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Research Article

Daily Digital Currency Values Estimation Using Artificial Intelligence Techniques

Ahmet Tabanlıoğlu[a], Abdülkadir Gümüşçü[b]

[a]Kastamonu University, Vocational School, Department of Mechatronics, Kastamonu, Türkiye
[b]Harran University, Faculty of Engineering, Department of Electrical-Electronics Eng., Şanlıurfa, Türkiye

ORCID[a]: 0000-0002-3876-196X
ORCID[b]: 0000-0002-5948-595X

Corresponding Author e-mail: agumuscu@harran.edu.tr
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ABSTRACT: Recently, with the rapid rise in crypto money prices, Bitcoin has begun to be seen as an investment tool. Because of this trend, predictions in the digital money market gain importance. For this reason, in this study, a machine learning model was developed that can make daily predictions for Bitcoin, the most important currency in the digital currency market. An artificial neural network was used to make daily predictions for Bitcoin and the data set was designed with values from the coinmarketcap site. The next day's close price is estimated by using the open, high, low, volume, marketcap features from this site. In this study, unlike other studies, the closing price of the next day was tried to be estimated. Thus, a model has been developed that makes a value estimation that the investor will need. While creating the data sets, 300 days of data were used. In addition, considering the changes in the Bitcoin market, 3 different data sets were created as easy, moderate and hard. In this study, 0.9949, 0.9908 and 0.9503 R values were obtained in the test data sets of easy, moderate and hard difficulty levels, respectively. 70% of the data set was used for training. 15% of the data set was used to test the model. The remaining samples were used for validation. Considering the results obtained in the study, it was concluded that the estimation of Bitcoin closing values can be made daily using machine learning methods. In addition, it has been observed that there is a serious decrease in success rates on days when the price changes are too much.

KEYWORDS: Crypto-currency, Machine learning, Artificial neural networks

1. INTRODUCTION

Since the first years of humanity, money has been used to buy goods and services. Recently, the concept of money has evolved and the concept of digital money has gained importance (Li & Wang, 2017). Cryptocurrency is defined as a digital currency that uses blockchain technologies to secure money exchange transactions and approve these transfers. Cryptocurrencies have a decentralized and distributed structure, unlike centralized electronic currency generated by central banks or banking systems (Zhang et al., 2018). This distributed control structure is carried out with block-chain technology. (Chowdhury et al., 2020). These cryptocurrencies are used today in cash flows and the exchange of goods of some companies. As a result, in recent years, various studies have been carried out by researchers and scientists to model the price of cryptocurrencies and create real decision support systems (M. et al., 2020, Chen et al., 2020, Altan et al., 2019, Alessandretti et al., 2018, Akyildirim et al., 2020). Bitcoin, one of the most known and most valuable crypto currencies, is used as an investment tool today.

Bitcoin is one of the most valuable and decentralized cryptocurrencies. Introduced by Satoshi Nakamoto on October 31, 2008, Bitcoin covers approximately 35% of the total value of cryptocurrency markets (Zhang et al., 2018). Bitcoin's biggest difference is its blockchain technology, which is used to disrupt central parties' control of value transactions. Blockchain is the technology in which a record of any financial and economic transaction made in any cryptocurrency is kept using clusters of computers. Blockchain is a public data repository consisting entirely of blocks, and the security of the currency is ensured by this structure (Barkatullah & Hanke, 2015).

In addition to all these, the methods developed in the field of information technologies have enabled the effective use of data in the fields of meaning and information extraction. Machine learning algorithms, a sub-topic of artificial intelligence, are widely used in many fields such as agriculture (Gümüşçü et al., 2020, Gümüşçü et al., 2018), medicine (Gümüşçü & Tenekeci, 2018, Gerger & Gümüşçü, 2022, Gümüscü et al., 2017), economy (Altan et al., 2019), energy (Demirci et al., 2021) etc. In the field of economics, machine learning-based studies such as stock prediction (Altan et al., 2019) and credibility determination (Altan &

Demirci, 2022) were conducted. In these studies, the most well-known machine learning algorithms such as k-nearest neighbor (Keller et al., 1985), Artificial Neural Networks (ANN) (Burniston, 1994) were used.

As every investment tool, the correct determination of when to exit or enter the investment is very important for bitcoin in terms of ensuring the maximum profit from the investment. Therefore, many researchers have conducted studies on the value estimation of cryptocurrencies. Hitam and İsmail classified the value of bitcoin with an accuracy rate of 79.40% in their study (Hitam & İsmail, 2018). Chen et al. on the other hand, they classified the 5-minute bitcoin values with an accuracy rate of 67.2% (Chen et al., 2020).

In this study, the closing value of bitcoin, which is the most widely used and known cryptocurrency, was tried to be estimated the next day. In the study, 300-day bitcoin values were considered and studies were carried out with three different data sets. The reason for working with three different data sets is that the trends in bitcoin prices vary a lot and these changes can affect the prediction results of machine learning methods. For this reason, in the study, three different 300-day data sets were studied, as easy, moderate and hard. These difficulty levels have been determined by considering the 300-day change in bitcoin values. The data is taken from the coinmarketapp web page, and the next day's close price is tried to be estimated by using the open, high, low, volume, marketcap features from this site (Cryptocurrency prices, charts and market capitalizations, 2022). Thus, it is aimed to minimize the risk taken by investors.

In the article, the dataset and ANN are summarized in section 2. The results obtained are given in section 3 and the contribution of the study are highlighted in section 4.

2. MATERIALS AND METHODS

2.1. Datasets

In the study, applications have been made on bitcoin virtual currency value estimation, which has been in high demand by investors recently. For this reason, methods have been applied on the data taken from the coinmarketcap web page, which keeps the values of virtual currencies. The data set was prepared according to three different difficulty levels as easy, moderate and hard. These difficulty degrees were determined by considering the changes in bitcoin value over 300 days. It is considered easy if the trend follows a horizontal course for 300 days and considered hard if it follows a course with high changes. Table 1 shows which date ranges are taken when creating easy, moderate and hard data sets. Three difficulty levels are determined according to the changes in the 300-day closing prices trends. Trend change is determined as difficult if it has a lot of ups and downs within 300 days. The trend with average ups and downs was determined as medium difficulty.

Table 1. Data Sets Date Ranges

Difficulty Level	Start Date	End Date
Easy	02.03.2020	27.12.2020
Moderate	16.12.2021	11.10.2022
Hard	01.08.2019	27.05.2020

Figure 1 shows how daily bitcoin prices change according to the difficulty level of the data sets.

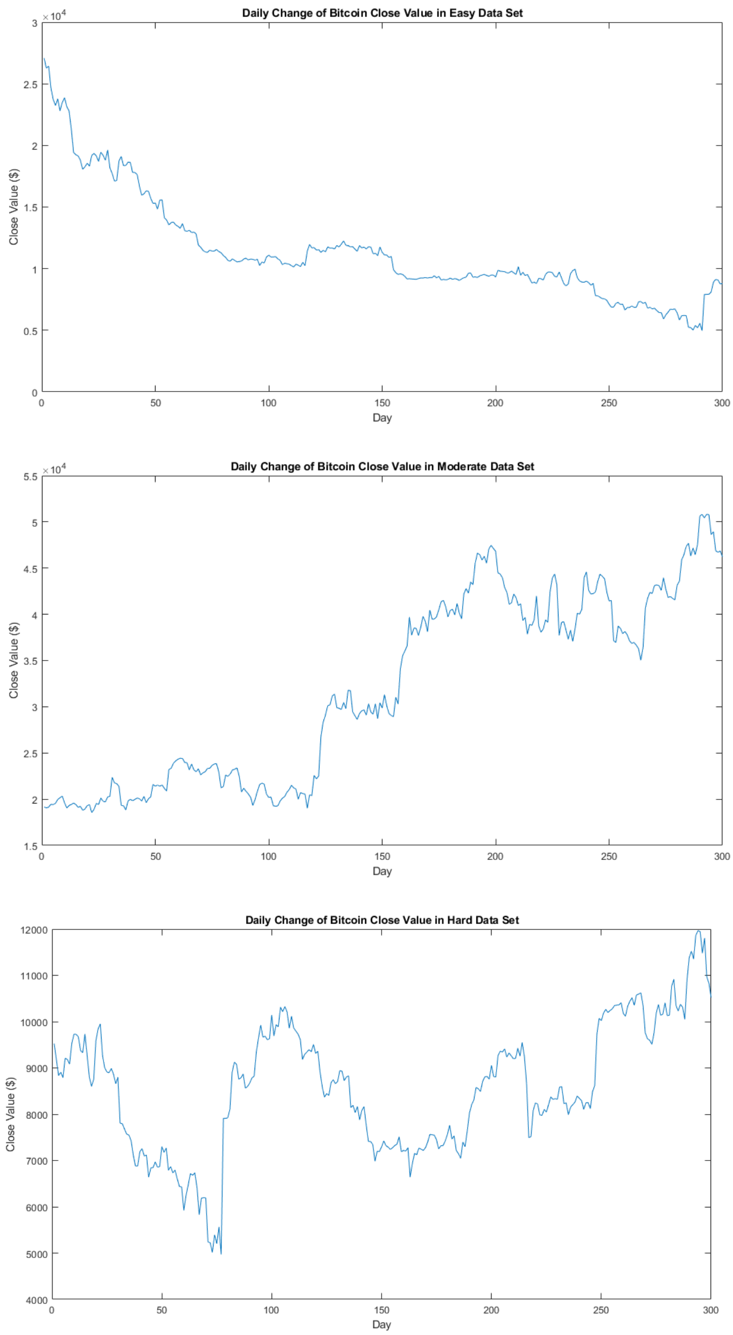

Figure 1. Daily Bitcoin Price Changes in the Data Set

In this study, it is aimed to predict the closing values of the next day by using the open, high, low, close, volume, marketcap features in the dataset. The mean and standard deviation values of the features are given in Table 2 below.

Table 2. Statistical Values of Features

Dataset	Feature	Mean	Standart Deviation
Easy	Open	1.125289e+04	4.109467e+03
	High	1.150981e+04	4.267729e+03
	Low	1.103042e+04	4.026745e+03
	Close	1.130968e+04	4.195608e+03
	Volume	3.271974e+10	1.214727e+10
	MarketCap	2.088561e+11	7.846092e+10
Moderate	Open	3.215831e+04	1.021162e+04
	High	3.280537e+04	1.039120e+04

	Low	3.137620e+04	1.002679e+04
	Close	3.205889e+04	1.019263e+04
	Volume	2.981718e+10	9.869960e+09
	MarketCap	6.096467e+11	1.917306e+11
Hard	Open	8.580044e+03	1.385316e+03
	High	8.751113e+03	1.374934e+03
	Low	8.395130e+03	1.385798e+03
	Close	8.576451e+03	1.384273e+03
	Volume	2.834769e+10	1.223527e+10
	MarketCap	1.553814e+11	2.446938e+10

As can be seen in Table 2, the value differences between the features in the data sets are very high. For example, while the average of the volume feature in the easy data set is 3.271974e+10, the average of the low feature in the same data set is calculated as 1.103042e+04. Considering that ANN will be used as a machine learning method, these value differences will negatively affect the model. Therefore, before applying the machine learning method, the values in the datasets were normalized with the formula in Equation 1.

$$X_{new} = \frac{X-\mu}{\sigma} \tag{1}$$

In equation 1, μ is accepted as the mean value of the given sequence and σ is accepted as the standard deviation of the given sequence. X is the sample to be normalized and Xnew is the normalized value of X. The variation intervals of the attributes were limited using the normalization process, and it was ensured that all features were equally weighted in the training phase of the ANN model.

2.2. Artificial Neural Networks

ANNs, inspired by human neural networks, aim to use neural network behavior in regression problems. Neurons, which are small processing units, combine to form a neural network. In addition, the weight coefficients between neurons express the strength of the connection between two neurons. During the training phase of the ANN model, these coefficients are updated according to their output values. This update is done iteratively. ANNs basically consist of three different layers: input, hidden and output layers. In the study, the number of hidden layers was taken as 10. The number of input layers is determined as 6, which is the number of features. It is also set as a single-layer structure at the output layer. In addition, scaled conjugate gradient algorithm was used in the training phase (Møller, 1993).

In this study, 70% of the data set was used to create the ANN network. 15% of the data set was used to test the success of the model. The remaining samples were used for validation.

3. RESULTS and DISCUSSION

In this study, bitcoin value estimation was made using ANN and experimental studies were carried out on the dataset with 3 different difficulty levels.

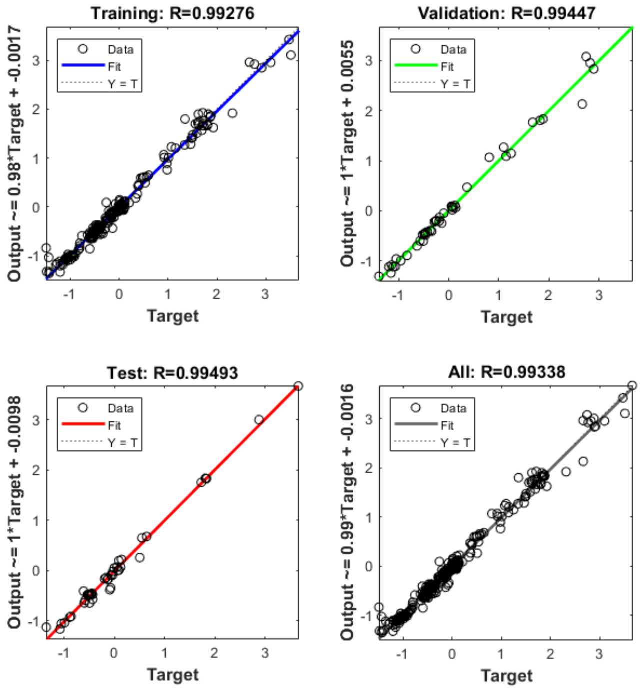

Figure 2. Result Graphs in Easy Dataset

In the easy dataset, the success rates in Figure 2 are provided in the training, testing and validation datasets. In the Moderate data set, ANN success graphs were obtained as in Figure 3.

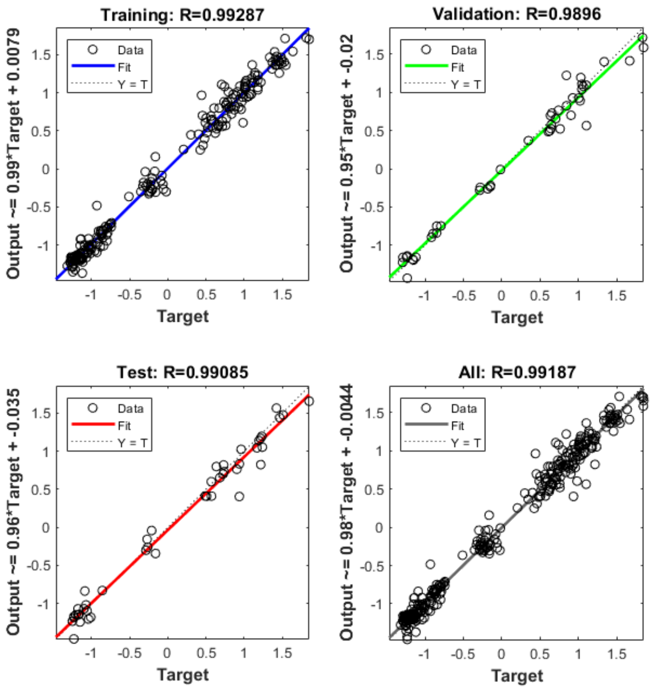

Figure 3. Result Graphs in Moderate Dataset

As can be seen in Figure 3, a success rate of 0.99 was obtained in the moderate test data set. In the hard data set, machine learning success graphs were obtained as in Figure 4.

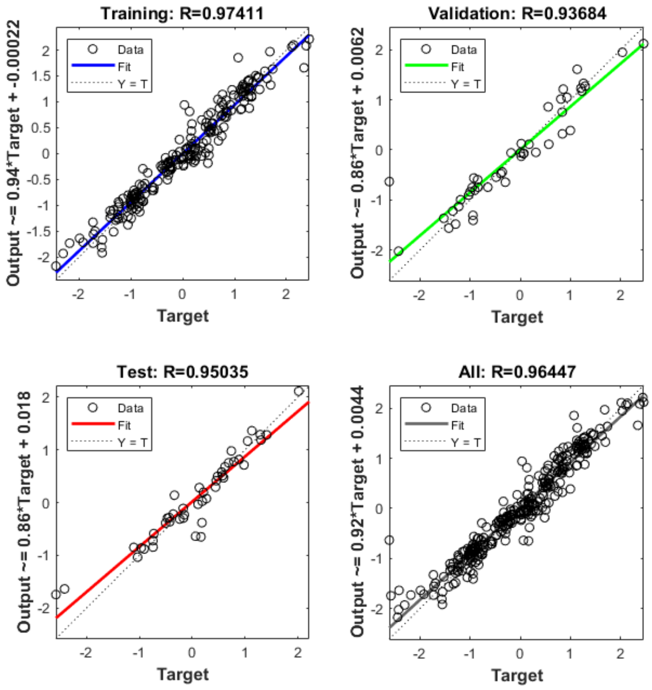

Figure 4. Result Graphs in Hard Dataset

As can be seen in Figure 4, a success rate of 0.95 was obtained in the hard test data set. In addition, the lowest success rate, 0.93, was obtained in the validation data set. In Table 3 below, the success rates obtained in the study are summarized according to the degree of difficulty.

Table 3. Obtained R success rates

Dataset	Training	Validation	Test
Easy	0.9927	0.9944	0.9949
Moderate	0.9928	0.9896	0.9908
Hard	0.9741	0.9368	0.9503

4. CONCLUSIONS

In this study, in order to observe the usability of artificial neural network methods in solving the next day value estimation problem of bitcoin crypto currency, it was carried out with three different difficulty levels as easy, moderate and hard.

Considering the results obtained, the value estimation made at easy and moderate difficulty levels was found at acceptable levels. In this case, it can be said that the closing price of the next day is predictable on days when bitcoin prices follow a horizontal course. In addition, when the difficult data set is considered, lower success parameters were obtained compared to the other difficulty levels.

Thus, it has been concluded that it is possible to successfully predict the value of cryptocurrencies using machine learning methods, and future studies will focus on a more difficult task such as five minutes-based cryptocurrencies value estimation.

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Author's Contributions

Data was collected from coinmarketcap by Ahmet Tabanlıoğlu. Conceptualization, formal analysis, methodology, and writing were performed by Ahmet Tabanlıoğlu and Abdülkadir Gümüşçü. Software was organized by Ahmet Tabanlıoğlu. Review & editing was organized by Abdülkadir Gümüşçü.

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