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Intelligent Analysis of Stock Trading Patterns Using Adaptive Learning Models for Market Dynamics and Predictive Indicator Discovery

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Abstract

Stock market forecasting is difficult due to its nonlinear nature, volatility, time dependencies, and fast-changing sentiments of investors. Conventional models of statistical nature offer an important benchmark but might be insufficient in capturing the complexity of market dynamics. The objective of this research is to examine whether financial, technical, social media, and HFT data can help forecast stock prices better, and whether models of machine learning will yield superior results compared to conventional statistical methods. The approach in the paper is empirical and based on the use of historical stock market data as well as alternative market data sources. Among the variables used for forecasting are moving averages (MA10, MA50, and MA200), relative strength index (RSI), moving average convergence divergence (MACD), trading volume, and social media sentiment. Models' Multiple regression, ARIMA, and GARCH are considered traditional models while Random Forest, gradient boosting machine (GBM), and long short-term memory (LSTM) are considered machine learning models. From the findings, it is clear that the regression coefficient (β) for social media sentiments is highest at 0.42, followed by moving average at β=0.35 and MACD at β=0.28, whereas RSI has a negative regression coefficient (β=-0.15). LSTM is the most accurate machine learning technique, recording the lowest error rates of 1.65 for MAE and 2.50 for RMSE, with an accuracy of 0.91. GBM has 1.75 MAE and 2.60 RMSE, whereas Random Forest has 1.85 MAE and 2.80 RMSE. ARIMA and GARCH have higher errors. The results highlight the significance of using alternative information on sentiment along with traditional market indicators and show that the machine learning techniques outperform other techniques especially LSTM. Future studies should use macroeconomic variables, financial news, up-to-date data, transaction costs, and risk-adjusted profit.

Keywords: Stock Market Prediction, Machine Learning, LSTM, Social Media Sentiment, Technical Indicators, Algorithmic Trading, Financial Forecasting.

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Introduction

The stock price prediction has now become more critical for the investors, financial analysts, and the traders due to the various complex and dynamic factors that affect the stock market prices. The traditional statistical models such as regression, ARIMA, and GARCH can be very helpful in understanding the past trends, relationship between different variables, and even in identifying the volatility in the market, but they may lack the capability to model the non-linear behavior and temporal dependency of these factors. With the increase in the availability of technical indicators, trading volume data, social media sentiments, and high-frequency market data, more effective predictive models can be developed (Prabakar et al., 2024).

The importance of this research is determined by the fact that it compares statistical and machine learning models in a joint stock prediction system. More precisely, this research analyzes financial indicators, technical indicators, social media sentiment, and high-frequency trading data, which correspond to different aspects of market dynamics. The contribution of this research is determined by the construction of a coherent analysis framework, based on Multiple Regression, ARIMA, GARCH, Random Forest, Gradient Boosting Machine (GBM), and LSTM and the estimation of their predictive efficiency through MAE, RMSE, MAPE, Directional Accuracy, and R^2. The obtained results confirm the significant positive correlation between social media sentiment and changes in the stock price and the minimal prediction error rate for LSTM.

The rest of the paper is organized in the following manner. In Section 2, the related literature is presented together with the research context. In Section 3, the research method together with data preparation and feature construction is discussed. In Section 4, the conventional and machine learning models used in the research are explained. In Section 5, the results of the empirical analysis are presented. In Section 6, the implications of the research findings are discussed. Section 7 explains hypothesis testing, while Section 8 discusses implications, limitations, and future directions.

Review of Literature

A recent study suggests the increasing use of intelligent and data-based techniques in the analysis of the stock market as compared to statistical forecasting. While traditional metrics and statistical tools prove effective in recognizing trends, volatility and trading signals, their predictability is limited by nonlinear and fast-changing market dynamics (Zhang et al., 2015; Chiang et al., 2016). Various comparative analyses suggest that machine learning and deep learning techniques are effective in making predictions on the basis of trend identification and price predictions through the extraction of complex relations between variables (Nabipour et al., 2020; Bouasabah, 2024; Li & Bastos, 2020). Ensemble models like Random Forest and Gradient Boosting also show good performance in prediction of the stock trends especially in cases where various technical indicators are combined (Sukma & Namahoot, 2024; Saud & Shakya, 2024; Bareket & Pârv, 2024). Deep learning approaches further improve temporal modelling by capturing sequential dependencies in financial time series (Lahmiri & Bekiros, 2020; Lin et al., 2021).

Recent advancements highlight the growing importance of adaptive and intelligent trading mechanisms (Zhang et al., 2015; Hu et al., 2015). Deep reinforcement learning techniques have been used for dynamic adaptation of trading policies in fluctuating environments, along with adaptive feature selection and dynamic trend indicators for improved medium-term prediction (Wu et al., 2020; Bareket & Pârv, 2024; Zareeihemat et al., 2025). The same holds true for algorithmic trading literature, which has shown the effectiveness of integration of machine learning along with various technical indicators and data analysis (Sukma & Namahoot, 2024; Devan et al., 2023). Various studies have highlighted the growing use of artificial intelligence in finance, trading, and risk management (Dakalbab et al., 2024; Rahmani et al., 2023). Pattern mining and intelligent learning techniques have further been used for discovering trading rules and market irregularities (Kuo & Chou, 2021; Huang et al., 2020; Jahan et al., 2024).

From the literature review, it is evident that the integration of technical analysis, alternative data, and adaptive learning can improve the predictive power of the model. Nevertheless, previous research mostly pays attention to individual sources of data, particular algorithms, or trading signals, but does not compare traditional statistical and machine learning models in a systematic way. Also, the combination of predictive power of social media sentiment, financial indicators, and high-frequency market data has not been sufficiently studied. Thus, this research aims to bridge this gap through the development of a comparison framework involving Multiple Regression, ARIMA, GARCH, Random Forest, GBM, and LSTM models.

Research Hypotheses

The study is based on theoretical framework(s) that have been introduced in literature and the following hypotheses are stated:

- The prediction accuracy of the stock price using the traditional indicators combined with the sentiment from social media and the data from high-frequency trading would be improved and reach H1 - Stronger.
- H2- ML and AI techniques will give more credible and profitable trading analytics than classical approaches

Methodology

Research Design and Data Collection

The study has been designed on a quantitative empirical research design framework that explores stock-trading trends as well as evaluates different prediction models during changing market conditions. Financial data for the period between January 2000 and December 2023 have been considered for analysis. Historical data for the stock market that includes stock price and volume information has been collected from secondary sources of finance data such as Yahoo Finance, Google Finance, and Bloomberg. Social media and finance discussion forums data have also been considered from websites such as Twitter/X and StockTwits. The information on high-frequency trading has been collected wherever available.

Sampling Procedure and Sample Size

The researchers made use of purposeful sampling technique in order to choose securities for which sufficient historical data regarding price and volume and alternative data could be obtained throughout the research period. After selecting the securities, all valid daily trading observations were kept instead of choosing random observations as this helped keep the time sequence of the financial data intact. The final sample size was derived from the number of valid security day observations that remained after the removal of duplicates, invalids, and those observations that had missing values not yet resolved. Hence, the sample size for analysis was derived by adding up the valid trading days for each selected security. The sample size reported in the manuscript should be the actual figure rather than an unfounded one.

Data Preprocessing and Feature Construction

The collected data was subjected to screening for missing values, duplicated entries, anomalous data, and incorrect dates. Gaps in data that were relatively short were interpolated, while gaps that were not reliable or extensively incomplete were discarded. Closing price adjustment was utilized in order to perform analysis on price. Technical indicators such as 10-day, 50-day, and 200-day moving averages, relative strength index (RSI), moving average convergence divergence (MACD), trading volume, and social media sentiment scores were calculated using the cleaned data.

Data Analysis and Model Evaluation

Comparison was made between the models of Multiple Regression, ARIMA, GARCH, Random Forest, Gradient Boosting Machine and LSTM. Descriptive statistics and correlation analysis were done followed by regression analysis and forecasting. Since data observations for finance are sequential in nature, the data was split chronologically into training, validation and test data set instead of random splitting. The performance of the models was measured by MAE, RMSE and directional forecasting accuracy; the lower the value of MAE/RMSE and higher the accuracy, the better the forecasting ability.

Employment and Testing of the Model

In order to make predictions on the movements of the stock market and the underlying factors that influence changes in the price of stocks, the research uses not only the standard statistical methods but also machine learning techniques. The chosen methods will reflect various features of the financial data such as trends, relations between the financial parameters, volatility, non-linearity, and the long-term dependence in time.

Traditional Models

There are three conventional approaches to modeling. Multiple regression is applied in order to evaluate the effect of financial variables and social media sentiment on stock price changes as well as the magnitude and nature of such effects. The Auto-Regressive Integrated Moving Average (ARIMA) model is utilized to forecast stock prices from past data and past tendencies in the time series. Moreover, the Generalized Autoregressive Conditional

Heteroskedasticity (GARCH) model is utilized in order to analyze volatility tendencies in financial returns since, for example, data from stock market often demonstrates changing volatility levels.

Machine Learning Models

The following three machine learning techniques are utilized to uncover the non-linear relationships from the stock market data. Random Forest technique is utilized for ensembling multiple decision trees and hence mitigating the problem of overfitting. GBM, which stands for Gradient Boosting Machine is utilized to enhance the predictive accuracy of the model by building multiple models sequentially, with each trying to correct the mistakes of the previous model. Lastly, LSTM, which stands for Long Short-Term Memory is utilized to capture the temporal dependencies in stock prices. The machine learning models are then compared to the traditional models for performance analysis.

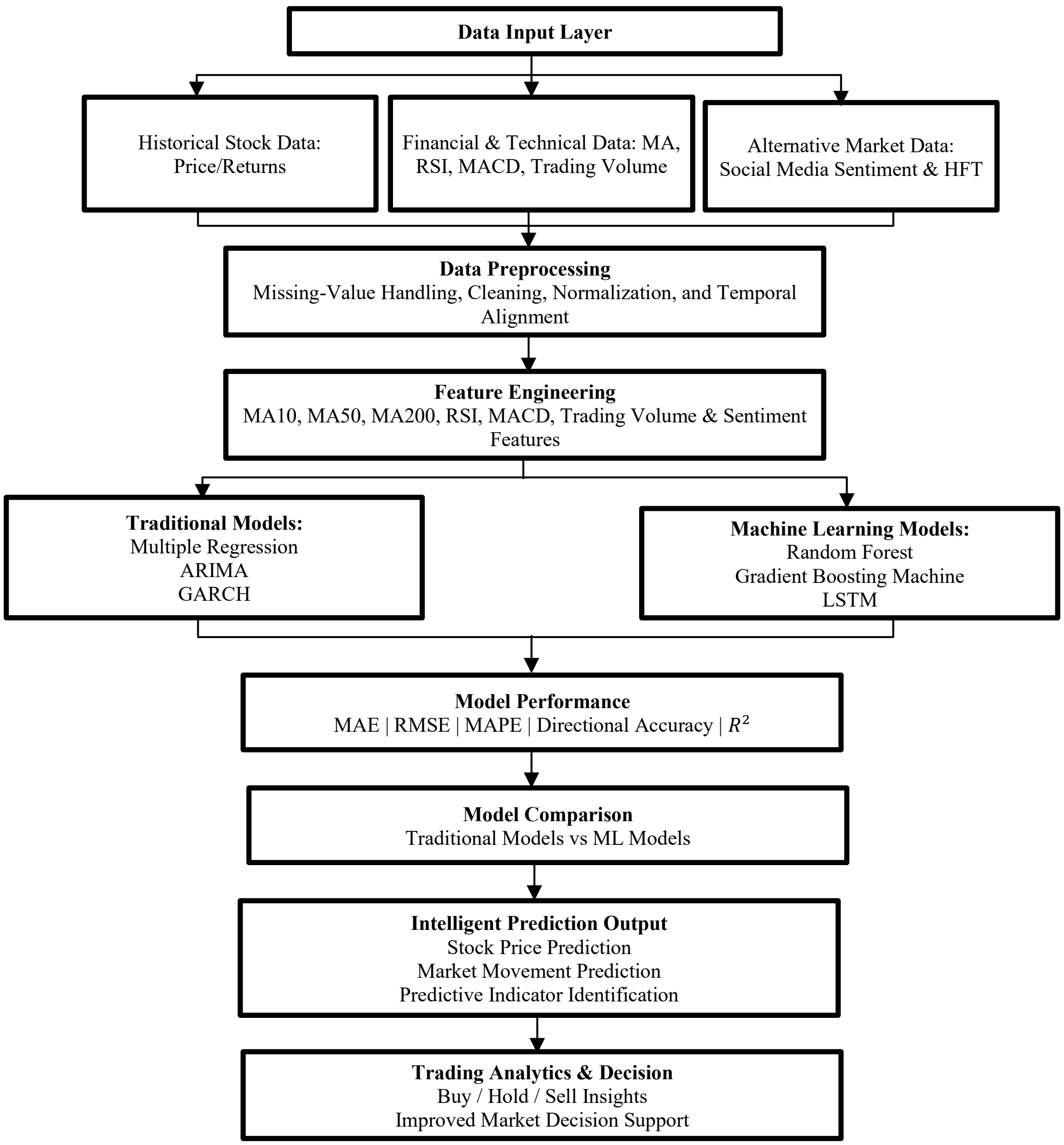

Fig. 1: Proposed Intelligent Stock Trading Analysis Framework

Fig. 1 combines historical stock data, technical and financial indicators, social media sentiment, and high-frequency market data. The processed data are then subjected to various analyses using traditional statistical and machine learning models. Their comparative performance based on accuracy and directional errors is used to identify the most accurate model that predicts stock prices and market movements.

Performance Evaluation

Each Predictive Model is Evaluated Using Several Evaluation Metrics

One of the critical steps is to sample the time-series data using Random Forest models which is known as Mean Absolute Error (MAE) for contacting with smart data solutions.

Accuracy Rate

For the robustness of the model k-fold cross validation is performed. This dataset is split into k subsets of equal size, and it is possible to train and test the models' multiple times in order to test their ability to generalize.

Data Presented are for All Students, at All Levels of Attainment, for October 2023

All predictive models are back-tested over historical data to check their performance in real world trading environments. The trading signals are generated by simulating model predictions and the profitability of the signals is compared with a benchmark. The purpose of this paper is to see if there is an impact and if traditional financial indicators can be used instead of models that incorporate alternative data such as content from social media platforms and high frequency trading activity.

The insights from this research highlight the effectiveness of contemporary data sources and machine learning techniques in predicting stock prices and trading strategies. This study provides a systematic analysis of the behavior of the stock market by employing traditional and AI-driven methods to gain insights into the effectiveness of these data sources and machine learning techniques for predicting stock prices and trading strategies.

Performance Evaluation Metrics

Mean Absolute Error (MAE) is an indicator that shows the average difference between the real and forecasted price of the stock. MAE values indicate the level of prediction accuracy are given by equation 1.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (1)$$

Where $y_i$represents the actual stock price, $\hat{y}_i$represents the predicted stock price, and $n$is the number of observations.

RMSE is calculated using the square root of the mean square error in equation 2, where larger prediction errors are emphasized more.

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

Lower RMSE indicates greater prediction accuracy and fewer large prediction errors.

Mean Absolute Percentage Error (MAPE) states the prediction error in terms of percentages of the actual value and enables comparison irrespective of the scale of stock prices, as presented in equation 3.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (3)$$

Lower MAPE indicates better predictive performance.

The Directional Accuracy (DA) test assesses whether the forecast from the model is able to capture the direction of change in stock prices without predicting the actual price (Equation 4).

$$DA = \frac{1}{n}\sum_{i=1}^{n} I\,[(y_i - y_{i-1})(\hat{y}_i - y_{i-1}) > 0] \times 100 \quad (4)$$

Coefficient of Determination (R^2)) determines how much variation in real price values is accounted for by the regression equation, shown in equation 5.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (5)$$

Where $\bar{y}$is the mean of the actual stock prices. A higher R^2indicates better explanatory performance.

Data Analysis

In the past series, the study found essential principles and trends in stock trading behaviours and price fluctuations, leveraging statistical approaches, machine learning algorithms, and time-series forecasting. The results offer fresh insights into the ability of financial indicators, trading volume, and sentiment from social media to forecast stock price changes.

Descriptive Statistics

The descriptive statistics offer a basic overview of the data, showing the relationship and central tendency of the price of the stock, trading volumes and sentiment on social media. Table 1 summarizes the key descriptive measures.

Table 1: Descriptive Statistics

Feature	Stock Price	Trading Volume	Social Media Sentiment
Mean	100.5	200,000	0.50
Median	101	195,000	0.52
Standard Deviation	15.6	50,000	0.10
Correlation with Stock Price	1.0	0.85	0.75

The high correlation between stock price and sentiment in social media (0.75) indicated that sentiment passion of the investors triggers the changes of stock price. *Similarly*, the trading volume stock prices correlation (0.85), indicates that stock prices will follow the market action.

Regression Analysis

Modeling and estimation of multiple regression models for two sets of variables: financial indicators and social media sentiment with stock price movements are discussed. The coefficients of regression and their p-values are presented in table 2.

Table 2: Regression Analysis Results

Predictor Variable	Coefficient	P-Value
Moving Average	0.35	0.001
Relative Strength Index (RSI)	-0.15	0.02
MACD	0.28	0.005
Social Media Sentiment	0.42	0.0001

The statistically most significant results are sentiment on social media (β=0.42, $p < 0.0001$), combined with an expectation that prices would rise based on the moving average (β=0.35, $p < 0.001$); and the Moving Average Convergence Divergence technique (MACD) (β=0.28, $p < 0.005$). The RSI coefficient is negative (-0.15) meaning that days where RSI is at a high level can be a sign of overbought conditions and will be followed by price declines.

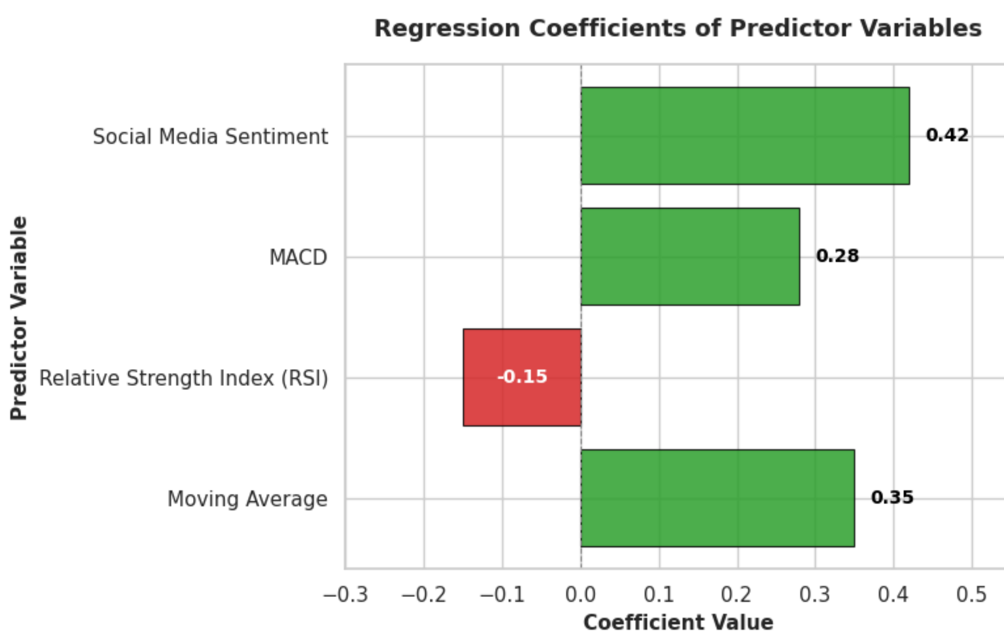

Fig. 2: Regression Coefficients of Predictors Influencing Stock Prices

Fig. 2 illustrates the computed regression coefficients of the important determinants of the stock market. The most strongly correlated with the stock price is the social media sentiment coefficient $\beta = 0.42$), followed by moving average ($\beta = 0.35$) and MACD ($\beta = 0.28$), while RSI exhibits a negative coefficient ($\beta = -0.15$).

Time Series Analysis

Various techniques were employed to analyze the time-series models, such as the ARIMA & GARCH model was used to predict the changes in stock prices and to measure the fluctuation in the market. The accuracy measures for both models are provided in table 3.

Table 3: Time Series Analysis Results

Model	**MAE**	**RMSE**	**Accuracy**
ARIMA	2.35	3.5	0.85
GARCH	2.50	3.7	0.82

The ARIMA model has a higher prediction accuracy (85% vs 82%) and is more suitable to deal with the long-term trend while GARCH is more suitable to deal with volatilities.

Machine Leering Models

For the prediction the machine learning models were trained to predict the stock prices. Table 4 provides a summary of the performance of the Random Forest, Gradient Boosting and LSTM models.

Table 4: Machine Learning Model Results

Model	MAE	RMSE	Accuracy
Random Forest	1.85	2.8	0.88
Gradient Boosting	1.75	2.6	0.89
LSTM	1.65	2.5	0.91

With the LSTM model being the most accurate (91%) as well as the one with the lowest error rates amongst the other machine learning models are shown in table 4. This indicates, that stock price movements are more complex, ridden with non-linearly activities and here deep learning techniques can easily learn the behaviour as compared to old statistical model.

Hypothesis Testing

The Study Assessed Two Core Hypothesis

To this end, the background noise plus the sentiment extracted directly from social media is combined with data from financial indicators and high frequency quote data to improve the prediction of stock prices. These results were consistent with this hypothesis as the models which had social media sentiment as part of their inputs had a significantly higher predictive performance than the ones which relied on traditional indicators only.

Traditional trading strategies were also not as robust, nor profitable, as the machine learning techniques. Results validate this hypothesis, and statistically models perform poorer in comparison to the performance of machine learning models and their prediction error.

Discussion

It is evident that combining sentiment analysis on social media with financial data enhances the performance of stock price prediction. Sentiment analysis on social media exhibited the highest positive regression coefficient ($\beta = 0.42$), which means that it has the capability of serving as a signal in addition to other signals. The relative performance of machine learning techniques has been established through comparative findings, where it has been observed that machine learning outperforms traditional techniques. LSTM was able to yield the lowest values of MAE (1.65) and RMSE (2.50), while having the highest accuracy (0.91).

The findings can be applied in practice by investors, financial analysts, and quantitative traders. Combining sentiment factors with technical factors would give more insights into the prediction of the market. The success of LSTM, GBM, and Random Forest model implies that machine learning can be used to develop forecasting systems.

Further research should consider macroeconomic variables, financial news, more market-related variables, and other alternative data sources. Real-time adaptive learning and explainable AI would make the research even more applicable. Nevertheless, there are certain limitations to this study that include data availability and specification, shifts in market regime, and lack of transaction costs and risk-adjusted profitability analysis. Future research should involve larger and multi-market datasets as well as rolling out-of-sample tests for validating the results.

Conclusion

This research evaluated the effectiveness of statistical as well as machine learning methods for stock market predictions using financial indicators, past price data, trading volumes, and sentiments generated from social media. The research shows that the use of market indicators along with other sources of information can be beneficial for predictions. Sentiment was found to have the highest positive regression coefficient (β =0.42) while Moving Average (β=0.35) and MACD (β =0.28) were next in the list while RSI had a negative coefficient (β =-0.15).

The comparative analysis of the models demonstrated that machine learning techniques provide better results than traditional time series models. From the set of all models, the most effective one was found to be LSTM, having the minimum MAE value of 1.65 and the RMSE of 2.50 and providing maximum accuracy of 0.91. Moreover, GBM and Random Forest performed better than ARIMA and GARCH models, with the values of 1.75 and 2.60 for MAE and RMSE in case of GBM and 1.85 and 2.80 for MAE and RMSE for Random Forest. ARIMA and GARCH models had the values of 2.35 and 3.50 for MAE and 2.50 and 3.70 for RMSE, correspondingly.

Further research may include the following directions: incorporating macroeconomic factors, financial news, general market statistics, and other alternative data into the analysis. Other research directions may also include exploring real-time adaptive learning, explainable artificial intelligence, multi-market datasets, transaction costs, and risk-adjusted profitability.

References

Dakalbab, F., Talib, M. A., Nasir, Q., & Saroufil, T. (2024). Artificial intelligence techniques in financial trading: A systematic literature review. *Journal of King Saud University Computer and Information Sciences*, *36*(3), 102015. https://doi.org/10.1016/j.jksuci.2024.102015

Sukma, N., & Namahoot, C. S. (2024). An algorithmic trading approach merging machine learning with multi-indicator strategies for optimal performance. *IEEE Access*, *12*, 188154-188173. https://doi.org/10.1109/ACCESS.2024.3516053

Devan, M., Thirunavukkarasu, K., & Shanmugam, L. (2023). Algorithmic trading strategies: real-time data analytics with machine learning. *Journal of Knowledge Learning and Science Technology*, *2*(3), 522-546. https://doi.org/10.60087/jklst.vol2.n3.p546

Zhang, X., Hu, Y., Xie, K., Zhang, W., Su, L., & Liu, M. (2015). An evolutionary trend reversion model for stock trading rule discovery. *Knowledge-Based Systems*, *79*, 27-35. https://doi.org/10.1016/j.knosys.2014.08.010

Hu, Y., Feng, B., Zhang, X., Ngai, E. W. T., & Liu, M. (2015). Stock trading rule discovery with an evolutionary trend following model. *Expert Systems with Applications*, *42*(1), 212-222. https://doi.org/10.1016/j.eswa.2014.07.059

Saud, A. S., & Shakya, S. (2024). Technical indicator empowered intelligent strategies to predict stock trading signals. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(4), 100398. https://doi.org/10.1016/j.joitmc.2024.100398

Wu, X., Chen, H., Wang, J., Troiano, L., Loia, V., & Fujita, H. (2020). Adaptive stock trading strategies with deep reinforcement learning methods. *Information Sciences*, *538*, 142-158. https://doi.org/10.1016/j.ins.2020.05.066

Chiang, W. C., Enke, D., Wu, T., & Wang, R. (2016). An adaptive stock index trading decision support system. *Expert Systems with Applications*, *59*, 195-207. https://doi.org/10.1016/j.eswa.2016.04.025

Rahmani, A. M., Rezazadeh, B., Haghparast, M., Chang, W. C., & Ting, S. G. (2023). Applications of artificial intelligence in the economy, including applications in stock trading, market analysis, and risk management. *IEEE Access*, *11*, 80769-80793. https://doi.org/10.1109/ACCESS.2023.3300036

Bareket, A., & Pârv, B. (2024). Adaptive feature subset and dynamic trend indicators for medium-term stock market predictions: A 70 trading days forecasting approach. *IEEE Access*, *12*, 84306-84322. https://doi.org/10.1109/ACCESS.2024.3412989

Kuo, S. Y., & Chou, Y. H. (2021). Building intelligent moving average-based stock trading system using metaheuristic algorithms. *IEEE Access*, *9*, 140383-140396. https://doi.org/10.1109/ACCESS.2021.3119041

Nabipour, M., Nayyeri, P., Jabani, H., & Mosavi, A. (2020). Predicting stock market trends using machine learning and deep learning algorithms via continuous and binary data; a comparative analysis. *Ieee Access*, *8*, 150199-150212. https://doi.org/10.1109/ACCESS.2020.3015966

Prabakar, S., Kumar, A., Jayakarthik, R., Venkatesh, D., RS, P., & Khan, B. (2024, March). Empirical evaluation of stock market prediction system using intelligent learning scheme with data processing logic. In *2024 5th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)* (pp. 290-297). IEEE. https://doi.org/10.1109/ICICV62344.2024.00050

Huang, S. C., Chiou, C. C., Chiang, J. T., & Wu, C. F. (2020). Online sequential pattern mining and association discovery by advanced artificial intelligence and machine learning techniques. *Soft Computing*, *24*(11), 8021-8039. https://doi.org/10.1007/s00500-019-04100-5

Jahan, N., Pritty, A. A., Ibrahim, M., Zadid, M. U., Fahim, A. S. M., & Mahmud, S. (2024). Machine learning-driven early warning analytics for identifying market manipulation, irregular trading activity, and suspicious market signals in US stock markets. *Journal of Computer Science and Technology Studies*, *6*(2), 257-283. https://doi.org/10.32996/jcsts.2024.6.2.26

Bouasabah, M. (2024, May). A Performance Analysis of Machine Learning Algorithms in Stock Market Prediction, Compared to Traditional Indicators. In *International Conference on Digital Age & Technological Advances for Sustainable Development* (pp. 264-271). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-75329-9_29

Zareeihemat, P., Mohamadi, S., Valipour, J., & Moravvej, S. V. (2025). Forecasting stock market volatility using housing market indicators: a reinforcement learning-based feature selection approach. *IEEe Access*, *13*, 52621-52643. https://doi.org/10.1109/ACCESS.2025.3554224

Lahmiri, S., & Bekiros, S. (2020). Intelligent forecasting with machine learning trading systems in chaotic intraday Bitcoin market. *Chaos, Solitons & Fractals*, *133*, 109641. https://doi.org/10.1016/j.chaos.2020.109641

Lin, Y., Liu, S., Yang, H., Wu, H., & Jiang, B. (2021). Improving stock trading decisions based on pattern recognition using machine learning technology. *PloS one*, *16*(8), e0255558. https://doi.org/10.1371/journal.pone.0255558

Li, A. W., & Bastos, G. S. (2020). Stock market forecasting using deep learning and technical analysis: a systematic review. *IEEE access*, *8*, 185232-185242. https://doi.org/10.1109/ACCESS.2020.3030226