower error rate.

Predicting some of the stock prices like Tesla (TSLA) and GameStop (GME) gives us a less accurate result. Because these kinds of companies are more volatile than other companies and subject to sudden changes in response to various factors such as economic news, political events, or even social media trends. Additionally, some stocks may be influenced by factors that are difficult to quantify or predict, such as changes in consumer preferences, shifts in market sentiment, or unexpected disruptions to supply chain.

In future work, deep learning models that incorporate financial news stories as well as traditional financial metrics, such as closing price, traded volume, and profit and loss statements, could be developed in order to achieve even better results. This approach would provide a more comprehensive understanding of the factors that influence stock prices and would enable the model to capture and learn from complex relationships between financial and non-financial events. Incorporating natural language processing techniques to extract relevant features from news articles and combining them with numerical data could potentially improve the accuracy and robustness of the predictive model.

Declaration of Interest

The authors declare that there is no conflict of interest.

Author Contributions

Foysal Ahamed Nirob contributed to the conceptualization, methodology, data collection, analysis, interpretation, and writing of the manuscript. He was primarily responsible for conducting the research, implementing the machine learning techniques, analyzing the results, and interpreting the findings.

Dr. Mohammad Mahmudul Hasan provided guidance and reviewed the research approach throughout the project. He played a crucial role in building the initial structure of the research paper. His expertise and insights were valuable in shaping the overall direction of the study.

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