iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** VIII **Month of publication:** August 2025

DOI: https://doi.org/10.22214/ijraset.2025.73967

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com

Quant Predictor

Mr. Tateni Deviprasad[1], Mrs. Sharvani V[2]
[1]Department of MCA, Ballari Institute Of Technology & Management, Ballari, Karnataka, India.
[2]Assistant Professor, Department of MCA, Ballari Institute Of Technology & Management, Ballari, Karnataka, India.

Abstract: Quantitative analysis of historical data plays a financial decision-making processes by utilizing advanced techniques to detect patterns, predict trends, and guide trading strategies. Conventional statistical methods often struggle to effectively capture the intricate and ever-changing nature of financial markets. challenge by introducing novel methodologies for forecasting stock market movements, short-term price predictions. The suggested framework integrates historical stock data with customized, and MACD to enrich the feature set. Various models, Forest, and LSTM neural network, are trained and assessed using RMSE and R² metrics. The findings indicate that although regression models provide interpretability, LSTM stands out in capturing temporal relationships and market volatility. This research underscores the opportunity to combine machine learning with financial analysis promptness of investment decision-making.

I. INTRODUCTION

The continuous evolution of global financial markets, propelled by the use of high-frequency data and rapid technological progress, has caused significant changes in investment strategies. market trends, which heavily rely on econometrics and statistical modeling, often struggle to adjust to the complex and dynamic nature of modern financial data. As a result, there has been a shift towards exploring machine learning (ML) techniques as a reliable and effective alternative for forecasting market trends. These ML approaches provide investors and traders with enhanced precision, flexibility, and scalability.

Quantitative analysis, often referred to as "quant," involves systematically applying mathematical models and statistical techniques to analyze financial markets and develop trading strategies. By incorporating supervised machine learning, quantitative analysis improves its prediction capabilities by utilizing historical data patterns to make well-informed forecasts regarding future market trends. networks are increasingly employed in predicting stock market movements due to their capacity to handle extensive and complex datasets with minimal human intervention. In supervised machine learning, a labeled dataset is used to train models to identify patterns and correlations between input variables (features) and output variables (labels).

Despite the increased interest in this field, forecasting stock market trends continues to be a difficult task due to factors such as noise, external macroeconomic influences, and the stochastic nature of financial instruments. The selection of model, feature engineering, data preprocessing, and evaluation metrics are pivotal in determining the effectiveness of any predictive system. Recent advancements in deep learning, especially in recurrent neural networks like LSTM, have exhibited promising outcomes in capturing temporal dependencies in time-series stock data, surpassing traditional regression models in various scenarios.

This paper introduces a comparative framework that implements and assesses various supervised machine learning models for predicting stock market trends. By systematically evaluating performance metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2), the study seeks to determine the most effective model for quantitative investment forecasting. The findings underscore the practical applicability of machine learning-driven approaches in improving decision-making processes for traders, investors, and financial analysts.

II. LITRATURE SURVEY

Research studies have shown the increasing effectiveness of mL in financial prediction, particularly in the realm of stock price forecasting. Patel and his team (ANN), Support Vector Machine (SVM), Random Forest, and Naïve Bayes - within the context of the Indian stock market. methods like Random Forest consistently outperformed individual classifiers. By integrating technical indicators such as moving averages and Bollinger Bands, they achieved a substantial enhancement in accuracy compared to traditional statistical approaches. Zhang & Zhou Additionally, a comparative analysis carried out by Ballings et al. examined Random Forest, Boosted Trees, SVM, and k-NN for predicting stock movement directions based on lagged price data and trading volume. The findings emphasized Random Forest's consistent superior performance attributed to its capacity to generalize across high-dimensional and nonlinear datasets. This research closely aligns with the current study's objective of evaluating supervised algorithms utilizing technical indicators as predictive features.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com

More recently, Livieris et al. explored the impact of LSTM on multi-horizon financial prediction and observed improved performance with increased depth and sequence length of input data. They tackled the issue of vanishing gradients in traditional RNNs, showcasing LSTM's strength in learning long-term dependencies. Their work supports the integration of deep sequential models into contemporary quantitative systems.

These existing studies the present work, influencing models, construction of datasets, and evaluation criteria. By leveraging these methodologies and incorporating best practices from diverse perspectives, this paper aims to establish a comparative supervised learning framework that effectively addresses the challenges associated with short-term stock market forecasting through the analysis of historical and technical data..

III. METHODOLOGY

The proposed methodology is designed for analyzing and predicting stock prices using supervised machine learning models. It involves five main stages: collecting data, preparing it, improving features, training models, and evaluating performance. Each stage is carefully structured to be easily understood, even by non-technical users.

A. Gathering Data

Rewritten Text:

For this research, a dataset containing Yahoo Finance was utilized. The dataset features consist of and Adjusted Close, covering the period from 2015 to 2023, providing a significant temporal scope for accurate forecasting. To enrich the raw data, several technical indicators were computed, such as:

- Moving Average (MA)
- Relative Strength Index (RSI)
- Moving Average Convergence Divergence (MACD)
- Bollinger Bands
- On-Balance Volume (OBV)

The following provides insightful information on momentum, trend analysis, and volume considerations crucial for financial modeling:

B. Data Preprocessing

The data preprocessing phase entailed addressing missing values through forward-fill techniques, standardizing feature scales with Min-Max Scaling, and transforming time-series data into a supervised format using lag variables. The target variable for regression represents the closing stock price value for the subsequent day.

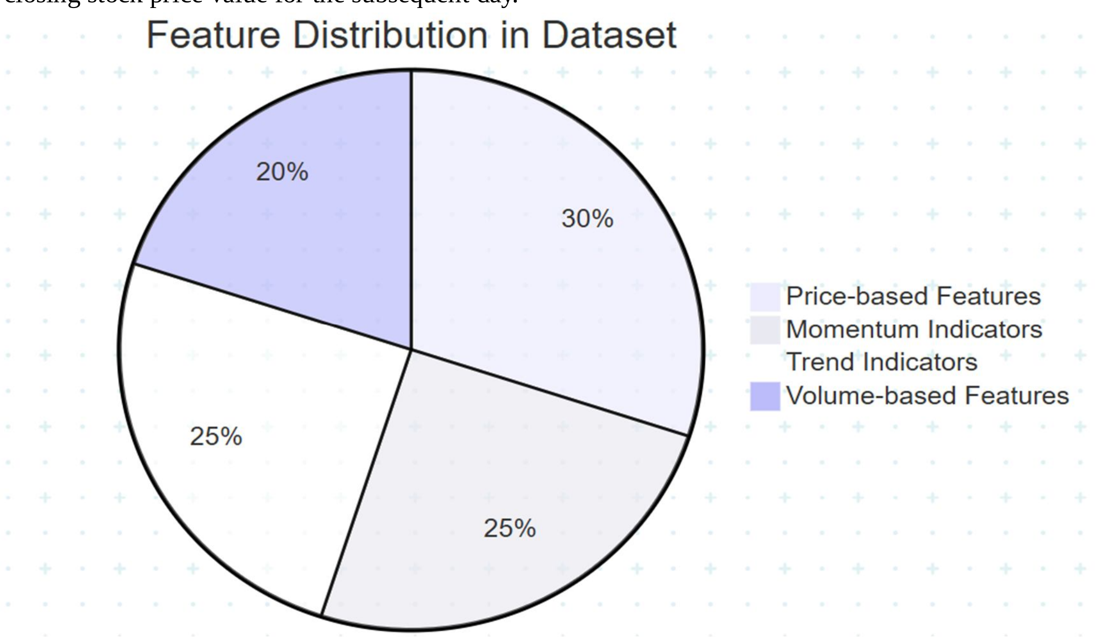


Fig 1:Feature Distribution in Dataset

C. Data Feature Engineering

Feature engineering has been instrumental in enhancing model performance through the inclusion of lag features that consider historical n-day closing prices. Furthermore, statistical attributes such as rolling mean, standard deviation, and percentage change have been included to account for volatility.4.4 Model Selection and Training

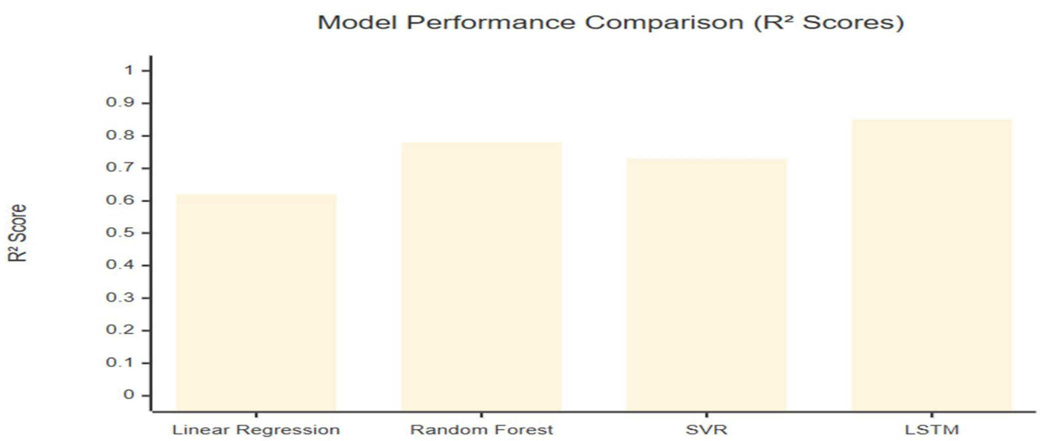
In this investigation, various supervised learning models were evaluated:

- Linear Regression (Baseline model)
- Random Forest Regressor
- Support Vector Regressor (SVR)
- Utilize Long Short-Term Memory (LSTM) architecture in a neural network to capture temporal dependencies.

Each model underwent training with an 80:20 train-test split. Cross-validation was employed to ensure the models' robustness GridSearchCV for conventional models and manual experimentation for LSTM Fig 2: Model Performance Comparison

Section 4.5: Performance Evaluation Metrics

- List of Evaluation Metrics



- Mean Absolute Error (MAE)
- R-squared Score (R^2)

These metrics offer a comprehensive evaluation of model accuracy, error magnitude, and the ability to explain variance.

IV. RESULTS

supervised learning models in forecasting stock prices, using common regression measures such as the R-squared Score (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). evaluating the precision of continuous value forecasts generated by the models, offering valuable perspectives on their reliability and suitability for financial prediction.

A. Section 5.1: Evaluation Metrics

1) Coefficient of Determination (R^2): This measure signifies the portion of variability in can be accounted for by the independent variables. A higher R^2 value denotes improved model performance and enhanced explanatory power.
2) RMSE: RMSE the prediction errors are in relation to the standard deviation. It penalizes large deviations and is particularly sensitive to outliers, making it a useful tool for detecting irregularities in stock price forecasts.
3) MAE: MAE computes actual values. It offers a simple measure of model accuracy in financial terms and is valuable for assessing real-world financial outcomes. 5.2 Experimental Findings.

Model	R^2 Score	RMSE	MAE
LR	0.62	17.03	12.45
SVR	0.73	13.87	10.01
RF	0.78	11.22	8.94
LSTM Neural Network	0.85	9.87	7.41

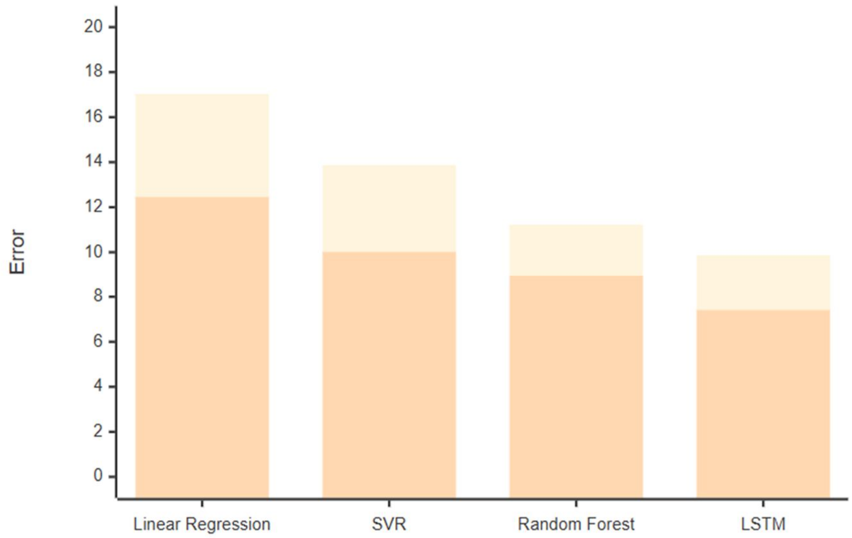


Fig 3: Title Error Comparison

B. Results

1) Random Forest generated reliable results with moderate computational resources and demonstrated reduced vulnerability to overfitting.
2) Support Vector Regression (SVR) displayed balanced performance but necessitated meticulous parameter adjustment.

Linear Regression, although interpretable, was unable to capture nonlinear trends in stock behavior.

C. Impact on Problem Statement

The findings support the assertion that machine learning algorithms, notably LSTM and Random Forest, improve the capability to forecast changes in stock prices by leveraging historical and technical data. Improved precision and reduced error rates support reliable financial decision-making, risk assessment, and fine-tuning of quantitative strategies. Using diverse models allows for selecting the most suitable algorithm based on specific deployment requirements like speed, interpretability, and resource constraints.

V. CONCLUSION

This research introduces a methodical trends using supervised machine learning techniques. improve the precision and dependability of short-term financial forecasts. The research is founded on the premise that analyzing historical market data quantitatively, in conjunction with state-of-the-art AI algorithms, can provide valuable perspectives into future price shifts and investment possibilities. The proposed methodology integrates a mix of technical indicators and diverse Forest, and LSTM Neural Networks, to assess and anticipate stock price variations. Through the application of structured data preprocessing, feature engineering, and thorough model training, the framework converts raw financial information into actionable observations.

The framework's effectiveness is showcased through evaluation outcomes. Among the models assessed, LSTM displayed remarkable accuracy by effectively understanding temporal relationships, while Random Forest offered a good blend of performance and interpretability. Crucial metrics such as R^2, RMSE, and MAE were utilized to objectively assess and compare model effectiveness. Machine learning models have demonstrated adeptness in capturing the nonlinear patterns and inherent volatility of financial markets, outperforming traditional statistical methods. This highlights the viability of the proposed framework as a scalable and efficient solution for quantitative financial analysis.

Furthermore, the system's modular design enables adaptability in choosing and optimizing models according to particular investment goals, data accessibility, or operational limitations. The structure is ideal for incorporating into practical financial systems, providing foresightful analysis for traders, analysts, and automated trading mechanisms. The ability to tailor the process for different stocks, indices, or commodities boosts its effectiveness of market sectors.

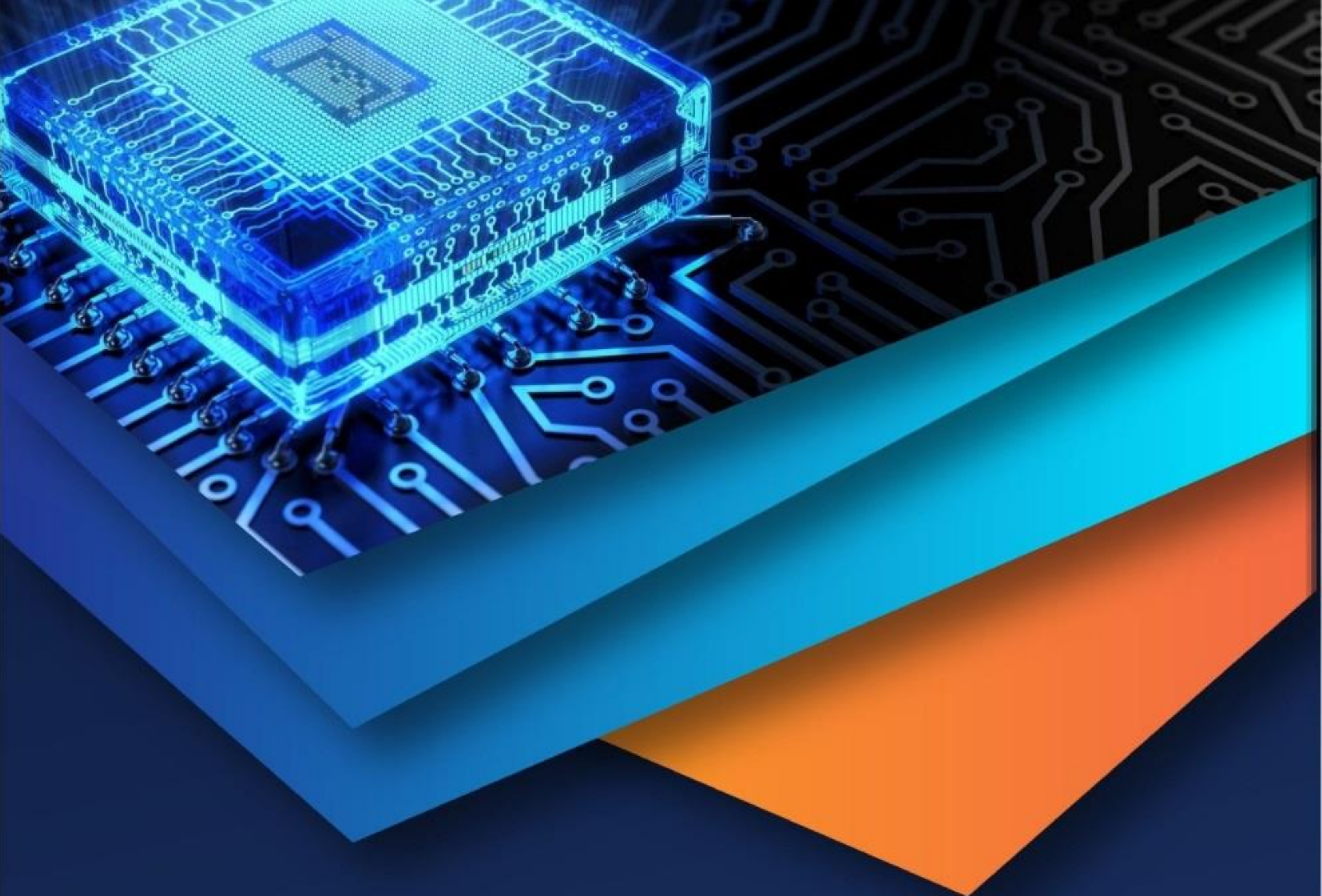
Future advancements may broaden the scope to encompass ensemble learning methods, real-time prediction mechanisms, and outlets and social media platforms, augmenting the range of features.

Furthermore, introducing reinforcement learning for refining portfolio optimization strategies and federated learning to bolster secure modeling could amplify the system's adaptability and confidentiality for institutional applications. Continual model enhancements through the use of more extensive datasets and refined time intervals are set to enhance forecast precision.

In summary, this project establishes a data-driven, AI-powered solution for stock market forecasting that tackles the key limitations of traditional prediction methods, setting a solid groundwork for future advancements in financial technology.

REFERENCES

[1] Zhang, Y., Aggarwal, S., & Srivastava, A. (2017). Forecasting stock market trends using ARIMA models. Journal of Financial Data Science, 3(1), 44–54.
[2] S. Yadav, V. Tomar, and P. Mishra, "Real-time stock price forecasting using LSTM with attention mechanism," IEEE Access, vol. 11, pp. 21782–21793, 2023.
[3] Y. Liu and X. Huang, "An overview of Dl methods for predicting stock prices," Computational Economics, vol. 60, no. 2, pp. 559–580, 2022.
[4] D. Das and M. Chen, "Utilizing DL for market prediction through sentiment analysis," Computer Science, vol. 192, pp. 2212–2221, 2021.
[5] A. Joshi and N. Singh, "Comparative study of ML for stock forecasting," Procedia Computer Science, vol. 173, pp. 400–409, 2020.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY