YIL (YEAR): 2026 CILT (VOLUME): 18 SAYI (ISSUE): 1 37-50
Doi:10.52791/aksarayiibd.1770977

AKSARAY ÜNİVERSİTESİ
İKTİSADİ VE İDARİ BİLİMLER FAKÜLTESİ DERGİSİ
JOURNAL OF AKSARAY UNIVERSITY FACULTY OF ECONOMICS AND ADMINISTRATIVE SCIENCES

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Araştırma Makalesi ● Research Article

Comparing Forecasting Powers of Traditional Methods and Learning Based Methods in Cryptocurrency Market: An Application On Bitcoin, Ethereum, Binance Coin and Monero[1]

Geleneksel Yöntemlerin ve Öğrenme Temelli Yöntemlerin Tahmin Güçlerinin Kripto Para Piyasasında Karşılaştırılması: Bitcoin, Ethereum, Binance Coin ve Monero Üzerine Bir Uygulama

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ARTICLE INFO

Keywords
Traditional Methods, Learning Based Methods, Cryptocurrency Market, Forecasting

Article History:
Received: 23 August 2025
Accepted: 17 February 2026

ABSTRACT

In this study, it is aimed to compare quantitative forecasting methods (traditional and learning-based) in the cryptocurrency market. For this purpose the daily prices between 16 September 2017 – 15 September 2022 of Bitcoin, Ethereum, Binance Coin and Monero were analyzed with five different methods. The methods used are ARIMA (Autoregressive integrated moving average), exponential smoothing, artificial neural networks, RNN (recurrent neural network) and LSTM (long short term memory).

The results revealed that exponential smoothing was the most successful method for predicting three of the four cryptocurrencies considered in the study. Exponential smoothing achieved high performance in daily price prediction for BTC, ETH, and BNB. However, artificial neural networks were the most successful method for daily price prediction for XMR.

Another finding of this study is that deep learning-based methods produced some unsuccessful forecasts. It is thought that this situation may be due to the fact that deep learning methods require more data and design and validation choices. The study contributes to the literature by examining the four cryptocurrencies in question with traditional and learning-based methods and by analyzing alternative cryptocurrencies such as Binance Coin and Monero, which are less covered in the literature. In future studies, using other quantitative methods (e.g. GRU, XGBoost, transformer models) on cryptocurrencies will contribute to the literature.

MAKALE BILGISI

Anahtar Kelimeler
Geleneksel Yöntemler, Öğrenme Tabanlı Yöntemler, Kripto Para Piyasası Tahminleme

ÖZET

Bu çalışmada nicel tahmin yöntemlerinin (geleneksel ve öğrenme tabanlı) tahmin güçlerinin kripto para piyasasında karşılaştırılması amaçlanmıştır. Bu amaca yönelik olarak Bitcoin, Ethereum, Binance Coin ve Monero'nun 16 Eylül 2017 – 15 Eylül 2022 aralığındaki günlük fiyatları beş farklı yöntemle analiz edilmiştir. Kullanılan yöntemler ARIMA (bütünleşik otoregresif hareketli ortalama), üstel düzeltme, yapay sinir ağları, RNN (yinelemeli sinir ağı) ve LSTM (uzun kısa süreli hafıza) yöntemleridir.

Tekin, T. G. & Patır, S. (2026). Comparing forecasting powers of traditional methods and learning based methods in cryptocurrency market: An application on bitcoin, ethereum, binance coin and monero. *Aksaray Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 18*(1), 37-50. DOI: https://doi.org/10.52791/aksarayiibd.1770977

Makale Geçmişi:
Geliş Tarihi: 23 Ağustos 2025
Kabul Tarihi: 17 Şubat 2026

Sonuçlar değerlendirildiğinde çalışma kapsamında ele alınan dört kripto para biriminin tahminlemesinin üçünde en başarılı yöntemin üstel düzeltme yöntemi olduğu görülmüştür. Üstel düzeltme yöntemi, BTC, ETH ve BNB günlük fiyat tahminlemesinde yüksek performansa sahiptir. Fakat XMR günlük fiyat tahminlemesinde yapay sinir ağları en başarılı olan yöntem olmuştur.

Çalışmada tespit edilen diğer bir husus derin öğrenme tabanlı yöntemlerin bazı başarısız tahminlemeler yapmasıdır. Bu durumun derin öğrenme yöntemlerinin daha fazla veriye ihtiyaç duymasından, tasarım ve doğrulama tercihlerinden kaynaklanabileceği düşünülmektedir. Çalışma söz konusu dört kripto para birimini geleneksel ve öğrenmeye dayalı yöntemlerle ele alması, Binance Coin ve Monero gibi literatürde az yer verilen alternative kripto paraları analiz etmesiyle literature katkı sunmaktadır. Gelecek çalışmalarda, başka nicel yöntemlerin (Örnek: GRU, XGBoost, transformer modeller) kripto para birimleri üzerinde kullanılması literatüre katkı sağlayacaktır.

The cryptocurrency market is a financial innovation that has deeply affected the world markets in recent years. Bitcoin, the cryptocurrency with the highest volume in the market, was introduced to the world by Nakamoto (2008). After Bitcoin, many cryptocurrencies were launched. They are called altcoin (short for "alternative coin"). All processes related to cryptocurrencies are executed on online platforms, mostly on cryptocurrency exchanges, e.g., Binance, Coinbase Exchange, MEXC etc. Cryptocurrencies have a market volume as high as 3.37 trillion dollars by May 2025 (Coinmarketcap).

Cryptocurrencies differ from other financial assets with their decentralized structure and blockchain technology (Krückeberg & Scholz, 2020; Tschorsch & Scheuermann, 2016; Gramlich et al., 2023; Alamsyah et al., 2024). Transparency, traceability and the public nature of transaction history make cryptocurrencies more trustworthy (Shah et al., 2023; Cong & He, 2019; Yousaf et al., 2019; Neisse et al., 2017). Additionally, the anonymity and confidentiality offered to investors make the cryptocurrency market more attractive (Miers et al., 2013; Rauchs & Hileman, 2017; Rahardja et al., 2023; Marella et al., 2020).

Besides these trustworthy characteristics of cryptocurrencies, they have also risky aspects too. For example, they are open to pump – dump manipulation (Corbet et al., 2019; Eigelshoven et al., 2021; Fratric et al., 2022; Barnes, 2018). The mining activities to obtain cryptocurrencies demand large amounts of electricity. Therefore cryptocurrency mining results in negative environmental impacts as a result of cryptocurrency mining (Böhme et al., 2015; Mora et al., 2018; Stoll et al., 2019; Jiang et al., 2021). Cryptocurrencies have high volatility, this feature affects the decisions of investors (İsabetli Fidan & Güz, 2022; Baur & Dimpfl, 2021; Al Guindy, 2021; Guizani & Nafti., 2019). They have experienced speculative price bubbles since they were introduced (Cheah & Fray, 2015; Gandal et al., 2018; Enoksen et al., 2020; Phillips & Gorse, 2018). Forecasting the prices of cryptocurrencies which have these characteristics and an extremely high market volume has significiant importance for investors around the world.

Although there are many studies which forecast cryptocurrency prices with different methods in the literature, there is still a lack of studies comparing traditional methods and learning based methods. This study compares forecasting powers of five quantitative methods: Auto Regressive Integrated Moving Average (ARIMA) (Box et al., 1994) and exponential smoothing (Holt, 1957; Winters, 1960) as traditional methods and artificial neural networks (ANN) (McCulloch & Pitts, 1943), recurrent neural network (RNN) (Rumelhart et al., 1986) and long – short term memory (LSTM) (Hochreiter & Schmidhuber, 1997) as learning based methods. The methods are tested on four cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB) and Monero (XMR). In addition to Bitcoin and Ethereum, which are frequently analyzed in other studies, the study also analyzes Binance Coin, which belongs to the largest cryptocurrency exchange, and Monero, one of the oldest cryptocurrencies. This is another important point that distinguishes this study from others. Thus, this study contributes to filling a gap in the literature.

1. LITERATURE REVIEW

1.1. Studies Using Traditional Time Series Methods

Traditional methods are widely used for time series analysis before the widespread adoption of deep learning methods and also today. In this section, a summary of some studies in the literature using traditional methods is provided.

Kristoufek (2013) investigated the relationship between Bitcoin prices and Google Trends and Wikipedia searching volumes by using time series regression techniques. As a result, the study found that information-seeking behavior can be effective in understanding Bitcoin price movements. Kristoufek (2015) examines factors affecting the Bitcoin price over time and across frequency dimensions using wavelet coherence analysis. The results indicate that Bitcoin is affected by traditional factors and also exhibits speculative behaviors.

Dyhrberg (2016) compared the volatilities of Bitcoin, gold and US dollar with GARCH models. The findings show that Bitcoin can be both a hedge and a speculative tool. Bariviera (2017) analyzed market activity of Bitcoin prices over time by Hurst exponent method. The findings showed that market activity changes over time.

Bouri et al. (2017) analyzed the portfolio diversification, hedge and safe haven functions with GARCH models and found out that Bitcoin can be a hedging tool in some circumstances. Corbet et al. (2018) researched the bubbles in Bitcoin and Ethereum markets with traditional bubble detection methods: SADF (Supremum Augmented Dickey – Fuller) and GSADF (Generalized SADF) which was introduced by (Phillips et al., 2015). The results indicated that there are some bubbles in Bitcoin and Ethereum markets. Also, irrational investor behaviors were detected. Atsalakis et al. (2019) compared the forecasting powers of ARIMA and ANN for Bitcoin prices. They found out that ANN gives better results than ARIMA.

1.2. Studies Using Learning Based Time Series Methods

Learning-based methods are widely used for analysis in the literature. Some examples are presented below.

Zhang et al. (1998) examined the forecasting power of ANN in different time series models including financial time series in their compilation study. Results indicated that ANN produces better results than traditional methods thanks to its ability of modelling non – linear structures. Almeida et al. (2015) forecasted next day Bitcoin price based on the price and volume of the previous days with ANN method. A large amount of profit was made with one of the established models. It was found that adding or removing Bitcoin volume as an input did not change performance.

Jang & Lee (2017) forecasted Bitcoin prices with bayesian neural Networks (BNN). Also, they included blockchain data into their model. In the findings, it is seen that the established model is very successful at forecasting Bitcoin prices. Jiang & Liang (2017) made a portfolio management experiment with deep reinforcement learning (DRL) on Bitcoin, Ethereum and Litecoin. In the findings, DRL method’s performance was approximately 90% better than other methods.

Alessandretti et al. (2018) used random forest (RF), gradient boosting and LSTM for forecasting prices of 1681 different cryptocurrencies. The results indicated that the forecasting performances of these methods are lower for altcoins because of low liquidity. Another result is RF is more stable than LSTM in short term forecasts.

Nakano et al. (2018) researched effective buy – sale strategies of Bitcoin by using ANN. The established model with seven layer provided more accurate suggestions than classical buy – sale strategies, especially in December 2017 – January 2018 era which Bitcoin gave negative return.

Hitam & Ismail (2018) used support vector machines (SVM), ANN and machine learning methods to forecast Bitcoin, Ethereum, Litecoin, Nem, Ripple and Stellar prices. The data between March 2013 and June 2017 were used for training. The SVM method gave the best results at the end of the study.

1.3. Gap and Contribution

When literature is examined, it is seen that the studies which analyzes cryptocurrencies mostly use same methods (e.g., ARIMA, ANN, SVM, LSTM). Moreover, most studies analyze Bitcoin and Ethereum, with less attention given to alternative coins like Binance Coin and Monero.

The studies which integrate statistical forecasting methods (e.g., exponential smoothing, moving averages) and learning based methods (e.g., ANN, RNN, LSTM) are limited in the literature. Therefore, this important gap limits our understanding of complex and volatile nature of cryptocurrency market and also how different models behave in this market.

To our knowledge, this is the first study that contributes to the literature by comparative analysis of five forecasting methods (including traditional statistical methods, artificial neural networks, and deep learning methods) applied to the daily prices of four major cryptocurrencies: Bitcoin, Ethereum (a platform coin), Binance Coin (an exchange coin), and Monero (a privacy coin). Thus, by incorporating methodological diversity and focusing on understudied digital assets, this study provides original findings on model performances and offers important academic and practical implications.

2. DATA AND METHODOLOGY

2.1. Data

Datasets consist of four cryptocurrencies: Bitcoin, Ethereum, Binance Coin and Monero. These cryptocurrencies account for 75% of the cryptocurrency market capitalization by May 2025. Data consists of five years period daily closing prices from 16 September 2017 to 15 September 2022 (1,826 days). All values are in US dollars. Datasets were taken from CoinMarketCap and CoinGecko websites. Descriptive stats of datasets, correlation table and time - prices graphs which were obtained from E – Views software are given in Table 1, Table 2 and Figure 1.

Table 1. Descriptive Stats Of Time Series

	BTC	**ETH**	**BNB**	**XMR**
Mean	19793	1096.23	134.79	148.16
Median	10290	432.57	22.11	122.90
Maximum	67617	4815	675.09	542.32
Minimum	1025	83.78	0.03	10.13
Standard Deviation	17261	1214.59	184.14	90.05
Skewness	1.05	1.23	1.17	1.01
Kurtosis	2.71	3.31	2.95	3.63
Jarque – Bera	343.92	475.27	423.89	342.34
Probability	0.00	0.00	0.00	0.00
Observations	1826	1826	1826	1826

It is seen in Table 1 that Bitcoin has the highest mean while Binance Coin has the lowest one. All skewness and kurtosis values are positive so all series are skewed to the right and have sharp dispersion.

Table 2. Correlation Matrix

	BTC	**ETH**	**BNB**	**XMR**
BTC	1			
ETH	0.92	1		
BNB	0.91	0.96	1	
XMR	0.67	0.69	0.61	1

All correlation values are positive. This means all time series have same – direction relationship. While the highest correlation is between BTC and ETH, the lowest correlation is between BNB and XMR.

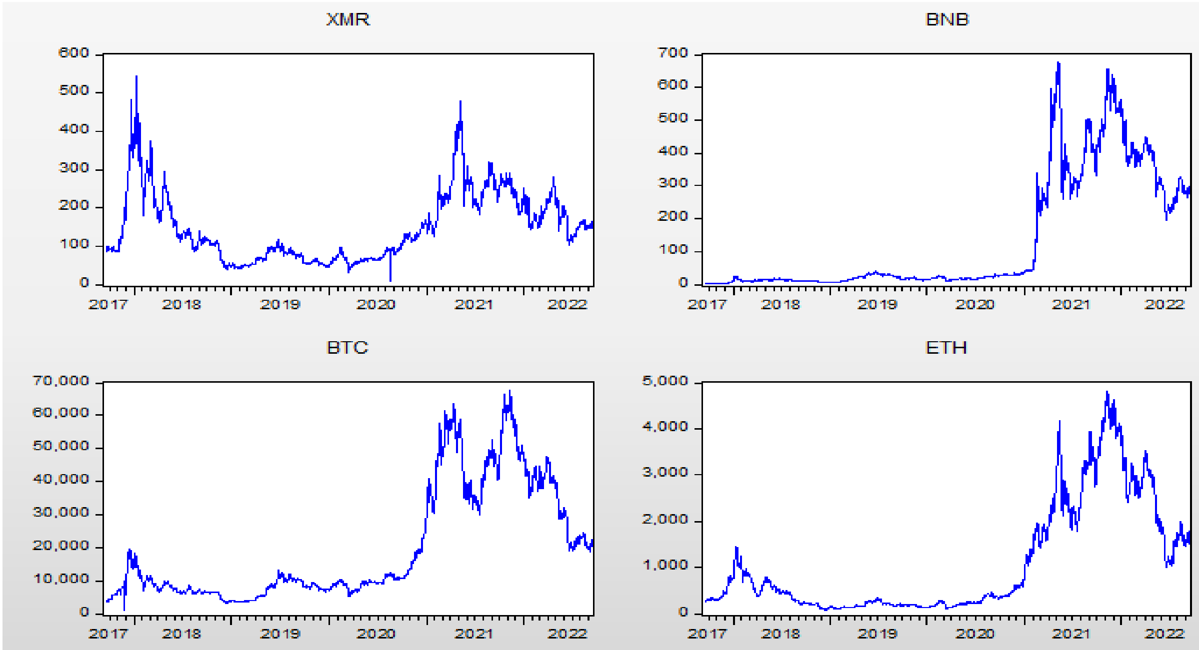

Figure 1. Time – Price Graphs

2.2. Methodology

In the study, four time series were forecasted by two traditional methods (exponential smoothing and ARIMA), ANN and two deep learning methods (RNN and LSTM). After the analysis, the success level of the methods in each cryptocurrency was reported and the methods were ranked according to their success levels. The first analysis in the study was the ADF (Dickey & Fuller, 1981) unit root test. After unit root tests, the results of ARIMA, exponential smoothing, ANN, RNN and LSTM analyses are given, respectively.

For measuring forecasting powers of methods, mean absolute percentage error (MAPE), mean absolute error (MAE) and mean squared error (MSE) are used. These error metrics are used in literature to evaluate financial forecast results widely. When Y is the observed value at time i, Y' is the forecasted value at time i, n is the total number of observations, ei is errors, their formulas are given in Table 3.

Table 3. The Formulas Of Error Metrics

MAPE	MAE	MSE
$\frac{100}{n}\sum_{i=1}^{n}\left\|\frac{Y-Y'}{Y}\right\|$	$\frac{\sum_{i=1}^{n}\|e_i\|}{n}$	$\frac{\sum_{1}^{n}(Y-Y')^2}{n}$

E – Views 10 software was used for unit root tests, ARIMA and exponential smoothing analyses. Python software was used for RNN and LSTM analyses. And MATLAB 2013 software was used for ANN analysis.

2.2.1. Exponential Smoothing

Exponential smoothing method is based on the works of Holt (1957) and Winters (1960). There are several variations of exponential smoothing, such as simple exponential smoothing, Brown linear exponential smoothing, triple exponential smoothing, Holt exponential smoothing method, Winters exponential smoothing method etc.

Time series which have trend component, but don't have seasonality component are analyzed with Holt exponential smoothing method (Chopra & Meindl, 2016). Therefore, Holt's method was used in this study. The Holt method predicts two smoothing parameters: the first one is α which is related to level and the second one is β which is related to trend. When L_t represents level, b_t represents trend, F_{t+m} represents forecast value, Holt exponential smoothing method can be formulated as:

$$L_t = \alpha\, Y_t + (1 - \alpha)(L_{t-1} + b_{t-1})$$

$$B_t = \beta\, (L_t - L_{t-1}) + (1- \beta) b_{t-1}$$

$$F_{t+m} = L_t + b_{tm}$$ (Tratar & Strmčnik, 2016).

2.2.2. ARIMA

ARIMA method is also known as Box – Jenkins method too. ARIMA method is used for forecasting discrete time series. ARIMA method is symbolized with (p, d, q). p represents the degree of autoregression parameter, q represents the degree of mean parameter and d represents difference degree. In this study all time series become stationary at first difference. Thus the d values are always equal to 1. When Z_t represents the differenced data, ϕ represents coefficients of data, a represents errors and Θ represents coefficients of errors, ARIMA can be formulated as:

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \phi_p Z_{t-p} + \delta + a_t - \Theta_1 a_{t-1} - \Theta_2 a_{t-2} - \dots - \Theta_q a_{t-q}$$ (Kaynar & Taştan, 2009).

2.2.3. ANN

ANN is a learning-based method which imitates human neural cells (neurons) (Dongare et al., 2012). The study McCulloch & Pitts (1943) made was the first one which an artificial neuron taking the human neuron as model. Since then, too many improvements have been recorded in this technology.

ANN systems are used in too many areas widely, e.g., finance, engineering, medicine etc. In these areas, ANN systems have some functions: Optimization, learning, feature specification, associating, classifying, generalizing etc. (Akaytay, 2010). ANN systems are used for financial forecasting widely too. In Figure 2, a human neuron and an artificial neuron are given, respectively.

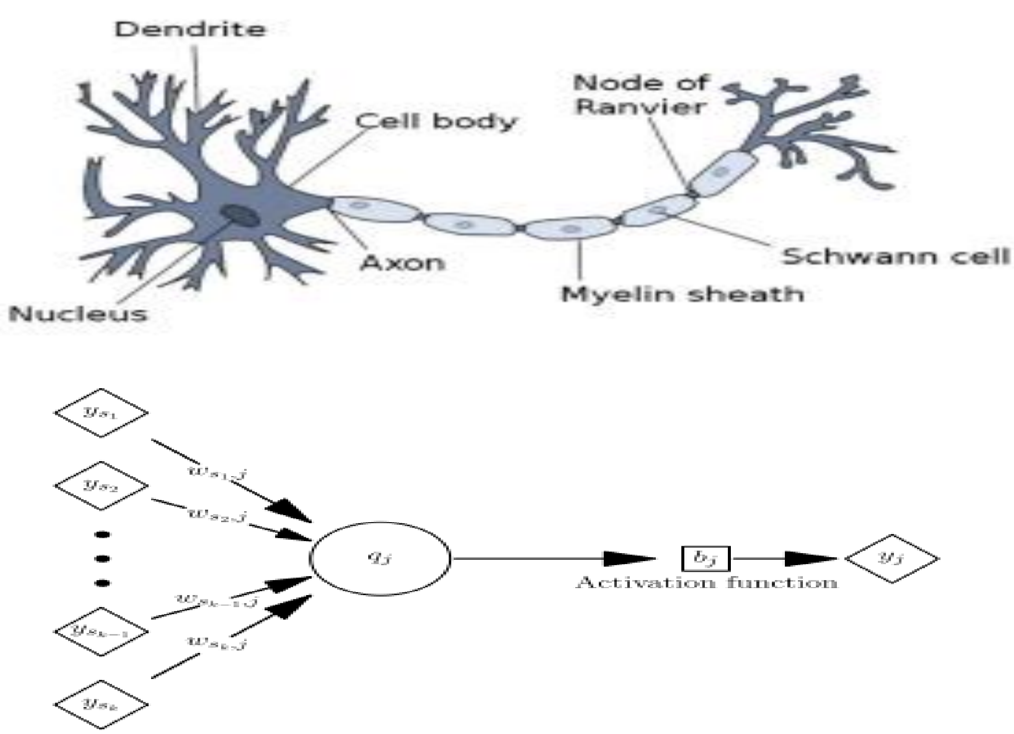

Figure 2. Human Neuron and Artificial Neuron

(Reference: Ray & Hesthaven, 2018)

ANN systems have some advantages and disadvantages. Some of them are given in Table 4.

Table 4. Some advantages and disadvantages of ANN systems

Advantages	Disadvantages
Adaptation during training	Dependence to hardware
Ability of organization by itself	Unexplainable behaviors
Real time operation	Difficulties during defining problems to system
Error tolerance by backup information coding	The problem of detection appropriate network structure
Parallel processing capacity	Duration of process

(Reference: Dumitru & Maria, 2013; Mijwel, 2021)

2.2.4. RNN

The first deep learning method used in this study is RNN. RNN systems are basically an extension of neural network systems. In RNN systems, time dependencies between consecutive observations are modeled (Rumelhart et al., 1986). So, RNN systems have successful results on forecasting of time series which have strong relations between observations.

While ht is current hidden state vector, xt is current input vector, Wxh is weight matrix from input to hidden state, Whh is weight matrix from previous hidden state to current hidden state, bh is bias vector, σ is activation function; mathematical expression of RNN can be written as:

$h_t = \sigma(W_{xh} x_t + W_{hh} h(t-1) + b_h)$ (Lipton et al., 2015)

A figure of a basic RNN system is given in Figure 3.

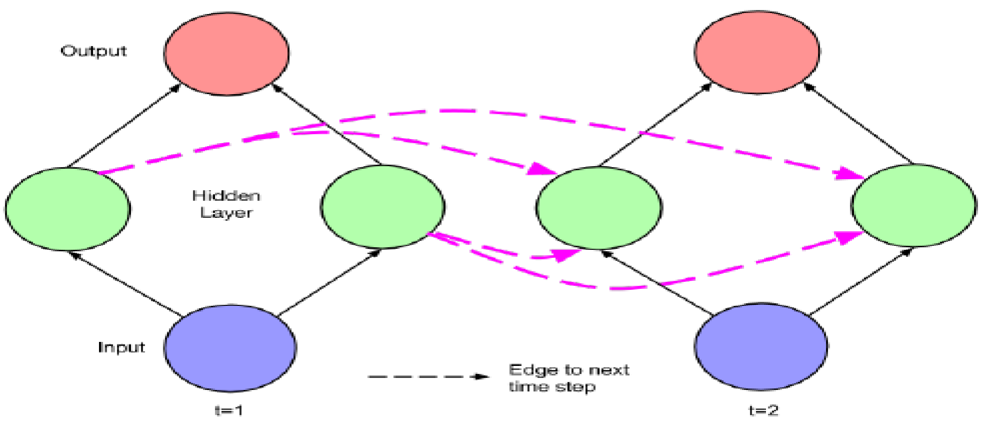

Figure 3. Simple RNN Model

(Reference: Lipton, 2015)

RNN systems may have some problems like vanishing gradient and exploding gradient while learning long term dependencies (Bengio et al., 1994). To overcome these problems LSTM (Hochreiter & Schmidhuber, 1997) and GRU (Cho et al., 2014) methods were improved.

2.2.5. LSTM

LSTM method was developed by Hochreiter & Schmidhuber (1997) to solve RNN’s vanishing gradient problem. It can be used for forecasting time series, robot controlling, natural language processing and in too many other areas.

A LSTM cell has three gates: Input gate, forget gate and output gate (Gers et al., 2000). While f_t is the forget gate, i_t is the input gate, $\tilde{C}_t$ is the cell candidate, C_t is the cell state, o_t is the output gate, h_t is the hidden state, W letters show matrices, b letters show vectors; the formula of LSTM model is as:

$f_t = \sigma (W_f . [h_{t-1} , x_t] + b_f)$

$i_t = \sigma (W_i . [h_{t-1} , x_t] + b_i)$

$\tilde{C}_t = \tanh (W_C . [h_{t-1} , x_t] + b_C)$

$C_t = f_t . C_{t-1} + i_t . \tilde{C}_t$

$o_t = \sigma (W_o . [h_{t-1} , x_t] + b_o)$

$h_t = o_t . \tanh(C_t)$ (Greff et al., 2016)

A figure of basic LSTM model is given in Figure 4.

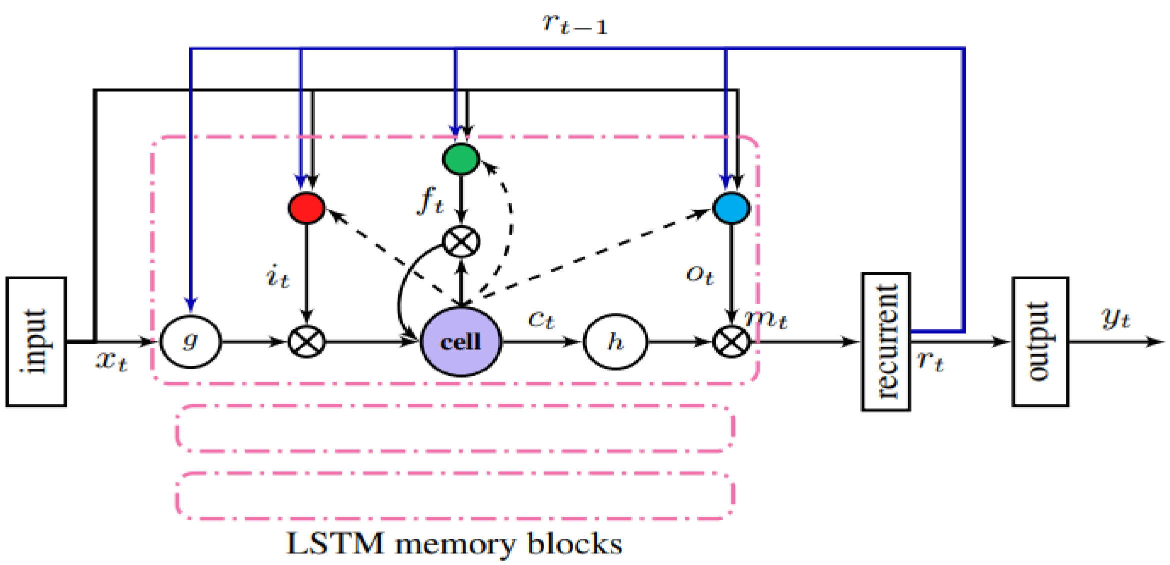

Figure 4. A Basic LSTM Model

(Reference: Sak et al., 2014)

3. RESULTS

3.1. Unit Root Test Results

The very first analysis applied to datasets is unit root test. Augmented Dickey Fuller (ADF) unit root test was applied and the results are given in Table 5.

Table 5. The Results of ADF Unit Root Test

	Intercept		**Trend and Intercept**	
	Level	1. Difference	Level	1. Difference
BTC	-1.481355 [0.5431]	-45.36573 [0.0001]	-1.492684 [0.8321]	-45.36305 [0.0000]
ETH	-1.365428 [0.6006]	-45.56597 [0.0001]	-1.781189 [0.7137]	-45.55469 [0.0000]
BNB	-1.410150 [0.5787]	-16.86916 [0.0000]	-2.184253 [0.4976]	-16.86438 [0.0000]

XMR	-2.515243 [0.1119]	-51.33365 [0.0001]	-2.533812 [0.3116]	-51.32048 [0.0000]

The hypotheses established during ADF unit root tests are as follows:

H_0: The series is non-stationary. (There is a unit root.)

H_1: The series is stationary. (There is no unit root.)

For all time series, at 5% significance level,

-H_0 could not be rejected in the constant model and level. The series is non-stationary and contains a unit root.

-H_0 was rejected in the constant model and at the 1st difference. The series is stationary and does not contain a unit root.

-H_0 could not be rejected in the constant and trend model and level. The series is non-stationary and contains a unit root.

-H_0 was rejected in the constant and trend model and at the 1st difference. The series is stationary and does not contain a unit root.

Unit root tests applied to all four time-series revealed that the series were not stationary at the level. However, they were stationary at first difference in both the constant model and the constant and trend model.

3.2. ARIMA Results

The first forecasting method used in the study is ARIMA. All the ARIMA analyses were conducted on "Automatic ARIMA Forecasting" module on E – Views 10 program. The module was instructed to use the Akaike Info Criterion (AIC) to determine the model it will choose. All of the "d" values in chosen models are 1, because all time series become stationary at first difference. In table 6, the chosen models for each time series and error metrics after forecasting are given.

Table 6. Chosen ARIMA models and error metrics for each time series

BTC	**ETH**	**BNB**	**XMR**
ARIMA (2,1,3)	ARIMA (4,1,5)	ARIMA (11,1,11)	ARIMA (4,1,6)
MAPE: 3.01	MAPE: 3.46	MAPE: 3.00	MAPE: 4.15
MAE: 971.11	MAE: 75.92	MAE: 10.30	MAE: 7.23
MSE: 1807454	MSE: 10228	MSE: 196.83	MSE: 101.23

When the forecasting performance of the ARIMA method is evaluated based on the MAPE error metric, it is observed that the method performs best on the BNB, BTC, ETH, and XMR time series, respectively. However, it is also observed that the forecasting performances for the BNB and BTC time series are quite similar.

3.3. Exponential Smoothing Results

Before forecasting with exponential smoothing method, it should be determined whether the series are stationary. We detected that all series were stationary at first difference. Therefore, exponential smoothing analysis was performed on the first-differenced series.

Before the analysis, it must be detected that which exponential smoothing method to use. If the series do not have seasonality, the Holt method is used for forecasting. As seen in time – price graphs and in correlogram graphs given in Figure 5, the time series in this study do not have seasonality. Also, Khedr et al. (2021) mentioned that the time series belong to cryptocurrencies do not have seasonality. So, the Holt method was used for forecasting. Forecasting results and alpha and beta values in the analysis are given in Table 7.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.998	0.998	1821.2	0.000
		2	0.996	0.056	3636.5	0.000
		3	0.994	0.005	5446.0	0.000
		4	0.992	-0.022	7249.4	0.000
		5	0.990	-0.028	9046.2	0.000
		6	0.988	-0.021	10836.	0.000
		7	0.986	-0.015	12619.	0.000
		8	0.984	0.031	14396.	0.000
		9	0.982	0.015	16166.	0.000
		10	0.979	-0.038	17929.	0.000
		11	0.977	-0.026	19686.	0.000
		12	0.975	-0.026	21434.	0.000
		13	0.973	0.050	23176.	0.000
		14	0.971	-0.015	24912.	0.000
		15	0.968	0.014	26640.	0.000
		16	0.966	0.013	28362.	0.000
		17	0.964	0.007	30077.	0.000
		18	0.962	-0.016	31785.	0.000
		19	0.960	0.012	33488.	0.000
		20	0.958	0.039	35184.	0.000
		21	0.956	-0.040	36874.	0.000
		22	0.954	0.011	38557.	0.000
		23	0.952	-0.014	40235.	0.000
		24	0.950	0.038	41908.	0.000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.998	0.998	1820.7	0.000
		2	0.996	0.058	3635.1	0.000
		3	0.994	-0.029	5442.7	0.000
		4	0.991	-0.021	7243.2	0.000
		5	0.989	-0.039	9036.0	0.000
		6	0.987	0.059	10822.	0.000
		7	0.984	-0.092	12600.	0.000
		8	0.982	0.017	14370.	0.000
		9	0.980	0.028	16133.	0.000
		10	0.977	0.005	17889.	0.000
		11	0.975	-0.017	19637.	0.000
		12	0.973	0.003	21377.	0.000
		13	0.971	0.065	23112.	0.000
		14	0.968	-0.037	24839.	0.000
		15	0.966	0.029	26559.	0.000
		16	0.964	-0.010	28273.	0.000
		17	0.962	0.055	29982.	0.000
		18	0.960	-0.051	31684.	0.000
		19	0.958	0.016	33380.	0.000
		20	0.956	0.034	35070.	0.000
		21	0.954	0.001	36754.	0.000
		22	0.952	-0.038	38433.	0.000
		23	0.950	-0.030	40105.	0.000
		24	0.948	0.011	41770.	0.000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.997	0.997	1819.6	0.000
		2	0.995	0.110	3633.0	0.000
		3	0.993	-0.080	5438.5	0.000
		4	0.990	-0.039	7235.6	0.000
		5	0.988	-0.017	9024.2	0.000
		6	0.986	0.101	10806.	0.000
		7	0.983	-0.078	12579.	0.000
		8	0.981	0.008	14345.	0.000
		9	0.978	-0.018	16102.	0.000
		10	0.975	-0.046	17850.	0.000
		11	0.972	-0.041	19588.	0.000
		12	0.969	-0.004	21317.	0.000
		13	0.967	0.071	23038.	0.000
		14	0.964	-0.020	24749.	0.000
		15	0.961	0.053	26452.	0.000
		16	0.959	-0.006	28148.	0.000
		17	0.956	0.009	29835.	0.000
		18	0.954	-0.006	31515.	0.000
		19	0.951	-0.054	33186.	0.000
		20	0.948	0.023	34849.	0.000
		21	0.946	0.035	36504.	0.000
		22	0.943	-0.060	38150.	0.000
		23	0.941	0.017	39788.	0.000
		24	0.938	0.032	41419.	0.000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.990	0.990	1793.2	0.000
		2	0.984	0.178	3564.8	0.000
		3	0.977	0.006	5313.1	0.000
		4	0.971	0.037	7041.4	0.000
		5	0.965	0.013	8749.6	0.000
		6	0.960	0.032	10440.	0.000
		7	0.952	-0.131	12104.	0.000
		8	0.944	-0.038	13742.	0.000
		9	0.937	0.030	15356.	0.000
		10	0.930	-0.004	16947.	0.000
		11	0.925	0.065	18519.	0.000
		12	0.918	-0.051	20068.	0.000
		13	0.912	0.059	21599.	0.000
		14	0.905	-0.025	23107.	0.000
		15	0.899	0.018	24596.	0.000
		16	0.891	-0.073	26062.	0.000
		17	0.885	0.019	27507.	0.000
		18	0.877	-0.056	28928.	0.000
		19	0.870	-0.015	30326.	0.000
		20	0.864	0.062	31705.	0.000
		21	0.855	-0.120	33057.	0.000
		22	0.847	0.012	34385.	0.000
		23	0.840	0.051	35692.	0.000
		24	0.833	0.001	36977.	0.000

Figure 5. Correlogram Graphs of Time Series (BTC, ETH, BNB and XMR respectively)

Table 7. The Results of Exponential Smoothing Analysis

	Alpha Value	Beta Value	MAPE	MAE	MSE
BTC	0.01	0.01	2.52	818.50	1368097.45
ETH	0.01	0.01	3.44	75.69	10201.11
BNB	0.00	0.00	2.79	9.65	175.81
XMR	0.01	0.02	4.21	7.37	93.02

When the results are evaluated according to MAPE, it is seen that the most successful forecasts were made for BTC, BNB, ETH and XMR, respectively.

3.4. ANN Results

Before the analysis with ANN, each time series was split into training (70%), validation (15%) and test (15%). The ANN method does not require assumptions unlike traditional methods.

During the training phase, Levenberg - Marquardt feed-forward back-propagation artificial neural network type, which has mostly yielded positive results in forecasting studies in the literature, was used. Neural network parameters were determined by trial and error. The number of neurons ranged from 5 to 15 and the number of delays ranged from 2 to 5. Training was performed multiple times and the lowest MSE values were preferred. In Table 8, the error metric values after forecasting with ANN, number of neurons and delays used in the analysis and correlation values for each time series are given.

Table 8. The Error Metric Values After Forecasting With ANN, Number Of Neurons, Delays and Correlation

	MAPE	MAE	MSE	Number of Neurons	Number of Delays	Correlation
BTC	2.90	515.60	1228523.16	10	2	0.99
ETH	3.92	41.19	5741.83	10	2	0.99
BNB	6.60	3.73	257.89	15	2	0.99
XMR	3.49	5.30	139.48	7	2	0.99

When the results are evaluated according to MAPE, it is seen that the most successful forecasts were made for BTC, XMR, ETH and BNB, respectively. Also, high correlation values for each analysis are detected.

3.5. RNN and LSTM Results

In the architecture used to analyze time series with the RNN and LSTM methods, % 70 of the data is divided as training data and 30% as test data. Before analysis, the data was normalized to the range [0,1] to prevent large values from dominating small values. After training, the data was denormalized and returned to their true values. The time step (number of data to look back) was set as 15 steps. Trial and error determined that the optimal epoch value was 50.

Python software was run in Google Colaboratory to forecast with RNN and LSTM. TensorFlow and Keras libraries are used for learning. Python 3.12.1, TensorFlow 2.15.0 and Keras 2.15.0 versions were used for the architecture. In the model architecture, "ReLu" activation function is used except for the last layer, while linear activation function is preferred since there is only one linear output in the last layer. The results after RNN analysis are given in Table 9, while LSTM results are given in Table 10.

Table 9. Results After RNN Analysis

	MAPE	MAE	MSE
BTC	7.29	1375.17	4129689
ETH	14.85	86.42	1834101
BNB	12.25	20.83	2105.31
XMR	10.88	11.53	241.74

Table 10. Results After LSTM Analysis

	MAPE	MAE	MSE
BTC	5.90	990.29	2403.891
ETH	8.03	106.07	47795.23
BNB	31.74	49.70	11138.49
XMR	6.10	7.91	172.59

When the results are evaluated it is seen that, RNN forecasted the most successfully BTC, XMR, BNB and ETH, respectively. LSTM performed best for BTC, XMR, ETH, and BNB, respectively.

4. CONCLUSIONS, DISCUSSIONS AND SUGGESTIONS

This study aims to use quantitative methods (traditional methods, ANN and machine learning methods) to forecast the daily value of major cryptocurrencies and to identify which methods perform best. For this purpose, we analyzed the daily values of Bitcoin, Ethereum, Binance Coin and Monero between 2017 – 2022 period. MAPE, MSE and MAE error metrics were used for forecasting performance evaluation.

The exponential smoothing method is the most successful method for forecasting BTC (2.52% error rate), ETH (3.44% error rate) and BNB (2.79% error rate) daily prices. However, ANN performed best for XMR forecasting. Jenčová et al. (2025) emphasized that if the error rate under 10%, it can be considered as a successful forecast. In our study, 16 error rates out of 20 forecasting analysis are under 10%. Therefore, 80% of our forecasts are successful.

In the study, it is seen that, the deep learning methods are more unsuccessful than other methods. Lecun et al. (2015) indicates that the deep learning methods need large amounts of data to make best forecasts. We think that's why they produced unsuccessful forecasts in this study.

When we look at other studies with similar topic, we can detect some different results. Most of these studies are interested only in BTC. Latif et al. (2023) forecasted the BTC price with ARIMA and RNN – LSTM hybrid model. In the results, it is found out that ARIMA method forecasted with 98.21% accuracy and the hybrid model forecasted with 99.73% accuracy, unlike our study. Gümüş (2024) forecasted the gold prices with ANN and deep learning-based methods. The results showed that deep learning methods have better performance than ANN in forecasting gold prices, unlike our study. Kaur et al. (2025) forecasted the BTC price with ARIMA and deep learning-based methods. In the results, it is shown that ARIMA method showed better performance much more than LSTM method, like our study.

Looking at these results from a financial perspective, different evaluations can be made for investors with short-term plans and investors with long-term plans. It would be rational for investors with short-term investment plans to consider the MSE error metric, which punishes high errors, while investors with long-term plans should consider the MAPE metric, which gives the average percentage error value. BTC and ETH investors should prefer the artificial neural network method in the short term and the exponential smoothing method in the long term. BNB investors, on the other hand, should prefer the exponential smoothing method in both the short and long term. In the XMR analysis, the best results according to the MSE error metric were obtained with the exponential smoothing method, while the best results according to the MAPE error metric were obtained with the artificial neural network method.

In future studies, we suggest to use different methods to forecast the prices of BTC and other cryptocurrencies. This matters to contribute to the forecasting and cryptocurrency literature.

AUTHOR DECLARATIONS

Declarations of Research and Publication Ethics: This study has been prepared in accordance with scientific research and publication ethics.

Ethics Committee Approval: Since this research does not include analyzes that require ethics committee approval, it does not require ethics committee approval.

Declaration of Use of Artificial Intelligence: In this study, limited artificial intelligence tools were used only for language editing purposes.

Author Contributions: Authors contributed equally to the study.

Conflict of Interest: There is no conflict of interest arising from the study for the authors or third parties.

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