

Comparing Linear Regression, Random Forest, and LSTM for Antam Gold Price Forecasting

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Abstract—Forecasting gold prices plays a crucial role in supporting investment decision-making and financial risk management, particularly in Indonesia, where Antam gold is widely used as an investment instrument. Although numerous forecasting techniques have been proposed, comparative studies evaluating statistical, machine learning, and deep learning models for Antam gold price prediction using long-term historical data remain limited. A systematic comparison is therefore important to identify forecasting approaches that can provide reliable and interpretable predictions for the Indonesian gold market, especially when different lengths of historical data are considered. This study compares the forecasting performance of Linear Regression, Random Forest, and Long Short-Term Memory (LSTM) using historical Antam gold price data spanning January 2010 to June 2026, collected from Kaggle and the official Logam Mulia website. The preprocessing stage included date parsing, chronological sorting, missing value inspection, data normalization for LSTM, lag feature engineering, and sequence construction. Five experimental scenarios were designed to investigate the influence of historical data length on forecasting accuracy. Model performance was evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2), with RMSE selected as the primary evaluation metric. The experimental results show that Linear Regression consistently achieved the best forecasting performance across all scenarios. The highest prediction accuracy was obtained using the 10-year historical data scenario, resulting in an RMSE of 17,064.29 and an R^2 of 0.9978. Random Forest produced competitive results only when the training dataset contained the highest observed gold price, whereas LSTM did not outperform Linear Regression in any experimental scenario. These findings demonstrate that, for Antam gold price forecasting with predominantly linear historical trends, a simple and interpretable statistical model can outperform more complex machine learning and deep learning approaches. Practically, the findings can support investors, financial analysts, and policymakers in Indonesia in selecting appropriate forecasting methods and developing more evidence-based investment strategies and financial risk management policies. The results also highlight the importance of selecting an appropriate historical data length to achieve reliable forecasting performance in financial time-series applications.

Keywords: Antam Gold Price; Gold Price Forecasting; Time-Series Forecasting; Linear Regression; Random Forest; Long Short-Term Memory (LSTM)

1. INTRODUCTION

Gold is one of the most important mining commodities and plays a significant role in the global economy. In addition to its use as a raw material for industrial applications and jewelry production, gold is widely regarded as an investment instrument and a store of value. Its relatively stable value makes it an attractive investment option for protecting assets against inflation and economic uncertainty. Historically, gold has also served as a medium of exchange and a monetary standard in many countries, highlighting its substantial economic importance within the modern financial system [1]. Gold prices are widely recognized as an important economic indicator that reflects market conditions and investor confidence in the economy. In Indonesia, gold prices are influenced by various factors, including fluctuations in global gold prices, the exchange rate of the Indonesian Rupiah against the US Dollar, inflation, interest rates, and global geopolitical conditions. These factors contribute to dynamic fluctuations in gold prices over time [2]. Consequently, predicting future gold prices is a challenging task that requires analytical approaches capable of generating reliable forecasts. However, the effectiveness of a forecasting model does not necessarily depend on its structural complexity. In markets such as Antam gold, where historical prices may exhibit relatively strong trends and temporal continuity, simpler statistical models may provide more stable, interpretable, and computationally efficient predictions than more complex machine learning and deep learning models. Therefore, empirically determining whether model complexity actually provides superior forecasting performance is important for the specific context of Antam gold prices.

Forecasting is the process of predicting future conditions by analyzing historical patterns embedded in previous data [3]. In the context of investment, gold price forecasting plays a crucial role in assisting investors in making more informed buying and selling decisions. Furthermore, accurate forecasting can support risk management strategies and financial planning by providing valuable insights into future market trends. With the rapid advancement of computational technologies, numerous forecasting techniques have been developed to improve prediction accuracy for time-series data. Traditional approaches primarily rely on statistical models that assume linear relationships among variables. Although these methods may be less flexible for highly nonlinear datasets, they can perform effectively when the underlying time-series exhibits strong linear or trend-based characteristics. Conversely, machine learning and deep learning approaches have gained increasing attention because of their ability to learn complex nonlinear relationships from historical data [4]. However, greater model complexity does not automatically guarantee better forecasting accuracy. The performance of each approach depends strongly on the characteristics of the dataset, the



availability of historical observations, feature representation, and the forecasting horizon. This issue is particularly relevant for Antam gold prices, where the relationship between historical observations and future prices needs to be empirically evaluated rather than assuming that more complex models will always produce better predictions.

This study employs three forecasting algorithms representing different modeling paradigms: Linear Regression, Random Forest, and Long Short-Term Memory (LSTM). Linear Regression is selected because it is a well-established statistical method for modeling relationships between variables [5]. It is frequently used as a baseline model due to its simplicity, interpretability, and computational efficiency. Recent studies on financial and commodity forecasting have also demonstrated that linear and other relatively simple models can remain competitive when financial price series exhibit strong temporal trends or approximately linear relationships [6]. Random Forest is included as a representative ensemble learning algorithm that has demonstrated strong performance in regression tasks and possesses the ability to model complex nonlinear relationships [7]. Its ensemble structure can improve robustness by combining multiple decision trees and reducing the dependence on a single estimator. Recent applications of machine learning to financial forecasting have further shown the potential of tree-based ensemble methods for modeling nonlinear relationships in market data [8]. Meanwhile, LSTM, a specialized architecture of Recurrent Neural Networks (RNNs), is designed to learn sequential dependencies in time-series data. Its memory mechanism enables the model to retain relevant information over long periods, making it particularly suitable for forecasting financial time-series such as gold prices [9]. Recent studies have continued to employ LSTM and related recurrent architectures for financial and commodity price forecasting because of their ability to represent temporal dependencies and nonlinear patterns [10], [11]. These three models therefore provide a meaningful comparison between interpretability and simplicity, nonlinear ensemble learning, and sequence-based deep learning.

Previous studies have investigated gold price forecasting using various approaches. For instance, Jayanti et al. applied the Autoregressive Integrated Moving Average (ARIMA) model to forecast gold prices for the 2024–2025 period. Their findings demonstrated that ARIMA can effectively generate forecasts based on historical time-series patterns [1]. However, the study focused exclusively on a conventional statistical approach and did not compare its performance with machine learning and deep learning models. Other studies have explored machine learning and deep learning approaches for financial and gold price forecasting, but their findings indicate that model performance can vary substantially depending on the characteristics, size, and temporal coverage of the dataset [9]–[11]. Moreover, comparative studies specifically evaluating Linear Regression, Random Forest, and LSTM for forecasting Antam gold prices remain limited. More importantly, previous studies generally focus on comparing different algorithms while giving less attention to the length of historical data used to train the forecasting models.

The length of historical observations is an important but relatively underexplored experimental factor in financial time-series forecasting. A longer historical period may provide a model with more observations and broader information about long-term price trends, but it may also introduce historical patterns that are less representative of current market conditions. Conversely, a shorter historical period may better represent recent market behavior but provide less information about long-term trends and structural changes. Therefore, the assumption that using more historical data will always improve forecasting performance requires empirical verification. In the context of Antam gold prices, this issue is particularly important because the Indonesian gold market has experienced substantial changes over the past decade, including periods of economic uncertainty, inflationary pressure, exchange-rate fluctuations, and changes in global gold prices. Evaluating multiple historical-data lengths under a consistent experimental framework can therefore provide a more comprehensive understanding of how data availability affects forecasting accuracy.

Based on these considerations, this study aims to develop and compare three forecasting models representing statistical, machine learning, and deep learning approaches, namely Linear Regression, Random Forest, and Long Short-Term Memory (LSTM), for predicting Antam gold prices. The models are evaluated under five different experimental scenarios to investigate the influence of historical data length on forecasting performance. Model performance is assessed using four widely adopted regression metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2), with RMSE serving as the primary evaluation criterion. By maintaining the same target variable and evaluation framework across all models and scenarios, this study enables a more consistent comparison of model performance.

The main contribution of this study is twofold. First, unlike previous studies that predominantly evaluate individual forecasting methods or compare models without systematically varying the historical observation period, this study provides a comparative evaluation of Linear Regression, Random Forest, and LSTM using a long-term Antam gold price dataset covering January 2010 to June 2026. Second, the study explicitly treats historical data length as an experimental variable through five forecasting scenarios, enabling an empirical assessment of whether additional historical observations improve or reduce forecasting accuracy. This design provides a more specific contribution to Antam gold price forecasting by examining not only which model performs best, but also under what historical-data conditions each model achieves its most reliable performance. The study is also motivated by the practical possibility that a simpler model may outperform more complex approaches when the underlying price series is predominantly trend-driven. Therefore, the findings are expected to contribute to the advancement of gold price forecasting methodologies while providing practical guidance for researchers, investors, financial analysts, and practitioners in selecting forecasting models that balance accuracy, interpretability, and computational complexity. The results may also support more evidence-based investment decision-making and financial risk management in the Indonesian gold

market. The remainder of this paper is organized as follows. Section 2 describes the research methodology, including the dataset, preprocessing procedures, forecasting models, experimental scenarios, and evaluation metrics. Section 3 presents and discusses the experimental results, while Section 4 concludes the study and outlines directions for future research.

2. RESEARCH METHODOLOGY

2.1 Dataset

This study utilizes historical Antam gold price data denominated in Indonesian Rupiah (IDR) obtained from two sources. Historical data covering the period from 2010 to 2024 were collected from the Kaggle platform, published by Yudi Faturohman. The dataset was originally sourced from the official Logam Mulia website and made publicly available through Kaggle. Kaggle is one of the widely recognized platforms in the fields of Data Science and Machine Learning, providing access to publicly available datasets in various formats [8]. To ensure data source consistency, historical gold prices from January 2025 to June 14, 2026, were collected directly from the official Logam Mulia website. The prices correspond to the official Antam gold prices published by the LM Graha Dipta Pulo Gadung Gold Boutique.

The dataset is structured as a daily time-series, in which each observation represents the Antam gold price recorded for a specific date. Thus, the temporal granularity of the dataset is daily rather than weekly or monthly. The use of daily observations enables the forecasting models to capture short-term price movements as well as longer-term trends in Antam gold prices. The date variable was used to maintain the chronological order of observations, while the corresponding gold price was treated as the target variable for forecasting. Any dates without available price observations were retained as missing temporal observations rather than being assigned artificial prices, ensuring that the original price information was not altered.

The integration of these two data sources produced a continuous historical time-series dataset covering January 2010 to June 14, 2026. The combined dataset was subsequently chronologically sorted and inspected for missing values and inconsistencies before being used in the forecasting experiments. The resulting dataset served as the basis for training and evaluating the forecasting models, namely Linear Regression, Random Forest, and Long Short-Term Memory (LSTM). The daily frequency and extended observation period provide sufficient temporal information for evaluating the effect of different historical data lengths across the five experimental scenarios.

2.2 Data Preprocessing

The preprocessing stage aims to clean, transform, and prepare the dataset to improve the efficiency and reliability of the forecasting models [9], [10]. The preprocessing pipeline consists of date parsing, chronological sorting, missing value inspection, data normalization, lag feature generation, and sequence construction for the LSTM model.

2.2.1 Date Parsing and Data Sorting

The date column was converted into the Python **datetime** format using the Pandas library. After the conversion process, the date column was assigned as the primary index of the dataset to facilitate time-series analysis. The observations were subsequently sorted in chronological order, from the earliest to the most recent date, ensuring that the temporal sequence accurately reflected the actual order of events.

2.2.2 Missing Value Inspection

A comprehensive inspection was performed to verify the completeness and consistency of the dataset before model development. The inspection focused on identifying missing values in the gold price records as well as detecting any missing dates that could disrupt the chronological continuity of the time-series data. Missing values were examined using the data validation functions provided by the Pandas library, while the chronological sequence of observations was checked to ensure that the dataset accurately represented the historical movement of Antam gold prices.

The inspection results indicated that the integrated dataset contained no missing price values or missing observation dates. Therefore, no imputation or interpolation procedures were required. Preserving a complete dataset is particularly important in time-series forecasting because missing observations may distort temporal dependencies, introduce bias during feature engineering, and reduce forecasting accuracy. By ensuring that the dataset was free from missing values, the subsequent preprocessing stages, including lag feature generation and sequence construction for the LSTM model, could be performed without interruptions while maintaining the temporal consistency of the data.

2.2.3 Data Normalization

Data normalization was applied exclusively to the LSTM model using the MinMaxScaler technique, which transforms the input values into a predefined range between 0 and 1 [11], [12]. MinMaxScaler was specifically selected for the LSTM model because recurrent neural networks are sensitive to the scale of input variables, and transforming the gold price values into a bounded range can improve numerical stability, facilitate gradient-based optimization, and support more stable model convergence during training. Compared with standardization techniques such as Z-score normalization, which transform data based on the mean and standard deviation, MinMaxScaler preserves the relative

distribution and temporal ordering of the original price series while constraining the input values to a consistent range. This characteristic is particularly appropriate for the LSTM architecture because its sigmoid and hyperbolic tangent activation functions operate within bounded ranges, making scaled inputs more suitable for the network's learning process [11], [12]. In addition, MinMaxScaler is straightforward to apply and allows the predicted values to be readily transformed back to the original IDR scale for interpretation and evaluation. To prevent information leakage, the scaler was fitted using only the training data, and the same fitted transformation was subsequently applied to the validation and testing data. This procedure ensures that information from future observations does not influence the model during training.

2.2.4 Lag Feature Engineering

For the Linear Regression and Random Forest models, feature engineering was performed by generating lag features, which represent historical observations from previous time steps [13]. Ten lag variables were created to represent gold prices from one to ten days before the prediction date. In addition, a trend feature representing the chronological order of observations was incorporated to assist the models in learning the long-term movement of gold prices.

2.2.5 Sequence Construction

For the LSTM model, the time-series data were transformed into sequential input samples using a sliding window approach. Each input sequence consisted of ten consecutive historical time steps, which were used to predict the gold price at the subsequent time step.

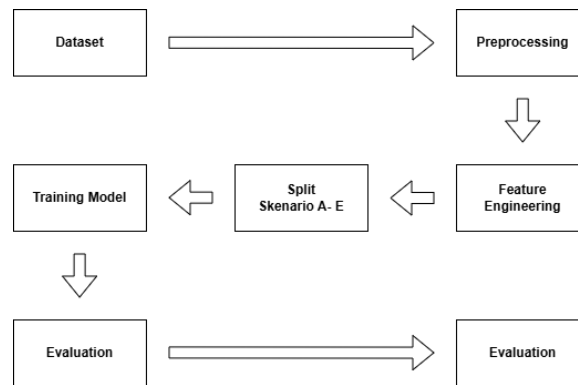


Figure 1. Data Preprocessing Workflow

Figure 1 illustrates the data preprocessing workflow applied before the forecasting models were trained. The preprocessing procedure begins with data collection and integration from Kaggle and the official Logam Mulia website, followed by date parsing and chronological sorting to preserve the temporal order of the observations. The dataset was then inspected for missing values and inconsistencies to ensure data quality. Subsequently, lag features were constructed for the Linear Regression and Random Forest models to represent the temporal dependence between previous and current gold prices, while sequential input windows were prepared for the LSTM model. Data normalization using MinMaxScaler was applied specifically to the LSTM input to transform the price values into a range between 0 and 1. Finally, the preprocessed data were organized according to the five experimental scenarios based on different historical data lengths and subsequently used for model training and evaluation. This workflow ensures that the same underlying time-series data are processed systematically while allowing each forecasting model to receive an input representation appropriate to its modeling characteristics.

2.3 Experimental Scenarios

To evaluate the robustness of the forecasting models under different historical data conditions, five experimental scenarios were designed. Each scenario represents a different training and testing strategy to investigate the impact of historical data length on forecasting performance.

Table 1. Experimental Scenarios

Scenario	Description	Training Data	Testing Data
A	Up to the Peak Price	From the beginning of the dataset to the highest gold price	From the peak price to the end of the dataset
B	Until the End of 2025	From the beginning of the dataset to the end of 2025	From the beginning of 2026 to the end of the dataset
C	Last 10 Years	80% of data from 2016–2025	20% of data from 2016–2025
D	Last 5 Years	80% of data from 2021–2025	20% of data from 2021–2025
E	Last 3 Years	80% of data from 2023–2025	20% of data from 2023–2025

These experimental scenarios were designed to assess how the length and composition of historical data influence the forecasting performance of the proposed models. Scenarios A and B simulate real-world forecasting conditions by training the models using historical observations up to a specific point in time and evaluating their ability to predict future gold prices. Scenario A investigates the impact of including the highest recorded gold price in the training dataset, whereas Scenario B evaluates the models' capability to forecast prices beyond the end of 2025.

In contrast, Scenarios C, D, and E examine the effect of different historical data lengths by using the most recent 10, 5, and 3 years of observations, respectively. For these scenarios, the datasets were divided chronologically into 80% training data and 20% testing data to preserve the temporal sequence and prevent information leakage from future observations. This chronological split reflects practical forecasting conditions, where models are trained using past data and evaluated on unseen future data.

By comparing forecasting performance across these five scenarios, this study investigates not only the predictive capability of Linear Regression, Random Forest, and LSTM but also the extent to which the amount of historical data affects forecasting accuracy. This experimental design provides a comprehensive evaluation of model robustness under different data availability conditions and offers practical insights into selecting appropriate forecasting models for Antam gold price prediction.

2.4 Forecasting Models

This study employs three forecasting models representing statistical, machine learning, and deep learning approaches, namely Linear Regression, Random Forest, and Long Short-Term Memory (LSTM). These models were selected because they represent different levels of model complexity and learning capability, enabling a comprehensive comparison between conventional statistical methods and more advanced artificial intelligence techniques for time-series forecasting.

Linear Regression serves as the baseline statistical model due to its simplicity, interpretability, and computational efficiency. Random Forest represents an ensemble machine learning approach capable of capturing nonlinear relationships through multiple decision trees, while LSTM is employed as a deep learning model specifically designed to learn temporal dependencies in sequential data. By evaluating these three models under identical experimental scenarios and using the same evaluation metrics, this study aims to identify the most suitable forecasting approach for Antam gold price prediction and to examine how model complexity influences forecasting accuracy.

2.4.1 Linear Regression

Linear Regression is a statistical technique that models the relationship between variables using a linear equation [14]. In this study, Linear Regression serves as the baseline model for learning the relationship between the current gold price and its historical values represented by lag features. The trained model estimates future gold prices based on the learned linear relationship.

2.4.2 Random Forest

Random Forest is an ensemble learning algorithm that constructs multiple decision trees and combines their predictions to generate the final output. This approach effectively captures nonlinear relationships while reducing the risk of overfitting commonly encountered in single decision-tree models. Random Forest has become a widely adopted forecasting technique due to its strong predictive performance, minimal hyperparameter tuning requirements, ease of implementation, and proven effectiveness across a wide range of real-world applications [15].

2.4.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a specialized Recurrent Neural Network (RNN) architecture designed to capture long-term dependencies in sequential data. The model incorporates memory cells regulated by input, forget, and output gates, enabling important information to be retained throughout the learning process. Owing to its capability to model temporal dependencies, LSTM has gained considerable attention in recent years and has been successfully applied in numerous domains, including financial forecasting [16].

2.5 LSTM Architecture

The LSTM architecture employed in this study consists of two stacked LSTM layers followed by Dropout layers to reduce the risk of overfitting. A fully connected dense layer with the ReLU activation function is then applied before the final output layer. The detailed network architecture is presented in **Table 2**.

Table 2. LSTM Architecture

Layer	Type	Configuration
LSTM Layer 1	LSTM	100 Units
Dropout 1	Dropout	Rate = 0.2
LSTM Layer 2	LSTM	50 Units
Dropout 2	Dropout	Rate = 0.2
Dense 1	Dense + ReLU	25 Units

Layer	Type	Configuration
Output Layer	Dense	1 Unit

The LSTM architecture was designed to provide sufficient capacity to learn temporal dependencies in the Antam gold price series while maintaining a relatively lightweight network to reduce the risk of overfitting. As presented in Table 2, the model consists of two stacked LSTM layers with 100 and 50 units, respectively, followed by two dropout layers, a fully connected Dense layer with 25 units and ReLU activation, and a single-unit output layer for predicting the gold price. The number of units was selected to provide a progressively decreasing representation of the temporal features learned by the network. The first LSTM layer uses 100 units to capture relatively rich temporal patterns from the input sequences, while the second LSTM layer uses 50 units to transform these representations into a more compact feature space before prediction. This 100-to-50 configuration provides a balance between model capacity and computational complexity and avoids using an excessively large network for the available historical dataset.

A dropout rate of 0.2 was applied after each LSTM layer to reduce the risk of overfitting by randomly deactivating 20% of the neurons during training. The relatively moderate dropout rate was selected because a higher dropout rate could remove too much temporal information and potentially limit the LSTM's ability to learn sequential dependencies from the gold price series. Conversely, omitting dropout could increase the risk of the model memorizing patterns in the training data rather than learning generalizable temporal relationships. Therefore, a dropout rate of 0.2 was used as a moderate regularization setting that maintains sufficient learning capacity while improving the model's ability to generalize to unseen observations. The Dense layer with 25 units and ReLU activation subsequently maps the learned temporal representations into a lower-dimensional feature space, while the final Dense layer with one unit generates the continuous gold price prediction.

2.6 Performance Evaluation

The forecasting performance of each model was evaluated using four widely adopted regression metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2).

Table 3. Performance Evaluation Metrics

Metric	Description
MAE	Mean absolute difference between predicted and actual values
MSE	Mean squared difference between predicted and actual values
RMSE	Square root of the Mean Squared Error
R^2	Proportion of variance in the observed data explained by the model

Among these metrics, RMSE was selected as the primary evaluation criterion because it quantifies the average prediction error while assigning greater penalties to larger forecasting errors [17]. Furthermore, RMSE is expressed in the same unit as the target variable (Indonesian Rupiah), making the forecasting error more interpretable in practical applications. A lower RMSE value indicates better forecasting performance and higher predictive accuracy.

3. RESULT AND DISCUSSION

3.1 Performance Evaluation Results

The performance of the forecasting models was evaluated using four evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). In this study, RMSE was selected as the primary evaluation metric because it is expressed in the same unit as the gold price value (Indonesian Rupiah), making the forecasting error easier to interpret in practical applications. The evaluation results of each model across the five experimental scenarios are presented in Tables 4–8.

Table 4. Evaluation Results of Scenario A (Until Peak Price)

Model	MAE	MSE	RMSE	R^2
Linear Regression	24,696.26	958,494,928.94	30,959.57	0.9065
Random Forest	87,162.23	9,422,480,059.04	97,069.46	0.0805
LSTM	36,917.40	2,457,079,199.83	49,568.93	0.7635

Table 4 presents the evaluation results for Scenario A, in which the historical data used for model development cover the period up to the peak gold price observed in the dataset. Linear Regression achieved the best performance among the three models, with an MAE of 24,696.26, an MSE of 958,494,928.94, an RMSE of 30,959.57, and an R^2 of 0.9065. LSTM produced a higher RMSE of 49,568.93 and an R^2 of 0.7635, indicating lower predictive accuracy than Linear Regression. Random Forest obtained the weakest performance, with an RMSE of 97,069.46 and an R^2 of only 0.0805. These results indicate that the relatively simple linear relationship captured by Linear Regression was more effective than the nonlinear and sequential approaches under the data characteristics of Scenario A.

Table 5. Evaluation Results of Scenario B (Until End of 2025)

Model	MAE	MSE	RMSE	R ²
Linear Regression	28,989.04	2,088,780,638.49	45,703.18	0.8256
LSTM	65,797.23	6,048,610,235.43	77,772.81	0.6521

Table 5 shows the forecasting performance for Scenario B, using historical data up to the end of 2025. Linear Regression again outperformed LSTM, achieving an MAE of 28,989.04, an MSE of 2,088,780,638.49, an RMSE of 45,703.18, and an R² of 0.8256. In comparison, LSTM produced an MAE of 65,797.23, an MSE of 6,048,610,235.43, an RMSE of 77,772.81, and an R² of 0.6521. The lower RMSE and higher R² obtained by Linear Regression indicate that it provided more accurate predictions for this historical-data configuration. The results further suggest that increasing the complexity of the forecasting architecture does not necessarily improve performance when the dominant patterns in the gold price series can be adequately represented by a linear model.

Table 6. Evaluation Results of Scenario C (Last 10 Years)

Model	MAE	MSE	RMSE	R ²
Linear Regression	11,164.62	291,190,062.63	17,064.29	0.9978
LSTM	34,974.40	2,302,683,186.22	47,986.28	0.9817

Table 6 presents the results for Scenario C, which uses the most recent 10 years of historical data. This scenario produced the strongest overall forecasting performance. Linear Regression achieved an MAE of 11,164.62, an MSE of 291,190,062.63, an RMSE of 17,064.29, and an R² of 0.9978. LSTM obtained an MAE of 34,974.40, an MSE of 2,302,683,186.22, an RMSE of 47,986.28, and an R² of 0.9817. Although LSTM also achieved a relatively high R² value, its RMSE was substantially higher than that of Linear Regression. Therefore, based on the primary evaluation metric, RMSE, Linear Regression was clearly the best-performing model in this scenario. The results indicate that the 10-year historical period provided a particularly suitable representation of the underlying price trend for Linear Regression.

Table 7. Evaluation Results of Scenario D (Last 5 Years)

Model	MAE	MSE	RMSE	R ²
Linear Regression	13,884.23	428,024,027.54	20,688.74	0.9945
LSTM	95,285.62	11,810,274,564.64	108,675.09	0.8407

Table 7 presents the evaluation results for Scenario D using the most recent five years of historical data. Linear Regression achieved an MAE of 13,884.23, an MSE of 428,024,027.54, an RMSE of 20,688.74, and an R² of 0.9945. LSTM performed substantially worse, with an MAE of 95,285.62, an MSE of 11,810,274,564.64, an RMSE of 108,675.09, and an R² of 0.8407. The considerably lower RMSE and higher R² of Linear Regression demonstrate its superior forecasting capability in this scenario. The deterioration in LSTM performance compared with Scenario C suggests that reducing the historical training period may limit the amount of temporal information available for learning sequential patterns, particularly for a relatively complex deep learning architecture.

Table 8. Evaluation Results of Scenario E (Last 3 Years)

Model	MAE	MSE	RMSE	R ²
Linear Regression	13,884.23	428,024,027.54	20,688.74	0.9945
LSTM	36,807.11	2,541,618,270.54	50,414.46	0.9657

Table 8 presents the forecasting results obtained using the most recent three years of historical data. Linear Regression achieved an MAE of 13,884.23, an MSE of 428,024,027.54, an RMSE of 20,688.74, and an R² of 0.9945, while LSTM obtained an MAE of 36,807.11, an MSE of 2,541,618,270.54, an RMSE of 50,414.46, and an R² of 0.9657. Linear Regression therefore remained the best-performing model according to both RMSE and R². Although LSTM achieved a relatively high R², its substantially higher RMSE indicates larger prediction errors compared with Linear Regression. Overall, the results demonstrate that the reduction of the historical data period does not necessarily favor the more complex LSTM architecture. Instead, Linear Regression maintained strong predictive performance across the tested historical-data configurations.

3.2 Analysis of Scenario A

In Scenario A, the training data covered the period from the beginning of the observation until the highest recorded gold price point. The experimental results indicate that Linear Regression achieved the best forecasting performance, with an RMSE value of 30,959.57 and an R² value of 0.9065. This performance was superior to LSTM, which obtained an RMSE of 49,568.93, and Random Forest, which produced an RMSE of 97,069.46.

The relatively better performance of Random Forest in this scenario compared with other scenarios can be attributed to the inclusion of the gold price peak within the training dataset. Consequently, the price patterns observed

in the testing period remained within the range of values previously learned by the model during training. However, its overall performance was still considerably lower than that of Linear Regression and LSTM.

3.3 Analysis of Scenario B

Scenario B utilized training data covering the period from the beginning of the dataset until the end of 2025, while the testing data consisted of observations from the subsequent period. In this scenario, Linear Regression again achieved the best forecasting performance, obtaining an RMSE value of 45,703.18 and an R^2 value of 0.8256. In contrast, LSTM produced a higher RMSE value of 77,772.81 with an R^2 value of 0.6521, indicating lower prediction accuracy compared with Linear Regression.

The absence of Random Forest results in several extrapolative scenarios should be interpreted in relation to the inherent prediction mechanism of tree-based models. Random Forest generates predictions by averaging the outputs of decision trees constructed from patterns observed during training. Consequently, it is generally more effective for interpolation within the range of observed responses than for extrapolation beyond that range. When the future Antam gold price rises above the levels represented in the training data, the model cannot naturally extend the learned trend in the same way as a regression equation. This characteristic explains the substantial deterioration observed when the testing period contains new price levels and should be stated explicitly when interpreting the Random Forest results.

3.4 Analysis of Historical Data Scenarios

Scenarios C, D, and E were designed to evaluate the influence of historical data length on forecasting model performance. These scenarios analyze how different historical periods affect the predictive capability of each model. A summary of the RMSE values obtained by each model is presented in Table 9.

Table 9. RMSE Comparison Across All Scenarios

Scenario	Linear Regression	LSTM	Random Forest
A	30,959.57	49,568.93	97,069.46
B	45,703.18	77,772.81	-
C	17,064.29	47,986.28	-
D	20,688.74	108,675.09	-
E	20,688.74	50,414.46	-

Based on Table 9, the best forecasting performance was achieved in Scenario C using Linear Regression, which obtained the lowest RMSE value of 17,064.29 and the highest coefficient of determination (R^2) of 0.9978. This result indicates that using ten years of historical data provides a sufficiently comprehensive representation of long-term price movements while maintaining relevance to recent market conditions. The larger amount of historical information enables the model to learn both the overall upward trend and short-term fluctuations in Antam gold prices, resulting in more accurate predictions. In Scenarios D and E, the RMSE values increased compared with Scenario C, indicating a decline in forecasting accuracy as the amount of historical data decreased. Although the performance degradation was relatively small, this finding suggests that shorter historical periods provide fewer observations for learning temporal patterns, thereby limiting the model's ability to generalize future price movements. Nevertheless, Linear Regression consistently maintained excellent predictive performance, achieving R^2 values above 0.99 across these scenarios, which demonstrates its robustness even when trained on more limited datasets.

The comparison also highlights the influence of historical data availability on model performance. While additional historical observations generally improve the learning process, excessively long datasets may include outdated market conditions that are less representative of current price dynamics. Conversely, datasets that are too short may fail to capture long-term trends and cyclical behavior. The results obtained in this study suggest that a ten-year historical period provides an appropriate balance between data quantity and data relevance for forecasting Antam gold prices.

Furthermore, LSTM consistently produced higher RMSE values than Linear Regression across all historical data scenarios. This result indicates that the additional complexity of deep learning did not provide a significant advantage for this forecasting problem. Since the dataset primarily exhibited a relatively smooth upward trend without incorporating external economic variables, the linear relationships captured by Linear Regression were sufficient to achieve highly accurate predictions. In contrast, LSTM requires larger datasets and richer feature representations to fully exploit its capability of modeling complex nonlinear temporal dependencies.

Overall, the findings demonstrate that the amount of historical data is an important factor affecting forecasting performance; however, model selection plays an equally critical role. The consistent superiority of Linear Regression across all scenarios suggests that a simpler and more interpretable statistical model can outperform more sophisticated machine learning and deep learning approaches when the underlying time-series data exhibit predominantly linear behavior. These findings provide practical guidance for researchers and practitioners in selecting forecasting models that achieve an effective balance between predictive accuracy, computational efficiency, and model interpretability.

3.5 Comparison of Forecasting Models

Across all experimental scenarios, Linear Regression consistently achieved the lowest RMSE values compared with the other forecasting models. These results indicate that the movement patterns of Antam gold prices during the observation period can be effectively represented through linear relationships between current prices and previous historical price values. Although LSTM is specifically designed to process sequential data and capture long-term dependencies, it was unable to outperform Linear Regression in any of the evaluated scenarios. One possible explanation is that gold price data in this study exhibited relatively stable trends, allowing a simpler linear approach to effectively model the underlying patterns.

Random Forest demonstrated the lowest overall performance in this study. The tree-based characteristics of Random Forest limit its ability to extrapolate values beyond the range of the training data. This limitation became more apparent when gold prices experienced significant increases during the testing period. Consequently, the model had difficulty generating predictions that accurately followed the upward price trend. Overall, the findings demonstrate that higher model complexity does not necessarily guarantee better forecasting performance. For Antam gold price forecasting, Linear Regression provided the most accurate and consistent results compared with Random Forest and LSTM.

3.6 Why Linear Regression Outperformed More Complex Models

The experimental results consistently demonstrate that Linear Regression achieved the highest forecasting accuracy across all experimental scenarios. Although Random Forest and LSTM are capable of modeling nonlinear relationships, the simpler Linear Regression model produced lower RMSE values and higher coefficients of determination (R^2). This finding suggests that the movement of Antam gold prices during the observation period was characterized by relatively smooth and continuous trends that could be effectively represented through linear relationships between historical observations. One possible explanation is that the forecasting task in this study relied solely on historical gold prices without incorporating additional explanatory variables such as exchange rates, inflation, interest rates, crude oil prices, or global economic indicators. Under these circumstances, the generated lag features contained strong linear information, allowing Linear Regression to capture temporal patterns efficiently without requiring highly complex model architectures.

Furthermore, Linear Regression benefits from low model complexity and fewer trainable parameters. Unlike deep learning models, which require extensive datasets to optimize a large number of parameters, Linear Regression can produce stable parameter estimation even with relatively limited training data. Consequently, the model exhibits lower computational cost, higher interpretability, and reduced risk of overfitting while maintaining excellent predictive performance.

3.7 Effect of Historical Data Length

Another important finding of this study is the significant influence of historical data length on forecasting accuracy. Scenario C, which utilized the most recent ten years of historical observations, consistently generated the lowest forecasting errors among all evaluated scenarios. This result indicates that an adequately long historical dataset provides richer temporal information, enabling the forecasting models to learn seasonal fluctuations, long-term upward trends, and gradual market changes more effectively. Conversely, reducing the amount of historical data, as implemented in Scenarios D and E, resulted in increased RMSE values. Although the degradation was relatively small for Linear Regression, the reduction in available observations limited the diversity of patterns learned during model training. Consequently, the forecasting models became less capable of generalizing future market behavior.

These findings indicate that historical data availability plays a critical role in financial time-series forecasting. While excessively old observations may occasionally become less relevant due to structural economic changes, the ten-year observation period used in this study appears to provide an appropriate balance between capturing long-term trends and maintaining relevance to current market conditions.

3.8 Interpretation of Random Forest and LSTM Performance

The relatively lower performance of Random Forest can be explained by the intrinsic characteristics of tree-based ensemble models. Decision-tree algorithms partition the feature space according to patterns observed during training and generally perform interpolation rather than extrapolation. Consequently, when future gold prices exceed the highest values observed in the training dataset, Random Forest encounters difficulties in generating predictions that follow the continuing upward trend. This limitation became particularly apparent in Scenario A, where Random Forest only produced competitive performance because the highest gold price had already been included in the training dataset. In the remaining scenarios, the model experienced substantial performance degradation due to its inability to estimate values outside the observed data range.

Although LSTM is specifically designed to model sequential dependencies and has demonstrated promising performance in numerous financial forecasting applications, it did not outperform Linear Regression in this study. Several factors may explain this outcome. First, the available dataset contained approximately sixteen years of daily observations, which may still be insufficient for fully exploiting the representational capability of deep neural networks. Second, only historical price information was used as model input. Without additional macroeconomic

indicators, the nonlinear relationships that LSTM is designed to learn may not have been sufficiently strong to justify its higher model complexity. Third, the selected hyperparameters, including the number of layers, hidden units, learning rate, and training epochs, may not represent the globally optimal architecture for this forecasting problem.

3.9 Discussion

The findings of this study can be compared explicitly with several recent studies on gold-price forecasting. [18] compared LSTM and Linear Regression for gold-price forecasting and reported that the relative performance of the two approaches depended on the characteristics of the observed series. Similarly, [18] compared ARIMA, LSTM, GRU, and Simple Linear Regression for monthly gold prices and demonstrated that no single model is universally superior across all data configurations. Further explored a hybrid SARIMA-LSTM approach with Random Forest techniques for daily global gold-price forecasting. These findings support the present result that greater model complexity does not automatically produce higher forecasting accuracy [19]. In the present study, Linear Regression consistently outperformed LSTM, with the best result obtained in Scenario C (RMSE 17,064.29; R^2 0.9978), suggesting that the dominant trend and lag relationships in the selected Antam gold-price series were sufficiently regular to be captured by a simpler model.

The present findings also differ from several studies that reported strong performance for deep-learning models. Septiana et al. [20] applied a CNN-LSTM model to Indonesian gold-price prediction, while Vega et al. [21] investigated LSTM for precious-metal price forecasting. More specifically, Ashari et al. [22] combined LSTM with Gradient Boosting for one-day-ahead ANTAM gold-bar forecasting. Additional recent studies have also compared LSTM with ARIMAX [23] and evaluated LSTM, GRU, and hybrid LSTM-GRU approaches for ANTAM gold prices [24]. This difference is methodologically important: the present study used historical price information as the principal input and specifically examined the influence of historical-data length. Therefore, the results should not be interpreted as evidence that LSTM is inherently inferior, but rather that its advantage depends on the data representation, forecasting design, available explanatory variables, and hyperparameter configuration. The comparison with previous studies consequently reinforces the central contribution of this research: model selection should be based on the empirical characteristics of the target series and experimental setting rather than on model complexity alone.

The findings of this study are consistent with previous research reporting that forecasting performance depends strongly on data characteristics rather than model complexity alone. Several earlier studies have shown that statistical and conventional machine learning models remain highly competitive when the underlying time series exhibits relatively stable trend behavior. Conversely, deep learning models generally demonstrate greater advantages when large-scale datasets containing highly nonlinear temporal relationships are available. To further examine the statistical characteristics of the Antam gold price series, a stationarity analysis was conducted using the Augmented Dickey-Fuller (ADF) test. The ADF test was applied to determine whether the observed price series contains a unit root and whether differencing is required to obtain a stationary series. The test results provide additional statistical evidence regarding the temporal characteristics of the dataset and complement the forecasting performance results obtained from the five experimental scenarios. A non-stationary result for the original price series would indicate the presence of persistent temporal trends, which is consistent with the substantial upward movement observed in Antam gold prices over the study period. However, stationarity should not be interpreted as direct evidence of linearity; rather, it provides information about the temporal structure of the series that may influence model performance.

The strong performance of Linear Regression, particularly in Scenario C, can therefore be interpreted in conjunction with the observed temporal characteristics of the dataset. The RMSE of 17,064.29 and R^2 of 0.9978 obtained using the 10-year historical period indicate that a substantial proportion of the variation in the observed gold prices could be effectively represented by a relatively simple model. This result suggests that the dominant trend structure in the selected historical period was sufficiently regular for Linear Regression to provide highly accurate predictions, without requiring the additional nonlinear representation capacity of Random Forest or LSTM.

Compared with previous studies that evaluated only a single forecasting approach, this research provides a more comprehensive comparison by evaluating statistical, machine learning, and deep learning models under identical experimental scenarios. In addition, this study explicitly evaluates different historical-data lengths, allowing the effect of the temporal coverage of the training data to be examined rather than assuming that a longer historical period will always produce better forecasts. The results therefore contribute empirical evidence regarding the suitability of different forecasting approaches for Antam gold price prediction using long-term historical data. More specifically, the findings demonstrate that model complexity should be selected according to the statistical and temporal characteristics of the target series rather than based solely on the assumption that more complex architectures will provide superior forecasting accuracy.

3.9.1 Practical Implications

From a practical perspective, the findings suggest that financial institutions, investors, and gold traders do not necessarily require highly sophisticated deep learning models to obtain accurate short-term forecasts of Antam gold prices. Linear Regression offers several practical advantages, including low computational requirements, straightforward implementation, rapid model training, and transparent interpretation of forecasting results. These characteristics make the model particularly suitable for deployment in decision-support systems and web-based forecasting applications where computational efficiency and prediction speed are important considerations.



Nevertheless, the results should not be interpreted as evidence that deep learning methods are inherently inferior for financial forecasting. Their performance may improve substantially when additional explanatory variables are incorporated or when larger datasets covering multiple financial markets become available.

3.9.2 Limitations and Future Research

Despite achieving promising forecasting performance, this study has several limitations. First, the forecasting models were developed using only historical gold prices, without incorporating external variables such as exchange rates, inflation rates, interest rates, international gold prices, or geopolitical indicators that may significantly influence domestic gold prices. Second, only three forecasting algorithms were evaluated, while many recently developed deep learning architectures, including Gated Recurrent Unit (GRU), Temporal Convolutional Networks (TCN), Transformer-based models, and hybrid forecasting approaches, were not investigated. Third, the hyperparameter optimization process focused primarily on obtaining stable model performance and did not explore exhaustive optimization strategies that might further improve prediction accuracy. Future research should therefore investigate multivariate forecasting approaches incorporating macroeconomic indicators, evaluate more advanced deep learning architectures, and explore ensemble or hybrid forecasting techniques. In addition, explainable artificial intelligence (XAI) methods may be incorporated to improve model interpretability and provide deeper insights into the factors influencing Antam gold price movements.

4. CONCLUSION

Based on the experimental results, it can be concluded that Linear Regression, Random Forest, and Long Short-Term Memory (LSTM) can be applied to Antam gold price forecasting; however, their predictive performance varies considerably across different historical-data scenarios. Among all evaluated models, Linear Regression consistently achieved the best performance, producing the lowest RMSE and the highest R^2 values across the experimental scenarios. The best overall performance was obtained in Scenario C, which used ten years of historical data, where Linear Regression achieved an RMSE of 17,064.29 and an R^2 of 0.9978. This result indicates that the ten-year historical period provided a favorable balance between sufficient historical information and the relevance of recent price trends, enabling Linear Regression to effectively capture the dominant pattern in the Antam gold price series. The results also demonstrate that increasing model complexity does not necessarily lead to improved forecasting accuracy. Random Forest showed relatively competitive performance when the training data included the highest observed gold price, but its performance deteriorated when forecasting values beyond the range represented in the training data, reflecting the model's limited extrapolation capability. Meanwhile, LSTM did not outperform Linear Regression in any experimental scenario, despite its capability to learn complex sequential dependencies. This finding suggests that the dominant temporal pattern of the Antam gold price series can be effectively represented by a simpler and more interpretable linear model. Overall, the findings highlight that both model selection and historical-data length are important factors in Antam gold price forecasting. The results provide practical evidence that a relatively simple statistical model can outperform more complex machine learning and deep learning approaches when the underlying price series exhibits a strong and consistent trend. This finding may assist investors, financial analysts, and practitioners in selecting forecasting approaches that balance predictive accuracy, interpretability, and computational efficiency for investment decision-making and financial risk management in Indonesia. Future research should investigate more advanced forecasting architectures, including Gated Recurrent Unit (GRU), Transformer-based models, and hybrid forecasting approaches, using the same experimental framework to enable a broader comparison. Future studies should also consider incorporating external variables, such as Indonesian Rupiah–US Dollar exchange rates, inflation rates, global gold prices, interest rates, and other relevant economic indicators, to provide a more comprehensive representation of the factors influencing Antam gold price dynamics.

5. DECLARATIONS

5.1 Author Contributions

Conceptualization: MIA, RBMR, FZMH, and AGK;
Methodology: MIA, RBMR, and FZMH;
Software: MIA and FZMH;
Validation: MIA, RBMR, and AGK;
Formal Analysis: MIA and FZMH;
Investigation: MIA, RBMR, FZMH, and AGK;
Resources: MIA, RBMR, and AGK;
Data Curation: MIA and FZMH;
Writing – Original Draft Preparation: MIA and FZMH;
Writing – Review and Editing: MIA, RBMR, and AGK;
Visualization: MIA and FZMH;



Supervision: RBMR and AGK.

All authors have read and agreed to the published version of the manuscript.

5.2 Data Availability

The data presented in this study are available on request from the corresponding author.

5.3 Funding

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5.4 Institutional Review Board Statement

Not applicable.

5.5 Informed Consent Statement

Not applicable.

5.6 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5.7 Generative AI and AI-assisted Technologies in The Writing Process

The authors used generative artificial intelligence (AI) tools solely to improve the clarity, grammar, and readability of the manuscript. All AI-assisted content was reviewed, verified, and edited by the authors. The authors take full responsibility for the accuracy, originality, and final content of the published manuscript.

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