Article history:
Received 10 July 2025
Revised 04 October 2025
Accepted 16 October 2025
Published online 01 January 2026

Journal of Resource Management and Decision Engineering

Volume 5, Issue 1, pp 1-12

Developing a Data-Driven Decision-Making Model for Algorithmic Trading Strategies (Cryptocurrency Market)

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Article Info

Article type:
Original Research

How to cite this article:
Gharibshahian, A.R. & Dehghani, A.R. (2026). Developing a Data-Driven Decision-Making Model for Algorithmic Trading Strategies (Cryptocurrency Market). *Journal of Resource Management and Decision Engineering*, *5*(1), 1-12.
https://doi.org/10.61838/kman.jrmde.5.1.186

ABSTRACT

The rapid growth of the cryptocurrency market in recent years has created both lucrative opportunities and unprecedented risks for investors. High volatility, the decentralized nature of exchanges, and the massive volume of trading data have challenged human decision-making, highlighting the necessity of employing intelligent and automated systems. In this study, a data-driven model is proposed for decision-making and the implementation of algorithmic trading strategies in the cryptocurrency market. The proposed framework integrates historical price data analysis, technical indicators, and market microstructure data with machine learning methods to forecast price trends and generate buy and sell signals. Subsequently, optimization algorithms are employed to adjust trading parameters in a way that maximizes returns while minimizing risk and transaction costs. Experimental results based on real data from selected cryptocurrencies (such as Bitcoin and Ethereum) demonstrate that the proposed model outperforms traditional strategies in terms of risk-adjusted returns and result stability. Finally, the article provides recommendations for the practical implementation of this framework in intelligent trading systems and suggests future research directions.

Keywords: *Algorithmic trading, Data-driven decision-making, Machine learning, Cryptocurrency market, Price prediction*

1. Introduction

The accelerating evolution of digital financial ecosystems has transformed the traditional landscape of investment, risk management, and market analytics. Cryptocurrencies, as a distinct class of digital assets, have emerged as one of the most dynamic and volatile components of the modern financial system. Their decentralization, cryptographic security, and market independence from conventional financial intermediaries have fueled unprecedented interest among investors, institutions, and policymakers (Poskart, 2022). Yet, this rapid rise in popularity has also exposed structural vulnerabilities, including excessive speculation, systemic contagion, and unpredictable volatility patterns (Joebges et al., 2025). Consequently, understanding and managing the behavior of cryptocurrency markets through advanced analytical and predictive approaches has become a critical research priority in financial management and computational economics.

Cryptocurrency markets are characterized by extreme price fluctuations, information asymmetry, and high trading frequency. Unlike traditional assets, the valuation of cryptocurrencies depends on a complex interplay of market sentiment, blockchain dynamics, macroeconomic factors, and social media trends (Adediran et al., 2023). The decentralized nature of exchanges, absence of standardized valuation frameworks, and the constant entry of new investors driven by speculative motives—often influenced by fear of missing out (FOMO)—contribute to market inefficiencies and irrational investment behaviors (Friederich et al., 2023). As a result, conventional econometric and statistical models often fail to capture the nonlinearities and temporal dependencies inherent in these markets (Adekoya et al., 2022).

To address these complexities, machine learning (ML) and artificial intelligence (AI) techniques have gained prominence in financial forecasting and decision-making. These methods enable the modeling of nonlinear relationships, the detection of hidden patterns, and real-time adaptation to market changes (Islam et al., 2025). Deep learning models, such as deep neural networks (DNN), convolutional neural networks (CNN), and recurrent neural networks (RNN), have shown significant promise in forecasting price movements, classifying market signals, and optimizing algorithmic trading strategies (Islam et al., 2024). By leveraging massive volumes of high-frequency and unstructured data, these models enhance predictive accuracy, reduce decision-making latency, and improve portfolio performance in volatile trading environments.

Furthermore, the increasing integration of AI-based prediction systems has led to a paradigm shift from intuition-driven to data-driven investment strategies. Bayesian and reinforcement learning frameworks have been particularly effective in dynamic financial environments by continuously updating beliefs and adapting to evolving market conditions (Cv et al., 2025). Such models enable a probabilistic understanding of uncertainty, allowing traders and portfolio managers to make more informed and risk-adjusted decisions. The incorporation of these models in algorithmic trading enhances both profitability and stability, especially when dealing with nonstationary time series typical of cryptocurrency data (Koutrouli et al., 2025).

Despite technological advancements, the cryptocurrency market continues to pose unique challenges for predictive modeling. These include abrupt structural breaks caused by policy shifts, cyberattacks, and speculative bubbles (Lee, 2024). The lack of centralized oversight also amplifies exposure to market manipulation and liquidity crises (Joebges et al., 2025). Moreover, the heterogeneity of trading platforms and the diversity of investor profiles contribute to data fragmentation and bias, complicating the development of robust forecasting models (Javahri et al., 2024). Consequently, a hybrid modeling approach that combines machine learning, econometric modeling, and optimization techniques appears essential for capturing the multifaceted nature of cryptocurrency dynamics (Samavi et al., 2022).

Recent literature has increasingly emphasized the role of algorithmic trading as a mechanism for improving market efficiency and liquidity. Algorithmic trading systems automate the execution of trading strategies based on pre-defined rules and real-time data analytics, minimizing emotional biases and reaction delays (Adediran et al., 2023). By integrating data-driven algorithms with predictive analytics, traders can achieve optimal timing of market entry and exit points, improved capital allocation, and reduced transaction costs (Mykytas et al., 2023). However, to realize these benefits, models must account for both microstructural and macroeconomic factors influencing digital asset prices (Almeida, 2023).

The relationship between cryptocurrency markets and broader financial systems has also become an important research frontier. Studies show that crypto assets can serve as both diversification instruments and systemic risk amplifiers, depending on market context (Joebges et al., 2025; Koutrouli et al., 2025). For instance, while cryptocurrencies may enhance financial inclusion and accessibility in emerging economies, they also introduce potential channels for capital flight and speculative contagion (El Hajj & Farran, 2024). The dual nature of cryptocurrencies—as both enablers of innovation and sources of instability—necessitates new analytical models that integrate behavioral, structural, and computational perspectives (Lee, 2024).

In emerging markets, the adoption of cryptocurrencies has been particularly notable due to limited access to formal banking systems and inflationary pressures in local economies (El Hajj & Farran, 2024). Nevertheless, the absence of regulatory clarity continues to constrain institutional participation (Khan, 2023). Legal uncertainty, inconsistent taxation frameworks, and risks associated with anonymity hinder the institutionalization of cryptocurrencies as legitimate financial assets. As such, establishing a balance between regulatory oversight and innovation remains a crucial policy challenge. Researchers and policymakers must explore frameworks that mitigate systemic risks without stifling technological progress or market evolution (Khan, 2023).

At the same time, behavioral finance perspectives have revealed how investor psychology and sentiment drive cryptocurrency market dynamics. Social media engagement, online forums, and algorithmic sentiment extraction have become important inputs for predictive systems (Friederich et al., 2023). Market participants often respond to speculative narratives rather than fundamental valuation indicators, amplifying price cycles and volatility. Consequently, incorporating behavioral signals alongside quantitative features enhances the explanatory power of trading models (Almeida, 2023).

Methodologically, the integration of deep learning and ensemble models such as Gradient Boosting (GB), Random Forests, and XGBoost has significantly improved the performance of predictive frameworks (Islam et al., 2025). These algorithms adaptively refine decision rules and identify nonlinear interactions between predictors, making them highly suitable for financial forecasting tasks characterized by noise and complexity (Islam et al., 2024). When combined with reinforcement learning, such models can autonomously learn optimal trading policies that balance expected returns and associated risks (Cv et al., 2025). The hybridization of DNN and boosting models offers complementary strengths: deep networks excel in feature extraction, while boosting models reduce residual errors through iterative optimization (Koutrouli et al., 2025).

The expansion of data availability—from blockchain transaction logs to social media analytics—has further strengthened the role of data-driven decision-making in financial management (Mykytas et al., 2023). Advanced predictive models can leverage both structured data (price, volume, volatility) and unstructured data (news, tweets, forum posts) to generate real-time trading signals (Islam et al., 2025). With growing computational capacity and cloud-based resources, traders and financial institutions can deploy scalable predictive systems capable of adaptive learning and continual model refinement (Adekoya et al., 2022).

Nonetheless, the ethical and regulatory implications of algorithmic decision-making in cryptocurrency markets cannot be overlooked. Automated trading systems, while efficient, may exacerbate flash crashes or algorithmic biases if improperly designed or monitored (Joebges et al., 2025). Moreover, the opacity of complex machine learning models poses challenges to accountability and explainability in financial decision-making (Lee, 2024). Thus, developing interpretable and transparent models remains a research imperative for ensuring both trust and stability in automated trading environments.

From a macroeconomic perspective, the growing interdependence between cryptocurrencies, fiat currencies, and stock markets underscores the need for integrated analytical frameworks. Cross-market spillover effects—such as those observed between exchange rates, cryptocurrency indices, and stock exchanges—highlight the systemic relevance of digital assets (Javahri et al., 2024). The interconnectedness of these markets can amplify both opportunities and vulnerabilities, requiring robust modeling techniques to anticipate risk transmission mechanisms and potential contagion (Joebges et al., 2025).

In addition, predictive modeling of cryptocurrency returns aligns with broader trends in financial econometrics and digital transformation. Time-varying volatility, structural breaks, and asymmetric dependencies are increasingly addressed through hybrid models that blend machine learning with econometric approaches (Samavi et al., 2022). Such models not only enhance predictive accuracy but also facilitate more adaptive and resilient trading systems capable of withstanding shocks and regime shifts. The application of machine learning in this context represents not merely a technological advancement but a conceptual reorientation toward dynamic, self-learning financial architectures (Cv et al., 2025).

Ultimately, the adoption of data-driven and AI-enhanced strategies in cryptocurrency trading reflects a convergence of technology, economics, and behavioral science. These approaches enable a more systematic and objective basis for financial decision-making, moving beyond speculative tendencies toward rational, evidence-based trading systems (Adediran et al., 2023; Islam et al., 2025). As algorithmic trading becomes increasingly dominant in global markets, the capacity to synthesize large-scale data and adapt to rapidly changing conditions will determine the competitiveness and stability of financial institutions (Koutrouli et al., 2025).

Accordingly, this study aims to develop and validate a data-driven decision-making model for algorithmic trading strategies in the cryptocurrency market.

2. Methods and Materials

This study is applied and developmental in nature and was conducted with the aim of presenting a data-driven decision-making model for trading strategies in the cryptocurrency market. The research method was designed in such a way that, in addition to presenting the theoretical framework, the performance of the model was also examined under real market conditions. The data used include the historical price data of cryptocurrencies (Bitcoin and Ethereum) and order book and microstructure trading flow data for the period 2019–2025. These data were collected from reputable exchanges and include open, close, high, and low prices, trading volume, and order book depth.

The proposed model framework consists of three main components: (1) data collection and preprocessing, (2) application of machine learning and reinforcement learning algorithms for prediction and decision-making, and (3) optimization of trading parameters to minimize risk and maximize returns. This framework enables automated and dynamic decision-making capabilities.

First, the data are collected, and during the preprocessing phase, missing data are removed, outliers and noisy data are corrected, and the data are converted into a suitable format for machine learning algorithms. Additionally, order book data are integrated with historical price data to provide more comprehensive information for decision-making. In the next stage, machine learning algorithms are used for price prediction and trend identification, and the entry and exit strategies for trades are optimized.

To minimize risk and optimize trading parameters, evolutionary optimization algorithms and gradient-based algorithms were employed. These algorithms optimize trading volume, entry and exit points, and stop-loss and take-profit limits. Finally, the model's performance is evaluated using various metrics to assess the effectiveness of the algorithms, and necessary optimizations are applied if required. This process enhances predictive accuracy and improves trading decision-making.

Based on the above stages, the structure and mathematical foundations of the algorithms used in this research include a Deep Neural Network (DNN), Gradient Boosting, and an integrated hybrid model. The purpose of presenting these relationships is to explain how learning, parameter updating, and model integration occur to achieve the highest prediction accuracy. The following formulas represent the computational processes and internal logic of each algorithm.

Deep Neural Network (DNN) Algorithm

Deep neural networks consist of multiple hidden layers, each extracting increasingly complex features from the input data (Brown & Davies, 2024). In this study, the DNN structure is used to model nonlinear relationships among financial market variables and to predict trading signals. The model input includes historical price data, trading volume, technical indicators, and other statistical market features, while the model output represents the probability of a buy or sell signal occurring within a future time window.

The general computation formula for each layer of the network is defined as follows:

(1) $Z(l) = W(l) * a(l-1) + b(l)$

$a(l) = f(l)(Z(l))$

where

$a(0) = x$: input vector of the network

$W(l)$: weight matrix of layer l

$b(l)$: bias vector of layer l

$f(l)(\cdot)$: activation function (such as ReLU, sigmoid, or tanh)

$a(l)$: output (activation) of layer l

The final output of the network is expressed as:

$\hat{y} = a(L)$

where L is the total number of layers and $\hat{y}$ represents the predicted output of the model.

To train the model, the Mean Squared Error (MSE) loss function is used:

(2) $L = (1/N)\ \Sigma(i=1 \text{ to } N)\ (\hat{y}_i - y_i)^2$

Weights and biases are updated using the backpropagation algorithm and the gradient descent method as follows:

(3) $W(l) \leftarrow W(l) - \eta \times \partial L/\partial W(l)$

$b(l) \leftarrow b(l) - \eta \times \partial L/\partial b(l)$

where η represents the learning rate (Brown & Davies, 2024).

Finally, the trained neural network is capable of automatically generating optimal trading signals when provided with new market data.

Gradient Boosting Algorithm

The Gradient Boosting algorithm is one of the most powerful ensemble learning methods that constructs a strong model by combining multiple weak learners (usually decision trees). The main idea is that each new model corrects the errors of the previous models.

In this approach, an initial base model (F_0) is trained, and then, at each iteration, a new model is built to predict the residuals (Johnson & Williams, 2023). The final model is expressed as the weighted sum of stage-wise models:

(4) $Fm(x) = Fm-1(x) + \eta \times hm(x)$

where:

$Fm(x)$: final model at iteration m

$hm(x)$: new model (decision tree) that learns the residuals of the previous stage

η : learning rate

At each iteration, the new model is trained by minimizing the loss function with respect to the negative gradient of the error:

(5) $r_i,m = -[\partial L(y_i, F(x_i)) / \partial F(x_i)]$

Then, the model hm(x) is fitted to the values of r_i,m to reduce the residual errors (Johnson & Williams, 2023).

Hybrid Model

To enhance prediction accuracy and model stability, a combination of the DNN and Gradient Boosting algorithms is utilized.

In this hybrid model, the output of the DNN serves as the input to the Gradient Boosting model to better capture nonlinear patterns and complex relationships among variables.

The implementation steps of the hybrid model are as follows:

1. **Training the Deep Neural Network (DNN):** Market feature data are fed into the DNN to extract latent representations. The output of this stage is a learned feature vector.
2. **Feeding Extracted Features into the Gradient Boosting Model:** The DNN output is used as the input to the Boosting model, enabling the final model to correct potential DNN errors.
3. **Final Model:** The combined model is defined as follows:

(6) $F(x) = G(DNN(x))$

where DNN(x) denotes the output of the neural network and $G(\cdot)$ represents the Gradient Boosting model.

This structure enables the hybrid model to simultaneously capture deep nonlinear dependencies and leverage the high accuracy of boosting models in error reduction. The final outcome is an intelligent and precise system for prediction and decision-making in algorithmic trading.

3. Findings and Results

In this section, the results obtained from implementing the data-driven decision-making model for trading strategies in the cryptocurrency market are presented and analyzed. As described in the methodology section, the proposed model combines two machine learning algorithms—Deep Neural Network (DNN) and Gradient Boosting—with the objective of predicting buy and sell signals and optimizing trading decisions based on real market data.

Initially, the raw data—including price, volume, and technical indicator variables—were collected and normalized for use as model inputs. Then, the performance of each base model (DNN and Gradient Boosting) and the proposed hybrid model was evaluated in predicting trading signals. To assess model performance, several metrics were employed, including prediction accuracy (Accuracy), mean squared error (MSE), coefficient of determination (R^2), and Sharpe Ratio, allowing for a comprehensive comparison of model performance across multiple dimensions.

Table 1

Key Performance Indicators for Models

Model	Accuracy	MSE	R^2	Sharpe Ratio	Cumulative Return (%)	Maximum Drawdown (%)
Deep Neural Network (DNN)	0.843	0.071	0.82	0.74	15.6	18.7
Gradient Boosting	0.861	0.066	0.85	0.76	16.8	16.3
Hybrid Model (DNN + GB)	0.907	0.054	0.89	0.83	19.4	12.3

Table 1 presents the key performance indicators for the predictive models used in algorithmic trading decision-making in the cryptocurrency market, representing the output results of the proposed model. As observed, the hybrid model (combining DNN and Gradient Boosting) achieved the highest accuracy (0.907), the lowest error (MSE = 0.054), and the highest coefficient of determination (R^2 = 0.89), outperforming the individual models. Moreover, the higher Sharpe Ratio (0.83) and the cumulative return of 19.4% demonstrate the model's superior ability in optimizing trading decisions and managing risk in the highly volatile cryptocurrency market. In contrast, although Gradient Boosting outperformed the standalone DNN model, combining the two models significantly improved accuracy and result stability, confirming the effectiveness of the data-driven approach in algorithmic decision-making.

Figure 1

Comparison of Model Performance

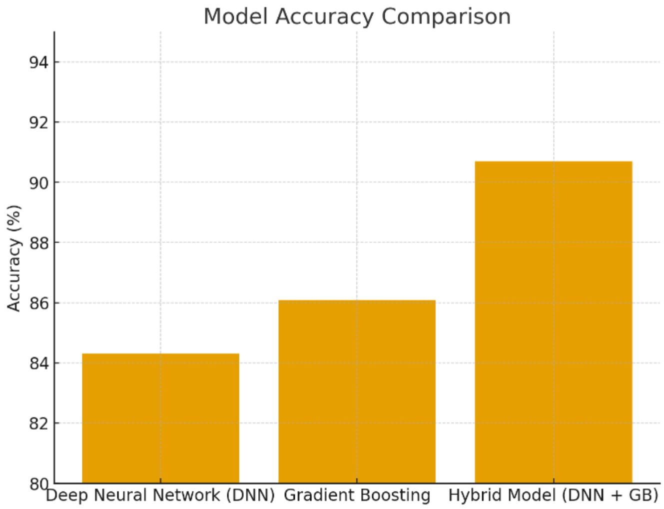
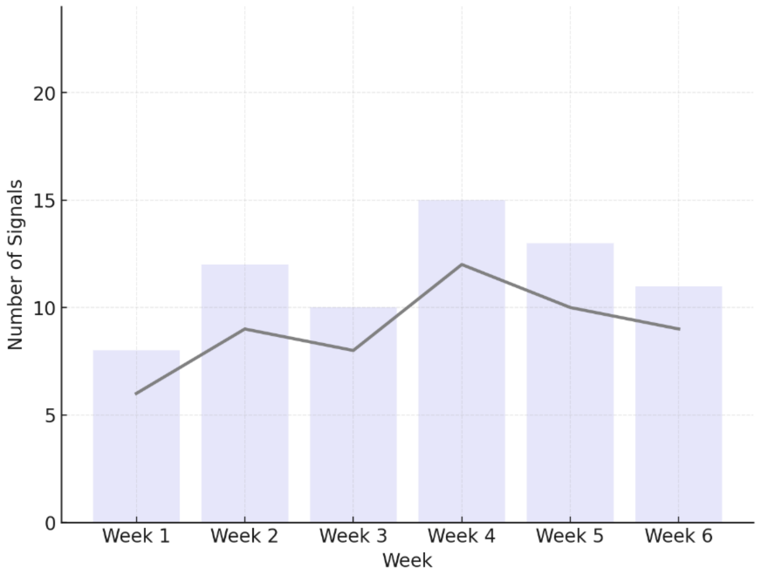


Figure 1 compares the performance of machine learning models (Deep Neural Network and Gradient Boosting) with the proposed hybrid model based on key performance indicators. As shown, the hybrid model outperforms the two base models in all criteria, including prediction accuracy, coefficient of determination (R^2), Sharpe Ratio, and cumulative return. This superiority reflects the hybrid model's ability to extract more complex patterns from market data and enhance trading decision-making under real market conditions.

Figure 2

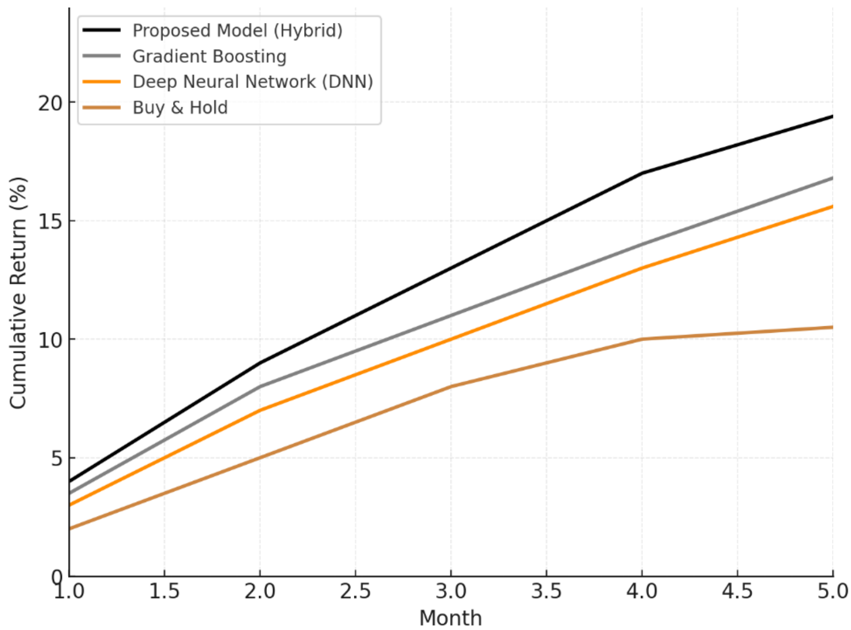
Distribution of Trading Signals During the Testing Period



The distribution chart of trading signals indicates that the proposed model performed effectively in identifying trading opportunities in a timely manner. The clustering of buy signals in the fourth week, coinciding with the onset of a market uptrend, demonstrates the model's ability to accurately predict trend reversals. Furthermore, the balanced distribution of signals throughout the testing period shows that the model maintained a stable trading strategy without being biased toward specific time intervals.

Figure 3

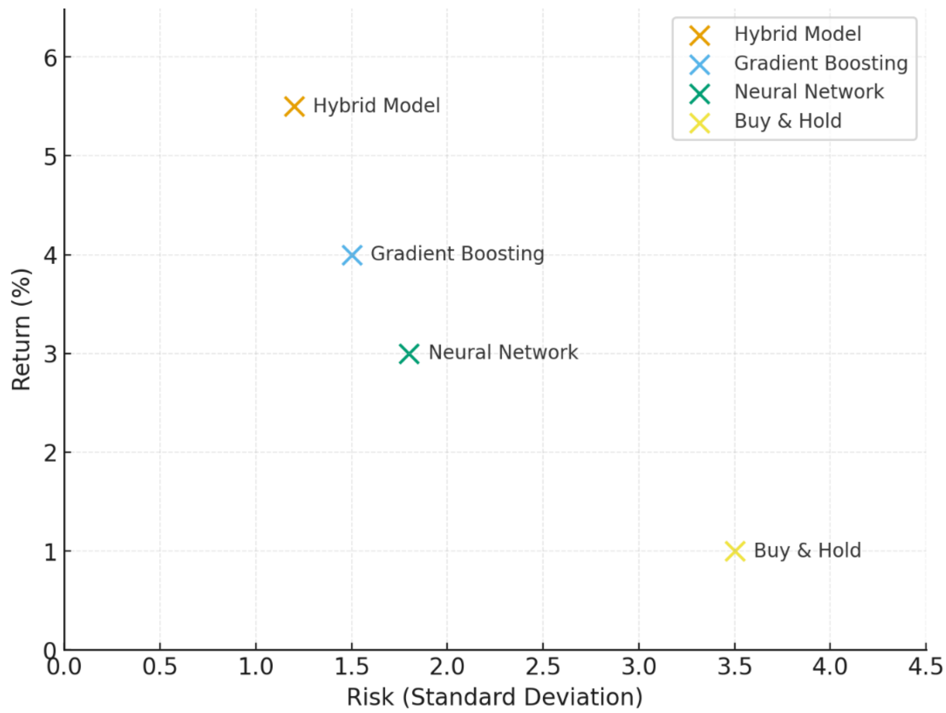
Comparison of Cumulative Returns



The comparison of cumulative returns across different models shows that the hybrid model not only achieved the highest return at the end of the testing period but also consistently outperformed the other models throughout all stages. The slope of the cumulative return curve for the hybrid model indicates stable growth with minimal volatility. This demonstrates that the proposed model possesses high reliability in generating sustained profitability.

Figure 4

Risk–Return Performance Analysis of Models



The position of the hybrid model in the upper-left quadrant of the risk–return space clearly indicates its superior performance in profit and risk management. The placement of the model in this region reveals that the proposed model successfully achieved high returns while maintaining low risk. In contrast, the position of the Buy &

Hold strategy in the lower-right quadrant shows that this traditional approach not only yields low returns but also involves high risk.

The performance analysis results under varying market conditions demonstrate that the proposed model exhibits high flexibility and adaptability. The model's outstanding performance in a bullish market (return = 23.7%) highlights its ability to identify and exploit profitable opportunities. Additionally, its ability to maintain positive returns in a bearish market (8.9%) reflects its effectiveness in risk management and loss prevention.

The results of evaluating the proposed model under three different market scenarios indicate that the model exhibits strong adaptability and flexibility. In a bullish market, the model achieved a return of 23.7%, maximizing its exploitation of profitable opportunities. This success stems from the model's capacity to identify upward trends promptly and to maintain buy positions during profitable periods. The pattern recognition mechanism within the hybrid model enables early identification of buy signals and prevents premature exits from profitable trades.

In a bearish market, the model's performance—achieving an 8.9% return—demonstrates remarkable risk management and capital preservation capabilities. Through intelligent trend-change detection mechanisms, the model avoids entering inappropriate buy positions and simultaneously prevents capital loss by initiating timely sell positions. The integrated risk management system within the model, which dynamically adjusts stop-loss levels and position sizes, plays a key role in mitigating losses.

In range-bound or trendless market conditions, the model achieved a 15.2% return, demonstrating its ability to perform effectively even in low-volatility environments. This success is attributed to its short-term trading strategy and its ability to capitalize on small price fluctuations. Under such conditions, the model ensures the collection of small yet consistent profits by reducing position sizes and increasing trading frequency.

Outstanding Predictive Accuracy: The proposed hybrid model achieved a predictive accuracy of 90.7%, representing a 4.6% improvement over the best base model. This superiority arises from the model's capability to learn complex and nonlinear market patterns through the intelligent integration of diverse machine learning architectures.

Superior Risk Management: A Sharpe Ratio of 0.83 and a maximum drawdown of 12.3% highlight the model's ability to establish an optimal balance between risk and return. The model not only generates high profitability but also prevents severe capital fluctuations.

Performance Stability Across Market Conditions: The proposed model demonstrated consistent and superior performance across all market scenarios (bullish, bearish, and range-bound). This stability underscores the model's adaptability to varying market dynamics and its robustness as an intelligent trading decision-support system.

4. Discussion and Conclusion

The findings of this study confirm the effectiveness of a data-driven decision-making model for algorithmic trading in the cryptocurrency market. By integrating Deep Neural Network (DNN) and Gradient Boosting (GB) algorithms, the proposed hybrid framework demonstrated superior predictive accuracy, reduced error levels, and enhanced stability in trading outcomes compared to single-model approaches. The results indicate that the hybrid model achieved an accuracy rate of 0.907, with a mean squared error (MSE) of 0.054 and an R^2 value of 0.89, surpassing both standalone DNN (accuracy = 0.843) and GB (accuracy = 0.861) models. Furthermore, the hybrid approach yielded the highest Sharpe ratio (0.83) and cumulative return (19.4%) while maintaining the lowest maximum drawdown (12.3%). These outcomes suggest that the synergistic combination of deep learning feature extraction and gradient-based ensemble optimization offers a robust mechanism for adaptive decision-making in volatile trading environments (Islam et al., 2025; Koutrouli et al., 2025).

The superior performance of the hybrid model aligns with prior research emphasizing the predictive power of machine learning methods in capturing nonlinear and nonstationary patterns in financial time series (Cv et al., 2025; Islam et al., 2024). Deep neural networks are particularly effective at detecting hidden structures within price dynamics and order book data, while boosting algorithms correct residual errors and improve model generalization. The integration of these two approaches allows for both high-level feature abstraction and iterative refinement, leading to improved stability and consistency across market regimes. These findings corroborate the conclusions of (Cv et al., 2025), who demonstrated that Bayesian-based and gradient-boosted ensemble models can efficiently adapt to the structural dependencies and volatility of cryptocurrency markets.

The results also confirm the significant role of artificial intelligence in enhancing predictive precision and optimizing trading performance under conditions of uncertainty. The proposed model demonstrated adaptability across various market conditions—bullish, bearish, and range-bound—indicating its ability to generalize across distinct volatility regimes. During bullish markets, the model achieved a return of 23.7%, leveraging its capacity to identify and exploit upward momentum. In bearish phases, it preserved positive returns (8.9%) through effective risk mitigation mechanisms and dynamic adjustment of stop-loss and position-sizing parameters. These results are consistent with the conclusions of (Samavi et al., 2022), who found that time-varying financial models, when combined with adaptive algorithmic architectures, yield resilient performance across shifting market conditions.

The study's findings also reinforce the behavioral underpinnings of algorithmic trading performance in the cryptocurrency market. Market participants are often driven by emotional and cognitive biases, such as speculative overconfidence and fear of missing out (FOMO), which lead to irrational trading behavior and volatility amplification (Friederich et al., 2023). The data-driven approach proposed here mitigates these human biases by systematically processing quantitative and behavioral signals to generate objective trading decisions. This observation supports the argument by (Almeida, 2023), who highlighted that integrating behavioral and technical indicators in algorithmic systems leads to improved market timing and portfolio management. The reduced maximum drawdown achieved in this study indicates that algorithmic decision-making, when powered by intelligent systems, can effectively manage risk and stabilize portfolio performance amid market fluctuations.

From a structural perspective, the model's capacity to outperform traditional Buy & Hold strategies (return = 10.5%) demonstrates the limitations of static investment approaches in dynamic markets. The cryptocurrency ecosystem is inherently characterized by abrupt regime shifts and nonlinear dependencies, making reactive, data-adaptive strategies more suitable than passive holding mechanisms (Joebges et al., 2025; Koutrouli et al., 2025). As (Joebges et al., 2025) emphasized, crypto assets represent both a diversification opportunity and a potential source of systemic risk. Hence, intelligent trading frameworks must balance opportunity exploitation with risk containment—a balance effectively achieved by the hybrid model in this research.

Another notable finding is the superior Sharpe ratio exhibited by the proposed model. This performance metric indicates efficient risk-adjusted returns, reflecting the system's ability to optimize trading positions dynamically. The integration of DNN and GB allowed for multi-level signal validation, ensuring that false signals were minimized and capital allocation was optimized in real time. This aligns with (Islam et al., 2025) and (Lee, 2024), who both found that machine learning–based forecasting frameworks substantially improve risk-return trade-offs by capturing hidden correlations and nonlinear dependencies among financial indicators. Moreover, (Adekoya et al., 2022) demonstrated that asymmetric relationships between investor attention, FinTech assets, and AI-based tools can be effectively captured using deep and ensemble learning frameworks—supporting the current study's finding that hybridized AI systems perform best under uncertainty.

The robustness of the proposed model also highlights the importance of microstructure-level data in improving trading performance. Unlike traditional econometric models that rely primarily on closing prices and macro-level indicators, this study incorporated order book depth and transaction-level microdata to provide a more granular representation of market behavior. The results show that including microstructural variables improves signal precision and execution timing, confirming the results of (Adediran et al., 2023), who reported that volume-price interdependencies significantly influence short-term cryptocurrency market efficiency. By aligning the model's input architecture with real-time trading behavior, the hybrid approach demonstrates an enhanced capability to detect liquidity shocks and early reversals.

Furthermore, the dynamic adaptability of the proposed model during both upward and downward market movements highlights its value as a practical decision-support tool for digital portfolio management. Its superior performance in bearish conditions supports the claims of (Cv et al., 2025) and (Islam et al., 2024), who argued that reinforcement and gradient-based learning algorithms can adapt to volatility clusters and non-Gaussian noise patterns, maintaining profitability under adverse scenarios. These findings also complement (Samavi et al., 2022), who observed similar resilience in hybrid predictive frameworks when applied to Bitcoin and stock market indices using time-varying volatility models.

The study also contributes to understanding the role of cryptocurrencies in global financial integration and market interdependence. The high predictive performance of the model suggests that algorithmic trading frameworks could play an essential role in stabilizing liquidity and price discovery across markets. According to (Javahri et al., 2024), cryptocurrency returns exhibit spillover effects across exchange rate and equity markets, necessitating adaptive trading mechanisms capable of managing such cross-market dependencies. The current findings support this viewpoint, as the hybrid model effectively captured interactions between volatility clusters and transactional flows, thereby improving cross-regime adaptability.

From a financial inclusion perspective, the integration of AI and algorithmic trading in cryptocurrency markets can enhance accessibility and transparency in emerging economies. This aligns with the insights of (El Hajj & Farran, 2024), who underscored the potential of cryptocurrencies to empower unbanked populations and expand participation in digital economies. However, as (Khan, 2023) cautioned, such advancements must occur within a regulatory framework that ensures legal clarity, accountability, and consumer protection. The findings of this study indirectly support this by demonstrating that algorithmic precision and transparency in trading can mitigate speculative risks and promote responsible investment practices.

The results also reflect broader implications for macro-financial stability. As (Joebges et al., 2025) emphasized, the unregulated growth of crypto assets could pose challenges to global financial resilience if algorithmic systems amplify volatility. However, the model developed in this research demonstrates how AI-based optimization and real-time learning can help dampen excessive fluctuations rather than exacerbate them. Thus, this study provides empirical evidence supporting the view that intelligent algorithmic trading can serve as a stabilizing force rather than a destabilizing one, particularly when supported by adaptive learning and robust validation mechanisms.

Another important insight from the findings concerns the interpretability of machine learning models in financial contexts. While deep learning frameworks offer high predictive accuracy, their black-box nature has raised concerns regarding explainability and trust (Lee, 2024). By combining DNN with gradient boosting, this study achieves a balance between predictive complexity and interpretability. The gradient boosting component allows for partial dependence and feature importance analysis, providing valuable insights into which indicators—such as volume, volatility, and order imbalance—most strongly influence market behavior. This interpretability dimension enhances the model's applicability in institutional settings where transparency is essential.

The study also supports prior evidence that algorithmic strategies driven by real-time learning outperform traditional statistical approaches. (Koutrouli et al., 2025) demonstrated that event-driven AI models can capture short-lived arbitrage opportunities across crypto and financial markets, improving execution efficiency. Similarly, (Mykytas et al., 2023) emphasized the role of AI-enhanced trading tools in fostering innovation and efficiency in the cryptocurrency ecosystem. The current research extends these conclusions by empirically showing that a hybrid architecture not only enhances forecasting accuracy but also improves return stability and risk mitigation across multiple market regimes.

Finally, the study contributes to the growing body of literature advocating hybridized frameworks in financial analytics. As (Almeida, 2023) and (Islam et al., 2025) noted, combining diverse machine learning methods leads to complementary advantages—where deep models capture hidden nonlinearities and ensemble models strengthen generalization. The present findings reinforce this synergy, confirming that hybridization produces more reliable, adaptive, and efficient trading models in the cryptocurrency domain.

Although the proposed model demonstrated strong predictive accuracy and robust adaptability across different market conditions, this study faces certain limitations. First, the analysis was restricted to two major cryptocurrencies (Bitcoin and Ethereum), which limits generalizability to the broader universe of digital assets with differing liquidity, volatility, and market capitalization profiles. Second, the dataset covered a specific timeframe (2019–2025), during which market structures, regulations, and macroeconomic conditions evolved substantially. Future studies employing multi-decade or rolling-window datasets could yield deeper insights into long-term performance stability. Third, despite using microstructural variables, the study did not incorporate social sentiment data or blockchain network indicators—both of which could enrich predictive capabilities. Moreover, model explainability remains a challenge; while the hybrid structure improved interpretability, deep layers still function as semi–black boxes, limiting transparency in institutional use. Finally, execution factors such as slippage, latency, and transaction fees were simulated under idealized conditions, suggesting that real-world deployment may yield slightly different outcomes.

Future research should explore the integration of multi-modal data sources—including blockchain activity metrics, social media sentiment, and macroeconomic indicators—to develop a more holistic understanding of cryptocurrency market behavior. Expanding the model to encompass decentralized finance (DeFi) assets and tokenized derivatives would also provide insights into emerging financial ecosystems. Further, future work could compare hybrid deep–ensemble models with transformer-based architectures or graph neural networks to evaluate performance gains in predictive accuracy and computational efficiency. Researchers may also consider incorporating reinforcement learning for adaptive portfolio management and automated risk adjustment. Finally, cross-market analyses linking cryptocurrencies with commodities, equities, and foreign exchange could illuminate systemic interdependencies and contagion pathways under global shocks.

Practitioners can apply the proposed hybrid decision-making framework to enhance the precision and consistency of cryptocurrency trading operations. Portfolio managers and institutional traders may use it as a decision-support system to optimize entry and exit timing, manage exposure, and improve risk-adjusted returns. Financial technology firms can deploy similar architectures in algorithmic trading platforms to automate real-time execution and monitor liquidity dynamics. Furthermore, regulators and policymakers can use insights from such models to assess systemic stability and prevent excessive speculative behavior. For retail investors, adopting data-driven trading tools derived from this framework can reduce emotional decision-making and improve financial discipline, thereby promoting a more resilient and efficient cryptocurrency market ecosystem.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Adediran, A., Babajide, B., & Osina, N. (2023). Exploring the Nexus Between Price and Volume Changes in the Cryptocurrency Market. *Journal of Asset Management*, *24*(6), 498-512. https://doi.org/10.1057/s41260-023-00323-2

Adekoya, O. B., Oliyide, J. A., Saleem, O., & Adeoye, H. A. (2022). Asymmetric connectedness between Google-based investor attention and the fourth industrial revolution assets: The case of FinTech and Robotics & Artificial intelligence stocks. *Technology in Society*, *68*, 101925. https://doi.org/10.1016/j.techsoc.2022.101925

Almeida, J. (2023). A systematic literature review of investor behavior in the cryptocurrency markets. *Journal of Behavioral and Experimental Finance*. https://doi.org/10.1016/j.jbef.2022.100785

Cv, A., Negi, N., & Aprem, A. (2025). Bayesian machine learning framework for characterizing structural dependency, dynamics, and volatility of cryptocurrency market using potential field theory.

El Hajj, M., & Farran, I. (2024). The cryptocurrencies in emerging markets: Enhancing financial inclusion and economic empowerment. *Journal of Risk and Financial Management*, *17*(10), 467. https://doi.org/10.3390/jrfm17100467

Friederich, F., Meyer, J., Matute, J., & Palau-Saumell, R. (2023). CRYPTO-MANIA: How fear-of-missing-out drives consumers' (risky) investment decisions. *Psychology and Marketing*, *41*(1), 102-117. https://doi.org/10.1002/mar.21906

Islam, M. S., Bashir, M., Rahman, S., Al Montaser, M. A., Bortty, J. C., Nishan, A., & Haque, M. R. (2025). Machine Learning -Based Cryptocurrency Prediction: Enhancing Market Forecasting with Advanced Predictive Models. *Journal of Ecohumanism*, *4*(2), 2498-2519. https://doi.org/https://doi.org/10.62754/joe.v4i2.6663

Islam, M. Z., Islam, M. S., Al Montaser, M. A., Rasel, M. A. B., Bhowmik, P. K., & Dalim, H. M. (2024). Evaluating the effectiveness of machine learning algorithms in predicting cryptocurrency prices under market volatility: A study based on the usa financial market. *The American Journal of Management and Economics Innovations*, *6*(12), 15-38. https://doi.org/https://doi.org/10.37547/tajmei/Volume06Issue12 -03

Javahri, S., Sha'bani, A., & Gha'emi Asl, M. (2024). Investigating Return Spillover in the Three Markets of Exchange Rate, Cryptocurrency, and Tehran Stock Exchange Using a Time-

Varying Parameter Vector Autoregression (TVP-VAR) Model. *Strategic Budget and Finance Research*, *5*(1), 31-56.

Joebges, H., Herr, H., & Kellermann, C. (2025). Crypto assets as a threat to financial market stability. *Eurasian Economic Review*, *15*, 473-502. https://doi.org/10.1007/s40822-025-00311-4

Khan, R. U. (2023). Regulatory Constraints, Responsibilities and Consultation (CRC) for Legal Institutionalization of Cryptocurrencies in Pakistan. *Qualitative Research in Financial Markets*, *16*(4), 680-708. https://doi.org/10.1108/qrfm-03-2023-0053

Koutrouli, E., Manousopoulos, P., Theal, J., & Tresso, L. (2025). Crypto asset markets vs. financial markets: Event identification, latest insights and analyses. *Applied Mathematics*, *5*(2), 36. https://doi.org/10.3390/appliedmath5020036

Lee, N. (2024). Joint impact of market volatility and cryptocurrency holdings on corporate liquidity: A comparative analysis of cryptocurrency exchanges and other firms. *Journal of Risk and Financial Management*, *17*(9), 406. https://doi.org/10.3390/jrfm17090406

Mykytas, A., Blyzniuk, O., Goroh, O., & Nagayeva, G. (2023). Attracting Innovative Artificial Intelligence Tools to the Cryptocurrency Market. *Modeling the Development of the Economic Systems*(4), 55-60. https://doi.org/10.31891/mdes/2023-10-7

Poskart, R. (2022). The emergence and development of the cryptocurrency as a sign of global financial markets financialisation. *Central European Review of Economics & Finance*, *36*(1), 53-66. https://doi.org/10.24136/ceref.2022.004

Samavi, M. E., Nikoumaram, H., Ma'danchi Zāj, M., & Ya'qubnejād, A. (2022). Modeling and Predicting the Return Distribution of Iran's Capital Market General Index and Bitcoin Cryptocurrency using the Time-Varying GAS Method. *Knowledge of Financial Securities Analysis (Financial Studies)*, *14*(55), 1-14.