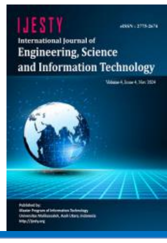
International Journal of Engineering, Science and InformationTechnology
Volume 4, No. 4 (2024) pp. 63-71
ISSN 2775-2674 (online)
Website: http://ijesty.org/index.php/ijesty
DOI: https://doi.org/10.52088/ijesty.v4i4.577
Research Paper, Short Communication, Review, Technical Paper



Comparison of Triple Exponential Smoothing and ARIMA in Predicting Cryptocurrency Prices

Adi Prasetyo[1], Nurdin[2]*, Hafizh Al Kautsar Aidilof[1]

[1]Department of Informatics, Faculty of Engineering, Universitas Malikussaleh, Aceh, Indonesia
[2]Department of Information Technology, Faculty of Engineering, Universitas Malikussaleh, Aceh, Indonesia

**Corresponding author Email: nurdin@unimal.ac.id*

The manuscript was received on 11 March 2024, revised on 26 April 2024, and accepted on 18 September 2024, date of publication 10 October 2024

Abstract

Cryptocurrency has emerged as a prominent digital asset over the past decade, attracting widespread attention due to its decentralized nature and potential for high returns. However, its extreme price volatility presents significant challenges for investors, making accurate price forecasting crucial for risk management and investment optimization. This study evaluates and compares the effectiveness of two widely used time series forecasting methods: Triple Exponential Smoothing (TES) and Autoregressive Integrated Moving Average (ARIMA). TES is particularly suited for capturing long-term trends and seasonal patterns in data, while ARIMA is more versatile in modeling autoregressive patterns and moving averages, making it suitable for both stationary and non-stationary time series. The research focuses on predicting the prices of five major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Solana (SOL), and Ripple (XRP). The dataset, comprising daily price data from January 2021 to December 2023, is divided into 80% for model training and 20% for testing. The performance of both models is evaluated using two error metrics: Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), which are essential for assessing forecast accuracy. The findings reveal that TES outperforms ARIMA in forecasting Bitcoin and Binance Coin prices, with MAPE values of 10.38% and 13.81%, respectively, while ARIMA delivers better accuracy for Ethereum, Solana, and Ripple, with MAPE values ranging from 8.78% to 32.84%. Notably, Ethereum records the lowest MAPE at 8.78%, and Ripple exhibits the smallest RMSE at 0.08. These results highlight that TES is more effective for relatively stable cryptocurrencies, while ARIMA is better suited for predicting the prices of more volatile assets, emphasizing the importance of choosing the appropriate model based on asset-specific characteristics.

Keywords: *Cryptocurrency, Volatility, Forecasting, Triple Exponential Smoothing, ARIMA.*

1. Introduction

In the past decade, cryptocurrencies have rapidly grown as digital assets, particularly in the financial world, attracting investors, traders, and users with their unique characteristics such as security, decentralization, and transparency. Bitcoin is a decentralized cryptocurrency, which is a type of digital asset that provides the basis for peer-to-peer financial transactions based on blockchain technology. One of the main problems with decentralized cryptocurrencies is price volatility, which indicates the need for studying the underlying price model [1]. However, the high volatility of cryptocurrency prices poses significant challenges for investors, making accurate price prediction essential. The development of technology today makes all activities simple because access to information becomes easier and can be reached by anyone [2].
Today the development of information technology is increasing rapidly with the existence of websites, which have become a familiar need for the social community [3]. According to CoinMarketCap, the global cryptocurrency market capitalization reached $2 trillion in 2023, a significant increase from $100 billion in 2017. Despite this rapid growth, high volatility remains a major barrier to mass adoption. For instance, Bitcoin's price peaked at $68,000 in November 2021 but plummeted to $17,000 by June 2022, causing substantial losses for many investors. In Indonesia, the number of cryptocurrency investors has grown significantly, reaching 17.25 million in April 2023, an increase from 13.73 million in April 2022 [4]. The increase in the number of investors is due to the increasing public interest in investing

[5]. In addition, the survey also showed that the younger generation (millennials and gen Z) investing in cryptocurrencies has doubled from late 2020 to 2021. All of this shows the growing interest of Indonesians in crypto investment[6].

Bitcoin is the largest cryptocurrency in the world, but its lack of quantitative qualities makes fundamental analysis of its intrinsic value difficult[7]. Many factors influence cryptocurrency prices, including speculation, economic conditions, government regulations or policies, decisions by central banks, and others[8]. Focusing on the top five cryptocurrencies—Bitcoin, Ethereum, Binance Coin, Solana, and XRP provides relevant and beneficial insights for investors and stakeholders. These cryptocurrencies have large market capitalizations, high liquidity, and widespread adoption, making accurate price predictions crucial for informed investment decisions and risk management strategies.

The Triple Exponential Smoothing (TES) method, and the ARIMA model are widely used for time series forecasting. TES is based on three smoothing equations for stationary, trend, and seasonal components. ARIMA, on the other hand, uses previous values of the time series for forecasting and can capture patterns in both stationary and non-stationary data. While these methods have been applied in various forecasting scenarios, their effectiveness in cryptocurrency price prediction needs further exploration. This study aims to compare the performance of TES and ARIMA in predicting the prices of five major cryptocurrencies: Bitcoin, Ethereum, Binance Coin, Solana, and Ripple. By using historical data and evaluation metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), this study seeks to determine which method provides more accurate forecasts for each cryptocurrency.

There are several previous studies related to the research topic that the author did, such as research conducted by[8] Implementation of Triple Exponential Smoothing is used to predict the Rupiah exchange rate against cryptocurrencies to overcome the problem of price fluctuations in the crypto market. The method shows a relatively accurate prediction with a small margin of error when applied to a dataset consisting of fifty data samples from May 2022 to June 2022, according to the MAPE value of 3.7249%. Then research conducted by[9] examining the most optimal crypto prediction model ability to remember and store data records. The data collected are price records of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Cardano (ADA), and Dogecoin (DOGE).

Another research by[10] The research results in this journal show the ARIMA model with parameters p, d, q (0,2,1) as the best model in forecasting the close stock price of PT. Telekomunikasi Indonesia with the equation in the model is $\mathrm{Y}tt = YYY -1 - 0{,}01039 - 0{,}9680\varepsilon\varepsilon\varepsilon -1$. The author also takes reference from a previous research journal from[11] Based on the results of ARIMA analysis, it is found that the best forecasting model for confirmed COVID-19 is the model (1:0:1) with AIC values (14.22672), SIC (14.33357), while for COVID-19 recovered is the model (1:2:3) with AIC values (13.93054), SIC (13.03738), and the COVID-19 case died is the model (1:2:1) with AIC values (10.76105) and SIC (10.86790).Conclusion: From the results of this study, it is predicted that there will be an increase in COVID-19 cases in July 2022, January 2023 and June 2023.

There are several previous studies related to the comparison of the two methods used by the author[12] Based on the comparison between the ARIMA and Triple Exponential Smoothing models, it can be seen that the best method for forecasting non-oil and gas export data in East Kalimantan is using the Triple Exponential Smoothing method where the resulting RMSE value is 42.68, and MAPE is 1.9344. This study investigates the influence of gold prices and five supporting variables in the form of economic indicators, namely crude oil prices, federal funds rate, consumer price index, effective exchange rate, and S&P 500 stock market index between 2002 and 2022. The model was built using ARIMA and LSTM methods. Comparison of the actual gold price with the predicted value of each model shows that LSTM has the best performance compared to the ARIMA model [13].

This research aims to fill the gap in cryptocurrency price forecasting studies by comparing the effectiveness of Triple Exponential Smoothing (TES) and Autoregressive Integrated Moving Average (ARIMA) methods in forecasting the prices of the top five crypto coins: Bitcoin, Ethereum, Binance Coin, Solana, and XRP. Given the high volatility of the cryptocurrency market, accurate analysis is necessary but often requires complex calculations. Using accurate historical price data, this study will identify the method that provides the most accurate price predictions for each coin. The significance of this research lies in its potential to provide valuable insights into the relative performance of the two methods, serve as a foundation for better investment decision-making, and assist investors in choosing the right forecasting method. The results of the study are expected to not only contribute to the academic understanding of cryptocurrency market dynamics, but also have significant practical implications for market participants, including providing a basis for the development of analytical systems that can assist novice investors in analyzing price movements and determining optimal investment strategies.

2. Literature Review

2.1. Previous Research

In research by Kate Murray et al. (2023), titled "On Forecasting Cryptocurrency Prices: A Comparison of Machine Learning, Deep Learning, and Ensembles", the authors explore the effectiveness of various forecasting models, including ARIMA, LSTM, and hybrid models, in predicting cryptocurrency prices. The study focuses on popular cryptocurrencies like Bitcoin, Ethereum, and XRP, demonstrating that LSTM (a deep learning model) consistently outperforms other methods in terms of accuracy, highlighting the importance of model selection based on specific crypto assets[14].

In research by M. Dritsaki and C. Dritsaki (2021)**,** titled "Comparison of the Holt-Winters Exponential Smoothing Method with ARIMA Models: Forecasting of GDP per Capita in Five Balkan Countries Post COVID"**,** the authors compare the forecasting accuracy of ARIMA and Triple Exponential Smoothing (TES) in predicting GDP per capita. The study evaluates both models using metrics such as RMSE and MAPE. The findings indicate that ARIMA is more accurate for long-term forecasts, while TES performs better in datasets with seasonal patterns, due to its ability to assign higher weight to recent data. This highlights the importance of selecting a forecasting method based on the data's characteristics[15].

In research by Kirill Kashtanov et al. (2022)**,** titled "Using Triple Exponential Smoothing and Autoregressive Models to Forecast Mining Equipment Details Sales"**,** the authors employ both TES and ARIMA to predict sales in the mining industry. This study highlights how TES is more effective in dealing with seasonality, while ARIMA works better in datasets without clear seasonal patterns. This can provide a solid basis for understanding how these models compare in forecasting trends with seasonality, relevant to cryptocurrency price predictions[16].

In the research by Konstantinos P. Fourkiotis and Athanasios Tsadiras (2024)**,** titled "Applying Machine Learning and Statistical Forecasting Methods for Enhancing Pharmaceutical Sales Predictions", the authors explore the application of machine learning techniques like XGBoost and traditional models such as ARIMA and Triple Exponential Smoothing (TES) to predict pharmaceutical sales. Their findings show that while TES handles seasonality well, advanced machine learning models, such as XGBoost, significantly improve accuracy in sales forecasting[17].

2.2. Forecasting

Forecasting is the process of calculating future requirements for goods or services, including the quantity, quality, time, and location required to meet demand. Prediction is a process to forecast something that might happen in the future based on past and present data information, so that errors can be minimized[18]. The forecasting process is done by scientific and systematic methods. Qualitative properties such as feelings, experiences, and others are very important in forecasting and use scientific or organized procedures[19]. Accurate forecasting results allow companies to plan strategies and make informed business decisions. Some of the most commonly used forecasting models include time series models, such as moving averages, smoothing, linear regression, and ARIMA; causal models, such as multiple regression analysis; and qualitative methods, such as Delphi, sales force polling, and executive opinion.

2.3. Triple Exponential Smoothing

The Triple Exponential Smoothing forecasting method, which was proposed by Brown and uses a quadratic equation, is used to forecast data subjected to tidal surges. This method extends basic Exponential Smoothing by incorporating multiple smoothing equations that estimate level, trend, and seasonal components. The interesting thing about exponential smoothing is that the most weight is given to the most recent observations[20]. The method allocates more importance to recent data points, which allows the model to adapt more quickly to recent changes in the data. The three equations are defined to estimate the level, trend, and seasonal elements respectively. Therefore, quadratic smoothing the basic approach is to include an additional level of smoothing (triple smoothing) and apply quadratic forecasting equations[21].
In this study, the method used is Triple Exponential Smoothing which is used as a method to forecast cryptocurrency, the working steps of the Triple Exponential Smoothing Method are as follows:

Exponential smoothing of original data, level pattern ( ):

( ) ( )( ) .... (1)

Trend pattern smoothing ( ):

( ) ( ) .... (2)

Seasonal pattern smoothing (S_t):

( ) ( ) .... (3)

Forecast m periods ahead ( ):

$$F_{t+m} = A_t + T_t m + S_{t-L+m}$$ .... (4)

Description:

α, β, γ	= Alpha, beta, gamma parameters
y_t	= Actual value at time t
A_t	= Smoothed level value at time t
T_t	= Trend level value at time t
S_{t-L}	= Seasonal component in the previous period (lag of L).
A_{t-1}	= The smoothed level value in the previous period.
T_{t-1}	= The smoothed trend value of the previous period.
1	= Smoothing for observation values.
Ft+m	= The forecasting result for the next m periods.
m	= The number of periods to be forecasted in the future.

2.4. Autoregressive Integrated Moving Average

The Autoregressive Integrated Moving Average or ARIMA forecasting method is a statistical model used for the analysis and forecasting of time series data. This model incorporates a combination of Autoregressive (AR), Moving Average (MA), and differencing models. ARIMA is also known as the Box-Jenkins method. ARIMA can be used if the time series data observations are interconnected[22]. In this study, the method used is Autoregressive Integrated Moving Average which is used as a method to forecast cryptocurrency, the ARIMA (p,d,q) model can be written as follows:

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B) e_t \quad \ldots\ldots (5)$$

Description:

$\phi_p(B)$ = Autoregressive polynomial of order p

$(1-B)^d$ = Operator differencing of order d

Z_t = Time series data observed at time t

$\theta_q(B)$ = Polynomial moving average of order q

e_t = Error term / white noise at time t

2.5. Cryptocurrency

Cryptocurrency is a digital or virtual currency that can be used online or virtually because it is protected by cryptographic algorithms. Therefore, the country's central bank or Bank Indonesia cannot reject cryptocurrencies, which makes it unable to be manipulated by the government[9]. Blockchain is a distributed ledger that records all transactions that occur within a cryptocurrency network.

3. Research Methods

The system plan for comparing Triple Exponential Smoothing and ARIMA in cryptocurrency price prediction involves several stages. First, historical cryptocurrency price data, including open, close, high, and low values, is collected using financial data sources such as Yahoo Finance. The data is then preprocessed data. Next, hyperparameter tuning is performed for both models. Both the TES and ARIMA models are built and trained. The models are evaluated using test data, with Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) as evaluation metrics. The research flow is depicted in Figure 1.

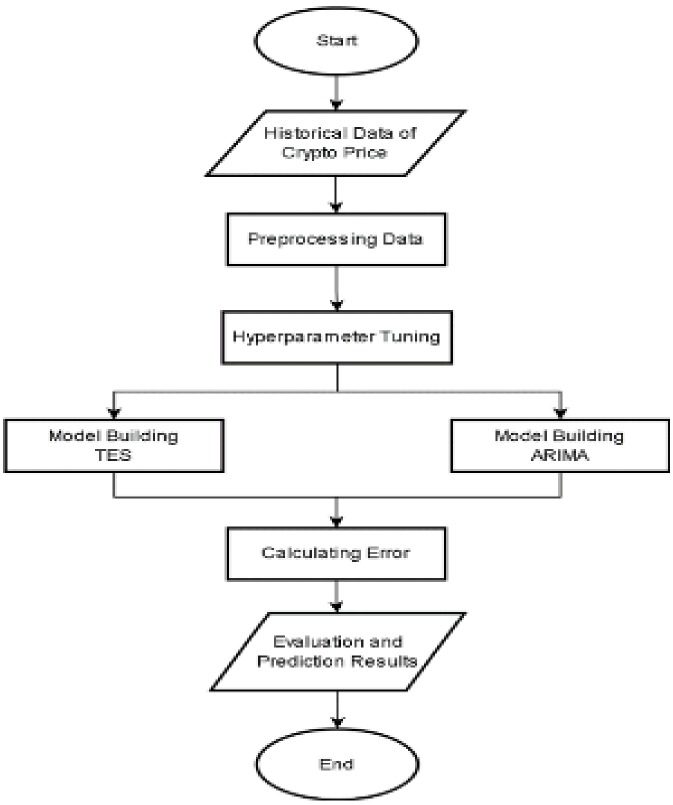


Fig 1. Research Flow Diagram

3.1. Library Import

Before building a model, import libraries are imported to facilitate model building, in this case, the libraries used are as follows.

1. Streamlit library: Streamlit is an open-source application framework used to create and share data applications. This is very useful for data science and machine learning projects.
2. Numpy Library: Numpy is a fundamental package for scientific computing in Python. It provides support for arrays, math operations, and other functions related to numerical computing.
3. Pandas library: pandas is a library for data manipulation and analysis. It offers data structures and operations for manipulating numerical tables and time series.

4. Scikit-Learn Library: Scikit-Learn is a library for machine learning in Python. Used to evaluate the prediction accuracy of cryptocurrency price forecasting models by measuring the model error.
5. Statsmodels Library: Statsmodels is a library that provides various statistical and econometric tools for time series analysis. In this research, statsmodels is used to develop a cryptocurrency price forecasting model using the Triple Exponential Smoothing (TES) and Autoregressive Integrated Moving Average (ARIMA) methods.
6. Plotly library: Plotly is a library for interactive data visualization. Graph objects is used to create various graphs, such as line, bar, and candlestick graphs.
7. YFinance Library: a library that allows easy access to historical market data from Yahoo Finance.

3.2. Data Import

The dataset or historical data used is taken from one of the historical data provider platforms, namely finance.yahoo.com. The dataset used in this study consists of daily price data of the top five cryptocurrencies (Bitcoin, Ethereum, Binance Coin, Solana, and XRP) over a three-year period, from January 1, 2021 to December 31, 2023. This data includes daily price movements that reflect the dynamics of the cryptocurrency market over a significant period, including various market phases and global economic events. This historical data is the basis for the analysis and predictions that will be carried out in this study.

3.3. Data Preprocessing

Data visualization is an important early stage in understanding the trends and patterns that exist in Yahoo Finance's stock closing price data. The main plot with four plot lines (Opening Price, Closing Price, Low Price, and High Price) gives an overview of how stock prices fluctuate over time. It helps in identifying general trends, volatility, and patterns of crypto price movements.

Preprocessing is an essential phase to ensure the data is ready for forecasting models. First, missing values are managed by cleaning irrelevant data, removing duplicates, and replacing incomplete data using methods like interpolation, depending on the nature of the missing values. Outliers, which can impact model performance, are detected using Z-scores to identify data points that deviate significantly from the mean. Decisions are then made to remove, adjust, or retain these outliers. Finally, the dataset is divided into two parts, namely training data (train) and test data (test). This division is done by taking 80% of the data (876 data) as training data and the remaining 20% (219 data) as test data. to evaluate the model's performance on unseen data, ensuring it generalizes well to new datasets. This structured preprocessing step enhances model accuracy and reliability.

3.4. Hyperparameter Tunning

Hyperparameter tuning is a critical step in the model development process, ensuring optimal performance for both Triple Exponential Smoothing (TES) and ARIMA models. For TES, key hyperparameters include smoothing parameters for level (alpha), trend (beta), and seasonality (gamma), which are adjusted within a range of 0.10 to 0.90. A grid search technique is employed to find the combination that minimizes forecasting error, specifically targeting the lowest Mean Absolute Error (MAE).

Similarly, for ARIMA, parameters such as p (autoregressive), d (differencing), and q (moving average) are optimized based on the analysis of ACF and PACF, with values ranging from 1 to 3. The grid search tests various parameter combinations to identify the optimal settings for minimizing MAE. By fine-tuning these parameters, the models are adapted to capture complex patterns in cryptocurrency price data, ensuring accurate and reliable forecasts. This meticulous optimization process strengthens the predictive power of both models, improving their performance on unseen data.

3.5. Model Building TES and ARIMA

The model building phase involves developing and fine-tuning the forecasting models using the preprocessed data and optimized hyperparameters identified in the previous step to predict cryptocurrency prices. For this study, two models are constructed: Triple Exponential Smoothing (TES) and Autoregressive Integrated Moving Average (ARIMA). TES focuses on capturing the level, trend, and seasonality in the data, while ARIMA models the autoregressive, differencing, and moving average components.

3.6. Results and Model Evaluation

After training, the TES and ARIMA models were evaluated using test data. Testing the results is intended to obtain accurate data from the system built, ensuring it runs according to the research objectives[23]. The evaluation was conducted by calculating several metrics, including Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE).

MAPE is a performance accuracy evaluation method by calculating the average absolute deviation percentage of the actual value divided by the actual value[24]. The MAPE formula is presented in the equation below:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \times 100 \quad \ldots\ldots\ldots\ldots \quad (6)$$

Description:

$\hat{y}_i$ = Forecasting result value.

yi = Actual value.

n = Number of data samples.

RMSE serves as a reliable measure of prediction accuracy, so it is often used as a benchmark indicator to assess model performance. The smaller the RMSE value, the better the model performance[25]. The RMSE formula can be seen in equation below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \quad \ldots\ldots\ldots\ldots \quad (7)$$

Description:

$\hat{y}_i$ = Forecasting result value.
yi = Actual value.
n = Number of data samples.

These metrics help assess how accurately the models predict cryptocurrency closing prices by comparing predicted results with actual data. Visualizations of predicted versus actual data provide a clear understanding of the model's performance, highlighting areas where predictions may fall short.

Further discussion explores the strengths and weaknesses of the Triple Exponential Smoothing (TES) and ARIMA models, identifying where one model outperforms the other and suggesting potential improvements for future use. Once the evaluation is complete, the final step is to save the trained models in Pickle format, allowing the models, along with their optimized parameters, to be reused without retraining, thus improving operational efficiency. Both TES, with tuned alpha (α), beta (β), and gamma (γ) parameters, and ARIMA, with tuned p, d, and q parameters, are stored for future predictions, ensuring their long-term utility in forecasting cryptocurrency prices.

4. Results And Discussion

4.1. Prediction Results

In this research, the problem analysis, database analysis, and implementation of TES and ARIMA methods to predict crypto prices are crucial to ensure the success of this research. The chosen period for forecasting is the daily crypto price movements. The following table shows the evaluation scores of TES and ARIMA predictions for the top 5 cryptocurrencies, covering the period from January 2021 to December 2023. The prediction is done in the same way for both methods. The results are summarized in Table 1:

Table 1. Prediction Results

No	Cryptocurrency Coins	RMSE TES	RMSE ARIMA	MAPE TES	MAPE ARIMA
1	Bitcoin (BTC-USD)	4,130.77	4,731.45	10.93%	10.95%
2	Ethereum (ETH-USD)	205.33	204.64	8.97%	8.79%
3	Binance Coin (BNB-USD)	41.46	53.42	13.10%	15.63%
4	Solana (SOL-USD)	20.32	19.12	29.75%	32.84%
5	Ripple (XRP-USD)	0.09	0.08	9.15%	10.54%

The TES algorithm shows satisfactory prediction results with an RMSE of 4,130.77 and a MAPE of 10.93% for Bitcoin (BTC-USD), demonstrating its ability to predict the price of this cryptocurrency with a relatively low error rate. Ethereum (ETH-USD) also shows good prediction results with an RMSE of 205.33 and a MAPE of 8.97%, indicating a solid performance by the TES model for this coin. Binance Coin (BNB-USD) exhibits an RMSE of 41.46 and a MAPE of 13.10%, while Solana (SOL-USD) has an RMSE of 20.32 and a MAPE of 29.75%, and Ripple (XRP-USD) achieves an RMSE of 0.09 and a MAPE of 9.15%. These results suggest that the TES model is capable of providing relatively accurate price predictions across various cryptocurrencies, although the error rate varies depending on the coin, with MAPE values ranging from 8.97% to 29.75%.

Meanwhile, the ARIMA algorithm also shows satisfactory prediction results. For Bitcoin (BTC-USD), ARIMA obtains an RMSE of 4,731.45 and a MAPE of 10.95%, while for Ethereum (ETH-USD), it achieves an RMSE of 204.64 and a MAPE of 8.79%. Binance Coin (BNB-USD) shows an RMSE of 53.42 and a MAPE of 15.63%, Solana (SOL-USD) has an RMSE of 19.12 and a MAPE of 32.84%, and Ripple (XRP-USD) achieves an RMSE of 0.08 and a MAPE of 10.54%. These findings indicate that the ARIMA model also performs well in predicting cryptocurrency prices, although, similar to TES, the error rates vary across different coins, with MAPE values ranging from 8.79% to 32.84%.

Based on the table data above, it is observed that the TES algorithm has more consistency in predicting cryptocurrencies, leading with three out of the five coins showing lower RMSE and MAPE values compared to the ARIMA algorithm. This suggests that TES may have a slight edge over ARIMA in terms of prediction accuracy for the top cryptocurrencies analyzed in this study.

4.2. Analysis of TES and ARIMA Prediction Results

The results from the previous table show that the ARIMA model predicts the prices of three cryptocurrencies—Ethereum, Solana, and Ripple—with better evaluation scores compared to TES, which predicts two cryptocurrencies—Bitcoin and Binance Coin—with better scores. The following analysis explores whether there are any distinct patterns or similarities in the cryptocurrencies predicted more accurately by either ARIMA or TES. The ARIMA model achieved better evaluation scores for Ethereum, Solana, and Ripple, while TES performed better for Bitcoin and Binance Coin. To further examine potential patterns in price movements and volatility among these cryptocurrencies, Figure 2 below provides a visualization of the price trends.

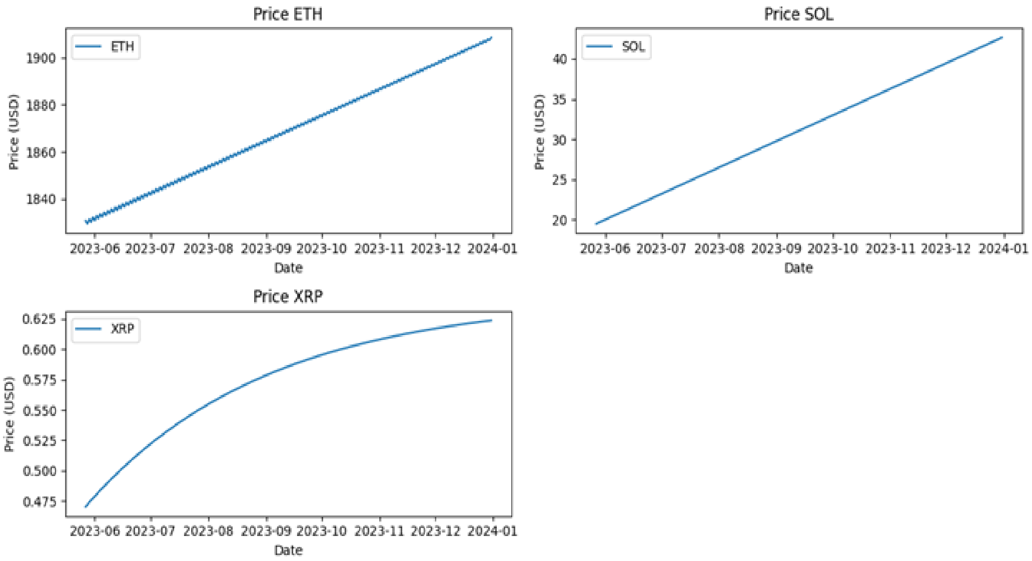


Fig 2. Graph Visualization of ARIMA Superior Coin Data

Based on the graph above, Ethereum (ETH) and Solana (SOL) exhibit similar characteristics with consistent upward price trends and minimal fluctuations, indicating stable growth through early 2024. In contrast, Ripple (XRP) also experiences price increases, but at a slower pace, with the trend flattening towards the end of 2023, suggesting price stabilization after an initial rise. These patterns indicate that while ETH and SOL demonstrate strong and steady growth, XRP shows signs of stabilization following more gradual price increases.

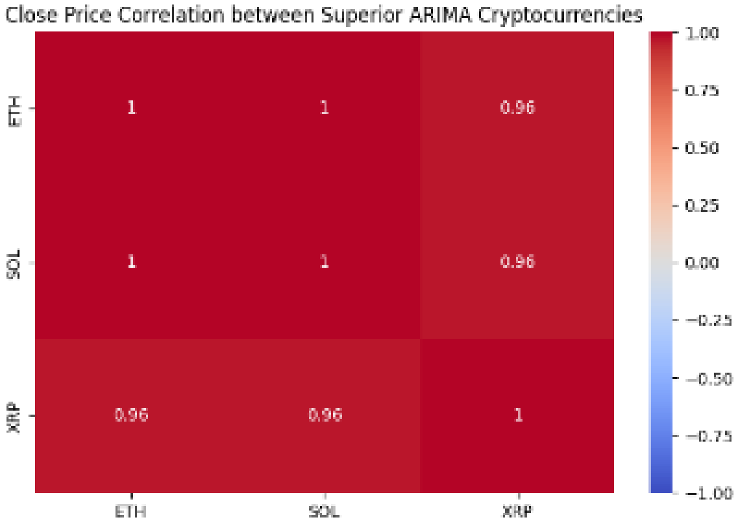


Fig 3. Superior Crypto ARIMA Correlation Visualization

Based on the correlation visualization, it can be concluded that several cryptocurrencies, namely Ethereum (ETH), Solana (SOL), and Ripple (XRP), exhibit a very high correlation in their closing prices. ETH and SOL have a perfect correlation of 1.00, indicating that their price movements are almost identical. Additionally, XRP shows a strong correlation with both ETH and SOL at 0.96, suggesting that the price patterns of these three cryptocurrencies tend to follow similar trends. This high degree of correlation implies that external factors influencing the price of one of these cryptocurrencies may similarly affect the others.

Meanwhile, the TES method recorded better evaluation results for two cryptos. To explore the possibility of special patterns in the price movement chart and the correlation between the cryptos, here is a Figure 4 below is a visualization.

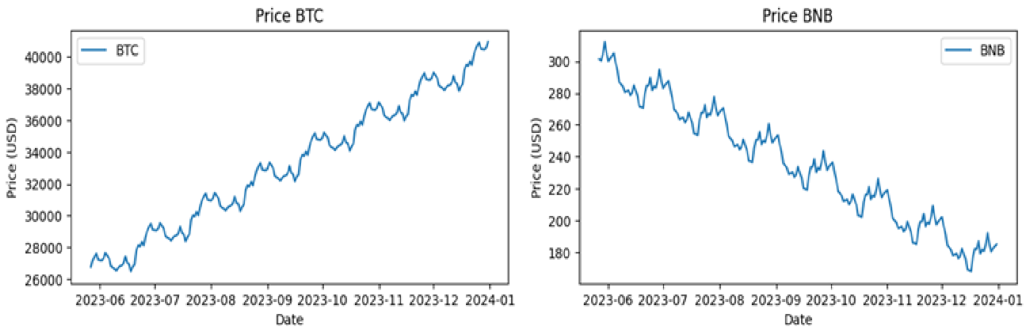


Fig 4. Graph Visualization of TES Superior Coin Data

Based on the observation of the chart, it can be seen that there are no similarities in the price movement trends between Bitcoin (BTC) and Binance Coin (BNB). The chart for BTC shows a consistent upward trend, indicating a steady increase in price over the analyzed period. In contrast, BNB demonstrates a significant downward trend, with its price steadily declining. These distinct and opposite trends highlight the variation in price movement patterns between the two cryptocurrencies, suggesting that they respond differently to market conditions.

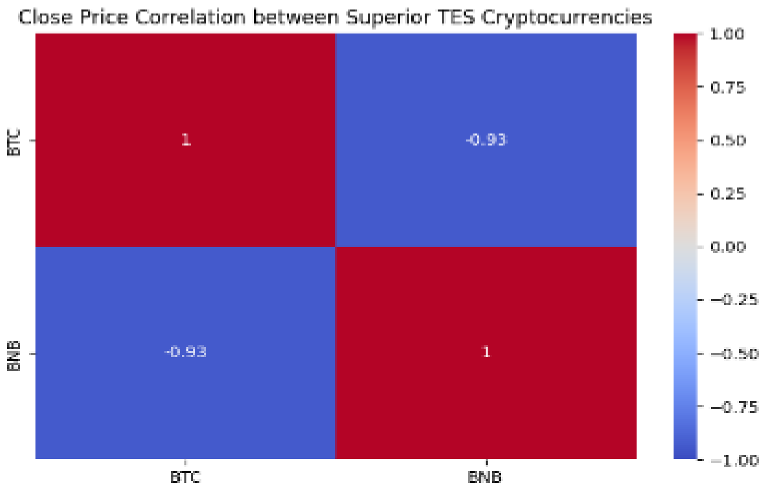


Fig 5. Superior Crypto TES Correlation Visualization

Based on the correlation chart, it can be concluded that Bitcoin (BTC) and Binance Coin (BNB) have a strong negative correlation of -0.93. This suggests that their price movements tend to move in opposite directions—when the price of Bitcoin increases, Binance Coin tends to decrease, and vice versa. This negative correlation indicates that the factors influencing the price movements of these two cryptocurrencies may differ significantly, leading to contrasting price trends.

5. Conclusion

This study explored and compared the prediction performance of the Triple Exponential Smoothing (TES) and Autoregressive Integrated Moving Average (ARIMA) models for forecasting the prices of five major cryptocurrencies: Bitcoin, Ethereum, Binance Coin, Solana, and Ripple. ARIMA demonstrated better performance in predicting the prices of Ethereum, Solana, and Ripple, as it effectively handled the more complex and volatile price patterns of these cryptocurrencies. In contrast, TES performed better for Bitcoin and Binance Coin, which exhibited more stable price trends. TES proved to be more suitable for long-term trend forecasting, making it a more reliable option for cryptocurrencies with less volatility. The findings indicate that neither TES nor ARIMA is universally superior for all cryptocurrencies.

The correlation analysis showed that Ethereum, Solana, and Ripple, where ARIMA excelled, had strong positive correlations, indicating similar price patterns. In contrast, Bitcoin and Binance Coin, where TES outperformed, showed a strong negative correlation, suggesting opposite price movements. This reflects how different cryptocurrencies respond differently to market conditions.

The choice of model should be based on the specific characteristics of the cryptocurrency being analyzed. TES tends to work better for stable assets, while ARIMA excels in handling volatile markets. These insights can help investors and analysts select the most appropriate forecasting model based on the volatility and trend characteristics of the cryptocurrency, leading to more informed decision-making and improved investment strategies. Overall, this research provides valuable insights for improving cryptocurrency price prediction models and offers practical guidance for market participants.

References

[1] M. Mudassir, S. Bennbaia, D. Unal, and M. Hammoudeh, "Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach," *Neural Comput Appl*, Jul. 2020, doi: 10.1007/s00521-020-05129-6.

[2] Nurdin, Balqis, and Z. Yunizar, "Application of Triple Exponential Smoothing Method to Predict LQ45 Saham Stock Price," *Jurnal CoreIT: Jurnal Hasil Penelitian Ilmu Komputer dan Teknologi Informasi*, vol. 8, no. 2, p. 40, Nov. 2022, doi: http://dx.doi.org/10.24014/coreit.v8i2.14935.

[3] S. S. Muna, Nurdin, and Taufiq, "Tokopedia and Shopee Marketplace Performance Analysis Using Metrix Google Lighthouse," *International Journal of Engineering, Science & InformationTechnology (IJESTY)*, vol. 2, no. 3, pp. 106–110, 2022, doi: 10.52088/ijesty.v1i4.312.

[4] A. Hamdhi, "Investor Kripto di Indonesia Mencapai 17,25 Juta Orang pada April 2023." Accessed: Mar. 24, 2024. [Online]. Available: https://investasi.kontan.co.id/news/investor-kripto-di-indonesia-mencapai-1725-juta-orang-pada-april-2023/

[5] R. Irmanita, S. S. Prasetiyowati, and Y. Sibaroni, "Classification of Malaria Complication Using CART (Classification and Regression Tree) and Naïve Bayes," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 5, no. 1, pp. 10–16, Feb. 2021, doi: 10.29207/resti.v5i1.2770.

[6] D. Setyowati, "Survei: Jumlah Generasi Muda Berinvestasi Kripto Melonjak 2 Kali Lipat." Accessed: Mar. 24, 2024. [Online]. Available: https://katadata.co.id/digital/fintech/6205e94e9dbab/survei-jumlah-generasi-muda-berinvestasi-kripto-melonjak-2-kali-lipat

[7] R. Adcock and N. Gradojevic, "Non-fundamental, non-parametric Bitcoin forecasting," *Physica A: Statistical Mechanics and its Applications*, vol. 531, p. 121727, Oct. 2019, doi: 10.1016/j.physa.2019.121727.

[8] M. Zanardi and H. Jaen, "APPLICATION OF TRIPLE EXPONENTIAL SMOOTHING METHOD FOR PREDICTING THE PRICE MOVEMENT OF CRYPTOCURRENCY ETHEREUM," 2023. [Online]. Available: https://bestijournal.org

[9] Moch Farryz Rizkilloh and Sri Widiyanesti, "Prediksi Harga Cryptocurrency Menggunakan Algoritma Long Short Term Memory (LSTM)," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 6, no. 1, pp. 25–31, Feb. 2022, doi: 10.29207/resti.v6i1.3630.

[10] D. Ayu Rezaldi and Sugiman, "Peramalan Metode ARIMA Data Saham PT. Telekomunikasi Indonesia," *PRISMA, Prosiding Seminar Nasional Matematika*, vol. 4, pp. 611–620, 2021, [Online]. Available: https://journal.unnes.ac.id/sju/index.php/prisma/

[11] Y. Baitur Roziqoh, M. Syafriadi, and Sugiyanta, "FORECASTING OF COVID–19 WITH AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA) METHOD IN EAST JAVA PROVINCE," *Jurnal Berkala Epidemiologi*, vol. 11, no. 2, pp. 160–169, May 2023, doi: 10.20473/jbe.v11i22023.160-169.

[12] F. N. Hayati, M. Silfiani, and D. Nurlaily, "PERBANDINGAN METODE ARIMA, DAN TRIPLE EXPONENTIAL SMOOTHING PADA STUDI KASUS DATA EKSPOR NON MIGAS DI KALIMANTAN TIMUR," *Jurnal Sains, Nalar, dan Aplikasi Teknologi Informasi*, vol. 1, no. 2, 2022, doi: 10.20885/snati.v1i2.10.

[13] Y. R. Madhika, Kusrini, and T. Hidayat, "Gold Price Prediction Using the ARIMA and LSTM Models," *Sinkron*, vol. 7, no. 3, pp. 1255–1264, Jul. 2023, doi: https://doi.org/10.33395/sinkron.v8i3.12461.

[14] K. Murray, A. Rossi, D. Carraro, and A. Visentin, "On Forecasting Cryptocurrency Prices: A Comparison of Machine Learning, Deep Learning, and Ensembles," *Forecasting*, vol. 5, no. 1, pp. 196–209, 2023, doi: 10.3390/forecast5010010.

[15] M. Dritsaki and C. Dritsaki, "Comparison of the Holt-Winters Exponential Smoothing Method with ARIMA Models: Forecasting of GDP per Capita in Five Balkan Countries Members of European Union (EU) Post COVID," *Modern Economy*, vol. 12, no. 12, pp. 1972–1998, 2021, doi: 10.4236/me.2021.1212104.

[16] K. Kashtanov, A. Kashevnik, and N. Shilov, "Using Triple Exponential Smoothing and Autoregressive Models to Mining Equipment Details Sales Forecast," 2022, pp. 506–521. doi: 10.1007/978-3-030-93715-7_36.

[17] K. P. Fourkiotis and A. Tsadiras, "Applying Machine Learning and Statistical Forecasting Methods for Enhancing Pharmaceutical Sales Predictions," *Forecasting*, vol. 6, no. 1, pp. 170–186, 2024, doi: 10.3390/forecast6010010.

[18] Nurdin, Fajriana, Maryana, and A. Zanati, "Information System for Predicting Fisheries Outcomes Using Regression Algorithm Multiple Linear," *JOURNAL OF INFORMATICS AND TELECOMMUNICATION ENGINEERING*, vol. 5, no. 2, pp. 247–258, Jan. 2022, doi: 10.31289/jite.v5i2.6023.

[19] D. Abdullah, Fajriana, C. I. Erliana, M. Chaizir, and A. Putra, "A solution to reduce the environmental impacts of earthquakes: Web GIS-based forecasting," *Caspian Journal of Environmental Sciences*, vol. 21, no. 2, pp. 361–373, Apr. 2023, doi: 10.22124/CJES.2023.6514.

[20] V. W. Nirmala, D. Harjadi, and R. Awaluddin, "Sales Forecasting by Using Exponential Smoothing Method and Trend Method to Optimize Product Sales in PT. Zamrud Bumi Indonesia During the Covid-19 Pandemic," *International Journal of Engineering, Science & InformationTechnology (IJESTY)*, vol. 1, no. 4, pp. 59–64, 2021, doi: 10.52088/ijesty.v1i1.169.

[21] Ummarrazai and Nurdin, "PERAMALAN JUMLAH KEUNTUNGAN MIE INSTAN PADA SUMBER REZEKI KOTA LHOKSEUMAWE MENGGUNAKAN METODE TRIPLE EXPONENTIAL SMOOTING," *Jurnal Sistem Informasi*, vol. 1, no. 2, pp. 185–218, 2020.

[22] M. Elsaraiti and A. Merabet, "A comparative analysis of the arima and lstm predictive models and their effectiveness for predicting wind speed," *Energies (Basel)*, vol. 14, no. 20, Oct. 2021, doi: 10.3390/en14206782.

[23] M. Faisal, Nurdin, and Z. Fitri, "Information and Communication Technology Competencies Clustering for students for Vocational High School Students Using K-Means Clustering Algorithm," *International Journal of Engineering, Science & InformationTechnology (IJESTY)*, vol. 2, no. 3, pp. 111–120, 2022, doi: 10.52088/ijesty.v1i4.318.

[24] A. N. M. F. Faisal, A. Rahman, M. T. M. Habib, A. H. Siddique, M. Hasan, and M. M. Khan, "Neural networks based multivariate time series forecasting of solar radiation using meteorological data of different cities of Bangladesh," *Results in Engineering*, vol. 13, p. 100365, 2022, doi: https://doi.org/10.1016/j.rineng.2022.100365.

[25] W. Lu, J. Li, J. Wang, and L. Qin, "A CNN-BiLSTM-AM method for stock price prediction," *Neural Comput Appl*, vol. 33, no. 10, pp. 4741–4753, 2021, doi: 10.1007/s00521-020-05532-z.