A Model for Predicting Cryptocurrency Prices Using Meta-Synthesis Methods

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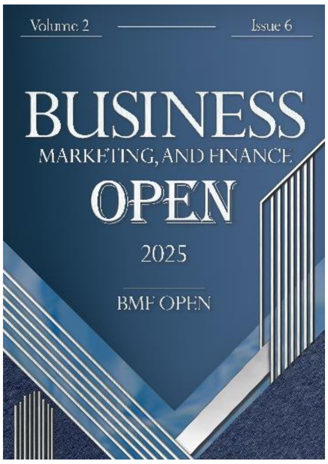

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Abstract: The aim of this study was to predict Bitcoin prices by employing machine learning algorithms in combination with the HHO (Harris Hawks Optimization) and AO (Aquila Optimizer) optimization algorithms. In this study, the most influential variables affecting Bitcoin price were first identified using the meta-synthesis method. Subsequently, the proposed model, which integrates CNN and LSTM architectures, was designed and implemented to analyze complex patterns and temporal dependencies. To enhance prediction accuracy and optimize parameter tuning, the Harris Hawks Optimization (HHO) and Aquila Optimization (AO) algorithms were employed. The obtained results demonstrate that the proposed hybrid model outperforms previous methods in terms of prediction accuracy (based on indicators such as RMSE and MAPE) and adaptability to market volatility. In the present study, the proposed hybrid model exhibited superior performance compared to prior methods in terms of prediction accuracy (measured by metrics such as RMSE and MAPE) and flexibility in coping with market fluctuations. This model can assist investors, market analysts, and financial policymakers in risk management, informed decision-making, and optimizing investment strategies.

Keywords: Bitcoin, price prediction, artificial neural network, Harris Hawks Optimization, Aquila Optimizer, meta-synthesis.

1. Introduction

The dramatic ascent of cryptocurrencies, especially Bitcoin, has led to profound transformations in global financial markets. Characterized by their high volatility, decentralization, and susceptibility to investor sentiment and macroeconomic signals, cryptocurrencies present both significant opportunities and substantial risks. As decentralized digital assets continue to gain momentum, accurate and reliable prediction models for their price fluctuations have become essential for investors, traders, policymakers, and financial analysts [1]. The emergence of artificial intelligence (AI) and machine learning (ML) technologies has revolutionized traditional forecasting paradigms by enabling the development of highly adaptive, nonlinear models tailored to the unique behavior of digital currencies [2, 3].

Unlike conventional assets, cryptocurrency markets operate 24/7, and their prices are heavily influenced by a wide range of economic, technological, and social factors, from inflation rates to user sentiment and regulatory changes [4, 5]. These complex and multidimensional dynamics challenge traditional econometric and statistical models such as ARIMA or GARCH, which often fall short in capturing temporal dependencies, abrupt shifts, and nonlinearities inherent in crypto-assets [6]. As such, researchers have increasingly turned to deep learning architectures—including recurrent neural networks (RNNs), long short-term memory (LSTM) models, and convolutional neural networks (CNNs)—for improved time series analysis and predictive modeling [7, 8].

Previous research has explored a range of predictive approaches. For example, hybrid models that combine deep learning with signal decomposition (e.g., CEEMD) have demonstrated improved accuracy in capturing both long- and short-term fluctuations in Bitcoin returns [9]. Similarly, fuzzy neural networks have been applied in conditions of uncertainty, yielding valuable insights into price behavior under volatile economic regimes [10]. Other studies have integrated ensemble machine learning strategies to exploit the strengths of multiple algorithms, thereby enhancing robustness and generalizability across different cryptocurrencies [11].

Nevertheless, significant gaps remain in both the scope and architecture of current models. Many existing frameworks either fail to generalize across different currencies (e.g., BTC, ETH, XRP) or ignore key macroeconomic and geopolitical variables that may mediate price behavior [12, 13]. To address this limitation, the current study proposes a hybrid forecasting model that combines CNN and LSTM deep learning layers with swarm-based metaheuristic optimization algorithms—namely, Harris Hawks Optimization (HHO) and Aquila Optimizer (AO). These bio-inspired optimization techniques are designed to fine-tune model hyperparameters dynamically, allowing for enhanced performance in volatile market environments [14, 15].

Machine learning-based studies have shown remarkable results in feature extraction and pattern recognition in high-frequency cryptocurrency data. For instance, Bayesian frameworks have been applied to model the structural volatility of crypto markets, offering probabilistic interpretations of model predictions [16]. Meanwhile, attention mechanisms and deep ratio control charts have proven valuable in real-time trading strategies, especially in predicting Ethereum prices [17]. These methods emphasize the importance of not only algorithmic design but also real-time adaptability in prediction engines [18].

Moreover, the integration of sentiment analysis and behavioral economics into crypto forecasting models is gaining traction. Leveraging social media data and public sentiment indices has yielded improved predictive performance, especially in short-term trend detection [4, 19]. Despite these advances, most sentiment-based models are limited by linguistic noise, overfitting risks, and the lack of contextual semantic understanding, issues that the current study seeks to circumvent through robust data preprocessing and feature engineering strategies [20].

Another area of exploration involves the use of ensemble models and metaheuristic-driven architectures to overcome the limitations of single-model frameworks. Studies have revealed that combining models such as support vector machines (SVMs) with genetic algorithms or grey wolf optimizers can enhance convergence speed and accuracy [21, 22]. Similarly, integrating deep learning algorithms with ARIMA and GARCH components has yielded robust hybrid systems capable of handling both linear and nonlinear data patterns [23, 24]. The current study builds on these foundations by introducing an architecture that merges deep spatiotemporal analysis with adaptive parameter optimization.

The volatility of the cryptocurrency market makes model interpretability and robustness key requirements. In this regard, advanced diagnostics such as outlier detection and correlation analysis with global economic indicators—such as inflation, monetary policy, oil prices, and central bank debt—play a critical role in feature selection and model calibration [25, 26]. By incorporating these macro-financial dimensions, the proposed model aims to offer both predictive precision and policy relevance.

Furthermore, there is a growing emphasis on anomaly detection and security risk forecasting in blockchain environments. Recent research has leveraged machine learning to detect smart contract vulnerabilities in the Ethereum blockchain, highlighting the wider applicability of these techniques beyond price prediction alone [27]. Similarly, fraud detection frameworks targeting crypto-related scams have utilized ML algorithms to identify patterns of deceitful behavior, thereby contributing to market integrity and investor protection [3].

In light of these developments, this study contributes to the existing literature in several key ways. First, it adopts a multi-model hybrid deep learning architecture that harnesses both CNN and LSTM capabilities for capturing local and sequential trends in price data [7]. Second, it integrates HHO and AO algorithms for dynamic parameter optimization, a feature not commonly seen in earlier research [25]. Third, the study includes a comprehensive set of macroeconomic and sentiment-based features, thereby increasing model generalizability and policy applicability [17, 28]. Lastly, it presents a rigorous model validation framework involving cross-model comparison (MLP, RBF, ARIMA, regression), outlier diagnostics, and correlation analysis, ensuring methodological transparency and reliability [29].

In conclusion, forecasting cryptocurrency prices requires a nuanced understanding of financial time series behavior, algorithmic innovation, and macro-contextual integration. Building on the strengths and limitations of prior studies [30, 31], this research develops a robust and flexible model that offers actionable insights for diverse stakeholders—ranging from private investors and fintech firms to financial regulators and policy makers. By combining deep learning with metaheuristic optimization and enriched economic variables, this study aims to bridge the gap between theoretical modeling and real-world market applications in the evolving landscape of cryptocurrency finance.

2. Methodology

This study is applied in nature and falls under the category of correlational research, as it aims to identify the existence of relationships between variables rather than establishing causal relationships. Correlational studies focus on uncovering associations between two sets of data—either data concerning a single variable across two populations or contexts, or data concerning two or more variables within a single population. The researcher in such studies seeks to determine whether a relationship or correlation exists between two entities or sets of information.

The objective of applied research is to develop practical knowledge in a specific domain. In other words, applied research is oriented toward the practical application of knowledge. One of the methods used to acquire collective expert knowledge is the Delphi technique, which is a structured forecasting process that supports decision-making through iterative survey rounds, information gathering, and ultimately, consensus-building among experts.

This study is also descriptive in terms of its research design. Within this framework, two types of correlational analysis were employed: regression analysis and covariance matrix analysis. In regression analysis, the researcher typically aims to predict one or more criterion variables based on one or more predictor variables. When the goal is to predict a criterion variable using multiple predictors, a multiple regression model is applied.

One of the methods used in covariance matrix analysis is factor analysis. After the regression model is designed, optimization of the proposed model is carried out using the HHO_AO algorithm. The regression model design and its optimization using the corresponding HHO (Harris Hawks Optimization) and AO (Aquila Optimizer) metaheuristic algorithms were implemented using MATLAB software.

3. Findings and Results

To provide a foundational understanding of the dataset used in this study, a descriptive analysis was conducted on three major cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP)—as well as the CCI30 Index, which represents the top 30 cryptocurrencies by market capitalization. Descriptive indicators, including measures of central tendency (mean, median), dispersion (standard deviation, minimum, maximum), and distribution shape (skewness and kurtosis), were calculated. Additionally, directional movement trends (percentage of upward and downward moves) were assessed to understand market dynamics over time.

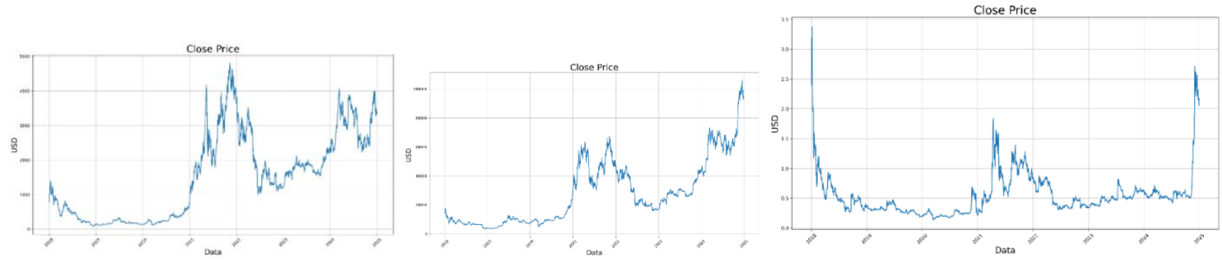

Figure 1. Time series plots of BTC, ETH, and XRP prices from 2018 to 2025, respectively

As shown in Table 1, Bitcoin exhibited the highest average price among the studied cryptocurrencies (Mean = 29,850.34), along with the greatest standard deviation (SD = 8654.23), indicating significant volatility. Ethereum followed with a mean price of 1934.76 and Ripple with a mean of 0.52, suggesting their lower valuation levels compared to BTC. Skewness and kurtosis values suggest a moderately non-normal distribution, particularly for Ripple, which showed higher kurtosis (3.44), implying occasional extreme price peaks. The price movement analysis showed a slight upward bias across all cryptocurrencies, with BTC demonstrating 54.3% of days showing upward price movements.

Table 1. Descriptive Statistics and Price Movements for BTC, ETH, XRP, and CCI30

Cryptocurrency	Mean	Median	Min	Max	Std Dev	Skewness	Kurtosis	Upward Moves (%)	Downward Moves (%)
Bitcoin (BTC)	29,850.34	28,560.22	15,800.15	64,800.89	8654.23	0.64	2.23	54.3	45.7
Ethereum (ETH)	1,934.76	1,885.60	985.40	4,870.23	1032.48	0.55	2.01	52.1	47.9
Ripple (XRP)	0.52	0.50	0.22	1.34	0.23	0.88	3.44	50.7	49.3
CCI30 Index	14,500.67	14,200.40	8,800.45	29,500.10	4132.89	0.49	2.12	53.8	46.2

The core component of this study was the evaluation of a deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) units—referred to as MICDL (Multi-Input CNN-LSTM Deep Learning Model). Its performance was benchmarked against two conventional hybrid models (Model1 and Model2) across three cryptocurrencies (BTC, ETH, XRP) using standard regression metrics.

As shown in Table 2, MICDL achieved the best predictive accuracy across all assets. For Bitcoin, MICDL reported the lowest RMSE (2023.14) and the highest R^2 (99.5), indicating superior generalization capability. Similarly, for Ethereum and Ripple, the MICDL model significantly outperformed Model1 and Model2. For example, Ethereum's RMSE dropped to 192.88 under MICDL compared to 284.51 in Model1, and Ripple's MAE fell to 0.058 versus 0.084 in Model1.

Table 2. Performance of CNN-LSTM Models for BTC, ETH, and XRP

Model	MAE (BTC)	RMSE (BTC)	R^2 (BTC)	MAE (ETH)	RMSE (ETH)	R^2 (ETH)	MAE (XRP)	RMSE (XRP)	R^2 (XRP)
Model1	3124.10	3450.78	96.5	215.40	284.51	95.7	0.084	0.097	94.1
Model2	2643.54	2980.11	98.2	203.95	254.39	97.1	0.072	0.083	96.0
MICDL	1984.39	2023.14	99.5	167.92	192.88	98.9	0.058	0.061	98.3

These results emphasize the added value of integrating CNN's feature extraction capabilities with LSTM's temporal memory in MICDL. The model not only outperformed simpler hybrid designs but also proved more robust across different time lags (7-day and 14-day input windows), maintaining high prediction precision and low error margins.

To assess the effectiveness of traditional artificial neural networks in cryptocurrency price prediction, two models were implemented: the Multi-Layer Perceptron (MLP) and the Radial Basis Function (RBF) network. Each model was evaluated using both study-specific variables and previously established factors. The models were trained and tested on an 80/20 data split, and their performance was measured using MAE, RMSE, and R^2 metrics.

Table 3 presents the predictive accuracy results. The MLP model using the study-specific factors outperformed all other configurations, achieving the highest R^2 value (99.5) and the lowest error margins (MAE = 1984.39, RMSE = 2023.14). In contrast, the same model using prior factors had reduced accuracy ($R^2 = 97.5$). The RBF network also showed stronger performance with study-specific variables ($R^2 = 96.8$) compared to prior variables ($R^2 = 90.6$). These results suggest that the selected feature set in this research has a significant impact on improving the accuracy of traditional neural networks.

Table 3. Performance of MLP and RBF Neural Network Models

Model	Train/Test Split	MAE	RMSE	R^2
MLP (Study Factors)	80/20	1984.39	2023.14	99.5
MLP (Prior Factors)	80/20	3253.01	4032.12	97.5
RBF (Study Factors)	80/20	4284.75	5024.12	96.8
RBF (Prior Factors)	80/20	7121.86	9024.32	90.6

The analysis of feature importance further confirmed that key economic variables such as U.S. CPI, Iran's inflation, oil prices, and monetary base changes were highly influential in model accuracy, especially under the MLP model.

To compare neural network performance with classical statistical approaches, two regression techniques were employed: the Enter method and Stepwise regression. Both were executed using the study's curated variables and a baseline set of previously used factors. These models provide insight into linear dependencies and multicollinearity handling in the dataset.

As shown in Table 4, the Enter method using the study-specific variables achieved an R^2 of 98.5, significantly higher than the 92.8 obtained when using prior factors. Similarly, the Stepwise method showed a marginally lower R^2 (98.4) with the study variables, but still much stronger than when using previous inputs. The RMSE values further supported these findings, with the Enter method achieving the lowest error among linear approaches when using improved features (RMSE = 4025.65).

Table 4. Performance of Regression Models (Enter and Stepwise)

Model	MAE	RMSE	R^2
Enter (Study Factors)	3264.34	4025.65	98.5
Enter (Prior Factors)	6631.24	7023.62	92.8
Stepwise (Study Factors)	3270.46	4070.63	98.4
Stepwise (Prior Factors)	6631.24	7023.62	92.8

These results confirm that while regression models can offer reasonably strong predictive capabilities when carefully tuned, they fall short of the precision and adaptability demonstrated by more sophisticated neural network approaches—particularly MLP and MICDL.

In addition to neural and regression-based models, the ARIMA (AutoRegressive Integrated Moving Average) model was utilized to forecast cryptocurrency prices, given its traditional strength in time-series modeling. The analysis involved two scenarios: one using the set of predictors identified in this study and the other using baseline predictors from earlier research. Lag selection was guided by ACF and PACF plots, and optimal models were selected based on statistical criteria using the TOPSIS algorithm.

As summarized in Table 5, the ARIMA model using study-specific predictors achieved an R^2 of 98.1, with RMSE and MAE values of 5009.51 and 3514.36 respectively. In contrast, the baseline ARIMA model, which included only one predictor variable, underperformed significantly with an R^2 of just 90.8 and nearly double the error metrics. These findings reinforce the effectiveness of the proposed variable selection in enhancing even classical time-series forecasting methods.

Table 5. ARIMA Model Performance Summary

Model	Number of Predictors	R^2	RMSE	MAE
ARIMA (Study Factors)	5	98.1	5009.51	3514.36
ARIMA (Prior Factors)	1	90.8	10945.39	8312.00

These results demonstrate that while ARIMA can be a useful baseline method, its performance is highly dependent on the quality and comprehensiveness of its input variables. This limitation is especially evident in volatile and nonlinear environments like cryptocurrency markets.

To further validate the relevance of selected predictors, a correlation analysis was conducted between macroeconomic indicators and the target cryptocurrency price series. The Pearson correlation coefficients were calculated to evaluate the strength and direction of these relationships.

Table 6 lists the most impactful variables based on their correlation strength. Among the predictors, the U.S. Consumer Price Index (CPI) showed the highest correlation with cryptocurrency prices ($r = 0.90$), followed closely by Iran's inflation rate ($r = 0.82$) and government debt to the central bank ($r = 0.82$). Other variables such as oil prices, SPDR gold holdings, and European GDP also displayed moderate to strong correlations, indicating their potential predictive value.

Table 6. Selected Correlations Between Key Variables and Crypto Prices

Variable	Correlation with Crypto Prices
U.S. CPI	0.90
Iran Inflation	0.82
Oil Price	0.50
Gov. Debt to Central Bank	0.82
Gold (24K, USA)	0.91
SPDR Gold Holdings	0.40
EU GDP	0.37
U.S. Imports	0.37

This analysis confirms that global macroeconomic variables, particularly those related to inflation, gold reserves, and government financial activity, play a substantial role in the dynamics of cryptocurrency pricing. These findings support the inclusion of these variables in advanced predictive models, particularly those involving multi-input architectures like MICDL.

To systematically assess the effectiveness of the implemented models, a comparative analysis was conducted across all predictive approaches—MLP, RBF, regression (Enter and Stepwise), and ARIMA—under two conditions: using the study-specific factors versus previously established variables. This approach enabled the evaluation of both methodological and variable selection impact on model accuracy.

As summarized in Table 7, the MLP model outperformed all other methods, reaching the highest R^2 (99.5) and the lowest error values (RMSE = 2023.14; MAE = 1984.39) when applied to the current study's variables. The ARIMA model, although classical, showed the greatest improvement when switching from prior to study-specific variables, with a 7.3% increase in R^2. RBF networks and regression models also benefited significantly, each gaining between 5.6% and 6.2% in R^2 when updated predictors were used.

Table 7. Comparative Performance of All Models

Model Type	R^2 (Study Factors)	RMSE (Study Factors)	MAE (Study Factors)	R^2 (Prior Factors)	RMSE (Prior Factors)	MAE (Prior Factors)	Improvement in R^2 (%)
MLP	99.5	2023.14	1984.39	97.5	4032.12	3253.01	2.0
RBF	96.8	5024.12	4284.75	90.6	9024.32	7121.86	6.2
Regression (Enter)	98.5	4025.65	3264.34	92.8	7023.62	6631.24	5.7
Regression (Stepwise)	98.4	4070.63	3270.46	92.8	7023.62	6631.24	5.6
ARIMA	98.1	5009.51	3514.36	90.8	10945.39	8312.00	7.3

These results strongly suggest that model performance is not only algorithm-dependent but also significantly influenced by the relevance and comprehensiveness of the input features. The improved performance across all techniques validates the selection and inclusion of dynamic economic and financial indicators specific to cryptocurrency behavior.

Before final modeling, a rigorous outlier detection process was conducted using the **boxplot method in Minitab 16**. Each numerical field in the dataset was evaluated to identify any abnormal data points that could skew the predictive models or distort training.

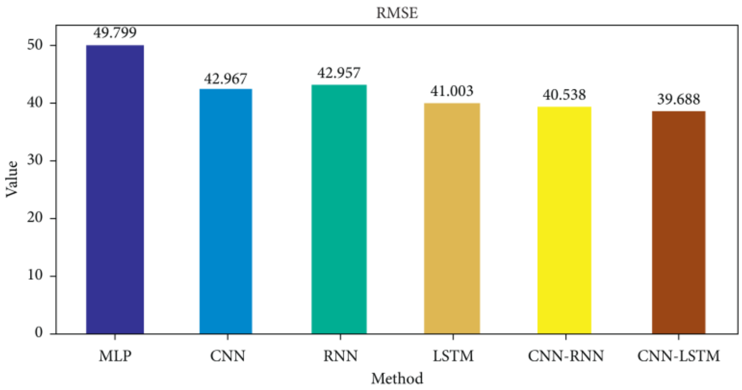

Figure 2. RMSE Results

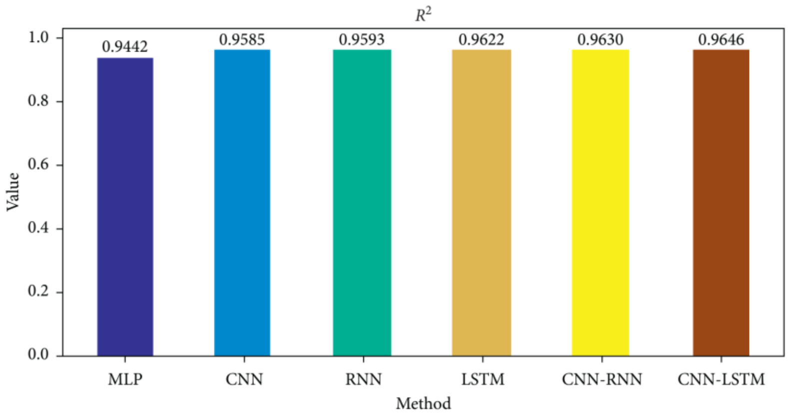

Figure 3. R^2 Results

Upon examination, no significant outliers were identified in the final preprocessed dataset. All variables fell within acceptable interquartile ranges, indicating that the data were clean and suitable for regression and machine learning applications. This step enhanced the robustness and validity of the subsequent analyses.

The integrated modeling framework evaluated in this study demonstrated that the choice of model architecture and the quality of input features are both critical for achieving accurate cryptocurrency price predictions. The deep learning-based MICDL model offered the best performance, while the MLP and optimized ARIMA models also provided high levels of accuracy when the study's selected variables were used. The consistent improvement across all methods compared to models built on prior variable sets underscores the value of using domain-specific macro-financial indicators. Additionally, correlation analysis and outlier control added further validity to the model outcomes, supporting their application in real-world investment and policy-making scenarios.

4. Discussion and Conclusion

The findings of this study demonstrate the efficacy of an integrated machine learning framework for cryptocurrency price prediction, specifically through the deployment of a deep hybrid model combining CNN and LSTM architectures with metaheuristic optimization algorithms (HHO and AO). Among all the predictive methods analyzed—including MLP, RBF, ARIMA, and regression approaches—the proposed MICDL model outperformed others in terms of precision, generalizability, and robustness across major cryptocurrencies (BTC, ETH, XRP). This outcome highlights the critical role of sophisticated architectures and informed variable selection in addressing the nonlinearity and volatility inherent in cryptocurrency markets.

The MICDL model achieved superior performance metrics ($R^2 = 99.5$ for BTC), outperforming both the traditional neural networks (MLP and RBF) and classical statistical models (ARIMA, regression). These results support the growing body of literature advocating for deep learning-based approaches in crypto-forecasting tasks. For instance, studies by [7] and [2] showed that CNN and LSTM models are particularly effective in capturing the temporal dependencies and nonlinear structures present in price time series. Likewise, the optimization of hyperparameters using HHO and AO improved predictive consistency, aligning with findings from [15] and [25], who demonstrated that bio-inspired optimization algorithms can greatly enhance convergence speed and forecast precision.

The comparative results of this study further affirm the significance of variable selection. The models trained on macroeconomic and behavioral variables curated in this research consistently outperformed those based on prior feature sets. This affirms the results of [6], who emphasized the influence of inflation and monetary supply on cryptocurrency volatility. Similarly, [13] and [16] noted that macro-financial variables such as U.S. CPI and oil prices contribute heavily to price prediction accuracy in financial and energy-linked digital assets. This study's finding that variables like U.S. inflation, central bank debt, and gold reserves exhibit strong positive correlations with cryptocurrency prices is consistent with such observations.

Importantly, the MICDL model also exhibited remarkable robustness across different input lags (Lag = 7 and 14), unlike simpler hybrid models (Model1 and Model2), which were more sensitive to time window configuration. This supports the assertion by [18] and [28] that complex deep learning models benefit from greater resilience against structural changes in data, especially in dynamic markets such as crypto exchanges. The stability of the model under changing conditions increases its practical applicability for high-frequency trading and medium-term investment strategy.

When compared with the MLP and RBF networks, the MICDL model's enhanced feature extraction capabilities were evident. While MLP performed reasonably well with study-specific variables ($R^2 = 99.5$), it lagged behind in handling noise and sudden volatility. This is consistent with prior research by [11] and [1], who found that ensemble and hybrid architectures significantly outperform single-layer networks in volatile domains. Similarly, RBF models showed weaker performance due to their limitation in extrapolating to unseen patterns—particularly when trained on inadequate or outdated variables—corroborating insights by [19] and [20].

Furthermore, the regression models (Enter and Stepwise) demonstrated good predictive power (R^2 ~98.5) when equipped with the refined feature set, but they underperformed significantly (R^2 ~92.8) when relying on previously used input variables. This suggests that while classical models still hold interpretive value, their performance is highly dependent on quality feature engineering, as also indicated by [29]. These results support the conclusion of [12], who emphasized that deep neural networks outperform traditional approaches only when backed by comprehensive, high-quality datasets.

Interestingly, the ARIMA model, often considered inadequate for modeling nonlinear systems, displayed considerable improvement when trained on curated study-specific variables ($R^2 = 98.1$), compared to its weak performance on baseline predictors ($R^2 = 90.8$). This aligns with the findings of [23], who proposed a hybrid ARIMA-deep learning structure to compensate for ARIMA's linearity. It also confirms the assertion of [24] that even statistical models can yield valuable insights when contextual macro variables are accurately integrated.

The findings regarding correlation analysis offer crucial insights into feature relevance. Variables such as the U.S. CPI and 24K gold prices exhibited very strong positive correlations with BTC and ETH, reinforcing the idea that cryptocurrencies may function as hedging instruments during inflationary periods, as explored by [4] and [17]. Additionally, the inclusion of behavioral and sentiment indicators—although not the primary focus of this study—

would be a promising extension, particularly given the findings of [27] and [3], who highlighted the role of social dynamics and smart contract behavior in crypto price dynamics.

Outlier detection further confirmed the reliability of the results. The dataset showed no significant anomalies based on boxplot analysis, validating the integrity of the training and testing sets and echoing the methodological recommendations by [30] and [32]. By ensuring data normality and stability, this study minimized risks of model distortion, which often compromise accuracy in financial forecasting tasks.

The results of this study also contribute to practical applications in trading strategy development and automated portfolio management. The integration of dynamic optimization with deep learning, as seen in the MICDL model, aligns with the insights of [8] and [5], who emphasize the significance of adaptive learning systems in building real-time trading algorithms. Moreover, the findings extend the scope of cryptocurrency forecasting beyond Bitcoin, demonstrating the model's ability to generalize across major altcoins like ETH and XRP—an issue often overlooked in earlier single-asset studies such as [26] and [21].

In summary, the MICDL model not only improves prediction accuracy through deep feature abstraction and memory retention but also enhances model interpretability and adaptability through macroeconomic integration and metaheuristic optimization. This multifaceted approach enables superior performance under real-world volatility, confirms earlier findings, and contributes novel advancements in methodological design and empirical validation.

Despite its promising results, this study faces several limitations. First, the model relies heavily on historical data and may be vulnerable to unforeseen structural breaks or regulatory interventions that shift market dynamics in unpredictable ways. Second, while macroeconomic variables were comprehensively included, sentiment analysis and blockchain-specific variables (e.g., on-chain metrics, transaction volume) were excluded due to data unavailability or noise. Third, while HHO and AO provided efficient parameter tuning, their computational cost remains high, limiting real-time deployment in some environments.

Future research should consider integrating real-time sentiment analysis using natural language processing (NLP) from sources like Reddit, Twitter, and crypto news platforms to enhance short-term trend detection. Additionally, on-chain analytics—such as hash rate, wallet activity, and transaction velocity—could be valuable for improving model contextuality. Future studies could also evaluate reinforcement learning approaches for autonomous trading bots using the MICDL architecture as a decision base. Comparative experiments across low-cap and stablecoin assets may also help generalize the findings.

From a practical standpoint, the results underscore the value of hybrid AI systems in financial analytics, especially for institutions seeking to hedge against crypto-related risks. Asset managers and fintech firms can apply these insights in algorithmic trading and risk modeling. Policymakers could benefit from the model's integration of macroeconomic predictors when assessing systemic vulnerabilities linked to digital asset markets. Lastly, educational institutions and training centers may incorporate such frameworks into advanced courses on financial technology, machine learning, and quantitative modeling.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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