JEESS
Journal of Empirical Economics and Social Sciences
Uygulamalı Ekonomi ve Sosyal Bilimler Dergisi

Cilt/ Volume: 8 Sayı/ Issue: 1 Mart/ March s s . / pp. 27-46

Y. Demir, H. N. Mohammed DOI: 10.46959/jeess.1803960

FORECASTING CRYPTOCURRENCY VOLUMES WITH ARTIFICIAL NEURAL NETWORKS AND SUPPORT VECTOR MACHINES[1]

Assist. Prof. Yıldırım DEMİR (Ph.D.)[*]

Haitham Nadhim MOHAMMED[**]

ABSTRACT

In this study, 50-day volume forecasts for Bitcoin, Ethereum, Binance Coin, and Ripple were conducted using Artificial Neural Networks and Support Vector Machines. The root mean square error, mean absolute error, and error autocorrelation at lag 1 were used to compare model performance. These metrics were selected because RMSE and MAE effectively measure the average magnitude of forecasting errors, enabling an accurate assessment of model precision, while ACF1 evaluates the temporal independence of residuals, which is essential for validating forecasting reliability in financial time series. Analyses were carried out in R using data from investing.com. The findings show that the ANN model generally exhibits lower error metrics compared to SVM and has a better performance in the context of the current dataset. According to 50-day forecasts, BTC volume is expected to increase, while BNB volume decreases with the ANN model but increases with the SVM model. For ETH and XRP, the ANN model indicates stable horizontal movements, whereas the SVM model predicts a sharp increase in ETH volume and a decline in XRP volume. Overall, although cryptocurrencies are innovative financial assets, their high volatility poses significant risks, suggesting they are not yet reliable investment instruments.

[1] This study is derived from the master's thesis of Prediction of Cryptocurrency States with Artificial Neural Networks and Support Vector Machines.

[*] Van Yuzuncu Yil University, Faculty of Economics and Administrative Sciences, Department of Econometrics, Van/ Türkiye, E-mail: ydemir@yyu.edu.tr.

[**] Independent Researcher, Al-Qadisiyah/ Iraq, E-mail: haitham1981hh@gmail.com.

Makale Geçmişi/ Article History

Başvuru Tarihi/ Date of Application	: 15 Ekim/ October 2025
Düzeltme Tarihi/ Revision Date	: 3 Kasım/ November 2025
Kabul Tarihi/ Acceptance Date	: 19 Kasım/ November 2025

Research Article

Keywords: *Cryptocurrency, Neural Networks, Support Vector Machines.*

Jel Codes: *F3, E4, G1, L1.*

1. INTRODUCTION

The crypto money ecosystem, which has developed rapidly in recent years and whose participant network is growing day by day, stands out as a new alternative to the traditional financial order. In addition to the alternative payment method it offers, cryptocurrencies that have entered our lives with blockchain technology also offer various opportunities in a wide range from financing projects to loan supply. Many entrepreneurial teams are implementing their projects by crowdfunding through the new crypto money supply. Generally, these projects stand out as projects that are planned in line with a roadmap and contain blockchain technology in some way. Some projects that have started life through cryptocurrencies in recent years are also opening the doors of a blockchain-based decentralized financial order as an alternative to today's financial order developed based on centralized institutions.

Stock markets play an important role in the economy since they have increased the efficiency in capital formation of states and companies from the past to the present. Due to these important roles, stock exchanges fulfill important functions such as providing liquidity for governments and companies, being an indicator of the economy, and providing an environment of trust in the market (Karataş, 2019). Known as the pioneer of cryptocurrencies, Bitcoin entered the market in 2008 as an alternative instrument to investment instruments. It is thought that high commissions from banking transactions and various government policies play an important role in the spread of cryptocurrencies. The fact that cryptocurrencies do not belong to a single country and manufacturer, the amount of production is limited and the spread of the currency bring possible risks. Not every country accepts cryptocurrencies as official currency and there are legal deficiencies regarding these currencies. For this reason, cryptocurrencies have as many risks as their returns. Despite all the minuses, cryptocurrencies are not limited to Bitcoin and new virtual currencies are released every day (Kanat and Öget, 2018).

Technological developments allow digital currencies to emerge and develop rapidly. Digital currency enables the storage and transfer of a physical asset electronically with the help of computer systems and internet networks. In this context, over time, many electronic money institutions have emerged in many countries that offer electronic money at the same rate in exchange for the real money they receive from their users. In this way, they can quickly transfer this electronic money to anyone in any country and receive it in return as fiat money (Bakır, 2021).

Cilt/ Volume: 8 Sayı/ Issue: 1 Mart/ March s s . / pp. 27-46
Y. Demir, H. N. Mohammed DOI: 10.46959/jeess.1803960

There are undoubtedly some popular cryptocurrencies in the cryptocurrency market other than Bitcoin, Litecoin and Ripple. Ethereum, Bitcoin Cash, Dash, NEM and Monero are examples of popular cryptocurrencies. These currencies, like Bitcoin, have proven themselves today and have begun to be accepted for investment and payment purposes by investment companies and many commercial organizations, as well as ordinary users. In fact, Bitcoin is not the first cryptocurrency, and previous attempts have been made to produce cryptocurrencies, but these attempts have failed (Thakur et al., 2018).

The most important features of cryptocurrencies are that they do not have a centralized system and use the blockchain system. The absence of a centralized system means that it does not belong to any person or state. Their functioning is provided entirely by cryptography. A person can transfer money to the other side of the world by keeping his identity completely confidential. Therefore, it is not suitable for today's legal orders. Illegal transactions or tax evasion are completely hidden in the crypto money system because there is no central structure controlling it (Ömrüuzun, 2019).

The aim of this study; It is to make future volume predictions of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB) and Ripple (XRP) cryptocurrencies, which have been in great demand recently, with ANN and SVM methods, which are machine learning methods. Trading volume is a crucial indicator of market activity and investor sentiment in cryptocurrency markets, as it reflects liquidity and often precedes price movements (Kristoufek, 2015). Therefore, forecasting volume helps to better understand market dynamics and potential volatility, providing valuable insights for investors (Liu and Serletis, 2019). Thus, it is thought that investors will be able to benefit from this study and get an idea about cryptocurrencies and make healthier decisions in their investments.

2. LITERATURE REVIEW

Karame et al. (2012) mentioned that if malicious users try to send their bitcoins to two or more people at the same time, there will be a problem in the system and they have put forward some opinions to solve these problems. Plohmann and Gerhards-Padilla (2012) put forward information on how bitcoin mining can be done with software to provide an overview of bitcoin mining.

It is stated by Eyal and Sirer (2013) that most of the work on cryptocurrencies is done by computer experts to understand and develop blockchain technology. It is also stated that the bitcoin protocol has an incentive structure that will cause it to lose its decentralized structure.

By Kristoufek (2015), bitcoin prices have been studied from various aspects such as speculative or technical factors. The aim of the study is to investigate the potential impact of the Chinese market, and daily data covering the period 14.09.2011 and 28.02.2014 were used in the study. As a variable; Blockchain data such as BTC/USD rate, USD/CNY rate, BTC/CNY rate, daily and weekly search engine data for Bitcoin term by Google Trends, search data for Bitcoin term on Wikipedia, Financial Stress Index and Gold Ounce prices are taken. Wavelet Coherence analysis results show that factors such as price level, money supply, and the use of Bitcoin in trading have a long-term effect on Bitcoin price. It has been determined that the increase in Bitcoin price encourages users to mine, this effect disappears over time and Bitcoin is not seen as a safe haven by users. In addition, there is no clear finding that the Chinese market affects Bitcoin. In the study conducted by Dyhrberg (2015), as a variable; Bitcoin price, Gold Ounce value, CMX gold futures, 100 Ounces USD, USD/EUR exchange rates, USD/GBP exchange rates and FTSE Index, consisting of daily data covering the period 19.06.2010-22.05.2015, were taken. It has been noted that, according to the GARCH model, Bitcoin resembles gold in many ways; these variables have similar hedging abilities and respond similarly to good or bad news. Atik et al. (2015) examines the effect of Bitcoin on exchange rates with daily price data between 2009 and 2015. It has been seen that Bitcoin and Japanese Yen affect each other and there is a unilateral causality relationship from Japanese Yen to Bitcoin. In addition, it has been observed that exchanges with high trading volume play a market maker role in price formation, while small exchanges play a market watcher role.

Liu and Serletis (2019) discussed cryptocurrencies returns and market returns in terms of volatility and analyzed the relationship between their spread to traditional markets. As a result, it has been revealed that cryptocurrencies are similar to financial assets in many respects. Ji et al. (2019) used Deep Neural Network and Long Short-Term Memory methods from deep learning methods for bitcoin price prediction. When the performances of these two methods are compared, it is seen that deep neural network modeling gives more successful results in Bitcoin price prediction. Atlan (2019) has proposed a model that predicts Bitcoin price using Artificial Neural Networks, Adaptive Neural Fuzzy System, Curve Fitting and Long Short Term Memory methods. The results show that the Curve Fitting and Adaptive Neural Fuzzy System models are successful in terms of prediction. Using the Artificial Neural Networks and Support Vector Machines methods, Mallqui and Fernandes (2019) made predictions for Bitcoin's price direction, daily high and low price, and daily closing price. It was seen that the most successful estimations according to mean absolute error, mean absolute percent error and root mean error were obtained by Support Vector Machines method. Artificial Neural Networks were used by Ömrüuzun (2019) for long-term price predictions of cryptocurrencies. It has been observed that Artificial Neural Networks give more successful results in price estimation as the data volume increases. Gagarina et al. (2019) used linear regression analysis to determine young people's attitudes towards cryptocurrencies. The results reveal that young people's attitudes towards cryptocurrencies stem from their financial autonomy and distrust of government institutions. Valencia et al. (2019) tried to predict the price movements of cryptocurrencies such as BTC, ETH, XRP and LTC with machine learning and sentiment analysis.

In this direction, social media and market data were analyzed with neural networks, support vector machines and random forest algorithms. As a result, it has been determined that cryptocurrency movements can be predicted from social media data and neural networks perform better.

Chen et al. (2020) used machine learning techniques to predict Bitcoin price. Five-minute and daily data of Bitcoin price were analyzed by Logistic Regression, Linear Discriminant Analysis, Random Forest Algorithm, XGBoost, quadratic discriminant analysis, Support Vector Machine and Long Short Term Memory methods. While Logistic Regression was the most successful method with 66% accuracy in daily data, Long Short Term Memory was the most successful method with 67.2% accuracy in five-minute data. It has been seen that statistical methods give more successful results in long-term data, while machine learning methods give more successful results in short-term data. Lahmiri and Bekiros (2020) used machine learning methods to predict Bitcoin's price series during the day. The data were analyzed by DVR, Gauss Poisson Regression, Regression Trees, KNN, Bayesian Regulatory Neural Network, Feed Forward Neural Networks and Radial Based Functional Neural Networks methods. It was seen that Bayesian Regulatory Neural Network had the lowest error value and the KNN algorithm had the highest error value.

3. MATERIALS AND METHODS

As with financial markets, volume is a crucial factor in forecasting price movements within the cryptocurrency market. This research employed regression analysis with machine learning algorithms, ANN and SVM, to estimate the trading volumes of certain cryptocurrencies.

In the study, the volumes of Ethereum, Binance Coin and Ripple cryptocurrencies were examined, taking into account their market value and popularity, as well as Bitcoin. The dataset was acquired from Investment.com, which encompasses the cryptocurrency market. BNB, the most recent cryptocurrency examined in the study, was launched on 3 July 2017, and this date was considered in dataset creation. Accordingly, the dataset comprises a time series spanning 1461 days from January 2018 to December 2021.

All analyses were conducted in the R statistical software environment. The readr, tsibble, forecast, fpp3, and timetk packages were used for data preprocessing, time series structure generation, and forecasting. The SVM model was created and trained using the e1071 package. The ANN model was implemented using the nnetar() function in the forecast package, while the fpp3 and timetk packages were used for data preparation and performance evaluation. Model parameters were optimized using five-fold cross-validation and grid search to minimize forecast errors. The SVM model used a radial basis function (RBF) kernel, and the C (regularization coefficient) and gamma

Cilt/ Volume: 8 Sayı/ Issue: 1 Mart/ March s s . / pp. 27-46
Y. Demir, H. N. Mohammed DOI: 10.46959/jeess.1803960

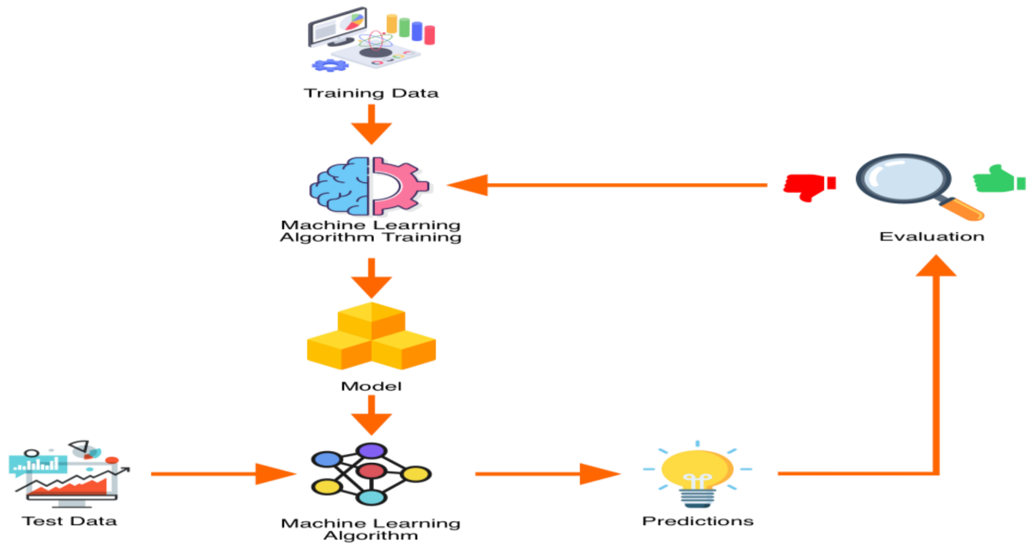
parameters were determined through cross-validation. Model performance was measured using RMSE, MAE, and ACF1 metrics to assess both accuracy and the temporal independence of residuals.

3.1. Machine Learning

Machine learning is a subdiscipline of artificial intelligence that aims to objectively synthesis the fundamental relationships between data and information. Its initial aim was to allow computers to predict future events or scenarios without human intervention, but the extensive application of machine learning in various fields and its impressive performance in subsequent periods have given rise to several new methodologies and applications. Arthur Samuel initially defined machine learning in the 1960s as "the field of study that grants computers the capability to learn without being explicitly programmed" (Samuel, 1959). Turing established a benchmark standard for demonstrating machine intelligence and paved the way for the idea of machine learning by arguing that "a machine ought to exhibit intelligence and precision indistinguishable from a human being" (Turing, 1950).

As technology and ideas advance, knowledge structures can evolve and bring about new learning methodologies for machine systems. These methodologies allow for the detection of flaws in existing models which the systems can then redesign themselves to adapt to new information (Awad and Khanna, 2015). Figure 1 provides a detailed representation of the basic learning process employed by machine systems.

Figure 1. Basic Transaction Process in Machine Learning (URL, 2021)



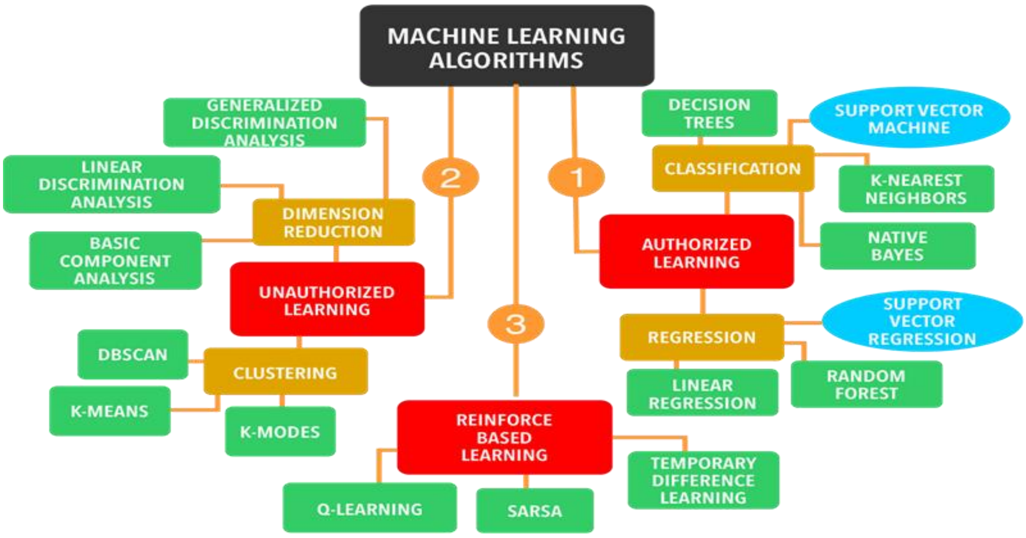
In the first stage of the learning algorithm, the model is trained using training data. In the second stage, the algorithm makes predictions according to the model created when it encounters new test data that is not included in the training dataset. Prediction accuracy is evaluated and if the accuracy rate is at an acceptable level, the model is considered successful. However, if the accuracy is not at an acceptable level, the machine learning algorithm re-trains the model with a structured dataset.

Equipped with a range of algorithms and techniques designed to provide computers with human-like learning strategies, machine learning has been extensively utilized in recent years across a variety of fields, including web search, automation, telecommunications, behavior analysis, big data analytics, weather forecasting and numerous other applications. This technology is expected to significantly influence many future developments.

3.2. Machine Learning Types And Algorithms

The selection of the algorithm used in machine learning is not at the discretion of the machine, but is influenced by both the information that needs to be learnt and the structure of the data that requires analysis (Barnes, 2015). Due to the plethora of approaches and algorithms, the fundamental elements necessary for learning vary according to the dataset's characteristics and the subject being learned. Therefore, the achievement of success from the application depends on the chosen algorithm. Machine learning algorithms can be categorized into supervised, unsupervised, and reinforcement learning categories depending on the correlation between the input data presented during the data mining phase and the anticipated output (Mitchell, 1997). ANN and SVM algorithms classify using a supervised learning method (Niculescu-Mizil and Caruana, 2005).

Figure 2. Learning Types in Machine Learning Technique (Galimberti, 2017)

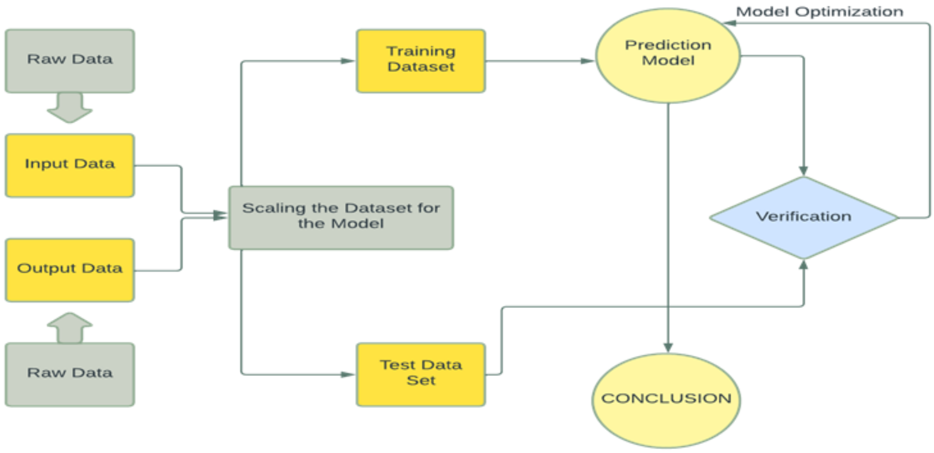


Supervised learning is a mechanism that objectively determines the fundamental relationship between input data and a predicted target variable (output data). In this technique, algorithms attempt to express the relationship between input and output values. The learning function uses training data to synthesis the model that attempts to generalize the link between input and output values. The

Cilt/ Volume: 8 Sayı/ Issue: 1 Mart/ March s s . / pp. 27-46
Y. Demir, H. N. Mohammed DOI: 10.46959/jeess.1803960

training data consists of observed input and desired output values. A competent functional model using a supervised learning algorithm predicts the resulting value based on a new example and related inputs describing the same thing (Bonaccorso, 2017). The process graph of this technique is presented in Figure 3.

Figure 3. The Operation of the Process for the Supervised Learning Technique



3.2.1. Artificial Neural Networks

Artificial neural networks are an analytical technique that draws inspiration from the learning capacity of the human brain and the biological nervous system. In this technique, the computer system acquires knowledge of the interconnections among events from past examples and determines the next steps to take (Öztemel, 2012). One of the primary advantages of using the artificial neural network method in predicting time series is its applicability for nonlinear modelling without assuming any underlying distribution of observations (Adhikari and Agrawal, 2013).

When implementing artificial neural network models for time series analysis, patterns that relate to data are observed and inferences are made by imitating the learning style of the human brain. An artificial neural network typically comprises *input*, *hidden* and *output* layers containing fundamental processing components (Lewis, 2017).

In the analyses of artificial neural networks, different models have been proposed for different needs and in terms of network architecture; two types of structures can be mentioned according to the connections between nodes. One of them is “feed forward artificial neural networks (FFNN)” and the other is “feedback artificial neural networks (RNN)”. If there is no feedback from the output nodes to the inputs in the network structure, such structures are called feed-forward artificial neural networks (Sazli, 2006). A feedforward neural network is the simplest neural network architecture. Information moves in only one direction, from the input nodes, through the hidden nodes (if any) and towards the output nodes. The most common training method of such a network is to use the output result backwards to adjust the weights of the connections between the nodes (Moldovan et al., 2020). In feedforward neural networks, if there is a “feedback” from the output nodes to the input nodes, such structures are called recurrent neural networks (RNN). Feedback artificial neural networks can provide an ideal approach to solving very complex problems by storing a lot of historical information in practice. The main function of the feedback neural network is to repeat the network information in stages (Sun et al., 2021).

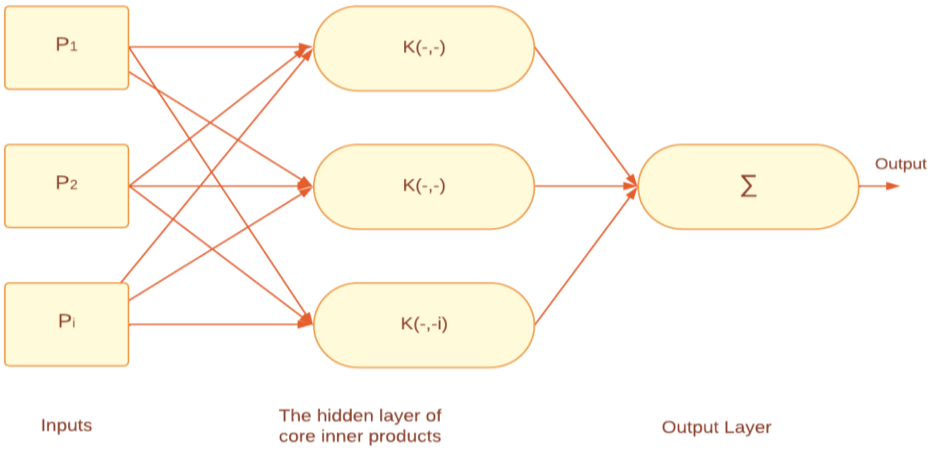
3.2.2. Support Vector Machines

SVM is a vector space based machine learning algorithm. SVMs were first proposed by Vapnik in 1995 for solving regression type problems. SVM is based on structural risk minimization and statistical learning theory. Support vector machines solve the regression or classification problem by transforming it into a quadratic programming problem without getting stuck in local solutions. One of the reasons why support vector machines are advantageous over other techniques is that they do not get stuck in local solutions. Another feature of SVM is that it can generalize. Support vector machines have different application areas. Face recognition, handwriting recognition, banking, medicine, insurance, voice recognition, text classification, 3D object recognition, speaker recognition are some examples of these applications.

It is observed that SVM performs better than ANN and other models and generally gives successful results in applications. In order to use support vector machines more effectively, it is necessary to know their systems well. It is important to make the right decisions when training a support vector machine. The knowledge and experience of the user is important when making these decisions. First of all, it should be decided how the data should be processed, which kernel function should be used and which parameters should be prioritized. The more accurate the choices, the higher the success will be. The schematic representation of the support vector machine with polynomial kernel function is given in Figure 4.

Cilt/ Volume: 8 Sayı/ Issue: 1 Mart/ March s s . / pp. 27-46
Y. Demir, H. N. Mohammed DOI: 10.46959/jeess.1803960

Figure 4. Schematic Representation of SVM (Ak, 2021)



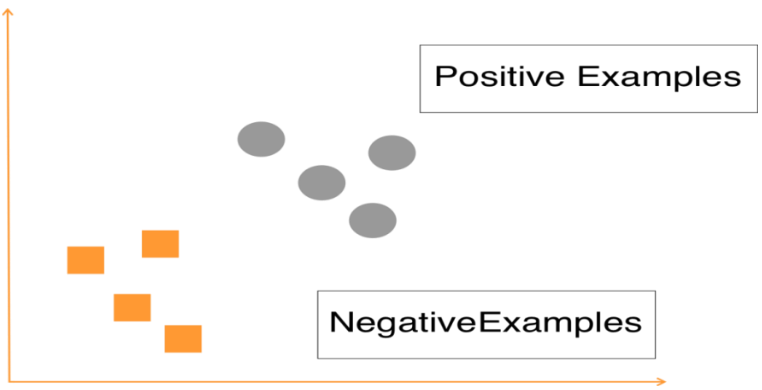
SVM consists of input layer, hidden layers of kernel inner products and output.

Figure 5 shows the basic structure of SVMs. The main purpose of the system is to create a hyperplane that separates the points with maximum margin. For this, points are defined as positive and negative. For example, suppose there is a training dataset in the following format:

$$(x_1, y_1), \dots, (x_n y_n)$$

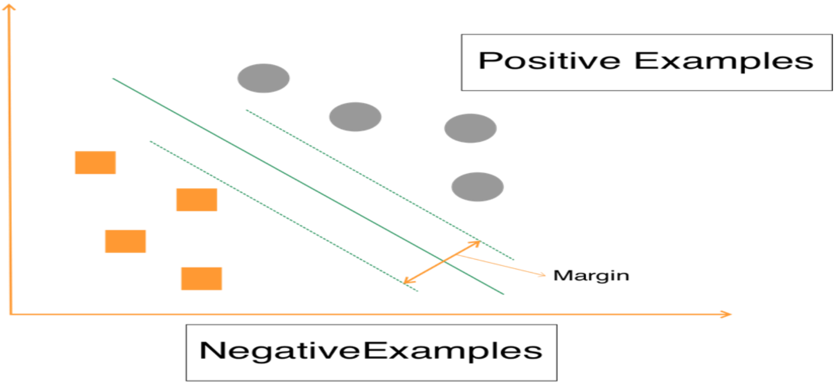
The points in the hyperplane are denoted by x_i, the cluster to which the points belong is denoted by y_i and y_i takes one of the values +1 or -1. In the two-dimensional dataset given in Figure 5, yellow colours indicate y_i=-1 and the others indicate y_i=+1.

Figure 5. Example dataset in 2D space (Ak, 2021)



After separating the data into negative and positive, an infinite hyperplane can be created. The optimal separating plane is where the margin is maximum. The margin term here refers to the minimum distance from the separation plane to the nearest data point. An example of this separation is shown in Figure 6.

Figure 6. Example of Hyperplane Separating Two Datasets (Ak, 2021)



3.2.3. Sequential Minimal Optimization Algorithm (SMO)

SMO algorithm uses the Support Vector Machines method. It works with subsets that recursively select two-dimensional working sets. By fitting the objective functions that fit this selection, it performs the partitioning to the extreme point. Since it works with two-dimensional data sets, the compatibility subproblem can be solved analytically. The algorithm is iterated until all training samples fulfil the fitness condition.

At each stage, the SMO algorithm targets the optimal value for the Lagrange multiplier and aims for the smallest optimization result. The advantage of the SMO algorithm is that it can solve two Lagrange multipliers. Since it does not use a matrix algorithm, it responds more to sensitivity (Elmas, 2003).

According to the suitability of the data set, forecasting can be performed with the help of many algorithms and models. The method of comparing error rates can be used to determine which of the predictions is more successful. In this study, error rates; root mean square error (RMSE), mean absolute error (MAE) and autocorrelation information criterion of errors at lag-1 (ACF1) methods are used to find out which of the algorithms performs more successful predictions.

4. FINDINGS

In this study; 50-day forward volume forecasts of BTC, BNB, ETH and XRP coins were made using ANN and SVM methods. Table 1 presents some descriptive statistics for the cryptocurrency dataset.

Table 1. Some Descriptive Statistics for the Cryptocurrency Dataset

Crypto Unit	Stat.	Now	Opening	High	Low	Volume	Difference
BTC	Min.	3229	3229	3282	3177	0.26	-0.391800
	1st Qu.	7081	7081	7284	6852	103.36	-0.015700
	Median	9455	9454	9672	9243	225.36	0.001300
	Mean	18357	18335	18850	17756	330.81	0.001654
	3rd Qu.	28949	28867	29299	28025	533.42	0.019600
	Max.	67528	67529	68991	66335	999.53	0.194100
BNB	Min.	4.52	4.52	4.60	4.13	1	-0.440000
	1st Qu.	13.37	13.36	13.88	12.91	2.24	-0.020000
	Median	19.71	19.71	20.33	18.85	3.39	0.000000
	Mean	107.65	107.31	111.73	102.57	73.79	0.004743
	3rd Qu.	38.23	38.10	39.21	36.84	5.58	0.030000
	Max.	676.56	676.25	690.87	634.81	997.13	0.700000
ETH	Min.	83.81	83.81	85.07	77.65	1	-0.445500
	1st Qu.	186.63	186.64	191.48	180.70	3.28	-0.021800
	Median	346.51	346.48	355.69	334.11	8.95	0.001700
	Mean	936.32	934.34	968.26	895.60	127.71	0.002498
	3rd Qu.	1135.50	1129.40	1256.13	1045.02	20.13	0.029700
	Max.	4808.38	4808.34	4864.06	4715.43	993.86	0.259600
XRP	Min.	0.1360	0.1358	0.1492	0.1057	51.98	-0.417800
	1st Qu.	0.2674	0.2674	0.2745	0.2565	184.50	-0.024800
	Median	0.3621	0.3621	0.3785	0.3464	388.17	0.00000
	Mean	0.5219	0.5226	0.5470	0.4952	446.80	0.001403
	3rd Qu.	0.6553	0.6553	0.6838	0.6231	701.47	0.023400
	Max.	2.7800	2.7800	3.2900	2.5800	999.25	0.566700

When Table 1 is examined, it is seen that the lowest value for BTC is 3177, the highest value is 68991 and the lowest opening is 3229 and the highest opening is at $ 67529. In terms of volume, the lowest change in 24 hours was 0.26 and the highest change was 999.53. It is seen that the lowest value for BNB is 4.13, the highest value is 690.87, and the lowest opening is 4.52 and the highest opening is at $ 676.25. In terms of volume, it is seen that the lowest change in 24 hours is 1 and the highest change is 997.13. It is seen that the lowest value for ETH is 77.65, the highest value is 4864.06, and the lowest opening is 83.81 and the highest opening at $ 4808.34. In terms of volume, it is observed that the lowest change within 24 hours is 1 and the highest change is 993.86. It is seen that the lowest value for XRP is 0.1057, the highest value is 3.29, and the lowest opening is 0.1358 and the highest opening at $ 2.78. In terms of volume, it is seen that the lowest change in 24 hours is 51.98 and the highest change is 999.25.

Table 2 shows the results of the appropriate model selection criteria for 50-day volume forecasts. ACF1 value shows how much the current value is affected by the previous values in a time series and the closer this value approaches 0, the closer the predicted value gets to the previous value.

Cilt/ Volume: 8 Sayı/ Issue: 1 Mart/ March s s . / pp. 27-46
Y. Demir, H. N. Mohammed DOI: 10.46959/jeess.1803960

Table 2. Appropriate Model Selection for Volume Forecasting

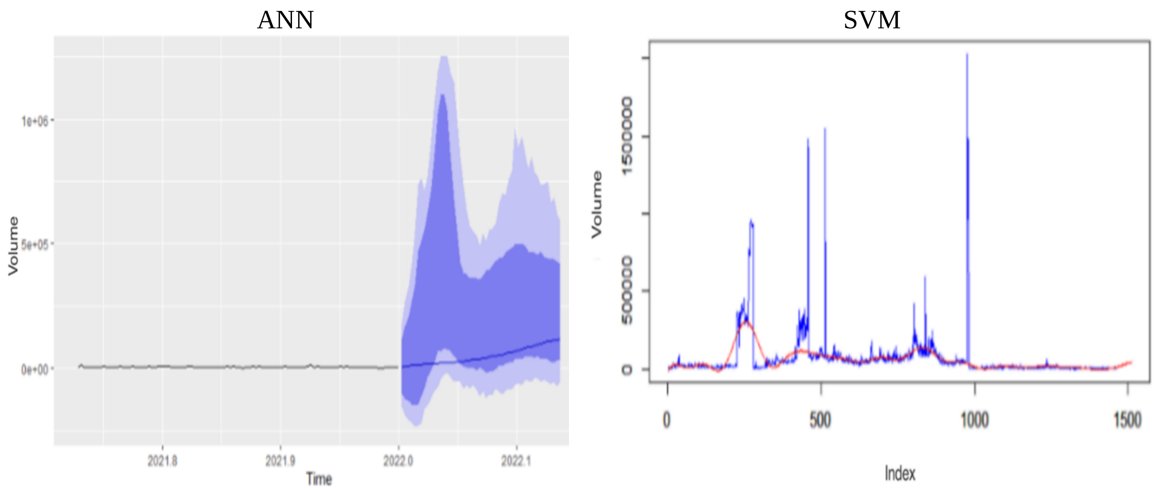
Crypto Unit	Model	RMSE	MAE	ACF1
BTC	ANN	84674.90	17879.55	0.008542
	SVM	133369.00	39031.62	0.684922
BNB	ANN	4286.63	1205.911	-0.0063516
	SVM	23043.83	8302.879	0.5439924
ETH	ANN	6635.83	3406.14	-0.010186
	SVM	22075.30	12414.14	0.361162
XRP	ANN	72.21	57.46	-0.014668
	SVM	163824.70	120693.10	0.568399

When Table 2 is examined; it is seen that the RMSE and MAE values calculated with ANN for the cryptocurrencies used in the study are smaller than the values calculated with SVM. In addition, it is seen that ACF1 values are closer to 0 in ANN and according to these results, it can be said that ANN method gives stronger results than SVM in BTC, BNB, ETH and XRP cryptocurrency volume forecasts.

Figures 7, 8, 9 and 10 show forward-looking forecast graphs for cryptocurrency volumes drawn by both algorithms. However, SVM uses an index instead of a time axis, and each index corresponds to 1 day.

The volume forecasts made with ANN and SVM for BTC are given in Figure 7.

Figure 7. Volume Forecast Chart for BTC



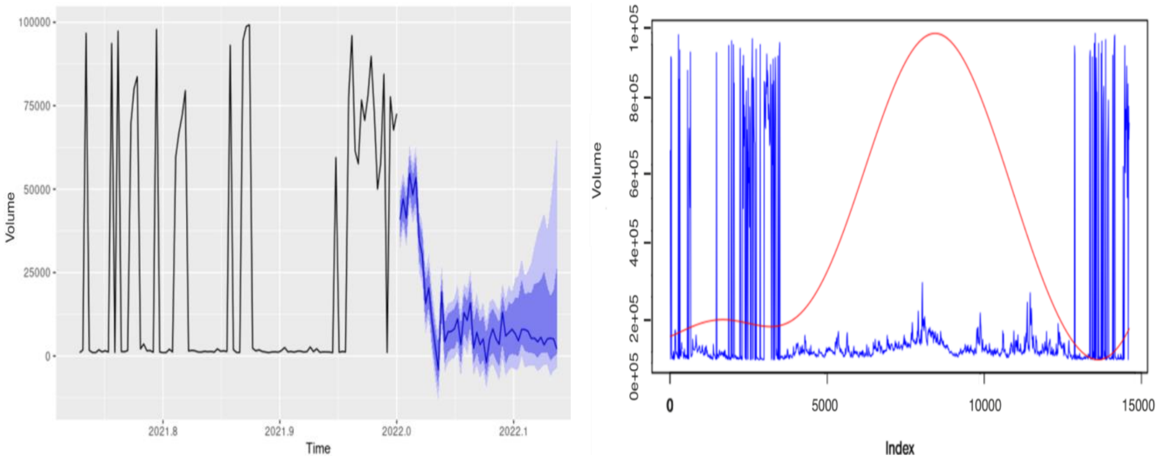
When Figure 7 is examined, it is observed that there is an increase in the 50-day volume forecast for BTC according to the ANN method. In addition, it can be said that there is a slight increase in the 50-day volume forecast for BTC according to the SVM method.

The volume forecasts made with ANN and SVM for BNB are given in Figure 8.

Cilt/ Volume: 8 Sayı/ Issue: 1 Mart/ March s s . / pp. 27-46
Y. Demir, H. N. Mohammed DOI: 10.46959/jeess.1803960

Figure 8. Volume Forecast Chart for BNB

ANN SVM

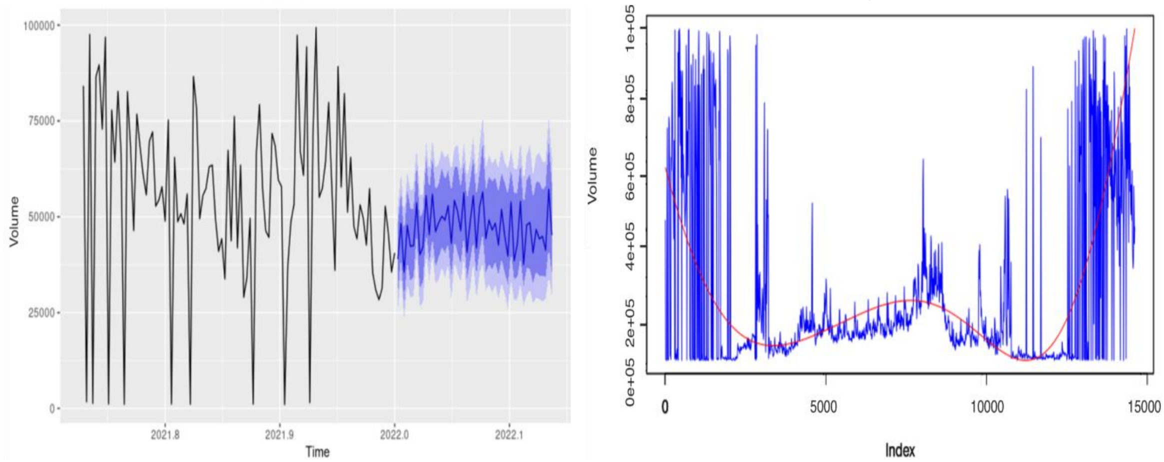


When Figure 8 is examined; while there is a decrease in BNB volume according to the volume forecasts made by ANN method for 50 days, there is an increase in BNB volume according to the forecasts made by SVM method.

The volume forecasts made with ANN and SVM for ETH are given in Figure 9.

Figure 9. Volume Forecast Chart for ETH

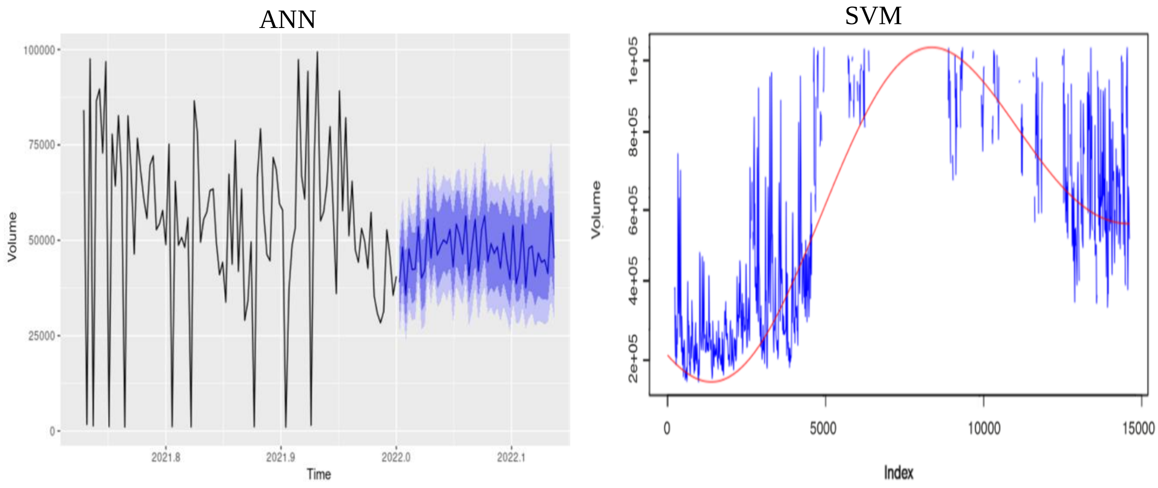
ANN SVM



When Figure 9 is examined, it can be said that there is a horizontal movement and constant movements in ETH volumes according to the volume forecasts made with the ANN method for 50 days, and there is a rapid increase in ETH volumes according to the forecasts made with the SVM method.

The volume forecasts made with ANN and SVM for XRP are given in Figure 10.

Figure 10. Volume Forecast Chart for XRP



When Figure 10 is examined; it can be said that there is a horizontal movement and constant movements occur in XRP volumes according to the volume estimates made with the ANN method for 50 days, and there is a decrease in XRP volumes according to the estimates made with the SVM method.

5. DISCUSSION AND CONCLUSIONS

Although cryptocurrencies are new to the markets, they have become part of the new way of life due to their great demand. With the rapid technological developments taking place every day, it is thought that it will be impossible not to use these currencies in the future. While cash the main payment method in the early 2000s, the use of physical money has declined considerably, and credit cards have become more widespread. In the coming years, cryptocurrencies are expected to be widely used through mobile applications.

The interest in cryptocurrencies, which have a very simple and low-cost transfer mechanism and are not dependent on any central authority, is increasing day by day. Despite this growing attention, these currencies still lack a fully developed and reliable structure for investors, primarily due to their high volatility and persistent security risks on exchanges. The worldwide recognition and use of cryptocurrencies, one of the emerging components of today’s global economic system, should therefore be evaluated from multiple perspectives. Some countries have adopted regulatory frameworks for these assets, while others have not yet recognized them as legitimate financial instruments. Given the global integration of financial systems, international and national regulations will play a crucial role in shaping the future of cryptocurrency markets.

The most appropriate model for volume forecasts was determined using three different criteria, and the ANN model was selected as the most successful according to all three indicators.

Accordingly, it can be stated that the ANN model provides more reliable results in forecasting the trading volumes of BTC, BNB, ETH, and XRP cryptocurrencies.

The finding that the ANN model outperformed the SVM model in forecasting cryptocurrency volumes is consistent with several previous studies emphasizing the strong predictive capability of neural networks in nonlinear and highly volatile markets. For instance, Ji et al. (2019) and Ömrüuzun (2019) also reported that ANN-based models provided more accurate forecasts for cryptocurrency prices and trends. Similarly, Atlan (2019) found that artificial intelligence methods such as Artificial Neural Networks and Adaptive Neuro-Fuzzy Systems yielded robust results in predicting cryptocurrency values. However, the results differ from those of Mallqui and Fernandes (2019), who observed higher predictive performance for SVM in estimating Bitcoin's daily price direction and volatility. These contrasting findings suggest that model performance may depend on dataset characteristics, input variable selection, and forecast horizon. Overall, the present study supports the view that neural network models can better capture the nonlinear patterns and dynamic relationships inherent in cryptocurrency markets.

Furthermore, the differences observed between the models in forecasting certain cryptocurrencies—such as the opposite directional predictions for BNB—may be related to the distinct structural and market dynamics of each coin. For example, BNB is primarily used within the Binance ecosystem for transaction fee reductions and platform-specific services, making its trading volume more sensitive to exchange-driven factors rather than overall market sentiment. In contrast, BTC and ETH exhibit stronger relationships with macroeconomic indicators and investor sentiment due to their higher market capitalization and broader adoption. These variations imply that differences in usage purpose, liquidity structure, and community-driven demand can affect how machine learning models identify temporal patterns, leading to divergent predictive behaviors across algorithms.

When the 50-day volume forecasts were analyzed, both models predicted an increase in BTC trading volume. However, while the ANN model forecasted a decrease in BNB volume, the SVM model indicated an increase. For ETH and XRP, the ANN model predicted relatively stable movements, whereas the SVM model suggested a sharp rise in ETH volume and a decline in XRP volume.

When the historical prices and growing popularity of cryptocurrencies are considered, it is evident that market peaks tend to occur periodically, followed by significant corrections. Bitcoin's popularity particularly surges during bull market phases, drawing in new investors who often rely on traditional financial assumptions in a highly risky environment. Therefore, various factors influencing cryptocurrencies, such as 24-hour volume changes, should be carefully analyzed.

Cilt/ Volume: 8 Sayı/ Issue: 1 Mart/ March s s . / pp. 27-46
Y. Demir, H. N. Mohammed DOI: 10.46959/jeess.1803960

Although cryptocurrencies represent an innovative financial asset class, their pronounced volatility can lead to substantial investor losses. As a result, cryptocurrencies cannot yet be considered stable or reliable investment instruments.

Although it is a relatively new field, numerous studies have been published on cryptocurrencies in recent years. It is believed that this study contributes to the understanding of cryptocurrency-related concepts, enhances insight into their inherent risks, and provides methodological evidence for forecasting approaches using artificial intelligence models.

REFERENCES

Adhikari, R. and Agrawal, R. K. (2012) "Forecasting Strong Seasonal Time Series with Artificial Neural Networks", Journal of Scientific & Industrial Research, 71(10), 657-666.

Ak, B. (2021) "Nehirlerdeki Akış Miktarının Destek Vektör Makineleri ve Bulanık Mantık Yöntemleri ile Modellenmesi", Unpublished Master's Thesis, Iskenderun Technical University Graduate Education Institute, İskenderun/ Mersin.

Atik, M., Köse, Y., Yılmaz, B. and Sağlam, F. (2015) "Crypto Currency: Bitcoin and Effects on Exchange Rates", Bartın University Journal of Faculty of Economics and Administrative Sciences, 6(11), 247-261.

Atlan, F. (2019) "Kripto Para Değerlerinin Yapay Zeka Teknikleri ile Tahmini", Yayımlanmamış Yüksek Lisans Tezi, Burdur Mehmet Akif Ersoy Üniversitesi, Sosyal Bilimler Enstitüsü, Burdur.

Awad, M. and Khanna, R. (2015) "Efficient-learning Machines: Theories, Concepts, And Applications for Engineers and System Designers", Springer Nature.

Bakır, E. (2021) "Covıd-19 Pandemisi Sürecinde Kripto Para Birimleri ile Ekonomik Göstergeler Arasındaki İlişki", Balıkesir Üniversitesi, Sosyal Bilimler Enstitüsü, Balıkesir.

Barnes, J. (2015) "Azure Machine Learning: Microsoft Azure Essentials", Microsoft Press.

Bonaccorso, G. (2017) "Machine Learning Algorithms", Packt Publishing Ltd.

Chen, Z., Li, C. and Sun, W. (2020) "Bitcoin Price Prediction Using Machine Learning: An Approach to Sample Dimension Engineering", Journal of Computational and Applied Mathematics, 365, 1-13.

Dyhrberg, A. H. (2015) "Bitcoin, Gold and the Dollar – A GARCH Volatility Analysis", Finance Research Letters, 16, 85-92.

Elmas, Ç. (2003) "Yapay Sinir Ağları (Kuram, Mimari, Eğitim, Uygulama)", Seçkin Yayıncılık.

Eyal, I. and Sirer, E. G. (2013) "Majority Is Not Enough: Bitcoin Mining Is Vulnerable", Communications of the ACM, 61(7), 95-102.

Gagarina, M., Nestik, T. and Drobysheva, T. (2019) "Social and Psychological Predictors of Youths' Attitudes to Cryptocurrency", Behavioral Sciences, 9(12), 118.

Galimberti, E. (2017) "The Tree of Machine Learning Algorithms", Date of Access: 12.5-2022, https://www.teradata.com/Blogs/The-Tree-of-Machine-Learning-Algorithms.

Ji, S., Kim, J. and Im, H. (2019) "A Comparative Study of Bitcoin Price Prediction Using Deep Learning", Mathematics, 7(10), 898.

Kanat, E. and Öget, E. (2018) "Bitcoin ile Türkiye ve G7 Ülke Borsaları Arasındaki Uzun ve Kısa Dönemli İlişkilerin İncelenmesi", Research of Financial Economic and Social Studies, 3(3), 601-614.

Karame, G., Androulaki, E. and Capkun, S. (2012) "Two Bitcoins at The Price of One? Double-Spending Attacks on Fast Payments in Bitcoin", 19th ACM Conference on Computer and Communications Security, November 11 – 15, London.

Karataş, İ. (2019) "Ulusal ve Küresel Makroekonomik Faktörlerin Gelişen Borsalar Üzerindeki Etkileri: Türkiye ve BRICS Ülkeleri Üzerine Ampirik Bir Araştırma", Yayımlanmamış Doktora Tezi, Karabük Üniversitesi, Sosyal Bilimler Enstitüsü, Karabük.

Kristoufek, L. (2015) "What Are the Main Drivers of The Bitcoin Price? Evidence from Wavelet Coherence Analysis", Plos One, 10(4), 1-15.

Lahmiri, S. and Bekiros, S. (2020) "Intelligent Forecasting with Machine Learning Trading Systems in Chaotic Intraday Bitcoin Market", Chaos Solitions & Fractals, 133, 1-7.

Lewis, N. D. (2017) "Neural Networks for Time Series Forecasting with R", Copyright N.D.

Liu, J. and Serletis, A. (2019) "Volatility in the Cryptocurrency Market", Open Economies Review, 30, 779-811.

Mallqui, D. C. A. and Fernandes R. A. S. (2019) "Predicting the Direction, Maximum, Minimum, and Closing Prices of Daily Bitcoin Exchange Rate Using Machine Learning Techniques", Applied Soft Computing Journal, 75, 596-606.

Mitchell, T. M. (1997) "Machine Learning", WCB/McGraw-Hill.

Moldovan, A., Caatron, A. and Andonie, R. (2020) "Learning in Feedforward Neural Networks Accelerated by Transfer Entropy", Entropy, 22(102), 1-19.

Niculescu-Mizil, A. and Caruana, R. (2005) "Predicting Good Probabilities with Supervised Learning", In Proceedings of the 22nd International Conference on Machine Learning, August, Bonn.

Ömrüuzun, B. (2019) "Yapay Sinir Ağları ile Kripto Paraların Fiyat Modellemesi", Yayımlanmamış Yüksek Lisans Tezi, İstanbul Üniversitesi, Sosyal Bilimler Enstitüsü, İstanbul.

Öztemel, E. (2012) "Yapay Sinir Ağları", Papatya Yayıncılık.

Plohmann, D. and Gerhards-Padilla, E. (2012) "Case Study of The Miner Botnet", 4th International Conference on Cyber Conflict, 5-8 June, Tallinn.

Samuel, A. L. (1959) "Some Studies in Machine Learning Using the Game of Checkers, IBM", Journal of Research and Development, 44(1), 210–229.

Sazli, M. H. (2006) "A Brief Review of Feed-Forward Neural Networks", Communications Faculty of Sciences University of Ankara Series, 50, 11-17.

Sun, L., Liang, F. and Cui, W. (2021) "Artificial Neural Network and Its Application Research Progress in Chemical Process", Date of Access: 26.06.2022. https://arxiv.org/ftp/arxiv/papers/2110/2110.09021.pdf.

Thakur, Krishna K. and Banik, D. G. (2018) "Cryptocurrency: Its Risks and Gains and The Way Ahead", Journal of Economics and Finance, 9(2), 38-42.

Turing, A. M. (1950) "Computing Machinery and Intelligence", Mind, LIX (236), 433–460.

URL, (2021) "Basic Transaction Process in Machine Learning", Date of Access: 26.06.2022. https://www.google.com/search?q=What+are+machine+learning+algorithms&sxsrf=AJOqlzXmDTK73vppnHxc9eDuFOwwvQijGg:1675067237449&source=lnms&tbm=isch&sa=X&ved=2ahUKEwi11abd7-78AhXqR_EDHX0HBEQQ_AUoAXoECAEQAw&biw=1366&bih=657&dpr=1#imgrc=oV5vJtrXGtQPeM.

Valencia, F., Gomez-Espinosa, A. and Valdes-Aguirre B. (2019) "Price Movement Prediction of Cryptocurrencies Using Sentiment Analysis and Machine Learning", Entropy, 21(6), 1-12.

Hakem Değerlendirmesi: Dış bağımsız.

Çıkar Çatışması: Yazarlar çıkar çatışması bildirmemiştir.

Finansal Destek: Yazar bu çalışma için finansal destek almadığını beyan etmiştir.

Teşekkür: -

Peer-review: Externally peer-reviewed.

Conflict of Interest: The author has no conflict of interest to declare.

Grant Support: The author declared that this study has received no financial support.

Acknowledgement: -