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Stock Market Analysis and Prediction for Nifty50 using LSTM Deep Learning Approach

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***Abstract*— Designing and developing a prediction model with an accurate stock price prediction has been an active field of research in the stock market for a long time. On the other hand, predicting stock price movement is the most critical aspect of the entire forecast process. While some market hypotheses argue that precisely predicting stock price movement is impossible, research shows that stock price movement can be expected to some extent. Stock price movement can be precisely measured if prediction models are correctly designed, developed, and refined. The Deep Learning (DL)-based Long Short-Term Memory (LSTM) Algorithm is proposed in this study. India's National Stock Exchange (NSE) provided us with ten years of historical stock price data for the NIFTY 50 index. The historical dataset was picked from 10 December 2011 to 10 December 2021. This dataset is used for model training and testing after normalized. The proposed model's results are pretty promising, with an accuracy of 83.88 percent.**

***Keywords*— Long Short-Term Memory; Price Prediction; Deep Learning; Stock Market; Nifty50; National Stock Exchange**

I. INTRODUCTION

Stock price prediction is an interdisciplinary research study area. It is a majorly used application in the field of time series prediction. In the financial sector, time series prediction could be helpful for investors to make a strong strategy and overcome the risk of existing erroneous investment. Time is generally a significant parameter used for making crucial decisions in time-series predictions. To comprehend the time series forecast, we need extensive previous data over some time. In the stock price prediction domain, researchers generally use historical stock price data to predict the future price of stocks.

For time series prediction analysis, many traditional strategies based on statistics modelling are proposed. Linear regression, auto-regression, and moving average were among the approaches used (ARMA). Time series prediction analysis is easily handled by a model based on Auto-Regression Moving Average (ARMA). This model can handle time series data in a succession. The Auto- The regression element of this model dealt with one part of the data, while the Moving Average part dealt with another. Only non-stationary time series data can be handled using the ARMA model [1-2]. Auto-regressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) are two more auto-regressor models that can deal with time series variable variation [3]. Following that, various models are suggested that are particularly suitable for the prediction and analysis of volatility [4]. These models are particularly useful for predicting time series data.

We also discovered several hybrid models such as multivariate-factors fuzzy time series forecasting and hybrid forecast model that can predict time series data using k-means clustering and particle swarm optimization in this work. Traditional techniques have a significant problem in that they cannot deal with unstable swings in time-series data, such as stock price movement [5-7]. Some researchers have recently expressed an interest in new techniques such as Machine Learning (ML) and Artificial Neural Networks (ANNs) (ANNs). ANNs are widely regarded as one of the most accurate methods for predicting stock price fluctuations. Back-propagation neural networks and radial basis function neural networks have been utilized to predict market indices and stock price changes in the past [8-11]. A recent study [12-15] suggested that LSTM and RNN can be used to estimate stock price prediction.

To address the aforementioned shortcomings, the suggested Deep Learning (DL) based LSTM model to forecast Nifty50 stock price movement based on historical data in this study. Historical data from the National Stock Exchange (NSE) for a ten-year period, from December 10, 2011, to December 10, 2021 [16] has been used for forecasting. The remaining portion of the study has been divided into three sections. Section 2 described a related investigation, and it includes a brief literature review. The study's data and methodology are discussed in Section 3. Section 4 contains the results, and Section 5 has illustrated the conclusion and future directions.

II. RELATED STUDY

Stock movement prediction is a fascinating and difficult scientific project [17]. Many prediction models for stock price forecasting were suggested by a literature analysis, with ANNs being one of them. Many research, including statistical regression and discriminant analysis [18-19], have used ANNs. ANNs are often employed in conjunction with the ARIMA model to forecast financial volatility [20-22]. For parameter optimization of stock price prediction, ANNs are also integrated with statistical models [23-24]. Stock market trends have recently been predicted using probabilistic neural networks (PNN) and back propagation neural networks [25-26]. For stock price forecasting, back propagation neural networks and genetic algorithms are used. LSTM and an artificial bee colony algorithm were employed to predict stock prices in a recent study [27-28].

III. DATA USED AND PROPOSED MODEL

The goal of this research is to create a stock price prediction model that can predict the price movement of ten NIFTY 50 equities. We obtained 10-year historical data from the National Stock Exchange (NSE) for 10 random NIFTY 50 equities for the period 10 December 2011 to 10 December 2021 [16]. The shortlisted stocks for this study on random basis such as BPCL, L&T, INFY, IOC, SBI, ITC, UPL, TCS, HDFC and CIPLA. These NIFTY50 stock are consisting the 12 parameters but many of them have no significant use in our study. The significant parameters of the stocks of a given trading day have been mentioned in this study as: (i) Open (ii) High (iii) Low (iv) Close and (v) *Date*. We have applied the data normalization technique on the parameters to change the values in the scale of 0 to 1 so that difference in the scale could not cause feature scale problem during the modeling. After the data pre-processing step and transformation of the parameters have been carried out on all ten NIFTY 50 stocks, we have used this processed data for training and testing of the LSTM model. The ratio of training and testing data set is 75:25 respectively.

A. Long Short-Term Memory Deep Learning Model

Sepp Hochreiter and Jürgen Schmidhuber proposed the notion of the LSTM model in 1997. Several researchers have found that LSTM improves through time [29]. A RNN model with a memory extension is known as Long Short-Term Memory. The model was built to handle the problem of gradient disappearing and explosion. This is a significant challenge for any deep neural network, but particularly for RNNs. The architecture of LSTM neurons differs from the architecture of regular RNN neurons. Every neuron in this paradigm is a memory cell that connects the current task to previous information.

In figure 1, the LSTM cell has been defined. In this cell, there are three gates are available namely as Forget gate, Input gate and Output gate. The key idea of this model is that the network can learn, through and read from the stored long-term state. The long-term state $c_{(t-1)}$ first goes through a forget gate and dropping some memories, and then it uses the addition operation to add few new memories that is picked by an input gate. The result $c_{(t)}$ is sent out of the network without any changes. So, at every time stamp, some memories are added and some memories are dropped. Meanwhile, after the addition operation, the *tanh* function has been processed the long-term state by copied and passed through it and finally the result is passed to the output gate. The result of output gate is equal to the cell's output $y_{(t)}$ and short-term state $h_{(t)}$.

Here, the first step is to calculate the output of forget gate. Based on this calculation, information has to be removed from that cell state. Inputs of this gate are the previously hidden state $h_{(t-1)}$ and current input x_t. The equation (1) shows the output of this gate and it is calculated as follows:

$$f_{(t)} = \sigma(W_{xf}\, T_{x_t} + W_{hf} T_{h_{t-1}} + b_f) \quad (1)$$

The next step is the calculation of the output that governs the information added from the current input to the cell state. The input of this gate is the previous hidden state $h_{(t-1)}$ of the model. The equation (2) shows the output of this gate and it is representing as follows:

$$i_{(t)} = \sigma\left(W_{xi}\, T_{x_t} + W_{hi} T_{h_{t-1}} + b_i\right) \quad (2)$$

In this step, we calculated the new candidate vector $g_{(t)}$ and the value of the new vector lies within -1 and 1 it is representing as follows:

$$g_{(t)} = tanh(W_{xg}\, T_{x_t} + W_{hg} T_{h_{t-1}} + b_g) \quad (3)$$

Now, update the old cell state $c_{(t-1)}$ into the newly constructed cell state $c_{(t)}$. It is representing as follows:

$$c_{(t)} = f_{(t)} \otimes c_{(t-1)} + i_{(t)} \otimes g_{(t)} \quad (4)$$

In the final step, the calculation of the output state has begun by transmit the recent cell state from the equation (4) to the function *tanh* then it is multiplied by the output $o_{(t)}$ of output gate. The output gate $o_{(t)}$ having $h_{(t-1)}$ and the inputs x_t and it is calculated as represented below.

$$o_{(t)} = \sigma(W_{xo}\, T_{x_t} + W_{ho} T_{h_{t-1}} + b_o) \quad (5)$$

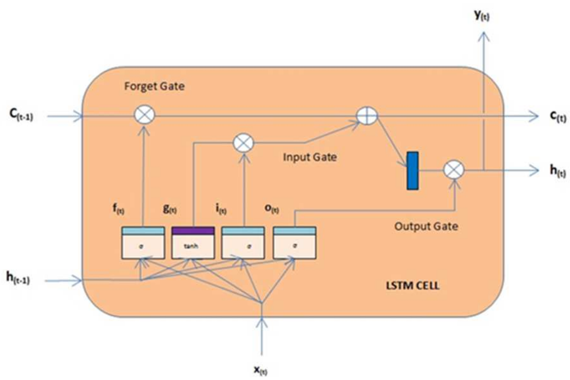

Figure 1 LSTM CELL Structure

B. System Design for Stock price prediction

The figure 2 depicts the system design, In the first step, the Nifty50 stocks price data has been loaded in the model followed by the step 2 that is standardization and normalization of stock price data. In the step 3 the partition of the dataset has been done. The data have been partition into two parts with the ratio of 75% for the training and 25 % for the testing. Instead of using all the parameter available in the data set we have used the five basic parameters from the historical stock prices data as the (i) Open (ii) High (iii) Low (iv) Close and (v) *Date*. Using these five-parameter model has been trained in the step 4.

The model summary has been presented in the figure 3. In the model summary, four LSTM layers have been used. Each LSTM layer has been connected to the dropout layer to avoid the model to over fit. At last dense layer has been used as one fully connected layer with one neuron. We have used *Adam* as an optimizer with 25 epochs. In the step 5, we have tested our model on test data set and calculated various performance parameters:

(i) *Root Mean Square Error (RMSE)*- One of the most used metrics for calculating regression error is root mean square error (RMSE). It's the square root of the MSE. This statistic indicates how well data fits around the regression line. The lower value of the RMSE considered as the best suitable value of RMSE. The equation RMSE is given in equation (6) as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{6}$$

(ii) *Mean Square Error (MSE)* – It is used to measure the model performance based on the average forecasting error. This function is used to verify the results of the regression models. The formula of the MSE is given in equation (7) as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \tag{7}$$

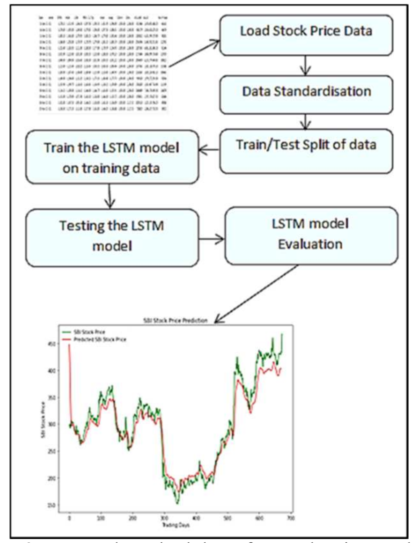

Figure 2 Proposed Methodology for stock price prediction

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 60, 50)            10400

 dropout (Dropout)           (None, 60, 50)            0

 lstm_1 (LSTM)               (None, 60, 50)            20200

 dropout_1 (Dropout)         (None, 60, 50)            0

 lstm_2 (LSTM)               (None, 60, 50)            20200

 dropout_2 (Dropout)         (None, 60, 50)            0

 lstm_3 (LSTM)               (None, 50)                20200

 dropout_3 (Dropout)         (None, 50)                0

 dense (Dense)               (None, 1)                 51

=================================================================
Total params: 71,051
Trainable params: 71,051
Non-trainable params: 0
_________________________________________________________________
```

Figure 3 LSTM model Summary

(iii) *Mean Absolute Error (MAE)* - MAE has referred as the magnitude of difference between the prediction value and the true value of that dataset. MAE takes the average of absolute errors for predictions value and measurement of the magnitude of errors for the entire dataset. The formula of the MAE is given in equation (8) as:

$$MAE = \sum_{i=1}^{n} \frac{|y_i - x_i|}{n} \tag{8}$$

(iv) *Mean Absolute Percentage Error (MAPE)* – The accuracy of the model has been calculated per the given equation (9):

$$MAPE = [(1 - \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right| *100) * 100] \tag{9}$$

IV. RESULTS

The results of the experimental setup produced from the suggested model are discussed in this section. The measurements that we utilised in the methodology section were used to calculate the findings. The model's matching obtained findings for Nifty50 index stocks are listed in Table 1. HDFC, INFY, BPCL, TCS, SBI, ITC, LT, UPL, CIPLA, and IOC are the 10 stocks. The results of our proposed model having the average accuracy of approximately 83% for all the 10 stocks. Whereas, the maximum accuracy has been noted for the SBI stock as 83.88% and highlighted in the result Table 1.

The graphs of the prediction are also mentioned in the Figure 4 (a) HDFC (b) *INFY* (c) *BPCL* (d) *TCS* (e) *SBI* (f) *ITC* (g) *LT* (h) *UPL* (i) *CIPLA* and (j) *IOC*.

TABLE 1. RESULT TABLE

S. No.	STOCK	MSE	RMSE	MAE	MAPE	Accuracy
1	HDFC	0.0019	0.0434	0.0268	0.1644	0.8356
2	INFY	0.0067	0.0821	0.0512	0.1651	0.8349
3	BPCL	0.0089	0.0945	0.0626	0.1700	0.8300
4	TCS	0.0025	0.0497	0.0397	0.1715	0.8285
5	SBI	0.0054	0.0737	0.0614	0.1612	0.8388
6	ITC	0.0039	0.0624	0.0451	0.1633	0.8367
7	LT	0.0052	0.0725	0.0546	0.1652	0.8348
8	UPL	0.0019	0.04	0.0302	0.1701	0.8299
9	CIPLA	0.0017	0.0406	0.0298	0.1666	0.8334
10	IOC	0.0035	0.0590	0.0416	0.1687	0.8313

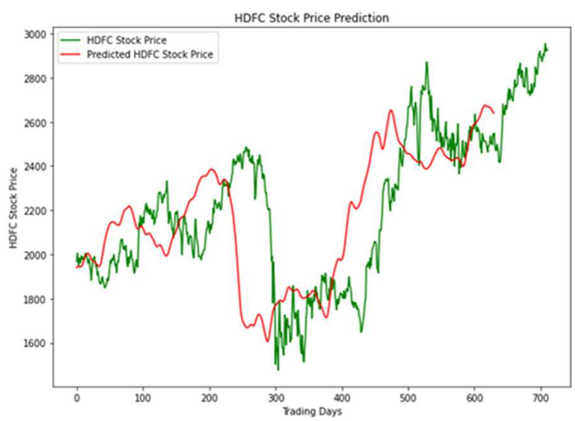

Figure 4 (a) HDFC stock price prediction

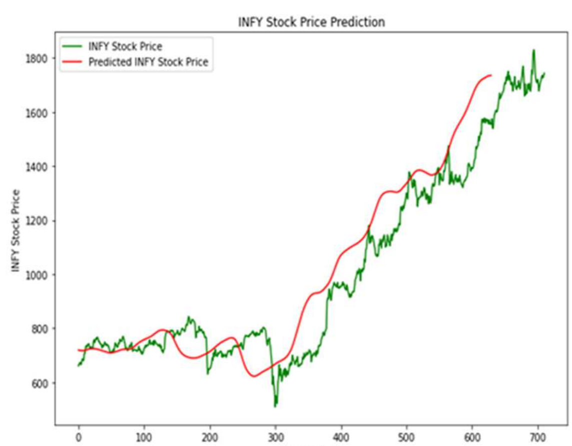

Figure 4 (b) INFY stock price predictions

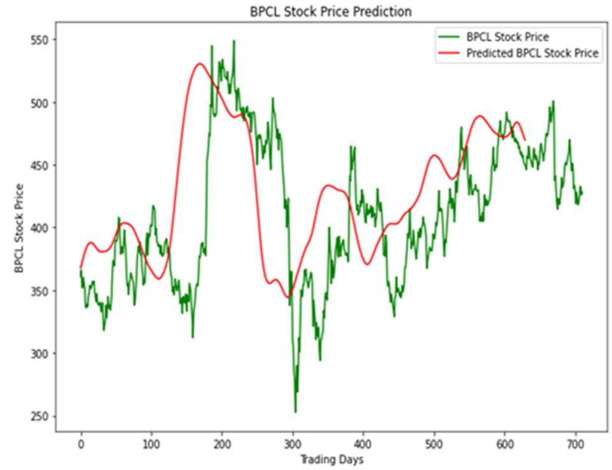

Figure 4 (c) BPCL stock price predictions

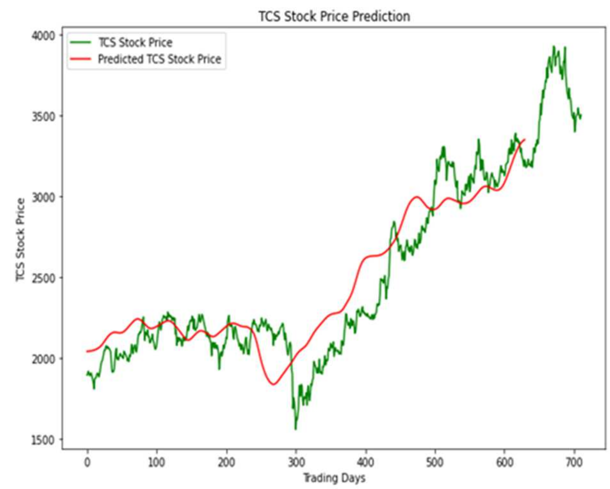

Figure 4 (d) TCS stock price predictions

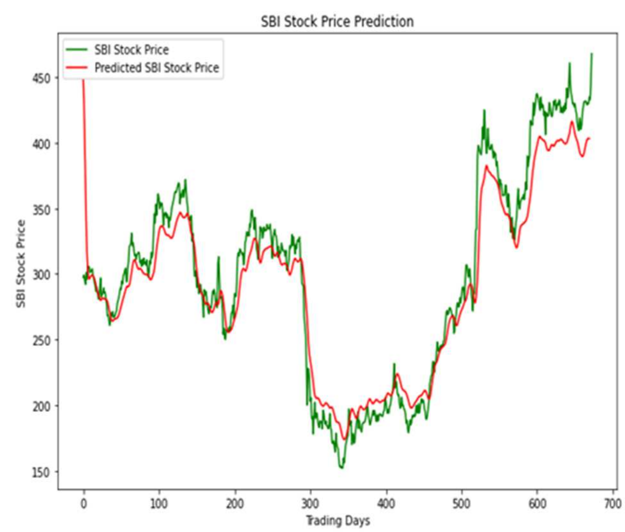

Figure 4 (e) SBI stock price predictions

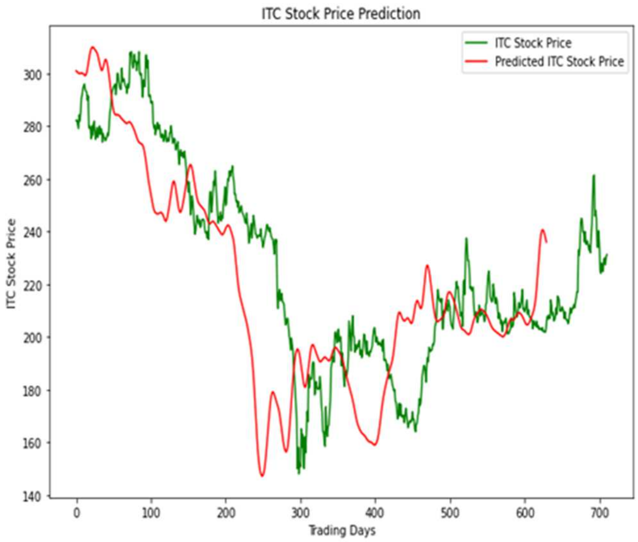

Figure 4 (f) ITC stock price predictions

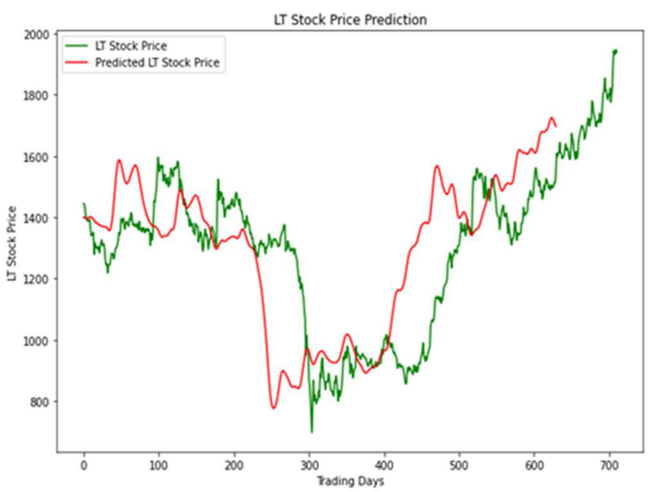

Figure 4 (g) LT stock price predictions

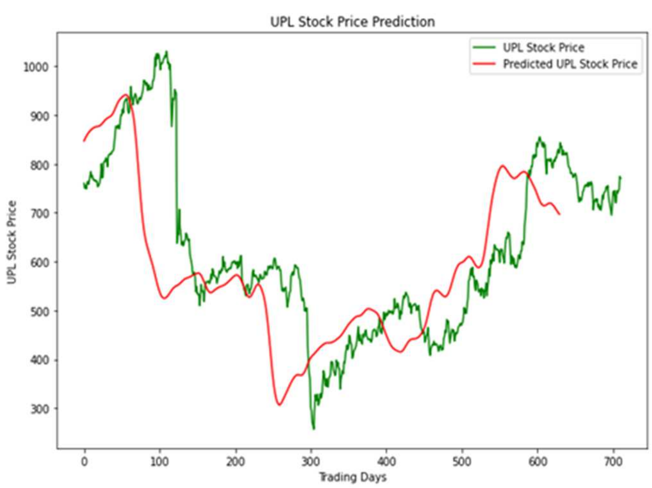

Figure 4 (h) UPL stock price predictions

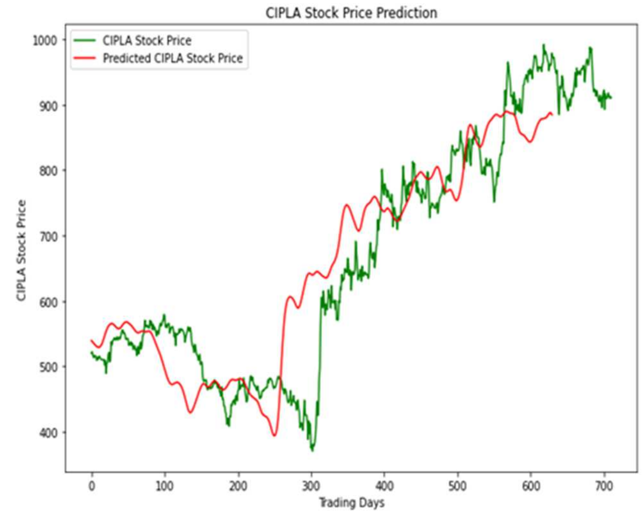

Figure 4 (i) CIPLA stock price predictions

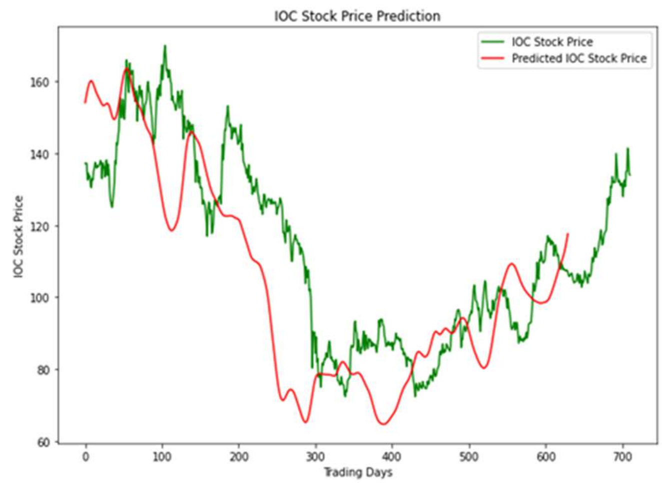

Figure 4 (j) IOC stock price predictions

V. CONCLUSION AND FUTURE WORK

This research study offered an LSTM model for forecasting Nifty50 stock price prediction for ten equities. The research was conducted on 10 Nifty50 stocks with data from the previous ten years. The results of the suggested model are very effective in predicting stock price with correct prediction values in the study. The RMSE, MSE, MAE, and MAPE metrics show that the ten stocks in the Nifty50 have the lowest predicted errors. The SBI stock had the highest accuracy of 83.88 percent in the analysis. Every model has room for development. We will endeavor to improve the accuracy of our forecast results in the future.

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