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CryptoAR: scrutinizing the trend and market of cryptocurrency using machine learning approach on time series data

Abu Kowshir Bitto[1], Imran Mahmud[1,2], Md. Hasan Imam Bijoy[3], Fatema Tuj Jannat[1], Md. Shohel Arman[1], Md. Mahfuj Hasan Shohug[1], Hasnur Jahan[1]
[1]Department of Software Engineering, Daffodil International University, Dhaka, Bangladesh
[2]Graduate School of Business, Universiti Sains Malaysia, Penang, Malaysia
[3]Department Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh

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ABSTRACT

Cryptocurrencies are encrypted digital or virtual money used to avoid counterfeiting and double spending. The scope of this study is to evaluate cryptocurrencies and forecast their price in the context of the currency rate trends. A public survey was conducted to determine which cryptocurrency is the most well-known among Bangladeshi people. According to the survey respondents, Bitcoin is the most famous cryptocurrency among the eight digital currencies. After that, we'll explore the four most well-known cryptocurrencies: Bitcoin, Ethereum, Litecoin, and Tether token. The 'YFinance' python package collects our cryptocurrency dataset, and the relative strength index (RSI) is employed to investigate these cryptocurrencies. Autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models are applied to our time-series data from 2015-1-1 to 2021-6-1. Using the 'closing' price and a simple moving average (SMA) graph, bitcoin and tether are identified as oversold or overbought cryptocurrencies. We employ the seasonal decomposed technique into the dataset before implementing the model, and the augmented dickey-fuller test (ADF) indicates too much seasonality in the dataset. The autoregressive (AR) model is the most accurate in predicting the price of Bitcoin, Ethereum, Litecoin, and Tether-token, with 97.21%, 96.04%, 95.8%, and 99.91% accuracy, consecutively.

Corresponding Author:

Abu Kowshir Bitto
Department of Software Engineering, Daffodil International University
Dhanmondi, Dhaka-1207, Bangladesh
Email: abu.kowshir777@gmail.com

1. INTRODUCTION

Cryptocurrency like bitcoin uses peer to peer connections. In the real world, these cryptocurrencies have no physical existence. They have no visible presence. There has no authority of the government over cryptocurrency. Functioning cryptocurrency relies on a technology called a blockchain. This blockchain was founded to relieve the double-spending problem and interrupt the centralized parties' control in the asset's transaction. It is Bitcoin's most significant invention. The blockchain is used to keep track of all economic and financial transactions. This blockchain uses a cluster of computers. It can be said simply that this technology is so strong that it can keep records permanently of transactions of business, assets, financial data, contract conversion, and property which is intellectual [1]. Because of increasing blockchain interest, the continuous acceptance and FinTech technology by private equity companies and traditional financial institutions, cryptocurrency assets markets have seen huge capital inflows in current years. Cryptocurrencies approachable number for investment climbed to approximately 2000 this time [2]. There have a public address and private key for all cryptocurrencies. The currencies owner got these for receiving and giving coins. This public key address is utilized to find the address and where the coin will deposit. But, without the private key, one will not be able to get them. It is a form of digital cash that may be used to hide one's identity. As a result, its popularity has grown in recent years for these factors. As of February 2017, with 720 cryptocurrencies in existence, since 2009, many cryptocurrencies have been founded [3], [4].

There are now over 1500 active currencies. This research will look at five cryptocurrencies: Bitcoin, Ethereum, Dogecoin, Litecoin, and Stellar (2015-2021). There has been shifting competition among these currencies. The network also affects the currency exchange. A positive shift occurred because of using it more by the people. The more money is utilized, the more precious it becomes [5], [6]. When the exchange is larger and more popular, it becomes more winning to buyer and seller. August 18, 2008, at first bitcoin.org domain name was registered. Bitcoin is the cryptocurrency that is the most decentralized and valued. pseudonym Satoshi Nakamoto introduced it on January 3, 2009 [7]-[9]. Some businessmen began to accept it as traditional currency from 2010 mid. It happened because of approximately 35% of overall market capitalization. The most popular and largest cryptocurrency is Bitcoin. For 81% of the global cryptocurrency market, it is accounting approximately. Although the cryptocurrency idea was introduced in 2009, it became interested among people in 2012. Ethereum is the second most widely used cryptocurrency. It was first presented in 2013 by Vitalik Buterin, a programmer. This currency went online on July 30, 2015, with an insufficient 72 million coins. Elon Musk believes that Dogecoin will be the future of cryptocurrency. Dogecoin was launched on December 6, 2013. Then it swiftly established itself in the internet community, reaching a market value of US$85,314,347,523 on May 5, 2021.

On October 13, 2011, it became live on the internet. Stellar was launched in 2014 by Mt. Gox founder and Ripple co-founder Joyce Kim, a former lawyer. Market players are constantly aware of numerous negative limits; investors in cryptocurrency markets appear to be unaware of the aversion to high risk when significant unfavourable market moves occur. They also appear to be unaware of the danger they are taking since they are caught up in the speculative frenzy of crypto-currency markets [10]. Despite all these efforts to examine the predicting performance of cryptocurrencies, knowing the link between cryptocurrencies is critical for investors who have cryptocurrencies in their portfolios and regulators whose job it is to keep financial markets stable [11]. Cryptocurrency has been around for years and has grown in popularity, acceptance, and controversy because of inventive advances. Cryptocurrencies, as opposed to conventional money, are based on cryptography [12].

We looked at a lot of publications to analyze prior studies. Sifat *et al.* [2] used the vector error correction model (VECM), granger causality, autoregressive moving average (ARMA), autoregressive distributed lag (ARDL), and wavelet Coherence models. There were a total of 9008 observations. He unearthed that crypto traders could not use premium pricing respectively bitcoin (BTC) and ethereum (ETH) to scalp or make a decent profit using hourly and daily statics, and that discrepancies were the price research process respectively BTC and ETH. Chowdhury *et al.* [1] utilized a gradient boosted trees approach to analyse seven features and split data into two groups for testing and training. The functionality of the models looks to be better and more competitive. The ensemble learning approach had a 92.4% accuracy rate, and the gaps were less than in other models; the K-nearest neighbor (K-NN) model hasn't shown to be very successful. In their research, Stoi *et al.* [13] used random matrix theory and the minimum spanning tree approach. The cross-correlation matrix demonstrates non-trivial hierarchical patterns and groupings of cryptocurrency pairings that are not visible in partial cross-correlations, according to the results and daily closing values of the cryptocurrencies mentioned. Using tweets, retweets, and cryptocurrency prices, Li *et al.* [14] depict price variations within ZClassic coin or the alternative cryptocurrency market. They use a classification algorithm of natural language processing, XGboost, Gradient boosting Tree, cross-validation of 10-fold for the entire process. There have some gaps like that they should have trained the positive exhibited trained data.

Abraham *et al.* [15] predict the cryptocurrencies price by applying sentiment analysis to collected tweets to determine if the tweets are typically positive or negative in their thought of cryptocurrencies. There is an effect of these tweeters' sentiment on increasing and decreasing the price of cryptocurrencies in the future. Songmuang [5] used five cryptocurrencies (BTC, ETH, XRP, ADA, XEM) market prices to find the correlation between currencies and forecast the future price. The relationship between ETH and other cryptocurrencies is not studied there. Farell *et al.* [16] showed a breakdown of 21 coins, the evolution of the network security mechanism, and the market capitalization of cryptocurrencies. He also revealed that the industry would be owed to bitcoin for pioneering anarchic coins in the future. Bouri *et al.* [17] investigate equicorrelation return is time-varying and unstable. Between January 1st, 2016, and April 24th, 2016, Alessandretti *et al.* [18] forecast the price of the currencies at day, 2018, using XGboost, different regression, LSTM of the cryptocurrency whose age is greater than 50 and price is more than 100000. But they have ignored fluctuations of intra-day price. The simulated model and its outputs prices of Bitcoins are analyzed and compared to actual prices to find the presence of different trader populations. Cocco *et al.* [19] used the Heterogeneous agent and hypothesis models. They did not consider the dependency on the company of various traders' people. Gandal and Halaburda [4] showed Litecoin was the 2nd strongest cryptocurrency after bitcoin. Bitcoin accounted for 90% of all digital currencies at the end of February 2014. Several researcher also work on non-ML techniques like structural equation modelling [20]-[23] and hybrid model like artificial neural network (ANN) [24] to analysis this type of data.

Many countries have allowed this money to be used till now. Like Japan (called the hub of cryptocurrency), the United States, Nigeria, Germany, Canada, Philippines, France, and Australia. But some countries refuse to provide authorization to use it. Like Bangladesh, Algeria, Bolivia, Morocco, Nepal, Pakistan, and Vietnam. Because it is one of the safest ways to exchange currency in the illegal market. According to people's interest in cryptocurrencies, we conducted a poll for choosing these coins.

2. METHOD

This section is a portion of our systematic workflow procedure. Three segments of methodology are discussed below as: data description that we used in this study, three implemented model descriptions, model implementation procedures and performance metrics of the applied model to predict the bitcoin price and workflow diagram presented in Figure 1.

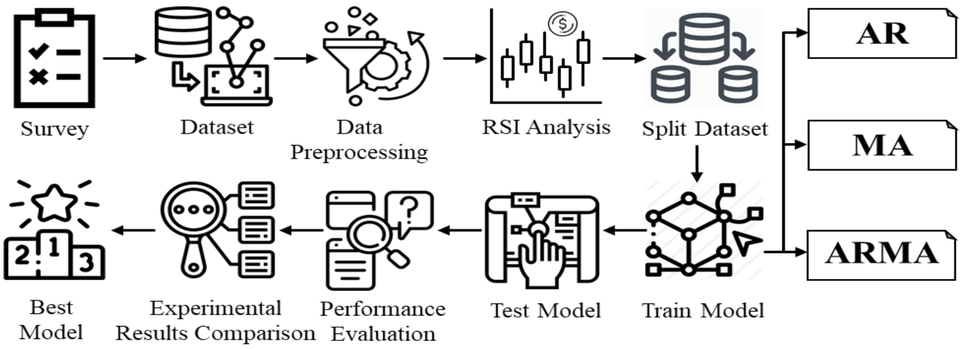


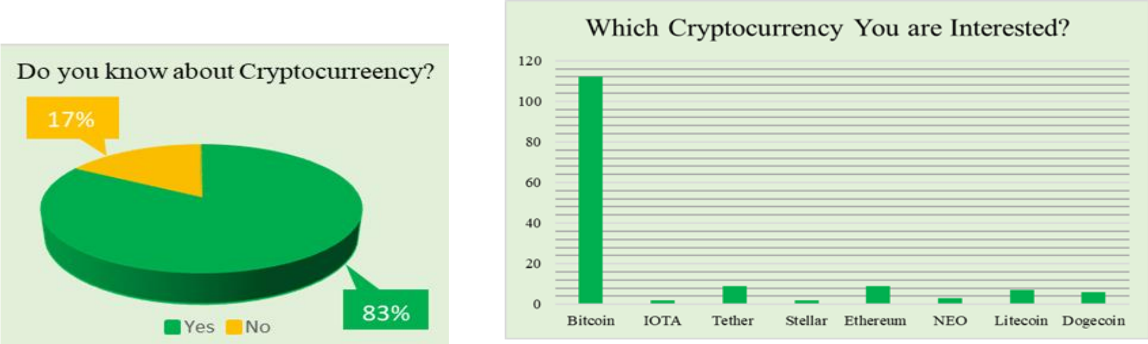
Figure 1. Systematic workflow diagram to predict the cryptocurrency using AR, MA, and ARIMA

2.1. Public survey and selection of cryptocurrency

First and foremost, we conducted a public survey of Daffodil International University's software engineering students. A two-question online survey was conducted, and questions were i) Do you know about cryptocurrency?, ii) Which cryptocurrency you are interested in?. From Figure 2 explain the popularity and interested where Figure 2(a), 150 individuals have signed up to help fill these out. Only 25 individuals out of 150 are unfamiliar with cryptocurrencies, yet they are all familiar with bitcoin. One hundred twenty-five persons are aware of cryptocurrencies, with the majority of them interested in bitcoin. Others are interested in Ethereum, Litecoin, Dogecoin, Neo, Stellar, Tether, and IQTA. We selected these cryptocurrency analyses based on public interest. From Figure 2(b), we picked Bitcoin, Ethereum, Litecoin, and Tether cryptocurrency for study and prediction.

2.2. Dataset and preprocessing

After our selection from Figure 2, we go for data collection based on four cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Tether). Then, we gather time-series data from Yahoo Finance by employing the 'Yfinance' python package. In a time, series, there are six columns. All currency data sorted are obtained from ‘2015-1-1’ through ‘2021-6-1’. There are 2121 rows and 6 columns in our collected dataset. We looked for null values for data preprocessing but could not find any, so we opted to use the dataset as-is. For instance, the screenshot of two datasets from four cryptocurrencies is given below in Figure 3. Figures 3(a) and (b) show the sample data for Bitcoin and Ethereum, respectively.



(a) (b)

Figure 2. Public (a) familiar with cryptocurrency and (b) interested on cryptocurrency

Date	Open	High	Low	Close	Adj Close	Volume
2015-12-31	425.875000	432.920990	418.734985	430.566986	430.566986	45996600
2016-01-01	430.721008	436.246002	427.515015	434.334015	434.334015	36278900
2016-01-02	434.622009	436.062012	431.869995	433.437988	433.437988	30096600
2016-01-03	433.578003	433.743011	424.705994	430.010986	430.010986	39633800
2016-01-04	430.061005	434.516998	429.084015	433.091003	433.091003	38477500
...	...	...	...	...	...	...
2021-05-27	39316.890625	40379.617188	37247.902344	38436.968750	38436.968750	43210968721
2021-05-28	38507.082031	38856.968750	34779.039062	35697.605469	35697.605469	55200191952
2021-05-29	35684.156250	37234.500000	33693.929688	34616.066406	34616.066406	45231013335
2021-05-30	34607.406250	36400.667969	33520.738281	35678.128906	35678.128906	31646080921
2021-05-31	35658.593750	37468.250000	34241.945312	37332.855469	37332.855469	39009847639

(a)

Date	Open	High	Low	Close	Adj Close	Volume
2015-12-31	0.912098	0.975414	0.910277	0.933542	0.933542	663994
2016-01-01	0.933712	0.954822	0.931442	0.948024	0.948024	206062
2016-01-02	0.947401	0.969637	0.936560	0.937124	0.937124	255504
2016-01-03	0.938430	0.991362	0.934313	0.971905	0.971905	407632
2016-01-04	0.972045	0.976438	0.929835	0.954480	0.954480	346245
...	...	...	...	...	...	...
2021-05-27	2888.752441	2888.752441	2642.607910	2736.488525	2736.488525	33373635283
2021-05-28	2742.468994	2761.363281	2336.361328	2419.906250	2419.906250	39999114805
2021-05-29	2414.067139	2566.938477	2208.490967	2279.514160	2279.514160	33773720220
2021-05-30	2278.288818	2472.187744	2188.834473	2390.305420	2390.305420	25876619428
2021-05-31	2387.198486	2715.854980	2279.505127	2714.945312	2714.945312	31007383150

(b)

Figure 3. Sample (a) Bitcoin and (b) Ethereum price data (partial)

2.3. Relative strength index (RSI)

The RSI is indeed a technical indicator that assesses the size of recent price fluctuations to identify if a share or other investment is overbought or oversold. Its goal is to depict companies or market's present and historical strengths and weaknesses using closing prices from past trading periods. A wide trend may also be seen using the RSI. The following is the RSI (1).

$$RSI = 100 - \frac{100}{1+\frac{Average\ Upward\ Price\ Change}{Average\ Downward\ Price\ Change}} \quad (1)$$

2.4. Model implementation (train and test model)

During the model implementation phase, we split our dataset in half, using 80% of the data to train the model and 20% to evaluate its performance. Our train data was used to train the AR, MA, and ARMA. The autoregressive (AR) model stands for the autoregressive model. The order of this model is specified as 'p'. The symbol AR denotes ‘p’ an autoregressive model of order (p). As follows is a description of the AR(p) model:

$$Y_t = \varphi_0 + \varphi_1 \times y_{t-1} + \varphi_2 \times y_{t-2} + \varphi_3 \times y_{t-3} \dots + \varphi_m \times y_{t-m} \quad (2)$$

where,
T = 1, 2, 3…………., t
y_t= signifies Y as a function of time t
φ_m = is in the autoregression coefficients

The moving average (MA) model is a time series model that adjusts for severe short-run autocorrelation. It means that the next observation is the average of all the preceding ones. The order of the moving average model 'q' may usually be determined by looking at the ACF plot of the time series. The symbol MA denotes ‘q’ a satisfied average model order (q). As follows is a description of the MA(q) model:

$$Y_t = \sigma_0 + \sigma_1 \times \sigma_{t-1} + \sigma_2 \times \sigma_{t-2} + \sigma_3 \times \sigma_{t-3} \dots + \sigma_k \times \sigma_{t-k} \quad (3)$$

where, σ the mean of the series is, the parameters of the mode are $\sigma_0, \sigma_1, \sigma_2, \dots \dots \dots . \sigma_k$ and the white noise error terms are $\sigma_{t-1}, \sigma_{t-2}, \sigma_{t-3} \dots \dots \dots \sigma_{t-k}$.

ARMA is used to describe weakly stationary stochastic time series. The first polynomial represents autoregression, while the second represents the moving average. The order of the autoregressive polynomial is denoted by p. The moving average polynomial's order is ‘q’:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{4}$$

where, $\varphi =$ the autoregressive model’s parameters, $\theta =$ the moving average model’s parameters, c = constant, $\sum =$ summation notation, $\varepsilon =$ error terms (white noise).

2.5. Performance measure (error/accuracy)

Based on their forecasting accuracy and error, the estimated models are evaluated and contrasted. With MAE [25], we understood the mean absolute error. In measurement, the amount of the error is the mean absolute error. It is an error measurement between the coupled observations, which express the same event. It also the differences between the actual value and the measured value. It is the total absolute error’s arithmetic average. For example, Y versus X include differences in the predicted value against the observed value. The equation for mean absolute error is (5).

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |x_i - x| \tag{5}$$

Here, n = Errors numbers, $|x_i – x|$ = Absolute errors, Σ = symbol of summation (it means to add all). In statistics, the estimator’s mean square error calculates the error’s square’s average. This average squared find the contrast of the absolute value and estimated values. It shows how near a regression line needs to a set of points. By distance from regression line point, it shows that and then squares them. By this square, it makes all the negative values positive. With mean square error, we find the court of error. It forecasts better when the MSE is low. The equation for mean square error is (6).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} |Actual - forcast|^2 \tag{6}$$

Here, n = items number, Σ = summation, *Actual* = original y-value, *Forecast* = regression y-value. The standard deviation of prediction error is called root mean square error. With residuals or prediction errors, we can calculate where the data points of the regression line are situated. Root mean square error (RMSE) figure out how to expand these prediction errors are. Root mean square error is generally utilized for climatology, regression analysis, forecasting for verifying the result, which is experimental. MSE is a good accuracy measurement. But it only compares the different model’s prediction error for a specific variable, not among variables because it’s scale dependent. The equation for root means square error is (7).

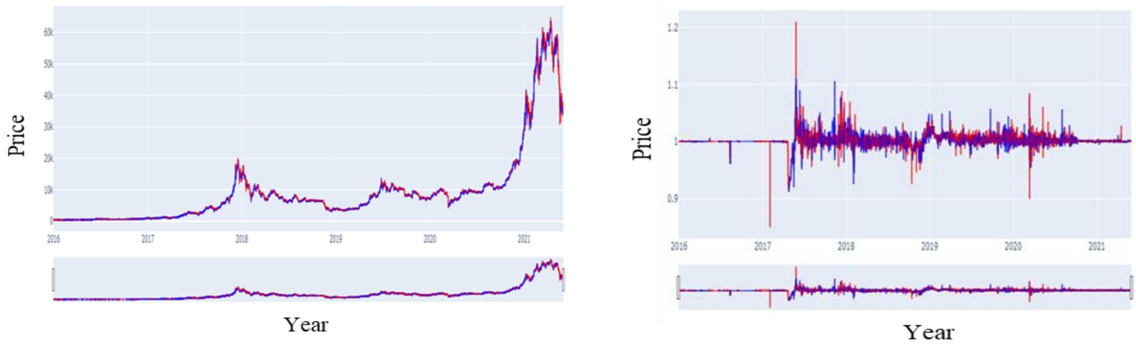
$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} |s_i - o_i|^2} \tag{7}$$

Here, o_i = observations, s_i = variables predicted values, n = Observations number for analysis which is available.

3. RESULTS AND DISCUSSION

We observe an analysis between Bitcoin and Tether based on current trends. Bitcoin, often known as a cryptocurrency or virtual money, is a virtual form of currency. Bitcoin is a peer-to-peer (P2P) computer network primarily used to share digital media files. From Figure 4 provide the analysis Bitcoin and tither where from Figure 4(a), we can observe when the bitcoin price is low and high by looking at the close and open times. Stripe, an online payment company, stated on January 24 that it would phase out bitcoin payments by late April 2018, citing falling demand, higher rates, and lengthier transaction times as causes. PayPal and several stock market companies enabled bitcoin in 2020, and from then until 2021, its price will steadily rise above that of other currencies, putting it at the top of the heap. Tether tokens are the Tether network's native tokens. To decrease the friction of transferring actual money around the cryptocurrency ecosystem, each token is priced at $1.00. We can observe that the price of a token ranges from 0.8 to 1.2 in Figure 4(b).

Figure 5 and Figure 6 shows when bitcoin and tether are oversold or overbought using the close price and a simple moving average (SMA) graph. SMA is an arithmetic moving average produced by combining recent prices, generally closing costs, and dividing that figure by the number of periods in the computation. Manipulate this using a 14-day period where everything below 0 is down, and anything over 0 is up.



(a) (b)

Figure 4. Analysis of (a) Bitcoin and (b) Tether

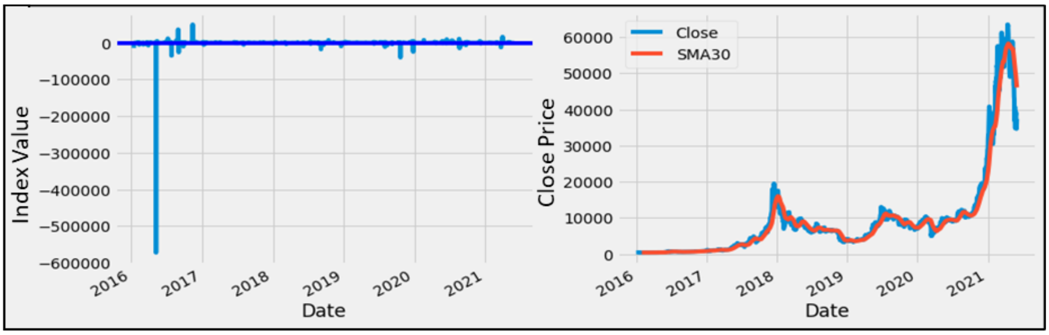


Figure 5. Bitcoin RSI

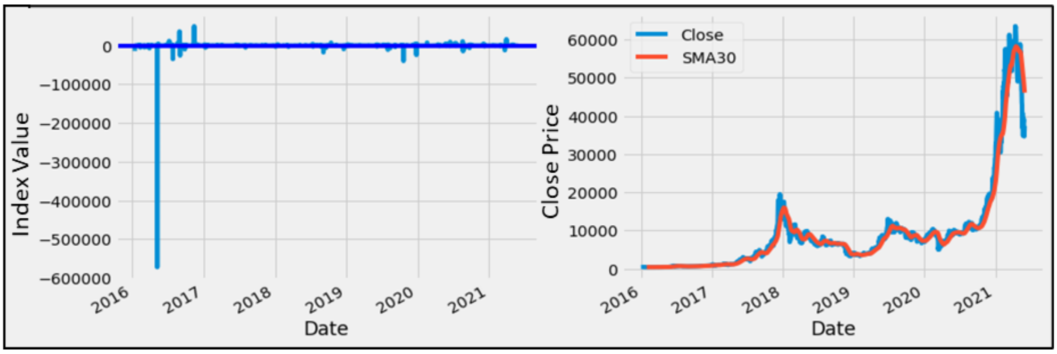


Figure 6. Tether RSI

In this section, we analyze our findings of those cryptocurrencies using a multiple time series model for time series analysis. Here we use three models: AR, MA, and ARIMA models and explore those models for individual currency and predicting the future. First, we need to preprocess the data according to this model; in those models, we need to check the stationary for all cryptocurrencies. This stationarity is limited according to the P-value for those time-series data. Then, we analyzed the 'Close' price for Bitcoin, Ethereum, Litecoin and Tether tokens. Figure 7 shows the plot for predicting the future 'Close' price according to the historical data and where Figures 7(a)-(d) show individually for Bitcoin, Etherum, Litecoin and Tehther Token, respectively.

In this data set for building the time series model for this series data. The autocorrelation plot in Figure 8 refers to observations of a single variable across a specified time horizontal axis for Bitcoin in Figure 8(a), Etherum in Figure 8(b), Litecoin in Figure 8(c), and Tether token in Figure 8(d). From Figure 9 (in Appendix), using the seasonal decomposed method in Figures 9(a)-(c) (in Appendix) this data set has too much seasonality; that is why we are applying the augmented dickey-fuller test (ADF), after founding the rolling mean and slandered deviation for this series dataset and according to the P-value, which is less than 0.05.

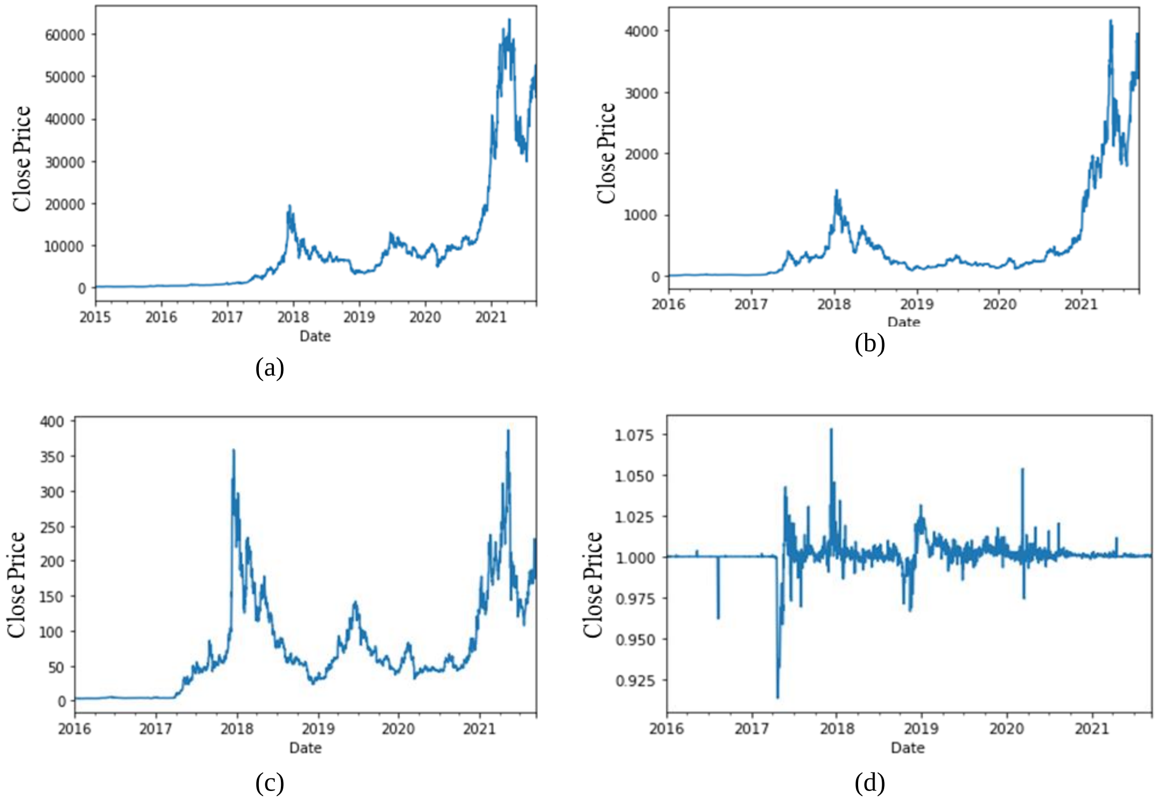


Figure 7. Predecting future close price for (a) Bitcoin, (b) Etherum, (c) Litecoin, and (d) Tehther Token

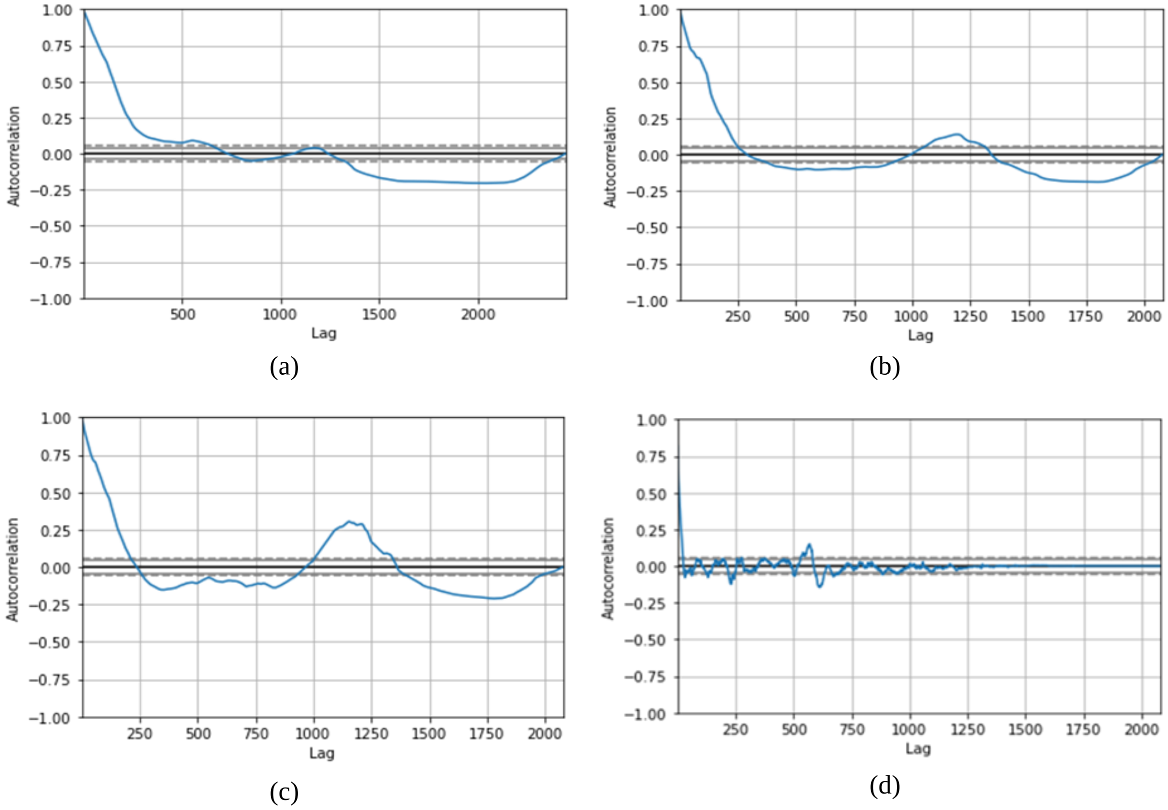
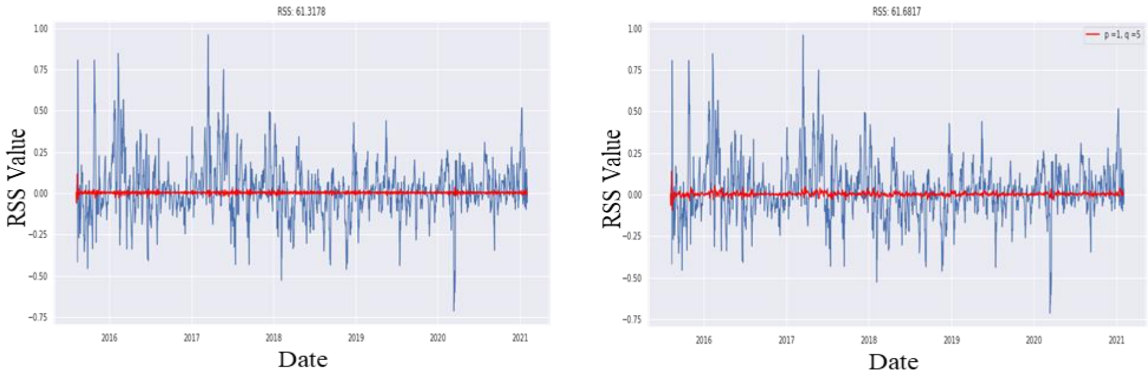


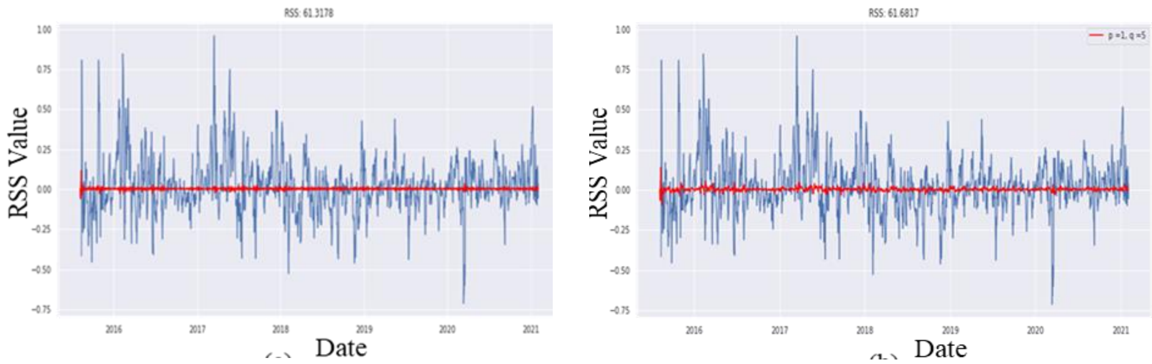
Figure 8. Auto correlation for (a) Bitcoin, (b) Etherum, (c) Litecoin, and (d) Tehther Token

From Figure 10, we applied the AR (1) model and MA (10) with residual sum of squares (RSS) value and ARMA (1, 10) with RSS value where the arguments are p and q which present in Figure 10(a) and (b), respectively. In this fundings which are shown [Tab: 1] models' evaluation where p = 1 and q = 10. We find those values according to the RSS. This RSS defines that RSS defines variance as the amount of variation in a data set. From Figure 11, for this Ethereum coin, we use AR(1) model MA(5) and also ARMA(1, 5) model where p = 1 and q = 5 with the rest of the minimum RSS value. For MA(5), the minimum value of RSS is 62.32 in Figure 11(a), and for ARMA(1,5), the minimum value of RSS is 61.68 in Figure 11(b). From Figure 12, after that, for this Litecoin data set, we build AR (1) model, MA (4) model with the minimum value of RSS is 52.03 and ARMA (1, 2) with the minimum RSS value of 52.02. Build the best model and define which the best for the application is. Finally, here p = 1, and q = 2.



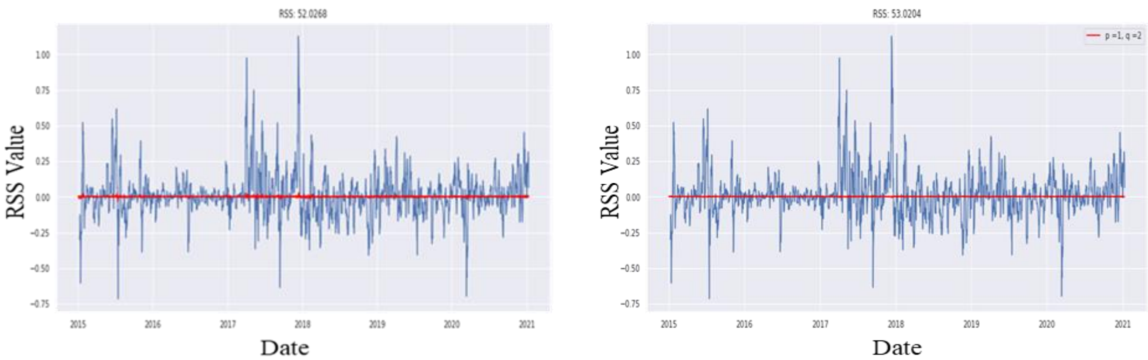
(a) (b)

Figure 10. RSS value with (a) ARMA (1, 10) and (b) MA (10) for Bitcoin



(a) (b)

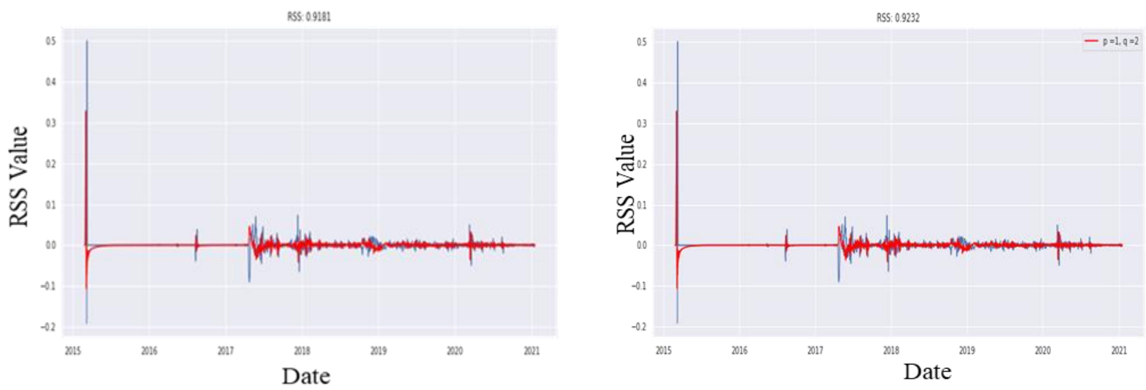
Figure 11. RSS value with (a) MA (5) and (b) ARMA (1, 5) for Ethereum



(a) (b)

Figure 12. RSS value with (a) MA (4) and (b) ARMA (1, 2) for Litecoin

From Figure 13, for building the time series model AR(1). With the minimum value of RSS for the for MA(2) is 0.91 in Figure 13(a) and for the ARMA(1,2) is 0.92 in Figure 13(b). The model evaluation is shown in Table 1 with the mean value, MAE value, RMSE value, and model accuracy after model implementation and performance computation.



(a) (b)

Figure 13. RSS value with (a) ARMA and (b) MA for Tether Token

Table 1. Applied model performance evaluation based on each cryptocurrency

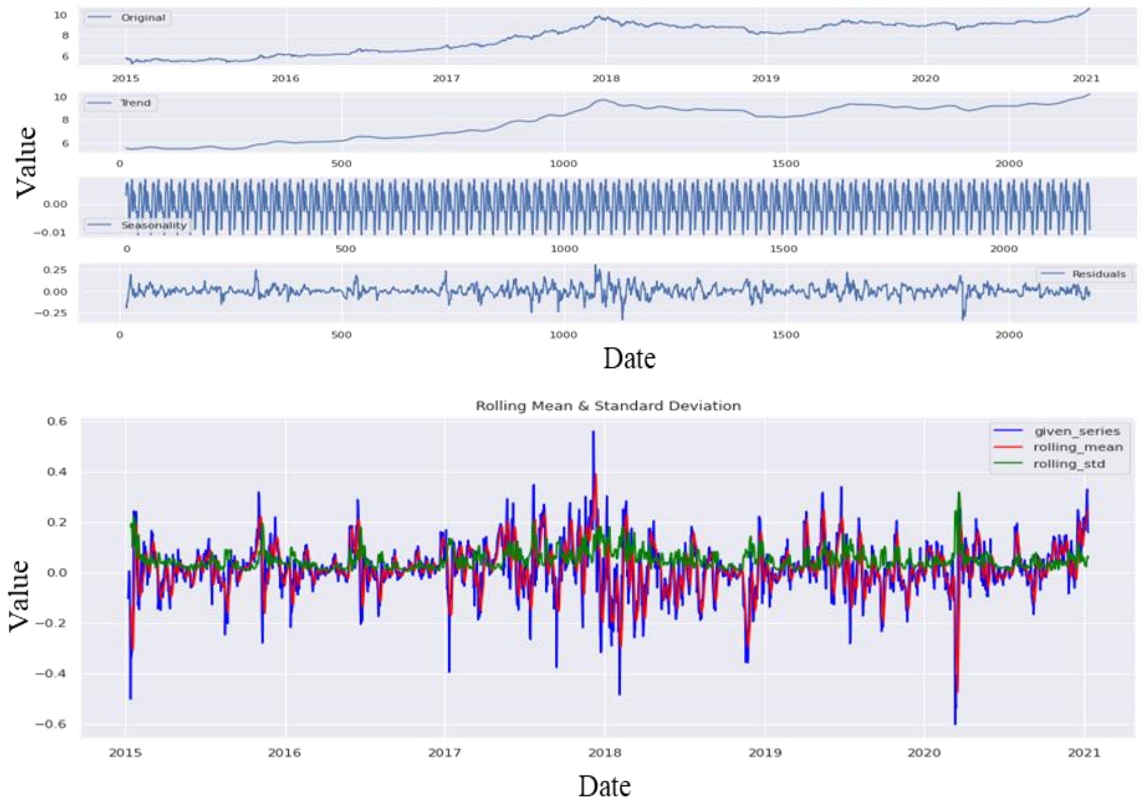
Cryptocurrency	Model	Mean Value	MAE Value	RMSE Value	Model Accuracy (%)
	AR	9248.93	924.74	1480.58	97.21%
Bitcoin	MA	9248.93	13140.41	14841.25	67.97%
	ARMA	9248.93	2084.47	3570.15	81.32%
	AR	489.53	61.29	111.59	96.04%
Etherum	MA	489.53	524.19	698.15	80.70%
	ARMA	489.53	539.66	717.48	80.25%
	AR	72.95	6.01	11.25	95.8%
Litecoin	MA	72.95	33.29	36.26	92.88%
	ARMA	72.95	60.93	72.75	74.25%
	AR	1.001067	0.000939	0.001832	99.91%
Tether Token	MA	1.001067	0.001354	0.001640	99.86%
	ARMA	1.001067	0.001442	0.001739	99.87%

From Table 1, we can choose the AR model for predicting Bitcoin ‘Close’ prices. We also favored the ARMA model. However, we did not utilize the MA model to forecast the Bitcoin’ Close' price because it would not perform better. The AR and MA models outperformed the other two models for Ethereum and Litecoin. Finally, with the Tether Token, we can see that all models worked well and correctly predicted the price, as we previously said. As a result, we may apply any time series model to forecast the future using this dataset.

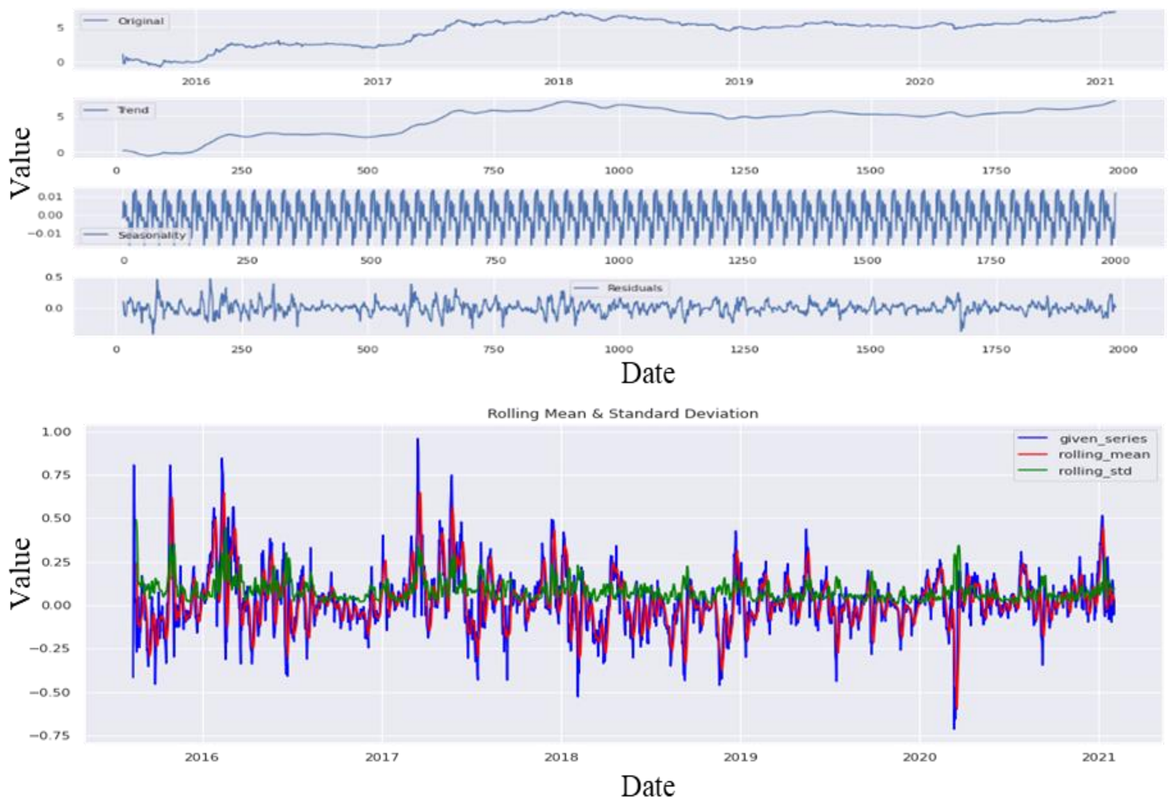
4. CONCLUSION

In this study, we use AR, MA, and ARMA models to forecast cryptocurrency prices. Among the eight cryptocurrencies, Bangladeshis are most familiar with Bitcoin, Ethereum, Litecoin, and Tether token, according to a public survey. The related strength index (RSI) determines if Bitcoin and Tether are overbought or oversold by measuring the magnitude of recent price movements. Based on prior currency periods to closing prices, a coin's present and historical strengths and weaknesses. The P-value for the time-series data determines if all cryptocurrencies are stationary. The P-value, which is less than 0.05, is significant. The null hypothesis (H_0) is rejected since the data does not have a unit root and is stationary. According to our testing data, models give high accuracy in predicting the price of crypto. This research examines the popularity of which cryptocurrency is most familiar to Bangladeshis and the potential for the cryptocurrency sector to grow. Our applied model also displays the anticipated closing price for chosen coins. In the future, an optimization method to fine-tune the closing price to the most acceptable value may be helpful in the study. Alternate response functions can also be used to investigate how the market reacts to additional data.

APPENDIX


Original
Trend
Seasonality
Residuals
Value
Date
Rolling Mean & Standard Deviation
given_series
rolling_mean
rolling_std
Value
Date

(a)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Rolling Mean & Standard Deviation
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rolling_mean
rolling_std
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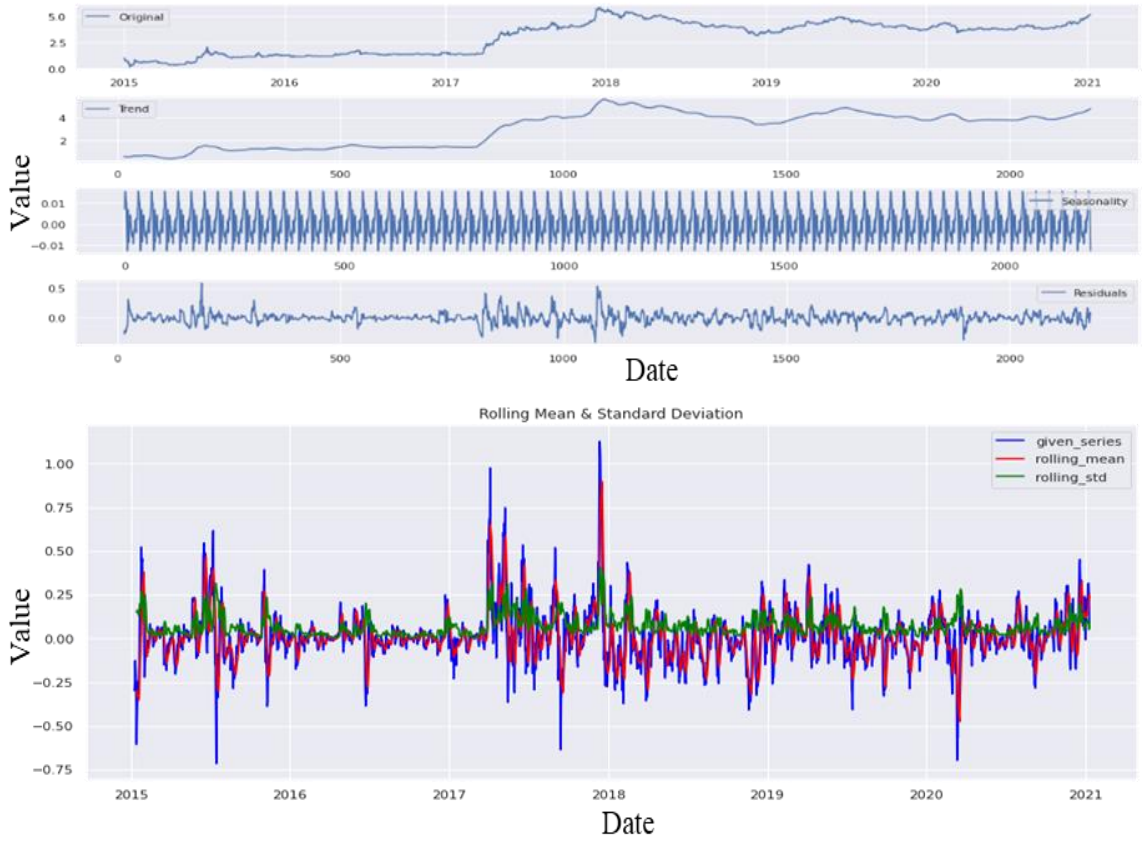
Date

(b)



(c)

Figure 9. The seasonality and ADF test results for (a) Bitcoin, (b) Ethereum, and (c) Litecoin (Continue)

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BIOGRAPHIES OF AUTHORS

Abu Kowshir Bitto received his undergraduate degree in Software Engineering Major in Data Science at Daffodil International University (DIU), Dhaka, Bangladesh. He is currently attending MediprospectsAI as a Research and Development Engineer. He is member of International Association of Engineers. He is a Chief Human Resource Executive (CHRE) at Virtual Multsidisciplinary Research Lab. He previously worked as a Research Assistant at the Data Science Lab DIU. He is an energetic, focused and hard-working person since his student life. His research experience and interest now in Computer Vision, Data Science, and Natural Language Processing. He can be contacted at email: abu.kowshir777@gmail.com.

Dr. Imran Mahmud is an Associate professor and head of the Department of Software Engineering (SWE) at Daffodil International University. He is also an adjunct professor at the Graduate School of Business, Universiti Sains Malaysia. Dr. Imran is an expert in Business Analytics, Technology Management, and Structural Equation Modeling. He can be contacted at email: imranmahmud@daffodilvarsity.edu.bd.

Md. Hasan Imam Bijoy pursued his bachelor's degree (B. Sc) in Computer Science and Engineering (CSE) at Daffodil International University (DIU), Dhaka, Bangladesh. Currently he is working as a Lecturer in CSE department at DIU. He is a Convener of the Virtual Multidisciplinary Research Lab. He is a research zealot, having published over 15 conference papers, 4 journal publications, and one programming book [A Handbook of C Programming with Example]. He is presently acting as a reviewer at MLIS 2022, and performed the role of Reviewer at ICECET2022, ICECET2021 and ICECCME2022, ICECCME2021. His area of interest includes Machine Learning, Deep Learning, Computer Vision, Natural Language Processing, Image Processing, Internet of Things, and so many field. He can be contacted at email: hasan15-11743@diu.edu.bd.

Fatema Tuj Jannat received her undergraduate degree in Software Engineering at Daffodil International University (DIU), Dhaka, Bangladesh.She is a professional Graphic and UI/UX designer. She also works on several UI/UX design contractual projects. She is a quick learner and hard working person in her life. Her research experience and interest now in Machine Learning. She can be contacted at email: jannat.fatema7940@gmail.com.

Md. Shohel Arman is Assitant Professor and alumni of Department of Software Engineering under Faculty of Science & Information Technology in Daffodil International University, Dhaka, Bangladesh. He is an energetic and focused man since his student life. His research interests are distributed database system, machine learning, data mining nternet of things (IoT), software security and management information system (MIS). He can be contacted at email: arman.swe@diu.edu.bd.

Md. Mahfuj Hasan Shohug completed his graduation in Software Engineering major in Data Science from Daffodil International Dhaka, Bangladesh. He is currently a Web Designer at Bardown Sports Inc. He is an ambitious, hard-working, and very punctual person in his life. His research interest is in Machine Learning and Data Science. He can be contacted at email: mahfuj.shohug@gmail.com.

Hasnur Jahan is a Teaching Apprentice Fellow (TAF) of the Department of Software Engineering at Daffodil International University, Dhaka Bangladesh. Also, she completed her bachelor of science degree in software engineering there. Her interest in research is machine learning, Image processing, and natural language processing. She can be contacted at email: hasnur35-2297@diu.edu.bd.