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KASBIT Business Journal, 15(2), 15-27, June 2022

Forecasting Cryptocurrencies using the Classical Time Series Approach

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Abstract

As technology leads toward a new era of tools, there are also some sudden changes in business and marketing. Cryptocurrency is a new and emerging investment and exchanging tool for business and marketing. This work aims to develop a time series model that efficiently forecasts cryptocurrency values. To achieve this end, we use the classical time series model Autoregressive integrated moving average (ARIMA), also known as the Box-Jenkins methodology. This work demonstrates that by using ARIMA models, the future behavior of the series can be efficiently guessed. The work suggests some ARIMA models by utilizing the Box-Jenkins methodology that can efficiently guess the future behavior of the cryptocurrency, and these models are selected based on forecast accuracy. Namely root mean square error (RMSE), mean absolute percentage error (MAPE), and the Akaike information criteria (AIC). The results show that different models are selected to model and forecast the four cryptocurrencies. These results will provide an initial guess to the investors and consumers to know the behavior of the cryptocurrencies in the upcoming days.

Keywords: *ARIMA, Time series, Cryptocurrency, Forecasting*

JEL: C12, C22, C53

Background and Literature

As the world progresses toward technology, investment instruments are changing with time; cryptocurrency or digital currency is also one of the modern tools of investment and serves as an alternative payment method. Cryptocurrency is acknowledged as a virtual currency that can be exchanged between groups or individuals. It has been found that digital currency had revolutionary progress as a mass of exchange for past years in the financial market due to its popularity and profitability. For the last decades, it has also been found that this digital currency has the exact nature of stock prices.

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By this nature, cryptocurrency possesses fluctuations in nature, and therefore, the prediction of cryptocurrency is the most attractive topic among researchers. Several cryptocurrencies have been introduced in the last decade, i.e. Bitcoin, Litecoin, Peercoin, Auroracoin, Dogecoin, Ripple, etc. Due to easy and free access, cryptocurrency is becoming the most popular and well-known phenomenon among investors and consumers. Bitcoin is the foremost and most famous cryptocurrency globally (Nakamoto, 2008). Classical time series models are one of the most powerful tools to predict and forecast the behavior of the time-series data and give us efficient results to get the idea of underlying phenomena. ARIMA models stand for Autoregressive Integrated Moving Average, also known as the Box-Jenkins methodology, which serves as the linear forecasting model for the time series data. In this work, we predict and forecast the four cryptocurrencies by using the Box-Jenkins methodology.

The importance of this study links with the technology and decentralization of money in terms of the medium of exchange. This study elaborates that how this phenomenon changes concerning time and interventions of some circumstances. In this article, the authors propose the best fit model that follows the law of parsimony and models the top trending cryptocurrencies. According to the literature, there are several models proposed to analyze different digital currencies but the behavior of the decentralized currencies is not found. This work attempts to capture this fact as well. This work also explains the Extrapolatory analysis which further results in finding the best fit model for the cryptocurrencies.

This work is organized as follows. Section 2 presents the related work and literature review; next, we present the methodology; furthermore, we present the data analysis and process. In the final section, we present the results and discussions.

It has been examined from the past studies that several studies carried out on the ARIMA model in prediction and forecasting problems. Mittal et al. (2018) used the ARIMA model to forecast cryptocurrency. Derbentsev et al. (2019b), in this work, the author compared forecasting the short-term price of the cryptocurrency. Munim et al. (2019) this article used machine learning algorithms and the time series method to forecast the next day's bitcoin price (digital currency). Derbentsev et al. (2019a), in this article, the authors used the (BART), (C&RT) autoregressive models to forecast the cryptocurrency. (Khedr et al., 2021) conducted a survey study using the traditional and machine learning algorithm to forecast the cryptocurrency. Duvodq et al. (2018) worked on the Prophet and ARIMA model to forecast the bitcoin. Patel et al. (2020) utilized the LSTM, GRU, and Neural network models to forecast the short-term prices of the cryptocurrency. Neural et al. (2018) conducted a comparative study to forecast cryptocurrency prices. Pratama et al. (2020) forecasted Cryptocurrency is utilizing the α-Sutte Indicator, ARIMA, and Long Short-Term Memory LSTM model.

Yamak et al. (2019) made a comparative study to forecast the cryptocurrency using ARIMA, LSTM, and GRU models. Bakar & Rosbi (2017) utilized the ARIMA model to forecast cryptocurrency prices in the presence of high volatility. Ensafi et al. (2022) compared the time series models, i.e. SARIMA and triple exponential smoothing and machine learning models, to forecast the e-sales of furniture. The model was selected based on key performance indicators (KPI). Kim et al. (2022) used nonlinear error correction models (ECMs) to forecast the log return price of bitcoin. Tandon et al. (2021) used the ARIMA model to forecast the cryptocurrency's price in the impact of social media massage. Benzekrı & Özütler (2021) utilized the ARIMA model to forecast the bitcoin for the short term and found that the ARIMA(1,1,0) is the best fit for forecasting quarterly price

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movements. Khasanova et al., (2021) conducted a comparative study to model and forecast gold, cryptocurrency, and oil adaptive analysis.

Methodology

In early 2022, it has been observed that the research interest in digital currency has an increasing trend due to investors' and consumers' popularity and global attention. Numerous methods, i.e. classical time series analysis and machine learning techniques, are applied to forecast the behavior of the digital currency. This study uses the classical time series models to model and forecasts the cryptocurrency data.

Cryptocurrency Price Prediction Approach

ARIMA is a classical time series model used to model and forecast linear time series data. This model is the sum of three components, namely, the autoregressive component denoted by (p); it gives us information about the number of lags used in the model to account for the use of the history of the series and the integrated component denoted by (d). It is used when the series is not stationary, and the last is the moving average denoted by (q). This refers to the error as a combination of previous error terms. Mathematically by using the backshift operator, the model ARIMA (p,d,q) and SARIMA (p,d,q)x(p,d,q) can be written as:

$$\Phi_p(B)\Delta^d z_t = \theta^q(B)e_t \ldots\ldots (1)$$

$$\varphi(B)\Phi(B)\nabla^d\nabla_s^D Z_t = \theta(B)\Theta(B)e_t \ldots\ldots (2)$$

The model is written in the form of a backshift operator; here, z_t represents the values of the cryptocurrency, and ϕ_p is the (AR) coefficient; moreover, θ^q is stood for the moving average model (MA).

This model gives us the efficient result if and only if the time series is stationary and it satisfies the following conditions to be stationary.

- The mean should be independent of time.
- The variance of the time series should not be a function of time
- The covariance of the i^{th} and the $(i+m)^{the}$ term should not be a function of time.

To check whether the time series data is stationary, we use the Augmented Dickey-Fuller test, which calculates the series's different parameters (p, d, q). The P-value should be low to ensure stationarity, i.e.(0.01). Suppose the series is found to be non-stationary. In that case, we apply the transformation or go for the differencing technique as I(d) is applied to the series to make it stationary, which results in the reduction of the p-value, hence making the series stationary.

Forecast Accuracy Measures

The forecasting models are selected based on their forecast accuracy in time series analysis. In this work, we use Mean Absolute Percent Error) **(MAPE), To select the model, Root Mean Squared Error (RMSE) and Akaike information criterion (AIC)**.

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(dt-zt)^2}{n}} \ldots\ldots\ldots\ldots 2$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{(d_t - z_t)}{d_t}\right| \ldots\ldots\ldots 3$$

$$AIC = n\log\sigma^2 + 2K \ldots\ldots\ldots 4$$

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Empirical Results

The analysis begins with the graphical display of all four daily time series of cryptocurrency. The graphical display of the bitcoin and other alternative coins is given below.

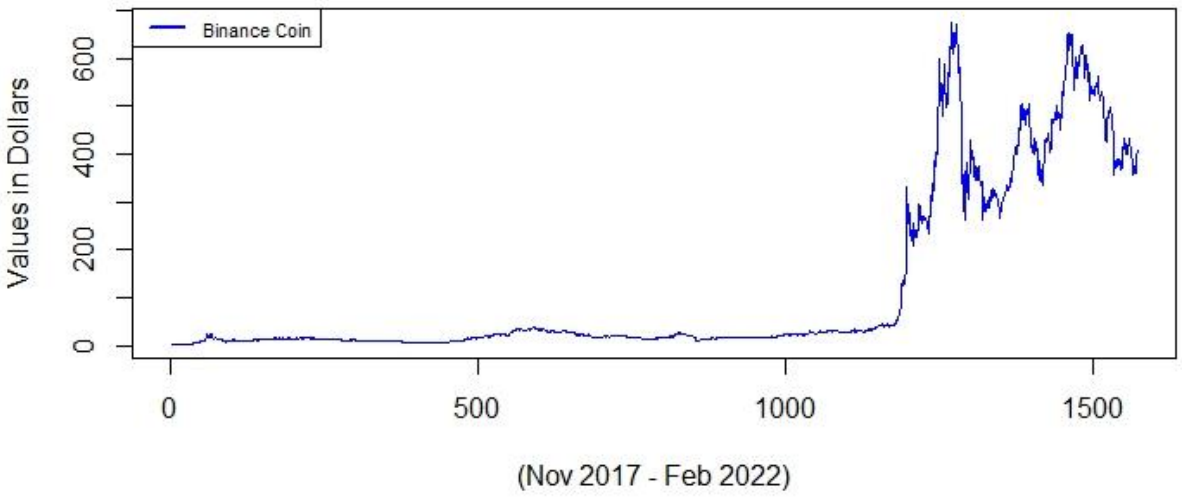

Figure No 1: Time series plot of Daily values of Binance coin (BNB) in dollars

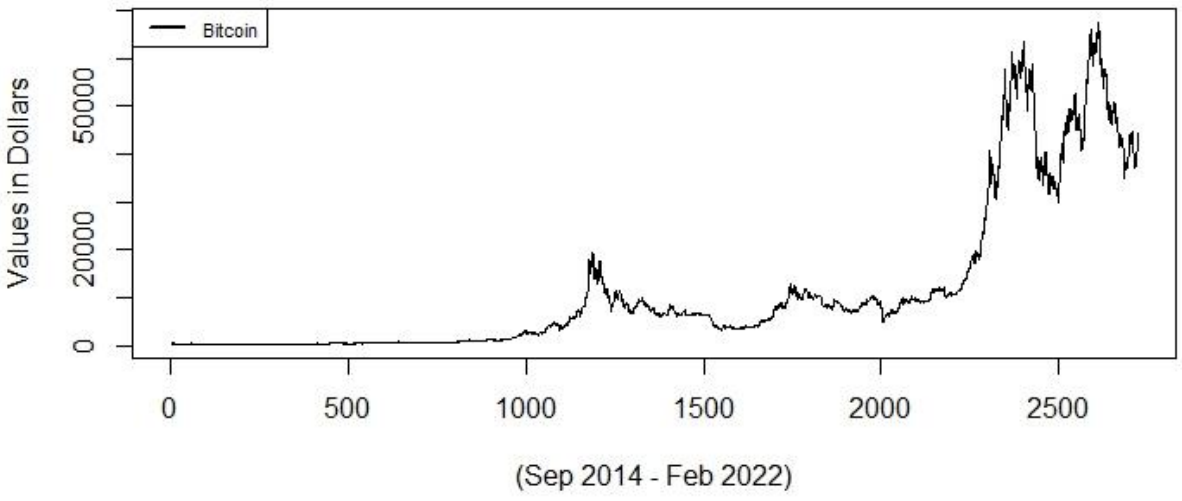

Figure No 2: Time series plot of Daily values of bitcoin (BTC) in dollars

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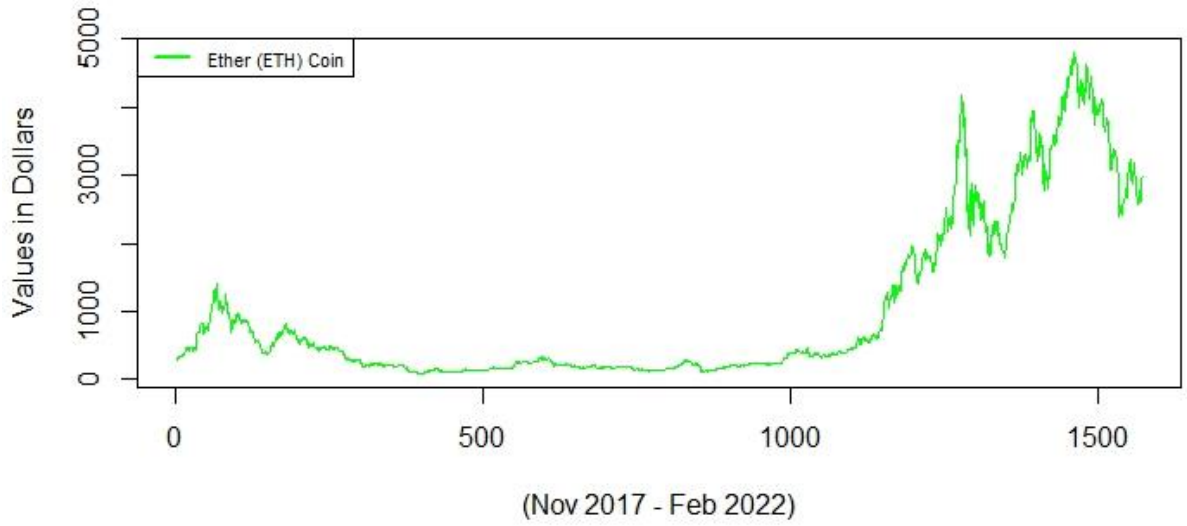

Figure No 3: Time series plot of Daily values of ether coin (ETH) in dollars

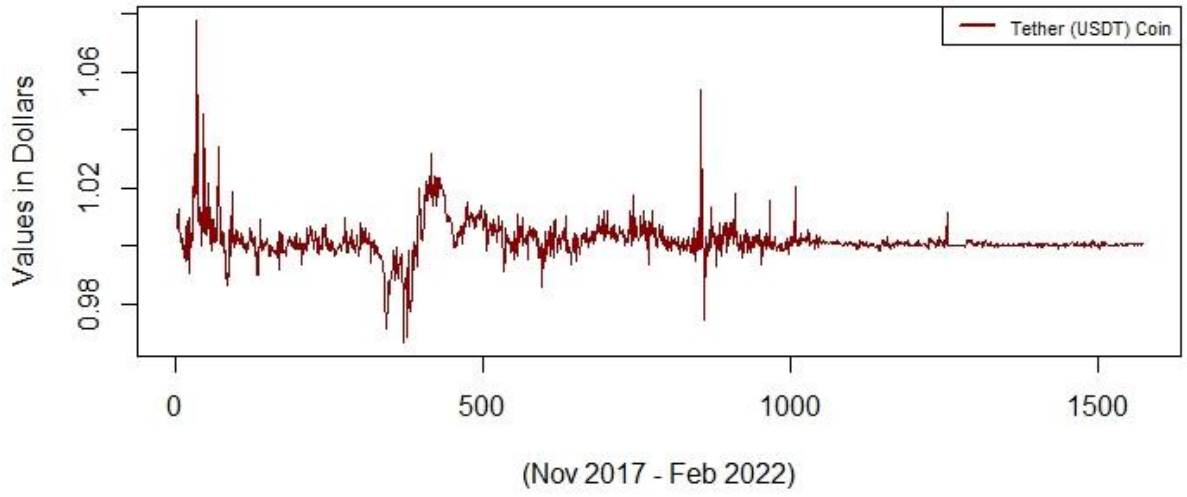

Figure No 4: Time series plot of Daily values of tether coin (USDT) in dollars

From the visual display, all three crypto coins, i.e. Binance, bitcoin, and ether coin, show an increasing trend, while the tether coin (USDT) has no trend, and it seems to be white noise. The graphical behavior of the series gives us an initial guess that all the crypto coins are non-stationary except the tether (USDT) coin. Now, to check this fact mathematically, we apply the Augmented Dicky-fuller test, which is the most popular test to test whether the series is stationary or not. The null hypothesis assumed when we apply the ADF test is that there presents a unit root in the series, and if the P-value comes out greater than 5% or 0.05, we do not reject the null hypothesis and conclude that there presents a unit root. The results are shown in the table for all four crypto coins.

Table No: 1 Augmented Dickey-Fuller Test for cryptocurrencies

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	Dickey-Fuller	P-Value
Binance	-2.37	0.42
Bitcoin	-2.05	0.56
Ether (EHT)	-1.82	0.66
Tether(USTD)	-5.20	0.01

From table no 1, it can be examined that the only tether (USDT) has a value that is lower than 0.05, which means only the (USDT) is stationary while the other needs transformation or difference to become stationary. After this, we make the series stationary by applying the difference operator. After removing the stationary component from the series, we make a correlogram of all the series to check the best order of the candidate model. We first draw the correlogram of the Binance coin to check the order of the series. The correlogram of the series is given below.

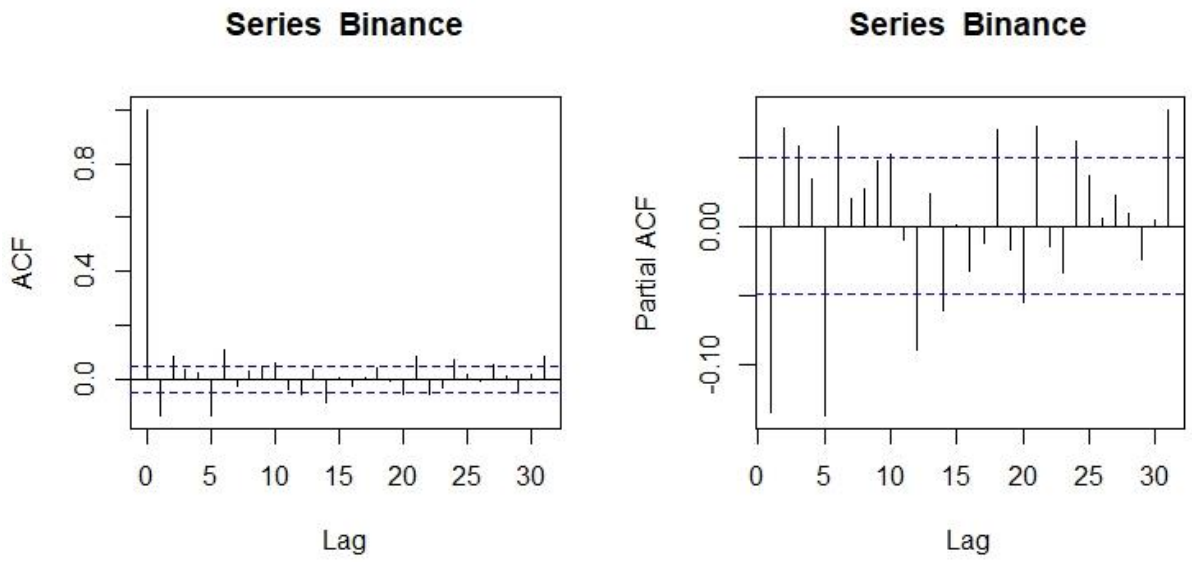

Figure No: 5 Correlogram of Binance coin after 1st difference

The order for the candidate models can be initiated; we can apply different candidate models to the Binance series and select the model that fulfills the forecast accuracy demand. We here only present the correlogram for the Binance coin; the correlogram is given in the appendix for the other coins.

After finding the best order for the candidate model, the next step is to check the diagnostic testing of the model. We apply five candidate models to forecast the Binance coin data. The various candidate models for forecasting the Binance coin are given in table no two below.

Table No: 2 Candidate models for forecasting the Binance coin.

ARIMA (p,d,q)	RMSE	MAPE	AIC
ARIMA(5,1,4)	12.41	4.00	12408.77
ARIMA(5,1,5)	12.24	4.00	12374.54
ARIMA(5,1,6)	12.25	4.15	12377.98

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ARIMA(6,1,5)	12.29	4.01	12384.78
ARIMA(6,1,6)	12.30	4.15	12386.15

From the result, it is found that the candidate model ARIMA (5,1,5) is the best fit model among all as it has the lowest root mean square error (RMSE) of 12.24, and mean absolute percentage error (MAPE) of 4.00, and the lowest Akaike value (AIC) 12374.54. To access the efficiency of the candidate model, we plot the actual values of the Binance coin and the model's fitted values. The graph for this is given below. Additionally, we use this model to forecast the future value of the Binance coin.

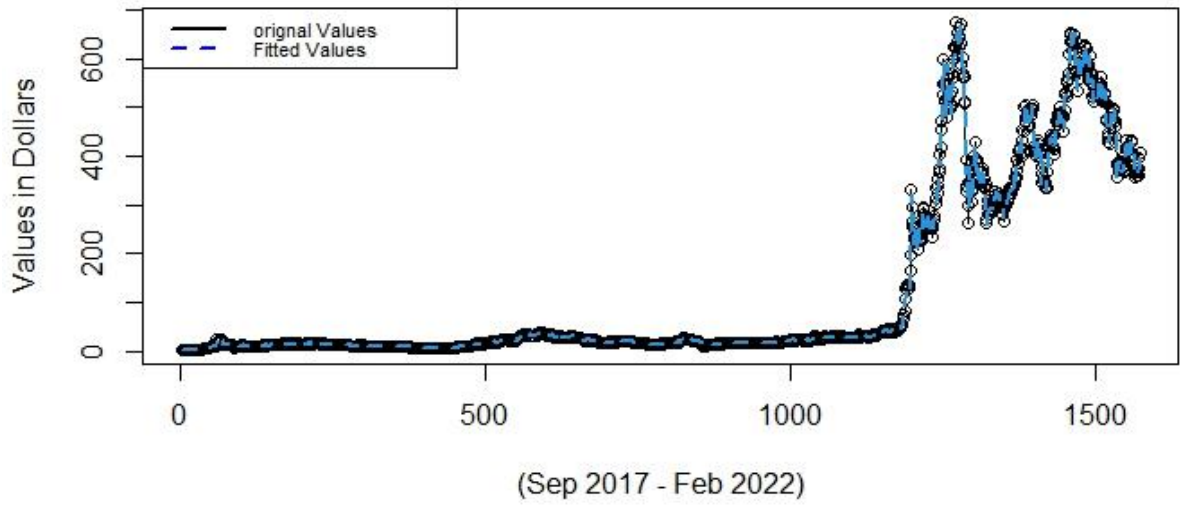

Figure No: 6 Original and fitted values for the Binance coin

From the graphical display, the model's efficiency is traced; now, we use this model to forecast the future values of the Binance coin, and the graph is shown below.

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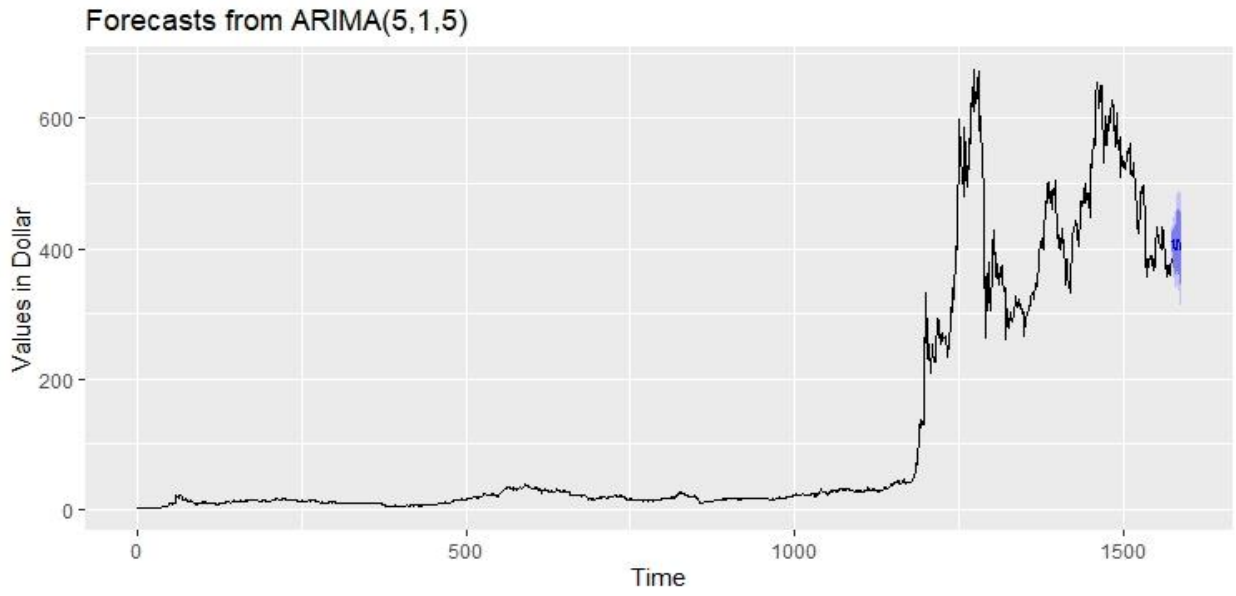

Figure No: 7 Visual display of the forecasted values of the Binance coin

Table No: 3 Forecasted values of Binance coin using ARIMA (5,1,5) model.

Sample Number	Forecast	Low C.I. 95%	Hi C.I. 95%
1	408.73	385.90	434.09
2	415.09	383.02	447.15
3	412.33	372.77	451.90
4	401.80	356.03	447.55
5	402.21	350.40	454.03
6	400.06	343.61	456.53
7	398.31	337.16	459.48
8	407.60	342.50	472.70
9	413.03	344.41	481.66
10	410.55	338.39	482.71
11	412.70	336.96	488.43
12	408.46	329.44	487.51
13	399.00	316.45	481.54
14	399.90	314.03	485.78
15	402.25	313.46	491.04

Furthermore, we repeat the procedure for the other three cryptocurrencies as well.

Bitcoin prediction

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We present the candidate models for bitcoin, as this is the emerging and most famous coin in the world of cryptocurrency due to its dynamicity and market behavior. We draw the correlogram of the series to find the order of the candidate model; the graphical display is shown in Appendix A.

Table No: 4 Candidate models for forecasting the bitcoin.

ARIMA (p,d,q)	RMSE	MAPE	AIC
ARIMA(4,1,4)	773.51	2.58	43953.41
ARIMA (4,1,5)	777.64	2.66	43982.67
ARIMA (4,1,6)	774.71	2.70	43967.12
ARIMA(5,1,4)	777.63	2.59	43982.61
ARIMA(5,1,5)	775.07	2.70	43969.34

The result shows that the candidate model with parameter ARIMA(4,1,4) is the best fit among the other models with the lowest RMSE of 773.54, MAPE 2.58, and AIC value of 43958.41. we use this model to forecast the y_{t+1} values for the bitcoin. The graph of the residuals versus fitted values and bitcoin is given in appendix A.

Table No: 5 Forecast values of bitcoin using ARIMA (4,1,4) model.

Sample Number	Forecast	Low C. I 95%	Hi C.I 95%
1	44395.17	42872.96	45917.37
2	44674.83	42528.74	46820.92
3	44930.84	42304.94	47556.74
4	44729.07	41688.26	47769.88
5	44488.28	41056.19	47920.36
6	44376.60	40600.43	48152.76
7	44584.88	40497.77	48672.00
8	44887.74	40524.45	49251.02
9	44879.22	40252.95	49505.49
10	44671.62	39783.66	49559.59
11	44409.57	39269.93	49549.22
12	44472.10	39093.13	49851.07
13	44740.86	39145.09	50336.63
14	44911.03	39108.17	50713.89
15	44820.77	38812.92	50828.61

Ether (ETH) coin

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To begin the forecast and analysis of the ether (ETH) coin, we begin to make a correlogram of the ether coin to find the order of the candidate model. The visual display of the ether coin is given in appendix A. we present the candidate models that are fitted to the series and choose a model that is the most suitable among all according to the forecast accuracy criteria.

Table No: 6 Candidate models for forecasting the bitcoin.

ARIMA (p,d,q)	RMSE	MAPE	AIC
ARIMA(2,1,2)	78.18	3.62	18188.83
ARIMA (2,1,3)	78.17	3.60	18190.54
ARIMA (2,1,4)	77.60	3.64	18169.93
ARIMA(3,1,3)	78.60	3.59	18209.61
ARIMA(3,1,4)	77.58	3.60	18169.90

From the results, it is examined that the candidate model ARIMA (3,1,4) is the best fit among all the models with the lowest root mean square error (RMSE), mean absolute percentage error (MAPE), and Akaike information criteria (AIC). We use this model to forecast the ether (ETH) coin for future values. The forecast values of the model are given in the table below.

Table No: 7 Forecast values of bitcoin using ARIMA (3,1,4) model.

Sample Number	Forecast	Low C. I 95%	Hi C.I 95%
1	2991.60	2839.15	3144.05
2	2987.24	2776.28	3198.20
3	3003.27	2746.09	3260.44
4	2990.70	2694.58	3286.81
5	3008.00	2674.29	3341.71
6	2994.26	2629.70	3358.81
7	3008.14	2611.15	3405.13
8	2998.50	2575.01	3421.98
9	3005.79	2553.91	3457.68
10	3002.82	2526.92	3478.72
11	3002.82	2501.91	3503.73
12	3006.29	2482.89	3529.69
13	3000.59	2454.95	3546.22
14	3008.21	2441.19	3575.22
15	2999.81	2412.71	3586.91

Tether (US-DT) coin

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To model and forecast the tether (US-DT) coin, we begin with the visual display of the series by making the ACF and PACF of the tether (US-DT) coin. The visual display is given in appendix A. The correlogram is made to find the right order of candidate model for the tether (US-DT) coin. The suggested candidate models are given below.

Table No: 8 Candidate models for forecasting the bitcoin.

ARIMA (p,d,q)	RMSE	MAPE	AIC
ARIMA (2,0,3)	0.004	0.002	-12706.31
ARIMA (2,0,4)	0.004	0.002	-12703.99
ARIMA(3,0,2)	0.004	0.002	-12705.98
ARIMA(3,0,3)	0.004	0.002	-12704.34
ARIMA(3.0.4)	0.004	0.002	-12706.67

We learned that the model ARIMA (2,0,4) is the most efficient and suitable model among all the candidate models. Further, this model is utilized to forecast the tether (USDT) coin values. The original versus the fitted values graphical display is given in appendix A. We present the forecasted values of this model in the table below.

Table No: 9 Forecast values of bitcoin using ARIMA (3,1,4) model.

Sample Number	Forecast	Low C. I 95%	Hi C.I 95%
1	1.000641	0.9922853	1.008998
2	1.000719	0.9916743	1.009763
3	1.000770	0.9913679	1.010171
4	1.000814	0.9911898	1.010439
5	1.000857	0.9910163	1.010697
6	1.000898	0.9908705	1.010925
7	1.000937	0.9907354	1.011139
8	1.000975	0.9906177	1.011333
9	1.001012	0.9905107	1.011513
10	1.001047	0.9904160	1.011678
11	1.001081	0.9903306	1.011830
12	1.001113	0.9902545	1.011971
13	1.001144	0.9901862	1.012102
14	1.001174	0.9901252	1.012223
15	1.001203	0.9900705	1.012335

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Discussion

In modeling the digital currency one of the major points to keep in mind is the accuracy criterion and the data span used to explore the feature of the study. Yamak et al., (2019) used different time series and machine learning algorithms to model 500 observations. Munim et al., (2019) used comparative analysis to model the price forecast for the bitcoin for the next day. (Mittal et al., 2018) used different cryptocurrencies to validate the ARIMA model, the deficiency of this study is that the author use this model to forecast the future prices for the next 30 days while these linear models are used only for the short-term forecast. (Cryer et al., 2008; Munim et al., 2019). In this study, the authors combine the four digital currencies with rich data and model them also this work extends the visual analysis of the series to find the best fit for these series. This study uses the correlogram to explore the auto correlational and dependency of series on itself in search of the best fit, further the model is selected based on parsimony law and this model is used for the short term forecasting.

Conclusion

This work aims to model and forecast the future values of the cryptocurrency, namely Binance coin bitcoin, ether coin, and tether coin. To achieve this end, we apply the classical time series approach ARIMA models, also known as the Box-Jenkins methodology, to model and forecast the data series. By applying the model to the different series, we learned that all four cryptocurrencies follow the different structures of the ARIMA model. The model is selected based on forecast accuracy. Namely, root means square error (RMSE), mean absolute percentage error (MAPE), and the Akaike information criteria (AIC). It is found that the Binance coin follows the ARIMA (5,1,5) model, and the other bitcoin, ether coin, and tether coin follow ARIMA (4,1,4), ARIMA (3,1,4), ARIMA (2,0,4) respectively. Furthermore, we use these models to forecast the future values of all four cryptocurrencies with 95% probability limits. Furthermore, this work can be extended to the machine learning approach and correlational study.

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