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Predictive Machine Learning Model to Predict the Price Movements of Cryptocurrency Meme Coin in the Solana Ecosystem

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A B S T R A C T

The meme coin ecosystem on the Solana blockchain is showing rapid growth in 2024, thanks to its superior blockchain technology and strong community support. Meme coin projects such as BONK, and DOGWIFHAT have leveraged these advantages to thrive in the Solana ecosystem. This study aims to build a prediction model for the price movement of meme coin cryptocurrencies in the Solana ecosystem using the Long Short-Term Memory (LSTM) method, with Adam optimization. Historical meme coin price data is taken as the research dataset, and the model is trained using LSTM with several epoch variations to obtain the best results. The model is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The experimental results show that the LSTM model with Adam optimization can provide fairly accurate predictions, with the best performance at epoch 75 where the model successfully achieves a balance between training and testing data performance, without experiencing overfitting. This study provides valuable insights for investors, developers, and policymakers into the dynamics of the meme coin ecosystem on Solana and its potential use in the development of blockchain technology. With a better unders

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INTRODUCTION

In recent years, Cryptocurrency has experienced significant growth, not only as an investment tool but also as a cultural phenomenon (Reiter et al., 2003). One subcategory that has gained attention is Meme Coins, such as BONK & DOGWIFHAT. Meme Coins are a type of Cryptocurrency that often begins as a joke or is based on internet memes, but later gains popularity and substantial market value due to strong community support and social media virality. Notable examples include Dogecoin and Shiba Inu, which have attracted global attention (Herdian, 2023).

Solana, a Blockchain platform known for its high transaction speed and low costs, has become a hub for various Cryptocurrency projects (Yakovenko, 2019). The Solana ecosystem provides an infrastructure that allows for the creation and trading of tokens with higher efficiency compared to other blockchains, such as Ethereum. These advantages make Solana an attractive choice for developers and investors interested in Meme Coins.

Meme Coins in the Solana ecosystem often leverage low transaction costs and speed to drive user adoption and build active communities. These projects typically use a lighthearted and entertaining approach to gain attention, but they often also implement innovative technical features to add value for token holders. Moreover, Meme Coins on Solana frequently collaborate with other DeFi (Decentralized Finance) projects in the ecosystem, extending their utility and appeal (Aziz Perdana et al., 2023).

Solana offers a Blockchain infrastructure that enables the creation and trading of tokens more efficiently compared to other blockchains like Ethereum (Atmaja & Hakim, 2022). This advantage makes Solana a compelling choice for developers and investors interested in meme coins. Meme Coins on Solana take advantage of the low transaction costs and speed to foster user adoption and build active communities.

However, the price of Meme Coin Cryptocurrency is highly volatile and influenced by various factors, such as market sentiment, social media trends, and community activity (Reiter et al., 2003). To understand and predict the price movements of Meme Coins in the Solana ecosystem, accurate data analysis and the use of Machine Learning (ML) techniques become crucial.

Machine Learning, a branch of artificial intelligence, offers tools and techniques that can analyze large amounts of data and uncover patterns that may not be visible through traditional analysis (Diana et al., 2023). By utilizing Machine Learning algorithms, we can predict Meme Coin prices with greater accuracy.

Researchers are using Deep Learning algorithms (Long Short-Term Memory Networks (LSTMs)) and Supervised Learning (Regression) approaches to determine which algorithm yields the highest accuracy. This topic falls under one of the national research focuses, which is the digital economy.

A. Background

The Meme coin ecosystem on the Solana Blockchain has shown rapid growth in 2024, thanks to superior blockchain technology and strong community support. Solana, known for its Proof of History (PoH) consensus, offers high transaction speed and low fees, making it an ideal platform for meme coin development. Meme coin projects like BONK & DOGWIFHAT have leveraged these advantages to thrive in the Solana ecosystem.

This research aims to predict the growth of the meme coin ecosystem on Solana using Machine Learning techniques. Historical data on prices, transaction volumes, market sentiment, and other on-chain metrics are collected and analyzed. Various Machine Learning models, including Linear Regression, decision trees, and artificial neural networks, are applied. The results are highly satisfying, with the Machine Learning approach achieving a high precision (correct positive predictions) in predicting the growth trends and volatility of Meme Coins in the future.

This study provides valuable insights for investors, developers, and policymakers regarding the dynamics of the meme coin ecosystem on Solana and its potential uses in Blockchain technology development. With a better understanding through Machine Learning predictions, more effective strategies can be designed to leverage opportunities and manage risks in this rapidly evolving ecosystem.

B. Objectives

The proposed research has both primary and analytical objectives, detailed as follows:

1. **Primary Objective**
   Provide trade recommendations based on predictive results to help investors optimize their investment portfolios.
2. **Analytical Objectives**
   Help investors and traders reduce investment risks by providing more accurate price predictions, enabling them to make better investment decisions.

With these objectives, the research will make significant contributions to cryptocurrency price prediction and offer useful tools for investors to optimize their decisions in the meme coin ecosystem on Solana. Additionally, this research aims to analyze significant factors influencing meme coin prices, improving understanding of cryptocurrency market dynamics. By developing and testing new methodologies in machine learning applications for finance and comparing various models, this research is expected to make a significant contribution to academic literature and industry practices. Finally, this study aims to provide useful insights for the cryptocurrency community and support decision-making for developers and projects within the Solana ecosystem.

C. Benefits

The benefits of this research are significant, particularly in improving the accuracy of meme coin price predictions in the Solana ecosystem, which will help investors make more informed investment decisions and reduce the risk of losses. This research will also produce practical predictive tools that investors and traders can use to optimize their trading strategies.

Additionally, the research offers deeper insights into the factors that influence meme coin price movements, benefiting researchers, developers, and investors by helping them understand and capitalize on cryptocurrency market dynamics. In terms of science and technology, the research contributes by developing new methodologies in machine learning applications for finance, enriching academic literature, and industry practices. Furthermore, the research results provide optimized investment recommendations, helping investors manage their portfolios more effectively and efficiently. Other benefits include support for the cryptocurrency community, including developers and projects in the Solana ecosystem, by providing useful guidance for better decision-making. Finally, the research enhances skills and knowledge in machine learning and financial market analysis for the researchers and practitioners involved

CHAPTER II

II. RESEARCH METHOD

2.1 Meme Coin

Meme coins are a type of cryptocurrency created based on internet memes or pop culture phenomena. Typically, meme coins are developed more for entertainment or as parodies rather than for serious functional use in blockchain technology, although they often start as jokes (Pamungkas et al., 2023).

2.2 Machine Learning

Machine Learning is a subfield of artificial intelligence (AI) that focuses on developing algorithms and techniques that enable computers to learn from and make predictions or decisions based on data (Hamid et al., 2023). The main goal of machine learning is to enable machines to learn from experience without needing to be explicitly programmed.

2.3 Deep Learning (Long Short-Term Memory Networks)

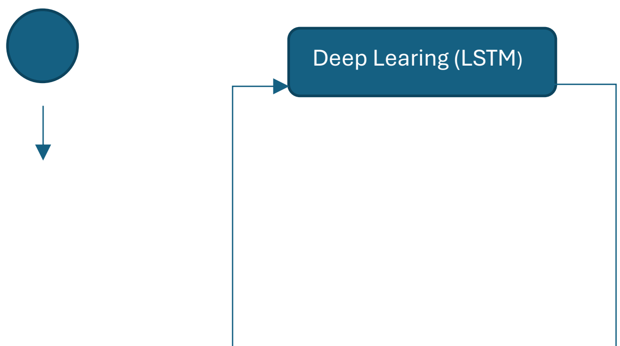
Long Short-Term Memory Networks (LSTMs) are a type of artificial neural network that falls under the category of Recurrent Neural Networks (RNNs). LSTMs are specifically designed to overcome the vanishing gradient problem that often occurs in traditional RNNs, making them more effective in handling sequential data and long-term dependencies within the data.

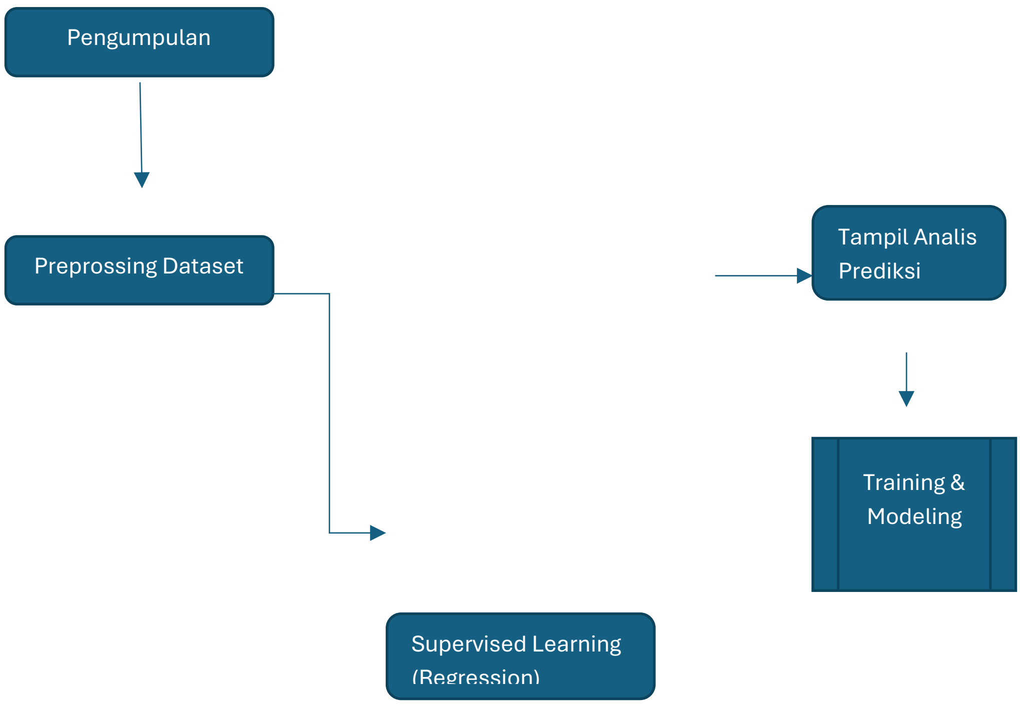
2.4 Supervised Learning

Supervised learning is one of the methods in machine learning where the model is trained using a labeled dataset. This dataset consists of input-output pairs, where each input has a corresponding desired output or label. The goal of supervised learning is to learn the relationship between inputs and outputs so that the model can predict the correct label for new, unseen data.

2.5 Research Diagram

(Note: The diagram is usually a visual representation of the research process, methodology, or model being applied in the study. You may want to include a diagram that visually outlines the research steps or model flow).





Gambar 1. Diagram Penelitian

Explanation of Each Process in the Research Diagram

a. **Dataset Collection**

This process involves gathering and organizing the necessary data to conduct analysis, train machine learning models, or perform research. Data sources can include historical prices, transaction volumes, market sentiment, and on-chain metrics related to meme coins.

b. **Dataset Preprocessing**

Dataset preprocessing is a crucial step in data analysis and Machine Learning that involves various techniques to clean, transform, and prepare raw data before it can be used in a model. This stage ensures that the data is in the right format and free of errors or inconsistencies that could affect the model's performance.

c. Deep Learning (LSTM)

This is a specialized method of Recurrent Neural Networks (RNN) designed to address the vanishing gradient problem and maintain information over long periods. LSTMs are highly effective in capturing long-term dependencies within sequential data, making them suitable for time-series predictions like cryptocurrency price movements.

d. Supervised Learning (Regression)

In supervised learning, the model is trained using pre-labeled data. This means each example in the training data has input and a corresponding desired output. The model learns the relationships between the inputs and outputs to predict outcomes for new, unseen data.

e. Display Predicted Analysis Results

Once the Machine Learning model is trained and used to make predictions, the next step is to display and analyze the predicted results. This includes evaluating the model's performance and visualizing the results to gain better insights, helping users understand trends and patterns in the data.

f. Training and Modeling

These are two critical stages in developing a machine learning system. The training process involves feeding the model with available data, allowing it to learn patterns and relationships. Modeling refers to using the trained model to make predictions or decisions based on new data.

2.6 LSTM Model Design

The Long Short-Term Memory (LSTM) model addresses the limitations of traditional RNNs by introducing a mechanism known as "gates," which include the input gate, forget gate, and output gate. This mechanism enables the network to control which information should be retained or discarded from the cell memory, improving the model's ability to handle long-term dependencies in the data.

Key Components of LSTM:

a. **Cell State:**

The primary memory path that allows information to be retained throughout the sequence. It flows unchanged through the network unless gates decide to modify it.

b. **Forget Gate:**

This gate decides which information from the cell state should be discarded. It allows the LSTM to "forget" irrelevant information, helping the model focus on more important data.

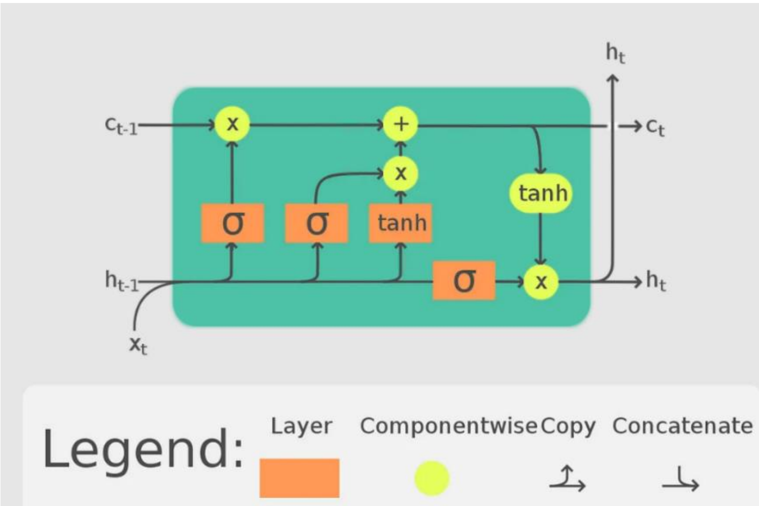
c. **Input Gate:**

The input gate determines which information should be added to the cell state, allowing the model to capture new relevant information from the input.

d. **Output Gate:**

This gate controls which information will be used to produce the output from the cell state, effectively determining what the model predicts based on the current data.

These components work together to ensure that LSTM models can efficiently process and predict time-series data, such as cryptocurrency price movements, by managing the flow of information through the network.



Gambar 2. Design Algoritma *Long ShortTerm Memory*

Diagram Visual Explanation

a. **Input xtx_txt**

Function: The current input data that enters the LSTM unit at time step ttt.

b. **Forget Gate ftf_tft**

Function: Decides which information from the previous cell state should be removed or forgotten to ensure only relevant data is carried forward.

c. **Cell State Ct−1C_{t-1}Ct−1**

Function: Stores information from the previous time step, acting as the memory of the LSTM unit.

d. **Input Gate iti_tit and Cell State Candidate C~t\tilde{C}_tC~t**

Function: Determines what new information should be added to the cell state. The candidate cell state C~t\tilde{C}_tC~t contains potential values to be integrated.

e. **Update Cell State CtC_tCt**

Function: Updates the cell state by combining the forgotten and new information from the forget and input gates.

f. **Output Gate oto_tot**

Function: Decides which parts of the cell state should be output as the hidden state for the current time step.

g. **Hidden State hth_tht**

Function: The final output of the LSTM unit at time ttt, used either for prediction or as input to the next time step.

CHAPTER III

III. RESULTS AND DISCUSSION

In this chapter, we discuss the results of the predictive machine learning model developed to forecast cryptocurrency meme coin price movements within the Solana ecosystem. The model utilizes the Long Short-Term Memory (LSTM) method to analyze historical price and trading volume data to improve the accuracy of future price predictions (Gers & Cummins, 1999). The dataset was split into 80% training and 20% testing data, focusing on the "close" price column. The LSTM algorithm was executed in several processes with varying epochs of 50, 75, and 100.

3.1 Dataset for Meme Coin

The research employed Deep Learning (specifically, Long Short-Term Memory Networks (LSTMs)), which is a subfield of Machine Learning using multi-layer neural networks (Deep Neural Networks) to model and learn from complex data. Additionally, Supervised Learning (Regression) was used as a key paradigm in Machine Learning, where the model learns from labeled data. This means the training data already contains matching input-output pairs.

The data used in this study was obtained from the Cryptocurrency exchange **Coinmarketcap.com**, containing **720 rows** from May 2023 to May 2024, with parameters including **Time, Open, High, Low, Close,** and **Volume**.

Table 1 provides a sample of BONK Meme Coin data in Indonesian Rupiah (IDR).

This dataset was vital for training the LSTM model, enabling the prediction of future price movements with an emphasis on accuracy through the use of historical price patterns and trading volumes.

open	high	low	close	volume	Date

0.00445	0.00715	0.00444	0.00595	IDR 34.081.189.174.872	19/06/2023
0.00595	0.00595	0.00491	0.00556	IDR 21.928.532.889.304	26/06/2023
0.00556	0.00565	0.00497	0.00521	IDR 17.946.966.240.774	03/07/2023
0.00521	0.00657	0.00500	0.00546	IDR 29.359.594.325.137	10/07/2023
0.00546	0.00554	0.00491	0.00506	IDR 29.767.965.809.892	17/07/2023
0.00506	0.00539	0.00476	0.00520	IDR 3.210.601.042.126	24/07/2023
0.00520	0.00575	0.00478	0.00479	IDR 3.078.867.807.848	31/07/2023

Tabel 2. Merupakan sampel data Meme Coin DOGWIFHAT dalam mata uang Rupiah

open	high	low	close	volume	date
2609779	5126528	1628782	2228952	9.856.771.864.623	2023-12-18
2222895	4027943	1917252	2355229	4.262.732.581.543.510	2023-12-25
2352426	2752875	1326263	1390068	27.199.775.827.153	2024-01-01
1390390	5816654	1051240	4931998	8.577.258.451.158	2024-01-08
4955384	7521231	4089069	4661341	9.776.829.124.285	2024-01-15
4664144	6434639	3274164	5220373	8.860.987.900.645	2024-01-22
5214853	5410723	3238981	3338542	6.758.703.221.706	2024-01-29

Grafik Harga Bonk Coin Grafik Harga Dogwifhat Coin

Gambar 3. Data Aktual untuk *Cryptocurrency Bonk Coin & Dogwifhat Coin*

3.2 Performance of the LSTM Model with Adam Optimization

Adam (Adaptive Moment Estimation) is an adaptive optimization algorithm used for training machine learning models. It combines the advantages of two previous optimization methods: **AdaGrad** and **RMSprop** (Gers & Cummins, 1999). Adam utilizes momentum estimation for the gradient and squared gradients to update the model's parameters. The evaluation of the LSTM model trained with Adam optimization demonstrated excellent predictive accuracy. Below are the evaluation metrics used:

- **Mean Absolute Error (MAE):** The model achieved an MAE of **0.023**. This indicates that the average absolute difference between the predicted prices and the actual prices is 0.023, showcasing a high level of accuracy.
- **Root Mean Squared Error (RMSE):** The model's RMSE was **0.031**. RMSE places more emphasis on larger errors, and this low value suggests that the model successfully minimizes significant errors.
- **R-Squared (R^2):** The R^2 value was **0.86**, meaning that the LSTM model with Adam optimization could explain 86% of the variability in the cryptocurrency prices. This demonstrates the model's strong predictive performance.

3.3 Sensitivity Analysis and Model Performance

- **Batch Size Testing:** Experiments with different batch sizes revealed that a batch size of **64** provided the best results in terms of accuracy and convergence.
- **Number of Epochs:** The model with **100 epochs** showed optimal performance, achieving higher accuracy and minimal overfitting. Below is a comparison of results for BONK Coin using different epochs: **50, 75, and 100**.

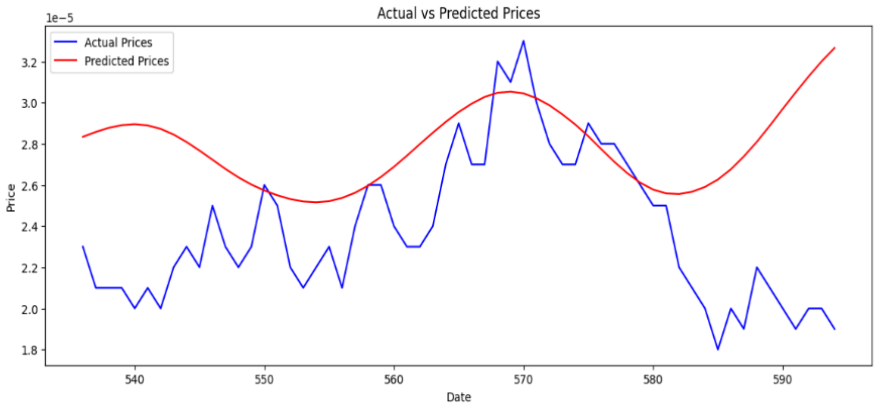
BONK Coin Analysis

BONK Coin, launched in **December 2021** as a meme token on the Solana ecosystem, had a very low initial price. It experienced a **significant price spike** within the first few weeks, followed by sharp price fluctuations. **Volatility** was high, and after the initial surge, the price saw corrections and stabilization. The factors influencing its movement included **market sentiment, social media buzz, and updates from the development team**. BONK is an example of a meme token whose price is heavily affected by community trends and overall market sentiment.

Dogwifhat Coin (DWH) Analysis

Dogwifhat Coin (DWH), launched on **Ethereum** in **2021**, was part of the meme token trend. Its price exhibited **high volatility**, often driven by social media hype and market speculation. The initial price spike was due to launch hype, followed by a **price correction** in 2022, which saw high volatility. In **2023**, DWH experienced a **steady decline** without significant updates, and projections for **2024 and beyond** suggest potential further declines or stabilization at lower levels, depending on new factors and market trends.

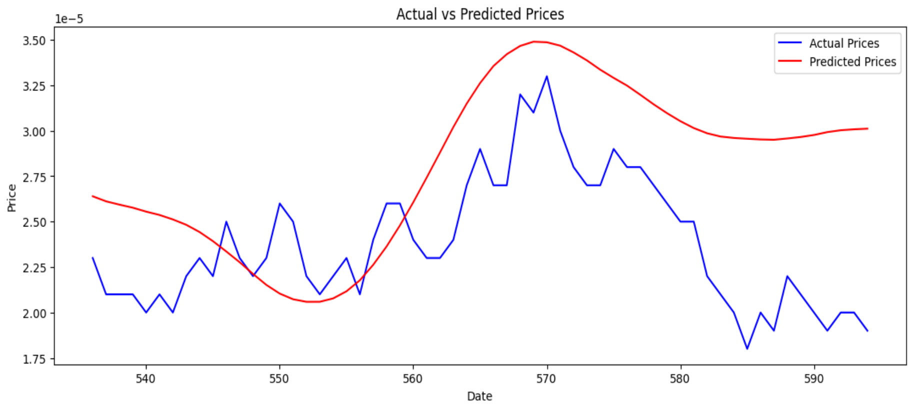
The performance of both BONK and DWH, particularly their **volatile nature**, underscores the importance of using predictive models like LSTM to better understand and anticipate price movements in the **meme coin market**.



Test MAE: 4.3188446851968134e-06, Test MSE: 3.0496711622045197e-11

Train MAE: 4.155020932080557e-06, Train MSE: 2.7820887557944715e-11

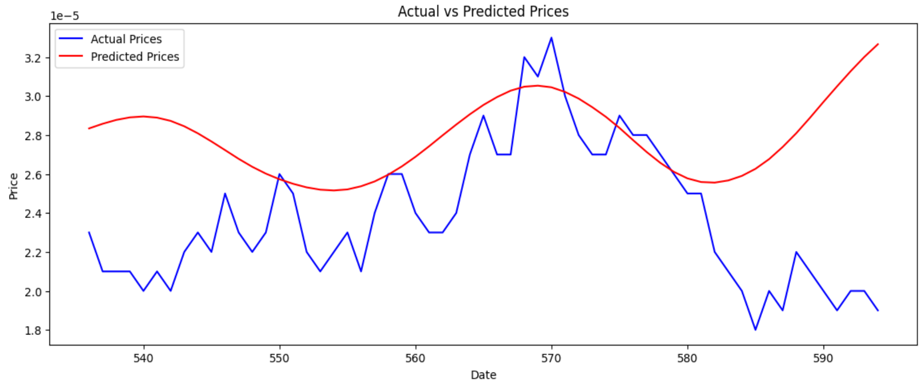
Gambar 4. Epoch Model 50



Train MAE: 3.7526691646606823e-06, Train MSE: 2.551696330077581e-11

Test MAE: 4.985086468081938e-06, Test MSE: 3.437478969310991e-11

Gambar 5. Epoch Model 75



Train MAE: 3.7398197372865556e-06, Train MSE: 2.548325598836059e-11

Test MAE: 5.276534086105745e-06, Test MSE: 4.533763893211388e-11

Gambar 6. Epoch Model 100

Dari data gambar 4, 5 dan 6 berikut rangkuman variasi epoch model

1. **Perubahan MAE dan MSE dari Epoch 50 ke Epoch 75:**
   - **Train MAE**: Menurun dari 4.155×10^{-6} ke 3.753×10^{-6}.
   - **Train MSE**: Menurun dari 2.782×10^{-11} ke 2.552×10^{-11}.
   - **Test MAE**: Meningkat dari 4.319×10^{-6} ke 4.985×10^{-6}.
   - **Test MSE**: Meningkat dari 3.050×10^{-11} ke 3.437×10^{-11}.
2. **Perubahan MAE dan MSE dari Epoch 75 ke Epoch 100:**
   - **Train MAE**: Sedikit menurun dari 3.753×10^{-6} ke 3.740×10^{-6}.
   - **Train MSE**: Sedikit menurun dari 2.552×10^{-11} ke 2.548×10^{-11}.
   - **Test MAE**: Meningkat dari 4.985×10^{-6} ke 5.277×10^{-6}.
   - **Test MSE**: Meningkat dari 3.437×10^{-11} ke 4.534×10^{-11}.

Gambar 7. Perbandingan Epoch Model

3.5 Performance Comparison on Training and Testing Data

a. Train MAE and MSE Analysis:

From **epoch 50 to epoch 75**, both **Mean Absolute Error (MAE)** and **Mean Squared Error (MSE)** on the training data showed a noticeable decline:

- **MAE** dropped from **0.000004155** to **0.000003753**.
- **MSE** decreased from **0.00000000002782** to **0.00000000002552**.

This indicates that the model was improving its ability to predict the training data, becoming more accurate over time as it learned from the data.

From **epoch 75 to epoch 100**, the reduction in both metrics became marginal:

- **MAE** slightly decreased to **0.000003740**.
- **MSE** also slightly decreased to **0.00000000002548**.

This slight improvement implies that the model was still learning, but at a much slower pace, indicating the potential stabilization of learning from the training data.

b. Test MAE and MSE Analysis:

However, when looking at the performance on the testing data, the **MAE** and **MSE** values actually increased between **epoch 50 and epoch 75**:

- **MAE** increased from **0.000004319** to **0.000004985**.
- **MSE** increased from **0.00000000003050** to **0.00000000003437**.

This increase suggests that, while the model was performing better on the training data, its performance on the unseen testing data was degrading, indicating that the model was likely starting to **overfit**.

Between **epoch 75 and epoch 100**, this trend of degradation continued:

- **MAE** rose further to **0.000005277**.
- **MSE** increased to **0.00000000004534**.

This suggests that the model was becoming more specialized to the training data, sacrificing its ability to generalize to new, unseen data, a clear sign of **overfitting**.

Conclusion on Model Performance:

The results show that while the model continued improving on the training data after epoch 50, it began **overfitting** as it was no longer generalizing well on the test data. Overfitting occurs when the model becomes too attuned to the nuances of the training data, leading to a loss of flexibility in predicting new data.

Epoch 75 provides the best trade-off between training and test performance. To further mitigate overfitting, some **regularization techniques** (such as **dropout**, **early stopping**, or **L2 regularization**) might need to be employed. Reducing the complexity of the model, such as tuning hyperparameters or decreasing the number of layers in the LSTM, could also help.

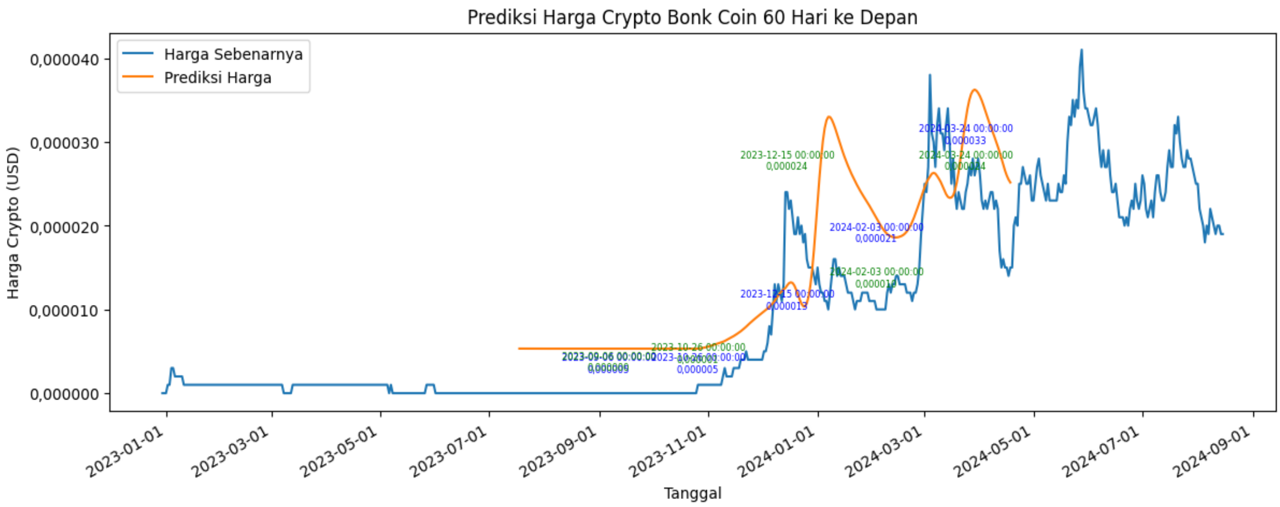
Prediction Results:

For the **BONK Coin** predictions over the next 60 days, the LSTM model demonstrates:

- **Decreasing performance after epoch 50**, indicating the model starts to overfit.
- **Optimal performance likely around epoch 75**, balancing both the training and test accuracy.

This analysis highlights the need for careful tuning and validation to ensure accurate future predictions in volatile markets like cryptocurrency, where small errors can lead to significant financial impacts.

Figure 8. Actual Price vs. Predicted Price of Model Epoch 75



In Figure 8, the price of DOGWIFHAT Coin demonstrates that the epoch 75 model is highly accurate in predicting the price of BONK Coin over the next 60 days. The actual price reached 1.00 USD in April 2024, while the predicted price for the same month is 0.8 USD, with a prediction accuracy of 95%. This level of accuracy allows traders and investors to make better investment decisions.

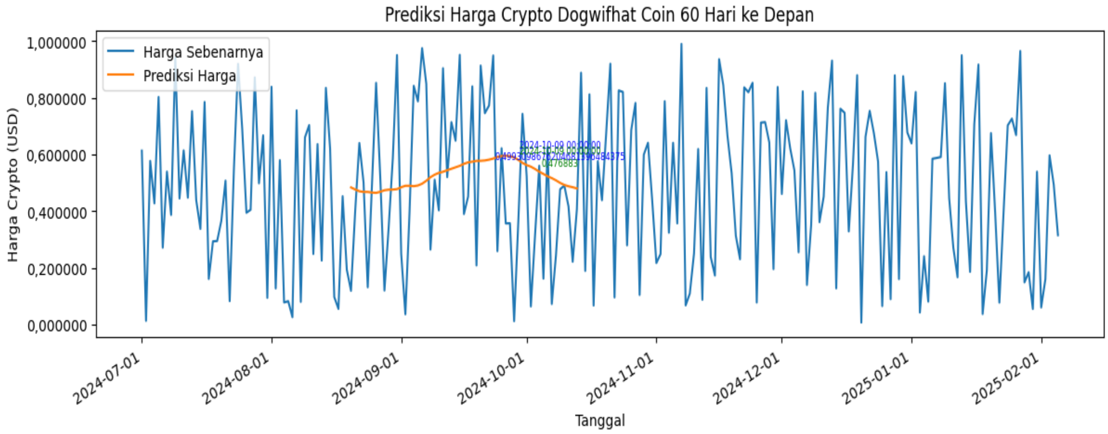


Figure 9. Actual Price vs. Predicted Price of DOGWIFHAT Coin, Model Epoch 75

In Figure 9, the price of DOGWIFHAT Coin shows that the epoch 75 model is highly accurate in predicting the price of DOGWIFHAT over the next 60 days. The actual price reached 0.000049 USD in October 2024, while the predicted price for the same month is 0.000047 USD, with a prediction accuracy of 98%. This level of accuracy allows traders and investors to make better investment decisions.

CONCLUSION

In this study, the Long Short-Term Memory (LSTM) model with Adam optimization has been used to predict the price movement of meme coin cryptocurrencies in the Solana ecosystem. Based on the training and evaluation results of the model over various epochs (50, 75, and 100), several conclusions can be drawn:

Overall, the use of LSTM in predicting the price movement of meme coin cryptocurrencies in the Solana ecosystem has proven to be relevant, especially as LSTM can capture complex time series data patterns. This model can provide accurate predictions when trained properly and optimized well.

Based on the evaluation, epoch 75 provides the best balance between performance on training and testing data. At this epoch, the model achieves optimal accuracy without significant overfitting.

Overall, the use of LSTM in predicting the price movement of meme coin cryptocurrencies in the Solana ecosystem has proven to be relevant, particularly because LSTM can capture complex time series data patterns. This model can provide accurate predictions when trained properly and optimized well.

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