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Comparison of Exponentially Weighted Moving Average and Triple Exponential Smoothing Methods for Cryptocurrency Price Forecasting

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Abstract
Cryptocurrencies have rapidly become a prominent part of today's information landscape. Bitcoin (BTC), one of the first cryptocurrencies, was introduced by Satoshi Nakamoto, a pseudonym whose true identity remains unknown. Nakamoto is credited with creating the blockchain system that underpins Bitcoin. As technology has advanced, cryptocurrencies have evolved into digital currencies that can be used as a medium of exchange. This has garnered significant attention from investors, particularly due to the substantial fluctuations in cryptocurrency values over time. Therefore, choosing the right method for making investment decisions is crucial. This research compares two leading methods for cryptocurrency price forecasting: Exponentially Weighted Moving Average (EWMA) and Triple Exponential Smoothing (TES). Each method has its own strengths and weaknesses in forecasting. In this study, EWMA achieved an average MAPE score of 54% and an MSE of 1818, while TES recorded an average MAPE of 45% and an MSE of 11408. The results indicate that TES outperforms EWMA by a margin of approximately 10%. To assess the methods' effectiveness, evaluation metrics were applied, categorizing performance as excellent, good, feasible, or not feasible.
Keywords: Cryptocurrency, EWMA, TES, Metric, Forecasting

Introduction

Now a days, cryptocurrency has gained significant popularity worldwide and is recognized by many individuals, banks, governments, and companies. However, many still do not fully understand the importance of this digital currency. Cryptocurrency consists of cryptographic codes designed to be securely stored on personal computers. The cryptographic algorithms used in cryptocurrencies are similar to other types of digital data but have enhanced security features that prevent tampering or forgery [1]. Currently, the rise of various high-value cryptocurrencies globally holds substantial potential to impact the world economy. Examples include Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). The use of digital currencies dates back to 2009. While governments and regulators around the world are still drafting legislation regarding crypto usage, consumers and businesses must be protected from fraudulent activities and illegal crypto operations. Some countries are making progress, but it remains a lengthy and often controversial process [2].

Virtual currency has been circulating and traded on commodity futures exchanges in Indonesia following the announcement by the Indonesian Commodity Futures Supervisory Agency (Bappebti), which issued Bappebti Regulation No. 5 of 2019. This regulation, consisting of 28 articles, came into effect on February 8, 2019 [3]. While Bappebti has authorized the use of digital currencies, Bank Indonesia (BI) and the Financial Services Authority (OJK) continue to prohibit their use as legal tender in Indonesia. Currently, cryptocurrencies are emerging as alternative payment systems that operate without the need for third-party intermediaries. One prominent example is Bitcoin (BTC) [4].

The fundamental issue with comparing Bitcoin to traditional financial assets, like stocks, lies in their volatility. Both internal and external factors cause stock prices to fluctuate continuously, making it challenging for investors to predict whether prices will rise or fall in the near future [5].

The prices of staple food commodities are often a hot topic in the market, with fluctuations influenced by various factors such as weather conditions and oil prices. Accurately predicting these price changes is essential for farmers, consumers, and government bodies alike. This paper examines the use of Linear Regression and the Fourier model combined with ARIMA (Autoregressive Integrated Moving Average) to forecast staple food prices, considering external factors. The results from both methods show strong alignment with observed market prices. Specifically, Fourier regression with ARIMA delivers the highest accuracy in predicting onion prices, with an accuracy rate of 96.57%, while multiple linear regression with ARIMA performs best for red chili prices, achieving 99.84% accuracy. Overall, the research demonstrates that Fourier regression with ARIMA outperforms multiple linear regression with ARIMA, providing more consistent accuracy despite fluctuations in the data [6].

The challenge with cryptocurrencies is that they are still in their early stages and not yet widely recognized by the general public, especially when compared to conventional investment vehicles like stocks or traditional stock markets, which have been established for much longer [7]. Although interest in cryptocurrencies is growing, there remain several hurdles that must be addressed to enhance public understanding and promote broader adoption of these digital assets.

Triple Exponential Smoothing can be an effective tool for predicting cryptocurrency prices, especially when there are identifiable seasonal or long-term trends [8]. However, due to the extremely high volatility of the crypto market, it is important to use this method along with other approaches such as fundamental analysis or more advanced machine learning algorithms to get better predictions and be adaptive to rapid changes.

The Exponentially Weighted Moving Average (EWMA) is a statistical method used in market analysis that assigns varying weights to historical data points, with the most recent data receiving the highest weight [9]. This technique is commonly used to forecast future trends and values, as EWMA prioritizes more recent data while assigning progressively lower weights to older data points.

Literature Review

With the advancement of technology, cryptocurrency has emerged as a form of digital currency, developed through cryptography and blockchain technology. Its journey to becoming a widely-used transaction medium has seen significant fluctuations in value. Cryptocurrencies can be traded against traditional currencies, and are increasingly utilized in transactions such as online banking and shopping, facilitated by a transaction ledger known as the Blockchain system [10]. There are various types of cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), and many others.

Forecasting is the process of estimating future outcomes based on historical data, aiming to provide reliable predictions through scientific methods. The goal of forecasting is to support the planning process and reduce the risk of error [11]. It is a critical component of data science, helping to anticipate future events by analyzing past trends. Various techniques, from traditional statistical methods like ARIMA to machine learning approaches such as neural networks, are employed to improve prediction accuracy. Each method has its own strengths and weaknesses, depending on the complexity and characteristics of the dataset being analyzed [12].

Yahoo Finance is a media property owned by Yahoo that provides a wide range of financial information, including cryptocurrency data, stock quotes, press releases, financial reports, and original content. The platform offers historical price data and financial news, making it a valuable resource for evaluating the financial performance of cryptocurrencies [13].

Historically, various programming languages and environments have been used for machine learning research and application development in Python [14]. However, as a general-purpose language, Python has seen a significant rise in popularity within the scientific computing community over the past decade. Today, most modern machine learning tools are Python-based. For data extraction, Python systems can retrieve historical cryptocurrency price data, including calculated features such as Open, High, Close, and Volume, from websites or by using libraries like Yahoo Finance to access current price data. In the data preprocessing stage, the process includes tasks such as data normalization, feature selection, and splitting the data into training and testing sets.

For forecasting, this research implements the Exponentially Weighted Moving Average (EWMA) and Triple Exponential Smoothing (TES) methods, including selecting appropriate model architectures. Model evaluation is conducted using metrics such as Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) to assess the model's performance. Finally, after model evaluation and saving, the next step involves developing a system or application using Streamlit, a tool commonly employed by data science professionals.

Data normalization is the process of transforming data values to a specific scale, typically ensuring that all features or variables fall within the same range [15]. In forecasting, normalization is crucial, especially when using scale-sensitive models such as machine learning algorithms and certain statistical techniques. This step is essential for preparing raw data for modeling or further analysis. Data collected directly from sources often contains imperfections, such as missing values, irrelevant or redundant information, duplicates, or extreme outliers. Data cleaning involves addressing these issues by correcting or removing missing data, eliminating irrelevant or redundant entries, and managing outliers.

The Exponentially Weighted Moving Average (EWMA) method is used to estimate future volatility by assigning greater weight to more recent observations, while past data points are weighted progressively less [16]. The weights in EWMA decrease exponentially as observations get older, and because this method incorporates previously calculated averages, the results are cumulative. Consequently, all data points contribute to the final outcome. EWMA is one of the statistical forecasting techniques first introduced by Brown, utilizing quadratic equations.

Triple Exponential Smoothing (TES) is an extension of Holt's linear two-parameter exponential smoothing method, enhanced by adding a seasonal component and a third smoothing parameter for trend adjustment [17]. The primary advantage of TES is its ability to perform triple smoothing, leading to more accurate predictions.

Evaluation metrics are crucial tools for measuring the performance of models and algorithms in data analysis. They help assess how effectively a model functions and the accuracy of its predictions. A widely used metric is Mean Squared Error (MSE), which calculates the average of the squared differences between predicted and actual values. Essentially, MSE quantifies the average squared prediction error; a smaller MSE value indicates better model performance. Another commonly used metric is Mean Absolute Percentage Error (MAPE), which measures the average percentage difference between predicted and actual values. MAPE expresses error as a percentage, with a lower MAPE reflecting a more accurate model [18].

Materials & Methods

The materials and methods used in system development for this research, utilizing Python, follow the waterfall methodology, a widely adopted approach within the software development life cycle. The method is called "waterfall" due to its linear, sequential nature, much like the flow of a waterfall. While the waterfall model is easier to use and understand, it comes with its own set of advantages and disadvantages. One key advantage is that it allows for effective control over the outcomes at each stage—starting from analysis, through design, development or implementation, and finally, evaluation. The development process is outlined below.

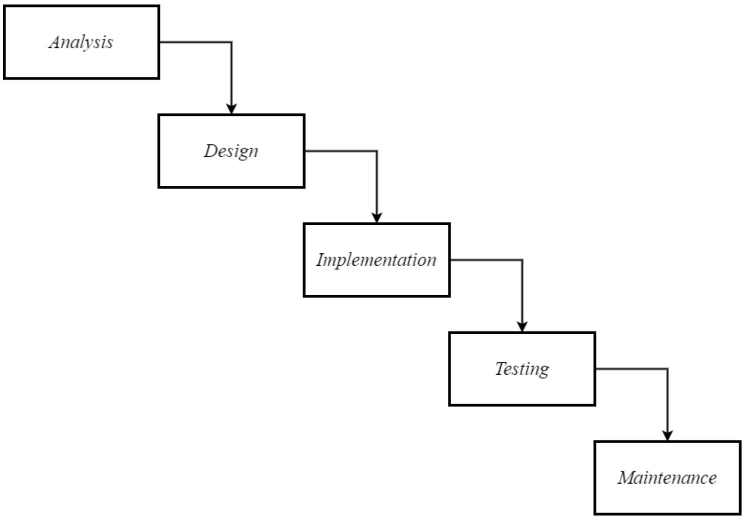

Figure 1. Development diagram with waterfall method

In the analysis stage, data collection is conducted to identify any deficiencies and gather the necessary information for future predictions. This process, often referred to as data collection for predictive purposes, is followed by system design, which includes configuring the model and integrating Python with a web-based interface. The implementation stage involves building the system using Python, followed by testing to ensure the website functions correctly after all the steps have been executed. Finally, the system enters the maintenance stage to ensure it continues to operate smoothly as a forecasting system.

A Data Flow Diagram (DFD) is a visual representation of the data flow within a process, often referred to as a system. It illustrates the flow of information between inputs, outputs, and the processes themselves. According to Kenneth Kozar, the primary purpose of a DFD is to serve as a communication tool, bridging the gap between users and the system.

The research method of the research conducted is testing historical data from 10 cryptocurrency coins sourced from yahoofinance.com that have been collected and conducting in conducting this library method is this will compile information in such a way from the same previous literature where collecting journals according to topics related to this research case study and related to forecasting.

This system scheme presents to the reader to make it easier to understand the flow of research steps from start to finish. The system scheme for comparing the Exponentially Weighted Moving average (EWMA) and Triple Exponential Smoothing (TES) methods can be seen in the figure below.

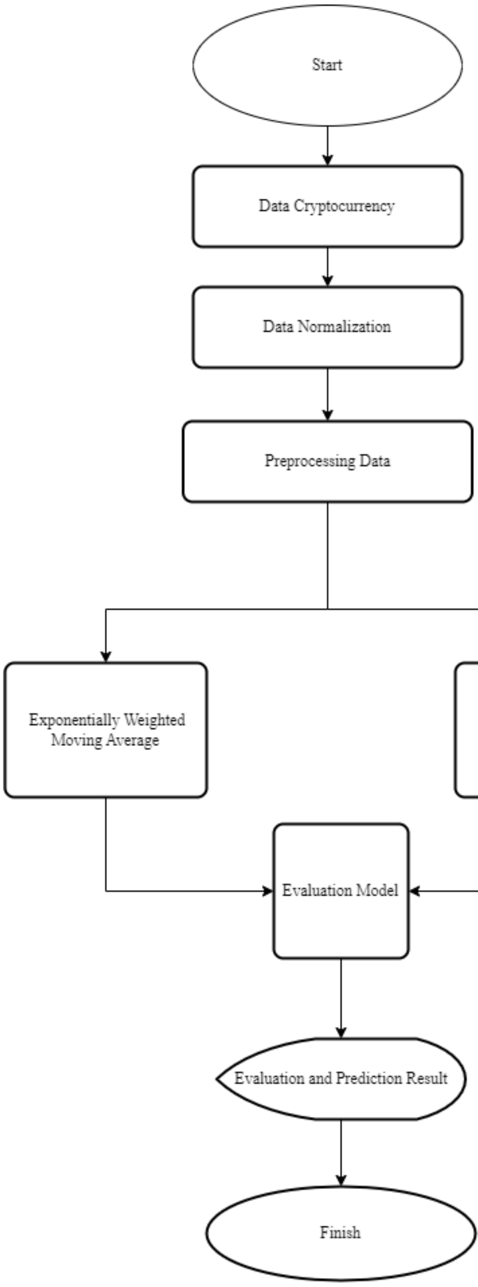

Figure 2. Schematic of the overall system

The data used in this study includes crypto data from ten coins, such as BTC, ETH, and SOL. These top 10 coins have undergone filtering and standardization to convert daily data into weekly for further processing. This step ensures the raw data is prepared for modeling or analysis. Since raw data often contains flaws like missing values, irrelevant information, duplicates, and outliers, data cleaning is essential. After preprocessing, the analysis model is configured, including setting parameters for the two methods used in this study: EWMA and TES.

The specific steps to predict cryptocurrency prices using Exponentially Weighted Moving Average can be seen in the figure below.

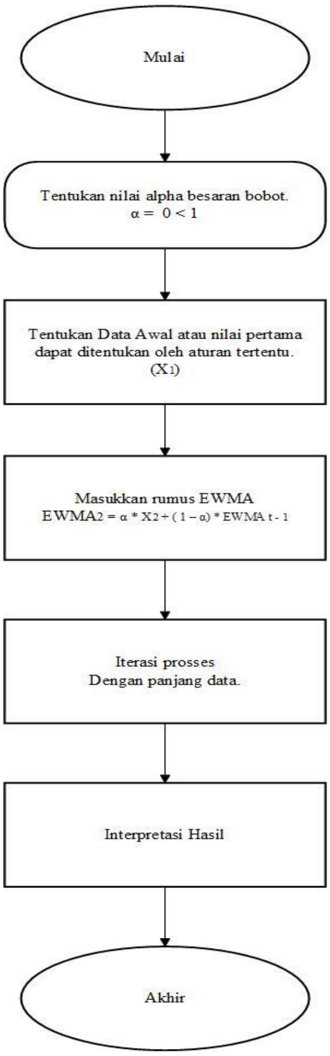

Figure 3. Application Scheme of Exponentially Weighted Moving Average Method

The flow chart above outlines the calculation process using the Exponentially Weighted Moving Average (EWMA) method, a technique for time series averaging. The first step is determining the weight parameter, typically between 0 and 1, where a higher value gives more importance to recent data. In practice, a value of 0.3 is often used to make the data responsive to changes. The initial value X1X_1X1 is either the first point in the dataset or user-defined. The formula is applied, and the process iterates through the dataset until all data is processed. The resulting EWMA values provide smoothed data, helping identify long-term patterns while minimizing short-term fluctuations.

Meanwhile, the process of applying the Triple Exponential Smoothing method can be seen in the picture on the next page.

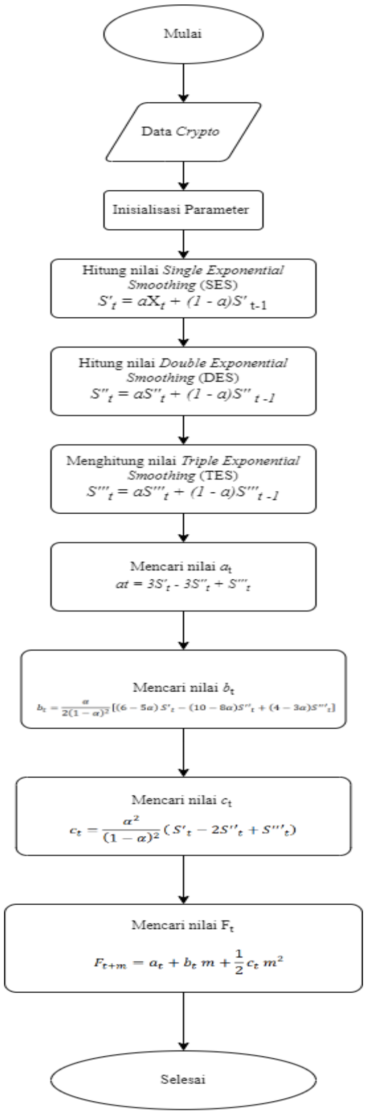

Figure 4. Application of Triple Exponential Smoothing method

The figure above shows the process of forecasting cryptocurrency data using the Triple Exponential Smoothing (TES) method. TES calculates Single (SES), Double (DES), and Triple Exponential Smoothing to capture trends and seasonal patterns from historical data, producing future predictions based on level, trend, and seasonal components. This method is particularly useful for forecasting volatile time series like cryptocurrency prices. The results of TES and other methods are then compared to identify which offers the best performance, guiding further recommendations and improvements.

Results and Discussion

This research aims to compare two prominent forecasting methods—Exponentially Weighted Moving Average (EWMA) and Triple Exponential Smoothing (TES)—in the context of the rapidly evolving digital currency market. The volatile and unpredictable price movements in the crypto market make it challenging for investors to develop effective strategies. Using historical data from 2021 to 2024, this study will analyze this issue, explore the database, and apply the EWMA and TES methods to forecast future prices. Focusing on weekly trends, it will use data from the top 10 cryptocurrencies by market capitalization to evaluate the effectiveness of both methods, providing insights to guide smarter investment decisions in this dynamic market.

At this stage, using historical crypto price data, which includes the 10 highest and most popular crypto coins in the world. The table below will present.

Table 1. 10 cryptocurrencies of 2024

No	Coin name	Code Coin
1	Bitcoin	BTC-USD
2	Ethereum	ETH-USD
3	Tether	USDT-USD
4	BNB	BNB-USD
5	Solana	SOL-USD
6	USD Coin	USDC-USD
7	XRP	XRP-USD
8	Lido Staked ETH	STETH-USD
9	Toncoin	TON11419-USD
10	Dogecoin	DOGE-USD

During this period, data was consistently collected from January 2021 to December 2023. The ten cryptocurrencies analyzed exhibit a wide range of minimum and maximum values, reflecting diverse market dynamics. The figure below provides a graphical visualization of the price movements for each cryptocurrency in this study, specifically showing the closing prices of the top 10 cryptocurrencies. These graphs offer valuable insights into the market's complexity. The visualizations were generated using Python within the Jupyter Lab environment, enabling precise and detailed data analysis.

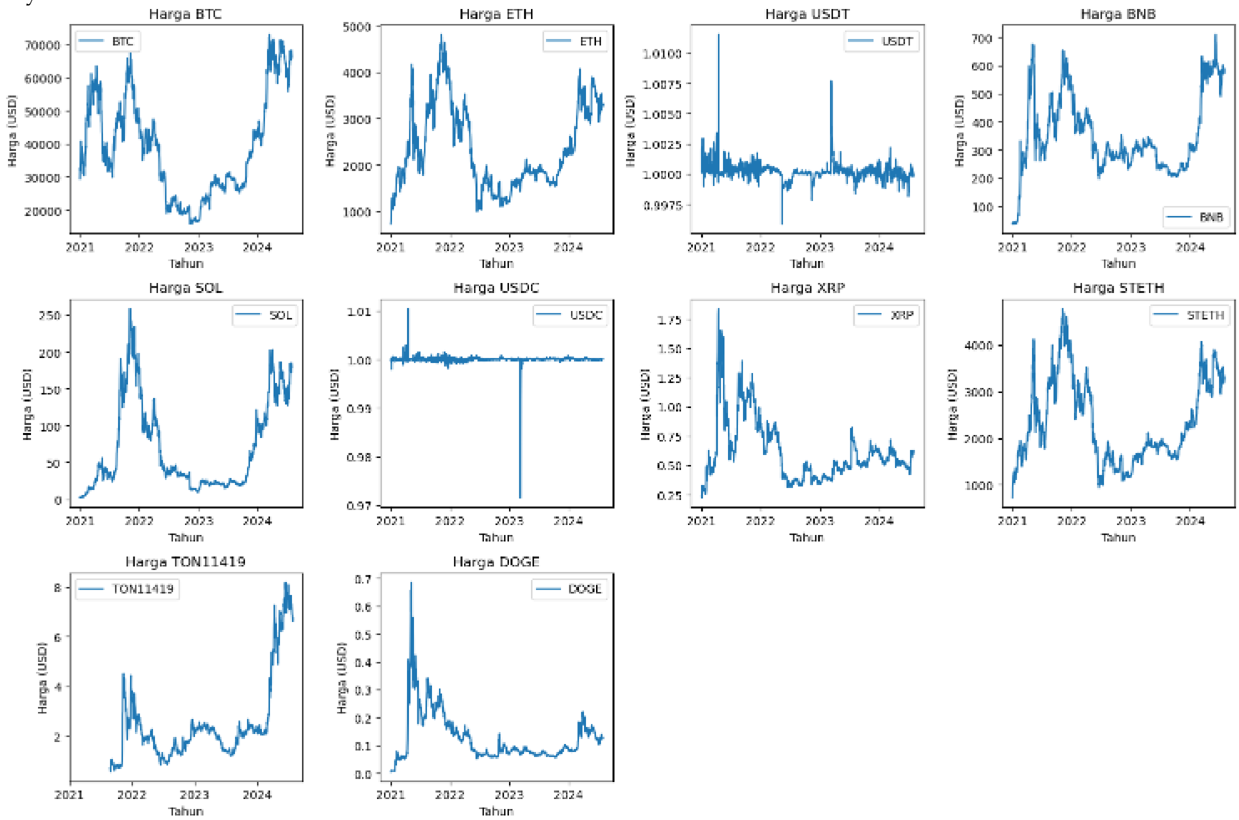

Figure 5. chart showing the top 10 highest cryptocurrencies

The image above displays 10 cryptocurrencies, highlighting their price variations from 2021 to 2023. The charts illustrate the highly volatile nature of the crypto market, with price surges in late 2021 driven by market enthusiasm, followed by periods of decline and stabilization. Stablecoins like USDT and USDC show expected price stability, while volatile coins such as BTC, ETH, and DOGE reflect greater market uncertainty. These visualizations offer valuable insights into cryptocurrency market behavior and emphasize the importance of analyzing price trends.

This research uses historical data collected from the finance.yahoo.com site. As an example of the initial coin data, researchers took a sample coin from BTC.

Table 2. Price coin BTC

Date	Open	High	Close	Volume
2021-01-01 00:00:00	737,708374	749,2018433	730,3675537	13652004358
2021-01-02 00:00:00	730,4026489	786,7984619	774,5349731	19740771179
2021-01-03 00:00:00	774,5118408	1006,565002	975,5076904	45200463368
2021-01-04 00:00:00	977,0588379	1153,189209	1040,233032	56945985763
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2024-07-27 00:00:00	3275,891602	3327,426514	3247,60791	15198233287
2024-07-28 00:00:00	3247,507324	3283,1521	3271,4646	8959236446
2024-07-29 00:00:00	3271,453369	3396,625732	3320,539307	18334852719
2024-07-30 00:00:00	3320,635254	3365,32251	3278,667725	14045773047

The table shows Bitcoin price fluctuations from around $20,000 to a peak near $70,000 in 2021, followed by a significant drop in 2022. It then rises again towards 2023.

This system showcases the development of an application that implements Exponentially Weighted Moving Average (EWMA) and Triple Exponential Smoothing (TES) models for cryptocurrency price prediction. The application provides visualizations to help users easily analyze prediction data. Built with Python, the system uses the popular Streamlit framework for data display.

Figure 6. Home page of the system

On the home page there is a sidebar a menu of options, namely the menu, crypto list, main predictions, manual predictions and future predictions. On the home page, provides author and researcher information on this page there is a contribution name and provides email and social media such as Instagram and Linkedin.

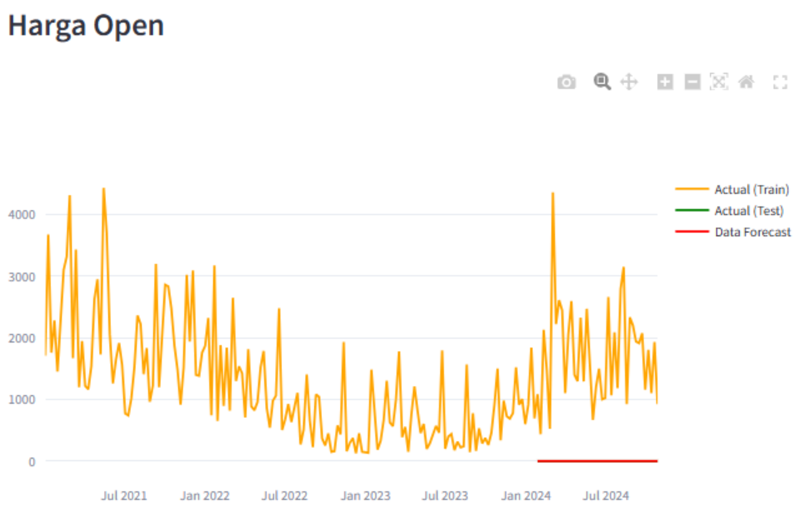

Figure 7. Prediction page on BTC coin

This page features a sub-header on the left where users can select a coin from the study, such as BTC, set a date manually, and choose a method (e.g., EWMA) using a radio button. Users can also select the variable they want to predict, with the "open" variable chosen in this example. For EWMA, the alpha weighting is set to 0.3 for better responsiveness to data changes. The model evaluation metrics used are MAPE and MSE, with MAPE scoring 0.04 for a 3-year time series. A line chart is implemented to visualize the movement of training data, testing data, and forecasts.

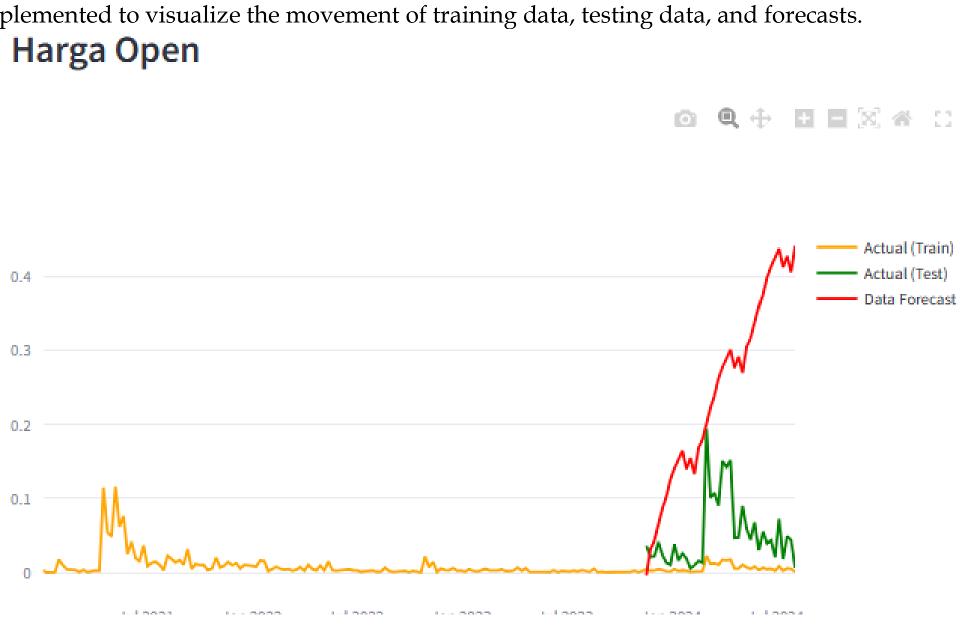

Figure 8. Predictions using Doge coin

On this page, the researcher uses the Triple Exponential Smoothing model with historical data from the DOGE-USD coin. The feature selected is the open price, with manual settings for TES parameters: alpha, beta, and gamma each set to 0.5, and a seasonal value of 12. The page displays a line chart and table, where the yellow line represents the trained data, the green line shows the testing data, and the red line indicates the forecasted data.

Date	Actual Price	Forecast	Accuracy (%)	Loss
2023-12-10	0.041308	0.067443	36.730737	0.026135
2023-12-17	0.023964	0.086174	-159.593754	0.062210
2023-12-24	0.013440	0.102680	-563.974274	0.089240
2023-12-31	0.010566	0.125688	-989.572153	0.115122
2024-01-07	0.038460	0.140761	-165.996363	0.102301
2024-01-14	0.016586	0.153523	-725.633893	0.136937
2024-01-21	0.025848	0.164419	-436.089945	0.138571
2024-01-28	0.019066	0.139642	-532.398882	0.120576
2024-02-04	0.005614	0.154785	-2556.893261	0.149171
2024-02-11	0.010197	0.132966	-1104.007557	0.122770

Figure 9. Forecasting results with TES method

This table displays the forecasting results, calculating the open variable using previously normalized data. For weekly forecasts, it shows the original price, predicted price, accuracy (based on a defined metric), and the loss, calculated using a predetermined loss function.

The researcher shows the model that has been trained and displays the results of the evaluation table comparing the EWMA and TES methods, this stage compares a method that has been recapitulated by the researcher, the metrics that evaluate the MSE and MAPE methods, this table presents the results of the two methods can be seen below.

Table 3. Model evaluation matrix results table

No	Coin Name	Code coin	EWMA		TES	
			MAPE	MSE	MAPE	MSE
1	Bitcoin	BTC-USD	47%	0.03467	91%	11.408
2	Ethereum	ETH-USD	50%	0.01029	68%	0.0224
3	Tether	USDT-USD	79%	0.0013	15%	0.0036
4	BNB	BNB-USD	40%	0.01088	10%	0.021
5	Solana	SOL-USD	45%	0.0380	48%	0.0638
6	USD Coin	USDC-USD	16%	1.818	25%	0.0007
7	XRP	XRP-USD	50%	0.00150	35%	0.0029
8	Lido Staked ETH	STETH-USD	45%	0.0102	64%	0.023
9	Toncoin	TON11419-USD	79%	0.021	87%	0.0479
10	Dogecoin	DOGE-USD	89%	0.0019	11%	0.0051
	average of each metric		54%	1818	45%	11408

The results show that both MAPE and MSE metrics were used to evaluate the models on a weekly prediction basis, with only small differences between the two methods. The average MAPE for EWMA is 54%, while TES scores 45%, indicating that TES performs better. EWMA's limitation lies in its reliance on a single parameter, while TES benefits from multiple parameters and better handling of time series data. However, both methods have their own strengths and weaknesses.

The variation value of the Mean Absolute Percentage Error value

Table 4 . Mape value variation

Value	Program Capabilities
0%- 10 %	Very good
10% -20%	Good
20% - 50%	worth
>50%	not feasible

From table 4, it is known that from this value, we can understand the value of good MAPE to those that are not suitable for use, the MAPE value can still be used if it is not more than 50%, then if the MAPE value is more than 50%, forecasting cannot be used.

Equations

Before the data is processed further, weekly grouping is performed by applying the aggregation method. In this process, the data is processed using the standard deviation method to aggregate the values per week. This method is one of the techniques commonly used by experts in the field of data science to analyze and summarize data more effectively.

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{\mathcal{N}}} \qquad (1)$$

Formula Description
σ = standard deviation population.
x_i= every value in the data set.
μ = average population.
$\mathcal{N}$ = total amount in the sample.

standard deviation gives an idea of how varied the data is within a dataset. This is very important when we want to know the level of homogeneity or inhomogeneity in the data. Determining Dispersion Standard deviation measures the spread of the data, which helps in assessing how well the average represents the dataset [19]. Evaluating Risk or Uncertainty, in finance and science, standard deviation is often used to assess risk for example, stock price volatility or uncertainty in experiments.

Min-Max Scaling works by changing each value in the dataset based on the minimum and maximum values of the feature. The lowest value in the data will be changed to 0, and the highest value will be changed to 1, with all other values scaled proportionally between 0 and 1 [19]. In this way, the range of data becomes uniform, and each feature or variable is on the same scale.

Min-Max Scaling

$$\mathcal{X}' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

$\mathcal{X}'$ = Normalized value
$\mathcal{X}$ =The original value of the data
$\mathcal{X}_{min}$ = Minimum value of the data set or feature
$\mathcal{X}_{max}$ = The maximum value of the data or feature

Min-Max Scaling is a very effective normalization technique that is used to make data fall within a more manageable range, especially in scale-sensitive statistical algorithms.

Formula using the Exponentially Weighted Moving average method

$$EWMA_t = aX_t + (1 - a)EWMA_{t-1} \quad (3)$$

$EWMA_t$ = The updated moving average value at time t.
aX_t = Actual or observed data at time t
$EWMA_{t-1}$ = The EWMA value of the previous period.
a = Smoothing factor, or smoothing parameter, with a value between 0 and 1 ($0 < \alpha < 1$).

The steps in the Triple Exponential Smoothing method are as follows:

$$S'_t = aX_t + (1- a)\, S'_{t-1} \qquad (4)$$

$$S''_t = aS'_t + (1- a)\, S''_{t-1} \qquad (5)$$

$$S'''_t = aS'''_t + (1- a)\, S'''_{t-1} \qquad (6)$$

$$at = 3S'_t - 3S''_t + S'''_t \qquad (7)$$

$$bt = \frac{\alpha^2}{2(1-\alpha)^2}\left(6 - 5\alpha)S'_t - (10 - 8a)\, S''t + (4 - 3a)S'''\right. \qquad (8)$$

$$ct = \frac{a^2}{(1-a)^2}\,(S'_t - 2\,S''_t + S'''_t) \qquad (9)$$

$$F_{t+m} = at + bt(m)\,\frac{1}{2}\,ct(m) \qquad (10)$$

Formula Description:

S'_t = value SES
S''_t = value DES
S'''_t = value TES
X_t = actual data value
A = alpha value whose value is between 0 – 1
a_t, b_t, c_t = Konstanta Smoothing
F_{t+m} = the magnitude of the forecasted period

Because Triple Exponential Smoothing still has advanced calculations, so this method is called Triple Exponential Smoothing which is repeated three times so that the results are smoother than Single Exponential Smoothing.

Evaluation metrics are an important tool for evaluating methods used to measure the performance of models, algorithms in data analysis. These metrics help in assessing how well the model works and how accurate the results are in the context of forecasting.

Formula MSE

$$\text{MSE} = \frac{\sum(yi - \hat{y}i)2}{n} \qquad (11)$$

n = Number of samples in the data
y_i = actual value
y_i = forecasting value

Formula Mape

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} | \frac{y_i - \hat{y_i}}{y_i} | * 100 \qquad (12)$$

y_i = The actual value at the i-th data.
$\hat{y_i}$ = Predicted value on the i-th data.
n = Total number of observations (data points).
$\frac{y_i - \hat{y_i}}{y_i}$ = Absolute error in percentage for each data point.

Conclusions

Based on the results and conclusions of the study comparing the performance of a good model with in this case the method used Exponentially Weighted Moving average and Triple Exponential Smoothing. Where its use against cryptocurrency digital currencies for 10 coin currencies in this application example takes BTC to DOGE coin by evaluating each using evaluation metrics where the discussion of the results of the model evaluation has been included in the results and discussion.

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References

[1] Wątorek, M., Drożdż, S., Kwapień, J., Minati, L., Oświęcimka, P., & Stanuszek, M. (2021). Multiscale characteristics of the emerging global cryptocurrency market. *Physics Reports*, *901*, 1-82.

[2] Kevin George, "Cryptocurrency Regulations Around the World," Investopedia. Accessed: Mar. 25, 2024. [Online]. Available: https://www.investopedia.com/cryptocurrency-regulations-around-the-world-5202122

[3] Artemov, N. M., Arzumanova, L. L., Sitnik, A. A., & Zenin, S. S. (2017). Regulation and Control of Virtual Currency: to be or not to be. *Journal of Advanced Research in Law and Economics*, *8*(5 (27)), 1428-1435.

[4] Irma, Dasih, et al. "The future of cryptocurrency legality in Indonesia." *Journal of Economics and Business Letters* 1.1 (2021): 20-23.

[5] Hanley, Brian P. "The false premises and promises of Bitcoin." *arXiv preprint arXiv:1312.2048* (2013).

[6] S. F. Asnhari, P. H. Gunawan and Y. Rusmawati, "Predicting Staple Food Materials Price Using Multivariables Factors (Regression and Fourier Models with ARIMA)," 2019 7th International Conference on Information and Communication Technology (ICoICT), Kuala Lumpur, Malaysia, 2019, pp. 1-5, doi: 10.1109/ICoICT.2019.8835193. keywords: {Predictive models;Linear regression;Mathematical model;Data models;Correlation;Computational

modeling;Oils;Staple food;price;predicting;ARIMA;multiple linear regression;Fourier,
[7] Al-Omoush, Khaled Saleh, Ana M. Gomez-Olmedo, and Andrés Gómez Funes. "Why do people choose to continue using cryptocurrencies?." *Technological Forecasting and Social Change* 200 (2024): 123151.
[8] Zanardi, Maurizio, and Hizamrul Jaen. "APPLICATION OF TRIPLE EXPONENTIAL SMOOTHING METHOD FOR PREDICTING THE PRICE MOVEMENT OF CRYPTOCURRENCY ETHEREUM." *Bulletin of Engineering Science, Technology and Industry* 1.2 (2023): 66-75.
[9] Khedmati, M., F. Seifi, and M. J. Azizi. "Time series forecasting of bitcoin price based on autoregressive integrated moving average and machine learning approaches." *International Journal of Engineering* 33.7 (2020): 1293-1303.
[10] Irina, Cvetkova. "Cryptocurrencies legal regulation." *BRICS law journal* 5.2 (2018): 128-153.
[11] Gamal Thabroni. (2022). Forecasting: Definition, Factors, Methods, Steps, etc. Similar.Id. https://serupa.id/forecasting-peramalan-pengertian-faktor-metode-langkah-dsb/
[12] Kourentzes, N., Petropoulos, F., & Trapero, J. R. (2014). Improving forecasting by estimating time series structural components across multiple frequencies. *International Journal of Forecasting*, *30*(2), 291-302.
[13] Boritz, J. Efrim, and Won Gyun No. "How significant are the differences in financial data provided by key data sources? A comparison of XBRL, Compustat, Yahoo! Finance, and Google Finance." *Journal of Information Systems* 34.3 (2020): 47-75.
[14] Korstanje, Joos. *Advanced forecasting with Python*. United States: Apress, 2021.
[15] Singh, Dalwinder, and Birmohan Singh. "Investigating the impact of data normalization on classification performance." *Applied Soft Computing* 97 (2020): 105524.
[16] Hunter, J. Stuart. "The exponentially weighted moving average." *Journal of quality technology* 18.4 (1986): 203-210.
[17] Dev, S., AlSkaif, T., Hossari, M., Godina, R., Louwen, A., & Van Sark, W. (2018, September). Solar irradiance forecasting using triple exponential smoothing. In *2018 International Conference on Smart Energy Systems and Technologies (SEST)* (pp. 1-6). IEEE.
[18] González-Sopeña, J. M., V. Pakrashi, and B. Ghosh. "An overview of performance evaluation metrics for short-term statistical wind power forecasting." *Renewable and Sustainable Energy Reviews* 138 (2021): 110515.
[19] Lee, Dong Kyu, Junyong In, and Sangseok Lee. "Standard deviation and standard error of the mean." *Korean journal of anesthesiology* 68, no. 3 (2015): 220-223.