Evaluating GRU Algorithm and Double Moving Average for Predicting USDT Prices: A Case Study 2017-2024

Rahmat Rizky[1]*, Munirul Ula[2], Zara Yunizar[3]
Dept. of Informatics Engineering, Universitas Malikussaleh [1], [2], [3]
Lhokseumawe, Indonesia
rahmat.200170114@mhs.unimal.ac.id [1] , munirulula@unimal.ac.id [2], zarayunizar@unimal.ac.id [3]

Abstract— **The cryptocurrency market is highly volatile, requiring advanced analytical methods for accurate price forecasting. This study evaluates the effectiveness of Gated Recurrent Units (GRU) and Double Moving Average (DMA) in predicting USDT (Tether Coin) prices using historical data from 2017 to 2024, sourced from Investing.com. Implemented in Jupyter Notebook, the research explores the strengths of each method in analyzing market fluctuations and price trends. GRU, a deep learning-based recurrent neural network, processes sequential data using a gating mechanism, making it effective for capturing short-term price dynamics. DMA, in contrast, is a statistical method that filters market noise to identify long-term trends, making it more reliable for stable market conditions. Performance evaluation shows DMA achieving lower errors (MAE: 5.494, MAPE: 0.0339%) than GRU (MAE: 5.984, MAPE: 0.0369%), suggesting higher accuracy for trend-based predictions. However, GRU's lower RMSE (8.531 vs. 8.715 for DMA) indicates better adaptability to sudden price fluctuations, making it more responsive to volatile markets. A hybrid approach combining GRU and DMA reveals their complementary strengths—DMA's minimal bias (-0.0013% MPE) supports stable trend analysis, while GRU's slight positive bias (0.0286% MPE) captures short-term fluctuations. Additionally, a comparison with Long Short-Term Memory (LSTM) demonstrates its superior predictive accuracy, outperforming both GRU (MAE: 5.98, RMSE: 8.53) and DMA (MAE: 5.49, RMSE: 8.72) with the lowest MAE (4.31), MAPE (0.027%), and RMSE (5.64), alongside minimal bias (MPE: 0.007%). This study highlights the need for integrating multiple forecasting techniques in cryptocurrency price prediction. While DMA is well-suited for stable trends and GRU excels in volatile conditions, LSTM outperforms both, reinforcing the effectiveness of deep learning for financial time-series forecasting.**

Keywords: Cryptocurrency, Forecasting, Historical Data, Jupyter Notebook

I. INTRODUCTION

The cryptocurrency market is characterized by significant volatility and unpredictability, presenting both challenges and opportunities for market participants. These rapid price fluctuations necessitate sophisticated analytical tools and predictive models to support informed decision-making in trading and investment activities [1][2][3] .

The selection of Gated Recurrent Units (GRU) and Double Moving Average (DMA) methods for USDT price prediction is fundamentally driven by their complementary strengths in addressing the complexities of cryptocurrency markets. GRU demonstrates exceptional capability in processing sequential data and identifying intricate patterns within cryptocurrency price movements. Its sophisticated architecture enables the retention of critical long-term historical data while maintaining sensitivity to emerging market trends [4][5]. The method's superior performance in managing the vanishing gradient problem, coupled with its computational efficiency, makes it particularly well-suited for analyzing the dynamic nature of cryptocurrency markets [6].

The implementation of DMA methodology complements the GRU approach through its effective filtering of market noise and precise identification of price trends via dual-timeframe analysis. This method has proven especially valuable in generating accurate trading signals for USDT, which exhibits subtle price variations despite its stablecoin designation [7][8]. Research by Sari has demonstrated DMA's reliability in projection accuracy based on historical data analysis, validating its applicability to USDT price movement analysis [9].

The strategic integration of GRU and DMA methodologies creates a comprehensive analytical framework that leverages their respective strengths. While GRU excels in deep pattern recognition and sequential data processing, DMA provides structured trend analysis, forming a synergistic approach to USDT price prediction. This combined methodology aims to deliver enhanced predictive accuracy and deeper market insights, ultimately providing traders and investors with a more robust foundation for strategic decision-making.

USDT (Tether), as a prominent stablecoin, maintains a value pegged to the US dollar through reserve asset backing equivalent to its circulating supply. Its widespread adoption in cross-border transactions, cryptocurrency exchange trading, and decentralized finance (DeFi) ecosystems underscores the importance of accurate price prediction models [10][11]. This

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2328, Copyright ©2025
Submitted : December 2, 2024, Revised : January 8, 2025, Accepted : January 28, 2025, Published : January 31, 2025

research utilizes historical data from 2017 to 2024 to develop a precise predictive model, aiming to enhance the quality of investment decisions in the USDT market through data-driven analysis.

II. LITERATURE REVIEW

A. Cryptocurrency

Cryptocurrency is a digital or virtual form of currency that employs cryptography to secure transactions and control the creation of new units. Built on decentralized technology, commonly referred to as blockchain, it allows for the verification of transactions and maintenance of an ownership ledger without relying on a central authority. Since the advent of Bitcoin in 2008, cryptocurrencies have become integral to global financial markets, reaching a market capitalization exceeding $600 billion. However, debates persist regarding the role and value of cryptocurrencies, such as Bitcoin, and their correlation with global economic indices [12][13].

B. Investment in Cryptocurrency

Cryptocurrency investments are gaining traction due to speculative opportunities and their potential as a store of value. However, these markets are highly volatile, with prices heavily influenced by market demand, regulatory announcements, and technological innovations [14][15].
Formulas Used
Volatility (σ):

$$\sigma - \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (r_i - \bar{r})^2} \tag{1}$$

Explanation :
σ : Standard deviation (volatility)
N : Number of data points
r_i : Return at time i
$\bar{r}$: Mean return

Expected Return ($E[R]$) :

$$E[R] - \sum_{i=1}^{N} P_i \cdot r_i \tag{2}$$

Explanation :
$E[R]$: Expected return
P_i : Probability of outcome i
r_i : Return at outcome i

C. USDT(Teather coin)

USDT, a stablecoin, maintains its value by pegging it 1:1 with the US dollar. This stability has made it a preferred cryptocurrency for transactions in a volatile market [16]. Tether's value stability can be modeled as:

$$V_{\text{USDT}} - \frac{\text{Reserves}}{\text{Circulating Supply}} \tag{3}$$

Explanation :
$V_{\text{USDT:}}$ Value of USDT
Reserves: Assets backing USDT
Circulating Supply: Total USDT units in circulation

D. Gated Recurrent Units (GRU)

GRU is a simplified Recurrent Neural Network (RNN) model effective for sequential data predictions, such as time series forecasting. Unlike LSTM, GRU uses two gates—the update gate and the reset gate—to control the flow of information between time steps [17][18].
Update Gate (z_t) :

$$z_t - \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{4}$$

Explanation :
z_t : Update gate value at time t
σ : Sigmoid activation function
W_z : Weight matrix for the update gate
h_{t-1} : Previous hidden state
x_t : Input at time t
b_z : Bias term

Reset Gate (r_t) :

$$r_t - \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{5}$$

Explanation :
r_t : Reset gate value at time t
W_r : Weight matrix for the reset gate
b_r : Bias term
New Memory Content $(\bar{h}_t)$:

$$\bar{h}_t - \tanh\,(W \cdot [r_t * h_{t-1}, x_t] + b) \tag{6}$$

Explanation :
$\bar{h}_t$: New memory content
tanh: Hyperbolic tangent activation function
W: Weight matrix for new memory content
r_t : Reset gate value
*: Element-wise multiplication
b: Bias term

Final Hidden State (h_t) :

$$h_t - (1 - z_t) * h_{t-1} + z_t * \bar{h}_t \tag{7}$$

Explanation of Symbols:
h_t : Final hidden state at time t

E. Double Moving Average (DMA)

The Double Moving Average (DMA) method is used for smoothing time series data and identifying price trends [19]. It calculates two moving averages with different periods:
Short-Term Moving Average (SMA):

$$\text{SMA}_{\text{short}} - \frac{\sum_{i-1}^{n} P_i}{n} \tag{8}$$

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2328, Copyright ©2025
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Explanation of Symbols:
SMA $_{short:}$ Short-term moving average
P_i: Price at time i
n : Short-term period

Long-Term Moving Average (SMA):

$$\mathrm{SMA_{long}} - \frac{\sum_{i-1}^{m} P_i}{m} \quad (9)$$

Explanation of Symbols:
SMA $_{long:}$: Long-term moving average
m : Long-term period

Signal:
A buy signal occurs when SMA $_{short}$ $>$ SMA $_{long,}$ and a sell signal occurs when SMA $_{short}$ $<$ $\mathrm{SMA_{long}}$.

F. Technical Analysis

Technical analysis uses mathematical models to predict trends and guide investment decisions. A common tool is the Moving Average Convergence Divergence (MACD) [20]:
Formulas Used

MACD:
$$\mathrm{MACD} - \mathrm{EMA_{short}} - \mathrm{EMA_{long}} \quad (10)$$

Explanation of Symbols:
MACD: Moving Average Convergence Divergence
$\mathrm{EMA_{short}}$: Short-term exponential moving average
$\mathrm{EMA_{long:}}$ Long-term exponential moving average

G. In Newer Pesearch

The previous study in "*A Novel Cryptocurrency Price Prediction Model Using GRU, LSTM and bi-LSTM Machine Learning Algorithms*" by Mohammad J. Hamayel and Amani Yousef Owda, explores the implementation of three machine learning algorithms—GRU, LSTM, and Bi-LSTM—for predicting cryptocurrency prices, including Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC), using historical data. The results indicate that GRU outperforms LSTM and Bi-LSTM in terms of prediction accuracy, achieving lower Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) across all tested cryptocurrencies. The dataset spans daily data from January 2018 to June 2021, with performance evaluated using RMSE and MAPE metrics. GRU is proven to be the most reliable and efficient model for price prediction in highly volatile markets. The study also recommends future exploration of additional factors, such as social media sentiment analysis and trading volume, to further enhance prediction accuracy.

In similar new research, The study, titled *"Methods of Forecasting the Prices of Cryptocurrency on the Financial Markets"* by Yurii Pronchakov and Oleg Bugaienko, analyzes various moving average techniques for cryptocurrency price forecasting, including Simple Moving Average (SMA), Exponential Moving Average (EMA), and Weighted Moving Average (WMA). The research shows that SMA has the lowest mean-square deviation (0.46), making it the most stable method, while EMA, with a deviation of 0.50, is more responsive to short-term price changes, which is advantageous for volatile markets. WMA has a higher deviation of 0.69. The authors recommend using EMA for short-term analysis and SMA for long-term trends. The study concludes that integrating these techniques into real-time financial tools, such as mobile applications, could enhance decision-making for cryptocurrency traders.

III. RESEARCH AND METHOD

This study was conducted in Lhokseumawe City from December 2023 until its completion, as part of the graduation requirements for the Informatics Engineering Program at Universitas Malikussaleh. It focused on developing predictive models for USDT (Tether Coin) prices using historical data from 2017 to 2024, sourced from Investing.com and supplemented by the Stock Market API (api.marketstack.com). Data from January 2024 was reserved for model testing to assess the predictive accuracy of the proposed methods. Additionally, secondary data from academic journals and books was utilized to provide theoretical context and insights into cryptocurrency market behavior and price dynamics.

The research methodology included a literature review and data analysis. The literature review examined prior studies, academic journals, and relevant publications to establish a theoretical framework emphasizing the unique characteristics of USDT and its role in the cryptocurrency market. Data analysis involved preprocessing the historical price dataset through cleaning, outlier detection, and normalization using Min-Max Scaling to ensure the data was suitable for machine learning models. Two predictive methods were applied: Double Moving Average (DMA), which calculated short-term (10-day) and long-term (50-day) moving averages to identify trends and market signals, and Gated Recurrent Units (GRU), a sequential modeling approach leveraging TensorFlow and Keras for time-series prediction.

Performance evaluation of the predictive models employed metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to quantify accuracy. DMA demonstrated effectiveness in identifying long-term trends, while GRU excelled at capturing short-term market fluctuations. The results, visualized through comparative charts and tables, revealed distinct strengths for each method, offering a comprehensive understanding of USDT price trends.

This study focuses solely on evaluating two predictive methods, namely Double Moving Average (DMA) and Gated Recurrent Units (GRU), for modeling USDT prices. It does not compare other methods that could potentially be applied to cryptocurrency price analysis, nor does it aim to develop new techniques that might outperform the two methods under investigation. The primary objective of this research is to assess the effectiveness of these existing methods in predicting USDT

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2328, Copyright ©2025
Submitted : December 2, 2024, Revised : January 8, 2025, Accepted : January 28, 2025, Published : January 31, 2025

prices using historical data from 2017 to 2024. Therefore, the findings are not intended to compare a range of approaches or to introduce innovative new methods, but rather to evaluate how well DMA and GRU perform in analyzing time-series data for cryptocurrency prices, specifically USDT.

Despite the promising results obtained from the GRU and DMA methods, there are several limitations that must be considered. First, both methods rely on historical data patterns to make predictions, which can be problematic in the context of the cryptocurrency market, known for its high volatility and dynamic nature. Since cryptocurrency prices often experience sudden shifts due to various factors, these methods may struggle to capture emerging trends or adapt to sudden market changes. Additionally, the data used in this study is based on daily closing prices, which presents another limitation. While historical data spanning multiple years provides valuable insights, it only captures a snapshot of the market at a single point in time each day. Cryptocurrency prices, however, can fluctuate dramatically within a single day, and the daily resolution of data may not fully account for these intra-day changes, limiting the accuracy of predictions. As such, while GRU and DMA are effective within the constraints of their data and modeling techniques, they cannot be regarded as absolute references for predicting cryptocurrency prices due to the constantly evolving nature of the market and the limitations in data granularity.

IV. RESEARCH RESULT

The results and discussion of the research conducted on predicting the cryptocurrency USDT (Tether) prices using the Gated Recurrent Units (GRU) and Double Moving Average (DMA) algorithms are presented in this chapter. It will provide a detailed explanation of the data description used, the calculation process, the results of the algorithm implementation, as well as a comprehensive analysis of the obtained outcomes. This chapter also includes tables and charts to support the explanation and help readers understand the prediction patterns generated from the implemented models.

The process begins with the collection of daily USDT prices in IDR, followed by preprocessing to ensure the data is clean and consistent. The first step involves calculating a three-day moving average to identify short-term trends. Next, a six-day moving average is computed using the results of the first moving average to identify long-term trends. The level and trend components are then determined based on the differences between these two moving averages. Finally, price predictions for the next five days are generated by adding the level component to the trend component, multiplied by the number of days to be forecasted. Data collection is a critical initial step in implementing the Double Moving Average (DMA) method for predicting cryptocurrency prices, specifically USDT in IDR. Daily price data for USDT is sourced from reliable providers offering real-time or historical information. Once the data is gathered, preprocessing ensures that the dataset is clean and consistent.

Moving Average (MA) calculations are widely employed in financial market analysis to identify price trends, including daily price assessments. An MA is computed as the average of prices over a specific period, offering a smoother representation of price movements and filtering out temporary fluctuations. And The Implementation Flow is :

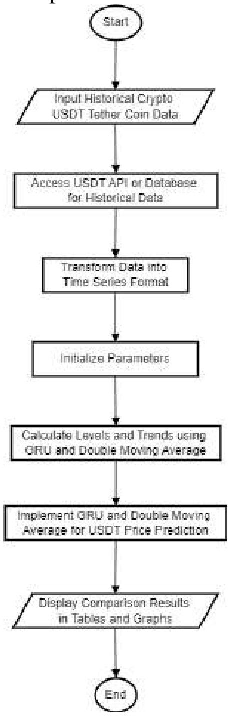

Fig 1. Scheme system

Details :

- *Start*
- *Input historical data for Crypto USDT (Tether Coin).*
- *Access the USDT API or Database for historical data on USDT.*
- *Transform the data into a time series format.*
- *Initialize parameters.*
- *Calculate levels and trends using GRU and Double Moving Average.*
- *Implement Gated Recurrent Units (GRU) and Double Moving Average to predict USDT prices.*
- *Display the comparison results in the form of tables and graphs.*
- *End process*

Based on the diagram below, the implementation process of the Gated Recurrent Units (GRU) and Double Moving Average (DMA) methods for cryptocurrency price prediction begins with loading historical USDT data from 2017 to 2024. The data is cleaned, normalized, and split into training and testing sets. For the DMA method, short-term and long-term moving averages are calculated to identify level and trend components, which are used to generate price predictions. Meanwhile, the data is transformed into a time-series format to train the GRU model. After predictions are generated from both methods, their performance is evaluated using metrics such as MAE, RMSE, and MAPE. Based on the comparison, the more reliable method is selected: DMA is recommended for stable trends, while GRU is suited for volatile market conditions. The final results are saved and visualized to support investment decisions.

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2328, Copyright ©2025
Submitted : December 2, 2024, Revised : January 8, 2025, Accepted : January 28, 2025, Published : January 31, 2025

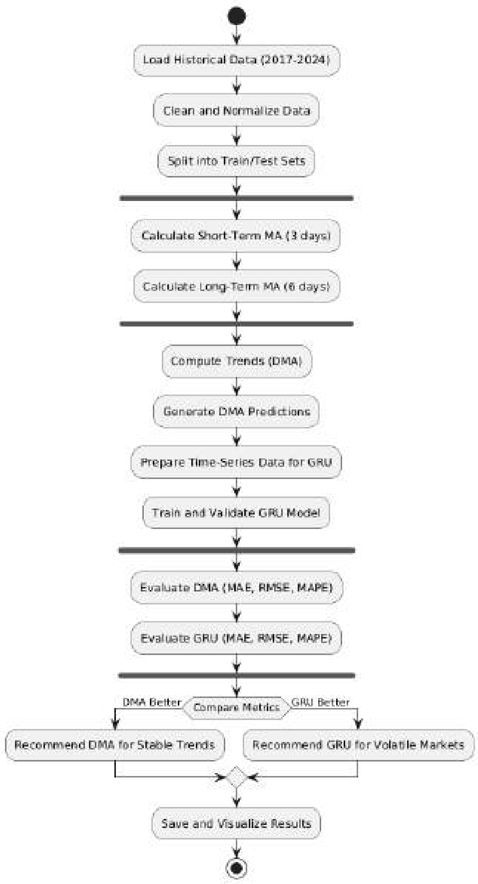

Fig 2 Data Flow

A. Training Data

The results of the research conducted, including data analysis and the application of prediction algorithms, will be discussed in this chapter. The results from the use of the Gated Recurrent Units (GRU) and Double Moving Average (DMA) algorithms will be presented to evaluate the effectiveness of the models in predicting the price of the cryptocurrency USDT (Tether). This analysis will also include a comparison between the predicted results and the actual data to assess the accuracy of the developed models.

Table I. Tether Coin USDT Historical Data (2017-2024)

No	Date	close	Open	High	low
1	14/04/2017	16.028,36	16.093,13	16.127,13	15.688,33
2	15/04/2017	16.023,50	16.028,36	16.028,36	15.667,28
3	16/04/2017	15.406,59	16.023,50	16.023,50	15.406,59
4	17/04/2017	15.207,43	15.406,59	15.702,90	14.914,36
5	18/04/2017	15.301,35	15.207,43	15.589,56	14.907,88
6	19/04/2017	15.317,54	15.301,35	15.461,65	15.175,05
7	20/04/2017	15.366,11	15.317,54	15.461,65	14.896,55
8	21/04/2017	15.160,48	15.366,11	15.382,31	14.572,71
9	22/04/2017	14.815,59	15.160,48	15.382,31	14.815,59
….	….	….	….	….	….
….	….	….	….	….	….
10	12/07/2024	16.198,38	16.196,76	16.201,62	16.196,76
11	13/07/2024	16.200,00	16.198,38	16.203,23	16.195,14
12	14/07/2024	16.201,62	16.200,00	16.204,85	16.198,38
13	15/07/2024	16.200,00	16.201,62	16.208,09	16.196,76
14	16/07/2024	16.200,00	16.200,00	16.203,23	16.195,14
15	17/07/2024	16.191,90	16.200,00	16.200,00	16.191,90
16	18/07/2024	16.188,66	16.191,90	16.195,14	16.187,04
17	19/07/2024	16.188,66	16.188,66	16.191,90	16.187,04

The table above presents the historical price data of USDT (Tether) used as the training data in this study. The data includes the closing price, opening price, highest price, and lowest price over the period from April 14, 2017, to July 19, 2024. This data is used to train the prediction model, where price movement patterns are analyzed using the Gated Recurrent Units (GRU) and Double Moving Average (DMA) algorithms. Each row represents daily data collected sequentially to capture trends and fluctuations over the given period. This information is crucial in helping the model learn and generate more accurate predictions for the future.*Identify the Headings.*

B. Testing Data

Table II. Tether Coin USDT test Historical Data (2017-2024)

No	Date	Close	Open	High	Low
1	01/01/2020	16.387,82	16.345,72	16.397,54	16.318,20
2	02/01/2020	16.277,72	16.455,83	16.462,30	16.274,48
3	03/01/2020	16.255,05	16.277,72	16.358,68	16.248,57
4	04/01/2020	16.272,86	16.295,53	16.342,48	16.271,24
5	05/01/2020	16.243,71	16.272,86	16.326,29	16.242,09
6	06/01/2020	16.258,29	16.258,29	16.279,34	16.240,48
7	07/01/2020	16.217,81	16.279,34	16.284,19	16.212,95
8	08/01/2020	16.212,95	16.217,81	16.238,86	16.209,71
9	09/01/2020	16.230,76	16.212,95	16.245,33	16.212,95
….	….	….	….	….	….
….	….	….	….	….	….
10	12/07/2024	16.198,38	16.196,76	16.201,62	16.196,76
11	13/07/2024	16.200,00	16.198,38	16.203,23	16.195,14
12	14/07/2024	16.201,62	16.200,00	16.204,85	16.198,38
13	15/07/2024	16.200,00	16.201,62	16.208,09	16.196,76
14	16/07/2024	16.200,00	16.200,00	16.203,23	16.195,14
15	17/07/2024	16.191,90	16.200,00	16.200,00	16.191,90
16	18/07/2024	16.188,66	16.191,90	16.195,14	16.187,04
17	19/07/2024	16.188,66	16.188,66	16.191,90	16.187,04

The table above presents the test data used in this research, containing historical USDT (Tether) prices from the period of January 1, 2020, to July 19, 2024. The data includes the closing price, opening price, highest price, and lowest price for each day. This test data is used to evaluate and validate the accuracy of the prediction model that has been trained on prior data. The prediction models, both using the Gated Recurrent Units (GRU) and Double Moving Average (DMA) algorithms, will be tested against this data to assess how well the models can predict the actual prices based on the historical patterns already analyzed. The predicted results from the models will then be compared with the actual values from the test data to evaluate the effectiveness and performance of the developed models.

Table III. Comparison Results of GRU and DMA Metrics

Metric	DMA	GRU
MAE	5.494285	5.983858
RMSE	8.715295	8.530839
MAPE	0.033918	0.036935
MPE	-0.001262	0.028594

The comparison between Double Moving Average (DMA) and Gated Recurrent Unit (GRU) in predicting closing prices

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2328, Copyright ©2025
Submitted : December 2, 2024, Revised : January 8, 2025, Accepted : January 28, 2025, Published : January 31, 2025

reveals that both methods have their own strengths. Overall, DMA performs better in terms of absolute error metrics, with MAE at 5.494 and MAPE at 0.0339%, compared to GRU .

(MAE at 5.983 and MAPE at 0.0369%). This indicates that DMA provides more stable predictions with lower average errors.

However, GRU excels in handling large errors, as reflected in its lower RMSE (8.5308) compared to DMA (8.7153). Additionally, GRU is more responsive to rapid price fluctuations, making it more suitable for use in dynamic and volatile market conditions.

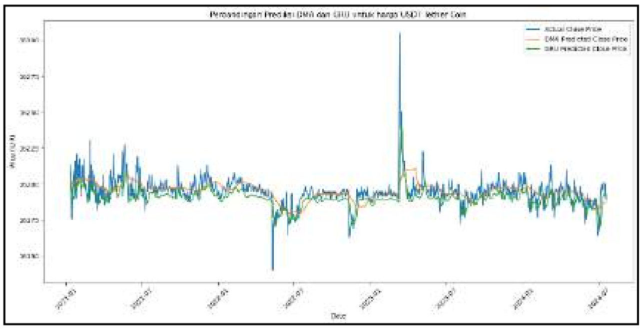

Fig 3. Comparison graph between original prices and DMA prediction results

The comparison between GRU and DMA reveals distinct strengths for each method. Overall, DMA demonstrates lower average errors (MAE: 5.494285, MAPE: 0.033918%) compared to GRU (MAE: 5.983858, MAPE: 0.036935%), making it more accurate on average. However, GRU is better at handling large errors, as indicated by its lower RMSE (8.530839 vs. DMA's 8.715295). In terms of bias, DMA has minimal systematic bias (MPE: -0.001262%), while GRU exhibits a slight positive bias (MPE: 0.028594%). DMA is more stable and suited for long-term trend analysis, but less responsive to rapid price changes. In contrast, GRU excels in capturing daily fluctuations, making it ideal for volatile market conditions. Both methods have their merits: DMA for stable, long-term predictions, and GRU for dynamic, high-volatility environments, with the choice depending on specific analytical needs.

In conclusion, DMA is better suited for long-term trend analysis with greater stability, while GRU is more effective at addressing significant and rapid price changes. The choice of method depends on the specific context of the analysis and the need for accurate price predictions. In difference with other research, *"Forecasting the Prices of Cryptocurrency on the Financial Markets"* by Yurii Pronchakov and Oleg Bugaienko and journal *"Parent Coin-Based Cryptocurrency Price Prediction Using Regression Techniques"* by Jg Aravindan and Ram Sankara.The first referenced study focuses on applying various moving average techniques, including SMA, EMA, and WMA, to forecast cryptocurrency prices.

It emphasizes that EMA performs best in volatile conditions due to its responsiveness to short-term changes, while SMA excels in long-term trend stability. However, the study does not explore the combination of moving averages with advanced machine learning models such as GRU, limiting its ability to handle dynamic and highly volatile market conditions comprehensively. In contrast, your research integrates DMA, a specific variation of moving averages, with GRU, offering a hybrid approach to balance trend stability with responsiveness to rapid fluctuations.

The second referenced study introduces regression-based methods for price prediction using parent coin relationships and machine learning models like Decision Trees and Ridge Regressors. While these methods are effective for capturing interdependencies among cryptocurrencies, they lack the temporal dynamics needed for precise predictions in real-time or short-term fluctuations. Compared to your study, which combines DMA for trend identification with GRU's strength in modeling sequential data, your approach provides a more holistic view by addressing both trend stability and temporal volatility, ensuring better adaptability in real-world scenarios.

This research builds upon these methodologies by not only validating the effectiveness of DMA in capturing trends but also integrating it with GRU to enhance predictions in volatile market conditions. The results from your study show that DMA has lower average errors (MAE: 5.494285, MAPE: 0.033918%) and stability in long-term analysis compared to GRU, which excels in handling large errors and rapid fluctuations. This hybrid model addresses the gaps in both referenced studies, as it successfully combines the strengths of traditional moving average techniques and advanced machine learning algorithms. This innovation positions your research as a significant step forward in cryptocurrency price forecasting, offering a balanced and adaptable solution for both stable and volatile market environments.

Comparison With LSTM Algorithm

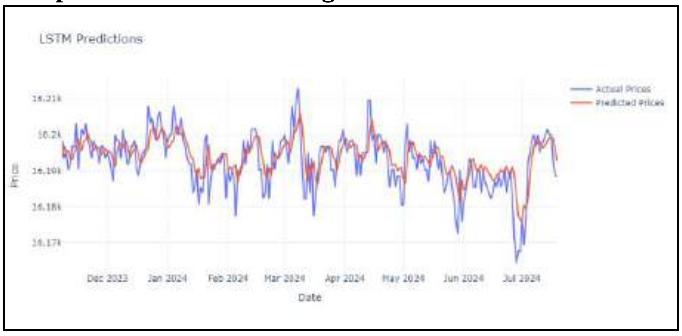

Fig 4. Comparison With LSTM

The comparison between the manual LSTM model, GRU, and DMA highlights the distinct strengths of each method. The manual LSTM model demonstrates superior accuracy, as evidenced by its lower MAE (4.3143) and MAPE (0.0266%) compared to GRU (MAE: 5.9839, MAPE: 0.0369%) and DMA (MAE: 5.4943, MAPE: 0.0339%).

This indicates that the LSTM model performs better in predicting average values with minimal deviations. Additionally, the RMSE of the manual LSTM model (5.6415) is significantly lower than both GRU (8.5308) and DMA (8.7153), showcasing its ability to handle large prediction errors more effectively. In terms of bias, the LSTM model's MPE

p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2328, Copyright ©2025
Submitted : December 2, 2024, Revised : January 8, 2025, Accepted : January 28, 2025, Published : January 31, 2025

(0.0072%) is close to DMA (-0.0013%) and notably better than GRU (0.0286%), highlighting its minimal systematic bias.

While GRU and DMA excel in specific contexts, the manual LSTM model appears to combine their strengths. DMA is often preferred for its stability and suitability for long-term trend analysis, but it struggles with rapid market changes. GRU, on the other hand, excels in dynamic, high-volatility environments but introduces slightly higher average errors and bias. The manual LSTM model strikes a balance by providing both accurate average predictions and effective error handling, making it a robust choice for both stable and volatile market conditions. This versatility positions the LSTM model as a strong contender in predictive analytics across diverse scenarios.

V. CONCLUSION

The comparison between the Gated Recurrent Unit (GRU) and Double Moving Average (DMA) methods for predicting USDT (Tether Coin) prices highlights the unique strengths of each approach. GRU demonstrates superior performance in capturing price dynamics and trends in volatile markets, evidenced by its lower Root Mean Squared Error (RMSE) of 8.530839, indicating better handling of significant deviations. Conversely, DMA offers more stable predictions with a lower Mean Absolute Error (MAE) of 5.494285 and a Mean Absolute Percentage Error (MAPE) of 0.033918%, showcasing its ability to minimize average errors and filter out market noise effectively. When it comes to practical applications, GRU proves to be highly effective in responding to real-time market volatility, accurately forecasting rapid price changes.

In contrast, DMA is better suited for identifying and analyzing long-term market trends, making it particularly beneficial for traders seeking stability and consistent insights. Therefore, the choice between GRU and DMA depends on the specific objective, whether it is to adapt to short-term price fluctuations or to gain a comprehensive understanding of broader market movements.Future research should address the limitations of this study by incorporating more granular data, such as intra-day price fluctuations, to better capture rapid market changes. Additionally, integrating external factors like social media sentiment analysis, macroeconomic indicators, and trading volume could enhance the predictive capability of GRU and DMA. Exploring hybrid models that combine these techniques with other machine learning approaches, such as transformers or ensemble models, may further improve accuracy in both stable and volatile market conditions. Finally, real-time testing on live markets with dynamic updates can validate the practicality and scalability of this approach for broader adoption in cryptocurrency trading platforms.

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p-ISSN 2301-7988, e-ISSN 2581-0588
DOI : 10.32736/sisfokom.v14i1.2328, Copyright ©2025
Submitted : December 2, 2024, Revised : January 8, 2025, Accepted : January 28, 2025, Published : January 31, 2025