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Gold Price Prediction using Long Short-Term Memory Algorithm

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Abstract

Gold is one of the most popular investment instruments among the public because it has low risk, stable value, and is resistant to inflation. In Indonesia, ANTAM gold attracts strong demand due to its authenticity and relative price stability; however, frequent supply limitations and external economic factors cause price fluctuations that complicate investment timing decisions. In this paper, we utilize a data-driven analytical approach to model and predict gold price movements by applying the Long Short-Term Memory (LSTM) algorithm, which is well-suited for capturing temporal dependencies in time series data. We adopt historical ANTAM gold price data to train and evaluate the model, allowing it to learn underlying price patterns and long-term trends effectively. The experimental results demonstrate that the proposed LSTM model achieves high predictive accuracy, as reflected by an RMSE of 0.021781 and a MAPE of 1.94% when trained with 100 epochs, indicating a very low average prediction error. These findings confirm that the LSTM-based approach is effective for forecasting precious metal gold prices and shows strong potential as a practical decision-support tool for short- and long-term investment planning.

Keywords:
Gold Price, Prediction, LSTM, Time Series

1. Introduction

Gold plays a crucial role as a global safe-haven asset, widely used for hedging against inflation, currency depreciation, and economic uncertainty. Fluctuations in gold prices directly affect investment decisions, monetary policies, and portfolio risk management. However, gold prices exhibit strong volatility, non-linearity, and dependency on historical trends, macroeconomic indicators, and speculative behavior, making accurate prediction a persistent challenge. Traditional forecasting techniques often struggle to capture long-term dependencies and complex temporal patterns inherent in gold price movements. These limitations motivate the adoption of deep learning approaches that can model sequential data more effectively, particularly in financial time-series forecasting contexts [1], [2], [10], [15].

Conventional statistical models such as ARIMA and econometric regression dominate early gold price forecasting research due to their interpretability and low computational cost. However, these models assume linearity and stationarity, which rarely hold in real-world financial markets. Empirical studies consistently show that gold price data contain

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non-stationary components, abrupt trend shifts, and irregular seasonal effects that reduce the predictive accuracy of linear models. Comparative studies demonstrate that while ARIMA performs reasonably well in stable periods, it fails to adapt during market shocks and volatile regimes, highlighting a critical methodological gap in traditional forecasting approaches [10], [12], [16].

Recent advances in machine learning offer alternative solutions by enabling models to learn complex, non-linear relationships directly from data. Among these, Recurrent Neural Networks (RNNs) gain attention for time-series analysis due to their sequential memory structure. However, standard RNNs suffer from vanishing and exploding gradient problems, which limit their ability to learn long-term dependencies. This limitation becomes especially problematic in gold price forecasting, where historical patterns spanning long time horizons influence future prices. Consequently, researchers increasingly seek architectures that can preserve long-range temporal information more effectively [7], [14].

Long Short-Term Memory (LSTM) networks address these limitations by introducing gated mechanisms that regulate information flow across time steps. The input, forget, and output gates enable LSTM models to selectively retain or discard information, allowing them to capture both short-term fluctuations and long-term trends. Numerous empirical studies demonstrate that LSTM models outperform traditional RNNs and statistical methods in financial forecasting tasks. In gold price prediction, LSTM consistently achieves lower prediction error and better trend-following behavior, validating its suitability for modeling volatile and memory-dependent financial time series [1], [15], [16].

Several studies apply univariate LSTM models to gold price forecasting, focusing solely on historical price data. These approaches emphasize simplicity and robustness, showing that even single-variable LSTM models can outperform classical benchmarks. However, univariate models face inherent limitations, as they ignore external market signals and economic factors that influence gold prices. Researchers acknowledge that while univariate LSTM models capture temporal dynamics effectively, their predictive performance may degrade during abnormal market conditions or structural breaks [1], [15].

To address these challenges, comparative studies explore hybrid and multivariate forecasting frameworks. Research comparing LSTM with GRU, Bi-LSTM, and CNN-LSTM architectures reveals that enhanced recurrent structures often yield superior predictive stability and convergence speed. In particular, bidirectional and attention-based LSTM variants demonstrate improved performance by capturing forward and backward dependencies in financial sequences. These findings suggest that architectural optimization plays a critical role in improving prediction accuracy, yet also increases computational complexity and tuning difficulty [11], [13], [5].

Beyond gold price prediction, LSTM models show strong performance across various financial and economic forecasting domains, including stock prices, currency exchange rates, and cryptocurrency markets. Cross-domain evidence reinforces the adaptability of LSTM to diverse financial instruments characterized by volatility and temporal dependency. These studies consistently report improved accuracy, reduced error variance, and better generalization compared to baseline models. Such consistency strengthens the argument for applying LSTM as a core predictive engine in gold price forecasting research [4], [7], [17], [14].

Despite demonstrated success, several unresolved issues remain in LSTM-based gold price prediction. Model performance heavily depends on data quality, window size selection, hyperparameter tuning, and training stability. Overfitting risks arise when models learn noise instead of meaningful patterns, especially with limited historical data. Moreover, most existing studies focus on predictive accuracy without addressing interpretability, limiting practical adoption in financial decision-making contexts. These gaps highlight the need for systematic evaluation, optimized architectures, and transparent modeling strategies in future gold price prediction studies using LSTM [2], [11], [16].

2. Related Works

Recent studies have extensively explored the use of recurrent neural networks, particularly Long Short-Term Memory (LSTM), for forecasting gold prices due to their ability to model long-term temporal dependencies in financial time series. Sudiatmika and Putra [11] conducted a comparative study between LSTM and Gated Recurrent Unit (GRU) models using historical gold price data from Yahoo Finance. Their findings indicate that LSTM slightly outperforms GRU in terms of prediction accuracy, especially in capturing long-term trends. The strength of this study lies in its direct comparison of two popular deep learning architectures under identical conditions. However, the study is limited by its reliance on a single data source and the absence of external macroeconomic variables, which may influence gold price dynamics.

Several works have also compared LSTM with traditional statistical models, such as ARIMA, to highlight the advantages of deep learning approaches. Fitriyana Ningrum and Hisani [12] analyzed the performance of ARIMA and LSTM models in predicting the Jakarta Interbank Spot Dollar Rate (JISDOR), demonstrating that LSTM provides lower forecasting errors in non-linear and volatile conditions. Although the study focuses on exchange rates rather than gold prices, its findings are highly relevant due to the strong correlation between currency movements and gold prices. Similarly, Huang et al. [19] combined ARIMA and LSTM in a hybrid framework for gold price prediction and reported improved accuracy over standalone models. While hybrid models enhance robustness, they introduce higher computational complexity and require careful parameter tuning.

The effectiveness of LSTM for commodity and financial price prediction is further supported by domain-specific gold price studies. Dalimuthe et al. [15] implemented a standalone LSTM model for gold price forecasting and reported satisfactory predictive performance compared to baseline approaches. Lasijan et al. [16] extended this approach to world gold prices, emphasizing LSTM's capability to adapt to global price fluctuations. Hueng and Obeyd [18] proposed a deep learning-based time series framework for gold price prediction and highlighted LSTM's superior performance in capturing complex price patterns. Despite their effectiveness, these studies generally rely on univariate time series data, limiting their ability to account for external shocks such as geopolitical events or economic crises.

Beyond gold, LSTM has been widely applied to other financial assets, reinforcing its generalizability. Hanafiah et al. [14] applied LSTM-based recurrent neural networks to stock price prediction and demonstrated improved accuracy over conventional methods. Pratama and Utama [17] used LSTM to forecast Bitcoin prices, showing that deep learning models can handle highly volatile and speculative assets. These studies confirm LSTM's adaptability across different financial markets. However, cryptocurrencies and stock markets exhibit different volatility structures compared to gold, which is often considered a safe-haven asset, suggesting that model performance may vary across asset classes.

To enhance feature extraction and prediction accuracy, several studies integrate LSTM with convolutional neural networks (CNN). Livieris et al. [20] proposed a CNN–LSTM hybrid model for gold price forecasting and reported improved performance by capturing both local temporal patterns and long-term dependencies. Baradaran et al. [21] compared GRU and CNN–LSTM models in the Iranian gold market, finding that CNN–LSTM consistently outperformed simpler architectures. These hybrid models demonstrate strong predictive power but require larger datasets and higher computational resources, which may limit their applicability in real-time or resource-constrained environments.

Hybrid and optimization-based approaches represent another significant research direction. Woon et al. [22] introduced an ARIMA–LSTM hybrid model for gold price prediction and showed that combining linear and non-linear modeling improves forecasting stability. Kashif and Ślepaczuk [23] extended this hybrid concept to algorithmic investment strategies, demonstrating that LSTM–ARIMA models can enhance decision-making in financial markets. Taghipour et al. [24] incorporated a Gray Wolf Optimizer with LSTM and Multilayer Perceptron (MLP) models, achieving improved convergence and accuracy. While these methods improve performance, they increase model complexity and reduce interpretability.

Comparative studies provide further insight into the relative strengths of LSTM-based models. Siami-Namini et al. [25] conducted a comprehensive comparison of ARIMA, LSTM, and BiLSTM models for financial time series forecasting, concluding that BiLSTM often achieves the lowest error rates due to its bidirectional learning capability. Singh et al. [26] evaluated multiple machine learning algorithms for gold price prediction and found that deep learning models outperform traditional machine learning methods such as support vector machines and linear regression. However, these studies also note that deep learning models are sensitive to hyperparameter selection and data quality.

Finally, recent research has examined gold price prediction under extraordinary conditions. Mohtasham Khani et al. [27] investigated gold price forecasting during pandemic periods using deep learning models and showed that LSTM-based approaches remain robust under extreme market uncertainty. This highlights the importance of adaptive models capable of handling sudden regime shifts. Nevertheless, most existing studies do not explicitly incorporate exogenous crisis indicators, leaving room for further improvement. Overall, the reviewed literature confirms that LSTM and its hybrid variants are powerful tools for gold price prediction, while also revealing limitations related to data diversity, model complexity, and interpretability that gaps that motivate the proposed study.

3. Proposed Method

This paper utilized a structured research workflow to ensure methodological clarity, reliable data processing, and objective model evaluation. We adopted a sequential approach that covered problem identification, literature review, data collection, preprocessing, modeling, evaluation, prediction, and interpretation. This workflow was designed to produce clean and well-structured data, enable accurate time-series representation, and allow fair performance comparisons across different LSTM configurations. By following these stages systematically, we ensured that each step directly supported the research objective of evaluating LSTM performance for gold price prediction.

In this study, we construct a standard mathematical formulation of LSTM in a compact and commonly accepted form in time-series forecasting literature. Let x_t denote the input gold price at time step t, h_{t-1} the previous hidden state, and c_{t-1} the previous cell state. The LSTM computes:

$$
\begin{aligned}
f_t &= \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \\
i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\
\tilde{c}_t &= tan\,h(W_c[h_{t-1}, x_t] + b_c) \\
c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\
o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \\
h_t &= o_t \odot tan\,h(c_t)
\end{aligned}
$$

where:

- f_t, i_t, and o_t represent the forget, input, and output gates, respectively,
- $\tilde{c}_t$ is the candidate cell state,
- $\sigma(\cdot)$ denotes the sigmoid activation function,
- $\tanh(\cdot)$ denotes the hyperbolic tangent function,
- W_* and b_* are weight matrices and bias vectors,
- $\odot$ denotes element-wise multiplication.

The predicted gold price at time $t + 1$ is obtained from the hidden state as equation 1:

$$\hat{y}_{t+1} = W_y h_t + b_y \quad (1)$$

The LSTM model operates by maintaining and updating an internal memory structure that allows it to capture long-term dependencies in sequential gold price data. At each time step t, the model receives the current input x_t, representing the gold price, along with the previous hidden state h_{t-1} and cell state c_{t-1}. Three gating mechanisms called the forget gate f_t, input gate i_t, and output gate o_t to regulate the flow of information within the network. The forget gate determines which information from the previous cell state should be retained, while the input gate controls how much new information, represented by the candidate cell state $\tilde{c}_t$, is incorporated. Through these mechanisms, the cell state c_t is updated to selectively preserve historical price patterns that are relevant for forecasting future gold prices.

The hidden state h_t, derived from the updated cell state and modulated by the output gate, represents the encoded temporal features learned by the LSTM at time t. This hidden representation captures both short-term fluctuations and long-term trends in gold price movements. The final prediction $\hat{y}_{t+1}$ is generated by applying a linear transformation to the hidden state, allowing the model to estimate the gold price for the next time step. By iteratively applying these mathematical operations across the historical time series, the LSTM effectively models nonlinear and temporal dependencies in gold price data, making it well-suited for financial time-series forecasting tasks where price dynamics are complex and highly volatile.

In this paper, we identify the core research problem, which focuses on assessing how effectively the LSTM model predicted future gold prices based on historical data. This issue was particularly relevant because gold price fluctuations are influenced by multiple economic and market factors and play a significant role in investment decision-making. We then conducted a comprehensive literature review by examining national and international journals, theses, and scientific books related to gold price forecasting and LSTM-based time-series modeling. This review provided a strong theoretical foundation and helped us identify relevant methodologies, recent advancements, and research gaps addressed in this study.

For data collection, we systematically gathered historical daily gold price data for ANTAM gold per gram from the official website logammulia.com. The dataset consisted of 1,273 observations covering the period from January 1, 2022, to June 27, 2025, with date and price as the main variables. We stored the data in Excel (.xlsx) format to facilitate further processing. We then performed data preprocessing to clean and transform the raw data into a suitable format for modeling. This step ensured data consistency, removed potential noise, and prepared the time-series sequences required for effective LSTM training.

In the modeling stage, we applied two different LSTM architectures to compare predictive performance under different training configurations. We trained the first architecture for 50 epochs and the second for 100 epochs to analyze the effect of training duration on model accuracy. After training, we evaluated the models using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to measure prediction accuracy and error magnitude. We then utilized the best-performing model to predict gold prices for the next seven days, from June 28 to July 4, 2025, and visualized the results to illustrate predicted trends. Finally, we interpreted and discussed the results by analyzing model accuracy, strengths, limitations, and future improvement potential, ensuring that the research objectives were addressed both quantitatively and qualitatively.

4. Experimental Setup

1. Dataset

In this paper, we carried out the data collection stage to ensure the availability of accurate and reliable information for answering the research questions. We utilized historical price data of ANTAM gold per gram as the primary dataset because it represents official and widely used reference prices in the Indonesian gold market. We obtained the data directly from the official website logammulia.com, which provided consistent and authoritative daily price records. The dataset consisted of two main variables, namely the transaction date and the corresponding daily gold price, which allowed us to construct a clear time-series structure suitable for predictive modeling. In total, we collected 1,273 data points covering the period from January 1, 2022 to June 27, 2025, enabling the model to learn both short-term fluctuations and longer-term price trends. We stored the collected data in Microsoft Excel format (.xlsx) to facilitate data inspection, cleaning, preprocessing, and subsequent analysis, thereby ensuring smooth integration with the modeling and evaluation stages.

2. Preprocessing

In this paper, we carried out the data preprocessing stage to clean, transform, and prepare the raw data so that it could be effectively utilized in the model training process. We applied this stage to ensure that the dataset was clean, well-structured, and presented in a format suitable for learning temporal patterns using the LSTM model. We first performed data cleaning to handle potential inconsistencies, such as missing values, duplicate records, or irregular entries, to improve data quality and reliability. We then applied data normalization to rescale the gold price values into a uniform range, which helped stabilize the training process and prevented dominance of large numerical values during weight updates. After normalization, we adopted a sliding window technique to convert the time-series data into supervised learning samples, where sequences of past observations were used as input features to predict future gold prices. Finally, we performed data splitting to divide the dataset into training and testing subsets, enabling an objective evaluation of the model's predictive performance. Through these preprocessing steps, we ensured that the data supported optimal learning behavior and reliable performance assessment of the LSTM-based gold price prediction model.

3. Prediction and Visualization

In this paper, we utilize the trained LSTM model to predict gold prices for the next seven days as the final stage of the analysis. We apply historical gold price data as input to the model in order to estimate future prices for dates that have not yet occurred. The prediction process begins by arranging the most recent observations into sequences that follow the predefined sliding window length, which ensures consistency with the data structure used during training. We then feed this input sequence into the LSTM model to generate a one-step-ahead prediction, and we iteratively repeat this process to obtain forecasts for the entire seven-day horizon. In this study, we use the developed model to predict gold prices for the period from June 28 to July 4, 2025. To enhance interpretability and support analytical insights, we visualize the prediction results in graphical form, allowing us to clearly observe the projected gold price trends and compare them with historical patterns.

5. Result and Analysis

The LSTM model architecture used in this study consists of several layers. The first layer is the input layer, which receives time series data in three dimensions (samples, time steps, features). Next, the LSTM layer is used to study historical gold price patterns with the number of neurons varied according to the test scenario. The output from the LSTM is then passed to a dense layer that has one neuron, in order to produce a single prediction value. The model is trained using the Mean Squared Error (MSE) loss function and the Adam optimization algorithm to accelerate the convergence process and improve prediction accuracy.

This model consists of two consecutive LSTM layers, each with 128 and 64 units. The first layer returns the entire output sequence, while the second layer only returns the final output. Next, a dropout layer of 0.1 is added to prevent overfitting, followed by a dense layer that produces an output of 7 days, which is the number of forward prediction values.

The model was tested using test data to generate gold price predictions. The model evaluation process in this study was conducted using the RMSE and MAPE metrics. Evaluation is performed to measure the performance of the model's outputs. The evaluation metrics used in this study are the Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The equations for calculating the values of MAPE (Equation 2) and RMSE (Equation 3) are as follows:

$$MAPE \ = \frac{1}{n}\sum_{t=1}^{n}\frac{x_{t-}\, x_t}{x_t} \times 100\ \% \tag{2}$$

$$RMSE \ = \sqrt{\frac{1}{n}}\sum_{t=1}^{n}\frac{x_{t-}\, x_t}{x_t} \times 100\ \% \tag{3}$$

Table 1. LSTM Model Evaluation Results

Batch Size	***Window Size***	***Epoch***	**RMSE**	**MAPE**
32	30	50	0.026501	2.46%
32	30	100	0.021781	1.94%

The best configuration was obtained with a combination of batch size 32, window size 30, and 100 epochs, with an RMSE value of 0.021781 and a MAPE of 1.94%, which is lower than the 50-epoch configuration. These results show that increasing the number of epochs gives the model more learning time, enabling it to better recognize data patterns and produce more accurate predictions.

The results of the visualization comparing actual and predicted prices at epochs 50 and 100 can be seen in Fig. 1 and Fig.2:

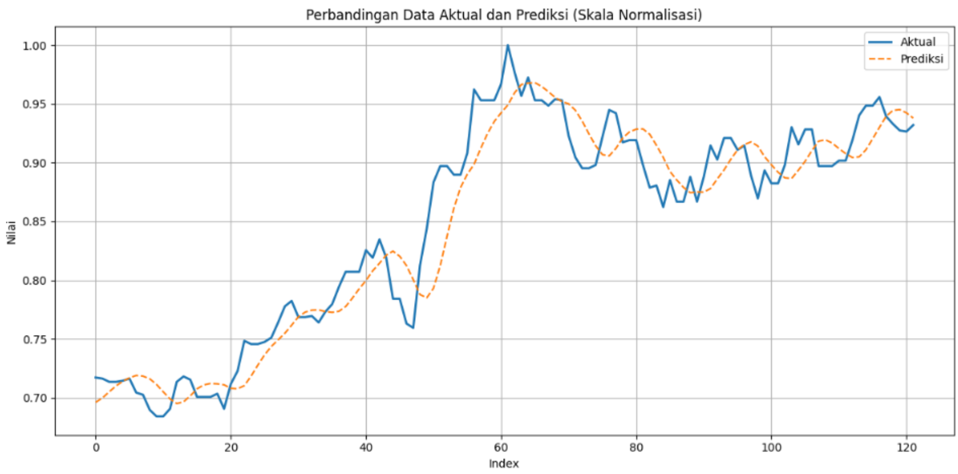

Fig 1. Visualization Results of Prediction Graphs with Epoch 50

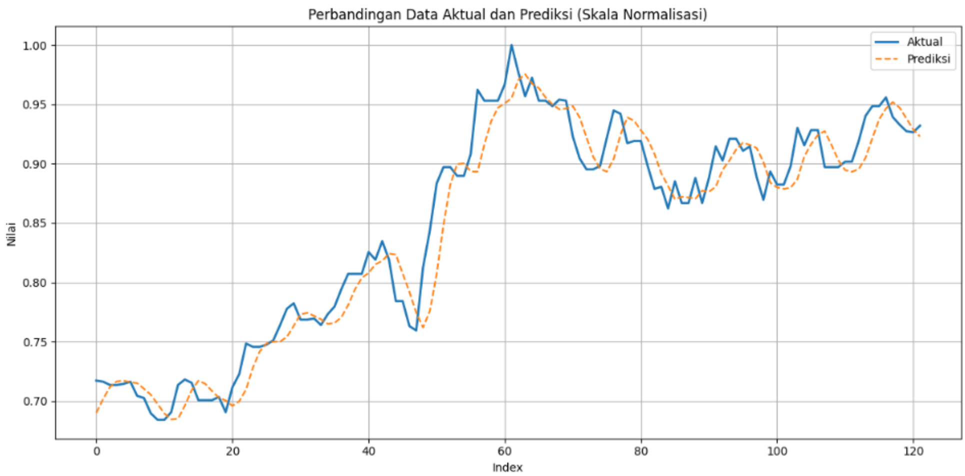

Fig 2. Visualization Results of Prediction Graphs with Epoch 100

Based on Fig. 1 and Fig. 2, the results of testing with test data can be seen, where the blue line represents the actual data and the red line shows the prediction results. In Figure 2, it can be concluded that predictions with 50 epochs did not provide optimal results, as there was a significant difference between the actual and predicted values. Meanwhile, Figure 3 shows that predictions with 100 epochs provided better results, as indicated by a smaller difference between the actual data and the predictions.

The testing was conducted in two scenarios, namely with 50 and 100 epochs, using a window size of 30 and a batch size of 32. The model evaluation was based on the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values, where the smaller the value, the more accurate the model prediction results. In the scenario with 50 epochs, the RMSE was 0.026501 and the MAPE was 2.46%, while in the 100 epochs scenario, the RMSE decreased to 0.021781 and the MAPE to 1.94%. Lower RMSE and MAPE values indicate that the model has a low prediction error rate and is capable of producing estimates that are close to the actual values.

Based on the sliding window size determination experiment, the best results were obtained with a combination of 100 epochs and a window size of 30, with an RMSE value of 0.021781 and a MAPE of 1.94%. This value is the lowest among all configurations tested, indicating that this configuration produces the most accurate prediction performance. Thus, the model trained with these parameters can capture data patterns more effectively and provide estimates that are closer to the actual values.

The model training results show an increase in performance as the number of epochs increases. At epoch 50, the loss value on the training data was recorded at 3.791004, while the val_loss on the validation data was 0.0014. After training continued to the 100th epoch, the loss and val_loss values decreased to 2.981404 and 0.0013, respectively. This decrease indicates that the model is increasingly able to understand patterns in the training data and perform better generalization on the validation data.

The results of the model evaluation on the testing data are shown in Figure 4.6 and Figure 4.7. Figure 4.6, which represents the prediction results after 50 epochs, shows a significant difference between the actual data and the prediction results. This indicates that at this stage, the model is not yet fully capable of accurately capturing data patterns. In contrast, Figure 4.7, which represents the prediction results after 100 epochs, shows that the prediction line is closer to the actual data line. This indicates an improvement in prediction quality after the model was trained longer, namely up to 100 epochs. Based on the ANTAM gold price prediction chart for the next 7 days, there is a gradual upward trend. The price of gold is expected to increase from 1,927,500 on June 28, 2025, to 1,945,000 on July 4, 2025.

6. Conclusion

Based on the testing and evaluation results, we observed that the gold price prediction model achieved improved performance as the number of training epochs increased. In this paper, we utilized two experimental scenarios, namely 50 epochs and 100 epochs, while consistently applying a window size of 30 and a batch size of 32. The experimental findings demonstrated that extending the training duration allowed the LSTM model to learn temporal patterns in gold price movements more effectively, thereby reducing prediction errors. This result confirmed that adequate training depth played a crucial role in capturing long-term dependencies within historical gold price data.

We obtained the best predictive performance when we applied a configuration of 100 epochs and a window size of 30. Under this optimal setting, the model achieved an RMSE value of 0.021781 and a MAPE of 1.94%, indicating a low prediction error and high forecasting accuracy. These results showed that the adopted LSTM architecture effectively modeled the nonlinear and sequential characteristics of ANTAM gold price data. Therefore, we concluded that the proposed model configuration was reliable and effective for short-term gold price prediction tasks.

Although the results were satisfactory, this paper identified several opportunities for further improvement. As future work, we suggested enhancing the model by incorporating external economic variables, such as currency exchange rates, inflation indicators, and global commodity prices, to provide richer contextual information for prediction. In addition, we recommended improving the model architecture by adding more LSTM layers and adopting more optimal regularization techniques, such as dropout, to reduce overfitting and further improve generalization performance in future studies.

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