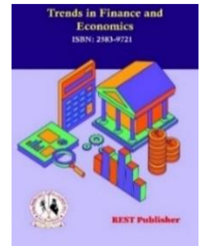
Trends in Finance and Economics

Vol: 3(2), June 2025

REST Publisher; ISSN: 2583-9721 (Online)

Website: https://restpublisher.com/journals/tfe/

DOI: https://doi.org/10.46632/tfe/3/2/3



Algorithmic Trading with AI That Redefines Market Strategy Using GBR and SVR and RFR Regressions

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Abstract: *The incorporation of artificial intelligence into an important change in how financial markets operate is represented by algorithmic trading. operate, evolving from traditional rule-based approaches to advanced machine learning methods that are capable of adapting to volatile market dynamics. The research examines the application of three key AI models – Random Forest regression, gradient boosting regression, and support vector regression predicting trading signal strength. The study uses a dataset containing twenty observations of six essential financial indicators frequently used in algorithmic trading: price momentum, volatility index, trading volume, moving average convergence divergence (MACD), and relative strength index (RSI) and trading signal strength. These indicators collectively provide a comprehensive view of market trends, price behavior, trading activity and signal reliability. The methodology involves a comparative evaluation of the three regression models, assessing their predictive accuracy through metrics such as R², explained variance score, The mean absolute error and the mean square error. The findings indicate that Support Vector Regression outperformed the other models with a test R² of 0.9478, followed by Slope Boosting Regression (0.8460) and Random Forest Regression (0.8388). The SVR showed strong consistency between training and testing results, indicating good generalization and minimal overfitting. Correlation analysis identified strong positive correlations between trading signal strength and several technical indicators, while the volatility index was negatively correlated with most variables. The findings emphasize the transformative impact of AI on market performance, liquidity, and risk management. However, challenges such as increased market volatility, systemic risks from high-frequency trading, cybersecurity threats, and the need for enhanced regulatory measures are also highlighted. The study concludes that while AI has significantly improved trading capabilities, its effective use requires significant investments in technology, skilled expertise, and management to uphold ethical standards and market stability.*

Key words: *Algorithmic Trading, Artificial Intelligence, Machine Learning, Trading Signal Prediction, Support Vector Regression, Slope Boosting, Random Forest, Financial Market Analysis, Risk Management, High Frequency Trading.*

1. INTRODUCTION

Traditional algorithmic trading was largely based on rule-based systems and quantitative models that executed trades according to fixed, predefined criteria. These early strategies emphasized speed, reduced transaction costs, and capitalized on short-term market inefficiencies. However, the rise of Artificial intelligence, especially deep learning and machine learning (ML), capabilities of algorithmic trading systems beyond simple automation.[1] Machine learning allows these Identify complex patterns, learn from historical data, and continuously refine their strategies without the need for explicit algorithms. This represents a major shift away from rigid, static models, enabling algorithms to dynamically adapt as market conditions change. AI-driven trading approaches can integrate a wide variety of data sources, from price trends and economic metrics to news sentiment and social media signals, providing a comprehensive, data-rich foundation for making informed trading decisions.[2] At the heart of AI-powered trading is the ability to optimize complex strategies. For example, reinforcement learning helps trading algorithms find optimal actions through trial and error, gradually improving their performance. AI models can simulate a wide range of market conditions to determine the best trade execution strategies, dynamically adjust portfolio allocations, and reduce drift and transaction costs.[3] In addition, Natural language processing (NLP)-enabled sentiment analysis helps trading algorithms extract market sentiment from unstructured data, including social media and financial news. This capability enables traders to respond to market-moving information more quickly than human traders.[4] AI-driven algorithmic trading plays a key role in increasing market liquidity by maintaining stable trading activity. A specialized area of algorithmic trading called high-frequency trading (HFT), rapidly places and cancels thousands of orders, which improves price discovery and overall market efficiency. However, this heightened activity also brings challenges. The speed and volume of AI-driven trades can also increase market volatility, especially during times of uncertainty. Events such as flash crashes – sharp and sudden price drops that occur within a few minutes – underscore the systemic risks associated with inadequately regulated algorithms.[5] To address these concerns, regulators and exchanges have introduced measures such as circuit breakers, which temporarily halt trading when excessive volatility is detected. While these interventions can help mitigate risk to some extent, the growing complexity of AI models calls for much more advanced oversight and continuous real-time monitoring to ensure market stability.[6] As algorithmic trading becomes increasingly autonomous, risk management approaches must evolve in parallel. AI is particularly useful in identifying potential risks, such as market anomalies or unusual trading behaviors, through predictive analytics and anomaly detection techniques. These tools are essential for managing credit, market, and operational risks in real time. Cybersecurity also presents a growing challenge. AI systems can be vulnerable to adversarial attacks and data tampering. Malicious actors can manipulate machine learning models by injecting harmful data to sway decisions – a tactic known as data poisoning. Financial institutions implement robust model validation to overcome these weaknesses. processes, implementing external detection mechanisms, and leveraging blockchain technology to maintain data integrity and improve transparency.[7] AI has expanded access to financial services, not just in institutional trading, but also through Robo-advisors. These automated platforms offer algorithmic portfolio management to individual investors at a much lower cost than traditional financial advisors. Using AI, Robo-advisors design investment plans Depending on a person's level of risk tolerance, financial objectives, and current market trends. They demonstrate how intelligent algorithms can be used to make wealth management more accessible and promote greater financial inclusion.[8] For institutional investors, AI is reshaping the competitive advantage landscape. Companies that successfully use AI can It helps them quickly and accurately evaluate large amounts of data and create well-informed decisions. investment choices and accurately predict market trends. As a result, AI is becoming essential in shaping portfolio strategies, assessing risks, and executing trades.[9] However, strategically integrating AI requires significant investments in infrastructure, skilled staff, and governance structures. Hiring expert AI engineers, securing powerful computing resources, and fostering collaboration across diverse teams are essential to staying ahead in this competitive industry. In addition, ensuring that AI applications Adhere to legal and ethical regulations is equally important.[10]

2. MATERIALS AND METHOD

Gradient Boosting Regression: An ensemble technique called gradient boosting regression (GBR) builds models one after the other with the goal of correcting the errors of the previous model. This method builds a robust predictive model by combining multiple weak learners, typically decision trees. GBR excels at regression problems because it iteratively reduces the residual error, improving the accuracy of predictions at each step. Its main strength lies in effectively capturing complex nonlinear relationships and interactions between input features. During training, GBR often achieves very high accuracy, sometimes approaching a near-perfect fit by drastically reducing the error loss function. A key advantage of gradient boosting is its adaptability, which allows it to be fine-tuned through hyperparameters such as the Learning rate and number of trees, and the depth of each tree. This tuning capability helps balance the bias-variance tradeoff, improving model performance. However, because GBR builds trees sequentially, it is computationally demanding and slow compared to parallel algorithms such as Random Forests. Another challenge is the potential for overfitting, especially if the model grows too many trees or is trained for too many iterations without sufficient regularization. Nevertheless, GBR is widely favored in financial forecasting and algorithmic trading due to its powerful predictive accuracy and ability to explain Feature importance, which makes it a useful tool for complex market behavior.

Support Vector Regression: Support Vector Regression (SVR) refers to a fundamentally different method rooted in support vector machine principles. Unlike tree-based algorithms, SVR aims to identify a function that approximates the target variable within a specified tolerance margin, called an epsilon-insensitive pipeline. Instead of minimizing every error, SVR allows for small deviations within this margin, while ignoring small fluctuations and focusing on fitting the data. This approach makes SVR particularly useful in high-dimensional feature spaces and when the relationship between the inputs and the target is linear or smoothly nonlinear, achieved through kernel functions such as radial basis functions or polynomial kernels. The main advantages of SVR include its robustness against outliers and its The ability to generalize effectively when training data is limited. Instead of the sudden jumps sometimes seen in tree-based approaches, it produces stable and smooth prediction curves. But the performance of SVR is limited by the epsilon margin, the penalty parameter (C) and kernel-specific settings. These parameters require careful tuning to achieve the right balance between underfitting and overfitting. Although SVR is computationally slow to train on very large datasets, its strong prediction accuracy and ability to handle noise make it well suited for financial modeling tasks where accurate trend estimation is important and noise control is critical.

Random Forest Regression: A powerful ensemble method called random forest regression builds multiple decision trees separately and combines their predictions to increase accuracy and reduce overfitting. Random forest is faster to train and more computationally efficient than gradient boosting because it builds trees in parallel. A bootstrapped subset of the training data is used to build each tree, and the node splits are determined using a random selection of features. This randomness promotes diversity among trees and reduces their correlation, resulting in consistent and reliable predictions. Performance-wise, Random Forest models typically provide high accuracy and maintain strong generalization to new, unseen data. They effectively capture complex, nonlinear relationships and variable interactions without requiring extensive preprocessing or feature engineering. While training errors are typically low, indicating a good fit to the data, test errors increase but remain within reasonable limits, Demonstrates the model's strong generalization capabilities. One of the primary advantages of Random Forest is its natural resistance to overfitting compared to boosting algorithms, due to averaging of predictions from multiple trees. In addition, Random Forest provides useful measures of feature importance, helping to identify which predictors have the most influence on outcomes. This interpretation is particularly valuable in Understanding the factors that affect model outcomes, areas such as algorithmic trading crucial. However, despite its strengths, Random Forest may be less effective than Gradient Boosting in capturing subtle patterns and fine-grained error corrections, which can be important in situations where highly accurate prediction performance is required.

This dataset contains twenty records covering six important financial indicators commonly used in algorithmic trading: Price Momentum (%), Trading signal strength, moving average convergence divergence (MACD), relative strength index (RSI), trading volume, and volatility index. When these factors are combined, market behavior, price trends, trading intensity, and the reliability of generated trade signals. Price Momentum shows considerable variation from -3.1% to 4.4%, reflecting both bearish and bearish market movements within the data. Positive momentum values such as 4.1% and 4.4% indicate rising prices, while negative figures such as -2.7% and -3.1% indicate falling trends. The Volatility Index ranges from 15.1 to 30.2, indicating varying degrees of market risk and uncertainty, with higher numbers indicating greater volatility. Trading volume varies moderately between 3.8 and 7.5, indicating changes in market participation that can affect liquidity and price dynamics. RSI ranges widely from 34 to 75, with higher values (around 75) often indicating overbought conditions, and lower values (around 34) indicating oversold conditions. This range reflects different momentum levels and potential points where price reversals may occur. MACD values range between -1.5 and 2.8, capturing changes in momentum: positive values typically indicate buying opportunities, while negative values indicate selling pressure. Similarly, trading signal strength varies from 39 to 91, indicating varying levels of confidence in the trading signals generated by the AI model. High values such as 91 indicate strong trading recommendations, while lower scores indicate weaker or less specific signals.

3. ANALYSIS AND DISSECTION

TABLE 1. Algorithmic Trading with AI Redefining Market Strategy descriptive statistical

	Price Momentum (%)	Volatility Index	Trading Volume	Relative Strength Index	Moving Average Convergence Divergence	Trade Signal Strength
count	20.0000	20.0000	20.0000	20.0000	20.0000	20.0000
mean	0.9450	21.2650	5.5450	55.5500	0.5750	67.1500
std	2.4328	4.8040	1.0773	12.3735	1.3695	16.2328
min	-3.1000	15.1000	3.8000	34.0000	-1.5000	39.0000
25%	-1.0500	17.4750	4.8250	45.7500	-0.6500	53.5000
50%	1.2000	19.8500	5.3500	57.5000	0.7500	70.0000
75%	2.8250	24.9000	6.3500	65.2500	1.6250	79.5000
max	4.4000	30.2000	7.5000	75.0000	2.8000	91.0000

Table 1 provides descriptive statistics for six important indicators involved in AI-driven algorithmic trading, providing a snapshot of their behavior and distribution across 20 data points. Price momentum, volatility index, trading volume, relative strength index (RSI), moving average convergence divergence (MACD), and trading signal strength are essential for analyzing AI-driven market strategies. The average values provide a general overview, with trading signal strength averaging 67.15 and RSI at 55.55, indicating a somewhat volatile market trend. The average of price momentum is 0.945%, indicating a slight upward movement in prices, while trading volume has a moderate average of 5.545 (assumed normalized units). The variability is reflected in the standard deviations, where trading signal strength (16.23) and RSI (12.37) show a high spread, indicating varying signal responses across trades. Conversely, trading volume (1.08) and price momentum (2.43) show less volatility, indicating more stable patterns. The data range between the minimum and maximum values highlights market volatility: price momentum varies from -3.10% to 4.40%, and MACD ranges from -1.5 to 2.8, reflecting both downward and upward market movements. Trading signal strength also shows a wide range from 39 to 91, underlining the diversity in AI-generated signals. Finally, the quarterly values highlight the distribution shape and variability, with the RSI ranging from 45.75 to 65.25 and the MACD between –0.65 and 1.625, indicating a generally balanced distribution, but allowing for some exceptions.

TABLE 2. Gradient Boosting Regression Models Trade Signal Strength Train and Test performance metrics

Gradient Boosting Regression	Train	Test
R2	1.0000	0.8460
EVS	1.0000	0.8599
MSE	0.0000	10.5082
RMSE	0.0000	3.2416
MAE	0.0000	2.7904
Max Error	0.0000	6.2045
MSLE	0.0000	0.0018
Med AE	0.0000	2.8476

Table 2 presents the evaluation metrics of the gradient boosting regression model for predicting trading signal strength on both the training and testing datasets. During training, the model achieves almost perfect accuracy, with both R^2 and Explained Variance Score (EVS) equal to 1.0000, indicating an excellent fit with no errors. All error metrics, including the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Maximum Error, Mean Squared Logarithmic Error (MSLE), and Mean Absolute Error (Med AE), are zero, indicating flawless performance on the training data. In contrast, the testing metrics provide a more practical measure of the model's ability to predict unobserved data. The R^2 drops to 0.8460, indicating an even stronger predictive ability, explaining approximately 85% of the variance in the testing results. The EVS of 0.8599 confirms that the model retains considerable explanatory power beyond training. The error measures increase, with MSE being 10.5082 and RMSE being 3.2416, indicating the average size of the prediction errors. The MAE of 2.7904 represents the typical absolute difference between the predicted and actual values, and the maximum error of 6.2045 represents the largest single deviation. The low MSLE (0.0018) and Med AE (2.8476) suggest that most of the errors are small and that the performance is consistent across the test samples.

TABLE 3. Support Vector Regression Models Trade Signal Strength Train and Test performance metrics

Support Vector Regression	Train	Test
R2	0.9951	0.9478
EVS	0.9951	0.9605
MSE	1.6681	3.5647
RMSE	1.2916	1.8880
MAE	0.8591	1.4903
Max Error	3.2374	3.7044
MSLE	0.0008	0.0008
Med AE	0.3516	0.9338

Table 3 presents the evaluation results of the Support Vector Regression (SVR) model for predicting trading signal strength on both the training and testing datasets. During training, the model achieves very high accuracy, with an R^2 and an Explained Variance Score (EVS) of 0.9951, indicating that it almost perfectly accounts for the variance in the training data. The error metrics are remarkably low, with a mean square error (MSE) of 1.6681, a root mean square error (RMSE) of 1.2916, and a mean absolute error (MAE) of 0.8591, all of which reflect minimal prediction errors. The maximum error recorded is 3.2374, and the mean square logarithmic error (MSLE) is 0.0008, confirming the accurate fit of the model. The mean absolute error (Med AE) of 0.3516 also indicates that the typical prediction errors are small. When applied to the test data, the model continues to perform strongly, with an R^2 value of 0.9478, indicating that it explains approximately 95% of the variance in the unobserved data. The EVS is high at 0.9605, indicating consistent model strength. Although the errors increase compared to training, they are overall low: MSE increases to 3.5647, RMSE to 1.8880, and MAE to 1.4903, indicating acceptable error margins. The maximum error increases slightly to 3.7044 but remains reasonable. The MSLE remains stable at 0.0008, indicating consistent logarithmic error behavior. The Med AE increases to 0.9338, indicating slightly larger but still moderate standard errors in the predictions in the test set.

TABLE 4. Random Forest Regression Models Trade Signal Strength Train and Test performance metrics

Random Forest Regression	Train	Test
R2	0.9962	0.8388
EVS	0.9962	0.8927
MSE	1.3113	10.9972
RMSE	1.1451	3.3162
MAE	0.9758	2.5475
Max Error	2.0650	6.7500
MSLE	0.0005	0.0018
Med AE	1.0275	2.4925

Table 4 outlines the performance of the random forest regression model in predicting the strength of the trading signal for both the training and testing datasets. In the training phase, the model achieves excellent accuracy with an R^2 and an explained variance score (EVS) of 0.9962, indicating that it accounts for almost all of the variation in the training data. The error metrics are very low, as reflected by a mean square error (MSE) of 1.3113, a root mean square error (RMSE) of 1.1451, and a mean absolute error (MAE) of 0.9758, indicating close alignment between the predicted and actual values. The maximum error is low at 2.0650, while the mean square logarithmic error (MSLE) of 0.0005 confirms consistent prediction accuracy. The mean absolute error (Med AE) of 1.0275 indicates generally small conventional errors. In the testing dataset, the model's performance decreases, but still shows reliable results. The R^2 value drops to 0.8388, meaning that the model explains approximately 84% of the variance in the new data, while the EVS remains robust at 0.8927. The prediction errors increase compared to training: MSE increases to 10.9972, RMSE to 3.3162, and MAE to 2.5475, reflecting higher mean deviations. The maximum error increases to 6.7500, indicating some outliers with significant prediction differences. The MSLE increases slightly to 0.0018, indicating a modest increase in logarithmic error, and the Med AE increases to 2.4925, indicating higher typical errors during testing.

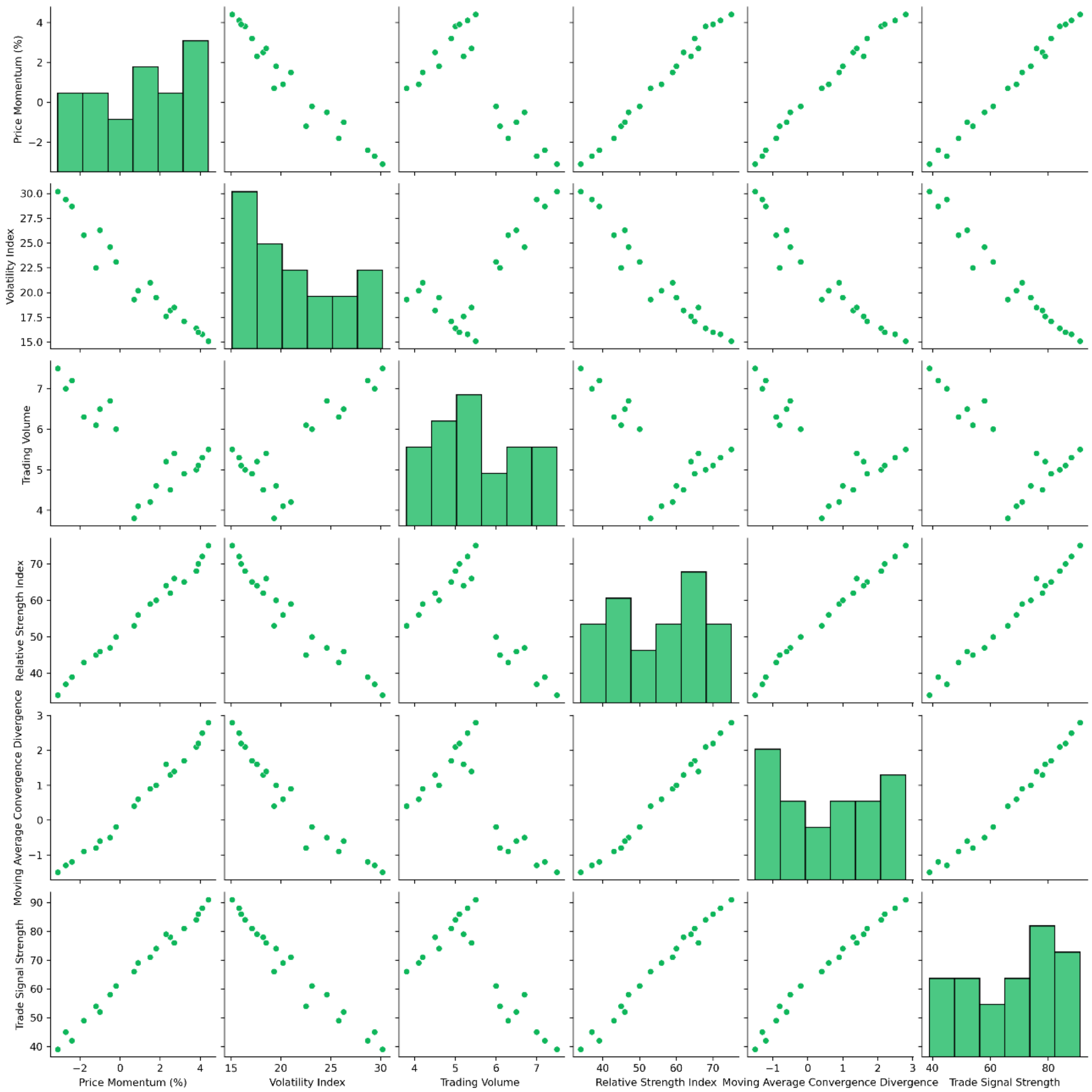

FIGURE 1. Effect of Process Parameters Trade Signal Strength

This scatterplot matrix illustrates the complex relationships between six key trading indicators, along with their individual distributions. The diagonal plots represent the frequency distributions for each variable - price momentum follows an approximately normal distribution, while the volatility index is significantly skewed to the right. Trading volume is tightly clustered around low values. The scatterplots illustrate the varying degrees of correlation between the indicators: some show clear linear trends, while others are more dispersed. The bias strength index and moving average convergence divergence both exhibit strong positive correlations with trading signal strength, as indicated by the upward-sloping data clusters. In contrast, trading volume shows relatively weak correlations with other indicators, suggesting that it may act independently in influencing trading signals.

FIGURE 2. Correlation heatmap Trade Signal Strength

The correlation matrix provides numerical validation of the patterns identified in Figure 1. The dark blue cells highlight the strong positive correlations (around 0.99) between trading signal strength and key indicators such as price momentum, relative strength index, and moving average convergence divergence. In contrast, the volatility index exhibits strong negative correlations (-0.97 to -0.98) with most other variables, indicating that increased volatility often corresponds with reduced signal strength. Trading volume exhibits weak correlations (-0.72 to 0.78), reinforcing its relative independence from other metrics. The presence of nearly perfect correlations between some variables may indicate multicollinearity, which can pose challenges in predictive modeling by undermining model interpretation and robustness.

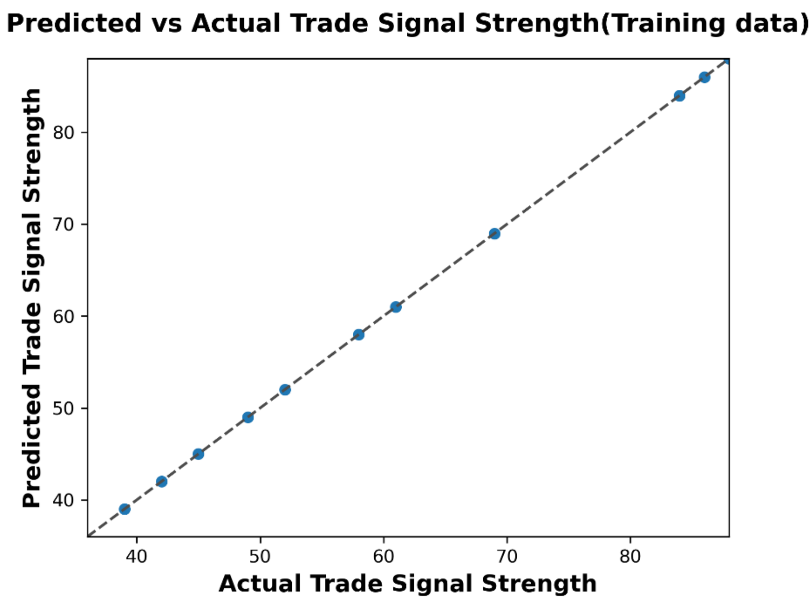

FIGURE 3. Gradient Boosting Regression Trade Signal Strength Training

The training performance of the gradient boosting model reflects excellent predictive accuracy, as demonstrated by the data points being closely aligned on the ideal diagonal from the bottom-left to the top-right corner. The model performs well across the entire spectrum of trading signal strength values (40–85), showing minimal deviation from the expected line. The tight concentration of points near the diagonal indicates low predictive bias and variance, indicating that the model has effectively learned the patterns within the training data. However, this nearly flawless fit may indicate potential overfitting, where the model may memorize the training set instead of identifying broadly applicable trends. The consistent accuracy across varying signal strengths also indicates that the model is equally adept at predicting weak and strong signals during training.

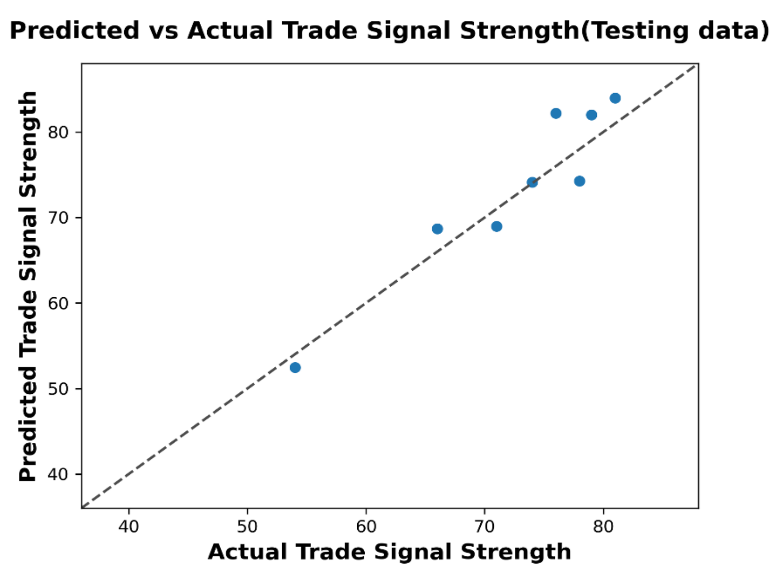

FIGURE 4. Gradient Boosting Regression Trade Signal Strength Testing

The experimental performance shows a slight decline compared to the training results, which is expected and indicates healthy model generalization. Although the predictions generally follow a diagonal trend, there is a significant amount of dispersion around the ideal line – especially in the middle range of trading signal strength (60–75). The model continues to perform well at extremes, but shows increased uncertainty in predicting moderate values. Several data points deviate significantly from the correct prediction line, highlighting the model's challenges in dealing with previously unseen patterns. However, the overall positive trend indicates that the gradient boosting model has captured the true underlying relationships, not memorized the training data. Although the accuracy is lower than the training, the experimental results show a reasonable level of generalization.

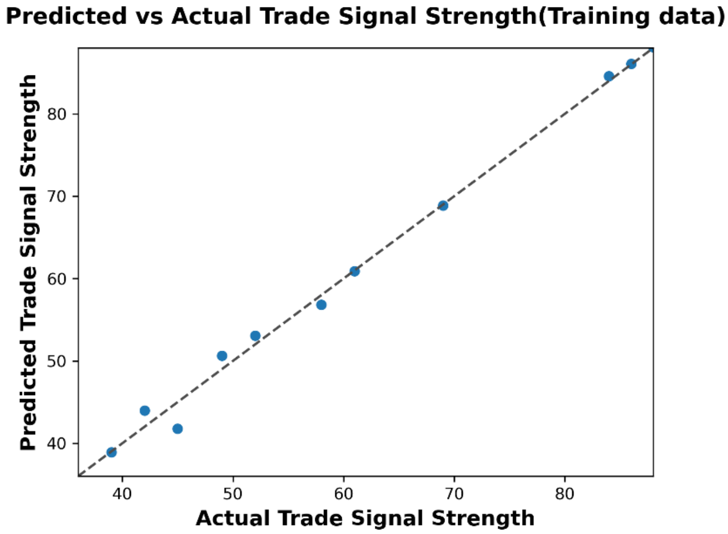

FIGURE 5. Support Vector Regression Trade Signal Strength Training

The Support Vector Regression (SVR) model exhibits strong training performance, with a clear linear alignment between the actual and predicted values. The data points closely follow the diagonal across the entire range of trading signal strength values, reflecting reliable predictions for both weak (40) and strong (85) signals. Unlike tree-based models that can produce truncated patterns, the SVR model produces smooth prediction curves, indicating a well-fitted regression. The tight clustering around the best fit line indicates that the model has effectively captured the mathematical relationships in the training data. In addition, the even spacing of the points highlights the consistent performance of the model across different regions of the input space – a common result of SVR's ability to generate optimal regression hyperplanes.

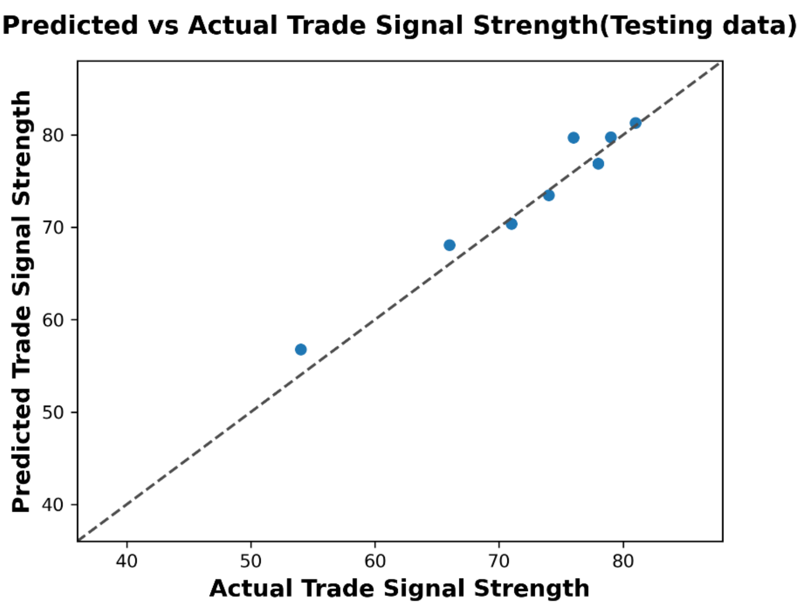

FIGURE 6. Support Vector Regression Trade Signal Strength Testing

The experimental results of the SVR model reflect a strong conservation of performance, with a small decline compared to the training phase. The predictions remain largely accurate across the entire spectrum of trading signal strength values, although a slight increase in dispersion is noticeable, especially in the range of 70–80. Most predictions lie close to the diagonal line, indicating low systematic bias. Although there are a few outliers, most of the data points are tightly clustered around the best fit. These results indicate effective generalization, as the SVR model successfully applies learned patterns to new, unseen data. The consistent accuracy of the model across varying signal strengths further highlights its robustness to specific training examples and resistance to overfitting.

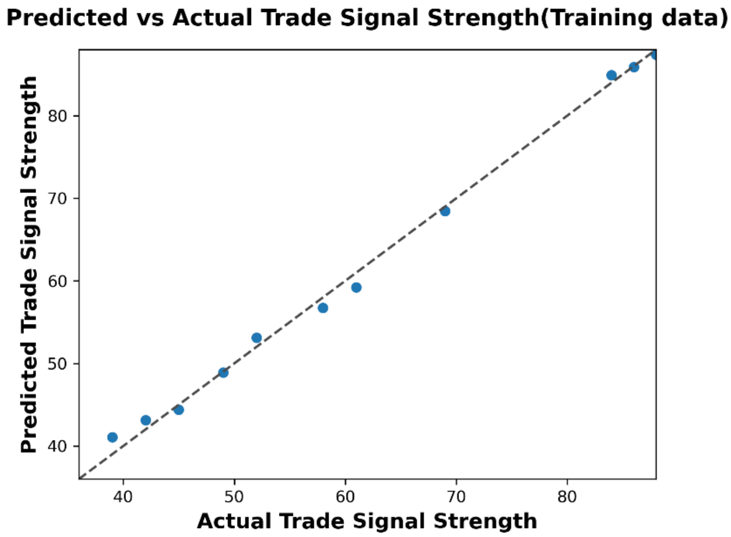

FIGURE 7. Random Forest Regression Trade Signal Strength Training

The Random Forest model demonstrates excellent training performance, with predicted values closely aligned on the diagonal, indicating high accuracy. The ensemble approach of combining multiple decision trees contributes to the smooth and consistent predictive behavior of the model over the entire range of trading signal strength values. The data points are densely clustered around the ideal line from 40 to 85, reflecting consistent accuracy. The model performs particularly well at the lower and upper ends of the signal strength range, showing minimal deviation from the ideal. These results indicate that Random Forest successfully captures the complex relationships between various trading indicators and leverages its ensemble structure to produce a robust and reliable representation of trading signal dynamics.

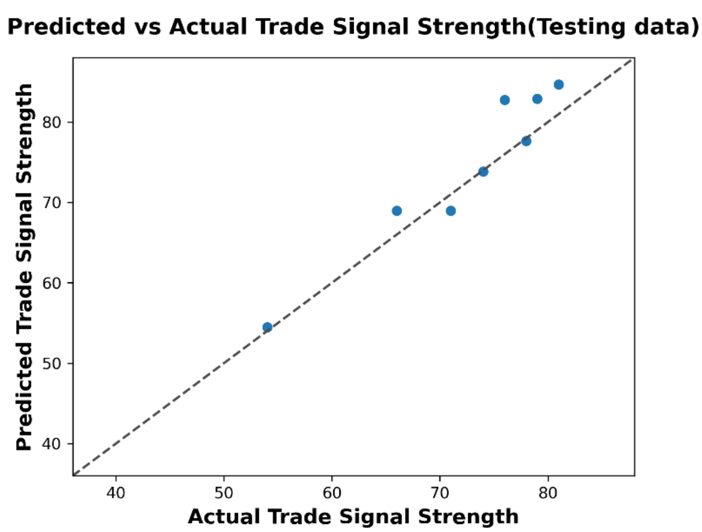

FIGURE 8. Random Forest Regression Trade Signal Strength Testing

The experimental performance of the Random Forest model indicates solid generalization, with reasonably accurate predictions across the entire range of trading signal strength values. While the overall diagonal trend is preserved, there is more variability than in the training phase – particularly in the range of 70–85, with some predictions deviating significantly from the best line. The model maintains strong accuracy for low signal strengths, but shows high uncertainty at the high end. Clusters of points above and below the diagonal indicate the presence of systematic patterns that the model does not fully capture. Nevertheless, the Random Forest demonstrates reliable predictive power on unobserved data, effectively generalizing from training, while also reflecting the inherent complexity of forecasting financial signals.

4. CONCLUSION

This comprehensive analysis of AI-driven algorithmic trading highlights the transformative influence of machine learning on contemporary financial markets. By comparing three regression techniques—slope incremental regression, support vector regression, and random forest regression—the study provides important insights into the relative performance of these AI models in predicting trading signal strength. Support vector regression emerged as the most reliable model, achieving a high-test R^2 of 0.9478 and demonstrating strong generalization across data sets. The results emphasize the benefits of incorporating AI into trading platforms, such as improved ability to detect complex patterns, improved accuracy in predictions, and the ability to analyze a variety of data sources, from traditional price indicators to sentiment derived from news and social media. The strong positive correlations identified between trading signal strength and technical measures such as RSI, MACD, and price momentum confirm the value of these indicators within AI-driven trading frameworks. Meanwhile, the negative correlation with the volatility index shows the model's ability to appropriately factor in risk components during signal generation. However, there are challenges with AI adoption in algorithmic trading. The study points to risks including increased market volatility, the threat of sudden outages, cybersecurity concerns such as data poisoning, and the need for advanced risk management systems. The nearly perfect training results of gradient boosting regression expose the persistent risk of overfitting, underscoring the need for rigorous validation and ongoing model oversight. Looking ahead, AI-powered Robo-advisors offer promising opportunities to expand financial inclusion by providing accessible, cost-effective investment management to retail investors. For institutional investors, leveraging AI to maintain a competitive advantage is critical, requiring significant investments in infrastructure, skilled talent, and management. As regulatory frameworks evolve to accommodate the growing role of AI, innovations such as reinforcement learning, natural language processing, and real-time anomaly detection will further refine algorithmic trading systems, contributing to more efficient, stable, and resilient financial markets.

REFERENCES

[1]. Addy, Wilhelmina Afua, Adeola Olusola Ajayi-Nifise, Binaebi Gloria Bello, Sunday Tubokirifuruar Tula, O. Odeyem, and Titilola Falaiye. "Algorithmic trading and ai: A review of strategies and market impact." World Journal of Advanced Engineering Technology and Sciences 11, no. 1 (2024): 258-267.
[2]. Oyeniyi, Lawrence Damilare, Chinonye Esther Ugochukwu, and Noluthando Zamanjomane Mhlongo. "Analyzing the impact of algorithmic trading on stock market behavior: A comprehensive review." World Journal of Advanced Engineering Technology and Sciences 11, no. 2 (2024): 437-453.
[3]. Olanrewaju, Ayobami Gabriel. "Artificial Intelligence in Financial Markets: Optimizing Risk Management, Portfolio Allocation, and Algorithmic Trading." International Journal of Research Publication and Reviews 6 (2025): 8855-8870.
[4]. Addy, Wilhelmina Afua, Adeola Olusola Ajayi-Nifise, Binaebi Gloria Bello, Sunday Tubokirifuruar Tula, Olubusola Odeyemi, and Titilola Falaiye. "Machine learning in financial markets: A critical review of algorithmic trading and risk management." International Journal of Science and Research Archive 11, no. 1 (2024): 1853-1862.
[5]. Omer, Mohammed. "The Role of Machine Learning in Transforming Financial Market Analytics and Algorithmic Trading." (2025).
[6]. Lee, Joseph, and Lukas Schu. "Regulation of algorithmic trading: frameworks or human supervision and direct market interventions." European Business Law Review 33, no. 2 (2022).
[7]. Onabowale, Oreoluwa. "The Rise of AI and Robo-Advisors: Redefining Financial Strategies in the Digital Age." International Journal of Research Publication and Reviews 6 (2024).
[8]. Ekundayo, Foluke. "Economic implications of AI-driven financial markets: Challenges and opportunities in big data integration." International Journal of Science and Research Archive 13 (2024): 1500-1515.
[9]. Patil, Dimple. "Artificial Intelligence in Financial Services: Advancements in Fraud Detection, Risk Management, And Algorithmic Trading Optimization." Risk Management, And Algorithmic Trading Optimization (November 20, 2024) (2024).

[10]. Yussuf, Moshood. "Advanced cyber risk containment in algorithmic trading: Securing automated investment strategies from malicious data manipulation." Int Res J Mod Eng Technol Sci 7, no. 3 (2025): 883.
[11]. Li, Ping, Qiang Wu, and Christopher Burges. "Mcrank: Learning to rank using multiple classification and gradient boosting." Advances in neural information processing systems 20 (2007).
[12]. Wu, Jingxian, Guikong Tang, Huapeng Shen, and Soora Rasouli. "Spatial heterogeneity in the nonlinear impact of built environment on commuting time of active users: A gradient boosting regression tree approach." Journal of Advanced Transportation 2023, no. 1 (2023): 6217672.
[13]. Zhang, Faming, Xinyan Zhu, Tao Hu, Wei Guo, Chen Chen, and Lingjia Liu. "Urban link travel time prediction based on a gradient boosting method considering spatiotemporal correlations." ISPRS International Journal of Geo-Information 5, no. 11 (2016): 201.
[14]. Nguyen-Sy, Tuan, Jad Wakim, Quy-Dong To, Minh-Ngoc Vu, The-Duong Nguyen, and Thoi-Trung Nguyen. "Predicting the compressive strength of concrete from its compositions and age using the extreme gradient boosting method." Construction and Building Materials 260 (2020): 119757.
[15]. Bentéjac, Candice, Anna Csörgő, and Gonzalo Martínez-Muñoz. "A comparative analysis of gradient boosting algorithms." Artificial Intelligence Review 54 (2021): 1937-1967.
[16]. Marković, Nikola, Sanjin Milinković, Konstantin S. Tikhonov, and Paul Schonfeld. "Analyzing passenger train arrival delays with support vector regression." Transportation Research Part C: Emerging Technologies 56 (2015): 251-262.
[17]. Pal, Mahesh, and Surinder Deswal. "Support vector regression-based shear strength modelling of deep beams." Computers & Structures 89, no. 13-14 (2011): 1430-1439.
[18]. Hsia, Jui-Yang, and Chih-Jen Lin. "Parameter selection for linear support vector regression." IEEE Transactions on Neural Networks and Learning Systems 31, no. 12 (2020): 5639-5644.
[19]. Klopfenstein, Quentin, and Samuel Vaiter. "Linear support vector regression with linear constraints." Machine Learning 110, no. 7 (2021): 1939-1974.
[20]. Benkedjouh, Tarak, Kamal Medjaher, Noureddine Zerhouni, and Saïd Rechak. "Remaining useful life estimation based on nonlinear feature reduction and support vector regression." Engineering Applications of Artificial Intelligence 26, no. 7 (2013): 1751-1760.
[21]. Shobayo, Olamilekan, Oluwafemi Zachariah, Modupe Olufunke Odusami, and Bayode Ogunleye. "Prediction of stroke disease with demographic and behavioural data using random forest algorithm." Analytics 2, no. 3 (2023): 604-617.
[22]. Pal, Mahesh, N. K. Singh, and N. K. Tiwari. "Pier scour modelling using random forest regression." ISH Journal of Hydraulic Engineering 19, no. 2 (2013): 69-75.
[23]. Reddy, A. Mallikarjuna, Snigdha Yarlagadda, and Haritha Akkinen. "An extensive analytical approach on human resources using random forest algorithm." arXiv preprint arXiv:2105.07855 (2021).
[24]. Shingala, Bansi, Piyushkumar Panchal, Sanketsinh Thakor, Prince Jain, Anand Joshi, Chandan R. Vaja, R. K. Siddharth, and V. A. Rana. "Random forest regression analysis for estimating dielectric properties in epoxy composites doped with hybrid nano fillers." Journal of Macromolecular Science, Part B 63, no. 12 (2024): 1297-1311.
[25]. Wang, Qi, Xiaona Wang, Yong Zhou, Dongyun Liu, and Haitao Wang. "The dominant factors and influence of urban characteristics on land surface temperature using random forest algorithm." Sustainable Cities and Society 79 (2022): 103722.

