Media Elektrik
Homepage: https://journal.unm.ac.id/index.php/mediaelektrik
Email: jurnal.mediaelektrik@unm.ac.id

p-ISSN 1907-1728; e-ISSN: 2721-9100
Media Elektrik, Vol. 23, No. 3, August 2026
Page 313-322

Comparative Forecasting of Antam Gold Prices Using LSTM, GRU, and Hybrid LSTM–GRU with Adam and SGD Optimizers

[1*]**Yuris Alkhalifi**
[1]Universitas Bina Sarana Informatika, Jakarta Indonesia,

ARTICLE INFO

Article history:
Submitted: July 14, 2026
Final Revised: Aug. 12, 2026
Accepted: August 13, 2026
Published: August 24, 2026

Keywords:
Gold Price Prediction; LSTM; GRU; Hybrid LSTM-GRU.

ABSTRACT

People commonly invest in gold to protect their assets because of its role as a stable, safe-haven asset against economic volatility. However, the uncertainty of future gold price movements creates challenges, making the ability to predict gold prices beneficial for analysis. This study proposes a comparative approach to forecasting PT Antam's gold prices, evaluating the performance of three architectures: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Hybrid LSTM-GRU. The study uses historical daily price data from 2010 to early 2025, chronologically split into 80% training and 20% testing sets. Data is processed through a 60-day sliding window framework, and recursive multi-step forecasting is applied for a 30-day horizon. Two optimization techniques, Adam and Stochastic Gradient Descent (SGD), are evaluated. The experimental results show that the Hybrid LSTM-GRU model with Adam optimization achieved the best performance among the evaluated configurations, evidenced by an R-Squared (R^2) value of 0.9972, a Mean Square Error (MSE) of 9.553542e+07, and a Root Mean Square Error (RMSE) of 9,774.22. An RMSE of 9,774.22 indicates that the standard deviation of the prediction errors is approximately IDR 9,774. When contextualized with the latest actual gold price, this yields an error ratio of 0.64%. The 30-day projection indicates a downward trend in prices until the end of January 2025. However, due to the univariate nature of the model, it should be viewed as a supplementary analytical tool rather than a sole basis for financial decision-making.

Doi: https://doi.org/10.59562/metrik.v23i3.13794

Introduction

Precious metals, especially gold, are widely recognized as safe-haven assets amid global economic uncertainty [1]. In Indonesia, PT Aneka Tambang Tbk (Antam) is the primary gold producer with internationally recognized purity standards [2]. Gold's stable nature and high liquidity make it essential for safeguarding long-term financial security [3]. In recent years, the interest of Indonesians in investing in gold has increased significantly, driven by easier access through digital platforms and growing financial literacy [4], [5]. However, high price volatility often causes uncertainty among the general public regarding the optimal time to buy or sell assets[6]. This volatility is heavily influenced by external fundamental factors such as global geopolitical uncertainties, inflation rates, and central bank interest rate policies [7], [8], [9].

Advances in digital technology have made it possible to approach price prediction challenges through data science. Machine learning, particularly deep learning architectures like Recurrent Neural Networks (RNN), has proven effective in recognizing complex patterns in historical time-series data. Advanced algorithms, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), can learn long-term trends and short-term fluctuations. LSTM, introduced by Hochreiter and Schmidhuber, utilizes memory cells and gate mechanisms (input, forget, output) to solve vanishing gradient problems in long sequences [10],[11]. Meanwhile, GRU offers a more concise structure with only reset and update gates, making its training process faster while maintaining efficiency in capturing temporal dependencies [12], [13].

Research on gold price prediction continues to evolve. Previous studies have applied various models to global gold prices, such as linear regression, LSTM, and GRU, with deep learning models generally outperforming traditional linear models [14], [15]. Other research has applied machine learning and deep learning models, demonstrating that architectures like LSTM generally outperform traditional linear models [16]. Furthermore, complex architectures like CNN-Bi-LSTM have been explored for highly volatile gold prices, achieving high accurac [17], while comprehensive pipelines including SVM, Random Forest, and ARIMA have also been evaluated [18]. However, a critical evaluation of previous literature reveals a methodological gap. Many studies focus on global gold prices, whereas domestic gold prices, such as Antam's, have distinct daily quotation mechanisms, buy-sell spreads, and local market dynamics that require specific modeling. Furthermore, previous studies rarely conduct comparative experiments combining standalone and hybrid recurrent architectures with separate optimizers (Adam and SGD) on domestic datasets.

Therefore, this study aims to compare the performance of LSTM, GRU, and Hybrid LSTM-GRU models optimized with Adam and SGD for Antam gold price forecasting, and to evaluate the best-performing configuration in a 30-day out-of-sample prediction horizon.

Materials and Methods

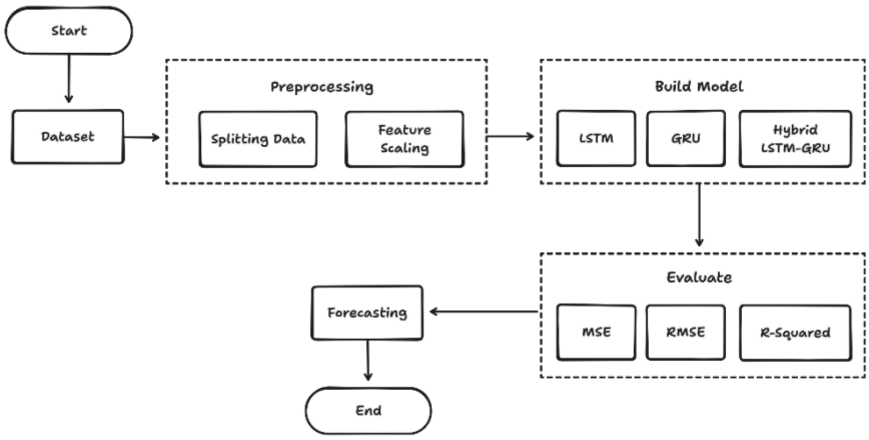

Figure 1. Research Method

A. Dataset

This study uses secondary data from the Kaggle website titled "Emas Batangan (ANTAM)". The dataset consists of two columns: Date and Price, with 4,547 data points spanning from January 2010 to January 2025 [19]. The data represents the nominal value of Antam gold prices in Indonesian Rupiah (IDR) per gram. To ensure data integrity, the chronological sequence was verified, and missing dates (such as weekends and non-transaction days) were handled sequentially without forward-filling to avoid artificial price stabilization. The variable data available in the dataset is as follows:

1. Date

This temporal variable shows the chronological recording of gold prices. It serves as a crucial time sequence reference that allows Deep Learning algorithms to recognize seasonal patterns, long-term trends, and daily cycles. The data covers the period from 2010 to January 2025. The accuracy of the date sequence is essential for the model to understand dependencies between time periods.

2. Price

This continuous numerical variable shows the nominal value of Antam gold prices in Indonesian rupiah (IDR) per gram. In the model training process, this column acts as the dependent variable (target). Fluctuations in this column's values reflect market dynamics, which the model processes to generate future predictions.

B. Preprocessing

The next stage is preprocessing, a crucial step for ensuring the model's ability to recognize Antam gold price patterns. This study includes two preprocessing steps: data splitting and feature scaling.

1. Splitting Data

The time series dataset is divided chronologically into 80% training (3,637 data points) and 20% testing (910 data points). This chronological split prevents data leakage, ensuring the model is evaluated on unseen recent data.

2. Feature Scaling

A Min-Max Scaler is applied to transform price values into a range of [0, 1]. Crucially, to prevent data leakage, the scaler is fitted *only* on the training data and subsequently applied to transform both the training and testing sets.

C. Build Model

This study implements three architectures: LSTM, GRU, and Hybrid LSTM-GRU. To ensure replicability, the model specifications are detailed as follows. The standalone LSTM model consists of a stacked configuration: an initial LSTM layer with 128 units (with return_sequences=True to pass the sequential output to the next layer), followed by a second LSTM layer with 16 units (return_sequences=False). This output is then passed through two fully connected (Dense) layers of 16 and 1 unit, respectively. The Hybrid LSTM-GRU model follows a similar structural pattern but integrates both recurrent mechanisms: an initial LSTM layer with 128 units (return_sequences=True) is followed by a GRU layer with 16 units (return_sequences=False), concluding with Dense layers of 16 and 1 unit. The standalone GRU model utilizes a configuration analogous to the LSTM model, stacking GRU layers with 128 and 16 units, respectively. A 60-day sliding window is used to form input-output pairs, where data from the past 60 days is used as a tensor input to predict the price on the 61th day. The models are compiled using Mean Squared Error (MSE) as the loss function. Adam (learning rate = 0.001) and Stochastic Gradient Descent (SGD, learning rate = 0.01, momentum = 0.9) are used as optimizers. Training is conducted for 10 epochs with a batch size of 16. A fixed random seed is applied to ensure reproducibility.

D. Evaluate

To measure the success of the experiment and validate the model's ability to accurately predict Antam gold prices, this study employs a regression evaluation approach. Regression evaluation measures how closely the model's predicted values align with actual prices. The metrics used include:

1. Mean Squared Error (MSE)

The average square difference between predicted and actual values is measured using this method [20]. This metric is highly sensitive to large errors, or outliers.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_t - \hat{x}_t)^2 \qquad (1)$$

2. Root Mean Squared Error (RMSE)

The square root of MSE is a calculation that returns the error value to a unit with the same scale as the target value. This makes it easier to interpret the magnitude of the model prediction error [20].

$$\text{RMSE} = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_t - \hat{x}_t)^2} \qquad (2)$$

3. R-Squared (R^2)

It is used to measure the extent to which a model can explain data variability. An R^2 value close to 1 indicates a very high fit between the model and the historical data pattern [20].

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(x_t - \hat{x}_t)^2}{\frac{1}{n}\sum_{i=1}^{n}(x_t - \bar{x}_t)^2} \qquad (3)$$

E. Forecasting

Following the model evaluation phase, the optimal performing configuration—the Hybrid LSTM–GRU architecture optimized with the Adam algorithm—was deployed to execute an out-of-sample price forecast for the subsequent 30 consecutive trading days beyond the historical dataset (extending through late January 2025). The multi-step out-of-sample projection was conducted using a recursive forecasting strategy. For the initial projection step, the model processed the final 60-day sequence of actual scaled prices from the historical dataset to predict the immediate next step. For subsequent time steps, the 60-day look-back window shifted forward by dropping the oldest historical observation and appending the model's own newly predicted value as the input feature. This process was repeated iteratively across 30 consecutive steps, allowing the model to project an extended out-of-sample price trajectory.

The resulting 30-day recursive projection indicates that PT Antam's gold price is expected to enter a phase of technical price consolidation and gradual downward correction through the end of January 2025. From a technical analysis perspective, this projected trajectory represents a natural stabilization response following the prolonged historical upward trend observed in the primary training and testing sequences. Rather than serving as an absolute trading signal or investment recommendation, this 30-day projection provides a quantitative supplementary tool for identifying historical univariate price patterns. Because the model operates on a purely technical univariate basis, real-world application requires contextualizing these recursive trend projections alongside macroeconomic indicators, foreign exchange fluctuations, and transactional buy-sell spreads.

Results

A. Dataset

This dataset is historical data on PT Antam obtained from the Kaggle website. There are 4547 data points with 2 columns, namely Date and Price, which can be seen in Table 1.

Table 1. Record of Dataset

Nu.	Date	Price (IDR)
1	04/01/2010	408,000
2	05/01/2010	410,000
3	06/01/2010	410,000
4	07/01/2010	412,000
5	08/01/2010	410,000
…	…	…
4543	28/12/2024	1,526,000
4544	29/12/2024	1,526,000
4545	30/12/2024	1,528,000
4546	31/12/2024	1,515,000
4547	02/01/2025	1,524,000

Figure 2. Movement Price Antam Gold by Day

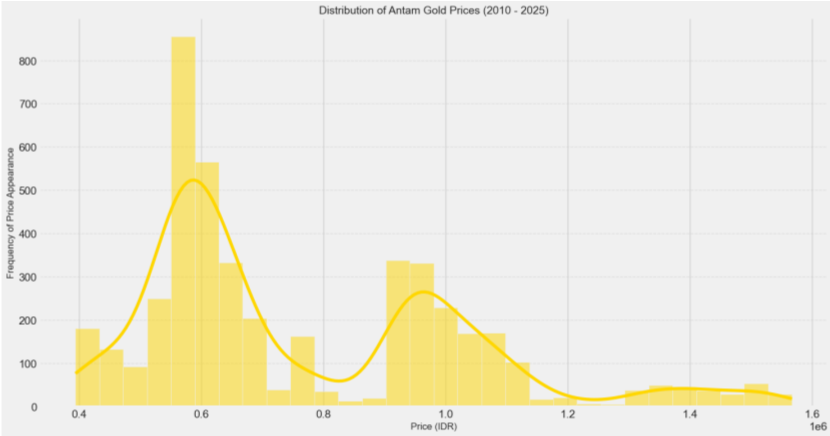

Figure 3. Histogram dan KDE (Kernel Density Estimation)

Figure 2 shows a graph starting from January 4, 2010, where the price of Antam gold was IDR 408,000. The price of gold experienced a continuous upward trend, although it sometimes fluctuated and experienced a downward trend until January 2, 2025, when the price of Antam gold reached IDR 1,524,000. Meanwhile, Figure 3 shows the relationship between price and frequency on a histogram graph, providing an in-depth picture of the stability and historical movements of the asset's value. The horizontal axis (price) represents the nominal value of gold in rupiah, while the vertical axis (frequency) shows how often or how many days the price remained at that level. It can be seen that the gold price appears most frequently in the IDR 550,000 price range, with a frequency of more than 800 times.

B. Preprocessing

Since the Antam gold price dataset has been cleaned and is ready for use, the pre-processing stage of this study focuses on two crucial steps: data splitting and feature scaling.

1. Splitting Data

The dataset consisted of 4,547 data points and was divided into two main parts: 80% was allocated to the training set, and 20% was allocated to the testing set. This division allocated 3,637 data points so the model could learn Antam gold price historical patterns in depth. The remaining 910 data points were set aside as test data to evaluate the model's ability to generalize to new data. Figure 4 shows the dataset division.

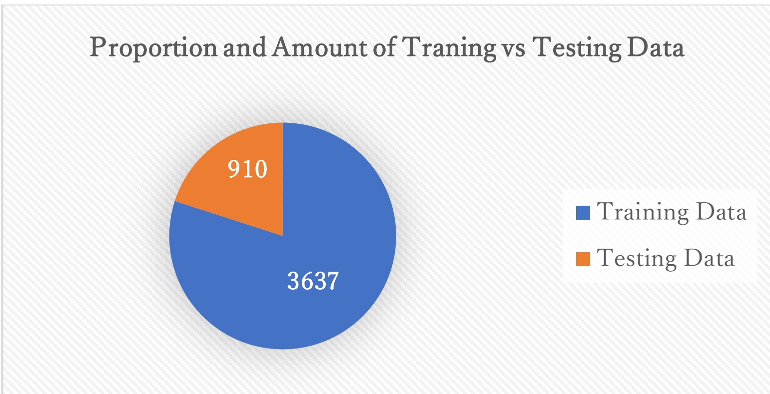

Figure 4. Proportion and Amount of Training vs. Testing Data

2. Feature Scalling

After dividing the dataset, the next process uses feature scaling, such as the Min-Max Scaler. This function converts price data into decimal numbers between 0 and 1. The lowest price in the dataset is converted to 0, and the highest price becomes 1. One advantage of the Min-Max Scaler is that it does not alter the original distribution of the data. If the original data has an upward or seasonal trend, this pattern is maintained on the 0–1 scale. The relative relationship between one day and another remains intact (only the scale of the distance between data points is reduced).

C. Build Model

Three deep learning architectures, Long Short-Term Memory, Gated Recurrent Unit, and Hybrid Long Short-Term Memory Gated Recurrent Unit—were constructed to model the temporal features. Each network architecture was trained and compiled under two separate optimization algorithms, namely Adam and Stochastic Gradient Descent, yielding six distinct experimental model configurations. All six models were compiled using Mean Squared Error as the objective loss function and trained for 10 epochs with a fixed batch size of 16. The optimal Hybrid architecture consists of an initial Long Short-Term Memory layer with 128 hidden units configured to pass full sequence outputs, a secondary Gated Recurrent Unit layer with 16 hidden units returning a single vector, a fully connected Dense layer with 16 hidden units, and a final single-unit Dense output layer with linear activation for continuous price regression.

D. Evaluate

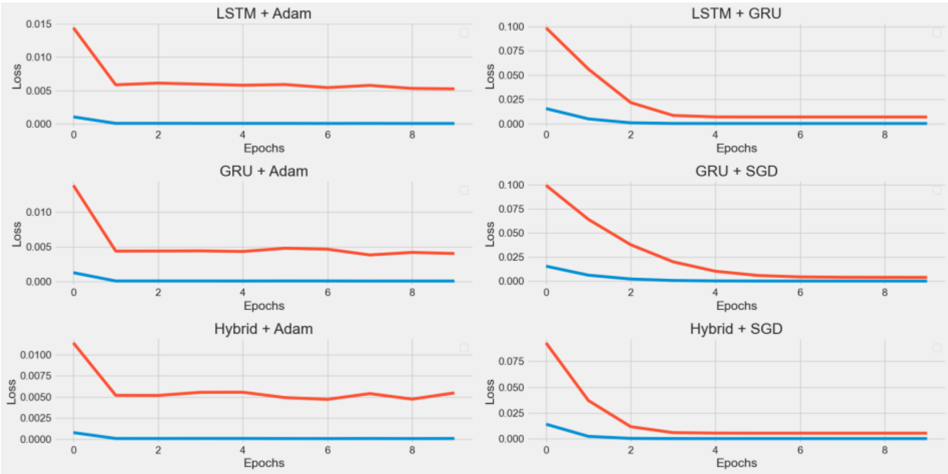

Figure 5. Training and Validation Loss Curves

Figure 5 shows that the blue line represents the training data, while the red line represents the validation data. The x-axis shows how many times the model was trained (10 epochs), and the y-axis shows the model's error rate, or the loss (MSE) value. In each model architecture, the loss value in the training and validation data decreased significantly from the first epoch. Both lines decreased simultaneously and remained close to each other, indicating that the model was in an ideal state of "good fit," enabling it to predict new data with similar accuracy. However, if the blue line keeps dropping while the red line keeps climbing or straying, it suggests that the model is overfitting or that it's only storing the training data and can't identify patterns in new data. If the blue and red lines remain high or fluctuate, it means the model is underfitting and still fails to understand patterns in existing data.

Table 2. Comparison of Research Architecture Model Results

Nu	Architecture Model	MSE	RMSE	R-Squared (R^2)
1	LSTM + Adam	9.219578e+08	30363.76	0.9732
2	LSTM + SGD	4.121751e+09	64200.86	0.8801
3	GRU + Adam	3.698738e+08	19232.10	0.9892
4	GRU + SGD	3.083095e+08	17558.75	0.9910
5	**Hybrid LSTM-GRU + Adam**	**9.553542e+07**	**9774.22**	**0.9972**
6	Hybrid LSTM-GRU + SGD	6.095117e+08	24688.29	0.9823

The overall results of the experiments in this study are summarized in Table 2. The tests were conducted six times, comparing the LSTM, GRU, and Hybrid LSTM-GRU architectures with two types of optimizations, Adam and SGD. The model with the lowest performance was found to be the LSTM architecture with SGD optimization. This model recorded an MSE value of 4.121751e+09, an RMSE of 64,200.86, and an R^2 score of 0.8801. Conversely, the best model produced in this study was the Hybrid LSTM-GRU architecture with Adam optimization. This model demonstrated exceptional accuracy, achieving an MSE value of 9.553542e+07, an RMSE of 9774.22, and an R^2 score of 0.9972. To provide further context on the practical magnitude of this error, the RMSE value of 9,774.22 was divided by the most recent actual gold price in the testing set (IDR 1,524,000 as of January 2, 2025). This calculation yields an error ratio of approximately 0.64% (9,774.22 / 1,524,000 × 100%), indicating that the model's standard prediction deviation is less than 1% of the current price scale. It should be noted that this is a contextual ratio derived from the RMSE, not a standard Mean Absolute Percentage Error (MAPE) across the entire dataset. These results demonstrate that integrating LSTM and GRU with Adam optimization effectively minimizes prediction errors compared to using a single model or SGD optimization.

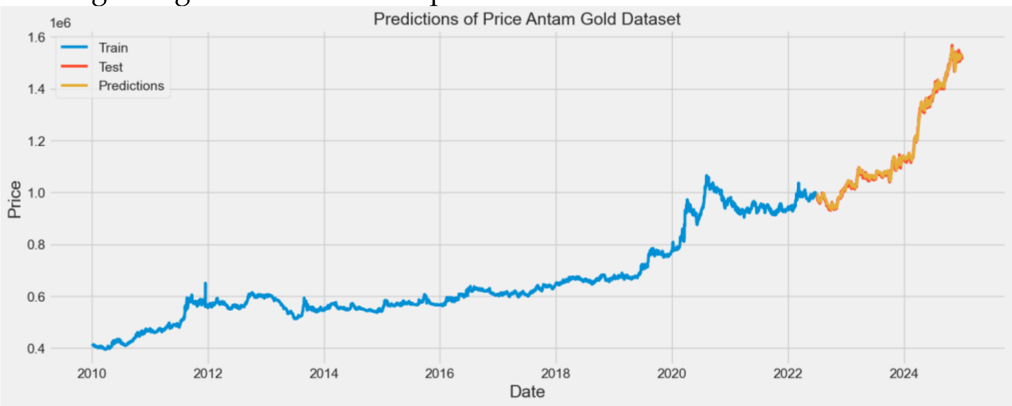

Figure 6. Prediction of Price

Figure 6 shows that Antam's gold price movements are represented by three components: the blue line shows the training data, the red line shows the testing data, and the orange line shows the model's predicted results. The X-axis represents the time range (date), and the Y-axis represents the gold price at that time. The graph shows that the best architecture in this study Hybrid LSTM-GRU with Adam optimization-is able to predict price fluctuations with a high level of precision. This is visually evident through the orange line, which consistently overlaps and covers the red line, indicating minimal difference between the predicted and actual values. The model's ability to follow the dynamic patterns of the test data suggests a good fit for this specific configuration, though a single training run without multiple seed iterations limits conclusive claims about its generalization capability.

E. Forecasting

After identifying the best-performing model through a series of tests, the final stage of this research is to forecast the price of Antam's gold for the next 30 days, ending in January 2025. The forecasting process uses the Hybrid LSTM-GRU architecture with Adam optimization, which has been proven to capture price patterns with the lowest error rate and highest stability.

Figure 7. Forecasting Antam Gold Price for 30 Day Later

Figure 7 shows a comparison of historical research data and future projections. The blue line represents the processed historical dataset, and the red line shows the gold price forecast for the next 30 days. Based on the model's generated pattern, Antam's gold price is predicted to undergo a correction phase or gradually decline until the end of January 2025. This finding provides supplementary analytical information regarding technical price trends. However, it should not be interpreted as a direct investment recommendation or purchase timing signal, as the model does not account for transactional spreads, macroeconomic shocks, or forecasting uncertainty.

Discussion

The experimental results demonstrate that the Hybrid LSTM-GRU model optimized with Adam achieved the best forecasting performance among the tested configurations, yielding an R^2 of 0.9972 and an RMSE of 9,774.22. This success stems from the complementary strengths of the architectures: LSTM's complex gating mechanisms capture long-term dependencies, while GRU's simplified structure efficiently processes sequential data, reducing computational overhead. The Adam optimizer further enhanced this by adaptively adjusting learning rates, accelerating convergence compared to SGD. Interestingly, in the standalone GRU model, SGD slightly outperformed Adam (R^2 = 0.9910 vs 0.9892). This suggests that for simpler architectures with fewer parameters, the constant learning rate of SGD combined with momentum might provide a more stable weight update trajectory than Adam's adaptive scaling. However, the marginal accuracy gain of the hybrid model over standalone architectures must be weighed against the increased computational cost and complexity of the network. While the 60-day sliding window provided structurally sound results in this setup, the claim that it is empirically validated is insufficient, as no comparative experiments using alternative window sizes (e.g., 5, 10, 20, or 30) were conducted. Furthermore, although the R^2 value is exceptionally high, it must be interpreted with caution. In non-stationary financial time series, high R^2 values can sometimes reflect the model's ability to capture long-term trends rather than its true generalization capability. Without comparisons against simple baselines (such as naïve persistence) or rolling-origin validation, the extent of the model's predictive superiority over simpler methods remains unconfirmed. Comparing the proposed model's performance directly with models from other studies, such as the CNN-Bi-LSTM proposed by [17] or the multi-model pipeline evaluated by [18] is methodologically invalid. These studies utilize different datasets, observation periods, price scales, forecasting horizons, and evaluation metrics. Therefore, without conducting experiments on a standardized dataset and evaluation scheme, it is inappropriate to declare that the proposed model "competes robustly" against these external architectures. The performance results in this study are strictly confined to the specific Antam dataset and experimental configuration utilized herein. Additionally, the recursive multi-step forecasting for 30 days inherently carries the risk of error accumulation, where initial prediction errors propagate and compound over time. The projected downward correction toward the end of January 2025 reflects technical pattern saturation from previous upward trends. However, because the model operates on a univariate basis, it cannot anticipate sudden structural breaks or price spikes triggered by unforeseen market events. Consequently, practical implications must be conveyed with caution. While the proposed model shows potential as a supplementary analytical tool for understanding historical price patterns, it is insufficient to recommend purchase timing. It does not incorporate Antam's buy-sell spread, transaction costs, macroeconomic conditions, or uncertainty intervals. Theoretically, this study contributes to the selection of recurrent neural network architectures for domestic price series, which possess distinct daily quotation mechanisms compared to international gold prices. Future analysis should integrate these projections with fundamental macroeconomic analysis—such as global geopolitical dynamics, inflation rates, and USD/IDR exchange rates—rather than relying solely on technical univariate projections.

Conclusions

Based on the experimental configuration, the Hybrid LSTM-GRU model with Adam optimization achieved the best performance among the six evaluated configurations for predicting PT Antam's gold prices, yielding an RMSE of 9,774.22 and an R^2 of 0.9972. The integration of LSTM and GRU demonstrates a strong technical capacity to model historical price patterns. The 30-day projection indicated a downward price trend; however, due to the univariate nature of the model and the absence of validation against actual subsequent prices or simple baselines, this projection should not be interpreted as a direct investment recommendation. The study is limited by its reliance on historical numerical patterns without incorporating external fundamental factors. Future research should incorporate multivariate approaches, rolling-origin validation, baseline comparisons, and external variables such as world gold prices, exchange rates, and market sentiment to generate projections that are more adaptive to real-world market shocks.

References

[1] N. U. Nikmah and O. A. D. Wulandari, "Kontruksi Makna Emas Sebagai Aset Safe Haven Di Era Perang Dagang Amerika Serikat Dan China: Studi Fenomologi Investor Ritel Indonesia," *Jurnal Witana*, vol. 3, no. 2, pp. 1–13, Aug. 2025, [Online]. Available: http://jurnalwitana.com/

[2] I. V. W. Ningsih, Sugiharto, and S. Utomo, "Perbandingan Return Investasi Emas Dan Investasi Saham (Capital Gain) PT. Aneka Tambang Tbk Pada Periode Januari 2019 – April 2020," *Smart Business Journal (SBJ)*, vol. 1, pp. 19–25, 2021, doi: 10.20527/sbj.v1i1.12786

[3] S. Kumari, S. P. Mandali', and P. L. N. Welingkar, "Gold as a Safe Haven: Analyzing the Investment Patterns of Indian Women," *Journal of Informatics Education and Research*, vol. 4, no. 3, pp. 1526–4726, 2024, doi: 10.52783/jier.v4i3.1346.

[4] C. O. Handayani and J. Marbun, "Pengaruh Digitalisasi, Gaya Hidup, dan Literasi Keuangan Terhadap Minat Menabung Emas Melalui PT Pegadaian (Studi Kasus pada Generasi Z di Jabodetabek)," *Seminar Nasional Akuntansi Dan Manajemen*, vol. 4, no. 2, Apr. 2023.

[5] S. Farokha and A. R. Rivai, "Pengaruh Persepsi Manfaat, Kemudahan Penggunaan Dan Keamanan Terhadap Niat Menabung Pada Produk Tabungan Emas Pegadaian," *Fair Value: Jurnal Ilmiah Akuntansi dan Keuangan*, vol. 4, no. 3, pp. 1323–1341, Jan. 2022.

[6] R. R. A.-A. Siagian, "Persepsi Masyarakat Indonesia Terhadap Kenaikan Harga Emas Sebagai Instrumen Investasi Jangka Panjang: Sebuah Tinjauan Literatur," *Future Academia : The Journal of Multidisciplinary Research on Scientific and Advanced*, vol. 3, no. 1, pp. 72–79, Jan. 2025, doi: 10.61579/future.v3i1.298.

[7] N. Sulistyowati, M. Idhom, and S. Shella May Wara, "Prediksi Volatilitas Harga Emas Dengan Model Garch," *Prosiding Seminar Nasional UNARS*, vol. 4, no. 1, pp. 144–153, Jan. 2026.

[8] W. Lai, "The Impact of Federal Reserve Interest Rate on Spot Gold Prices: An Event Study," *Advances in Economics, Management and Political Sciences*, vol. 248, no. 1, pp. 98–105, Dec. 2025, doi: 10.54254/2754-1169/2025.bl30550.

[9] Fathoni, M. Aziiz Irwansyah, A. Triana, E. Darmayanti Simanullang, Y. Nur Alinda, and A. Ibrahim, "Prediksi Harga Dan Volatilitas Emas Dunia Harian: Perbandingan Model Garch dan Long Short-Term Memory," *Jurnal Sistem Informasi*, vol. 7, no. 2, pp. 466–475, May 2025, doi: 10.31849/zn.v7i2.26764.

[10] M. F. Abdillah and K. Kusnawi, "Comparative Analysis of Long Short-Term Memory Architecture for Text Classification," *ILKOM Jurnal Ilmiah*, vol. 15, no. 3, pp. 455–464, Dec. 2023, doi: 10.33096/ilkom.v15i3.1906.455-464.

[11] S. M. Al-Selwi, M. F. Hassan, S. J. Abdulkadir, and A. Muneer, "LSTM Inefficiency in Long-Term Dependencies Regression Problems," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 30, no. 3, pp. 16–31, May 2023, doi: 10.37934/araset.30.3.1631.

[12] I. P. G. A. Sudiatmika and I. M. A. W. Putra, "Comparison of LSTM and GRU Models Performance in Forecasting Gold Prices: A Case Study Using Historical Data from Yahoo Finance," *ARRUS Journal of Engineering and Technology*, vol. 4, no. 1, Jul. 2024, doi:

10.35877/jetech2760.

[13] M. F. Julianto, M. Iqbal, W. F. Hidayat, and Y. Malau, "Perbandingan Penerapan Algoritma Deep Learning Dalam Prediksi Harga Emas," *INTI Nusa Mandiri*, vol. 19, no. 1, pp. 71–76, Aug. 2024, doi: 10.33480/inti.v19i1.5559.

[14] I. S. R. Harmain, N. Nurwan, I. K. Hasan, D. Wungguli, and N. I. Yahya, "Prediksi Harga Emas Dunia Menggunakan Deep Learning GRU dengan Optimasi Nadam," *Jurnal Riset Mahasiswa Matematika*, vol. 4, no. 6, pp. 310–322, Aug. 2025, doi: 10.18860/jrmm.v4i6.36007.

[15] M. Marwondo and T. Hidayah, "Perbandingan Algoritma Long Short-Term Memory (LSTM) dan Gated Recurrent Unit (GRU) untuk Prediksi Harga Emas Dunia," *In Search (Informatic, Science, Entrepreneur, Applied Art, Research, Humanism)*, vol. 21, no. 2, pp. 230–239, Apr. 2022, doi: 10.37278/insearch.v21i2.600.

[16] S. L. Sentiko, A. Y. Zakiyyah, and Meiliana, "Gold Price Prediction Using Machine Learning and Deep Learning," in *2024 6th International Conference on Cybernetics and Intelligent System (ICORIS)*, 2024, pp. 1–5. doi: 10.1109/ICORIS63540.2024.10903557.

[17] A. Amini and R. Kalantari, "Gold price prediction by a CNN-Bi-LSTM model along with automatic parameter tuning," *PLoS One*, vol. 19, no. 3 March, Mar. 2024, doi: 10.1371/journal.pone.0298426.

[18] S. R. Masud, A. Imtiaz, S. M. Hossain, and M. S. U. Miah, "A Comprehensive Approach to Gold Price Prediction Using Machine Learning and Time Series Models," in *2025 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, 2025, pp. 1–6. doi: 10.1109/IATMSI64286.2025.10984927.

[19] Y. Faturohman, "Emas Batangan (ANTAM)," Kaggle. Accessed: Mar. 03, 2026. [Online]. Available: https://www.kaggle.com/datasets/yudifaturohman/emas-batangan-antam/

[20] A. A. Mahgfirah, H. Hikmah, and P. I. Rahayu, "Analisis Support Vector Regression untuk Meramalkan Saham Perusahaan Dss di Indonesia," *VARIANSI: Journal of Statistics and Its application on Teaching and Research*, vol. 7, no. 01, pp. 44–54, Apr. 2025, doi: 10.35580/variansiunm356.

***Yuris Alkhalifi (Corresponding Author)**
Program Studi Informatika
Fakultas Teknik & Informatika, Universitas Bina Sarana Informatika, Jakarta Indonesia,
Jl. Kramat Raya No.98, RT.2/RW.9, Kwitang, Kec. Senen, Kota Jakarta Pusat
Email: yuris.yak@bsi.ac.id