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STOCK PRICE FORECASTING USING TIME SERIES AND MACHINE LEARNING MODELS: A CASE STUDY ON TATA CONSULTANCY SERVICES

[1] Divya P R, [2] Hafsa Shajahan, [3] Ansidha Aboobacker,
[1]Assistant professor, Department of Statistics, Vimala College (Autonomous), Thrissur, India
[2]Student, Department of Statistics, Vimala College (Autonomous), Thrissur, India
[3] Student, Department of Statistics, Vimala College (Autonomous), Thrissur, India
Email - [1] divyastat@vimalacollege.edu.in, [2]hafsashajahan700@gmail.com, [3]ansidha.abubacker.22@gmail.com

Corresponding Author Email: divyastat@vimalacollege.edu.in

Abstract: *This study aims to predict stock price movements of Tata Consultancy Services (TCS), a global IT services leader, using time series and machine learning techniques. Accurate stock price prediction is essential for investors and traders to make informed decisions. This paper discusses about various machine learning models, including linear regression, decision trees, and neural networks, to forecast TCS's stock prices based on historical data and technical indicators. The dataset, sourced from Yahoo Finance, includes monthly stock prices, as well as open, close, high, low prices, and trading volume from January 2014 to December 2024.Our findings evaluate the strengths and limitations of each model in forecasting stock prices. The results suggest that machine learning models can significantly enhance prediction accuracy, offering valuable insights for investors. This study contributes to the growing field of financial forecasting and has potential applications in automated trading systems. Experimental results show that machine learning models outperform traditional models in terms of prediction accuracy across all metrics.*

Key Words: *ARIMA, artificial neural network, LSTM, random forest, support vector regression, time series forecasting.*

1. INTRODUCTION:

The stock market is a dynamic system influenced by economic trends, company performance, and global events. Investing successfully requires research, strategy, and risk management. In India, the Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) host a wide range of companies across sectors, playing a vital role in economic growth.
One key sector is Information Technology (IT), with companies like Tata Consultancy Services (TCS), Infosys, Wipro, and HCL Technologies leading globally. TCS, in particular, has shown strong financial performance and global reach, making it a focus for investors. However, predicting stock prices in the IT sector is challenging due to market volatility, global dependencies, and rapid technological changes.
This study presents a comparative analysis of machine learning models to predict TCS stock prices using historical data from 2014 to 2024, sourced from Yahoo Finance. Models include ARIMA, k-Nearest Neighbors (kNN), Support Vector Regression (SVR), Random Forest, Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM).
Using Python libraries such as Pandas, Scikit-learn, Keras, and TensorFlow, the models are evaluated based on accuracy, error rates, and efficiency. Each model has unique strengths, ARIMA for time series, Random Forest for non-linear patterns, and LSTM for sequential data.
This research highlights the growing relevance of machine learning in financial forecasting, especially in emerging markets like India. Accurate stock price prediction can aid investors in making informed decisions and managing risks more effectively.

2. LITERATURE REVIEW:

Several research papers have explored stock market prediction using statistical and machine learning techniques. Alqahtani and Abdelhafez (2022) forecasted closing prices of six major sectors in the Saudi stock market using seven years of historical data, oil prices, and inflation rates. They applied ARIMA, SVR, Random Forest, LSTM, Bi-LSTM, and GRU models—finding GRU and Random Forest to perform best, while ARIMA underperformed across all sectors. Dhyani et al. (2020) studied ARIMA's effectiveness in modeling linear trends and short-term predictions, noting its limitations with non-linear patterns and volatility. They recommended combining ARIMA with models like GARCH or machine learning algorithms to improve performance. Pathak (2024) reviewed machine learning approaches such as decision trees, SVM, kNN, and neural networks. Deep learning models like LSTM and RNN were emphasized for capturing temporal dependencies. The study stressed aligning model selection with data characteristics and prediction goals. Priya and Aravinda (2019) used time series and regression analysis to study stock prices of construction companies, highlighting the influence of government policies and economic conditions. While focusing on traditional methods, they acknowledged the rising value of machine learning for improving predictive accuracy. Collectively, these studies reflect a growing trend of integrating machine learning with statistical methods to better address the complexities of financial markets.

3. OBJECTIVES :

The key objective of this study are:

- To show the pattern of stock market close price over the period 2014 to 2024.
- To find the best model for estimating stock market close price.
- To compare time series ARIMA(2,1,2) and machine learning models (kNN, SVR, Random Forest ,ANN and LSTM).
- To forecast the future stock market close price of Tata Consultancy Services using ARIMA(2,1,2) and Machine learning model LSTM .

4. METHODOLOGY :

This study employs six distinct models to analyze and forecast stock prices: ARIMA, k-Nearest Neighbour (kNN), Support Vector Regression (SVR), Random Forest, Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM). The dataset used comprises daily stock prices from January 2014 to December 2024. For model training and validation, data from January 2014 to September 2022 was used as the training set, while data from October 2022 to December 2024 served as the test set. Each model is then used to predict stock prices for the year 2025. All models underwent similar preprocessing steps, including outlier detection, normalization, and, where necessary, differencing for stationarity.
Statistical Software are used for time series analysis and machine learning analysis that are Gretl and python.

4.1. Materials and Methods:

4.1.1 ARIMA model:

The ARIMA (AutoRegressive Integrated Moving Average) model is a classical statistical approach for time series forecasting. It combines autoregression (AR), differencing (I), and moving average (MA) components, represented as ARIMA(p,d,q), where p is the number of lag observations, d is the degree of differencing, and q is the size of the moving average window. The dataset is first cleaned by removing outliers. Stationarity is then checked using the Dickey-Fuller test. If the data is non-stationary, differencing is applied. The optimal values for p and q are selected based on partial autocorrelation plots. After training, the ARIMA model is used to forecast the closing stock prices for 2025.

4.1.2 k-Nearest Neighbour (kNN):

kNN is a non-parametric, distance-based algorithm used here for regression. It works by averaging the values of the k-nearest data points based on a distance metric, typically Euclidean distance. The data is first cleaned and normalized to ensure uniformity across features. It is then split into training and test sets. The model is trained on past stock data, and predictions for future prices are made based on the closest data points in the feature space.

4.1.3 Support Vector Regression (SVR):

SVR is an extension of Support Vector Machines (SVM) for regression tasks. It seeks to find a function that approximates the data within a specified error margin (ε), while also maintaining model simplicity using a regularization parameter (C). The data undergoes preprocessing including outlier removal, normalization, and differencing if necessary. SVR is particularly useful for modeling complex, non-linear relationships in financial time series. After training, it is used to predict stock prices both for the test set and the 2025 forecast

4.1.4 Random Forest (RF):

Random Forest is an ensemble learning method that builds multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting. Each tree is trained on a bootstrap sample of the data and a random subset of features. Preprocessing involves handling missing values, normalization, and differencing where applicable. The ensemble approach helps Random Forest handle noisy and non-linear stock market data effectively. Predictions for the test period and 2025 are made by averaging the outputs of all trees.

4.1.5 Artificial Neural Network (ANN):

ANNs are inspired by the structure of the human brain and are capable of learning complex, non-linear relationships in data. This study uses a feedforward neural network trained using the backpropagation algorithm. After cleaning and normalizing the data, the model is trained to minimize error between predicted and actual stock prices. The ANN's flexibility allows it to capture intricate patterns, making it suitable for stock market prediction tasks. Once trained, it forecasts future stock prices for both the test set and the year 2025.

4.1.6 Long Short-Term Memory (LSTM):

LSTM networks, a specialized type of Recurrent Neural Network (RNN), are particularly effective for sequential and time series data. They incorporate memory cells and three types of gates—input, output, and forget gates—to manage the flow of information and maintain long-term dependencies. The LSTM model in this study consists of two hidden layers with 50 neurons each and an output layer with one neuron to predict the next price. It is trained on historical stock data to detect temporal dependencies and complex dynamics over time. After training, it provides predictions for the test data and extrapolates stock prices for the year 2025. LSTM's structure makes it the most suited model for time-dependent financial forecasting in this study.

5. DATA ANALYSIS

Forecasting predicts future trends using historical data, helping industries manage production, inventory, and resources efficiently. Accurate forecasts prevent losses from overproduction or missed opportunities.
This study uses secondary data—monthly stock prices from January 2014 to December 2024 (120 months), sourced from Yahoo Finance. A time series approach with ARIMA modeling is used. The data size is sufficient for ARIMA, which requires at least 50 data points. Analysis includes descriptive statistics, stationarity tests, model fitting, and forecasting. ARIMA model selection follows standard steps: identification, estimation, and forecasting, using AIC and SC for best-fit selection.

Table 5.1: Classification of Stock Price Based on Monthly Average

Month & Year	Close Price(in rupees)
2014 January	923.126
2014 February	889.2501
2014 March	883.1668
2014 April	896.797
2014 May	882.6986
2014 June	921.4828
2014 July	1023.915

2014 August	1047.559
2014 September	1107.317
2014 October	1091.569
………..	…………..
2024 March	3935.112
2024 April	3796.547
2024 May	3774.518
2024 June	3748.69
2024 July	4087.028
2024 August	4293.018
2024 September	4327.563
2024 October	4065.762
2024 November	4089.66
2024 December	4263.087

5.1 Descriptive Statistics

The descriptive statistics were presented in the table 2.2.1 which delineated the properties of all the variables under study.

Table 5.1.1: Descriptive Statistics of Stock price during 2014 to 2024

Year	No.of observations	Mean	Standarddeviation	Skewness	Kurtosis
2014	12	985.6652	93.5453	0.1183	-2.0563
2015	12	1077.7396	26.6076	-0.8632	0.1303
2016	12	1044.8138	55.7105	0.2323	-0.9996
2017	12	1089.1628	53.9591	0.4418	0.0192
2018	12	1601.4686	217.5325	-0.3859	-1.496
2019	12	1911.5818	91.4917	-0.7302	0.5169
2020	12	2088.6508	324.0502	0.4408	-0.9065
2021	12	3144.3898	250.3268	0.6121	-1.0421
2022	12	3230.7205	222.2017	0.5088	-0.881
2023	12	3267.3993	158.0040	0.5226	0.0818
2024	12	4002.4968	221.4055	0.1051	-1.3351

The TCS stock price data from 2014 to 2024 presented in Table 2.2.1 reveals a consistent upward trend in the mean stock price over the years. Starting at ₹985.67 in 2014, it shows steady growth, reaching ₹4002.50 in 2024. This reflects an overall significant increase in value. The standard deviation indicates variations in price stability, with higher deviations in certain years like 2020 (₹324.05) and 2018 (₹217.53), suggesting more price fluctuations during these periods. Skewness values hover around zero across years, indicating a nearly symmetrical distribution of prices, though certain years show mild negative or positive skewness. Kurtosis values, being mostly negative, suggest a flatter distribution compared to a normal distribution throughout the period. These data points collectively showcase both growth and periods of variability in TCS's stock performance.

6. STOCK MARKET PREDICTION USING ARIMA MODEL

6.1 Identification of ARIMA Model

This study based on Time series analysis and a mathematical model has been established to predict it with a reasonable prediction method.

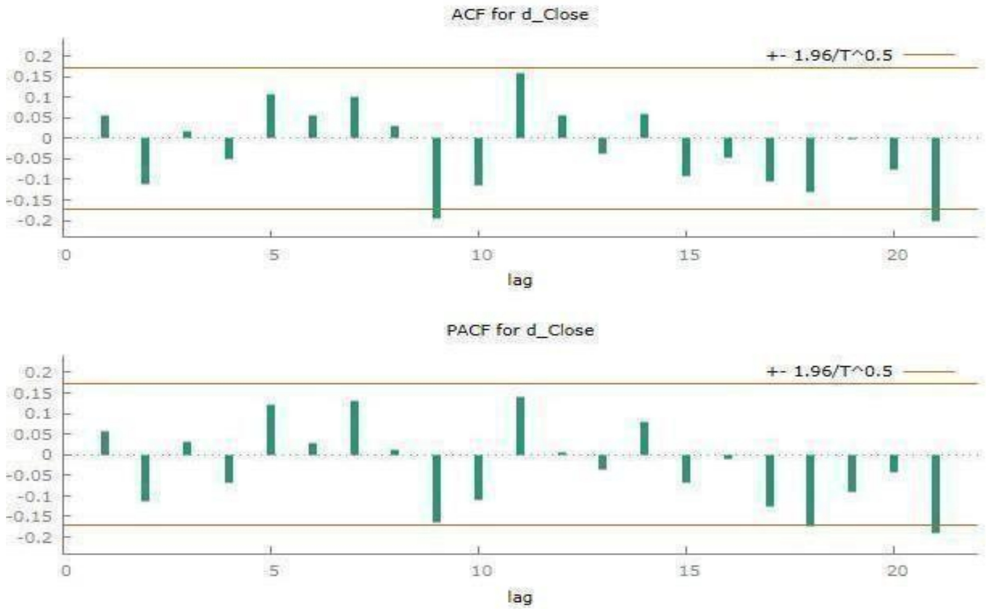

Figure 6.1.1: Correlogram of ACF and PACF of Stock price.

6.2 Establishing Time Series Model of Stock Price

The ARIMA (p,d,q) model is identified using autocorrelation and partial autocorrelation plots. Various p, d, q combinations were compared (Table 2.3.2.1) to select the optimal model. Stationarity was tested using the Augmented Dickey-Fuller (ADF) test. With a test statistic of -8.2431 and a p-value of 2.973×10^{-13}, the null hypothesis of non-stationarity was rejected, confirming the series is stationary. Correlogram errors were used to refine model selection.

Table 6.2.1: Comparison of ARIMA Models

Model	AIC	SC
ARIMA (0,1,0)	1560.96	1577.98
ARIMA (0,1,1)	1561.06	1580.92
ARIMA (0,1,2)	1554.80	**1577.49***
ARIMA (0,1,3)	1562.49	1588.02
ARIMA (1,1,0)	1562.21	1582.06
ARIMA (1,1,1)	1563.03	1585.72
ARIMA (1,1,2)	1564.91	1590.44
ARIMA (1,1,3)	1564.22	1592.58
ARIMA (2,1,0)	1561.51	1584.20
ARIMA (2,1,1)	1563.45	1588.97
ARIMA (2,1,2)	**1551.04***	1579.40
ARIMA (2,1,3)	1552.79	1583.99
ARIMA (3,1,0)	1563.30	1588.82
ARIMA (3,1,1)	1564.83	1593.20
ARIMA (3,1,2)	1552.77	1583.96
ARIMA (3,1,3)	1554.73	1588.77

Both AIC and SC represent the information criteria, and smaller the better for the model. From table 2.3.2.1 model ARIMA (2,1,2) is optimal. So the optimal model for estimating stock price is ARIMA (2,1,2). The following parameters are estimated for the model ARIMA (2,1,2) and the result are shown in the table given below

Table 6.2.2: Model ARIMA (2,1,2) parameter estimation

	coefficient	std. error	z	P value
constant	0.320169	0.254067	1.26	0.2076
phi_1	**−0.676025**	**0.21277**	**−3.177**	**0.0015 *****
phi_2	−0.0656995	0.0986248	−0.6662	0.5053
theta_1	−0.247088	0.198565	−1.244	0.2134
theta_2	**−0.752912**	**0.198043**	**−3.802**	**0.0001 *****

From the table, both θ_2 and φ_1 have p-values < 0.05, indicating significance. AIC = 1551.0471 and SC = 1579.4099. Based on the model, with stock prices at 4089.66 in Nov 2024 and 4263.087 in Dec 2024, the static method is used to forecast Jan 2025 prices. The ARIMA(2,1,2) model is given by:

$$\Delta y_t = \phi_1 \Delta y_{t-1} + \phi_2 \Delta y_{t-2} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \epsilon_t$$

Δy_t is the differenced series,

- Φ_1 and ϕ_2 are the autoregressive coefficients for the first and second lags of the differenced series,
- Θ_1 and θ_2 are the moving average coefficients for the first and second lags of the error terms,
- ϵ_t is the error term at time t.

With the differenced data, we can then fit the ARIMA (2, 1, 2) model. The model equation is:
$\Delta y_t = -0.676025\, \Delta y_{t-1} - 0.0656995\, \Delta y_{t-2} - 0.247088\, \epsilon_{t-1} - 0.752912\, \epsilon_{t-2} + \epsilon t$

Figure 6.2.1: Line graph of actual and predicted close price values using ARIMA(2,1,2)

Actual closing prices show a steady rise from 2022 to 2024, with predicted prices closely following. Some deviations, like in Jan 2024, hint at unexpected market factors. Prediction accuracy improves over time, showing the model effectively captures overall market trends.

6.3 Forecasting using ARIMA(2,1,2)

This forecast covers a period of 1 year (12 months) starting from January 2025

Table 6.3.1: Forecasted Values Using ARIMA (2,1,2)

Month & Year	Close Price(in rupees)
2025 January	4319.03
2025 February	4310.16
2025 March	4310.49
2025 April	4310.82
2025 May	4311.15
2025 June	4311.48
2025 July	4311.81
2025 August	4312.14
2025 September	4312.47
2025 October	4312.80
2025 November	4313.13
2025 December	4313.46

7. MACHINE LEARNING MODELS

Forecasting predicts future trends by analyzing past data and market conditions. In industries, it enhances production, inventory, and resource management, ensuring efficiency. Poor forecasting can lead to losses, while accurate forecasting supports proactive decision-making.
This study uses secondary data—monthly stock prices from January 2014 to December 2024—sourced from Yahoo Finance. With 120 data points, the sample is adequate for machine learning models. The analysis includes descriptive stats, stationarity tests, model fitting, and forecasting. Models used are kNN, LSTM, Random Forest, SVR, and ANN. Model selection follows standard steps: identification, estimation, and forecasting, using criteria like AIC and SC.

7.1 K-Nearest Neighbors (kNN) Model:

The K-Nearest Neighbors (kNN) algorithm is a simple method used for classification and regression, predicting outcomes based on the K closest data points using distance measures like Manhattan or Euclidean. For regression, it averages neighbors' values; for classification, it selects the most common class. kNN doesn't require training—it stores the dataset and predicts by comparing distances during testing. In this model, K is set to 3, using Manhattan distance.

7.2. Artificial Neural Network (ANN) Model

The ANN model consists of an input layer, two hidden layers (64 and 32 neurons), and an output layer, trained using backpropagation and gradient descent. Input data is normalized using Min-Max scaling, and the dataset is split into training (Jan 2014–Sep 2022) and testing (Oct 2022–Dec 2024). After evaluation, the model predicts stock prices for 2025 based on learned patterns.
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7.3. Support Vector Regression (SVR) Model

SVR predicts continuous values by fitting a function within a margin of tolerance (ε), focusing on support vectors. It uses kernels like RBF to handle non-linear data and was trained with $C = 10$ and $\varepsilon = 0.1$ after standardizing the dataset. The data was split into training (Jan 2014–Sep 2022) and testing (Oct 2022–Dec 2024), then used to forecast 2025 stock prices.

7.4 Random Forest

Random Forest is an ensemble model that builds multiple decision trees using random data subsets and features, averaging predictions to improve accuracy and reduce overfitting. It's effective with large datasets and handles both numeric and categorical data. In this study, data was cleaned, split (Jan 2014–Sep 2022 for training, Oct 2022–Dec 2024 for testing), and used to predict 2025 stock prices.

7.5 Long Short-Term Memory (LSTM) Model

LSTM, a type of Recurrent Neural Network (RNN), learns long-term dependencies using memory gates (forget, input, and output) and avoids vanishing gradients. The model has two LSTM layers with 50 neurons each and an output layer with 1 neuron.

It processes 4 features - volume, open, high, and low using BPTT to capture complex patterns for forecasting 2025 stock prices.

8. FINDINGS :

The dataset of monthly stock prices from TCS has been sourced from the secondary data from YAHOO FINANCE, including open, close, high, low prices, and trading volume, upto March 31 2025. The data is divided into training and testing sets with 80% of the data used for model development, and the remaining 20% reserved for evaluating model performance. To build the machine learning models, a lag value of 12 is applied. The models are compared using three error metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE).

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

Mean Absolute Percentage Error:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{14}$$

Mean Absolute Error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{15}$$

Where, y_i and $\hat{y}_i$ are the observed values and predicted values respectively.
The performance of the fitted models on the validation set is presented in Table 8.1.

Table 8.1: Error matrices for comparison of the proposed models

Model	**MAPE**	**MAE**	**RMSE**
ARIMA(2,1,2)	**3.81**	**141.50**	**179.67**
kNN	5.44	220.25	350.40
ANN	2.64	70.87	86.67
SVR	3.08	97.34	103.76
Random Forest	4.63	188.127	305.99
LSTM	**2.40**	**64.22**	**71.55**

LSTM delivers the best performance with the lowest MAPE (2.40%), MAE (64.22), and RMSE (71.55), followed by ANN (MAPE: 2.64%). ARIMA (MAPE: 3.81%) and SVR (MAPE: 3.08%) offer moderate accuracy. Random Forest

(MAPE: 4.63%) and kNN (MAPE: 5.44%) perform the worst, with higher error values. Overall, LSTM and ANN are the most accurate models, while kNN and Random Forest are the least effective.

The figure below displays the actual versus predicted plots for the best-performing model based on test data.

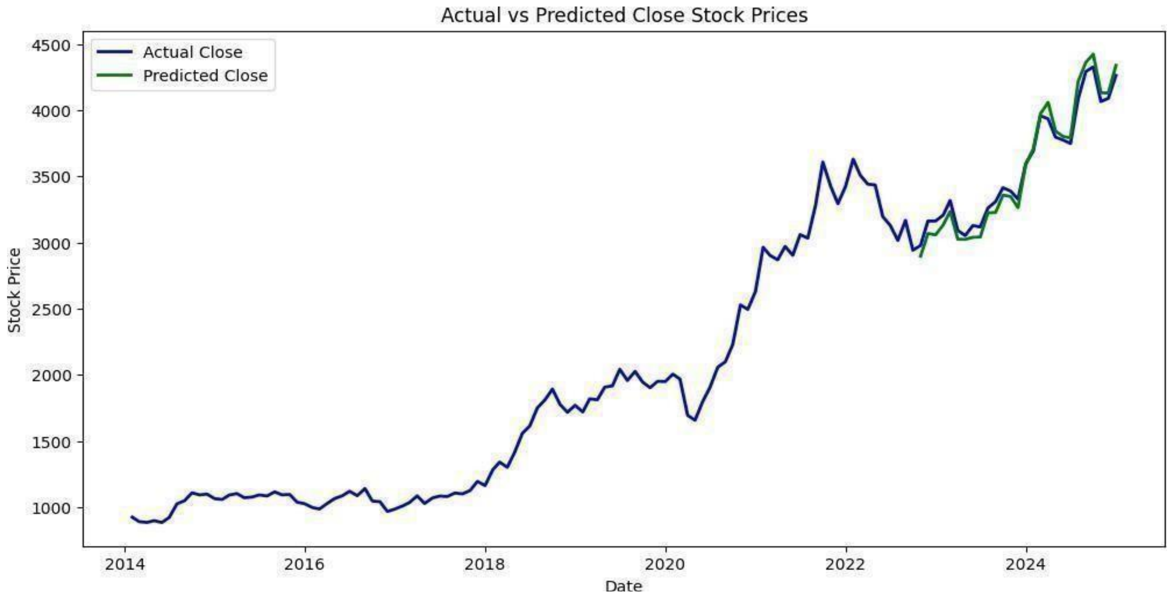

Figure 8.1: Plot of actual and predicted (LSTM) values of stock prices from TCS.

8.1 Forecasting using best model

This forecast covers a period of 1 year (12 months) starting from January 2025 to December 2025

Table 8.1.1 Forecasted Values Using LSTM Model

Month & Year	Close Price(in rupees)
2025 January	4345.48
2025 February	4800.78
2025 March	4845.58
2025 April	4849.86
2025 May	4850.26
2025 June	4850.3
2025 July	4850.31
2025 August	4850.31
2025 September	4850.31
2025 October	4850.31
2025 November	4850.31
2025 December	4850.31

9. CONCLUSION:

The stock market plays a crucial role in the global economy, serving as a vital platform for investment and wealth generation. Accurate forecasting of stock prices is essential for investors, traders, and policymakers to make informed decisions, manage risks effectively, and optimize resource allocation. India, being one of the fastest-growing economies, has seen significant participation in stock markets, with companies like TCS contributing substantially to economic growth and investor confidence.

Timely and precise stock price forecasting helps stakeholders determine market trends, evaluate investment opportunities, and implement strategic planning for financial stability. This research demonstrates that machine learning models offer superior accuracy compared to traditional statistical methods like ARIMA for stock price prediction using TCS data. Future studies could explore advanced deep learning techniques to further enhance the accuracy and robustness of stock price forecasting.

10. LIMITATIONS:

Forecasting stock market prices using time series and machine learning models has several limitations due to the complex and unpredictable nature of financial markets. Stock prices are highly volatile, non-stationary, and influenced by many external factors such as international market trends, global economic events, political decisions, and sudden news. While models like ARIMA, Random Forest, SVR, ANN, and LSTM can identify patterns in historical data, they often struggle with overfitting, require large and clean datasets, and may not generalize well to future market behavior. Moreover, they typically fail to capture human emotions, market sentiment, and irrational behavior, which play a big role in price movements. As a result, even advanced models may give inaccurate predictions when unexpected events or shifts occur.

11. RECOMMENDATIONS:

To improve the accuracy and reliability of stock market forecasting, it is recommended to use a combination of models (hybrid approaches) that capture both linear and non-linear patterns in data. Incorporating external data sources such as international market indicators, financial news, social media sentiment, and macroeconomic variables can help models understand broader influences on stock prices.

Areas for further investigation include optimizing the LSTM model's parameters, expanding the data feature dimensions, and exploring ensemble learning methods. Additionally, integrating techniques such as attention mechanisms could further boost the prediction accuracy and generalization capabilities. These advancements will aid in the evolution of machine learning applications in stock forecasting, ultimately offering investors more reliable decision-making tools to secure better returns in the market.

REFERENCES:

1. Majumder, A., Rahman, M. M., Biswas, A. A., Zulfiker, M. S., & Basak, S. (2022). Stock market prediction: A time series analysis. In A. K. Somani, A. Mundra, R. Doss, & S. Bhattacharya (Eds.), *Smart systems: Innovations in computing: Proceedings of SSIC 2021* (pp. 389–401). Springer Singapore. https://doi.org/10.1007/978-981-16-2877-1_35.
2. Kulkarni, M., Jadha, A., & Dhingra, D. (2020). *Time series data analysis for stock market prediction*. In *Proceedings of the 3rd International Conference on Innovative Computing and Communication (ICICC-2020)*. SSRN. https://dx.doi.org/10.2139/ssrn.3563111.
3. Ambashtha, K. L., & Singh, M. K. (2019). A study on Indian stock market prediction using statistical tools. *Journal of Emerging Technologies and Innovative Research*, 6(6), 759–773. http://www.jetir.org/papers/JETIR1908A61.pdf.
4. Sharma, R. P., & Sharma, A. (2019). Statistical analysis of stock prices of selected companies in construction industry. *Advances in Management*, 12(1), 39–47.
5. Zhao, C., Hu, P., Liu, X., Lan, X., & Zhang, H. (2023). Stock market analysis using time series relational models for stock price prediction. *Mathematics*, 11(5), Article 1130. https://doi.org/10.3390/math11051130.
6. Pathak, P. (2024). Stock market prediction using machine learning. *International Journal for Multidisciplinary Research*, 6(1), 1–12. https://doi.org/10.36948/ijfmr.2024.v06i01.12383.
7. Singh, S., Gutta, S., & Hadaegh, A. (2021). Stock prediction using machine learning. *WSEAS Transactions on Computer Research*, 9, 152–158. https://doi.org/10.37394/232018.2021.9.17.

8. Sarkar, A., Singh, A. K., Verma, S., Praveenkumar, A., Yadav, B. K., & Kumar, N. (2024). Machine learning models for time series forecasting: A case study of coconut price prediction. *International Journal of Research in Agronomy*, 7(9), 1–4. https://doi.org/10.33545/2618060X.2024.v7.i9a.1405.
9. Ji, S. (2024). Predict stock market price by applying ANN, SVM, and random forest. *SHS Web of Conferences*, 196, Article 02005. https://doi.org/10.1051/shsconf/202419602005.
10. Yousefi, N. (2021). Stock price prediction using statistical, machine learning, and deep learning models. *International Journal of Innovations in Engineering Research and Technology*, 8, 1–9. https://doi.org/10.17605/OSF.IO/Q58BE.
11. Liang, K., Wu, H., & Zhao, Y. (2024). Study of effectiveness of the ARIMA method in forecasting stock process in China. In Y. Ghadi (Ed.), *Proceedings of the 3rd International Conference on Computing Innovation and Applied Physics* (Vol. 43, pp. 33–44). EWA Publishing. https://doi.org/10.54254/2753-8818/43/20240781.
12. Anh, N. Q., & Son, H. X. (2023). Transforming stock price forecasting: Deep learning architectures and strategic feature engineering. In V. Torra, Y. Narukawa, & M. Daumas (Eds.), *Modeling Decisions for Artificial Intelligence* (Lecture Notes in Computer Science, Vol. 14106, pp. 237–250). Springer. https://doi.org/10.1007/978-3-031-68208-7_20.