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Bitcoin Crypto-Asset Prediction: With an Application of Linear Autoregressive Integrated Moving Average Method, and Non-Linear Multi-Layered and Feedback Artificial Neural Network Models

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ABSTRACT

This study aims to examine the forecasting performance of two widely used methods in time series analysis: the ARIMA and the MLP-ANN models, focusing on Bitcoin (BTC) price data. ARIMA represents a linear forecasting approach, while MLP-ANN is a nonlinear forecasting method. Both models were evaluated using R-Studio, and the stationarity of the dataset was validated through unit root tests. The dataset consists of weekly BTC price observations from 2020 to 2022. The analysis results indicate that the ARIMA model outperformed the MLP-ANN model in predicting BTC prices. This finding contradicts the growing consensus that nonlinear models are better suited to capture the complex dynamics of financial data. The study contributes to the cryptocurrency forecasting literature by providing empirical evidence on the strengths and weaknesses of both linear and nonlinear models.

Keywords: Crypto-assets, Bitcoin, Time Series Forecasting, ARIMA, Neural Network, Multilayer Perceptron.

JEL Classification Codes: C42, E17, G15

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INTRODUCTION

Cryptocurrencies represent a revolutionary form of digital assets, facilitating peer-to-peer transactions through the use of blockchain technology (Amiri, Tavana & Arman, 2024). This technology eliminates the need for intermediaries, significantly reducing transaction costs and increasing transaction speed. Bitcoin was introduced in 2008 by an anonymous author known as Satoshi Nakamoto (He, Li & Li, 2024), and since then, interest in cryptocurrencies has continued to grow among both individual and corporate investors (Sun, Liu, & Sima, 2020). Its decentralized nature, as a cryptocurrency not backed by any government authority, has garnered significant attention from speculators and investors due to its high price volatility. As of now, Bitcoin continues to be the most widely recognized cryptocurrency, accounting for more than 40% of the total market value among various cryptocurrencies (Koo & Kim, 2024).

As cryptocurrencies continued to grow in popularity, its impact on global financial markets became more evident, especially as it introduced a new decentralized model for digital transactions. The cryptocurrency market has experienced significant growth and development over the past decade, during which Bitcoin has emerged as the first and most successful example of a decentralized digital payment system (Park & Yang, 2024). By leveraging blockchain technology to provide secure and transparent transaction processes, Bitcoin has revolutionized the financial system and, on a global scale, become the leading and most successful model within the cryptocurrency ecosystem, attracting millions of users and investors.

The growing success of Bitcoin was further amplified by its unique features, which not only attracted individual investors but also prompted institutional adoption. Features such as anonymity, independence from central authorities, and protection against double-spending attacks have further increased the appeal of cryptocurrencies (Mostafa, Saha, Islam & Nguyen, 2021). As of July 28, 2023, the total market value of cryptocurrencies reached $1.18 trillion, highlighting the rapid growth and adoption of the market.

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Although cryptocurrencies initially emerged as a medium of exchange, their roles in financial markets have expanded, and they are now regarded as valuable financial instruments (Dierksmeier & Seele, 2018). This evolution has particularly led to increasing attention towards Bitcoin. As a new investment tool in the financial markets, Bitcoin has garnered significant investor interest due to its high volatility and the potential for substantial returns (Kang, Yuan, Zhang, Chen, & Li, 2024). Predicting the price of Bitcoin presents a significant challenge for researchers, investors, and other stakeholders in financial markets. The high volatility of Bitcoin and the investment risk associated with it, being perceived as more significant than that of traditional financial assets (Amiri, Tavana & Arman, 2024). have led to Bitcoin price forecasting becoming an important mathematical model in the FinTech sector (Han et al., 2025; Cheng et al., 2024). A comprehensive understanding, modeling, and forecasting of Bitcoin prices is crucial not only for making informed investment decisions in the digital asset market but also for effective risk management, optimizing portfolio performance, and minimizing potential financial losses. This process aids investors in better assessing market trends and volatility, thereby contributing to the development of long-term financial strategies (Liu, Tsyvinski, & Wu, 2022).

However, the very volatility that makes Bitcoin an attractive investment opportunity also presents a significant challenge when it comes to accurate price forecasting. Bitcoin, in particular, attracts attention for its portfolio diversification potential, offering investors the opportunity to optimize their risk-return profiles. Accurate cryptocurrency price forecasting helps investors make informed, risk-averse decisions, while also contributing to the development of more effective regulatory frameworks for policymakers.

Time series analysis provides powerful tools for modeling the future behavior of a variable based on its past data or interactions with other variables. These models can be useful and provide reasonably accurate predictions when there is insufficient information about the data generation process or when satisfactory explanatory models are not available (Zhang, 2003). Although price prediction models have been extensively studied in the literature, most studies focus on traditional asset classes, and cryptocurrency forecasting has received relatively less attention.

Given these challenges, time series analysis has become an essential tool for understanding and forecasting Bitcoin prices, as it allows for the modeling of future behavior based on historical data. One of the most widely used linear models in time series analysis is the ARIMA model, introduced by Box and Jenkins in 1976 (Box, Jenkins, Reinsel & Ljung, 2015). ARIMA's flexible structure allows for its use across various fields, including social, economic, and financial domains. In recent years, ANNs have gained increasing popularity due to their ability to model nonlinear relationships (Kumar & Yadav, 2023). However, while ANNs offer advantages in modeling nonlinear functions, they also present challenges such as the difficulty in interpreting their inner workings and the tendency for models to yield different results in each test.

In this study, BTC price predictions were made using the ARIMA model, a linear method, and the MLP-ANN model, a nonlinear approach. The comparison of these two methods' performances contributes to the growing literature on cryptocurrency price forecasting and highlights the strengths and weaknesses of both linear and nonlinear methods.

The primary objective of the study is not to provide a precise forecast of BTC's future value but rather to evaluate the performance of two widely utilized forecasting models. All analyses were conducted using R-Studio.

Using BTC data, time series forecasting was performed with the ARIMA and MLP-ANN models. While neither model achieved high forecasting accuracy, the findings reveal that the ARIMA model demonstrated better predictive performance for BTC. This result contradicts the growing acceptance that nonlinear models are more suitable for capturing the complex dynamics of financial time series. In conclusion, this study compares the performances of two distinct forecasting models, ARIMA and ANN, using BTC price data. Testing these models in the context of cryptocurrencies makes a significant contribution to the literature on financial time series forecasting and provides valuable insights for both researchers and industry professionals.

Following the introduction, the study proceeds with a review of selected literature in the first section, econometric methods in the second section, empirical findings in the third section, and a discussion of the results and recommendations for researchers and industry professionals in the conclusion section.

SELECTED LITERATURE

In this literature review, a bibliometric analysis method was utilized. Studies containing the keywords ARIMA and ANN were searched in the Web of Science

Table 1: Keywords, occurrences and total link strengh

Id	Keywords	Occurrences	Total Link Strength	Id	Keywords	Occurrences	Total Link Strength
1	Artificial Neural Networks	117	303	21	Particle Swarm Optimization	12	31
2	ARIMA	116	309	22	Support Vector Regression	12	30
3	Forecasting	87	243	23	Artificial Intelligence	11	44
4	Time Series	51	149	24	Forecast	11	27
5	Time Series Forecasting	50	126	25	Support Vector Machines	11	31
6	Neural Networks	43	122	26	Wavelet Transform	11	25
7	Artificial Neural Network (ANN)	38	86	27	Wind Speed	11	38
8	Hybrid Model	36	97	28	Wind Speed Forecasting	11	18
9	Machine Learning	28	84	29	Artificial Neural Network (ANN)	10	19
10	ANN	27	67	30	Empirical Mode Decomposition	10	28
11	Prediction	22	60	31	Genetic Algorithm	10	25
12	Neural Network	21	53	32	Lstm	10	26
13	Time Series Analysis	19	52	33	Autoregressive İntegrated Moving Average (ARIMA)	9	22
14	ARIMA Model	17	35	34	SARIMA	9	26
15	Deep Learning	15	50	35	Covid-19	8	21
16	ARIMA Models	14	31	36	Demand Forecasting	8	20
17	Hybrid Models	14	35	37	Wind Speed Prediction	8	24
18	Autoregressive Integrated Moving Average	13	39	38	Exponential Smoothing	7	29
19	ANFIS	12	28	39	Predictive Models	7	44
20	ANNs	12	34	40	Time Series Prediction	7	21

(WoS) database within the title and abstract sections, yielding a total of 718 studies. When filtered to include only journal articles, this number was reduced to 562. In the third stage, considering the SSCI, SCI (SCI-E), and ESCI indexes, 560 studies were identified. Finally, after excluding articles published in languages other than English, 540 studies published in English were included in the analysis. This analysis covers works published between January 1995 and August 2023.

A total of 1488 keywords from the 540 included articles were scanned, and 246 keywords that were used at least twice were examined in detail. This analysis was conducted using the VOSviewer software. VOSviewer is a bibliometric analysis tool with a user-friendly graphical interface that creates networks based on elements such as journals, authors, publications, organizations, and countries (Sharifi, Simangan, & Kaneko, 2021).

The bibliometric analysis performed with VOSviewer presents the 80 most frequently used keywords in Tables 1 and 2. Keywords used in scientific studies are considered an important data source to understand which models are more frequently utilized in the relevant literature.

Upon examining Table 1, it is observed that the top five most frequently used keywords are "Artificial Neural Networks" (117), "ARIMA" (116), "Forecasting" (87), and "Time Series" (51). These keywords also exhibit high total link strengths with other terms, indicating that these terms receive greater attention and are frequently associated with other concepts.

Table 2: Keywords, occurrences, and total link strength

Id	Keywords	Occurrences	Total Link Strength	Id	Keywords	Occurrences	Total Link Strength
41	Artificial Neural Networks (ANN)	6	14	61	Extreme Learning Machine	4	6
42	Auto-Regressive Integrated Moving Average (ARIMA)	6	20	62	Financial Markets	4	13
43	Fuzzy Logic	6	16	63	Financial Time Series Forecasting	4	9
44	LSTM	6	20	64	Groundwater Level	4	10
45	RNN	6	24	65	Hybrid System	4	16
46	Autoregressive Integrated Moving Average (ARIMA)	5	10	66	Multiple Linear Regression	4	11
47	Box-Jenkins	5	15	67	Nonlinear Time Series	4	8
48	Electricity Price Forecasting	5	5	68	Seasonality	4	8
49	Energy Consumption	5	16	69	Short-Term Forecasting	4	8
50	Feature Selection	5	14	70	Solar Energy	4	11
51	Price Forecasting	5	12	71	Support Vector Machine	4	13
52	Rainfall	5	10	72	Support Vector Machine (SVM)	4	6
53	Regression	5	16	73	Time Series Modeling	4	9
54	Time Series Model	5	14	74	Air Pollution	3	11
55	Time-Series Forecasting	5	13	75	Air Quality İndex (AQI)	3	2
56	Wind Power	5	14	76	Auto-Regressive Integrated Moving Average (ARIMA)	3	10
57	ARMA	4	7	77	Autoregressive Processes	3	23
58	Backpropagation	4	13	78	Autoregressive Integrated Moving Average	3	6
59	Cloud Computing	4	8	79	Back Propagation	3	9
60	Combined Forecast	4	14	80	Big Data	3	7

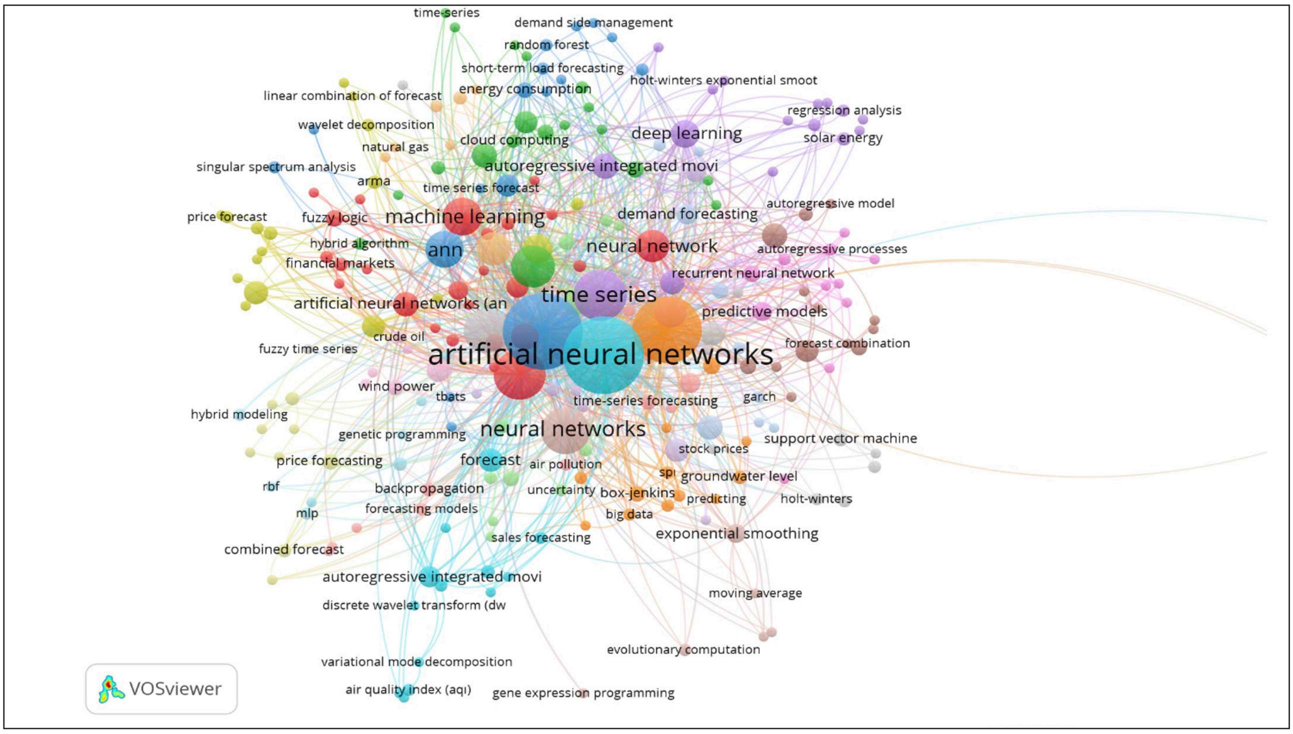

Figure 1: Keyword analysis
Source: Created by the authors.

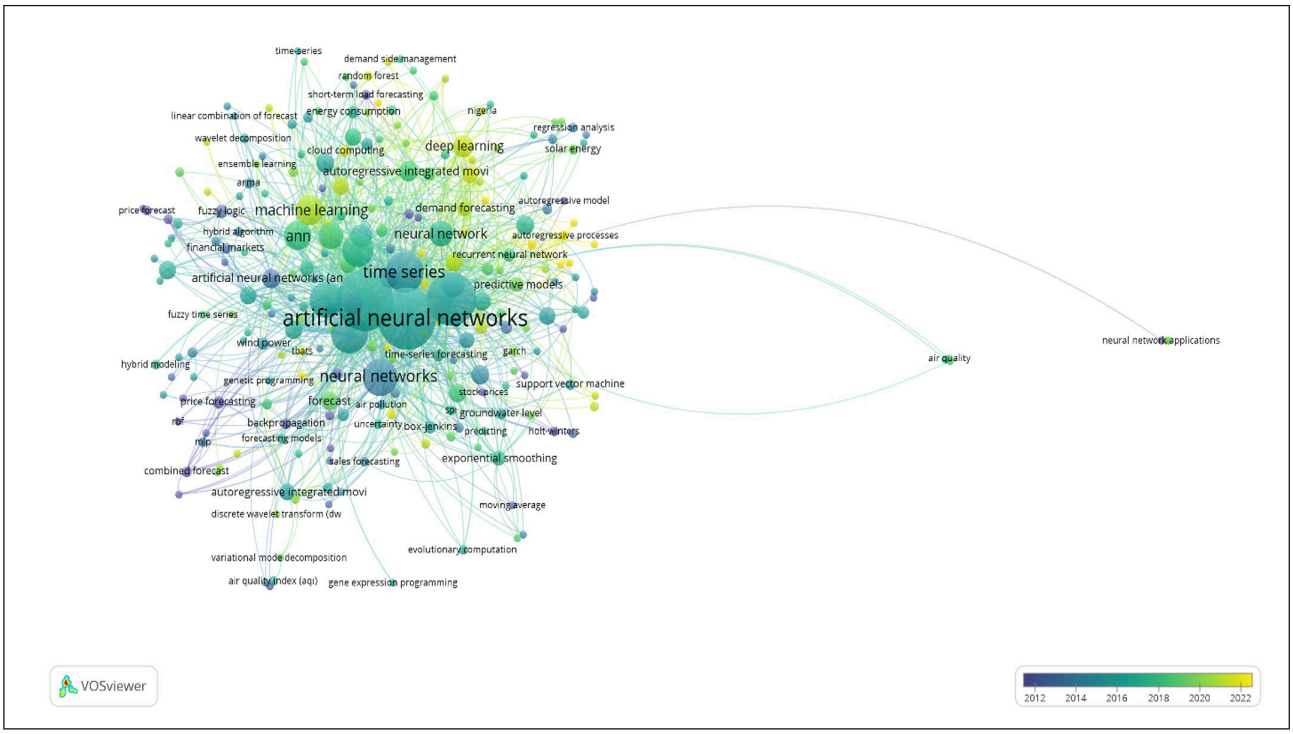

Figure 2: Keyword density analysis
Source: Created by the authors.

Table 2 presents the results of the co-occurrence analysis, which is used to identify the main themes in the literature and detect topics frequently discussed together. It appears that the most frequently used keywords focus heavily on forecasting and time series.

Figure 1 presents a cluster map derived from the analyzed keywords. It demonstrates that "ANN" and "ARIMA" models are heavily used in forecasting and time series prediction studies. These methods are also preferred in areas such as demand forecasting, wind speed forecasting, energy consumption, and solar energy.

Table 3: Business finance studies

Rank	Author	Years	Journal	Data
1	Mallikarjuna & Rao	2019	Fınancıal Innovatıon	Stock Market Returns
2	Ahmad et al.	2023	Internatıonal Journal of Fınance & Economıcs	Unemployment Rate
3	Fadlalla & Amani	2014	Intelligent Systems In Accountıng Fınance & Management	Stock Market Price
4	Kumar	2009	Asıan Academy of Management Journal of Accountıng And Fınance	Hang Seng Index (Hsı) And Standard & Poor's (S&P) 500 İndices Returns
5	Temur & Yıldız	2021	Istanbul Busıness Research	Monthly Sales Quantity Budget
6	Aras et al.	2017	Istanbul Unıversıty Journal of The School of Busıness	The Pairwise Combination of Methods.
7	Smith et al.	2016	South Afrıcan Actuarıal Journal	Financial Markets
8	Stebliuk et al.	2023	Fınancıal And Credıt Actıvıty-Problems of Theory And Practıce	Economic Trends

In Figure 2, trends regarding which topics have gained more attention over the years can be observed. For instance, in 2012, ARIMA and ANN models were used together in electricity price forecasting studies, while after 2020, new methods such as "Machine Learning," "Deep Learning," "LSTM," and "Demand Forecasting" have come to the forefront.

When the literature review is limited to studies in the field of corporate finance, eight studies were identified in which ARIMA and ANN models were used together, and these studies are presented in Table 3.

A search using the keywords cryptocurrency, BTC, and forecasting yielded 75 studies, and keyword analysis of these studies revealed that GARCH, EGARCH, GARCH-

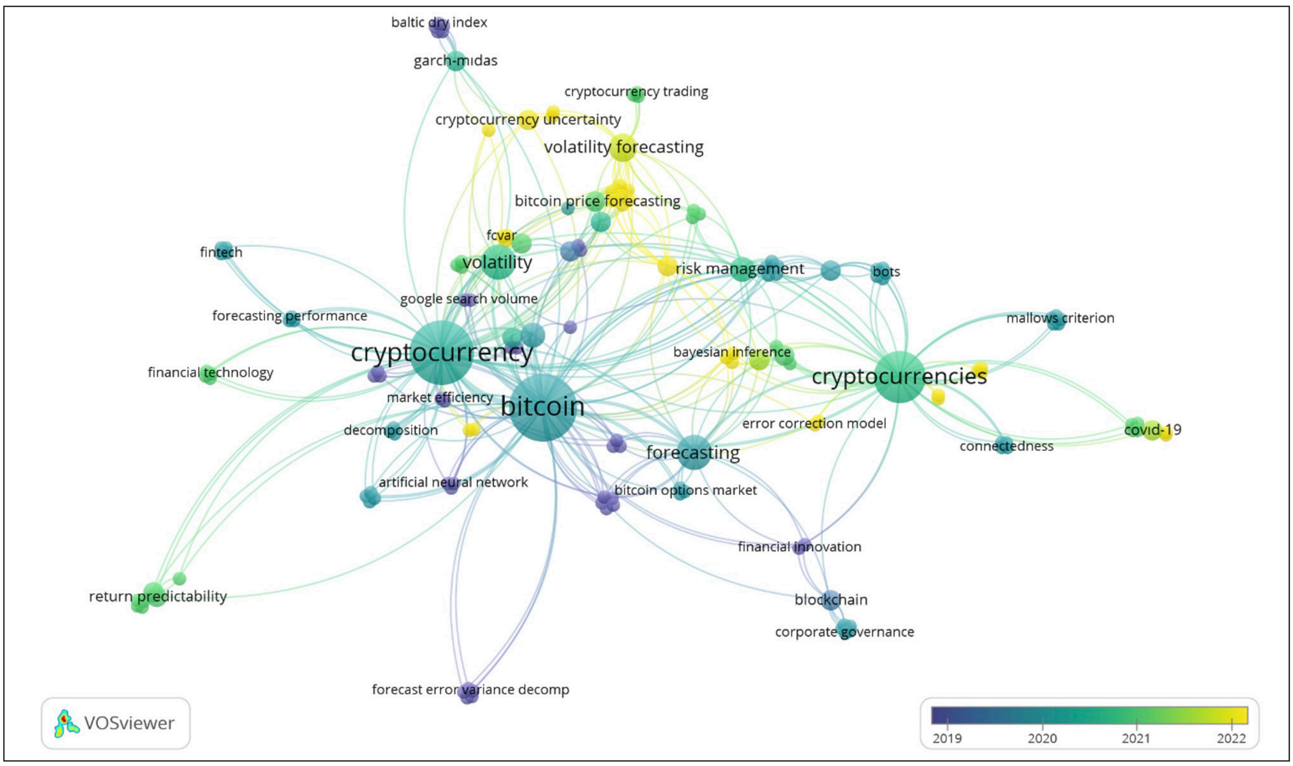

Figure 3: VOSviwer network graph of the reached studies

MIDAS, and Markov models were frequently used. The VOSviewer network graph is presented in Figure 3.

Upon examining Figure 3, the development of studies on cryptocurrency over the years can be observed. In 2019, topics such as "BTC," "forecast error variance," and "dynamic model averaging" were prominent, while after 2020, subjects like "volatility," "Ethereum," "fintech," "Ripple," and "cryptocurrency" became more frequently studied.

ECONOMETRIC METHOD

Time series data exhibit unique characteristics, and selecting the most appropriate forecasting method depends on the structure of the data and the desired outcomes. Several approaches are used in time series analysis, including linear methods (such as traditional ARIMA), nonlinear methods (e.g., artificial neural networks), and hybrid methods that combine both linear and nonlinear approaches to improve forecast accuracy. This study employs two commonly used methods for time series forecasting: the ARIMA model and the MLP-ANN architecture.

Linear models, particularly methods like ARIMA, require data preprocessing (such as removing trends, adjusting for seasonality, and ensuring stationarity), whereas artificial neural networks can work with raw data. However, the literature suggests that artificial neural networks perform better with preprocessed data. While ARIMA models are generally considered more suitable for smaller datasets, ANN models tend to yield better results on larger datasets. Despite the relatively small dataset of 135 weekly observations used in this study, both methods are compared to highlight their strengths and weaknesses.

The dataset used in this study consists of weekly Bitcoin (BTC) price data from the first week of 2020 to the thirty-first week of 2022, comprising a total of 135 observations. The data were obtained from Investing.com, with CoinMarketCap used as the final data provider. All analyses were conducted using the R-Studio program.

Forecasting with the ARIMA method

ARIMA is a well-established linear econometric method that forecasts future values by using the lagged values of a time series. ARIMA models can be particularly effective for small datasets, but financial time series often pose challenges due to their volatile and non-stationary nature, which may limit ARIMA models in capturing the complex dynamics of such data. Therefore, careful assessment of model assumptions and performance is necessary.

Several steps are followed when constructing an ARIMA model, as outlined below:

- Θ *Stationarity and seasonal adjustment:* The time series is first examined for stationarity and seasonal effects. If necessary, differencing (d) or seasonal differencing (s) is used to eliminate these effects. Since seasonal effects were addressed in the preprocessing phase, the model does not include a seasonal parameter (s).
- Θ *Determination of AR and MA lags:* The lag lengths of the autoregressive (AR) and moving average (MA) components are determined using the Autocorrelation Function and Partial Autocorrelation Function plots. Table 4 provides a guideline on how to interpret ACF and PACF results.
- Θ *Model estimation:* An ARIMA model is estimated based on the selected lags. In this study, the ARIMA (0,1,0) model was chosen, representing a random walk model.
- Θ *Model diagnostics:* After estimation, the residuals of the model are examined to determine whether they resemble white noise, thereby assessing the model's ability to capture patterns in the data.

Table 4: Provides a theoretical guideline for interpreting ACF and PACF results

p	*q*	ACF	PACF
1	0	Exponential decrease	Only the first coefficient is outside the confidence interval
2	0	Exponential decrease	Only the first coefficient is outside the confidence interval
0	1	Only the first coefficient is outside the confidence interval	Exponential decrease
0	1	Only the first coefficient is outside the confidence interval	Exponential decrease
1	1	Exponential decrease	Exponential decrease

Source: Eğrioğlu and Baş, (2020)

- Θ *Model validation:* If the model satisfies all diagnostic criteria, valid and reliable forecasts can be made.

- Θ *Forecast evaluation:* The final step is to assess the forecast accuracy of the model. Some commonly used error measurement methods in the literature are listed below:

  - *Root Mean Square Error (RMSE):* Calculated by taking the average of the squared differences between the predicted and actual values. Equation (1) is used for RMSE (Hyndman & Koehler, 2006).

$$RMSE = \sqrt{\frac{1}{ntest}\sum_{t=1}^{ntest}\left(x_t - \hat{}\ x_t\right)^2} \tag{1}$$

  - *Mean Absolute Error (MAE):* Represents the average of the absolute differences between the actual and predicted values. Equation (2) is used for MAE (Armstrong, 2001).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\chi_t - \chi\hat{}_t\right|\mathrm{x\_t} \tag{2}$$

  - *Mean Percentage Error (MPE):* Indicates the percentage of forecast error relative to the actual value (Kourentzes et al., 2014). Equation (3) is used for MPE.

$$MPE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{x_t - x_t}{x_t}\right) \times 100 \tag{3}$$

  - *Mean Absolute Percentage Error (MAPE):* Reflects how accurate the model predictions are and allows for comparison across data with different scales (Armstrong, 2001). Equation (4) is used for MAPE.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{\chi_t - \chi\hat{}_t}{x_t}\right| \tag{4}$$

A combination of methods like RMSE, MAE, MPE, and MAPE can provide a comprehensive analysis of forecast accuracy, consistency, and model fit. The results of these methods in this study offer valuable insights into the prediction of crypto assets, laying the foundation for future forecasting studies.

Artificial Neural Networks (ANN) for Forecasting

ANN are nonlinear machine learning techniques inspired by the functioning of biological neurons. They are particularly successful in capturing relationships in complex and nonlinear data structures. In this study, the MLP-ANN architecture was employed. This architecture consists of an input layer, one or more hidden layers, and an output layer.

The forecasting process using ANN involves the following steps.

- *Data normalization:* The dataset, consisting of weekly Bitcoin (BTC) prices, was normalized between 0 and 1 to ensure consistent results during model training.

- *Data splitting:* The dataset was divided into training and test subsets to evaluate the model's ability to generalize to unseen data.

- *Model design:* A feed-forward neural network model was developed using supervised learning, and it was trained using the backpropagation algorithm. The number of neurons in the hidden layers and the activation functions (e.g., sigmoid or ReLU) were determined experimentally to enhance model performance.

- *Optimization:* Various parameters (such as the number of neurons and learning rate) were optimized to minimize error and improve overall performance.

- *Performance evaluation:* The performance of the final model was made comparable to that of the ARIMA model and evaluated using the same error metrics.

- *Model selection:* The model with the lowest error rate was chosen as the best ANN model.

The choice of model architecture is critical when using artificial neural networks. Selecting the appropriate number of hidden layers and the quantity of neurons within those layers plays a crucial role. Using too many hidden layers or neurons can lead to overfitting, reducing the model's generalization capacity, while using too few neurons may negatively impact model performance. Therefore, it is important to strike a balance between the number of layers and neurons to determine the optimal architecture.

One approach for estimating the number of layers and neurons is the formula provided by Elmas (2018) in Equation (5).

$$Hmax = \sqrt{(\mathrm{NNHL} + \mathrm{NNOL} + 10)} \tag{5}$$

Equation (5) can serve as a guideline for determining the optimal number of neurons in hidden and output layers. Benli and Tosunoğlu (2014) state that, while there is no theoretical limit to the number of layers in an ANN, the optimum architecture is achieved by appropriately

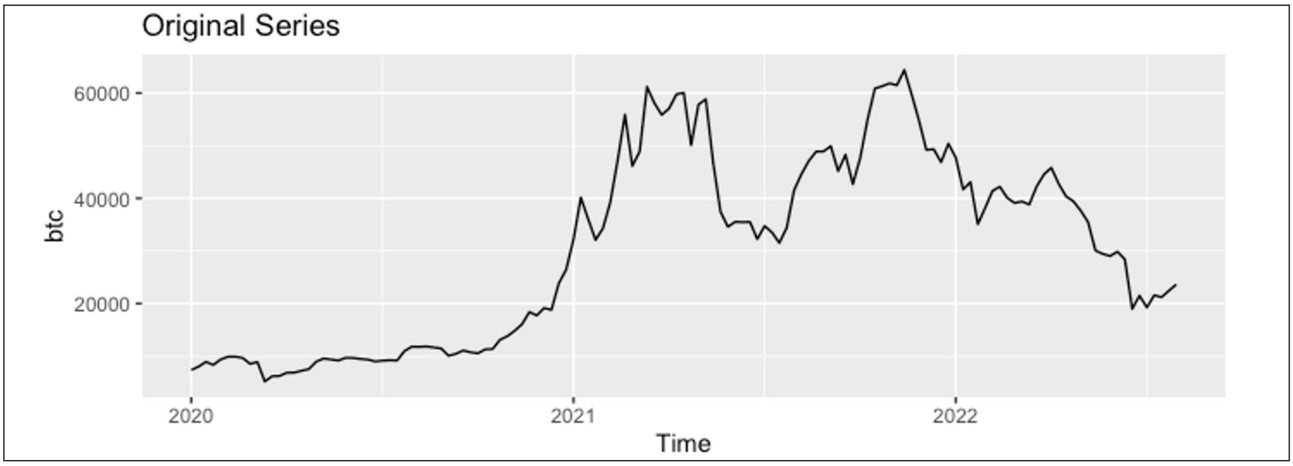

Figure 4: The original time path graph of BTC data (CoinMarketCap, https://coinmarketcap.com/, Access date: 22.08.2023)

adjusting the number of neurons. Many studies have shown that architectures consisting of an input layer, two hidden layers, and an output layer are preferred for solving complex problems (Esenyel, 2016).

Elmas (2018) further suggests that as the complexity of the relationships between the input and output layers increases, it may be necessary to increase the number of neurons in the hidden layers to improve model performance. This is especially true when modeling independent processes. However, these general recommendations do not guarantee the best result in every case, as the optimal architecture is often determined through trial and error based on error metrics (Tosunoğlu & Benli, 2012).

EMPIRICAL APPLICATION

In this study, the performance of two different methods was compared for forecasting cryptocurrency values. These methods include the linear forecasting model ARIMA and a non-linear forecasting model, Artificial Neural Networks (ANN). Testing both models across sectors provides valuable insights into determining which method is more suitable for a specific sector. In this context, the comparative empirical results between these two methods used for predicting cryptocurrency values contribute to the existing literature.

The aim of this study is not to predict the future value of the variable with absolute accuracy. Similarly, it would not be appropriate to claim that one method is superior to the other based on the results. The primary objective is to examine two commonly used methods in time series forecasting—both of which have been tested and validated with different examples in the literature—in the context of Bitcoin (BTC) and to present empirical evidence on their performance.

The dataset consists of weekly values of the BTC cryptocurrency in U.S. dollars, spanning from the first week of 2020 to the thirty-first week of 2022, with a total of 135 observations. The analysis was conducted using R-Studio software. The time series data's stationarity was examined using three unit root tests: ADF, PP, and KPSS. For the forecasting process, ARIMA from the linear methods and the MLP-ANN architecture were employed. The original time series graph of BTC prices is shown in Figure 4.

When examining Figure 4, it can be observed that BTC prices remained relatively flat between 2020 and 2021. However, starting from the early months of 2021, the prices entered an aggressive upward trend. By the second quarter of 2021, nearly half of these gains were lost, but the losses were recovered in the final quarter, reaching the highest level recorded. Over the following 15 months, BTC prices exhibited a relatively moderate downward trend, returning to levels observed 24 periods earlier.

Stationarity test application

The stationarity properties of the time series data were analyzed using ADF, PP, and KPSS unit root tests. The null hypotheses for these tests are as follows:

- *ADF and PP Tests:*
    - H0: The series has a unit root. (If the p-value < 0.05, H0 is rejected.)
- *KPSS Test:*
    - H0: The series is stationary. (If the p-value > 0.05, H0 is accepted.)

The results of these tests are presented in Table 5.

Table 5: Stationarity results

Test	Stationary Level	Lag Order	Pr(>|t|)	Result
ADF	I(0)	5	0.8	H0 Reject
	I(1)	5	0.01	H0 Accept
PP	I(0)	4	0.9	H0 Reject
	I(1)	4	0.01	H0 Accept
KPSS	I(0)	4	0.01	H0 Reject
	I(1)	4	0.1	H0 Accept

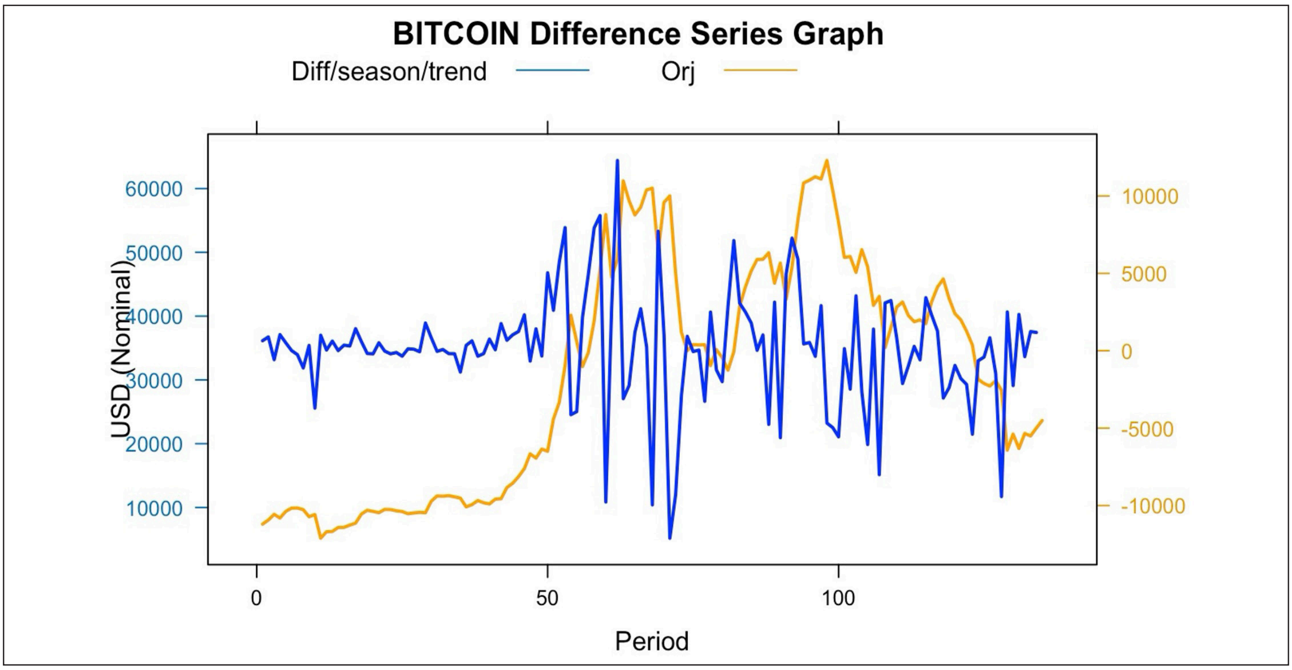

Figure 5: Original series and difference series plot graph

As shown in Table 5, the results of all three unit root tests indicate that the variable is not stationary at the *I*(0) level. However, after differencing, the tests reveal that the series becomes stationary at the *I*(1) level across all three tests. In the subsequent linear analyses, the differenced and stationary series were used. The graphical representations of both the original series and the differenced series are presented in Figure 5.

In Figure 5, the red graph represents the original series, while the blue graph shows the differenced series at the *I*(1) level, which has been rendered stationary. This indicates that the observations in the series fluctuate around a constant mean and exhibit constant variance.

Seasonality Test Application

Time series data typically consist of components such as trend, seasonality, and random walk. One of the key objectives in time series analysis is to differentiate these components in order to improve the accuracy of the analysis. The visual examination of the trend, seasonality, and other components of the time series is presented in Figure 6.

Based on the qualitative assessment of Figure 6, it can be suggested that there may be potential seasonality in the time series. However, for a quantitative analysis of seasonality, the "WO" function from the R programming environment can be utilized (Webel & Ollech, 2020). This function partitions the series into specific periods and calculates the averages. A value close to 1 in the test results indicates the presence of seasonality, while a value of 0 suggests that the series is not seasonal. The results of the WO Seasonality Test are presented in Table 6.

When Table 6 is examined, it is seen that there is no seasonality in the series.

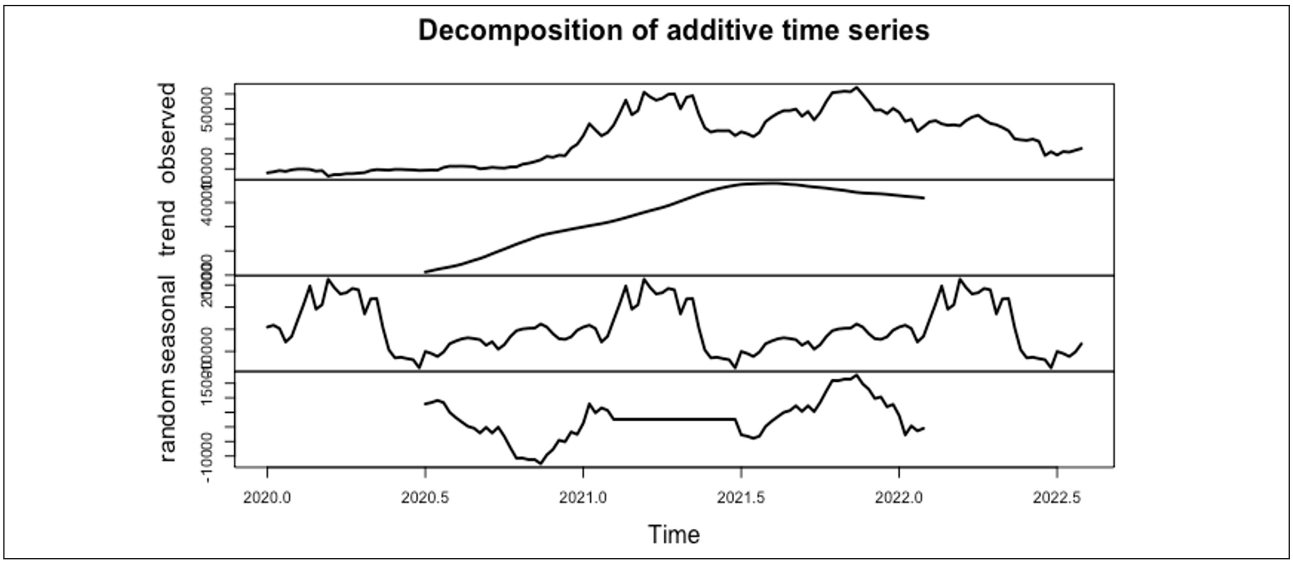

Figure 6: BTC time series decompose graph

Table 6: Seasonality results

Test	Test Result	P-value
WO	0	1 / 1 / 0.2695

Table 7: ARIMA model prediction statistics

Series	Pred. Model	sigma²	Log Likelihood	AIC	AICc	BIC
btc	ARIMA (0,1,0)	13237606	-1173	2349	2349	2352

ARIMA Model Application for Forecasting

The ACF and PACF plots created for the time series data are presented in Figure 7.

Upon examining Figure 7, it is observed that the autocorrelation in the ACF plot decreases regularly up to approximately the 32nd lag, remaining within the confidence intervals. However, starting from the 45th lag, the autocorrelation exits the confidence interval. This situation suggests that the series may be evaluated as AR(1) or AR(2), as well as MA(0). The stationarity analysis indicated that the series has become stationary at the I(1) level (Table 5).

Based on these assessments, it is anticipated that the ARIMA model could be (1, 1, 0) or (2, 1, 0). The "auto.arima" function in R can be used to quantitatively determine the parameters (p), (d), and (q) of the model (Wang, Smith & Hyndman, 2006). The best model statistics obtained from the "auto.arima" function are presented in Table 7.

As shown in Table 7, it has been determined that the ARIMA (0, 1, 0) model is the most suitable forecasting model. To validate the model's adequacy, the residuals were assessed using the Ljung-Box Test to determine whether they conform to a White Noise process. The null hypothesis for the test is presented below.

H0: The residuals of the ARIMA (0, 1, 0) model do not conform to a White Noise process, meaning the residuals do not exhibit a normal distribution. (H0 cannot be rejected for $p < 0.05$)

The results of the Ljung-Box Test are presented in Table 8.

According to Table 8, since the p-value of $0.3167 > 0.05$, it can be concluded that the residuals conform to a White Noise process. Additionally, the normality of the residuals was examined using the Shapiro-Wilk Test. The null hypothesis for this test is presented below.

H0: The residuals do not exhibit a normal distribution (H0 cannot be rejected for $p > 0.05$).

The test results are presented in Table 9.

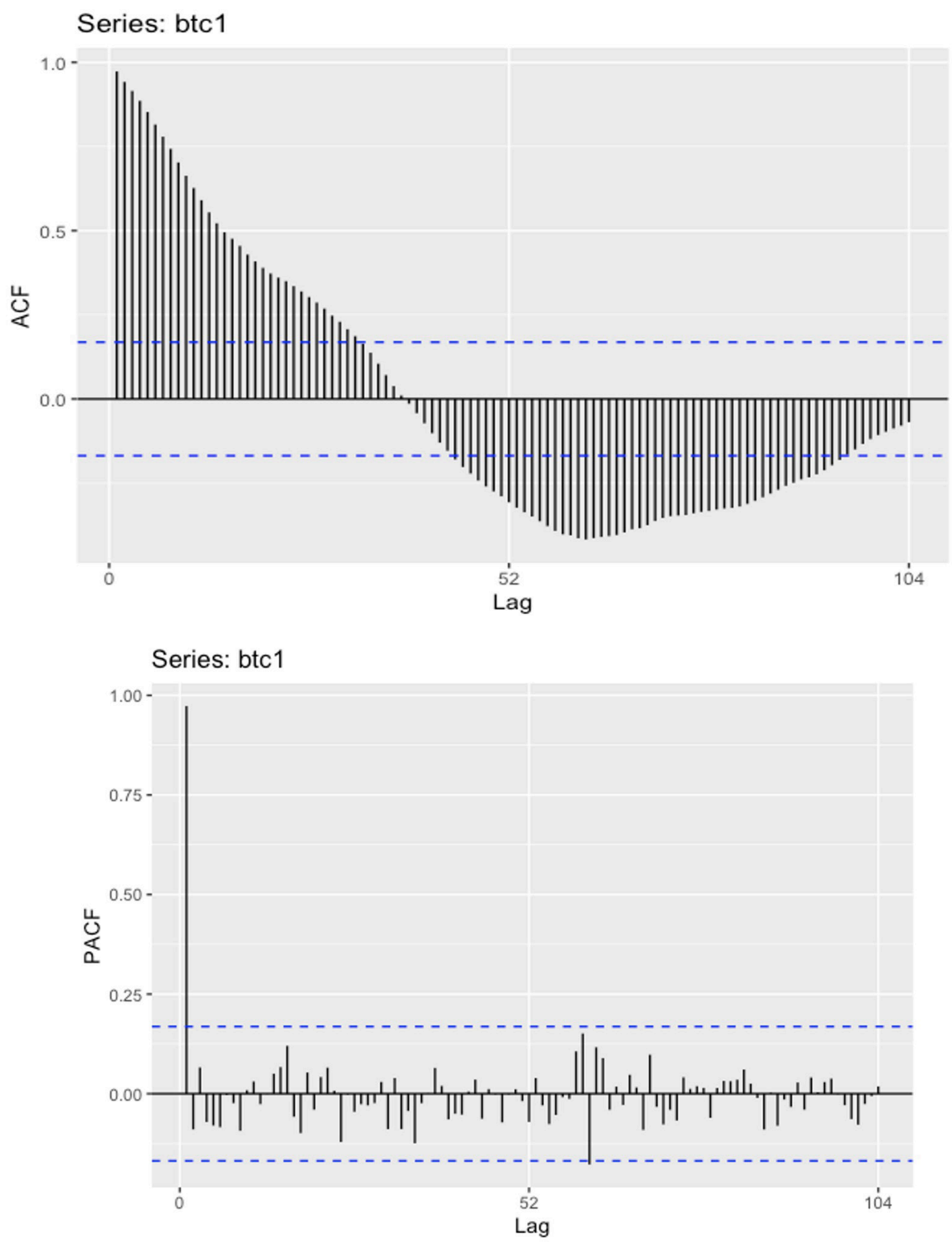

Figure 7: ACF) and PACF graphs

Table 8: Box-Ljung test statistics

x^2	df	*P*-value
11.544	10	0.3167

Table 9: Normality test results

Data	W	P-value	Result
ARIMA model residuals	0.93	0.000009	H0 Red

Table 10: Time series prediction results with ARIMA model

Period	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
1	124	35468	30727	40210	28217	42720
2	125	35468	28745	42192	25186	45751
3	126	35468	27212	43725	22841	48096
4	127	35468	25908	45028	20848	50089
5	128	35468	24751	46186	19077	51859
6	129	35468	23696	47241	17464	53473
7	130	35468	22718	48219	15968	54968
8	131	35468	21800	49136	14564	56372
9	132	35468	20931	50005	13235	57701
10	133	35468	20102	50834	11968	58968
11	134	35468	19308	51628	10753	60183
12	135	35468	18543	52394	9583	61353

From Table 9, it can be concluded that the p-value of $0.000009 < 0.05$ indicates that the residuals do not exhibit a normal distribution. Thus, the validity and reliability of the estimated ARIMA (0,1,0) model have been confirmed. Time series forecasts for twelve periods were made using this model, and the results are presented in Table 10.

Table 10 shows that in the twelve-period forecasts, the lowest and highest predicted values fall within the 80% and 95% confidence intervals.

In this study, the forecasting performance of the ARIMA model was evaluated using several different error measurement criteria. A detailed discussion of the forecasting performance, along with the MLP-ANN prediction results, is presented in Table 13.

Forecasting with the Multilayer Perceptron Artificial Neural Network (MLP-ANN) Model

In this study, a supervised ANN model known as MLP was employed for the nonlinear forecasting of the Bitcoin (BTC) time series. The forecasts were made based on the original observation values of the dataset. The BTC variable consists of a total of 135 observations. The first, second, fourth, and twelfth lagged values of the observation values were defined as the input variables of the model. In this context, the first variable (x1, also the dependent variable) consists of a total of 123 observations from the 1st observation to the 123rd observation of BTC. The second variable (x2) consists of observations from the 2nd observation to the 124th observation of BTC; the third variable (x3) includes observations from the 5th observation to the 127th observation; while the fourth variable (x4) comprises a total of 123 observations from the 13th observation to the 135th observation of BTC.

The dependent variable (x1) and the independent variables (x2, x3, and x4) of the dataset were normalized, and the observation values were scaled between 0 and 1. The normalized observation values are presented in Table 11.

As seen in Table 11, in the normalized dataset, the smallest observation value has been transformed to 0, while the largest observation value has been converted to 1. The optimal weight values calculated for the best-performing ANN model are presented in Table 12.

Table 11: Normalized observation values

Observation / Variables	X1	X2	X3	X4
1	0.04	0.05	0.07	0
2	0.05	0.06	0.08	0.01
3	0.06	0.05	0.08	0.01
...	…	…	…	…
120	0.59	0.58	0.42	0.26
121	0.58	0.55	0.41	0.26
122	0.55	0.51	0.4	0.28
123	0.51	0.42	0.42	0.3

Table 12: Optimal weight values calculated for the best ANN model

Input_1	Input_2	Input_3	Hid_1_1	Hid_1_2	Hid_1_3	Hid_1_4	Output_1
0	0	0	0.169	-0.223	0.271	0.142	0.000
0	0	0	-0.180	0.060	0.053	0.159	0.000
0	0	0	0.115	-0.229	0.036	-0.016	0.000
0	0	0	0.000	0.000	0.000	0.000	0.189

Table 13: Statistics of estimated errors for ARIMA and MLP-ANN models

Estimated error criteria	ME	RMSE	MAE	MPE	MAPE
ARIMA (0, 1, 0)	228,4	3623,5	2394	0,7	7,5
MLP-ANN	866,8	870,5	866,8	151410	151410

When the model is executed in R with the best-performing ANN architecture, the algorithm conducts the learning process based on iterations, error measurement criteria, and threshold values. Upon completion of the learning phase, a prediction is obtained. However, when the model is rerun, variations in error rates may be observed. This situation is one of the major disadvantages of ANN models, and to ensure prediction stability, it may be necessary to reuse the weights between neurons.

The error rates of the predictions made using the ARIMA and MLP-ANN models are compared in Table 13.

Table 13 presents the error metrics for the ARIMA (0, 1, 0) and MLP-ANN models. Based on these metrics, the following conclusions can be drawn.

- *ME:* Indicates the average difference between the predicted and actual values. A low ME suggests that the model's predictions are closer to the actual values.
- *RMSE:* Measures the magnitude of the errors and gives more weight to larger errors. A low RMSE indicates better performance of the model in the face of significant deviations.
- *MAE:* Reflects the absolute magnitude of the errors. A lower MAE signifies higher overall accuracy.
- *MPE:* Represents the percentage difference between the predicted and actual values. Positive values indicate overestimation, while negative values denote underestimation.
- *MAPE:* Represents the average percentage of the errors and is commonly used to evaluate model performance.

In conclusion, the ARIMA model outperformed the ANN model in both absolute and percentage error metrics. For instance, the ARIMA model's MAPE of 7.5% indicates that the predictions occurred with a 7.5% deviation, while the excessively high MAPE in the ANN model suggests significant deviations in its predictions.

These results serve as a significant finding regarding the difficulty of predicting crypto assets, as frequently discussed in the literature. High forecast errors reflect the complex and volatile nature of these assets. In this context, a detailed analysis of potential errors and limitations in the modeling process is provided in the results and discussion section of this study.

DISCUSSION AND CONCLUSION

This study compares the performance of linear and nonlinear models in predicting cryptocurrency values. Forecasts for BTC were made over a 12-period horizon using both ARIMA and MLP-ANN models. The forecasting performances of these two models were evaluated using various error metrics, including ME, RMSE, MAE, MPE, and MAPE.

Upon evaluating the forecasting results of the ARIMA model, the following error metrics were obtained: RMSE = 3623.5, MAE = 2394, ME = 228.4, and MAPE = 7.5%. These results indicate that the ARIMA model can make reasonably accurate short-term predictions in volatile markets like cryptocurrencies. In particular, the MAPE of 7.5% suggests that the ARIMA model provides an acceptable level of forecasting performance based on historical BTC data. The low error rates of the ARIMA model demonstrate its success in capturing cyclical patterns in past price movements. However, considering the high volatility of cryptocurrency assets, it is important to note that the ARIMA model may be inadequate for long-term predictions. This suggests that ARIMA is more suitable for short-term cyclical forecasts, while it may yield risky results in long-term forecasting.

Conversely, the predictions made using the MLP-ANN model yielded unexpectedly high error rates. The MLP-ANN model's forecasts showed excessive values, such as RMSE = 870.5, MAE = 866.8, ME = 866.8, and MAPE = 151410%. These results indicate that artificial neural networks fall short in speculative and volatile markets like BTC. The MLP-ANN model failed to capture the volatile nature of cryptocurrencies, resulting in a significantly low forecasting performance. Factors contributing to the model's failure include the inability to optimize parameter settings for a highly volatile asset like BTC, overfitting, and the model's failure to fully capture its complex nature.

Model comparison

The comparison of forecasting performances between the ARIMA and MLP-ANN models clearly reveals the fundamental differences between the two approaches. The ARIMA model appears to perform better with cyclical data and can capture volatility to a limited extent.

However, it should be noted that the performance of ARIMA may decline with increasing volatility in long-term forecasts. On the other hand, the ANN model has high error rates due to the sensitivity of parameter settings and difficulties in handling volatile data. Thus, it can be concluded that the ANN model is limited in its application in speculative markets due to its inability to fully capture the complex structure of cryptocurrencies.

Recommendations for researchers

This study highlights the differences between linear and nonlinear models in predicting cryptocurrencies. Various recommendations can be made for researchers who plan to conduct similar studies in the future.

- *Model selection:* The structure of the data is a crucial factor that directly affects model selection. Linear models like ARIMA can provide successful short-term predictions for cyclical and trend-influenced data. However, the success of nonlinear models can vary based on the complexity and multidimensional nature of the data. Researchers must choose models suitable for the characteristics of the assets they analyze.
- *Model tuning:* Nonlinear models, particularly artificial neural networks, must be optimized with appropriate parameters. Carelessness in parameter selection can lead to overfitting or insufficient learning. Researchers are advised to optimize the parameter settings of neural networks and use regularization techniques to avoid overfitting.
- *Hybrid models:* Instead of using solely linear or nonlinear models, hybrid models that combine the advantages of both approaches can yield better forecasting results. Utilizing different methods like ARIMA and ANN together can contribute to increased flexibility and accuracy in predictions. Future research should advance the development of such hybrid models.
- *Alternative forecasting models:* In addition to ARIMA and ANN models, alternative methods for time series forecasting in volatile markets exist. Particularly in volatile and unpredictable markets like cryptocurrencies, the following additional models may be considered.
- *GARCH models:* Commonly used to capture volatility, GARCH models are suitable for analyzing the volatile structure of cryptocurrencies. While GARCH models account for increases and decreases in volatility, ARIMA does not capture this volatility.
- *SARIMA models:* In markets where seasonal effects are pronounced, SARIMA models can be employed. If weekly or monthly cycles exist in cryptocurrency markets, these cycles can be integrated into predictions using SARIMA.
- *VAR models:* VAR models, which examine the relationships among multiple time series variables, are suitable for analyzing relationships among cryptocurrencies. Interdependencies between BTC and other cryptocurrencies can be investigated.
- *LSTM (Long short-term memory) models:* LSTM, a type of deep learning method, is effective in learning long-term dependencies. LSTM models may be evaluated for long-term predictions in volatile markets like cryptocurrencies.

Recommendations for industry professionals

Financial sector professionals should be aware of several important points when forecasting in cryptocurrency markets. This study provides various insights for professionals by considering the limitations of both linear and nonlinear models.

- *Short-term strategies:* The ARIMA model offers relatively low error rates in short-term predictions for cryptocurrencies. For short-term analyses and trades, the ARIMA model can be utilized as an appropriate tool for capturing cyclical patterns in cryptocurrency markets.
- *Caution in long-term forecasts:* Long-term predictions for cryptocurrencies may prove inadequate with both ARIMA and ANN methods. Professionals should not overly rely on these forecasts for long-term investment decisions and should employ a broader analytical framework.
- *Monitoring market dynamics:* Regulatory announcements, political events, and social media impacts are significant in cryptocurrency markets. Therefore, in addition to mathematical models, it is crucial to closely monitor market dynamics.

Recommendations for investors

The findings of this study can assist individual and institutional investors planning to invest in cryptocurrency markets in making more informed decisions.

Avoid over-reliance on forecasting models: Both ARIMA and ANN models have certain limitations in predicting cryptocurrency values. Investors should avoid excessive reliance on the results of these models and consider evaluating alternative analytical methods.

Awareness of volatility: Cryptocurrencies exhibit high volatility. Investors should be aware that significant gains and losses may occur in both the short and long term, necessitating the development of appropriate risk management strategies.

CONCLUSION

This study aims to fill a significant gap in financial markets by comparing the performance of linear and nonlinear models used in predicting cryptocurrencies. The findings indicate that linear models are more effective for short-term predictions, particularly for highly volatile cryptocurrencies like Bitcoin. Conversely, it was concluded that nonlinear models such as artificial neural networks are inadequate under current market conditions.

Future research can expand upon the findings of this study by conducting more comprehensive analyses regarding the prediction of cryptocurrencies. Actions taken by researchers and industry professionals based on these findings will contribute to more effective forecasting in financial markets and more informed investment decisions.

In conclusion, it is clear that further studies are needed on the dynamic structure and predictability of cryptocurrencies. Research that addresses both theoretical and practical aspects will facilitate a better understanding and management of cryptocurrencies in financial markets.

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