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Original scientific paper

A COMPREHENSIVE COMPARATIVE STUDY OF MACHINE LEARNING MODELS FOR PREDICTING CRYPTOCURRENCY

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Abstract. *This study aims to find the best performing model in predicting cryptocurrencies using different machine learning models. In our study, an analysis was performed on various cryptocurrencies such as Aave, BinanceCoin, Bitcoin, Cardano, Cosmos, Dogecoin, Ethereum, Solana, Tether, Tron, USDCoin and XRP. Decision Trees, Random Forests, K-Nearest Neighbours (KNN), Gradient Boost Machine (GBM), LightGBM, XGBoost, CatBoost, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Short Term Memory networks in Long Comparisons (LSTM) models were used. The performance of the models is compared with Mean Squared Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The study results show that there is no single model that consistently outperforms others for all cryptocurrencies. Models such as XGBoost and Random Forests show consistent and strong performance across different cryptocurrencies, proving their robustness in this particular use case. Deep learning algorithms, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Long Short Term Memory Networks (LSTMs), show significant accuracy in predicting some cryptocurrencies.*

Key words: *Cryptocurrencies, Machine Learning Forecasting Model, Prediction methods, Efficiency*

1. INTRODUCTION

Cryptocurrencies have recently attracted a great deal of attention as a distinctive and ever-changing type of investment. Investors and researchers have turned to cryptocurrencies due to their significant profit potential and market volatility. The ability to predict the prices of cryptocurrencies is crucial for investors, traders and financial analysts who want to make informed decisions in this rapidly growing industry. Machine learning and deep learning techniques have become powerful tools for accurately predicting cryptocurrency prices in

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recent years. These approaches are able to effectively capture complex temporal correlations and non-linear patterns in data collected from bitcoin prices.

Each cryptocurrency and its underlying platform contain different features and applications that contribute to the diverse environment of the cryptocurrency world. Aave is a decentralised finance (DeFi) protocol that allows users to borrow and lend different cryptocurrencies [1]. In this system, the lender earns interest on digital assets in liquidity pools. The borrower can obtain a loan by pledging collateral. The creators originally designed BinanceCoin as a utility token for the Binance cryptocurrency exchange, and later expanded its use. BinanceCoin's uses include powering Binance's decentralised applications (dApps) and paying transaction fees on the Binance Exchange [2]. Cardano is a blockchain platform that aims to provide a more secure and scalable infrastructure for the development of decentralised applications and smart contracts [3].

Cosmos is a decentralised network of independent blockchains powered by Byzantine Fault Tolerance (BFT) consensus algorithms [4]. Dogecoin, initially created as a meme coin, gained significant value and popularity by experiencing significant increases in its exchange rate [5]. Ethereum is a decentralised platform that enables smart contracts and decentralised applications to be created and run without any downtime, fraud, control or interference from a third party. Solana is a high-performance blockchain that enables fast, secure and scalable decentralised applications and cryptocurrencies [6]. Tether is a type of cryptocurrency, known as a stablecoin, designed to provide a stable value by being pegged to a reserve asset such as the US dollar. Tron is a blockchain-based decentralised platform that aims to create a free, global digital content entertainment system with distributed storage technology. USDCoin is a stablecoin cryptocurrency whose value is directly pegged to the US dollar. XRP is the native digital asset of XRP Ledger, a blockchain created by Ripple. In this study, analyses were conducted on various cryptocurrencies such as Aave, BinanceCoin, Bitcoin, Cardano, Cosmos, Dogecoin, Ethereum, Solana, Tether, Tron, USDCoin and XRP. Decision Trees, Random Forests, K-Nearest Neighbours (KNN), Gradient Boost Machine (GBM), LightGBM, XGBoost, CatBoost, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Short-Term Memory networks in Long Comparisons (LSTM) models were used. The organisation of the rest of this paper is as follows: Section 2 contains a literature review on forecasting methods and cryptocurrencies. Section 3 presents machine learning forecasting methods. The results of the study are presented in Section 4. Finally, final comments are given in Section 5.

2. LITERATURE REVIEW

In the digitalizing world, the use of cryptocurrencies for investment purposes has become widespread in recent years. For this reason, the number of studies on cryptocurrencies in the literature is increasing day by day. There are many studies on Bitcoin and other cryptocurrencies. Bitcoin, the groundbreaking cryptocurrency, has been extensively studied in terms of its preference and function in many areas [7]. Analyzes of Bitcoin often focus on economic policy uncertainty and volatility behavior, with insights into its potential as a financial instrument. Furthermore, the application of machine learning for ransomware classification in Bitcoin transactions has been evaluated, highlighting the importance of robust prediction models in the context of cryptocurrency security [8]. In general, studies have focused on Bitcoin, but other types of cryptocurrencies have also been examined. Gray prediction approach was used to predict the closing price of cryptocurrencies such as Bionic, Cardano, Dogecoin, Ethereum, XRP [9]. Another study examines price distortion and information efficiency before and during the COVID-19 outbreak using Bitcoin, BNB, Cardano, Ethereum and XRP cryptocurrencies [10].

The use of the Cardano formula in data-driven gradient flows highlights the mathematical foundations for cryptocurrencies beyond Bitcoin [11]. The feasibility of including different cryptocurrencies in investment portfolios for diversification was assessed and the potential benefits of diversification were highlighted, especially in the case of Terra [12]. In the field of sentiment analysis, comparative analyses using the Support Vector Machine and Naive Bayes algorithm have been performed on cryptocurrencies, shedding light on the potential applications of cryptocurrencies as digital goods for trading and investment assets. In addition, cryptocurrency price prediction based on ARIMA, Random Forest, and LSTM algorithms has been investigated; LSTM shows superior prediction accuracy compared to Random Forest and ARIMA models [13].

We enhance the existing body of research by doing a thorough examination of several machine learning models applied to a diverse set of cryptocurrencies. In contrast to typical research that concentrate on a solitary digital currency or a restricted range of models, we conduct a comparative analysis of the effectiveness of several models such as Decision Trees, Random Forests, KNN, GBM, LightGBM, XGBoost, CatBoost, ANN, CNNs, RNNs, and LSTMs across twelve different cryptocurrencies. This provides a more holistic understanding of the applicability and robustness of these models in cryptocurrency prediction, addressing a significant gap in the literature.

3. METHODOLOGY

In this study, Decision Trees, Random Forests, KNN, ANN, CNNs, RNN, LSTMs, GBM, LightGBM, XGBoost and CatBoost models are used in the comparisons. Table 1 provides a comprehensive list of the cryptocurrencies and prediction models that were used in the research.

Table 1 Cryptocurrencies and prediction models used in this paper

Cryptocurrencies	Models
Aave	Decision Trees
BinanceCoin	Random Forests
Bitcoin	Gradient Boosting Machines (GBM)
Cardano	XGBoost
Cosmos	LightGBM
Dogecoin	CatBoost
Ethereum	K-Nearest Neighbors (KNN)
Solana	Neural Networks
Tether	Convolutional Neural Networks (CNNs)
Tron	Recurrent Neural Networks (RNNs)
USDCoin	Long Short-Term Memory Networks (LSTMs)
XRP	

The dataset contains Date, Open, High, Low, Close, Volume and Market Cap information for Aave, BinanceCoin, Bitcoin, Cardano, Cosmos, Dogecoin, Ethereum, Solana, Tether, Tron, USDCoin and XRP cryptocurrencies. Table 2 provides explanations of the values in the data set. The date range of each cryptocurrency is given in Table 3.

Table 2 Characteristics of the dataset

Variable	Description
Date	Date of observation
Open	Opening price on the given day
High	Highest price on the given day
Low	Lowest price on the given day
Close	Closing price on the given day
Volume	Volume of transactions on the given day
Market Cap	Market capitalization in USD

Table 3 The range of dataset

Cryptocurrencies	Dataset	Cryptocurrencies	Dataset
Aave	05.10.2020 - 06.07.2021	Ethereum	08.08.2015 - 06.07.2021
BinanceCoin	26.07.2017 - 06.07.2021	Solana	11.04.2020 - 06.07.2021
Bitcoin	29.04.2013 - 06.07.2021	Tether	26.02.2015 - 06.07.2021
Cardano	02.10.2017 - 06.07.2021	Tron	14.09.2017 - 06.07.2021
Cosmos	15.03.2019 - 06.07.2021	USDCoin	09.10.2018 - 06.07.2021
Dogecoin	16.12.2013 - 06.07.2021	XRP	05.08.2013 - 06.07.2021

3.1. Decision Trees Model

The theoretical background of decision trees models includes internal nodes that represent attribute tests [14]. The tree structure includes branches that reflect test results and leaf nodes that represent class labels [15].

Decision trees are widely used due to their simplicity and efficiency in knowledge discovery, which are important factors. Decision tree algorithms are used in areas such as comparing Bitcoin and Ethereum [16], predicting the closing price of cryptocurrencies [17].

Figure 1 shows the fit of cryptocurrencies to the Decision Trees model. The practical application of these models to cryptocurrency prediction is diverse, with each sub-figure providing empirical evidence of the model predictive capacity for a specific cryptocurrency. The sub-figures in Figure 1 reflect the adaptability of decision trees across different cryptocurrencies, highlighting the model performance in terms of accuracy and its ability to capture trends within the highly volatile cryptocurrency market.

3.2. Random Forests Model

Random Forests models are a robust and adaptive learning approach widely used in many different domains [18]. The theoretical structure of random forests is a machine learning methodology that improves prediction accuracy and reduces overfitting by combining many decision trees [19]. Figure 2 shows the fit of cryptocurrencies to the Random Forests model.

Random forest algorithm has applications in areas such as financial fraud detection [20], bank failure prediction [21], and estimating cryptocurrency value [22].

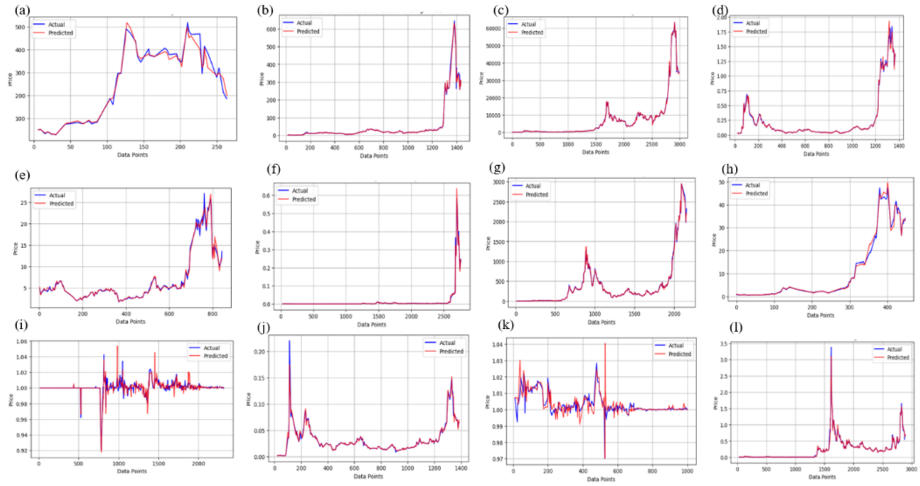

Fig. 1 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

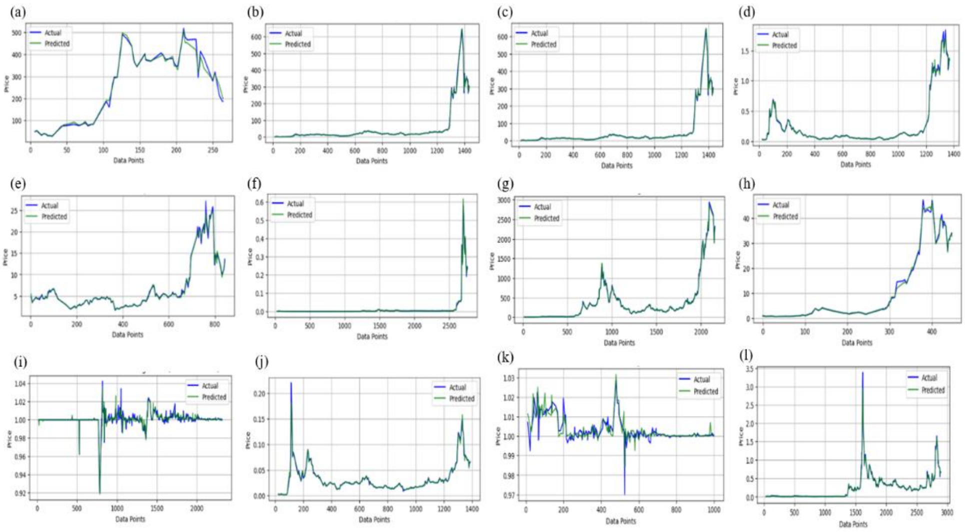

Fig. 2 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

3.3. K-Nearest Neighbours Model

K-Nearest Neighbours (KNN) models is a widely used and fundamental approach in the field of machine learning and pattern recognition [23]. The KNN method is a non-parametric machine learning technique that does not assume any particular data distribution and uses nearby examples to generate predictions [24]. The KNN method is widely used in stock price prediction [25,26]. Figure 3 shows the fit of cryptocurrencies to the KNN model.

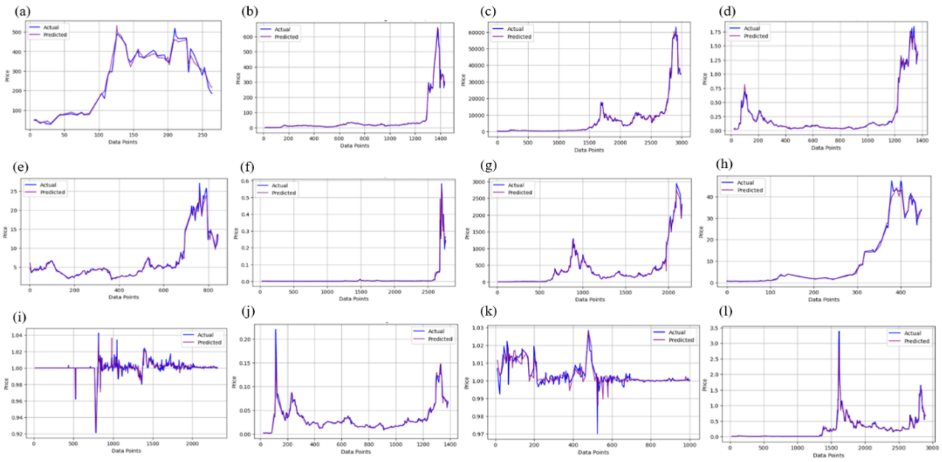

Fig. 3 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

3.4. Artificial Neural Networks Model

Artificial Neural Networks (ANN) models are powerful and flexible machine learning models that have attracted great interest in various fields [27]. Artificial neural networks (ANNs) are computational models that replicate the architecture and functioning of the human brain [28].

These systems are specifically designed to process complex data inputs and perform tasks such as classification, regression and pattern recognition. ANNs are highly valuable in a variety of applications including document recognition, reinforcement learning and predictive modelling due to their flexibility and malleability [29]. Figure 4 shows the fit of cryptocurrencies to the ANN model.

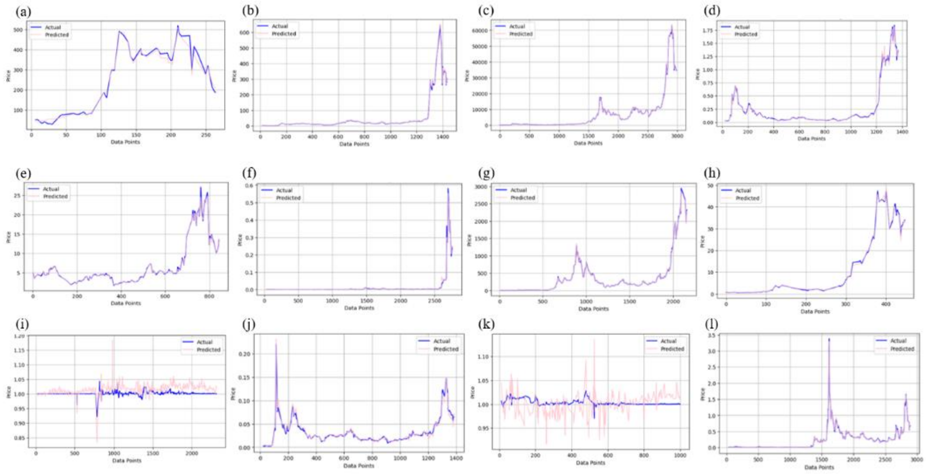

Fig. 4 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

3.5. Recurrent Neural Networks (RNNs) Model

Recurrent Neural Networks (RNNs) models are highly efficient and widely used deep learning models that have received significant acclaim in various fields [30]. Figure 5 shows the fit of cryptocurrencies to the RNNs model.

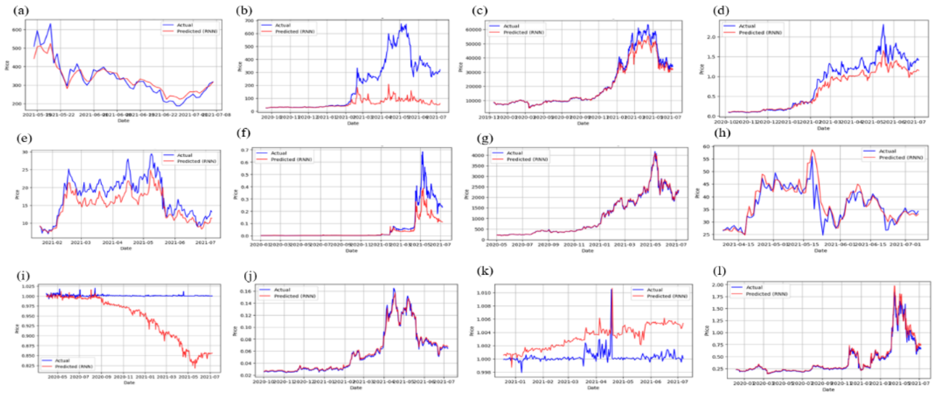

Fig. 5. (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

RNNs are computer models that efficiently capture the patterns and dynamics of sequences using cyclic connections between nodes in the network. RNNs provide a quality that makes them well suited for tasks involving the manipulation of sequential data [31]. RNNs have shown remarkable effectiveness in a variety of fields, including speech recognition, music classification, and the processing of time series data [32-34].

3.6. Convolutional Neural Networks Model

Convolutional Neural Networks (CNNs) models are highly effective and widely used deep learning models that have attracted great interest in various fields [35]. CNNs are specifically designed to process structured grid data such as photographs and time series data [36]. They have shown outstanding performance in a number of applications, including image identification, medical diagnostics and signal processing. Figure 6 shows the fit of cryptocurrencies to the CNNs model.

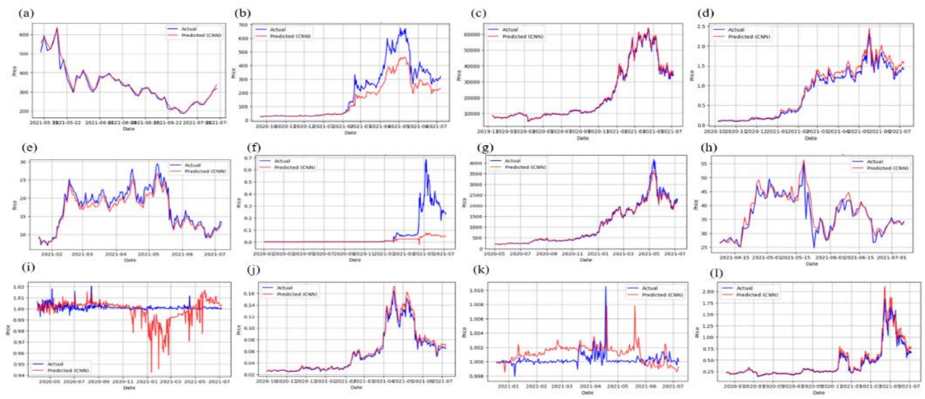

Fig. 6 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

3.7. Long Short-Term Memory Networks (LSTMs) Model

Long Short-Term Memory Networks (LSMs) models are very effective and widely used deep learning models that have received significant attention in various fields [37]. LSMs, also known as Long Short-Term Memory networks, are a special type of recurrent neural network (RNN) primarily designed to capture and comprehend long-term dependencies in sequential input [38]. LSTM models have performed well for tasks such as the analysis of time series data, natural language processing and speech recognition [39, 40]. Figure 7 shows the fit of cryptocurrencies to the LSTMs model.

Furthermore, LSTMs have been used in analysing time series data for various purposes such as increasing load shedding, predicting instantaneous load and predicting deformation in concrete dams. Their ability to collect temporal correlations and model complex time series data has made them very useful models for modelling data in areas such as engineering and energy management.

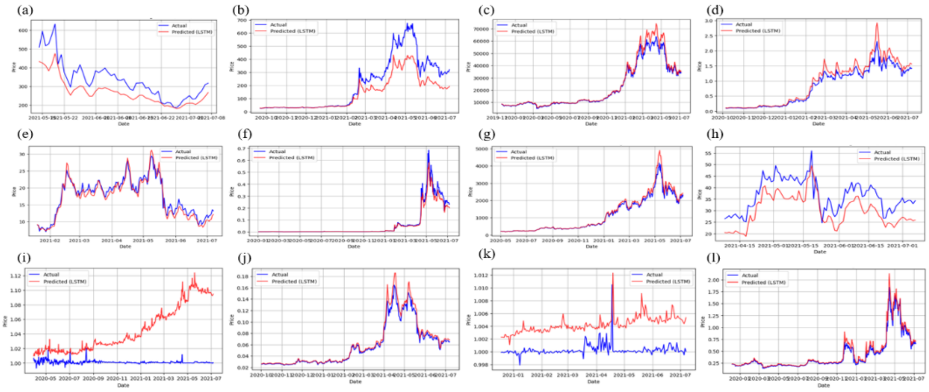

Fig. 7 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

3.8. Gradient Boosting Machines (GBM) Model

Gradient Boosting Machines (GBM) model is defined as a machine learning method that creates robust prediction models by combining the weak prediction model [41]. CPM is used in areas such as estimating credit risks [42], estimating bank failure [43], and estimating the value of cryptocurrency [44]. Figure 8 shows the fit of cryptocurrencies to the GBM model.

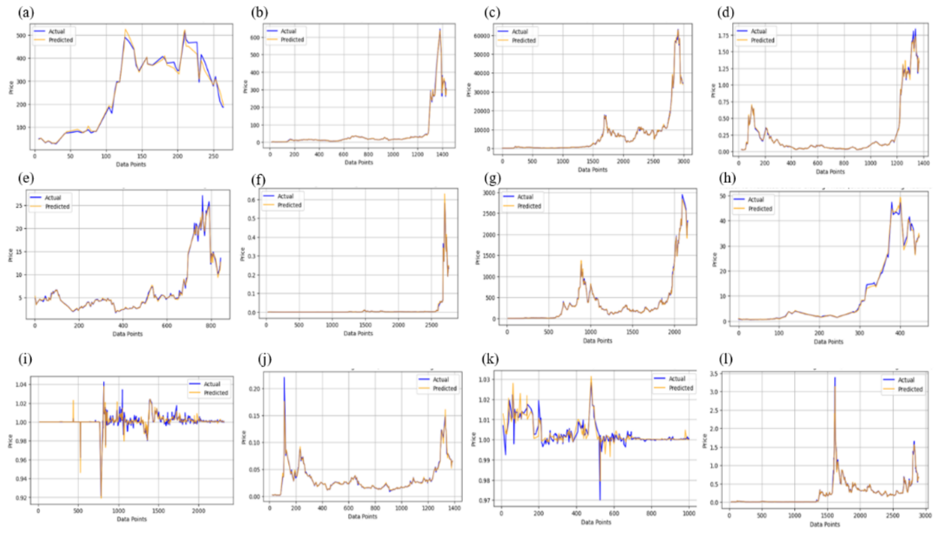

Fig. 8 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

3.9. XGBoost Model

The XGBoost models machine learning approach, commonly referred to as Extreme Gradient Boosting, is widely used in various areas of academic literature [45]. The theoretical infrastructure of the XGBoost model is based on the application of boosting techniques to create a robust prediction model. The XGBoost model is used in areas such as credit card fraud detection [46], corporate financial management risk model creation [47], and stock market volatility [48]. Figure 9 shows the fit of cryptocurrencies to the XGBoost model.

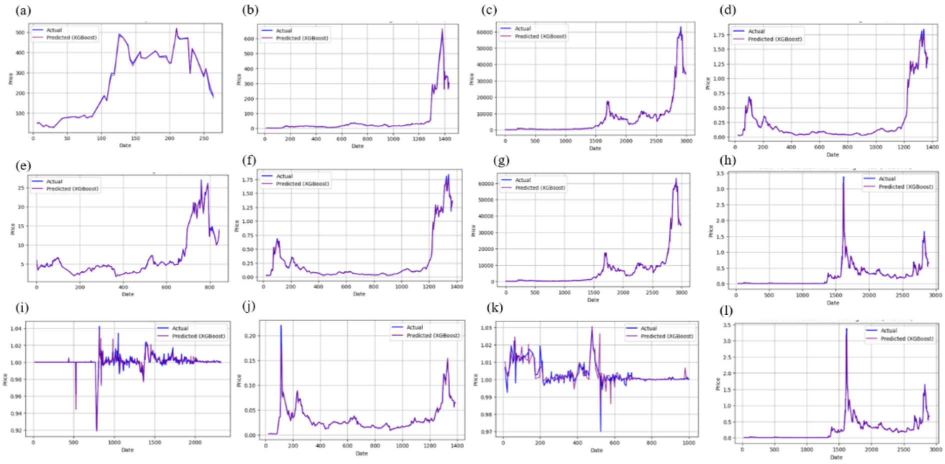

Fig. 9 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

3.10. LightGBM Model

LightGBM models short for Light Gradient Boosting Machine, is a highly effective machine learning model that can be applied in multiple domains [49]. Figure 10 shows the fit of cryptocurrencies to the LightGBM model.

LightGBM is a machine learning technique that uses boosting concepts to create an accurate predictive model, similar to the XGBoost model [50]. LightGBM has applications in predicting stock and cryptocurrency prices [51-53].

3.11. CatBoost Model

The CatBoost models algorithm has attracted much attention due to its ability to efficiently process categorical data and deliver outstanding performance in various applications. CatBoost algorithm uses gradient boosting [54]. According to Prokhorenkova et al. (2018), the CatBoost technique has shown better results in terms of quality compared to existing gradient boosting applications on widely recognised datasets [55]. CatBoost algorithm is used in the field of finance, such as comparing the performance of stock market strategies [56] and predicting the trends of stock indexes [57]. Figure 11 shows the fit of cryptocurrencies to the CatBoost model.

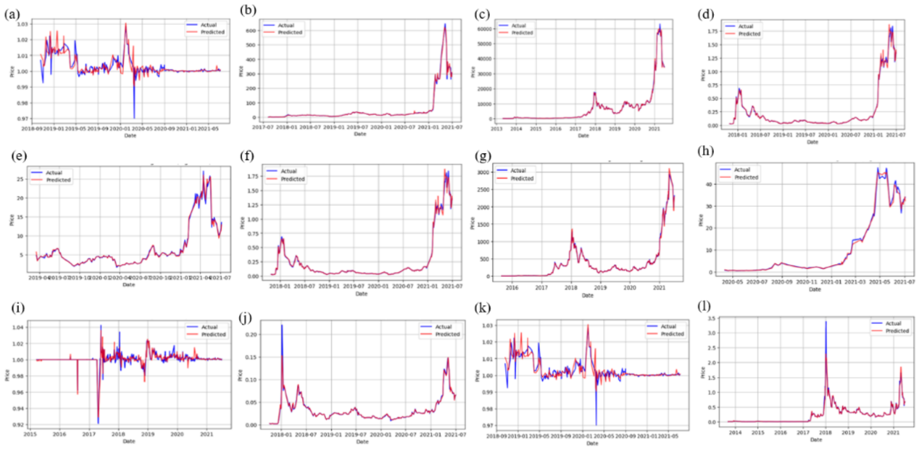

Fig. 10 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

CatBoost has shown to be a powerful and versatile gradient boosting method, demonstrating its effectiveness in handling categorical data, achieving outstanding prediction accuracy, and being applicable across several domains. The tool's ability to handle complex data types and provide understandable insights makes it a valuable asset for predictive modeling and interdisciplinary research.

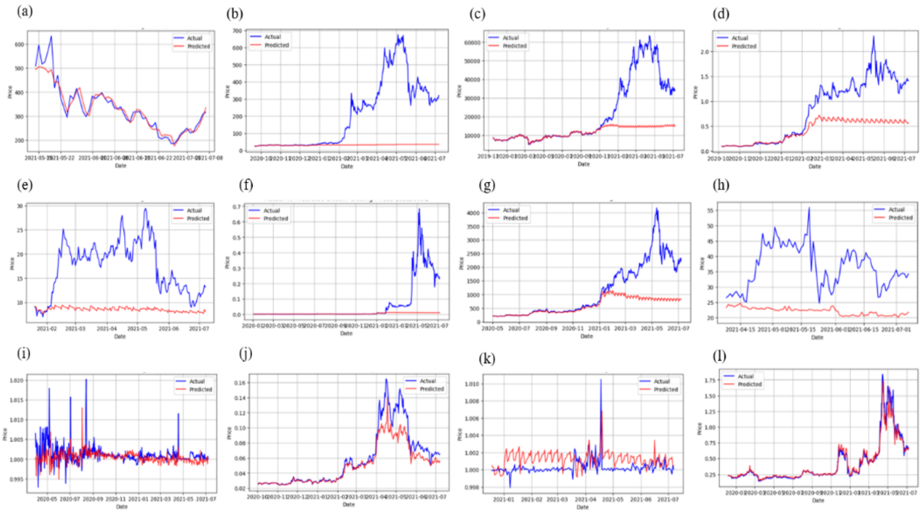

Fig. 11 (a) of constituent Aave. (b) of constituent BinanceCoin. (c) of constituent Bitcoin. (d) of constituent Cardano. (e) of constituent Cosmos. (f) of constituent Dogecoin. (g) of constituent Ethereum. (h) of constituent Solana. (i) of constituent Tether. (j) of constituent Tron. (k) of constituent USDCoin. (l) of constituent XRP. Source: Figure by authors

4. RESULTS

In this section, the results obtained using the methods of Decision Trees, Random Forests, K-Nearest Neighbors (KNN), Gradient Boosting Machine (GBM), LightGBM, XGBoost, CatBoost, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory networks (LSTMs) have been examined. The results have been compared using the MSE, RMSE, and MAE criteria. The mathematical expressions are given below.

$$\text{MSE} = \frac{1}{n}\sum (Y_i - \hat{Y}_i)^2 \tag{1}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum (Y_i - \hat{Y}_i)^2} \tag{2}$$

$$\text{MAE} = \frac{1}{n}\sum \left|Y - \hat{Y}_i\right| \tag{3}$$

The MSE, RMSE, and MAE values obtained for the cryptocurrencies Aave, BinanceCoin, Bitcoin, Cardano, Cosmos, Dogecoin, Ethereum, Solana, Tether, Tron, USDCoin, and XRP are provided in Table 4 and Table 5.

Table 4 MSE, RMSE and MAE value for Aave, BinanceCoin, Bitcoin, Cardano, Cosmos, Dogecoin, Ethereum, Solana, Tether, Tron, USDCoin, and XRP

	Aave			BinanceCoin		
	MSE	RMSE	MAE	MSE	RMSE	MAE
Decision Trees	418.708	20.462	13.388	54.428	7.377	1.865
Random Forests	229.562	15.151	9.78	20.659	4.545	1.398
KNN	463.522	21.529	15.641	43.932	6.628	2.309
GBM	275.487	16.597	11.52	17.365	4.167	1.399
LightGBM	285.093	16.884	12.097	24.586	4.958	1.517
XGBoost	33.012	5.745	3.647	5.822	2.412	0.758
CatBoost	1013.619	31.837	21.028	66507.27	257.89	172.51
ANN	316.178	17.781	13.629	14.794	3.846	1.416
CNNs	0.0007	0.027	0.017	0.014	0.121	0.079
RNNs	0.0034	0.058	0.042	0.109	0.33	0.215
LSTMs	0.015	0.125	0.107	0.02	0.144	0.096
	Bitcoin			Cardano		
	MSE	RMSE	MAE	MSE	RMSE	MAE
Decision Trees	76726.6	276.995	109.151	0.001	0.037	0.012
Random Forests	53947.48	232.265	90.785	0.0004	0.021	0.008
KNN	248067.6	498.063	213.448	0.0011	0.033	0.015
GBM	73052.82	270.282	118.201	0.0004	0.02	0.008
LightGBM	115722.3	340.179	113.87	0.0008	0.029	0.01
XGBoost	81810.14	286.02	88.537	0.0001	0.01	0.004
CatBoost	3.32E+08	18207.52	10177.2	0.328	0.573	0.573
ANN	66318.21	257.523	117.74	0.0004	0.021	0.012
CNNs	0.0001	0.012	0.008	0.0018	0.042	0.034
RNNs	0.002	0.044	0.024	0.008	0.094	0.067
LSTMs	0.0022	0.047	0.024	0.005	0.073	0.051

	Cosmos			Dogecoin		
	MSE	RMSE	MAE	MSE	RMSE	MAE
Decision Trees	0.469	0.685	0.355	0.00001	0.003	0.0005
Random Forests	0.192	0.438	0.238	0.00006	0.002	0.0004
KNN	0.418	0.646	0.388	0.00004	0.006	0.0009
GBM	0.2145	0.463	0.248	0.000008	0.002	0.0004
LightGBM	0.213	0.461	0.265	0.00006	0.008	0.0011
XGBoost	0.039	0.198	0.112	0.00005	0.002	0.0003
CatBoost	104.81	10.237	8.834	0.019	0.137	0.056
ANN	0.117	0.342	0.201	0.00001	0.004	0.0013
CNNs	0.003	0.052	0.041	0.031	0.177	0.071
RNNs	0.013	0.115	0.099	0.0096	0.098	0.039
LSTMs	0.0022	0.047	0.039	0.0009	0.031	0.012

Table 5 MSE, RMSE and MAE value for Aave, BinanceCoin, Bitcoin, Cardano, Cosmos, Dogecoin, Ethereum, Solana, Tether, Tron, USDCoin, and XRP

	Ethereum			Solana		
	MSE	RMSE	MAE	MSE	RMSE	MAE
Decision Trees	547.753	23.404	9.83	1.101	1.049	0.564
Random Forests	376.747	19.409	8.327	0.626	0.791	0.419
KNN	1379.609	37.143	16.824	1.986	1.409	0.67
GBM	386.734	19.665	8.967	0.906	0.952	0.524
LightGBM	444.698	21.087	8.776	0.929	0.964	0.964
XGBoost	211.86	14.555	6.643	0.917	0.958	0.283
CatBoost	835884.7	914.267	519.195	254.684	15.958	14.328
ANN	309.621	17.596	8.443	0.697	0.835	0.474
CNNs	0.0005	0.023	0.012	0.0021	0.046	0.029
RNNs	0.0002	0.014	0.007	0.004	0.064	0.037
LSTMs	0.0015	0.039	0.019	0.016	0.127	0.121
	Tether			Tron		
	MSE	RMSE	MAE	MSE	RMSE	MAE
Decision Trees	0.00002	0.005	0.002	0.00002	0.005	0.0016
Random Forests	0.00001	0.003	0.001	0.00001	0.003	0.0012
KNN	0.00001	0.003	0.001	0.00003	0.005	0.0019
GBM	0.00001	0.003	0.001	0.00002	0.004	0.0013
LightGBM	0.00001	0.003	0.001	0.00003	0.005	0.0014
XGBoost	0.00001	0.003	0.001	0.00001	0.003	0.0007
CatBoost	0.000006	0.002	0.001	0.0002	0.015	0.008
ANN	0.0005	0.022	0.016	0.00003	0.006	0.0033
CNNs	0.0002	0.0168	0.0108	0.0005	0.022	0.015
RNNs	0.017	0.132	0.095	0.0002	0.014	0.01
LSTMs	0.008	0.089	0.072	0.0008	0.029	0.017
	USDCoin			XRP		
	MSE	RMSE	MAE	MSE	RMSE	MAE
Decision Trees	0.00002	0.005	0.002	0.002	0.049	0.011
Random Forests	0.00001	0.003	0.001	0.001	0.033	0.008
KNN	0.00001	0.003	0.001	0.002	0.050	0.014
GBM	0.00001	0.003	0.001	0.001	0.038	0.009
LightGBM	0.00003	0.003	0.001	0.005	0.072	0.012
XGBoost	0.00001	0.003	0.001	0.002	0.051	0.008
CatBoost	0.00002	0.001	0.001	0.005	0.071	0.034
ANN	0.00007	0.027	0.019	0.001	0.038	0.012
CNNs	0.00005	0.022	0.017	0.0003	0.019	0.0115
RNNs	0.002	0.046	0.041	0.0002	0.014	0.008
LSTMs	0.003	0.056	0.054	0.0003	0.018	0.0113

When the results of Aave and BinanceCoin were examined, it was seen that XGBoost showed the best performance. When MSE values are examined, it is seen that the best performing model for Bitcoin is Random Forest and XGBoost. It is seen that the CatBoost model shows the worst performance for Bitcoin. It can be said that all prediction models for Cardano, Cosmos and Dogecoin give good results. However, similar to the Bitcoin results, it can be said that Random Forest and XGBoost performed well in Cardano, Cosmos and Dogecoin. When Ethereum values are examined, it is seen that the best performing model is Random Forest. On the other hand, it is seen that the KNN model shows the worst performance for Ethereum. When Solana values are examined, it is seen that the Random Forest model performs well, similar to other cryptocurrencies. After Random Forest, the best performing models are GBM, XBoost and LightGBM, respectively. It is possible to say that Tether performs well in all models. It can be said that the reason for this is due to the stable nature of Tether as a stablecoin. Additionally, when Tether's graphics are examined, it is seen that it fits all models well. It was concluded that CatBoost, Random Forests, KNN, GBM, LightGBM and XGBoost models fit very well, respectively. When Tron and USDCoin are examined, it is seen that the performance of the models is good. The worst performing model for Tron appears to be CNNs. It is seen that the best performing models are Random Forests and XGBoost. For USDCoin, Random Forests, KNN, GBM and XGBoost models appear to show the best results. It can be seen that the worst performing model is LSTMs. When XRP is examined, it is seen that there are large differences between the performances of the models. CNNs, RNNs and LSTMs appear to perform best. It can be seen that LightGBM and CatBoost perform the worst. Models such as ANN, CNNs, RNNs and LSTMs show different performances in different cryptocurrencies. It can be interpreted that CNNs perform well for Aave, BinanceCoin and Bitcoin. It appears to perform worse for Cardano, Cosmos and Dogecoin. It can be said that RNNs and LSTM models generally perform well, but are not the best performing models in the cryptocurrencies examined.

5. CONCLUSION

In this study, Decision Trees, Random Forests, KNN, GBM, LightGBM, XGBoost, CatBoost, ANN were used to predict the closing price of Aave, BinanceCoin, Bitcoin, Cardano, Cosmos, Dogecoin, Ethereum, Solana, Tether, Tron, USDCoin and Models such as CNNs, RNNs and LSTMs have been used. The efficiencies of these models were compared using MSE, RMSE and MAE criteria. The results show that there is no single good model for all cryptocurrencies. Different models appear to fit well in different cryptocurrencies. Stablecoins such as Tether appear to fit well with many models. The accuracy of deep learning models such as ANNs, CNNs, RNNs, and LSTMs appears to be strong on cryptocurrencies such as Aave, BinanceCoin, and Bitcoin. Although classical machine learning models such as XGBoost and Random Forests are mostly reliable, it has been concluded that the choice of model should depend on the different characteristics of each cryptocurrency. While our study provides valuable insights into the performance of predictive models for cryptocurrencies, it is important to acknowledge its limitations. In the beginning, the cryptocurrency market is inherently volatile, and the success of the models may be affected by rapidly evolving external variables. Future research in this area could explore: Investigating the development of real-time predictive models that can adapt to rapidly changing market conditions. Integrating external data sources, such as market sentiment analysis or news sentiment, to enhance predictive accuracy. Assessing the risks associated with cryptocurrency investments, considering the limitations of predictive models. This study builds on and extends the findings of previous research in the field of cryptocurrency prediction, reinforcing the idea that model selection should be tailored to the specific characteristics of each cryptocurrency. Our results are consistent with the broader consensus that cryptocurrency prediction is a multifaceted challenge and that no single model can excel in this complex environment.

As a result, this research serves as a valuable reference for investors, policymakers, and researchers who want to delve into the intricacies of cryptocurrency price prediction. While there is no crystal ball in the cryptocurrency world, our study sheds light on various machine learning models that can help make informed decisions in this ever-evolving environment.

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