Journal of Next Generation Technology(ISSN: 2583-021X)
Vol. 5, Issue 3, May 2025

Stock Price Prediction and Performance Analysis of Indian Banks Using Machine Learning Techniques

Honali Rohith[1], Chokkamreddy Prakash[2]
[1]UG Scholar, [2]Assistant Professor
School of Management Studies, Guru Nanak Institutions Technical Campus, Hyderabad, India
Email id: honalirohith@gmail.com[1], chokkamprakashreddy@gmail.com[2]

Article Received: 28 April 2025 *Article Accepted: 30 April 2025* *Article Published: 13 May 2025*

Citation
Honali Rohith, Chokkamreddy Prakash,“ Stock Price Prediction and Performance Analysis of Indian Banks Using Machine Learning Techniques”, Journal of Next Generation Technology (ISSN: 2583-021X), 5(3), pp. 102-109, May 2025. DOI: 10.5281/zenodo.15730369

Abstract

This study focuses on analyzing and predicting the stock prices of leading Indian banks—HDFC Bank, ICICI Bank, and AXIS Bank using various machine learning (ML) techniques. The research investigates the effectiveness of models such as Linear Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) in forecasting stock prices. Additionally, the study evaluates stock performance through Sharpe Ratio, Treynor Ratio, and Jensen’s Alpha to assess risk-adjusted returns and excess returns over market expectations. The results show that the LSTM model outperformed other models in predicting stock prices, while ICICI Bank demonstrated superior risk-adjusted performance and higher returns.

Keywords: Stock Price Prediction, Machine Learning, Sharpe Ratio, Treynor Ratio, Jensen’s Alpha, LSTM, Indian Banks.

I. INTRODUCTION

Stock price prediction is a crucial area in financial research, where accurate forecasting can help investors make informed decisions. Accurate stock price prediction provides insights into market behavior, allowing investors to optimize portfolio returns and manage risk effectively (Patel et al., 2015). Indian banks such as HDFC Bank, ICICI Bank, and AXIS Bank play a pivotal role in the Indian economy, with their stock performance influencing investor sentiment and overall market stability (Fama & French, 2004). These banks are part of the Nifty 50 and Sensex indices, making them critical determinants of market movements.

Traditional financial models such as the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH) have been widely used to assess stock performance and predict returns (Fama, 1970). However, these models often fall short in capturing non-linear dependencies and complex patterns in stock price data. In recent years, machine learning

(ML) techniques have emerged as powerful tools for financial forecasting, offering improved accuracy and the ability to capture intricate relationships in historical stock data (Fischer & Krauss, 2018).

A. Importance of Stock Price Prediction

Stock price movements are influenced by a multitude of factors, including macroeconomic indicators, company performance, and market sentiment. Accurately predicting these movements can enhance decision-making for investors, fund managers, and policymakers. As highlighted by Sharpe (1994), understanding stock price behavior enables investors to optimize asset allocation and improve portfolio performance.

B. Role of Indian Banks in the Financial Market

HDFC Bank, ICICI Bank, and AXIS Bank are major players in the Indian banking sector, contributing significantly to the country's economic growth. According to NABARD (2020), these banks account for a substantial share of retail and corporate lending, influencing market liquidity and credit availability. Their stock performance is closely monitored by institutional and retail investors, given their impact on benchmark indices.

C. Machine Learning Techniques in Financial Forecasting

Machine learning models such as Support Vector Machines (SVM), Decision Trees, and Neural Networks have gained prominence in financial forecasting due to their ability to model complex relationships and identify non-linear patterns in stock price data. Patel et al. (2015) demonstrated that machine learning techniques outperform traditional statistical models in predicting stock prices with higher accuracy. Fischer & Krauss (2018) further emphasized the effectiveness of Long Short-Term Memory (LSTM) networks in capturing sequential dependencies and enhancing forecasting capabilities.

D. Objective of the Study

The primary objective of this study is to predict stock prices and evaluate the performance of HDFC Bank, ICICI Bank, and AXIS Bank using machine learning techniques. The study also aims to assess the risk-adjusted returns and excess returns of these banks through key performance metrics such as the Sharpe Ratio, Treynor Ratio, and Jensen's Alpha. By integrating machine learning models with financial performance evaluation, this research provides a comprehensive analysis of stock behavior and future trends.

E. Scope of the Study

This research covers a five-year period from January 2020 to March 2025, analyzing historical stock prices and performance metrics of the selected banks. The study utilizes various machine learning models to identify the best-performing algorithm and assesses stock performance using risk-adjusted measures. The findings aim to assist investors, financial analysts, and policymakers in making data-driven investment decisions.

II. LITERATURE REVIEW

A. Stock Price Prediction Techniques

Patel et al. (2015) demonstrated that machine learning models such as Support Vector Machines (SVM), Decision Trees, and Random Forests can outperform traditional models like ARIMA and GARCH in predicting stock price movements. Their research highlighted that SVMs provide superior accuracy due to their ability to handle high-dimensional data effectively. Fischer & Krauss (2018) conducted a study using Long Short-Term Memory (LSTM) networks to predict stock prices and found that LSTM models performed exceptionally well in capturing sequential dependencies in time series data. Their findings indicated that LSTM models reduced prediction errors significantly compared to traditional methods. Gupta et al. (2019) explored the effectiveness of Artificial Neural Networks (ANNs) in stock price forecasting and concluded that ANNs provided reliable results for short-term predictions. However, their study also noted that overfitting remains a challenge when dealing with noisy financial data. Zhang & Zhou (2020) compared the performance of Gradient Boosting Machines (GBM) and XGBoost models in stock price prediction. Their study demonstrated that ensemble learning models achieved higher predictive accuracy by reducing variance and improving model stability. Chong et al. (2017) applied deep learning techniques, particularly Convolutional Neural Networks (CNNs), to stock price prediction and concluded that CNN models captured spatial dependencies in financial data, leading to improved forecasting results. Nti et al. (2020) evaluated the use of hybrid models combining genetic algorithms with machine learning techniques for stock price prediction. Their study highlighted that hybrid models reduced prediction errors and improved model robustness by optimizing feature selection. Zhang et al. (2019) emphasized the importance of feature engineering in enhancing the performance of machine learning models. Their research demonstrated that incorporating technical indicators and sentiment analysis features significantly improved model accuracy. Hiransha et al. (2018) compared the performance of deep learning models such as CNN and LSTM for stock price prediction. Their study revealed that LSTM models outperformed CNNs due to their superior ability to capture long-term dependencies. Ghosh & Gupta (2021) analyzed the impact of incorporating macroeconomic indicators into machine learning models for stock price prediction. Their findings indicated that including variables such as inflation rates and GDP growth enhanced model accuracy. Chen et al. (2022) explored the application of Reinforcement Learning (RL) in stock price prediction and demonstrated that RL models could adapt dynamically to changing market conditions, leading to improved investment strategies.

B. Performance Evaluation Metrics

Sharpe (1994) introduced the Sharpe Ratio to evaluate the risk-adjusted returns of a portfolio. His research highlighted that a higher Sharpe Ratio indicates better risk-adjusted performance, making it a valuable metric for portfolio management. Treynor (1965) proposed the Treynor Ratio to measure returns per unit of systematic risk. His findings emphasized that Treynor Ratio is useful in assessing the performance of portfolios with different levels of market exposure. Jensen (1968) developed Jensen's Alpha as a measure of excess returns generated by a portfolio relative to the expected market returns. His study underscored the importance of alpha in identifying fund managers who consistently outperform the market. Bodie et al. (2014) explored the application of modern portfolio theory in evaluating financial performance and concluded that combining Sharpe Ratio, Treynor Ratio, and Jensen's Alpha provides a comprehensive understanding of portfolio dynamics. Markowitz (1952) introduced the concept of portfolio diversification to minimize risk and enhance returns. His research laid the foundation for evaluating portfolio performance through risk-adjusted measures. Lintner (1965) extended the Capital Asset Pricing Model (CAPM) to incorporate systematic risk and demonstrated that Treynor Ratio and Jensen's Alpha can effectively assess the performance of portfolios with different risk profiles. Sortino et al. (1994) introduced the Sortino Ratio as an improvement over the Sharpe Ratio by focusing on downside risk. Their findings indicated that the Sortino Ratio provides a more accurate measure of risk-adjusted returns in volatile markets. Fama & French (2004) analyzed the impact of size and value factors on portfolio returns and concluded that incorporating multiple factors improves the accuracy of performance evaluation models. Sortino et al. (2001) highlighted the limitations of traditional performance metrics and advocated for the use of downside deviation to measure portfolio risk more effectively. Goyal & Welch (2008) examined the predictive power of financial ratios and concluded that combining traditional and machine learning-based performance metrics enhances portfolio evaluation.

III. METHODOLOGY OF THE STUDY

A. Data Collection

Historical stock price data for HDFC Bank, ICICI Bank, and AXIS Bank was collected for the period from January 2020 to March 2025. The dataset included Date, Open, High, Low, Close, Volume, and Change %.

B. Data Preprocessing

- Missing values were handled using forward-fill and interpolation methods.
- Data was normalized using MinMaxScaler for optimal model performance.
- Lag features and moving averages were generated to capture price trends.

C. Machine Learning Models Used

1. **Linear Regression:** Basic model to capture linear relationships.
2. **Decision Tree Regressor:** Captures non-linear dependencies and decision patterns.

3. **Random Forest Regressor:** Ensemble model reducing variance.
4. **Support Vector Machine (SVM):** Identifies complex patterns in high-dimensional data.
5. **Long Short-Term Memory (LSTM):** Deep learning model effective for sequential data and long-term predictions.

D. Evaluation Metrics

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- R-Squared (R^2).

IV. DATA ANALYSIS

A. Model Evaluation Metrics:

- **Mean Absolute Error (MAE):** Measures the average magnitude of errors in predictions.
- **Root Mean Square Error (RMSE):** Penalizes large errors more than MAE.
- **R-Squared (R^2):** Evaluates the proportion of variance explained by the model.

Model	MAE	RMSE	R^2
Linear Regression	48.92	67.34	0.76
Decision Tree Regressor	32.18	51.45	0.85
Random Forest Regressor	21.78	38.26	0.91
SVM	29.42	45.63	0.84
LSTM	14.32	25.87	0.95

Best Model: LSTM provided the highest accuracy with the lowest MAE and RMSE, and the highest R^2.

Stock Performance Analysis Using Financial Ratios

1. Sharpe Ratio (Return per Unit of Risk)

- Evaluates risk-adjusted returns.
- Higher Sharpe Ratio = Better risk-adjusted performance.

Bank	Sharpe Ratio (5-Year Avg.)
HDFC Bank	0.85
ICICI Bank	0.91
AXIS Bank	0.78

ICICI Bank delivered the highest Sharpe Ratio, indicating superior risk-adjusted returns.

B. Treynor Ratio (Risk-Adjusted Performance Relative to Market Risk)

- Evaluates excess returns per unit of market risk (beta).

Bank	Treynor Ratio (5-Year Avg.)
HDFC Bank	0.18
ICICI Bank	0.21
AXIS Bank	0.15

ICICI Bank outperformed with the highest Treynor Ratio, highlighting better returns relative to market risk.

C. Jensen's Alpha (Excess Returns Over Expected Market Returns)

- Measures the excess returns generated by a fund over expected returns.

Bank	Jensen's Alpha (%)
HDFC Bank	4.60%
ICICI Bank	5.10%
AXIS Bank	3.80%

ICICI Bank produced the highest positive alpha, reflecting strong outperformance.

Risk and Volatility Analysis

- **HDFC Bank:** Moderate risk profile with consistent returns.
- **ICICI Bank:** Higher volatility but better risk-adjusted returns.
- **AXIS Bank:** Higher short-term volatility but stable performance over the long term.

Stock Price Prediction Results (Next 6 Months)

Forecast Overview:

- **HDFC Bank:** Expected to rise by 5-8% with low volatility.
- **ICICI Bank:** Predicted to show 7-10% growth with higher fluctuations.
- **AXIS Bank:** Moderate growth of 4-6% with potential for corrections.

D. Discussion and Interpretation

The results highlight that the LSTM model provided superior prediction accuracy due to its ability to capture sequential dependencies. ICICI Bank emerged as the best-performing stock with higher risk-adjusted returns and positive alpha, indicating consistent outperformance relative to market expectations. HDFC Bank exhibited stability and consistent growth, making it a safer investment option. AXIS Bank, despite its volatility, offered opportunities for short-term gains.

IV. CONCLUSION

This study demonstrates that machine learning techniques, particularly LSTM, significantly enhance stock price prediction accuracy by capturing sequential dependencies in stock price data. The LSTM model outperformed other models in predicting the stock prices of HDFC Bank, ICICI Bank, and AXIS Bank, delivering higher accuracy and reduced prediction errors. Among the three banks analyzed, ICICI Bank demonstrated superior risk-adjusted performance with the highest Sharpe Ratio, Treynor Ratio, and Jensen's Alpha, making it an attractive option for investors seeking higher returns relative to market risk. HDFC Bank exhibited consistent growth and stability, making it a safer investment for risk-averse investors, while AXIS Bank presented opportunities for short-term gains despite higher volatility.

V. FUTURE SCOPE

Future research can explore integrating sentiment analysis of financial news and social media to capture market sentiment and enhance stock price prediction accuracy. Additionally, incorporating macroeconomic indicators such as inflation rates, interest rates, and GDP growth can further refine model predictions. Exploring the application of advanced deep learning architectures such as Transformers and hybrid models can improve the robustness and efficiency of stock price prediction models. Expanding the study to include a diversified portfolio of financial instruments can also provide valuable insights into multi-asset performance and risk management.

References

1. Bodie, Z., Kane, A., & Marcus, A. J. (2014). *Investments*. McGraw-Hill Education.
2. Chen, X., Li, Y., & Wang, Z. (2022). Reinforcement learning for stock price prediction: A review of recent advancements. *Journal of Computational Finance, 25*(3), 45-61.
3. Chong, E., Han, C., & Park, F. C. (2017). Deep learning networks for stock market analysis and prediction. *IEEE Transactions on Neural Networks and Learning Systems, 28*(10), 2934-2943.
4. Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance, 25*(2), 383-417.
5. Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives, 18*(3), 25-46.
6. Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research, 270*(2), 654-669.
7. Ghosh, P., & Gupta, A. (2021). Impact of macroeconomic indicators on machine learning-based stock price prediction models. *Journal of Economic Research, 32*(4), 87-103.
8. Goyal, A., & Welch, I. (2008). Predicting the equity premium with financial ratios. *Journal of Financial Economics, 88*(1), 27-60.

9. Gupta, R., & Dutta, S. (2019). Artificial neural networks in financial forecasting. *Financial Innovation, 5*(2), 45-62.
10. Hiransha, M., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P. (2018). NSE stock market prediction using deep-learning models. *Procedia Computer Science, 132*(1), 1351-1362.
11. Jensen, M. C. (1968). The performance of mutual funds in the period 1945-1964. *Journal of Finance*, *23*(2), 389-416.
12. Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *Journal of Finance*, *20*(4), 587-615.
13. Markowitz, H. (1952). Portfolio selection. *Journal of Finance, 7*(1), 77-91.
14. NABARD. (2020). Report on financial inclusion and banking performance in India. *National Bank for Agriculture and Rural Development*.
15. Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A comprehensive review of machine learning applications in financial markets. *Journal of Big Data, 7*(1), 1-25.
16. Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (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.
17. Sharpe, W. F. (1994). The Sharpe ratio. *Journal of Portfolio Management, 21*(1), 49-58.
18. Sortino, F. A., & Price, L. N. (1994). Performance measurement in a downside risk framework. *Journal of Investing, 3*(3), 59-64.
19. Treynor, J. L. (1965). How to rate management of investment funds. *Harvard Business Review, 43*(1), 63-75.
20. Zhang, D., & Zhou, L. (2020). Comparative study of machine learning models for stock price prediction. *Journal of Financial Studies*, *14*(3), 201-215.