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Long Short Term Memory and Gradient Boosting Model for One Day Ahead Forecasting of ANTAM Gold Bar Prices

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Abstract

This study develops and optimizes a hybrid LSTM-XGBoost forecasting model for daily ANTAM gold bar prices. The model utilizes historical time-series data of ANTAM gold prices, enriched with macroeconomic variables including the USD/IDR exchange rate and Brent oil prices, as well as derived features such as returns, lags, rolling statistics, and calendar effects. The LSTM component captures medium-term sequential patterns from the price series and macroeconomic variables, while the XGBoost component exploits a rich set of tabular features to model nonlinear relationships and volatility dynamics. Both models are trained and tuned separately, then combined through a weighted ensemble scheme in which the optimal weight is selected by minimizing Mean Absolute Percentage Error (MAPE) on the validation set. Experimental results on the test set show that the proposed hybrid model achieves Mean Squared Error (MSE) of 26,891,172.36, Root Mean Squared Error (RMSE) of 16,398.53, MAPE of 0.0058 (approximately 99.42% accuracy), and coefficient of determination \mathbit{R}^\mathbf{2} of 0.9971, outperforming a naïve baseline that assumes "tomorrow's price equals today's price". The optimized LSTM-XGBoost hybrid model proves highly effective for short-term ANTAM gold price forecasting, providing reliable decision support for Indonesian gold market stakeholders.

Keywords : *Criteria's Weighting, Integrated Primary Care Information System, Posyandu, Rank-Based Aggregation, Score-Based Aggregation, Voting-Based Aggregation.*

1. INTRODUCTION

The increasing volatility of financial markets and the widespread adoption of data-driven methods in investment decision-making have strengthened the role of gold as a safe-haven asset, particularly during periods of macroeconomic uncertainty [1][2]. In Indonesia, ANTAM gold bars are widely used by individual and institutional investors as a reliable store of value against inflation, currency depreciation, and financial shocks [3]. However, the daily price of ANTAM gold is affected by a complex interaction of factors, including global gold prices, the USD/IDR exchange rate, international oil prices, interest rates, and domestic economic conditions [4]. These dynamic and nonlinear relationships make it difficult for investors and financial institutions to accurately anticipate short-term price movements using traditional statistical models or intuitive judgment alone [5][6].

Recent empirical evidence suggests that the adoption of advanced machine learning and deep learning approaches can markedly enhance the accuracy of commodity and financial price forecasts [7][8][9]. Recent empirical evidence suggests that the adoption of advanced machine learning and deep learning approaches can markedly enhance the accuracy of commodity and financial price forecasts [10][11]. However, many existing works on gold price prediction still rely on single models, such as standalone LSTM, GRU, or Gradient Boosting, and therefore do not fully exploit the complementary strengths of sequence-based deep learning and feature-based ensemble learning [12]. This gap motivates

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the development of hybrid models that combine different algorithms into a single framework, as demonstrated in previous hybrid approaches such as ARIMA–SVR, ARIMA–LSTM, and Random Forest–Gradient Boosting for financial time-series forecasting [13].

This study develops an optimized LSTM-XGBoost hybrid model for one-day-ahead daily ANTAM gold bar price forecasting [14]. The model is designed to address several implicit problem points: the need to structure and preprocess historical ANTAM gold data and relevant macroeconomic variables so that they are suitable for hybrid modeling; the challenge of configuring and training the LSTM and XGBoost components so that each captures different aspects of the data [15][16][17]; and the question of how to combine the outputs of both models into a single prediction that improves accuracy and stability compared with naïve or single-model benchmarks [4]. By addressing these challenges, this study aims to develop a forecasting framework that demonstrates superior empirical performance on historical Antam gold price data (2013–2025), while serving as a practical decision-support system for retail investors, institutional analysts, and financial entities within Indonesia's gold market. [18] [19].

The study adopts a quantitative experimental methodology based on daily historical data of ANTAM gold prices from logammulia.com, supplemented with the USD/IDR exchange rate and Brent oil prices obtained from financial data providers over the period 21 May 2013 to 22 November 2025 (logammulia.com; investing.com). The data are preprocessed through cleaning, handling of missing values, normalization, and feature engineering, including the construction of lagged variables, rolling statistics, returns, and calendar-based indicators, in line with common practices in time-series and financial forecasting. The LSTM model is trained on sequential input windows to learn medium-term temporal dependencies in the ANTAM price series and macroeconomic variables, while the XGBoost model is trained on the engineered tabular features to capture nonlinear relationships and volatility dynamics [10]. Both models were hyperparameter-tuned, evaluated on separate validation/test sets, and combined via weighted ensemble with MAPE-optimized weights from validation data. Model efficacy was evaluated using MSE, RMSE, MAPE, and R^2 metrics, confirming the hybrid LSTM-XGBoost approach's effectiveness for ANTAM gold price forecasting.

2. METHOD

2.1 Gold Price Prediction Research

Gold price prediction has become an important area of study in economics and information technology, especially in supporting more measurable investment decision making. Various approaches have been proposed in previous studies to obtain more accurate prediction results. A study by [4] applied the Long Short-Term Memory (LSTM) method to predict gold prices by incorporating several optimization schemes, namely ADAM, NADAM, and ADAMAX. The results showed that the use of NADAM optimization with an 80 percent training data proportion and 20 percent testing data proportion produced the best performance. This was indicated by a Root Mean Square Error (RMSE) value of 0.0199 on the training data and 0.0260 on the testing data.

Conducted a similar study by comparing the performance of LSTM and Gated Recurrent Unit (GRU) models for gold price prediction. Although LSTM showed lower error rates based on several evaluation metrics, the study concluded that the GRU model provided better overall performance in capturing gold price movement patterns[7], [18], [20]. The use of Support Vector Regression and Linear Regression techniques is proposed to perform gold price forecasting. Based on the test results, Linear Regression outperformed SVR, with a Mean Squared Error (MSE) value of 4.04 for LR and 7.52 for SVR. These findings indicate that simpler methods can still deliver competitive results, although they have limitations in capturing the complex dynamics of gold prices [21], [22], [23], [24], [25].

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Developed a gold price prediction system in Indonesia using a GRU model while considering external variables such as PT Aneka Tambang stock prices and the US dollar exchange rate. This study produced a model with a relatively high level of accuracy, indicated by an R-Squared value of 0.97, which suggests that integrating multiple economic factors can improve prediction accuracy. Based on these studies, it can be concluded that efforts to improve the accuracy of gold price prediction continue to evolve through various modeling approaches. However, most previous studies have focused on single model applications. Therefore, this research proposes the development of a hybrid model that combines LSTM and Gradient Boosting to optimize the model's ability to process time series data while improving prediction accuracy. This approach is expected to make a meaningful contribution by providing more accurate and useful predictive information for investors and other related stakeholders.

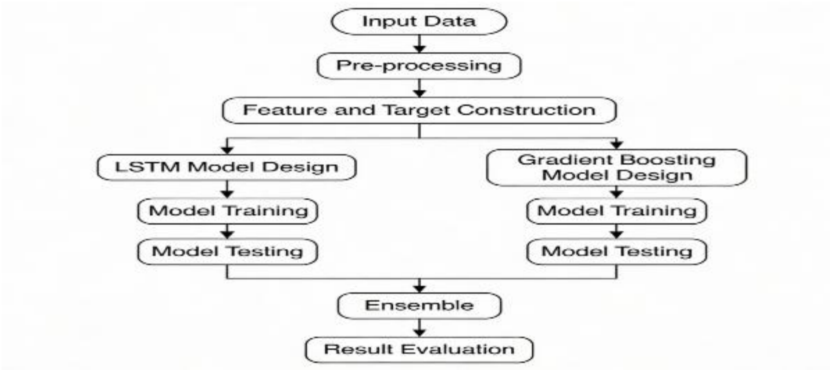

Figure 1. Workflow

2.2 Long Short-Term Memory (LSTM) Model Research

The Long Short-Term Memory (LSTM) model represents an evolution of Recurrent Neural Networks (RNN), specifically developed to manage difficulties in analyzing time-dependent data with extended dependencies. In 1997, Hochreiter and Schmidhuber introduced the Long Short-Term Memory network to mitigate the vanishing gradient problem that limits traditional Recurrent Neural Networks (RNNs) in capturing long-term dependencies characteristic of time series data[26]. LSTM integrates a gating mechanism designed to regulate the storage, modification, and removal of pertinent information within its memory cells. This architecture enables the model to preserve crucial information over varying time spans, which explains its extensive application in domains like commodity price prediction, financial analysis, natural language processing, and sequence-based pattern recognition [6]. LSTM has a special architecture consisting of three main gates, namely the input gate, forget gate, and output gate, which regulate the flow of information within the network . The functions of these components are as follows. Input Gate: Determines which new information is relevant and should be stored in the cell state

.Forget Gate: Regulates which information from the previous cell state should be discarded or retained. Output Gate: Controls which information will be produced as output at each time step. Mathematically, the LSTM mechanism can be described by the following equations [9]:

$$it = \sigma(Wixt + Uiht - 1 + bi) \quad (1)$$

$$ft = \sigma(Wfxt + Ufht - 1 + bf) \quad (2)$$

$$ot = \sigma(Woxt + Uoht - 1 + bo) \quad (3)$$

$$ct = ft * ct - 1 + it * \tan\mathrm{h}(Wcxt + Ucht - 1 + bc) \quad (4)$$

$$ht = ot * \tan\mathrm{h}(ct) \quad (5)$$

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2.3 Gradient Boosting Model Research

Gradient Boosting is an ensemble based machine learning method that is effective in improving prediction accuracy. According to Andriyani et al. (2024), Gradient Boosting works by building models sequentially to minimize prediction errors using a gradient descent approach. Ensemble learning operates by having each new model correct the prediction errors of previous models, ultimately producing a composite model with superior accuracy and robustness compared to standalone models. Gradient Boosting operates by constructing models in sequence, where each new model is designed to correct the mistakes of the previous one. This process is carried out by adjusting model predictions to pseudo residuals calculated from the derivative of the loss function. The approach uses gradient descent to gradually minimize the loss function until an optimal prediction result is achieved. Mathematically, the Gradient Boosting process can be described as follows. Let yi be the actual value, Fm(xi) be the model at iteration m, and L(y, F(x)) be the loss function used. The model starts with an initial prediction:

$$\mathbf{0}(\boldsymbol{x}) = \boldsymbol{arg\gamma mini} = \mathbf{1}\sum \boldsymbol{nL}(\boldsymbol{yi},\boldsymbol{\gamma}) \qquad (6)$$

After the residuals are calculated, a new model hm(x) is trained to predict these residuals. The model is then updated as:

$$\boldsymbol{rim} = -\left[\frac{\partial L(yi,F(xi))}{\partial F(xi)}\right]_{F(x)=Fm-1(x)} \qquad (7)$$

After the residuals are calculated, a new model $h_m(x)$ is trained to predict these residuals. The model is then updated as:

$$\boldsymbol{Fm}(\boldsymbol{x}) = \boldsymbol{Fm} - \mathbf{1}(\boldsymbol{x}) + \boldsymbol{\nu} \cdot \boldsymbol{hm}(\boldsymbol{x}) \qquad (8)$$

3. RESULT

3.1 Data

The data used in this study consist of daily time series containing three main variables, namely the price of Antam gold bars, the USD to IDR exchange rate, and the price of Brent crude oil. These three variables were collected and combined into a single dataset, where each row represents one observation date with corresponding information on gold price, exchange rate, and oil price on the same day.

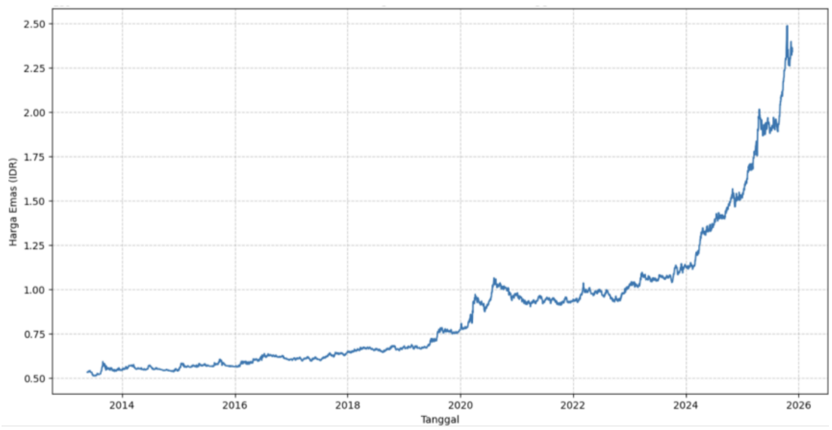

Figure 2. ANTAM Gold Bar Price Chart

The observation period spans from 21 May 2013 to 22 November 2025, with a sufficiently large number of daily observations to support the training of time series models based on LSTM and Gradient Boosting. During this period, Antam gold prices show a general upward trend over time with several

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phases of sharp increases and declines. Meanwhile, the USD to IDR exchange rate reflects fluctuations in the value of the rupiah against the US dollar influenced by macroeconomic dynamics. Brent crude oil prices also exhibit wide variations, representing changes in global energy market conditions, from periods of high prices to phases of significant decline. These three variables are presented in tabular form in Table .1 below

Table 1. Research Data

Date	Gold_Price	USD_IDR_Exchange_Rate	Oil_Price
2013-05-21 00:00:00	533,000.00	9,765	103.10
2013-05-22 00:00:00	533,000.00	9,765	102.14
2013-05-23 00:00:00	533,000.00	9,774	100.46
2013-05-24 00:00:00	536,000.00	9,772	101.24
2013-05-27 00:00:00	536,000.00	9,792	101.24
2013-05-28 00:00:00	536,000.00	9,810	103.77

3.2 Preprocessing Results

In the preprocessing stage, the dataset was read using Python, the column names were standardized, and the date column was converted into a datetime type so it could be processed as time series data. The gold price column, which was originally formatted in rupiah currency, was parsed using the parseidnum function. This process removed all non numeric characters and converted the values into real numbers with a float64 data type.

The exchange rate and oil price columns were also converted into numeric types using the to_numeric function. As a result, the three main variables were fully prepared for mathematical computation and further modeling.

```
Jumlah Missing Values per Kolom Utama:
tanggal        0
harga_emas     0
kurs_dollar    0
harga_minyak   0
dtype: int64
```

Figure 3. Output Missing Value

After the conversion process, a check was performed to identify the number of missing values in the date, gold_price, exchange_rate, and oil_price columns. The results showed that there were no missing values in any of the four columns, with each column containing 0 missing values. Therefore, the dataset could be fully utilized without the need for imputation. Next, the data were sorted in ascending order based on the date column, and the index was reset to form a clean and consistent time series structure.

	tanggal	harga_emas	kurs_dollar	harga_minyak	ret_1	ret_3	ret_7	price_next	ret_next
0	2013-07-04	515000.0	9945	106.12	0.001946	0.003899	-0.005792	514000.0	-0.001942
1	2013-07-05	514000.0	9945	107.46	-0.001942	0.000000	-0.007722	512000.0	-0.003891
2	2013-07-08	512000.0	9960	107.75	-0.003891	-0.003891	-0.001949	512000.0	0.000000
3	2013-07-09	512000.0	9960	107.90	0.000000	-0.005825	-0.001949	513000.0	0.001953
4	2013-07-10	513000.0	9970	108.43	0.001953	-0.001946	0.000000	516000.0	0.005848

roll_ret_mean_7	...	lag_price_27	lag_ret_27	lag_price_28	lag_ret_28	lag_price_29	lag_ret_29	lag_price_30	lag_ret_30	dow	month
-0.000823	...	536000.0	0.000000	536000.0	0.005629	533000.0	0.000000	533000.0	0.000000	3	7
-0.001100	...	536000.0	0.000000	536000.0	0.000000	536000.0	0.005629	533000.0	0.000000	4	7
-0.000277	...	535000.0	-0.001866	536000.0	0.000000	536000.0	0.000000	536000.0	0.005629	0	7
-0.000277	...	538000.0	0.005607	535000.0	-0.001866	536000.0	0.000000	536000.0	0.000000	1	7
0.000002	...	539000.0	0.001859	538000.0	0.005607	535000.0	-0.001866	536000.0	0.000000	2	7

Figure 4. Feature Engineering Output

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The target variable for the next day's gold price (price_next) was created by shifting the price column one step forward. Using the combination of today's price and the next day's price, the one day ahead target return (ret_next) was then calculated. To capture short term trends and volatility, rolling mean and rolling standard deviation of ret_1 were computed using 7 day, 14 day, and 30 day windows. Price lag features and return lag features were also generated for several previous days according to the LAGS parameter, which in this study was set to 30 lags. This allows the model to utilize sufficiently long historical information. Finally, calendar based features were added, including the day of the week (dow) and month (month) extracted from the date column, in order to capture potential seasonal patterns in gold price movements.

3.3 LSTM Model Training Results

The "LSTM Training Loss" graph shows the change in model loss values on the training and validation datasets for each epoch. The training loss gradually decreases from around 1.0 to approximately 0.85, indicating that the model is progressively adjusting its weights to better capture patterns in the training data. Meanwhile, the validation loss remains at a lower level, around 0.78 to 0.80, and stays relatively stable without a clear upward trend. This pattern suggests that the model maintains good generalization performance on unseen data and does not show strong signs of overfitting during the training process.

Figure 5. LSTM Training Loss Graph

In this study, an Early Stopping mechanism was applied to prevent overfitting and to select the optimal training epoch. The model monitored the loss value on the validation dataset using the parameter monitor = "val_loss" and automatically stopped training when no improvement in validation loss was observed for 12 consecutive epochs (patience = 12). The option restore_best_weights = True ensured that the model weights were restored to the state where the validation loss reached its lowest value, rather than using the weights from the final epoch before training stopped. With this configuration, training stopped at a middle epoch, well before the maximum limit of 200 epochs, precisely when the validation loss reached its minimum or began to plateau. As a result, the final model represents the best balance between learning the patterns in the training data and maintaining good generalization to unseen data.

3.4 Gradient Boosting Model Training Results

In this study, the XGBoost model was trained using a comprehensive set of tabular features (xgbcols). These features include gold prices, the USD to IDR exchange rate, Brent oil prices, calendar features (day of week and month), historical returns (ret_1, ret_3, ret_7), rolling features (mean and standard deviation with 7 day, 14 day, and 30 day windows), as well as all price lag features (lagprice*) and return lag features (lagret*). The prediction target was retnext in its original scale. The main parameters used in the model were max_depth = 4, which defines the maximum tree depth, and eta =

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0.02 as the learning rate. The subsample parameter was set to 0.85 and colsample_bytree to 0.85, meaning that each tree was built using 85 percent of the training samples and 85 percent of the available features. The model was trained with a maximum of 6000 boosting iterations (num_boost_round = 6000), using the reg:squarederror objective function and rmse as the evaluation metric.

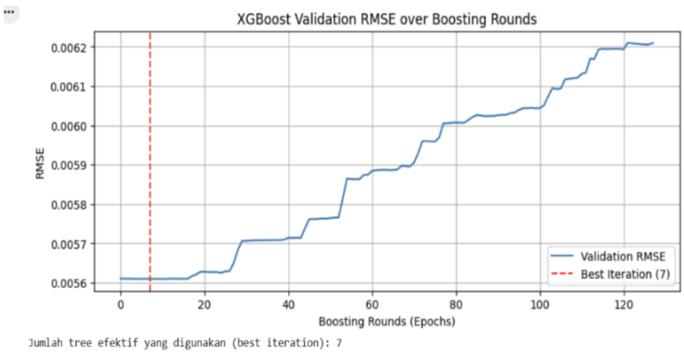

Figure 6. XGBoost Validation RMSE

The graph titled “XGBoost Validation RMSE over Boosting Rounds” illustrates how the RMSE value on the validation dataset changes as the number of boosting rounds increases. In the early stage of training, the validation RMSE decreases slightly and reaches its minimum value around iteration 7, which marks the model’s best performance on the validation data. After this point, the RMSE tends to stagnate and then gradually increase as more boosting rounds are added. This indicates that additional trees no longer improve performance and begin to cause overfitting to the training data. To prevent overfitting, an early stopping mechanism was applied with early_stopping_rounds = 120. This means that if no improvement in validation RMSE is observed for 120 consecutive iterations, the training process stops automatically. In the graph, a red dashed vertical line indicates the best iteration, which is boosting round 7 where the validation RMSE reaches its lowest value. Although num_boost_round was set to 6000, the final model effectively used only about 7 decision trees (best_iteration = 7), as shown below the graph. This approach ensures that the XGBoost model has sufficient complexity to capture important patterns in the data without overfitting to noise, thereby maintaining good generalization performance on unseen data.

3.5 Baseline vs Hybrid Model Performance

The hybrid model reduced the MSE from approximately 27.00 million to 26.89 million and lowered the RMSE from about 16,432 to 16,399. This means the average error in rupiah units is slightly smaller than that of the baseline model.

The MAPE values for both models are around 0.0058, or about 0.58 percent, which corresponds to a MAPE based accuracy of approximately 99.42 percent. In other words, the hybrid model maintains a very high level of accuracy and performs slightly better than the naive baseline approach of predicting that tomorrow’s price will be the same as today’s price.

The R^2 values of both models are approximately 0.9971, indicating that both the baseline and the hybrid model can explain more than 99 percent of the variation in gold prices on the test dataset. However, the combination of LSTM and XGBoost still provides an advantage through reductions in both the mean squared error and root mean squared error, even though the improvements are relatively small. This suggests that the additional information captured from time series patterns and derived features helps refine predictions beyond what can be achieved by a simple baseline model.

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```
=============== HASIL (TEST) ===============
LOOKBACK=30 | LAGS=30
Bobot terbaik: w(LSTM)=0.38 | w(XGB)=0.62

--- BASELINE (besok = hari ini) ---
MSE  : 270034662.05
RMSE : 16432.73
R²   : 0.9971
MAPE : 0.0058  -> Accuracy(MAPE): 99.42%

--- HYBRID (LSTM + XGB) ---
MSE  : 268911728.36
RMSE : 16398.53
R²   : 0.9971
MAPE : 0.0058  -> Accuracy(MAPE): 99.42%
============================================
```

Figure 7. Test Results Output

3.6 Time Series Graph Analysis

Figure 7. presents the time series of Antam gold prices during the test period, comparing three curves: the actual next day price (blue line), the predicted next day price from the hybrid LSTM–XGBoost model (orange line), and the baseline prediction that assumes tomorrow's price equals today's price (green line). All three curves appear to almost overlap throughout the period from March 2024 to the end of 2025. They follow a gradual upward trend at the beginning, followed by a steeper increase phase and several sharp spikes toward the final point of the time series data.

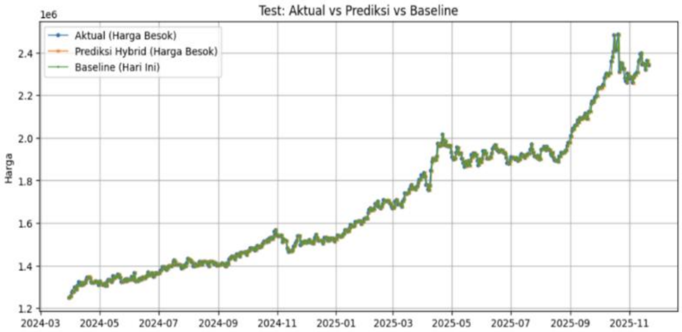

Figure 8. Time Series Graph Analysis

Both the hybrid prediction curve and the baseline closely follow the actual price pattern, including the peaks and troughs around mid and late 2025. The distance between the hybrid curve and the actual curve is generally very small and comparable to the gap between the baseline and the actual values. At many points, the lines are almost indistinguishable. This observation is consistent with the evaluation metrics presented earlier, where MAPE and R^2 are nearly identical for both the baseline and the hybrid model. However, when examined more closely, such as through a zoomed in plot or residual analysis, the hybrid model tends to produce slightly smoother predictions and in some segments tracks the actual price a bit more accurately. This behavior is reflected in the lower MSE and RMSE values achieved by the hybrid model compared to the baseline.

Table 2. Comparison of Results

Date	Actual Price	Predicted Price	Prediction Accuracy
2025-11-21 00:00:00	Rp 2.341.000	Rp 2.348.413	99.68%

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4. CONCLUSION

This study successfully developed and optimized a hybrid model based on LSTM and XGBoost to predict the next day price of Antam gold bars. The model uses historical gold prices, the USD to IDR exchange rate, Brent oil prices, and derived features such as returns, lags, rolling statistics, and calendar variables that represent momentum, volatility, and seasonal patterns. Evaluation results on the test dataset show that the hybrid model achieved an MSE of 26,891,172.36, an RMSE of 16,398.53, a MAPE of 0.0058 which corresponds to about 99.42 percent MAPE based accuracy, and an R^2 of 0.9971. These results indicate very strong performance for a one day ahead prediction horizon.

Individually, the LSTM model optimized with a 30 day LOOKBACK window excels at capturing medium term sequential patterns through its internal memory mechanism. Meanwhile, XGBoost, optimized in terms of the number of trees, maximum depth, and learning rate, shows strong performance in leveraging complex tabular features such as lags, rolling statistics, and calendar variables. Combining both models in a weighted ensemble reduced the MSE from 27,003,466.05 to 26,891,172.36 and lowered the RMSE from 16,432.73 to 16,398.53 compared to the baseline approach of predicting that tomorrow's price equals today's price. The MAPE and R^2 values remained very high at 0.0058 and 0.9971, confirming that the hybrid model provides measurable improvement even though the baseline is already very strong for a one day horizon.

The optimal ensemble weights, approximately 0.38 for LSTM and 0.62 for XGBoost, indicate that XGBoost contributes slightly more to the final prediction. This reflects the important role of tabular features in explaining gold price variation in this dataset. However, the still substantial weight assigned to LSTM confirms that direct sequential information from gold prices, exchange rates, oil prices, and daily returns adds value beyond a pure XGBoost model. This is especially evident in segments of the time series with sharper trend reversals around peaks and troughs, where the hybrid model adapts to turning points more quickly than the baseline.

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