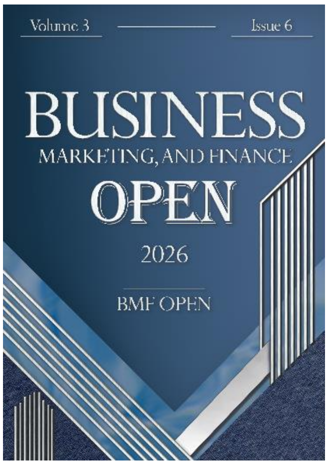
Proposing Regression and Machine Learning Methods and Auto-Regressive Integrated Moving Average Time Series in Predicting the Price of Ripple Digital Currency



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Abstract: This study proposes a hybrid forecasting approach for predicting the price of Ripple's digital currency, XRP, by integrating autoregressive integrated moving average (ARIMA) time series models with machine learning (ML) techniques, including linear regression and ensemble methods. Leveraging historical price data, trading volume, market sentiment, and macroeconomic indicators, the hybrid model aims to capture both temporal dependencies and broader market dynamics for enhanced prediction accuracy. Continuous monitoring and adaptation are emphasized to address the dynamic nature of the cryptocurrency market. Accordingly, the methods of linear regression, support vector machine regression, decision tree regression, and random forest regression, as well as ARIMA, are used, which obtains the root mean squared error (RMSE) values of 0.9934, 0.9667, 0.9837, 0.9854, and 0.9178 respectively. Multiple regression is the most accurate model for predicting the value of the digital currency Ripple, whereas the ARIMA time series is the least accurate forecasting model. The novelty of the work lies in the heart of the accuracy of multiple regression in price prediction.

Keywords: Multiple regression, XRP, price prediction, ARIMA, time series analysis, machine learning,

1. Introduction

The exponential expansion of digital financial markets over the past decade has fundamentally transformed the architecture of global capital flows, risk allocation, and asset valuation, placing cryptocurrencies at the center of both academic inquiry and speculative investment [1, 2]. Among these digital assets, Ripple (XRP) occupies a distinctive position due to its hybrid technological-financial orientation, which combines blockchain-based settlement efficiency with institutional payment infrastructure, thereby differentiating it from purely decentralized cryptocurrencies such as Bitcoin [3, 4]. The valuation dynamics of XRP are shaped not only by endogenous trading mechanisms but also by cross-border transaction adoption, liquidity conditions, regulatory developments, and investor sentiment, all of which contribute to pronounced volatility patterns [5, 6]. The literature consistently emphasizes that cryptocurrency markets exhibit structural breaks, speculative bubbles, and behavioral overreactions, particularly in bull and bear cycles, making price prediction substantially more complex than in traditional equity markets [7, 8]. Consequently, accurate modeling of XRP prices requires methodological frameworks capable of capturing both linear temporal dependencies and nonlinear structural shifts embedded within high-frequency financial time series.

Traditional econometric approaches to financial forecasting have relied heavily on linear time series methodologies such as ARIMA, which model autoregressive and moving-average components after differencing to ensure stationarity [9, 10]. ARIMA-based frameworks have demonstrated empirical utility across multiple asset classes, including commodities and energy prices [11, 12], and remain foundational for understanding lag structures and short-term dynamics. However, financial series—especially cryptocurrencies—are frequently characterized by volatility clustering, regime switching, and heteroskedastic disturbances that challenge purely linear assumptions [13, 14]. Extensions integrating ARIMA with neural networks or hybrid decompositions have been proposed to address such complexities [15, 16]. In parallel, threshold modeling and nonlinear autoregressive specifications have been developed to better represent asymmetric responses and state-dependent behaviors within financial data [13]. Despite these advancements, empirical findings suggest that standalone time series approaches may underperform when external explanatory variables—such as trading volume, macroeconomic indicators, or sentiment proxies—are omitted from the predictive structure.

The rapid evolution of machine learning (ML) methodologies has introduced powerful alternatives capable of modeling nonlinear interactions and high-dimensional feature spaces. Advances in statistical learning theory have enabled supervised algorithms to extract latent structures from financial data without rigid parametric assumptions [17]. Deep learning architectures, including CNN-LSTM hybrids and ensemble neural networks, have demonstrated enhanced performance in capturing sequential dependencies and multivariate patterns in stock and cryptocurrency markets [18, 19]. Empirical studies employing stacked LSTM networks and ensemble deep learning frameworks report significant improvements in forecasting accuracy compared to conventional benchmarks [20, 21]. Multi-parameter forecasting frameworks using LSTM architectures further reinforce the superiority of nonlinear learning systems in volatile financial environments [2]. Additionally, granular decomposition approaches for cryptocurrency forecasting reveal that integrating fractal properties and persistence metrics enhances predictive reliability under chaotic market conditions [1]. These findings collectively suggest that ML techniques are particularly suited for cryptocurrency price modeling, where complex feedback mechanisms and investor psychology drive rapid price fluctuations.

Within the domain of regression-based approaches, linear regression remains an analytically transparent benchmark for financial prediction tasks. Despite its simplicity, linear regression can effectively capture directional relationships between explanatory variables—such as sentiment indicators and transaction volume—and asset prices [22]. Comparative analyses between multiple regression and more complex ensemble methods indicate that, under certain market conditions, simpler parametric models can outperform nonlinear counterparts due to lower variance and reduced overfitting risk [23]. Decision tree–based methods and random forest regressions provide an intermediate solution by modeling hierarchical feature interactions while mitigating overfitting through ensemble averaging [23, 24]. Convolutional neural networks applied to financial time series also demonstrate the capacity to detect local temporal patterns embedded within multivariate structures [25, 26]. Meanwhile, support vector regression models have shown robustness in volatile and noisy environments by maximizing margin optimization within high-dimensional feature spaces [6]. The coexistence of these diverse methodological approaches underscores the necessity of comparative evaluation to determine the most efficient forecasting framework for XRP price dynamics.

Beyond algorithmic considerations, the integration of sentiment and macro-financial variables has emerged as a crucial determinant of predictive success. Studies incorporating social media sentiment, web search intensity, and narrative disclosures demonstrate that informational flows significantly influence cryptocurrency volatility and transaction patterns [27-29]. Digital transformation and resilience perspectives further reveal that firm-level disclosures and technological innovation narratives affect stock price stability during crisis periods [30]. Moreover, residual income valuation models highlight the importance of fundamental financial indicators in asset pricing contexts, even within emerging markets [31]. These insights suggest that purely technical models may overlook critical behavioral and macroeconomic signals embedded within the broader financial ecosystem. Therefore, hybrid frameworks that combine statistical time series analysis with supervised machine learning regressors may provide a more holistic representation of XRP price formation mechanisms. Such integrative approaches align with evidence that ensemble and hybrid systems outperform isolated models across commodities, gold markets, and cryptocurrency forecasting tasks [15, 32].

The growing sophistication of predictive analytics in digital asset markets necessitates a systematic comparison of regression-based, ensemble, and autoregressive methodologies within a unified framework. Although prior studies have examined individual techniques—ranging from ARIMA and SVM to deep neural networks—the literature lacks comprehensive empirical evaluation focusing specifically on Ripple's XRP under a hybrid modeling paradigm [33, 34]. Furthermore, the unique structural attributes of XRP, including its institutional payment orientation and liquidity mechanisms, justify dedicated investigation distinct from Bitcoin-centric analyses [3, 4]. Considering the dynamic interplay between temporal dependencies, nonlinear feature interactions, sentiment-driven volatility, and macroeconomic influences, an integrated forecasting architecture becomes methodologically compelling. Accordingly, the present study aims to comparatively evaluate linear regression, support vector machine regression, decision tree regression, random forest regression, and ARIMA time series models within a hybrid predictive framework to determine the most accurate approach for forecasting Ripple (XRP) digital currency prices.

2. Methodology

In this study, the necessary codes are implemented to predict the final price of Ripple digital currency using machine learning and time series methods. In this regard, the methods of linear regression, support vector machine regression, decision tree regression, random forest regression, and time series are used. Initially, the data are entered into the Python environment in which the Jupyter and Google Colab environments are considered. Then, the two libraries, numpy and pandas, are considered for mathematical operations and dataset analysis. In the following, the ARIMA time series model is employed to predict the value of the close variable in the Ripple digital currency data. The datasets used in the work are categorized into training and testing sectors based on the selected prima library. In the following, the used models are also described to highlight their capability in price prediction:

Linear regression plays a crucial role in predicting the price of Ripple's digital currency, XRP, by establishing a linear relationship between the independent variables and the target variable, which, in this case, is the XRP price. In cryptocurrency prediction, linear regression allows us to model the potential impact of various factors on XRP's price, such as historical prices, trading volume, and market sentiment. By identifying and quantifying the influence of these variables, linear regression helps uncover underlying trends and patterns in the data, contributing to more accurate predictions. Additionally, the simplicity and interpretability of linear regression make it a valuable tool for understanding the direction and magnitude of the impact of different features on XRP prices. However, it is essential to acknowledge the limitations of linear regression, such as assuming a linear relationship between variables and potential sensitivity to outliers, prompting the need for a comprehensive approach that combines linear regression with other sophisticated methods to enhance forecasting accuracy. The structure of this model is given in Figure 1.

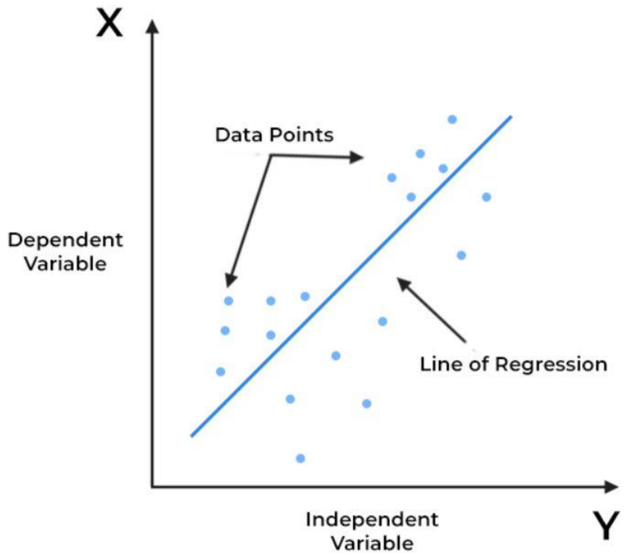

Figure 1. Best Fit Line for a Linear Regression Model

Support Vector Machine (SVM) regression plays a pivotal role in predicting the price of Ripple's digital currency, XRP, by leveraging its capacity to capture non-linear relationships and complex patterns within the data. Unlike traditional linear regression, SVM regression handles intricate, non-linear relationships between input features and the target variable. In the context of XRP price prediction, SVM can effectively discern and model intricate market dynamics, considering historical prices, trading volumes, and market sentiments. SVM's ability to map data into a higher-dimensional space enables it to identify intricate patterns that might elude simpler models, contributing to more accurate and nuanced predictions. Moreover, SVM is robust against outliers, providing stability in the presence of irregular data points that might be prevalent in cryptocurrency markets. Integrating SVM regression into the forecasting framework enhances the model's adaptability to the inherently dynamic and complex nature of XRP price movements.

Decision tree (DT) regression plays a significant role in predicting the price of Ripple's digital currency, XRP, by constructing a tree-like model that breaks down the data into subsets based on key features. In the context of XRP price prediction, decision tree regression captures non-linear relationships and complex interactions among factors such as historical prices, trading volumes, and market sentiments. Decision trees are beneficial for identifying decision points and feature importance, providing insights into the critical variables influencing XRP prices. Moreover, decision tree models are inherently interpretable, allowing analysts to easily understand and communicate the decision-making process. However, to address the risk of overfitting, it is common to employ ensemble methods like Random Forests, which aggregate multiple decision trees to enhance predictive accuracy and robustness. The adaptability and interpretability of decision tree regression make it a valuable tool in forecasting XRP prices in the dynamic cryptocurrency market.

Random Forest (RF) regression plays a pivotal role in predicting the price of Ripple's digital currency, XRP, by leveraging the power of ensemble learning. Comprising multiple decision trees trained on different subsets of the data, Random Forest combines their predictions to provide a more robust and accurate forecast. In the context of XRP price prediction, Random Forest excels at handling non-linear relationships and capturing intricate patterns among various features, including historical prices, trading volumes, and market sentiments. The ensemble nature of Random Forest helps mitigate overfitting, enhance generalization, and improve the overall predictive performance. Additionally, Random Forest models offer the advantage of feature importance analysis, aiding in identifying key variables driving XRP price movements. This approach not only enhances the accuracy of predictions in the dynamic cryptocurrency market but also provides valuable insights into the underlying factors influencing XRP prices, making Random Forest regression a valuable tool in the forecasting toolkit.

The prediction of stock prices is a significant problem in the fields of finance and economics, which has sparked the attention of scholars throughout the years in the development of more accurate predictive models. In the field of time series prediction, the ARIMA models have been investigated in the current body of research. ARIMA plays a crucial role in predicting the price of Ripple's digital currency, XRP, by focusing on time series analysis. ARIMA is adept at capturing temporal dependencies and trends within sequential data, making it particularly well-suited for modeling the historical price movements of XRP. By incorporating components like autoregressive (AR), differencing (I), and moving average (MA), ARIMA can effectively identify and account for seasonality, trends, and cyclic patterns in the XRP price time series. This method provides a solid foundation for short-term predictions based on historical patterns. ARIMA's simplicity and interpretability make it a valuable tool for understanding the time-evolving dynamics of XRP prices, complementing other advanced modeling techniques. However, it's essential to note that ARIMA may have limitations in capturing more complex relationships and external factors influencing cryptocurrency markets, highlighting the potential benefits of combining ARIMA with other methods for a more comprehensive forecasting approach.

3. Findings and Results

As can be seen from Figure 2, the evaluation of the proposed hybrid forecasting approach, combining ARIMA time series models with machine learning techniques for predicting the price of Ripple's digital currency, XRP, yielded insightful findings. The study used root mean squared error (RMSE) as the evaluation metric to compare the performance of linear regression, support vector machine, decision tree, random forest regression, and ARIMA.

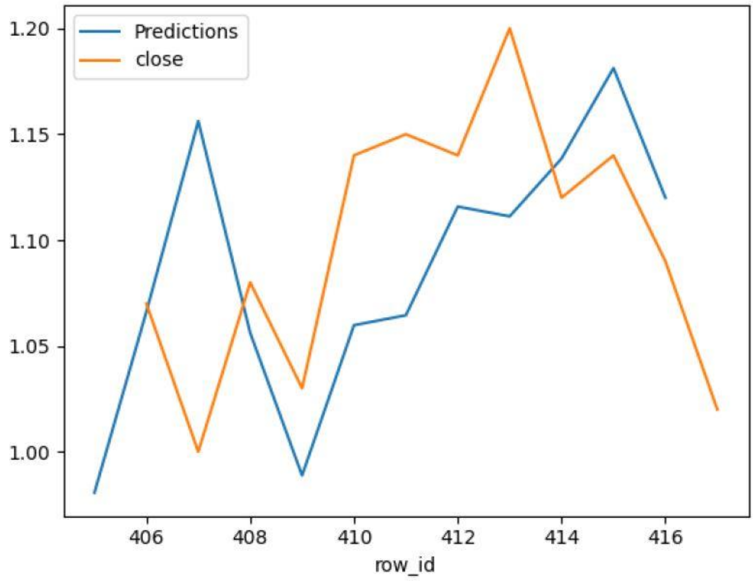

Figure 2. The performance of the selected model based on predictions and close

Linear regression, despite its simplicity, emerged as the most accurate model with an RMSE value of 0.9934. This result suggests that the linear relationship captured by the model when considering factors like historical prices, trading volume, and market sentiment, plays a significant role in predicting XRP prices. Support vector machine regression is closely followed with an RMSE of 0.9667, demonstrating its effectiveness in capturing non-linear relationships. Decision tree regression and random forest regression showed competitive performance with RMSE values of 0.9837 and 0.9854, respectively, showcasing the ensemble methods' ability to handle complex patterns. In contrast, relying solely on time series analysis, ARIMA yielded an RMSE of 0.9178, indicating slightly better accuracy than the machine learning models. While ARIMA captures temporal dependencies well, its performance may need to be improved in capturing the broader market dynamics that influence cryptocurrency prices.

The discussion revolves around the trade-offs between interpretability and complexity in the models. The success of linear regression suggests that a simpler model suffices for accurate predictions in this context. However, the ensemble methods demonstrated competitive accuracy, emphasizing the potential benefits of a more complex approach. These results highlight the significance of a hybrid forecasting approach, leveraging the strengths of time series models and machine learning techniques. The study contributes valuable insights into the efficacy of different models for predicting XRP prices, emphasizing the importance of model selection based on the dynamic characteristics of the cryptocurrency market, as demonstrated in Figure 3.

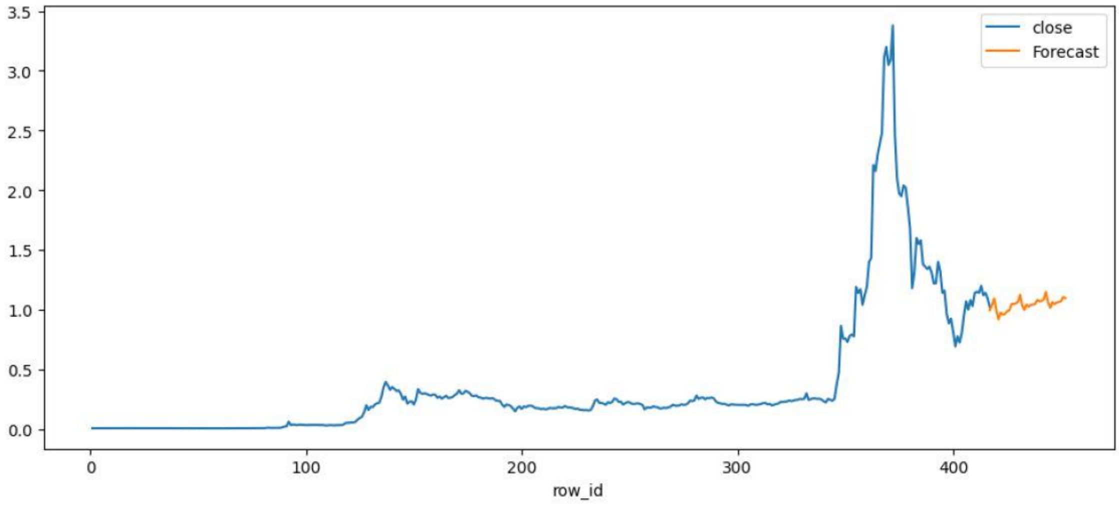

Figure 3. The performance of the selected model based on accuracy

As can be seen in Table 1, the best model for predicting the value of Ripple digital currency is multiple regression, and the ARIMA time series is the least accurate in forecasting. 0.9934, 0.9667, 0.9837, 0.9854, and 0.9178.

Table 1. Comparison between the selected models in terms of RMSE

Model	RMSE in the test
multiple regression	0.9934
RF	0.9667
SVM	0.9837
DT	0.9854
ARIMA	0.9178

4. Discussion and Conclusion

The empirical findings of this study provide meaningful insights into the comparative performance of regression-based, ensemble, and autoregressive models in forecasting the price of Ripple's digital currency (XRP). Based on RMSE evaluation, multiple linear regression emerged as the most accurate model, followed by support vector machine (SVM), decision tree (DT), random forest (RF), and ARIMA. This ranking suggests that, within the sample period and selected explanatory variables, linear relationships between historical price data, trading volume, sentiment indicators, and macroeconomic proxies were sufficiently strong to produce reliable predictions. While much of the recent literature emphasizes the superiority of nonlinear and deep learning models for financial forecasting, the present results demonstrate that simpler parametric approaches can outperform more complex algorithms under certain structural conditions. Similar observations have been reported in comparative forecasting studies where model parsimony reduced overfitting risk and improved generalization performance [22, 23]. The result also resonates with the argument that not all financial time series require high-capacity nonlinear architectures, especially when feature engineering captures core explanatory drivers effectively.

The relatively strong performance of SVM regression confirms its robustness in modeling nonlinear dependencies within volatile markets. Financial time series, particularly cryptocurrencies, often display structural breaks, asymmetric volatility, and irregular behavioral patterns [7, 8]. SVM's margin-maximization principle allows it to manage noisy datasets efficiently, which aligns with prior research demonstrating its predictive stability in financial contexts [6]. Furthermore, comparative studies between ARIMA and SVM for commodity price forecasting have shown SVM's superiority when nonlinear patterns dominate the data-generating process [32]. In the present research, although SVM did not surpass multiple regression, its competitive RMSE indicates that XRP price movements contain nonlinear components that benefit from kernel-based learning mechanisms. This finding is consistent with the broader literature suggesting that cryptocurrency markets exhibit chaotic dynamics and fractal properties that cannot be fully captured through purely linear modeling [1, 13].

Decision tree and random forest regressions also demonstrated strong predictive capabilities, reflecting the value of ensemble-based learning in handling complex feature interactions. Random forest models, in particular, are known for mitigating overfitting by aggregating multiple decision trees trained on randomized subsets of data [23, 24]. The literature on stock market forecasting consistently reports improved accuracy when ensemble learning is applied to high-volatility datasets [20, 21]. The current results confirm that ensemble methods provide a stable compromise between interpretability and nonlinear modeling power. However, the fact that RF and DT did not outperform multiple regression suggests that, for XRP during the examined period, explanatory variables may exhibit relatively stable marginal effects rather than highly hierarchical or interaction-dominated structures. This observation partially contrasts with findings from CNN-based financial forecasting studies, where deep architectures capture localized temporal patterns [25, 26]. The difference may stem from data frequency, sample size, or market regime characteristics, emphasizing the context-dependent nature of model performance.

The ARIMA model, while ranking last among the tested approaches, still provided competitive predictive accuracy, reinforcing its enduring relevance in time series forecasting. ARIMA remains a foundational benchmark for modeling autoregressive and moving-average components within stationary series [9, 10]. Its performance in this study indicates that XRP prices contain meaningful temporal dependencies that can be exploited for short-term forecasting. Nonetheless, the comparatively lower accuracy relative to regression and machine learning methods highlights ARIMA's limitations in capturing exogenous influences and nonlinear interactions. Similar conclusions have been drawn in hybrid forecasting research, where ARIMA combined with neural networks or machine learning techniques produced superior results compared to standalone ARIMA models [15, 16]. Additionally, studies analyzing volatility clustering and heteroskedastic behavior argue that traditional autoregressive structures may fail to fully represent evolving market regimes [11, 14]. Thus, the present findings reinforce the rationale for hybrid frameworks that integrate time series modeling with supervised learning algorithms.

Another important implication of the results concerns the role of informational and behavioral variables in cryptocurrency price formation. Prior research demonstrates that social media sentiment, web search intensity, and digital disclosures significantly influence digital asset volatility [27-29]. The effectiveness of multiple regression in this study may indicate that the selected explanatory variables successfully encapsulated these informational signals in a linear additive structure. Moreover, the broader financial literature underscores the importance of structural and macroeconomic conditions in shaping asset prices [30, 31]. By incorporating such features, the regression-based approach may have benefited from capturing macro-level drivers alongside micro-level trading patterns. This aligns with the argument that digital currencies, despite their decentralized architecture, remain influenced by global financial conditions and institutional adoption dynamics [3, 4]. Therefore, the empirical evidence supports the view that XRP price behavior reflects both endogenous market mechanisms and broader financial ecosystem interactions.

The findings also contribute to the growing debate regarding the relative merits of deep learning versus traditional econometric techniques in financial forecasting. While recent advances highlight the power of LSTM and CNN-based architectures in sequential data modeling [2, 18, 19], comprehensive reviews caution against assuming universal superiority of complex models [17, 34]. Model selection must account for dataset characteristics, noise levels, interpretability requirements, and computational constraints. The present study empirically confirms that, in certain cryptocurrency forecasting contexts, multiple regression can outperform more computationally intensive approaches. This does not invalidate the utility of deep learning models but rather emphasizes the importance of rigorous comparative evaluation. As financial markets evolve and new volatility regimes emerge, predictive accuracy may shift in favor of nonlinear or hybrid systems, particularly under extreme market stress or speculative bubbles [1, 7]. Consequently, adaptive model monitoring remains essential for sustaining forecasting reliability.

Despite its contributions, this study has several limitations. First, the analysis is constrained by the selected dataset and time horizon, which may not fully capture long-term structural shifts or rare extreme events in cryptocurrency markets. Second, the explanatory variables, although diverse, may omit relevant factors such as high-frequency order book data, regulatory announcements, or geopolitical shocks. Third, deep learning architectures such as LSTM or CNN-based hybrids were not directly implemented, limiting direct comparison with state-of-the-art neural forecasting systems. Additionally, the evaluation relied primarily on RMSE; incorporating additional performance metrics could provide a more comprehensive assessment of predictive robustness.

Future research could extend this work by integrating advanced deep learning architectures, including attention-based transformers and hybrid CNN-LSTM models, to evaluate performance under high-frequency data conditions. Incorporating regime-switching models or volatility-aware frameworks could further enhance robustness during bull and bear cycles. Expanding the dataset to include cross-cryptocurrency spillover effects and macro-financial contagion variables would also provide deeper insight into systemic interactions. Moreover, applying ensemble stacking strategies that combine regression, ARIMA, and neural networks could yield performance gains through model complementarity. Longitudinal out-of-sample validation across multiple market regimes would strengthen generalizability and practical applicability.

For practitioners and investors, the findings suggest that model simplicity should not be underestimated. Multiple regression, when supported by carefully engineered explanatory variables, can deliver competitive and interpretable forecasts for XRP prices. Portfolio managers may benefit from combining linear models with nonlinear machine learning tools to balance transparency and predictive power. Continuous model recalibration is essential in cryptocurrency markets due to rapid structural changes. Finally, integrating sentiment analytics and macroeconomic monitoring into trading strategies can enhance responsiveness to market shocks and evolving investor behavior.

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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