



Comparison of Airdrop Coin Prices in Cryptocurrency Using LSTM: A Case Study of Grass, Not Pixel, and Dogs Coins

Muhamad Ardi Alfatih^{1*}, Paradise², Nicolaus Euclides Wahyu Nugroho³

^{1,2,3}Bachelor of Informatics Engineering Study Program, Telkom University Purwokerto, Indonesia

E-mail: ¹ardialfatih@student.telkomuniversity.ac.id,

²Paradise@telkomuniversity.ac.id, ³Nicolousn@telkomuniversity.ac.id

Received Apr 01st 2026; Revised May 09th 2026; Accepted Jun 09th 2026; Available Online Jun 20th 2026

Corresponding Author: Muhamad Ardi Alfatih

Copyright © 2026 by Authors, Published by Indonesian Institute of Research and Publication (IRPI)

Abstract

The distribution of airdrops across the cryptocurrency ecosystem often leads to extreme price volatility, complicating data-driven strategic decision-making for investors. This study aims to implement a Long Short-Term Memory (LSTM) architecture to predict airdrop coin prices and integrate the results into an interactive dashboard-based Decision Support System (DSS). The research methodology employs a Recursive Multi-step Forecasting strategy to model nonlinear time-series data across three case studies: GRASS, NOT PIXEL, and DOGS, covering the period from August 2024 to March 2026. Data were obtained via the CoinGecko API v3 and evaluated using MSE, MAE, RMSE, and MAPE metrics. The experimental results demonstrate that the LSTM model achieved high accuracy with MAPE values of 10.75% for GRASS, 6.29% for NOT PIXEL, and 6.73% for DOGS, with NOT PIXEL recording the best overall performance. The primary contribution of this research is the transformation of numerical projections into automated decision signals (Strong Buy, Hold, Caution, and Strong Sell) integrated into the DSS. In conclusion, this system serves as an effective tool for mitigating investment risk, providing strategic guidance to airdrop cryptocurrency users amid dynamic market fluctuations.

Keywords: Airdrop, Cryptocurrency, Decision Support System (DSS), Long Short-Term Memory (LSTM), Price Prediction

1. INTRODUCTION

The development of blockchain technology has given rise to a massive digital asset distribution mechanism, one of which is the airdrop method. While effective as a marketing strategy to build an initial user base, airdrops often trigger extreme supply-and-demand imbalances when tokens start trading on exchanges [1]. This phenomenon results in very high price volatility in the initial phase of the listing, creating uncertainty for investors in determining whether to hold or sell the asset [2]. The ability to forecast price movements in the early phases of coin trading is crucial as a risk-mitigation tool. Without a foundation of objective quantitative analysis, investors tend to get caught up in emotional decision-making triggered by drastic market fluctuations. Therefore, research on price predictions on newly launched assets is very important to provide strategic guidance for asset holders in the face of potential post-distribution massive selling pressure.

To answer these prediction needs, an intelligent computing approach that is able to capture complex data patterns is needed. The characteristics of cryptocurrency prices as non-linear and non-stationary time-series data make conventional statistical approaches such as ARIMA often fail to capture long-term patterns [3]. The use of deep learning is urgent in this study because of its ability to process hidden features in data that have high noise levels, which cannot be accommodated by simple linear models.

In the realm of Deep Learning, the Long Short-Term Memory (LSTM) architecture has been widely proven to be highly effective in predicting the price of crypto assets. This is due to the ability of LSTMs to overcome vanishing gradient problems in sequential data, so that the model is still able to retain memory of historical information that is relevant for future projections [4], [5]. The implementation of LSTM allows for more precise identification of trends in the crypto market that operates for a full 24 hours non-stop.

The effectiveness of LSTM in this domain has been validated by various previous studies with similar cases. For example, the use of the LSTM model has been successfully applied to predict the price of Bitcoin and Ethereum with minimal error rates [6]. Other studies confirm that the LSTM variant is able to capture the volatility of digital assets better than traditional Machine Learning methods [7]. In addition, related studies on tokens with low market capitalization suggest that parameter optimization on LSTMs can result in stable prediction accuracy despite the relatively limited historical data available [8], [9].

Despite this, most literature studies still focus on key assets with high liquidity. There is a significant research gap in studying airdrop tokens such as Grass, Not Pixel, and Dogs that have very specific market behavior dynamics ranging from the instant euphoria phase to strong post-distribution selling pressure. The advantage as well as novelty of this research compared to previous research lies in the integration between the LSTM-based Recursive Multi-step Forecasting method and the interactive Decision Support System (DSS) decision support system. While previous research generally stopped at presenting predictive numbers, this study transforms those numerical projections into strategic decision signals (such as Strong Buy or Caution) automatically.

This study aims to implement the LSTM method in predicting price movements in three case studies: Grass, Not Pixel, and Dogs. Through an approach that integrates technical prediction aspects and the logic of decision signal classification, it is hoped that a system can be produced that is able to map the critical phases of post-airdrop (euphoria, correction, and stabilization) and assist users in making more objective and measurable investment decisions in the midst of dynamic market volatility.

2. RESEARCH METHODOLOGY

This study uses a computational experimental design to model the price volatility of airdropped coins. The systematic flow of this research is designed to ensure that experimental replication can be carried out accurately, from API integration to model performance evaluation, as shown in Figure 1.

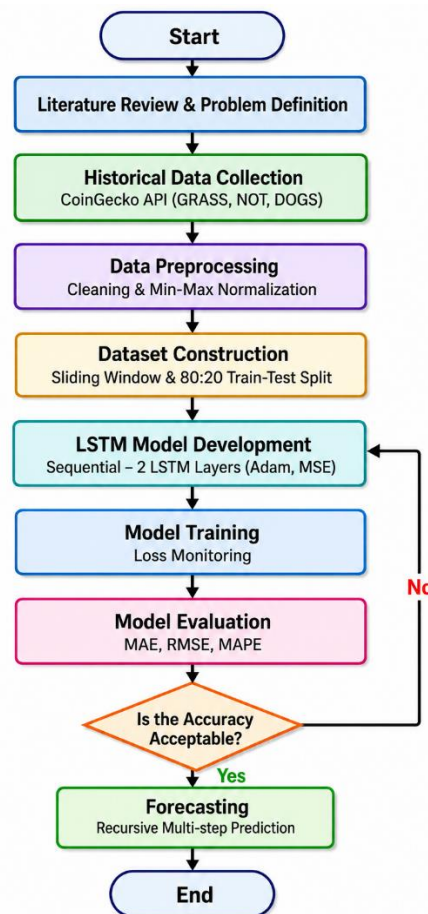


Figure 1. Research Stages

2.1. Data Acquisition and Research Variables

The data is collected through the CoinGecko API v3, which was chosen for its reliability in providing real-time crypto market data. The research focus is on three assets: GRASS, NOT PIXEL, and DOGS with a historical one-year time span. The dependent variable in this study is the daily closing price in USD, which represents the final market sentiment after the daily transaction dynamics end.

2.2. Pre-processing and Normalization

The initial stage involves data cleaning to detect missing values through linear interpolation techniques. Given the significant price scale differences between coins (e.g., coin prices of order 10^{-5} vs 101), the data is normalized using Min-Max Scaling to be in the range [0, 1] via Equation (1):

$$R' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

This normalization is crucial to prevent the dominance of large values in the LSTM model's activation function and to accelerate convergence during model training.

2.3. Time Series Dataset Formation

The data is transformed into a supervised learning format using the sliding-window method. With a window size of 30 days, the model uses data from -29 to predict the value of . The dataset was then divided into 80% for w(t)(t) + 1 training and 20% for testing.

2.4. Long Short-Term Memory (LSTM) Architecture

This study implements a Deep Learning model with a two-layer Sequential LSTM architecture. The use of two-layer LSTMs aims to capture more complex temporal features, including both short- and long-term dependencies in coin price time series data. Technically, LSTM is a development of the Recurrent Neural Network (RNN), which is designed to solve the problem of vanishing gradient through a cell state mechanism and three types of gates. The internal mechanism of each LSTM unit in processing information at the \$t\$ time step is governed by the following general equations [4], [17] :

1. Forget Gate (f_t)
Specifies the information from the previous cell state to be discarded based on the current (C_{t-1}) input and (x_t) the previous hidden state. (h_{t-1}).

$$f_t = \sigma(W_f \times [h_{t-1}, x_t] + b_f) \tag{2}$$

2. Input Gate (i_t dan C_t)
Sets the new information that will enter the cell state. is a candidate of a new value created using the function. $C_t \tanh$.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$

3. Cell State Update (C_t)
Updating long-term memory by combining old information retained and new information received.

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{5}$$

4. Output Gate (o_t dan h_t)
Specifies the output value to be passed to the next hidden state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{7}$$

Where symbolizes the sigmoid activation function, is the weight matrix, and σWb is the bias. In this study, the configuration of specific parameters used to train the model is shown in Table 1.

Table 1. Model Configuration Hyperparameters

Parameter	Value/Description
Hidden Layers	2 LSTM Layers (50 units each)
Activation Function	Tanh (Internal), Linear (Output)
Optimizer	Adam (Learning Rate: 0.001)
Loss Function	Mean Squared Error (MSE)
Regularization	Dropout 0.2 (Optional)
Batch Size / Epoch	32 / 50

2.5. Recursive Multi-step Forecasting

To project future trends, a recursive strategy is used. The results of the one-step-ahead prediction are dynamically reused as inputs. This repetition logic is described in the following algorithm:

```

Input : Test_set  $X_{test}$  , Horizon daysh = 7
Output : Multi-step Prediction  $Y_{pred}$ 
1. Get the last windows from  $X_{test}$ 
2. For to  $i = 1h$ :
3. Predict price using trained model  $y_{t+i}^{\wedge}$ 
4. Store  $\hat{y}_{t+i}$  into  $Y_{pred}$ 
5. Update window by sliding it with  $\hat{y}_{t+i}$ 
6. End For

```

2.6. Performance Evaluation Metrics

The accuracy of the prediction is evaluated using statistical metrics that measure the deviation between the actual value (y_i) and the predicted value ($\hat{y}$), with n as the number of test data points. Metrics used include:

1. Mean Squared Error (MSE)

MSE measures the average of the squares of the differences, thereby imposing a greater penalty on outliers. A value close to zero indicates better performance.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (8)$$

2. Root Mean Squared Error (RMSE)

RMSE is the square root of MSE, which returns the error unit to the original unit (USD), making it more intuitive to compare with the actual price scale. RMSE is calculated via Equation (2):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

3. Mean Absolute Percentage Error (MAPE)

Meanwhile, MAPE is used to provide an accurate interpretation as a percentage relative to each coin's price scale.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (10)$$

2.7. Integration of Decision Support System (DSS)

DSS is a computer-based information system that combines analytical models with specific data to support decision-making for semi-structured problems [16]. In the crypto ecosystem, DSS plays a crucial role in transforming complex, dynamic market data into actionable information. Previous research has emphasized that the use of intelligent systems capable of generating automated signals can significantly reduce the risk of losses arising from investors' emotional decisions amid extreme volatility [18].

In this study, the LSTM model's numerical output is converted into strategic recommendations using a threshold-based approach to percentage change. The system was developed using Δ the Flask Framework for backend management that integrates prediction models with the user interface. For data presentation, Chart.js is used to generate interactive chart visualizations on the dashboard, making it easier for users to visually identify price trends. In addition, this system allows users to automatically generate PDF reports of analysis results using the JsPDF library, ensuring transparent, portable documentation.

3. RESULTS AND DISCUSSION

3.1. Data Collection

The initial stage of this study is the collection of historical data on the prices of the crypto assets under study. The data acquisition process is automated using an API to fetch data.

3.1.1. Data Sources and Instruments

The data is obtained from the CoinGecko API v3, which is one of the most comprehensive cryptocurrency market-aggregator data providers globally. The use of this API was chosen because it is able to provide historical data that has been aggregated from various exchanges (exchanges), thus minimizing price bias that may occur if only taking data from one exchange. The data retrieval instrument is built in Python using the Requests library to handle HTTP requests to the API endpoint.

3.1.2. Data Characteristics and Variables

The data collected is time-series data with daily intervals. The main variable is the Closing Price in USD. The use of closing prices is considered most representative of market sentiment and the final positions of demand and supply at the end of the daily trading period.

3.1.3. Case Study Object Description

This study specifically took data from three airdrop coin projects with different ecosystem backgrounds to obtain valid comparison results:

1. GRASS
It is a token of DePIN (Decentralized Physical Infrastructure Network)-based AI infrastructure projects. The data covers an early growth phase where these assets show a fairly stable price appreciation trend.
2. NOT PIXEL
Coins that come from the Telegram-based game-fi ecosystem. The data characteristics reflect the high volatility in the early days of the listing, triggered by the massive distribution to the application's users.
3. DOGS
One of the most phenomenal memecoins on the TON network. The data for this coin have a very small nominal price (order 10^{-5}) but very extreme trading volume and a coefficient of variation (CV) of 108.35%.

3.1.4. Data Period and Volume

The data collection period runs from the time each coin is first officially traded on exchanges through March 2026. The total data collected covers the entire initial lifecycle of the coin, which consists of three critical phases:

1. Listing/Euphoria Phase: First 7-14 trading days.
2. Correction/Distribution Phase: The period in which the recipient of the airdrop begins to make a massive sell.
3. Stabilization Phase: The period where volatility begins to slope, and the price forms a new support level.

All crawled raw data is stored in .csv (Comma Separated Values) format before proceeding to the pre-processing stage. The selection of this format aims to facilitate data manipulation using the Pandas library at the next stage of analysis.

3.2. Data Preprocessing

Once the raw data has been successfully collected from the CoinGecko API, the next crucial step is data preprocessing. This stage aims to transform raw data into an optimal format so that it can be processed by the LSTM Deep Learning architecture in a stable, efficient manner. The steps taken are shown in Figure 2.

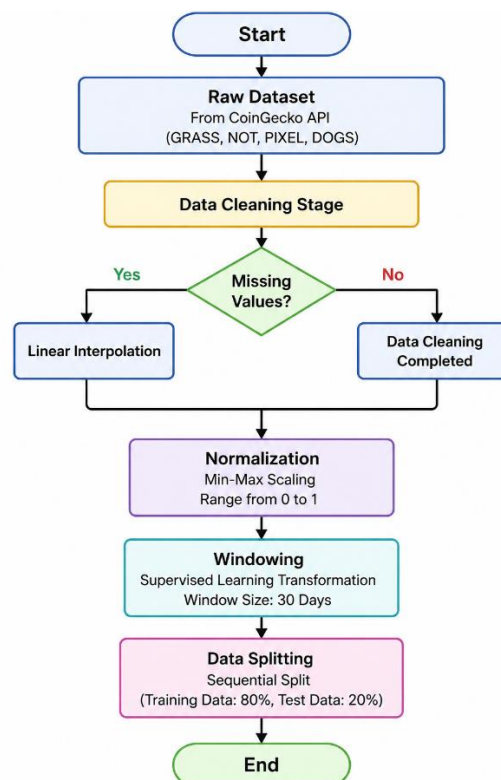


Figure 2. Data Pre-processing Flowchart

3.2.1. Data Cleaning

The first step is to ensure the integrity of time-series data. Because the data comes from a public API, the potential for missing values or data gaps on a specific date remains. In this study, the data were examined in chronological order. If missing data is found, the Linear Interpolation technique is carried out to fill in the gap. This is important because the LSTM algorithm relies heavily on the continuity of the data sequence to study temporal dependency.

1. Procedure

The date order in the dataset for the three coins (GRASS, NOT PIXEL, and DOGS) was verified. If a data gap is found, the Linear Interpolation technique is used to fill in missing values while maintaining temporal dependencies.

2. Data Analysis

Based on the cleaning results, the total data processed spans from August 2024 to March 2026. The results showed that the data from CoinGecko had good continuity, so there was no significant reduction in the number of samples after the cleanup.

3.2.2. Data Normalization (Feature Scaling)

The price data of the airdropped coins has a very contrasting (heterogeneous) range of values. For example, the GRASS coin trades in dollars, while the DOGS coin has a very small nominal in the 10-5 range. This extreme difference in scale can slow model training (stalling at a local minimum) or cause the model's weights to be dominated by a larger value. To overcome this, Min-Max scaling is used to map the entire price range to [0, 1]. This process is calculated based on formula 11.

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \quad (11)$$

Where x_{norm} is the normalization result, x is the actual price, while x_{max} and x_{min} are the highest and lowest values of the entire dataset of each coin.

3.2.3. Data Transformation to Supervised Learning Format (Windowing)

Time series data is basically a single sequence of values. For the LSTM model to learn, the data must be converted into input-output pairs (features and labels). This study applied the Sliding Window method with a window size of 30 days.

This means that the model will use price data from day 1 to day 30 to predict prices on day 31. This process is done iteratively by sliding the window one step forward along the entire data set, resulting in a data structure that is ready to be used for the supervised learning training process $(X)(Y)$.

3.2.4. Dataset Splitting

The datasets that have undergone preprocessing are then split into training and test sets using a chronological split, since the data is time-series. Divisions are carried out by the composition:

1. Training Data

It is allocated 80% of the total data population. This data is used by the model to study volatility patterns and price movement trends.

2. Testing Data

It is allocated 20% of the total data population. This section serves as validation data to evaluate the accuracy of model predictions on previously unstudied data.

This method was chosen to preserve the temporal order of the data, so that the model used only past data to predict the next period. The dataset is shared without a random shuffle to avoid data leakage in the time-series prediction model.

3.3. LSTM Modeling/ Process

The modeling stage is at the heart of the study, where the Deep Learning architecture is trained to recognize volatility patterns on airdrop coins. This process includes configuring the network structure, selecting optimization functions, and implementing medium-term prediction strategies.

3.3.1. LSTM Sequential Network Architecture

This study builds a model using a Sequential approach, where data flows linearly through neural layers. The selected architecture consists of several main layers:

1. First LSTM Layer (Input Layer)

It consists of 50 LSTM units. This layer captures the initial temporal dependencies in the previous 30 days' price data. The `return_sequences=True` parameter keeps the output of this layer as a sequence, which can be processed by the next LSTM layer.

2. Second LSTM Layer (Hidden Layer)

It also consists of 50 LSTM units. This additional layer aims to study more abstract and complex temporal features (long-term dependence). At this layer, `return_sequences` is set to `False` to reduce the data dimension before it enters the output stage.

3. Dense Layer (Output Layer)

Consists of 1 nerve unit with a Linear activation function. This single unit generates a single continuous value representing the prediction of the future closing price.

3.3.2. Configuration of Training Parameters (Hyperparameters)

To guarantee the model achieves optimal convergence, the hyperparameter configuration is set as follows:

1. Optimizer: Using the Adam (Adaptive Moment Estimation) algorithm with a learning rate of 0.001. Adam was chosen for his ability to independently adjust the learning rate for each parameter, making it more efficient in handling high-noise data such as crypto.
2. Loss Function: Uses Mean Squared Error (MSE) to calculate the squared difference between the predicted value and the actual value. MSE is highly sensitive to outliers, making it suitable for minimizing large prediction errors in extreme volatility phases.
3. Batch Size & Epochs: The training process was carried out with a batch size of 32 and the number of iterations (epochs) as many as 50. This configuration is chosen to maintain a balance between computational speed and stability in loss reduction, so that overfitting does not occur.

3.3.3. Implementasi Recursive Multi-step Forecasting

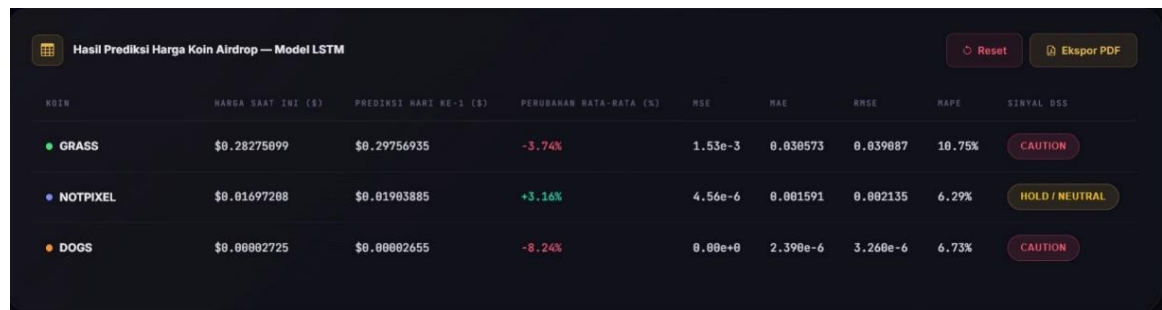
One of the technical advantages in this modeling is the use of the Recursive Multi-step Forecasting strategy. In contrast to standard predictions that only predict one day ahead (single-step), recursive strategies work with the following steps:

1. The model predicts prices for the Q+1 day using the actual data of the last 30 days.
2. The value of the T+1 prediction result is then put back into the input window as new "historical" data.
3. This process is repeated continuously until the model generates a trend projection for the next 7 days.

This method allows the decision support system (DSS) to provide investors with a medium-term view, though the risk of error accumulation increases as the prediction time horizon lengthens. The end result of this modeling process is a set of price projections that are then validated using test data before being integrated into an interactive dashboard.

3.4. DSS System Implementation and Interface

The system is implemented using a Client-Server architecture with Flask as the backend and a Python-based automated crawler. The resulting dashboard integrates visualizations of three critical phases of the airdrop coin price: Euphoria, Correction, and Stabilization, as shown in Figure 3.



Hasil Prediksi Harga Koin Airdrop — Model LSTM									Reset	Ekspor PDF
KOIN	HARGA SAAT INI (\$)	PREDIKSI HARI KE-1 (\$)	PERUBAHAN DATA-RATA (%)	MSE	MAE	RMSE	MAPE	SINYAL DSS		
GRASS	\$0.28275899	\$0.29756935	-3.74%	1.53e-3	0.038573	0.039887	10.75%	CAUTION		
NOTPIXEL	\$0.01697288	\$0.01983885	+3.16%	4.56e-6	0.001591	0.002135	6.29%	HOLD / NEUTRAL		
DOGS	\$0.00892725	\$0.00892655	-8.24%	0.00e+0	2.398e-6	3.268e-6	6.73%	CAUTION		

Figure 3. Web-Based DSS Dashboard Interface

A key feature of the system is Automated Narrative Interpretation, which converts the LSTM's numerical output into a descriptive explanation for the user. In addition, the system provides portable validation via PDF report exports using the JsPDF library, enabling on-demand transparency into predicted results data.

3.5. LSTM Model Architecture

The prediction model in this study uses a Long Short-Term Memory (LSTM) architecture based on a Sequential Neural Network to capture the temporal patterns and price volatility of cryptocurrency prices resulting from airdrops. The model was constructed using two LSTM layers to capture both short- and long-term dependencies in time-series data. The model architecture consists of:

1. The first layer LSTM with 50 neurons and the parameter `return_sequences=True`,
2. Layer dropout of 0.2 to reduce the risk of overfitting,
3. The second layer LSTM with 50 neurons,
4. Dense layer as the output of price prediction.

The activation function in the LSTM layer is the hyperbolic tangent ($\tanh$), and the optimizer is Adam with a learning rate of 0.001. The model was trained using a batch size of 32 for 50 epochs. The hyperparameter configuration for the LSTM model is shown in Table 2.

Table 2. LSTM Model Hyperparameter Configuration

Parameter	Value
Hidden Layer	2
Neuron per Layer	50
Activation Function	Fishy
Dropout Rate	0.2
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epoch	50

3.6. Recursive Multi-step Forecasting

This study uses the Recursive Multi-step Forecasting method to produce cryptocurrency price predictions over the next few days in stages. This method uses the results of previous predictions as inputs for subsequent predictions.

In the early stages, the model receives historical data with a 30-day lookback window to predict the price on the third day. Furthermore, the prediction results are fed back into the input sequence to predict the day's price. This process is repeated until it reaches the specified prediction horizon. The recursive forecasting approach was chosen because: $t + 1t + 2$. An illustration of the recursive forecasting process is shown in Figure 4.

1. Able to produce multi-step predictions using a single model,
2. More efficient than direct multi-step forecasting,
3. Suitable for cryptocurrency time-series data that is dynamic and volatile in nature.

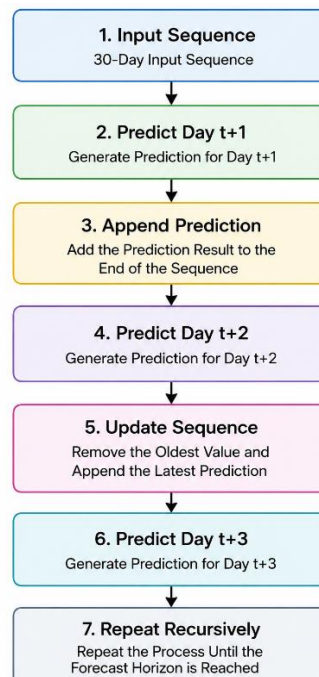


Figure 4. Process illustration recursive forecasting

3.7. LSTM Model Performance Evaluation

The test was conducted using a 1-year history of daily closing prices. The model is evaluated using four main metrics. Quantitative results are presented in Table 3.

Table 3. Quantitative Evaluation Metrics of LSTM Model Performance

Coins	MSE	IT IS	RMSE	MAPE (%)
GRASS	1.866×10^{-2}	0.1143	0.1360	10.75%
NOT PIXEL	1.276×10^{-5}	0.0034	0.0036	6.29%
DOGS	≈ 0.000	1.330×10^{-5}	1.542×10^{-5}	6.73%

Based on Table 3, the NOT PIXEL coin recorded the highest accuracy, with a MAPE of 6.29%, indicating it belongs to the Highly Accurate Forecasting category. In contrast, GRASS has the highest error (MAPE of 10.75%), which correlates with GRASS's daily volatility of 8.45% (Table 3), making it difficult for the model to determine a stable convergence point. Overall, the MAPE below 15% across all three coins confirms that the LSTM architecture with a 30-day window size is effective for modeling highly volatile crypto assets.

3.8. Analysis of Volatility Characteristics and Price Trends

The results showed significant differences in price behavior between coins post-airdrop distribution. A comparison of statistical indicators is presented in Table 4.

Table 4. Comparison of Volatility Statistics and Price Dynamics

Indicator	GRASS	NOT PIXEL	DOGS
Daily Volatility	8.4577%	6.6597%	6.5528%
Coeff. Of Variation (CV)	70.19%	67.17%	108.35%
Maximum Drawdown (MDD)	-95.31%	-92.79%	-98.26%
First 30 Day Trends	+203.96%	-67.34%	-29.13%

The GRASS coin showed a positive trend anomaly (+203.96%) in the early phase, driven by the fundamentals of decentralized AI infrastructure projects. In contrast, NOT PIXEL and DOGS showed a classic mass sell-off pattern with declines of -67.34% and -29.13%, respectively. DOGS recorded the highest CV (108.35%) and extreme MDD (-98.26%), proving that memecoins have a much higher speculative risk than utility coins. The MDD value of close to -100% on all coins confirms the life cycle of airdrop assets that tend to experience very deep depreciation in value after the euphoric phase ends.

3.9. Decision Signal Validation and Logical Consistency

The final stage is the validation of the integration between the LSTM prediction output with the DSS logic. The determination of decision signals (STRONG BUY, HOLD, CAUTION, STRONG SELL) is carried out through the Holding threshold mechanism at the percentage change of the prediction. Visualization of the LSTM prediction, focusing on the H+1 to H+30 horizon, can be seen in (Δ) Figure 5.



Figure 5. Visualization of LSTM Prediction Focus Horizon H+1 to H+30

According to Table 5, the system shows logical consistency between the latest historical data and future projections.

Table 5. Validation Results Output DSS Decision Signals

Coins	Δ Prediction	DSS Signal	Momentum Consistency
GRASS	-3.74%	CAUTION	Consistent (Correction Continues)
NOT PIXEL	+3.16%	HOLD	Consistent (Gradual Recovery)
DOGS	-8.24%	DEPOSIT	Consistent (Advanced Selling Pressure)

The LSTM model accurately captures market momentum; for example, in NOT PIXEL, the recovery trend at the end of the historical data is reflected in the model's projected increase of +3.16%. The use of the Recursive Multi-step Forecasting strategy allows the system to provide continuous projections, although the accuracy on the H+20 to H+30 horizon tends to decrease due to the accumulation of recursive errors. This validation demonstrates that the system is feasible as a risk mitigation tool for crypto investors.

3.10. Cryptocurrency Price Prediction Results

The trained LSTM model is then used to predict the price of the cryptocurrency resulting from the airdrop on the testing data. The prediction results are compared with actual data to evaluate the model's ability to follow price movement patterns.

1. GRASS Price Prediction

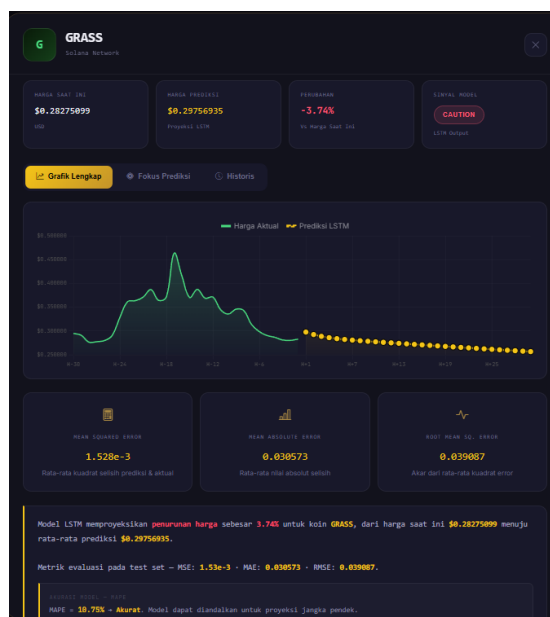
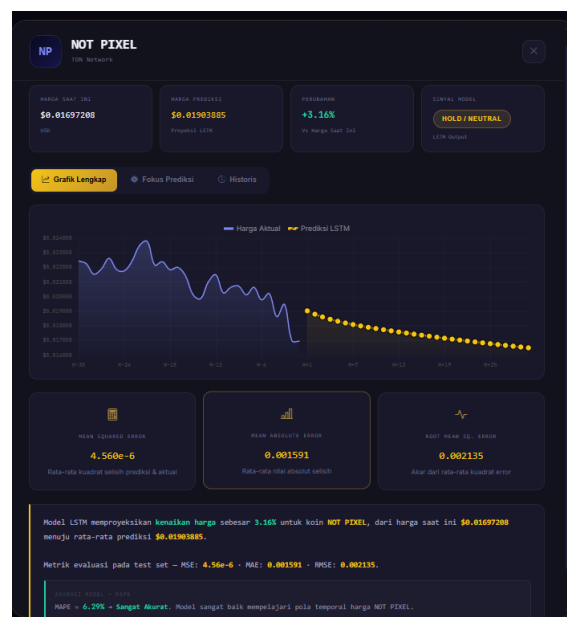
Figure 6 compares the actual price with the LSTM model's predictions for the GRASS coin. In general, the model follows the main trend of price movements but still experiences deviations during periods of high volatility.

2. NOT PIXEL Price Prediction

Figure 7 shows that the model produces the most stable prediction performance on the NOT PIXEL coin. The prediction curve has a pattern that is closest to actual data compared to other coins.

3. DOGS Price Prediction

Figure 8 shows that the model is still able to follow the DOGS price trend, despite the error fluctuations in the spike market phase

**Figure 6.** Price Prediction GRASS**Figure 7** Price Prediction NOT PIXEL.

4. DISCUSSION AND COMPARATIVE ANALYSIS

This section discusses the interpretation of the test results and compares the study's findings with relevant literature to provide a broader academic context.

4.1. Market Phenomenon Analysis and Model Performance

The experiment results showed that the LSTM model captured volatility patterns in airdrop assets with a fairly high level of accuracy (MAPE < 15%). The low error rate on the NOT PIXEL coin (6.29%) indicates that the 30-day window size is highly effective for modeling assets in a phase of consolidation or gradual price recovery. In contrast, in the GRASS coin, a 10.75% prediction error was triggered by a very aggressive positive

trend anomaly. This shows that Recursive Multi-step Forecasting strategies tend to be more sensitive to error accumulation when historical data do not exhibit a stable seasonal pattern.

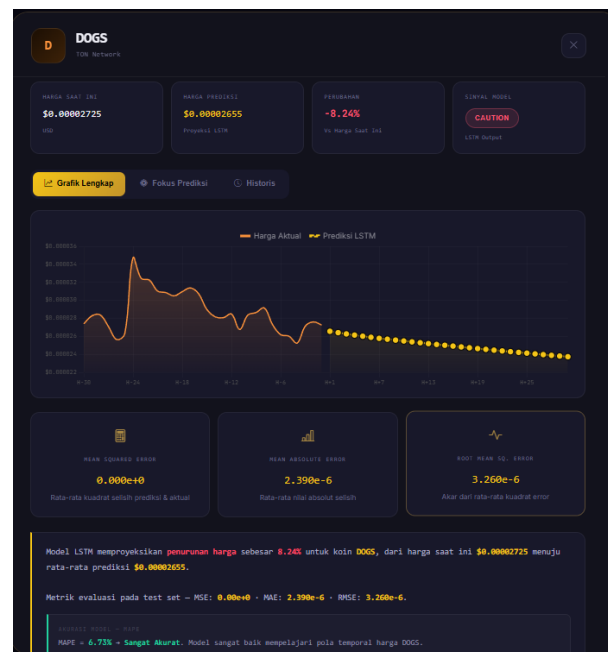


Figure 8. Price Prediction DOGS

4.2. Comparison with Previous Research

This research provides a new dimension to the study of cryptocurrency price prediction when compared to previous studies:

1. **Method Effectiveness:** These findings are in line with the research of Hamayel & Owda (2021) [7] who stated that LSTM architectures have advantages in capturing the non-linear nature of crypto data compared to conventional statistical methods. However, the study goes further by showing that LSTMs remain resilient on low-liquidity coins with mid-to-low market caps (airdrops), not just on major coins like Bitcoin.
2. **Data Scale and Accuracy:** Research by Nirraca & Hartati (2024) [17] on the price of Bitcoin results in high accuracy due to the sheer volume of historical data available. In this study, although the airdrop coin data had a much shorter time span (from listing to March 2026), the use of Min-Max Scaling normalization was shown to compensate for the limited volume of such data so that the RMSE value remained within a very small tolerance limit (on the DOGS coin of $1.542 \cdot 10^{-5}$).
3. **Novelty of System Integration:** If the research of Mutaqin & Kusumadiarti (2024) [15] focuses more on the mechanism of airdrop distribution qualitatively, this study makes a practical contribution by integrating the prediction results into the Decision Support System (DSS). Compared to the system developed by Saputra & Akbar (2025) [16], this study's advantage lies in its ability to provide predictive (forward-looking) signals rather than simply analyzing the current state.

4.3. Practical Implications for Investors

The integration of thresholding logic in the built system successfully bridges the gap between complex numerical predictions and the need for rapid decision-making. The resulting signals (such as Strong Buy or Caution) are shown to be consistent with market momentum. This justifies the claim that Deep Learning models combined with decision support systems can serve as an effective risk-mitigation tool for airdrop asset owners to avoid losses from post-distribution mass sell-offs.

5. CONCLUSION

The study concludes that the price movement of post-listing airdrop coins consistently passes through three critical phases: euphoria, correction, and stabilization. The findings show that there are positive anomalies in coins with strong fundamentals, such as GRASS, which jumped to +203.96%, inversely proportional to tap-to-earn-based coins, such as NOT PIXEL and DOGS, which immediately experienced a sharp correction due to massive sell-off pressure of -67.34% and -29.13%, respectively. From a computational perspective, the Sequential LSTM architecture has proven effective in producing high-precision predictions, with MAPE values

below 15% across case studies, successfully transforming numerical complexity into intuitive strategic decision signals through a Decision Support System.

The implications of this study provide an objective risk-mitigation instrument for investors to avoid emotional decision-making, while providing academic evidence that the Recursive Multi-step Forecasting strategy is feasible as the basis for an early-detection system for digital assets with low liquidity. As a direction for future development, this study suggests integrating community sentiment variables using Natural Language Processing (NLP) to enhance the model's sensitivity to the initial euphoria phase. In addition, the use of hybrid models such as CNN-LSTM or the Attention mechanism is also recommended to improve the accuracy of predictions over a longer time span, as well as extend the research object on a variety of different blockchain networks to test the consistency of the pattern universally.

REFERENCES

- [1] M. J. Hamayel and A. Y. Owda, "A Novel *Cryptocurrency* Price Prediction Model Using GRU, LSTM and bi-LSTM Machine learning Algorithms," *AI (Switzerland)*, vol. 2, no. 4, pp. 477–496, Dec. 2021, doi: 10.3390/ai2040030
- [2] D. W. E. Allen, "Crypto *airdrops*: An evolutionary approach," *J. Evol. Econ.*, vol. 34, no. 4, pp. 849–872, Dec. 2024, doi: 10.1007/s00191-024-00874-6.
- [3] J. Zaenal Mutaqin, R. Suwartika Kusumadiarti, P. Informatics Management Studies, P. Piksi Ganesha, and J. Jend Gatot Soebroto No, "Volume 3 Number 2 of 2024| 105 Mechanism *Airdrop* And Its Impact On The Growth Of Blockchain Projects.
- [4] J. Messias, A. Yaish, and B. Livshits, "*Airdrops: Giving Money Away Is Harder Than It Seems*," *Jul. 2025*, [Online]. Available: <http://arxiv.org/abs/2312.02752>
- [5] D. L. John, S. Binnewies, and B. Stantic, "Cryptocurrency Price Prediction Algorithms: A Survey and Future Directions," Sep. 01, 2024, Multidisciplinary Digital Publishing Institute (MDPI). doi: 10.3390/forecast6030034.
- [6] A. Kumar, V. Srivastava, M. Kumar Chaubey, and M. Sehgal, "International Journal of Intelligent Systems And Applications In Engineering Bitcoin Price Prediction Using Sentiment Analysis and Long Short-Term Memory (LSTM)." [Online]. Available: www.ijisae.org
- [7] T. Xie, Y. Ge, and K. Kannan, "Crypto *Airdrop* Success Blueprint: A Highdimensional Causal Study Using Double Machine learning."
- [8] J. Zaenal Mutaqin, R. Suwartika Kusumadiarti, P. Informatics Management Studies, P. Piksi Ganesha, and J. Jend Gatot Soebroto No, "Volume 3 Number 2 of 2024| 105 *Airdrop* Mechanisms And Their Impact On The Growth Of Blockchain Projects."
- [9] R. Fegiyanto, A. Hermawan, and F. Ardiani, "Crypto Price Prediction with Artificial Neural Network Algorithms," 2024. [Online]. Available: <https://journal.stmiki.ac.id>
- [10] S. M. Raju and A. M. Tarif, "Real-Time Prediction of BITCOIN Price using Machine learning Techniques and Public Sentiment Analysis."
- [11] I. P. B. Priadinata, I. G. I. Sudipa, N. P. S. Meinarni, I. M. L. Radhitya, and I. K. D. G. Supartha, "Comparative Analysis of LSTM, GRU, and Bi-LSTM Deep Learning Models for Time Series *Cryptocurrency* Price Forecasting," *Sinkron: Jurnal dan Penelitian Teknik Informatika*, vol. 9, no. 3, July 2025, doi: 10.33395/sinkron.v9i3.14795.
- [12] I. M. Anwas, F. Fahrianto, I. M. Shofi, and A. Y. Pratama, "Performance Comparison of LSTM, XGBoost, and Residual-Correction Hybrid LSTM–XGBoost Models for Bitcoin Price Forecasting," *MATRIC: Journal of Management, Informatics Engineering and Computer Engineering*, vol. 25, no. 2, March 2026, doi: 10.30812/matrik.v25i2.5983.
- [13] F. R. M. Muhammad, R. Permatasari, and A. R. E. Najaf, "Bitcoin Price Prediction Using a Deep Learning Approach with an LSTM Algorithm," *Bit-Tech (Binary Digital - Technology)*, vol. 8, no. 3, pp. [Page Numbers], April 2026, doi: 10.32877/bt.v8i3.3613.
- [14] D. L. John, S. Binnewies, and B. Stantic, "Cryptocurrency Price Prediction Algorithms: A Survey and Future Directions," *Forecasting*, vol. 6, no. 3, pp. 637–671, 2024, doi: 10.3390/forecast6030034.
- [15] J. Z. Mutaqin and R. S. Kusumadiarti, "Airdrop Mechanism and Its Impact on the Growth of Blockchain Projects," *JITS (Journal of Informatics Management and Information Technology)*, vol. 3, no. 2, p. 105, 2024.
- [16] A. D. Saputra and M. Akbar, "Decision Support System for Determining *Cryptocurrency* Investments Using the Weighted Product Method," *JIMAT (Journal of Informatics Management and Information Technology)*, vol. 5, no. 3, July 2025, doi: 10.47065/jimat.v5i3.570.
- [17] M. Nirraca and E. Hartati, "Bitcoin Price Prediction Using the Long Short Term Memory Method," *Journal of Digital Information Technology*, vol. 7, no. 1, pp. 55-65, March 2024, doi: 10.32502/digital.v7i1.7974.
- [18] R. Parluka, R. Hermawan, R. Ardika, A. N. Cahyo, M. W. Azmi, and M. Munir, "Implementation of Data Mining and Bot Notification Technology to Support Trading Decisions *Cryptocurrency*," *TelKa*

- Journal, vol. 15, no. 2, October 2025.
- [19] Indriyanti, N. Ichsan, H. Fatah, T. Wahyuni, and E. Ermawati, "Implementation of Orange Data Mining for Bitcoin Price Prediction," *Journal of Responsive*, vol. 4, no. 2, pp. 118-125, August 2022.
- [20] A. Arkadia, B. Hananto, and D. S. Prasvita, "Optimization of Long Short Term Memory with Adam Using DKI Jakarta City Air Data," *Proceedings of the National Seminar of Computer Science Students (SENAMIKA)*, vol. 3, no. 2, 2022.