

Stock Price Prediction Using Machine Learning algorithm with Web Interface (GUI)

Ashu Mittal, Nairit Joshi, Vijay Savani

Department of Electronics and Communication Engineering, Institute of Technology, Nirma University, Ahmedabad, India

Corresponding author: Ashu Mittal, Email: 18bec009@nirmauni.ac.in

Predicting the stock market trend is difficult due to the stock market's high level of uncertainty. Many approaches for stock price and market prediction have been developed in the past. Different algorithms such as Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Linear regression, and Decision trees are utilized in this study to forecast the future closing price of stocks for a specific firm. In this paper, the accuracy of these mentioned algorithms is also being compared. A seven-day study is also performed, illustrating the actual and anticipated closing prices for two companies using different algorithms. The outcome of the previous forecast is compared to the other algorithms, and a final algorithm is chosen based on it. A final model is created by taking many technical parameters in consideration in order to have more precise anticipated the price. Based on the final model, a 10-days examination of the actual and anticipated closing prices for ten different firms is also performed. Finally, A web application-based Graphical User Interface (GUI) was built using the Stream-lit library. The GUI includes features such as a forecast graph, a graph for historical data, and a company selection as well as the start and the end date.

Keywords: Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Linear Regression (LR), Decision Tree, Machine Learning (ML).

1 Introduction

The ability to predict the direction of stock price accurately is very important for market dealers in order to maximize their profits. However, because of the stock market's uncertainty, predicting the stock's direction or price is difficult. The Stock Market is an untidy place for estimating as there is no explicit formula to estimate or predict the price of shares in the share market. Fundamental analysis and technical analysis are the two types of analysis. The company's performance, economic conditions, and political factors are all addressed in fundamental analysis.

Technical criteria include the preceding n days' closing price, highest price, lowest price, and so forth. Because fundamental analysis is difficult to quantify and apply in computer language, we can use technical analysis to anticipate the stock's trend or price. Technical analysis does not quantify the stock's inherent security value, but it does employ technical stock charts to forecast the stock's trend. The goal is to use closed price to compare the accuracy's of various machine learning models in order to determine the best-suited model. Based on the best fit model, a final model will be created using various parameters as inputs in order to better correctly anticipate stock prices.

2 Literature Review

There has been a thorough evaluation of the literature in the field of stock index prediction. The main goal in [1] is to determine the current stock index movement pattern and forecast the likely future movements of the Bombay Stock Exchange (BSE) Sensex and National Stock Exchange (NSE) Nifty. The study's analysis clearly demonstrated that both the BSE-Sensex and the NSE-Nifty were robust in terms of index fluctuations based on current/existing daily closing prices. The readings of Momentum, Relative Strength Index, Williams R percent, and Commodity Channel Index exhibited both a positive and negative trend, implying that stock index movements of the Sensex and Nifty recorded similar tendencies, both before and after the crisis. The study in aimed to forecast the direction of stock price movement on the Istanbul Stock Exchange [2].

Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are two classification strategies used in the models. The proposed models' inputs were chosen from a list of ten technical indicators. The ANN model's average prediction performance (75.74%) was found to be much better than the SVM model's (71.52%). The study in [3] sought to forecast the challenge of anticipating the

direction of stock and stock price index movement for 23 Indian stocks. This paper focuses on short-term forecasting. The ANN, SVM, Random Forest (RF), and Naive-Bayes are four prediction models with two approaches: the first involves computing ten technical parameters using stock trading data, while the second involves representing these technical parameters as trend deterministic data. When learned using trend deterministic data, ANN, SVM, RF, and Naive-Bayes reaches an accuracy of 86.69%, 89.33%, 89.98%, and 90.19%, respectively.

The work in [4] presents a hybrid machine learning method for stock market prediction based on Genetic Algorithm (GA) and Support Vector Machine. As input characteristics, a set of technical indicators gathered from the stock to be predicted, as well as stocks with a high correlation with that stock were used. The GA-SVM hybrid model outperformed the SVM by a large margin. The accuracy of GA-SVM was 61.7328 percent for a particular company like Tata Consultancy Services (TCS), while the accuracy of the SVM was 58.09%. The study in [5] seeks to anticipate the direction of movement for the SP BSE Sensex index for the next day in two steps. The first step determined whether the expected movement would be up or down based on six technical indicators. Stage two takes the processed discretized data from stage one and uses it to make predictions. The single-stage results had an accuracy of roughly 61.0%, with the best being around 71.0%. With an average accuracy of 73.7%, performance in the two-stage configuration improved.

The Random Forest produced the greatest results, with an accuracy of roughly 75.0%. The results of ANN and SVC are comparable, with both providing measures of above 74%. Although NB had a slight performance lag, it was still over 70.0%. The study in [6] is to build a prediction-based strategy decision system to optimize the quality of each strategy and improve the success rate by distinguishing the potentially profitable trading signals from the failing ones. For that, they employ two statistical arbitrage cases to be the original strategies and construct multi-view features on the basis of their related dimensions, and also, the Ensemble learning model Gradient Boosted Decision Tree (GBDT) is utilized to obtain an integrated forecast result to tell the decision-maker what signals should be traded or filtered. Significant improvement of success rate in both cases demonstrates the good performance of the decision system.

In the paper [7], author have used two methods to predict the price which first used a single algorithm and another a hybrid model and by using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE). In this paper the error between predicted price and real price is calculated. So, if the error value for any technique is near zero that model is more accurate and

So, linear regression gave the most accurate results among K-Nearest Neighbour (KNN), SVM, Decision Tree, and Random Forest followed by SVM. The graph plotted by Linear Regression and SVM was quite accurately predicting the real-time price with a score mean of 0.9981 and 0.9982 respectively. When the hybrid model was applied with the base algorithm as linear regression, although the computation complexity increased, it was observed that when linear regression was used as the second algorithm then MAE was $6.0103e^{-15}$, MSE was $5.6911e^{-29}$ and RMSE was $7.7526e^{-8}$ which are very small thus highly accurate graph was obtained. Also, SVM gave second-best results where MAE was 0.072338, MSE was 0.030724 and RMSE was 0.268957 where the hybrid model with the second algorithm as linear regression and SVM provides better results than linear regression and SVM alone.

In the paper [8], they used a data construction method to eliminate the uncertainty in constructing indicator data images and proposed the multi-indicator channel Convolution Neural Network (CNN) to predict the trading signal of ten stocks from the Shanghai stock market. The accuracy of this model is about 61.58%. They integrated tag generation algorithm, correction strategy, and transaction strategy in the whole prediction model to make it more effective and practical. In the paper [9], the work proposes two models to predict the stock market data. The first model is a Hybrid Model combining popular ML algorithms like SVM, KNN, and RF algorithms using the Majority Voting Algorithm. The second model utilizes back-propagation optimized LSTM networks to predict stock market trends. The Hybrid model predicts the next-minute and daily stock prices with a very impressive accuracy (approx. 92.57%) and consistency. The LSTM model predicts stock prices accurately for therefore coming days but gives decent accuracy (approx. 86%) in predicting from the real-time stock data.

3 Machine Learning Algorithms & Proposed Model

In this section the Machine Learning Algorithms for Stock Price Prediction are explained along with algorithms. The various technical terms being used in stock market are described and finally the proposed model algorithm and block diagram is explained.

3.1 Different Machine Learning Algorithms for Stock Price Prediction

The different machine learning Algorithms being used for the stock price prediction as well as the proposed model for stock price prediction are described in

this section. LSTM (Long Short-Term Memory) networks are a type of recurrent neural network that can learn long-term dependencies. They are specifically developed to avoid the problem of long-term dependency. Every recurrent neural network is made up of a series of modules that repeat. The similar chain-like structure is used in LSTMs, but the repeating module structure is different. In contrast to ordinary neural networks, the Recurrent Neural Network (RNN) has a single layer repeating module, while LSTMs have a four-layer repeating module. The Linear Regression finds the “best” line to fit two qualities (or variables) so that one can predict the other is the goal of linear regression. A response variable, y , and a single predictor variable, x , are used in regression analysis. The method of least squares can be used to calculate these coefficients, which determines the best-fitting straight line as the one that minimizes the error between the actual data and the line estimate.

The Decision Tree algorithm unlike other supervised learning algorithms, may also be utilized to solve regression and classification issues. By learning simple decision rules inferred from past data, the purpose of employing a Decision Tree is to develop a training model that can be used to predict the class or value of the target variable (training data). The SVM is a supervised learning model that divides data into categories. The major goal is to categories the data, which entails moving data points away from the hyper-plane, which separates them into categories according to their labels. The SVM can still be used as a classifier for non-linear data, but it must be done using the kernel approach, which maps the data into a high-dimensional space before transforming it into linearly separable data.

3.2 Proposed Model for Stock Price Prediction

The previous models made using different algorithms were not reliable as they only produced predictions based on the closing price. Although the model’s accuracy were adequate, they were not practical. The model will fail if the market shifts dramatically. As a result, a novel model was created based on few technical parameters, making it far more trustworthy and practical. The various technical parameters being used in the final model are as follow:

3.2.1 Simple Moving Average:

A simple moving average (SMA) calculates the average of a selected range of prices, usually closing prices, by the number of periods in that range as shown

in equation 36.1.

For, $i = 9 \rightarrow n$

$$SMI(i) = \frac{\sum_{x=i-9}^{i+1} \cdot C_x}{10} \quad (36.1)$$

Here, n is the total no. of stocks price and C represent the stock Close price.

3.2.2 Weighted Moving Average (WMA):

A Weighted Moving Average gives recent data more weight than historical data shown in equation 36.2. This is accomplished by multiplying the price of each bar by a weighting factor. Here WMA will track prices more precisely than a related Simple Moving Average due to its unique formula.

For, $i=9 \rightarrow n$

$$WM(i) = \frac{\sum_{x=i-9}^{i+1} x \cdot C_x}{\sum_{x=i-9}^{i+1} x} \quad (36.2)$$

3.2.3 Rate of Change(ROC):

The Price Rate of Change (ROC) is a momentum-based technical indicator that measures the percentage change in price between the current price and the price a certain number of periods ago.

For, $i=9 \rightarrow n$

$$ROC(i) = \frac{C_i - C_{i-9}}{C_{i-9}} \quad (36.3)$$

3.2.4 Stochastic Oscillator K%

Stochastic are a favored technical indicator because it is easy to understand and has a high degree of accuracy. It is used to generate overbought and oversold trading signals, utilizing a 0–100 bounded range of values.

For, $i=9 \rightarrow n$

$a = \text{Min}(\text{Low price})$

$b = \text{Max}(\text{High price})$

$$STOK(i) = \frac{C_i - a}{b - a} \times 100 \quad (36.4)$$

3.2.5 Stochastic Oscillator D%:

Stochastic is measured with the K line and the D line. But it is the D line that we follow closely, for it will indicate any major signals in the chart.

For, $i=1 \rightarrow n$

$$STOD(i) = \frac{\sum_{x=i-2}^i stok(x)}{2} \quad (36.5)$$

3.2.6 Relative Strength Index(RSI):

The relative strength index (RSI) is a momentum indicator used in technical analysis that measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock or other asset.

For, $i=1 \rightarrow n$

$$t(i) = C_i - C_{i-1}$$

$$up(i) = t(i), t(i) > 0$$

$$dn(i) = -t(i), t(i) < 0$$

For, $i = 9 \rightarrow n$

$$u = \frac{\sum_{x=i-9}^{i+1} up(x)}{10} \text{ and} \quad (36.6)$$

$$d = \frac{\sum_{x=i-9}^{i+1} dn(x)}{10} \quad (36.7)$$

$$RSI = 100 - \frac{100}{1 + \frac{u}{d}} \quad (36.8)$$

Here, avg represent the average function.

3.2.7 Larry's Willams R%:

Williams %R, also known as the Williams Percent Range, is a type of momentum indicator that moves between 0 and -100 and measures overbought and oversold levels. The Williams %R may be used to find entry and exit points in the market.

For, $i=9 \rightarrow n$

$$a = \text{Min}(\text{Low price})$$

$$b = \text{Max}(\text{High price})$$

$$WR(i) = \frac{b - C_i}{b - a} \times (-100) \quad (36.9)$$

3.2.8 Accumulation Distribution Oscillator:

The accumulation/distribution indicator (A/D) is a cumulative indicator that uses volume and price to assess whether a stock is being accumulated or distributed. The A/D measure seeks to identify divergences between the stock price and the volume flow.

For, $i = 1 \rightarrow n$

$$ADO(i) = \frac{H_i - C_{i-1}}{H_i - L_i} \quad (36.10)$$

Here, H represents High Price and L represents Low price.

3.2.9 Price Volume Trend:

The volume price trend indicator is used to determine the balance between a security's demand and supply. The percentage change in the share price trend shows the relative supply or demand of a particular security, while volume indicates the force behind the trend.

$$PVT(i) = \frac{C_i - C_{i-1}}{C_{i-1}} \times Volume(i) \quad (36.11)$$

3.2.10 Five(5) Days Disparity:

The disparity index is a technical indicator that measures the relative position of an asset's most recent closing price to a selected moving average and reports the value as a percentage. Here, The average is taken for 5 days.

For, $i = 4 \rightarrow n$

$$a = \frac{\sum_{x=i-4}^{i+1} C(x)}{5} \quad (36.12)$$

3.2.11 Ten(10) Days Disparity:

The disparity index is a technical indicator that measures the relative position of an asset's most recent closing price to a selected moving average and reports the

value as a percentage. Here, The average is taken for 10 days.

For, $i = 9 \rightarrow n$

$$b = \frac{\sum_{i=9}^{i+1} C(x)}{10} \tag{36.13}$$

$$div10(i) = \frac{Ci}{b} \times 100 \tag{36.14}$$

3.2.12 Moving Average Convergence Divergence (MACD):

Moving average convergence divergence (MACD) is a trend-following momentum indicator that shows the relationship between two moving averages of a security's price.

3.2.13 Commodity Channel Index (CCI):

The Commodity Channel Index (CCI) is a technical indicator that measures the difference between the current price and the historical average price.

The previous models made using different algorithms were not that reliable as they only produced predictions based on single parameter i.e., closing price. As a result, a final model was created based on a set of technical parameters so that the model does not depends on a single parameter thus making it far more trustworthy and practical. Technical indicators are technical tools that help in analysing the movement in the stock prices whether the ongoing trend is going to continue or reverse. It helps the traders to make entry and exit decisions of a particular stock.

The Technical parameters like Moving Average, Relative strength index, Rate of change etc. were added to the LSTM in order to make final model. The LSTM is used as a base algorithm for final model because the accuracy for the LSTM did not deviate much for different data-set and was almost constant.

The LSTM is also part of deep learning algorithms based on recurrent neural networks and hence a better option for stock market prediction rather than the other machine learning algorithms.

The algorithmic code for the proposed model is shown in Algorithmic Chart 3.2.13. The Flow Diagram of the Proposed Model is shown the Figure 1.

```
[hbt!] START
IMPORT:The libraries including Keras, Scikit Learn, Pandas_datareader
IMPORT:The Dataset
```

DEFINE:Some common functions like average, minimum and maximum etc.

DEFINE:A function 'features':

INITIALIZE:Technical parameters variables with empty array

SET:The starting 10 values of all technical parameters to zero

CALCULATE:All the technical parameters

DEFINE:A empty array 'X'

APPEND:All the technical parameters in X

CALL:The function 'features'

SCALE:The Dataset

SET:The training data set length to 80%

CREATE:Training dataset

STORE:LSTM Model in a variable 'model'

COMPILE:The model

CREATE:Testing dataset

RUN:The model for test data

CALCULATE:The Accuracy

PLOT:Predicted and Actual Price V/s Date

END

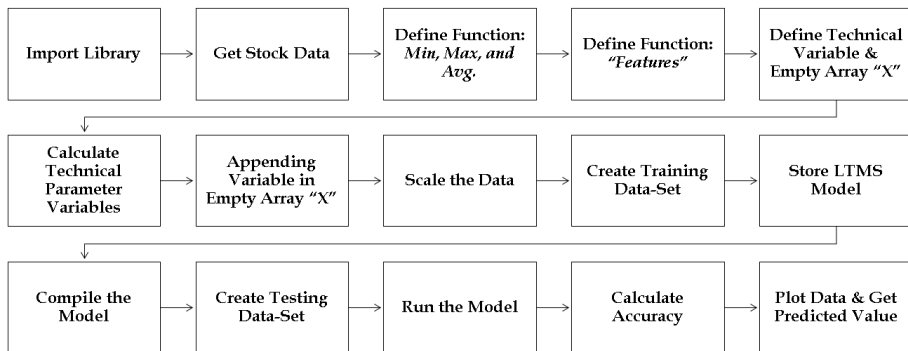


Figure 1: Flow Diagram of the Proposed model

4 Implementations and Results

The algorithms mentioned in Section 3 are implemented and results for the one of the company (e.g. APPLE) are derived.

4.1 Result for Different algorithms for Apple Data set

In Figure 1 the result of the predicted closing price of the APPLE company using the Long Short Term Memory model. Blue curve shows the training part, yellow curve shows the prediction part and red curve shows the actual value of closing price. The yellow and the red curve are almost overlapping hence it shows the accuracy of the model.

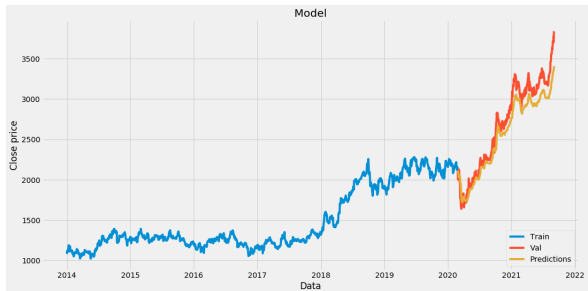


Figure 2: Prediction of stock price for APPLE Company using LSTM model

Figure 2 shows the result of the predicted closing price of the APPLE company using the Linear Regression model. Red curve shows the training part, blue curve shows the prediction part of closing price.

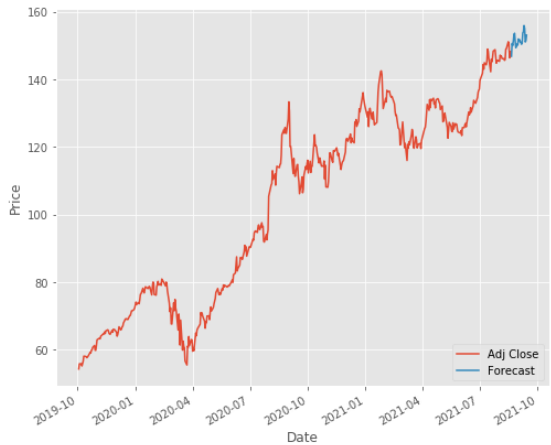


Figure 3: Prediction of stock price for APPLE Company using Linear Regression model

The result of the predicted closing price of the APPLE company using the Deci-

sion Tree model is shown in Figure 3. Blue curve shows the original part, yellow shows the predicted value and red curve shows the actual value of adjusted closing price. The yellow and the red curve are almost overlapping hence it can be concluded that the model works fine

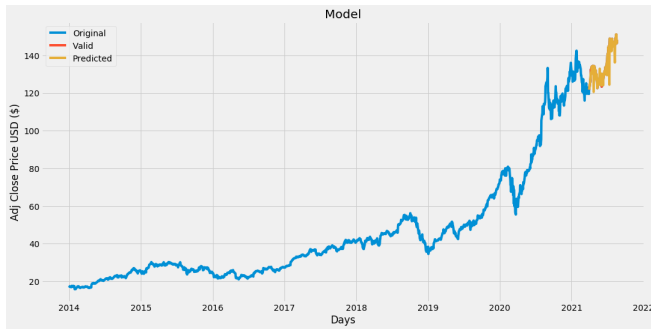


Figure 4: Prediction of stock price for APPLE Company using Decision Tree model

Figure 4 shows the result of the predicted closing price of the APPLE company using Support Vector Machine (SVM) model using 'rbf' Kernel. Red curve shows the training part, blue curve shows the prediction part of closing price.

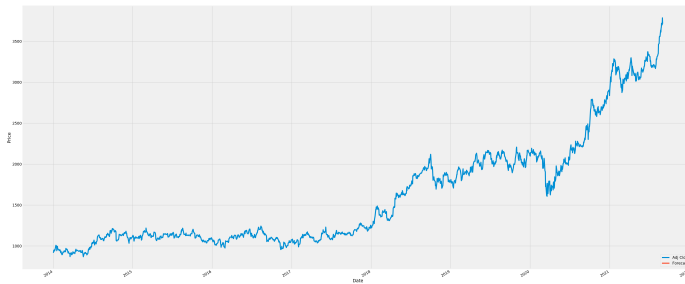


Figure 5: Prediction of stock price for APPLE Company using SVM model

4.2 Comparison of accuracy of different algorithms for stock price of various companies

The comparison of accuracies of different algorithms like LSTM, Linear regression, Decision tree, and SVM is done based on a single input parameter that is closing price and the comparison is done for 5 different companies are Apple, Amazon, Intel, KBH, and TCS. The comparison chart is shown in Table 1.

Table 1: Comparison of Accuracy using different algorithms for Various Company's Stock Price

Name of Company	LSTM (RMSE)	LR	SVM	Decision Tree
Apple	3.025	0.971	0.946	0.891
Amazon	111.938	0.981	0.247	0.889
Intel	2.110	0.934	0.981	0.678
KB Home	1.153	0.872	0.969	0.279
TCS	135.119	0.974	0.270	0.863

From the Table 1, it can be observed that the accuracy of the data is depend on the data-set also. So, as the data-set changes, accuracy also varies. In LSTM accuracy is compare with using RMSE means if RMSE is more than accuracy is less. Same for the other algorithms accuracy is compared.

4.3 Seven Days Stock Price prediction using different algorithms

Real-time 7-day analysis of different algorithms is done for two different companies that are Apple and Intel in order to compare the actual and predicted closing price. The analysis is done based on a single input parameter that is the closing price. The analysis for the two different companies is as follows. The results for the Apple and Intel companies stock price prediction are enumerated in Table 2 and Table 3 respectively.

Table 2: Seven-Day Apple Stock Value Prediction Analysis of different algorithms

Date of Prediction	Actual Price	Predicted Price using LSTM	Predicted Price using LR	Predicted Price using Decision Tree
15/10/2021	149.02	146.96	162.54	137.03
16/10/2021	148.78	147.48	161.66	136.17
17/10/2021	146.05	150.02	160.81	135.55
20/10/2021	142.94	155.25	159.74	134.67
21/10/2021	143.42	146.36	158.35	133.35
22/10/2021	145.08	141.47	156.92	132.26
23/10/2021	146.84	155.80	155.84	131.94

From the above comparison table for two different companies it can be seen that the difference between the actual price and the predicted price through Lin-

Table 3: Seven-Day Intel Stock Value Prediction Analysis of different algorithms

Date of Prediction	Actual Price	Predicted Price using LSTM	Predicted Price using LR	Predicted Price using Decision Tree
15/10/2021	55.11	52.97	54.52	53.96
16/10/2021	54.83	54.37	54.71	54.24
17/10/2021	54.25	56.12	54.88	54.46
20/10/2021	52.98	53.94	54.97	54.52
21/10/2021	52.86	53.08	54.89	54.29
22/10/2021	53.50	55.17	54.72	53.92
23/10/2021	54.20	54.90	54.58	53.65

ear Regression and Decision Tree varies abruptly as the companies change. For some company Decision tree performs well while for another Linear regression performs good but LSTM algorithm's performance remains almost same for all the companies and hence from the analysis it can be said that LSTM can be used as a base algorithm for the final model as it's prediction do not deviates much with the change in input company's data-set.

4.4 Ten-days analysis for different companies using the Proposed Model

The results of the prediction for ten-days analysis for different companies using the Proposed Model is listed in Table 4.

4.5 Developed Graphical User Interface

The goal of the implementation was to not only improve the accuracy of stock market price predictions, but also to establish a trading application that uses our machine learning model to predict prices. Python was used to create a web application with a graphical user interface. To personalize web apps, the Stream light library was utilized and Visual Studio Interpreter is used to do this. The GUI takes the two dates (start and end date) and Company Ticker as an input to plot the graph of Close price at that period, Close price Graph with the 100 days and 200 days Moving Average, it also plot the graph which compares the actual and predicted prices for the last 100 days of the time period and also it predict the future value of close price for the very next day of the end date given by user. The

Table 4: Ten-day Price Prediction and its Analysis for different companies using the Proposed Model

Companies	APPLE		INTEL		TCS		KBH		FACEBOOK	
Date	P	A	P	A	P	A	P	A	P	A
21/09/21	145.20	143.42	54.07	52.86	10.76	10.47	42.06	40.61	358.16	357.48
22/09/21	146.76	145.85	54.51	53.5	10.56	10.61	41.32	40.91	354.46	343.20
23/09/21	147.15	146.83	53.22	54.02	10.57	10.86	40.95	41.13	353.63	345.95
24/09/21	147.46	146.91	53.51	54.22	10.64	10.99	40.89	41.18	343.39	352.95
27/09/21	143.60	145.36	54.16	54.66	10.52	11.21	41.07	41.45	345.24	353.57
28/09/21	137.64	141.91	53.75	54.00	10.75	10.94	40.61	40.24	347.81	340.64
29/09/21	143.39	142.83	53.88	53.49	10.70	11.15	40.94	40.20	337.26	339.60
30/09/21	142.06	141.5	53.50	53.27	10.82	9.52	38.50	38.91	347.43	339.39
01/10/21	144.20	142.64	54.49	53.86	10.60	9.95	40.10	38.84	341.74	343.01
04/10/21	137.43	139.13	53.95	53.47	10.72	9.98	37.17	38.74	339.29	326.23

A - Actual & P- Predicted

Figure 6 Show the Interface where user has to enter the start and end date. The after entering the Ticker of any company it will provide us the whole description about the data like high value, low value, open and close value of price.

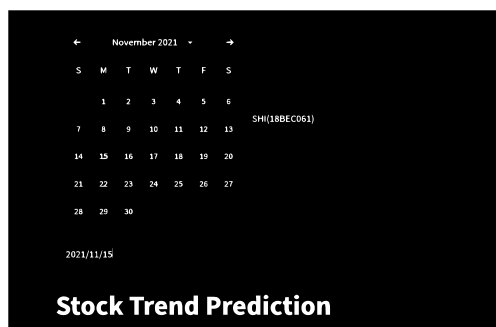


Figure 6: Choosing of Start and end date using calendar in GUI

The Figure 7 shows the trend of close price with respect to the data or time. It will show all the actual close price of stock for the window select by user using start and end date input.

The Figure 8 shows the comparison of Close price with 100- and 200-days Moving Average. Actually, there is a strategy followed by technical analyst using these terms like if the 100 days MA is above then 200 MA then it will show a uptrend in stock and if the 100 days MA is below the 200 days MA then it will

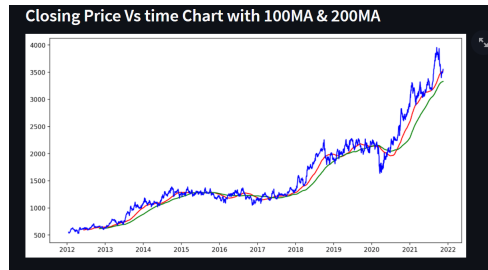


Figure 7: Comparison of Close Price With 100 and 200 days MA

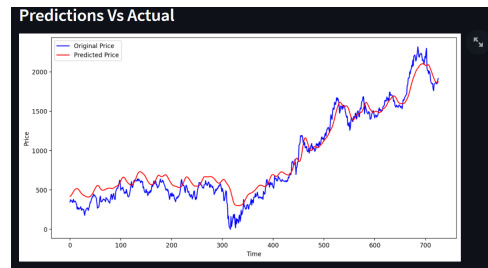


Figure 8: Prediction v/s Actual Closing Price for last 100 days

shows the down trend in stock price, same we can analyses from the graph.

5 Conclusion

The closing price of the stock was utilised as the input of the model for various algorithms. It looked at the closing prices for the previous 60 days and used the results to estimate the 61st day's closing price. The 60-day window then advances one day, drops the first-day closing price, and adds the 61st-day closing price to the window. The model's flaw was that it only produced predictions based on the closing price. Although the model's accuracy was adequate, it was not practical. The model will fail if the market shifts dramatically. As a result, a final model was created based on technical parameters, making it far more trustworthy and practical. However, the precision isn't 100 percent. Still, effect on the model of environment effects like Political news, company performance, CEO statements, and a variety of other factors all have not been considered. The sentimental analysis, which categorises these factors as very good, good, neutral, terrible, or worse, can be utilised to assign weight and anticipate an accurate trend.

References

- [1] Sigo, M. O. (2018). Predicting stock market movements of india using data deterministic approach. *Academy of Strategic Management*, 17(2).
- [2] Masoud, N. (2014). Predicting direction of stock prices index movement using artificial neural networks: The case of libyan financial market. *Journal of Economics, Management and Trade*, 597–619.
- [3] Patel, J. et al. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert systems with applications*. 42(1): 259–268.
- [4] Choudhry, R. and Garg, K. (2008). A hybrid machine learning system for stock market forecasting. *World Academy of Science, Engineering and Technology*, 39(3): 315–318.
- [5] Misra, P. and Chaurasia, S. (2018). Forecasting direction of stock index using two stage hybridization of machine learning models. In *7th International Conference on Reliability, Infocom Technologies and Optimization*, 533–537.
- [6] Li, Y., Bu, H. and Wu, J. (2017). A two-stage multi-view prediction method for investment strategy. In *2017 International Conference on Service Systems and Service Management*, 1–6.
- [7] Vazirani, S., Sharma, A. and Sharma, P. (2020). Analysis of various machine learning algorithm and hybrid model for stock market prediction using python. In *International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*, 203–207.
- [8] Yang, Z. et al. (2019). Prediction of stock trading signal based on multi-indicator channel convolutional neural networks. In *IEEE 8th Data Driven Control and Learning Systems Conference (DDCLS)*, 912–917.
- [9] Mustafa, Z. U. et al. (2019). Stock market prediction with the integration of daily news sentiments using long short term memory in artificial neural network with the ensemble approach. In *4th International Electrical Engineering Conference (IEEC 2019)*.