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Forecasting PT Pertamina Geothermal Energy Tbk Stock Prices Using LSTM

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ABSTRACT

This study employs a Long Short-Term Memory (LSTM) model to forecast the daily closing price of PT Pertamina Geothermal Energy Tbk (PGEO) and to assess its training and out-of-sample performance. The dataset comprises 233 daily closing-price observations from April 8, 2025, to March 31, 2026. The data were split chronologically into 186 training observations and 47 testing observations. Min-Max scaling and a 60-day look-back window were used to construct the input sequences. The model consisted of two LSTM layers with 64 and 32 units, each followed by a dropout layer with a rate of 0.20. It was trained for 100 epochs with a batch size of 32 using the Adam optimizer and mean squared error as the loss function. Performance was evaluated separately using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The training data produced an MSE of 3,322.34, an RMSE of 57.64, and a MAPE of 3.10%, while the testing data produced an MSE of 4,230.63, an RMSE of 65.04, and a MAPE of 5.02%. The higher testing errors indicate a moderate decline in performance on new observations. The model followed the broad price movement but had difficulty capturing abrupt daily changes. A recursive five-step forecast generated predicted prices ranging from IDR 951.32 to IDR 968.81. This increase applies only to the specified forecast horizon and should not be interpreted as evidence of a continuing upward trend or as investment advice.

1. Introduction

PT Pertamina Geothermal Energy Tbk (PGEO) is one of Indonesia's leading geothermal energy companies and has participated in national geothermal exploration and development since 1974. As a subsidiary of PT Pertamina (Persero), PGEO has grown into one of the country's largest geothermal producers. Its main revenue is generated from steam sales to Independent Power Producers (IPPs) and direct and indirect electricity sales (PGEO, 2025;Wikipedia,2025).

PGEO entered a new stage of corporate development after its Initial Public Offering (IPO) and listing on the Indonesia Stock Exchange (IDX) on February 23, 2023. The IPO broadened public participation in renewable energy investment, strengthened the company's capital structure, and funded expansion, particularly to increase its installed geothermal capacity.

The listing occurred amid growing domestic and international interest in investment instruments incorporating Environmental, Social, and Governance (ESG) considerations. As a renewable energy issuer, PGEO plays an important role in Indonesia's transition toward a green, low-carbon economy.

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Nevertheless, its shares remain exposed to market volatility and various fundamental and technical factors (Kusumawardani, 2024).

Stock price volatility refers to the degree of price fluctuation over a given period and is commonly measured using the standard deviation of stock returns or prices (Shankar et al., 2025). Estimating it is challenging because stock prices may change rapidly in response to market sentiment, monetary policy, corporate performance, and geopolitical developments (Srivinay et al., 2022; Akin & Akin, 2024). Company-specific indicators, including revenue growth, profitability, and price-to-earnings ratios, may also affect price movements. Volatility therefore reflects potential returns and investment risks, making its analysis important for investment decisions, portfolio management, and risk assessment. However, interactions among market, financial, and macroeconomic factors often produce nonlinear patterns that simple statistical methods struggle to explain.

Stock price forecasting has traditionally used technical analysis and time-series models, including Autoregressive Integrated Moving Average (ARIMA), Autoregressive Conditional Heteroskedasticity (ARCH), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). ARIMA is widely applied because it is relatively easy to implement and flexible for short-term forecasting (Vaibhava Lakshmi & Radha, 2021). Researchers commonly identify its parameters p, d, and q using the Augmented Dickey-Fuller test, Autocorrelation Function, and Partial Autocorrelation Function. In contrast, researchers may select models using the Akaike and Bayesian Information Criteria (Huang, 2022).

Although ARIMA can forecast average price movements, it is less suitable when financial data variance changes over time. Stock prices often exhibit volatility clustering, where periods of high volatility are followed by similarly volatile periods. ARCH and GARCH address this issue by modeling time-varying variance and are useful for volatility forecasting and risk management. However, conventional time-series models remain limited in capturing complex nonlinear relationships and long-term dependencies. Machine learning therefore offers an alternative approach to improving forecasting performance.

Long Short-Term Memory (LSTM) is a machine learning model developed as a variant of the Recurrent Neural Network (RNN). It is suitable for sequential and time-series data because it can identify nonlinear patterns and dependencies across different periods (Chathli et al., 2026). Its main advantage lies in the input, forget, and output gates, which regulate information flow and allow the model to retain relevant information while discarding unnecessary information (Yang, 2025). This mechanism enables LSTM to capture short-term and long-term temporal dependencies that simpler models may not adequately identify. Consequently, LSTM has been widely applied to stock price forecasting, either independently or in hybrid models with additional variables to improve predictive accuracy (Hafshejani & Mansouri, 2025).

Despite its extensive application, LSTM-based stock forecasting research remains concentrated in developed markets, particularly the United States and China. Evidence from emerging markets is therefore needed to evaluate its performance under different market conditions. In Indonesia, previous studies have used LSTM to forecast the Indonesia Composite Index (IHSG) (Andhika Viadinugroho & Rosadi, 2021) and stocks in the LQ45 index (Sinaga et al., 2025). However, its application to individual renewable energy stocks, particularly PGEO, remains limited.

Accordingly, this study applies an LSTM model to predict PGEO's daily closing price using Open, High, Low, Close, and Volume (OHLCV) data from April 8, 2025, to March 31, 2026. The model forecasts PGEO's closing price for the next five trading days. LSTM is selected because it can recognize nonlinear patterns and capture short-term and long-term dependencies in sequential financial data.

This study contributes empirical evidence on applying LSTM to an individual renewable

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energy stock in Indonesia's emerging capital market. Its novelty lies in focusing on PGEO, a publicly listed geothermal energy company, and using daily OHLCV data to produce short-term forecasts. The findings are expected to enrich the literature on machine learning-based stock forecasting and provide practical information for investors assessing renewable energy stock price dynamics.

2. Literature Review

2.1. Stock Prices

As a core component of the capital markets, stocks appeal to investors for their potential to generate competitive returns. Often referred to as equities, this asset class is frequently used in long-term investment strategies to build financial stability for retirement. Stocks represent ownership in businesses actively engaged in commerce and with a strong presence in the financial marketplace. A primary motivator for investors when selecting stocks is the opportunity to profit from price fluctuations over shorter timeframes.

Stock price volatility is primarily influenced by company performance, market conditions, and broader global economic trends. This volatility creates significant challenges for investors seeking to make informed decisions that support the long-term success of their investment portfolios.

2.2. Stock Price Prediction

The stock market serves as a platform for transactions between buyers and sellers and is profoundly affected by both local and global events. Its inherently volatile, fluid n`ature makes precise price forecasting difficult, despite the potential for substantial investment returns (W. M. et al., 2024).

Numerous factors, including internal company dynamics and external policies, contribute to variations in stock prices. These factors operate to varying degrees and in different ways, further complicating stock price predictions (Lin, 2024). Forecasting stock prices based on historical trends is intended to help investors maximize profits. Moreover, this methodology serves as a strategic framework for asset managers, helping them achieve equilibrium and mitigate investment risks.

2.3. Long Short-Term Memory (LSTM)

Accurate stock price forecasting is fundamental to quantitative finance, underpinning trading strategies, risk management, and portfolio optimization. Traditional econometric models, such as ARIMA and GARCH, as well as conventional machine learning methods like random forests and support vector machines (SVMs), have been extensively applied to this task. However, these approaches exhibit inherent limitations in modeling nonlinearity and long-term dependencies within financial time series. The emergence of deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, has transformed the field because they can model complex temporal patterns and adapt to volatile, noisy data (Yachou et al., 2026).

Long Short-Term Memory (LSTM) networks were specifically developed to address challenges in time series analysis (Reddy & Ramkumar, 2024). The architecture of Long Short-Term Memory (LSTM) networks, defined by memory cells and gating mechanisms, effectively addresses the vanishing gradient problem that constrains conventional Recurrent Neural Networks (RNNs) (Pradeep et al., 2026). This capability improves sequential data analysis, such as stock market prices (Bandhu et al., 2023). As financial markets become increasingly complex and high-frequency data proliferates, there is significant impetus to investigate advanced LSTM variants and to develop hybrid architectural frameworks (Reddy & Ramkumar, 2024).

2.4. Synthesis dan Research GAP

The need for precise stock price forecasting has grown significantly in investment risk management. Given the substantial volatility and unpredictability of financial markets, making highly accurate stock price predictions

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is vital to developing robust risk management strategies. Reliable forecasts not only help investors make well-informed decisions but also support optimal portfolio allocation, ultimately reducing losses and increasing returns. As a result, various predictive modeling methodologies, particularly machine learning and deep learning, have attracted heightened interest because of their potential to improve prediction accuracy and manage investment risk.

This research uses the Long Short-Term Memory (LSTM) model to forecast stock price variations based on historical data, including PGEO's study, using PGEO closing prices of prices from March 1, 2025, to April 1, 2026. This investigation differs from earlier studies by focusing on a different corporation and using a different time period.

3. Research Method

3.1. Research Design

A quantitative experimental framework incorporating time-series analysis investigates nonlinear associations and long-term dependencies in stock price fluctuations.

The methodology is primarily comparative, evaluating the effectiveness of Long Short-Term Memory (LSTM) networks against traditional statistical models such as ARIMA and machine learning techniques such as Support Vector Regression (SVR) and Random Forest (Yachou et al., 2026). The principal emphasis is on modeling long-term dependencies and nonlinear trends in complex datasets (Hargreaves & Fan, 2026).

3.2. Population and Sample

The dataset consists of 233 daily closing-price observations for PT Pertamina Geothermal Energy Tbk (PGEO) from April 8, 2025, to March 31, 2026. The observations were ordered by date and divided chronologically into 186 training observations (80%) and 47 testing observations (20%). This chronological split ensured that the model did not learn from later observations while training on earlier ones.

3.3. Data Types and Sources

This research uses secondary sources from reputable financial data providers, specifically Yahoo Finance (finance.yahoo.com) and the Indonesia Stock Exchange (www.idx.co.id). The analysis focuses on PGEO's stock prices from April 8, 2025, to March 31, 2026.

3.4. Data Analysis Techniques

3.4.1. LSTM Model Architecture and Training Configuration

The model utilizes closing prices from the preceding 60 trading days to predict the subsequent day's closing price. The architecture comprises two LSTM layers: the first has 64 units and returns the full sequence to a second LSTM layer with 32 units. Both layers employ the tanh activation function and sigmoid recurrent gates. Each LSTM layer is followed by a dropout layer with a rate of 0.20 to mitigate overfitting. The final Dense layer consists of a single unit with a linear activation function. The model is compiled using the Adam optimizer (learning rate 0.001) and mean squared error as the loss function. Training is performed for 100 epochs with a batch size of 32. Observations are not shuffled to preserve chronological order. A random seed of 42 is set to enhance reproducibility.

a. The analysis commenced with 233 PGEO daily closing price observations, ordered chronologically from the earliest to the most recent trading date.
b. Following the chronological split, Min-Max scaling was fitted exclusively on the training data and subsequently applied to both training and testing datasets. This approach transformed all values to the range [0, 1] without incorporating information from the testing period in the scaling process.
c. The dataset was partitioned chronologically into 186 training observations and 47 testing observations. The training period estimated the model parameters, while the testing period was reserved for out-of-sample evaluation.
d. A 60-day look-back window was employed to construct input sequences. During

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training, we used the first 60 observations to predict the 61st, resulting in 126 training sequences. For testing, each of the 47 targets was predicted using the preceding 60 observed prices as input. The initial testing sequence used the final 60 observations before the first testing target. This approach avoided data leakage, as all input observations preceded the predicted value.

e. Model performance was evaluated separately on the training and testing datasets using mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). Separate actual-versus-predicted plots were generated to assess model fit, detect potential overfitting, and evaluate performance on out-of-sample observations.
f. Finally, a recursive five-step simulation was conducted after the final observation. We appended each predicted value to the input sequence and used it to generate the next prediction.

3.5. Ethical Considerations

This research relies solely on secondary data from published sources; therefore, no human participants were involved, and ethical approval was unnecessary. However, all sources have been appropriately referenced to uphold intellectual property rights and ensure academic integrity.

3.6. Methodological Limitations

Using Long Short-Term Memory (LSTM) models for financial market forecasting entails several methodological and technical challenges. Their complex architecture demands substantial computational resources, leading to prolonged training times and limited parallelization. Additionally, LSTMs require large datasets to avoid overfitting, particularly in deep learning contexts.

While designed to capture long-term dependencies, LSTMs have limited capacity to retain distant information and can accumulate errors over long sequences. They often operate under static conditions and struggle with concept drift, which can reduce prediction accuracy. Their focus on historical data also hampers the ability to predict unforeseen market events or Black Swan scenarios.

Moreover, relying exclusively on structured data limits contextual interpretation, and incorporating news sentiment may introduce subjective biases rather than reflect genuine investor behavior. The "black box" characteristic of LSTMs further complicates transparency and interpretability, making it difficult for practitioners to understand the economic logic behind predictions.

Future research should explore hybrid models, such as GNN–LSTM or LSTM–Transformer, and incorporate multimodal data, including news sentiment and macroeconomic indicators, to address these challenges.

4. Results and Discussion

4.1. Research Results

The analysis used 233 daily closing-price observations for PT Pertamina Geothermal Energy Tbk (PGEO) from April 8, 2025, to March 31, 2026. We arranged the observations chronologically and divided them into 186 training observations (80%) and 47 testing observations (20%). We used a 60-day look-back window to form the input sequences. This process produced 126 training sequences and 47 testing predictions.

4.1.1. Description of PGEO Closing-Price Data

The dataset consisted of 233 daily closing-price observations for PGEO.JK from April 8, 2025, to March 31, 2026. Table 1 presents selected observations from the beginning and end of the study period, while Figure 1 presents the movement of all closing-price observations.

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Table 1 Selected PGEO Closing-Price Data

Ticker	Date	Closing Price (IDR)
PGEO.JK	April 8, 2025	736.70
PGEO.JK	April 9, 2025	741.51
PGEO.JK	April 10, 2025	775.22
PGEO.JK	March 27, 2026	1,005.00
PGEO.JK	March 30, 2026	1,020.00
PGEO.JK	March 31, 2026	1,020.00

Table 1 shows selected PGEO closing-price observations from the beginning and end of the study period. The ticker PGEO.JK refers to PT Pertamina Geothermal Energy Tbk. The complete dataset contains 233 daily observations arranged chronologically from the earliest to the latest trading date.

Figure 1 PGEO Closing Price Data

Figure 1 presents the movement of all 233 PGEO closing-price observations. The closing price increased during the first part of the study period and reached its highest level around mid-2025. The price then generally declined toward the end of the observation period. Several sharp changes also occurred, indicating that the closing price series did not move in a stable or uniform pattern.

4.1.2. Data Preprocessing and Sequence Formation

The closing prices were normalized using Min-Max scaling to scale the values to a range of 0 to 1. The scaler was fitted using the training data and then applied to both the training and testing data. This procedure prevented information from the testing period from influencing the scale used during model training.

The model used the closing prices from the previous 60 trading days to predict the closing price for the following trading day. Each input sequence consisted of 60 consecutive observations, while the next observation became the prediction target. The window then moved forward by one observation to create the next input-target pair. Table 2 presents the normalized values of the first 60-day input sequence and its corresponding prediction target.

Table 2 Sequential Structure of PGEO Closing-Price Data

Trading Day	Normalized Value	Trading Day	Normalized Value
1	0.00	31	0.52
2	0.00	32	0.51
3	0.04	33	0.52
4	0.04	34	0.48
5	0.07	35	0.48
6	0.08	36	0.48
7	0.06	37	0.50
8	0.07	38	0.52
9	0.07	39	0.52
10	0.09	40	0.64
11	0.09	41	0.59
12	0.14	42	0.76
13	0.18	43	0.80
14	0.14	44	0.75
15	0.15	45	0.67
16	0.13	46	0.59
17	0.13	47	0.53
18	0.13	48	0.54
19	0.15	49	0.53
20	0.16	50	0.54
21	0.17	51	0.62
22	0.16	52	0.59
23	0.18	53	0.57

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24	0.28	54	0.64
25	0.44	55	0.61
26	0.42	56	0.63
27	0.47	57	0.67
28	0.55	58	0.68
29	0.53	59	0.68
30	0.50	60	0.69

As shown in Table 2, we used the normalized closing-price values from trading days 1 to 60 as the first input sequence, while the normalized closing price on trading day 61 (0.679870) served as the corresponding target. The window then moved forward by one observation, so trading days 2 to 61 were used to predict the closing price on trading day 62. This process continued until the end of the training period

We divided the 233 observations chronologically into 186 training observations and 47 testing observations. After applying the 60-day look-back window, the training data produced 126 input-target sequences. The first training sequence used observations 1 to 60 as input and observation 61 as the target. The window then moved forward by one observation until it reached the final training target. For testing, the first testing target used the final 60 available observations before that target. This process produced 47 testing predictions. All input observations occurred before their corresponding targets, so we used no future information. Figure 3 shows the chronological split between training and testing data.

Figure 2 Chronological division of training and testing data

Figure 2 shows that the first 186 observations were used for training, while the final 47 observations were reserved for testing. The vertical dashed line marks the point separating the two periods. Because the data were divided chronologically, the model was trained on earlier observations and evaluated on later observations not included in training. This division ensured that the test data represented out-of-sample observations.

4.1.3. Actual and Predicted Values for Training and Testing Data

The LSTM model's performance was evaluated separately on the training and testing datasets. The training results show how closely the model fits the observations used during training, while the testing results show its performance on new observations not used during training. Separate actual-versus-predicted plots are presented for both datasets to support the assessment of model fit, possible overfitting, and out-of-sample performance.

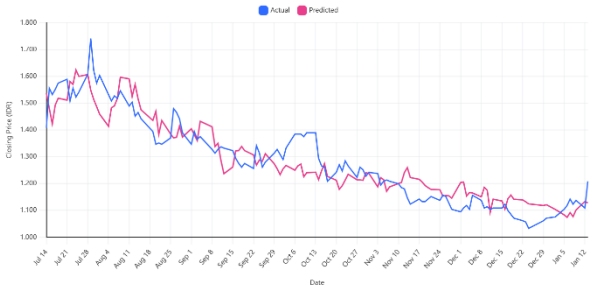

Figure 3 Actual versus Predicted PGEO Closing Prices for the Training Dataset

Figure 3 shows that the predicted values generally follow the overall trend of the actual closing prices in the training data set. However, the prediction line is smoother and does not fully capture several sharp price changes. This pattern suggests the model captures the training data's overall trend more effectively than sudden daily fluctuations.

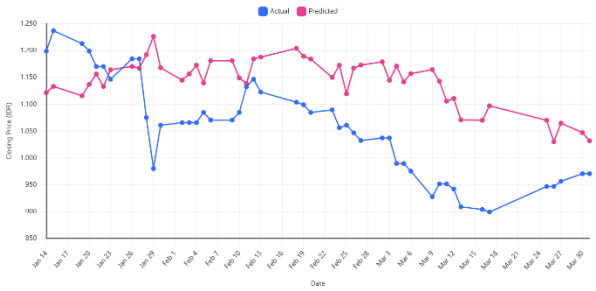

Figure 4 Actual versus Predicted PGEO Closing Prices for the Testing Dataset

Figure 4 shows that the predicted values follow the general trend of the actual closing prices in the testing dataset. However, discrepancies are larger during sudden price changes. Compared with the training results, the testing predictions differ more from the actual values, indicating weaker performance on observations not used during model training.

Table 3 LSTM model performance on training and testing data

Dataset	MSE	RMSE	MAPE
Training	3,322.34	57.64	3.10%
Testing	4,230.63	65.04	5.02%

Table 3 reports the LSTM model's performance separately for the training and testing datasets. The training data produced an MSE of 3,322.34, an RMSE of 57.64, and a MAPE of 3.10%. The testing data produced an MSE of 4,230.63, an RMSE of 65.04, and a MAPE of 5.02%. The testing RMSE was IDR 7.40 higher than the training RMSE, and the testing MAPE was 1.92 percentage points higher. These results indicate that the model performed less accurately on new observations than on the training observations. However, the difference between the training and testing results was moderate and did not indicate a severe training-testing gap in this model run.

4.1.4. Five-Step Closing Price Forecast

Following the final observation, a five-step recursive forecast simulation was conducted. Each predicted value was appended to the input sequence and utilized to generate subsequent predictions. Figure 5 illustrates the historical closing-price series, along with the actual and predicted values for the testing period and the five-step forecast.

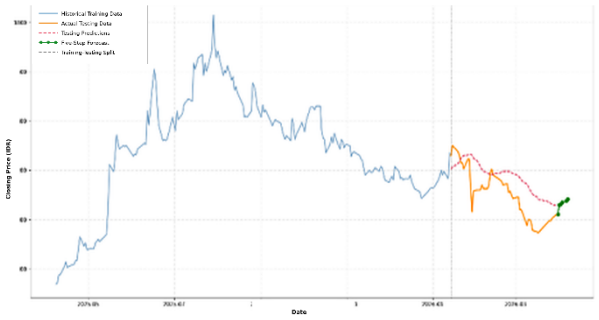

Figure 5 Historical data, testing predictions, and five-step PGEO forecast

Figure 5 shows the historical movement of PGEO closing prices, the actual and predicted prices during the testing period, and the numerical forecast for the next five trading steps. The testing predictions generally follow the broader trend of the actual prices but do not fully capture several sharp changes. The five-step forecast increases gradually from IDR 951.32 to IDR 968.81. This pattern applies only to the specified forecast horizon and should not be interpreted as evidence that PGEO prices will continue to increase beyond the five forecast steps.

Table 4 Five-step PGEO closing-price forecast

Forecast Step	Predicted Price (IDR)
T+1	951.32
T+2	955.60
T+3	960.01
T+4	964.43
T+5	968.81

The predicted closing prices increase gradually over the five-step forecast horizon, from IDR 951.32 at T+1 to IDR 968.81 at T+5. Because the actual closing prices for these future steps were not available at the time of the analysis, we could not calculate forecast errors. Therefore, interpret the reported values as numerical outputs of the fitted LSTM model rather than confirmed future prices or evidence that PGEO closing prices will continue to increase beyond the specified forecast horizon.

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4.2. Research Discussion

4.2.1. LSTM Model Performance on Training and Testing Data

Separate training and testing results provide a clearer basis for assessing the LSTM model's performance. The training data produced an MSE of 3,322.34, an RMSE of 57.64, and a MAPE of 3.10%, while the testing data produced an MSE of 4,230.63, an RMSE of 65.04, and a MAPE of 5.02%. The testing RMSE was IDR 7.40 higher than the training RMSE, and the testing MAPE was 1.92 percentage points higher. These increases indicate that the model fit the training observations more closely and performed moderately worse on observations not used during training.

The difference between training and testing results indicates possible overfitting. Higher testing errors are expected when a model is applied to new observations. In this study, however, the difference between the two datasets was moderate rather than extreme. Therefore, the results do not show a large training-testing performance gap in this model run. This interpretation should remain cautious because it is based on a single chronological data split and a relatively limited number of observations.

The actual-versus-predicted plots align with the evaluation metrics. Across both datasets, the prediction line follows the overall trend of the actual closing-price series. However, it is smoother and responds more slowly to sharp changes in the actual price. This difference is more apparent in the testing plot, particularly during sudden declines and reversals. The model therefore captures the general temporal pattern more effectively than short, abrupt daily price movements.

The testing MSE of 4,230.63 represents the average squared difference between the actual and predicted closing prices. Because MSE is expressed in squared units, it is less straightforward to interpret economically. However, MSE weights larger prediction errors more heavily and shows whether large differences between actual and predicted prices affect overall model performance.

The testing RMSE of IDR 65.04 expresses the prediction error in the same units as the stock price. This value indicates that the typical difference between predicted and actual testing prices was about IDR 65.04. During the testing period, PGEO closing prices generally ranged between IDR 899 and IDR 1,237. The RMSE was therefore roughly 5% to 7% of the observed price level. This percentage is approximate because the relative size of the error varies with the actual price on each trading day**.**

An error of approximately IDR 65 may be economically meaningful for short-term stock forecasting. If the expected daily price movement is smaller than the model error, the prediction may lack the precision needed for a trading decision. Transaction costs and narrow profit targets may also reduce the prediction's practical usefulness. Consequently, interpret the testing RMSE relative to the PGEO price level and daily price movements, rather than as evidence of satisfactory model performance.

The testing MAPE of 5.02% indicates that the average absolute prediction error across the testing observations was approximately 5.02% of the actual closing price. This result shows that the model can approximate the general price level, but it does not mean that every daily prediction differed from the actual value by exactly 5.02%. Some observations may have smaller errors, while others may have larger errors, particularly when the actual price changes suddenly.

5. Conclusion

This study shows that the LSTM model can capture the broad temporal pattern of PGEO daily closing prices. Separate training and testing indicate that the model performed better on the training data than on observations not used during training. The testing data produced an MSE of 4,230.63, an RMSE of 65.04, and a MAPE of 5.02%. The increase in error from training to testing was moderate,

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confirming that model performance declined on new observations.

The actual-versus-predicted results show that the model followed the general price direction but produced smoother predictions and struggled to capture sudden daily changes. The testing RMSE of IDR 65.04 was economically meaningful relative to the PGEO price level and potential short-term price movements. Therefore, treat the model output as supporting information rather than a precise basis for short-term trading decisions.

The recursive five-step forecast generated predicted closing prices ranging from IDR 951.32 at T+1 to IDR 968.81 at T+5. This gradual increase applies only to the specified forecast horizon and does not imply that PGEO closing prices will continue to rise over a longer period. It also does not independently demonstrate broad forecasting capability.

Overall, the findings provide company-specific empirical evidence on applying LSTM to PGEO closing-price forecasting. The conclusions remain limited to the observation period, historical closing-price input, selected model architecture, and evaluation procedure used in this study.

5.1. Summary of Key Findings

This study employed a Long Short-Term Memory (LSTM) model to predict the daily closing price of PT Pertamina Geothermal Energy Tbk (PGEO). The analysis utilized 233 daily closing-price observations spanning from April 8, 2025, to March 31, 2026. These observations were arranged chronologically and divided into 186 training observations and 47 testing observations. A 60-day look-back window was used to generate input sequences, resulting in 126 training sequences and 47 testing predictions.

The training data yielded a Mean Squared Error (MSE) of 3,322.34, a Root Mean Squared Error (RMSE) of 57.64, and a Mean Absolute Percentage Error (MAPE) of 3.10%. The testing data produced an MSE of 3,322.34, an RMSE of 65.04, and a MAPE of 5.02%. The higher errors in the testing phase suggest the model fit the training data more closely and showed a moderate decline in performance on unseen data.

Actual-versus-predicted plots indicate that the model generally followed the overall trend of PGEO's closing prices. However, the predicted values were smoother than the actual prices and did not fully capture several abrupt daily variations. These findings suggest the model captured the general temporal pattern better than short-term, rapid price fluctuations.

The recursive five-step-ahead simulation generated predicted closing prices ranging from IDR 951.32 at T+1 to IDR 968.81 at T+5. This gradual increase is specific to the forecast horizon and reflects the fitted model's numerical output. It does not imply that PGEO's closing prices will continue to rise beyond the five-step forecast period.

5.2. Theoretical and Empirical Contributions

This study contributes to the literature by providing company-specific empirical evidence on using LSTM for PGEO closing-price forecasting. Previous Indonesian studies have applied LSTM to banking and Sharia-compliant stocks, demonstrating its use across companies and sectors (Kurniansyah et al., 2025; Puteri, 2023). However, studies focusing specifically on PGEO remain relatively limited. (Hanifudin, 2024) included PGEO alongside KEEN and BREN in an LSTM-based forecasting study, while (Ramadhan et al.,2025) examined PGEO using an ARIMA and ARCH-GARCH framework. Therefore, the present study does not claim to be the first application of LSTM to PGEO. Instead, it extends the available evidence by using a different observation period, model configuration, and company-specific evaluation.

The empirical contribution also lies in reporting MSE, RMSE, and MAPE separately for the training and testing datasets and in providing corresponding actual-versus-predicted plots. This procedure provides clearer evidence of model fit, possible overfitting, and out-of-sample performance. The findings show that the model followed the

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broad movement of PGEO closing prices but struggled to capture abrupt daily changes. The study also interprets the testing RMSE relative to PGEO's price level, providing a more economically meaningful assessment of forecasting error.

5.3. Practical and Policy Implications

The findings have practical implications for investors, financial analysts, portfolio managers, and risk managers who use quantitative models to support stock-price analysis. The LSTM model may help identify the general direction of PGEO closing prices. However, the RMSE of IDR 65.04 and MAPE of 5.02% indicate that predictions still carry meaningful errors. Therefore, the model should serve as a supporting analytical tool rather than the sole basis for investment or trading decisions.

The smoother prediction line suggests the model may not respond quickly to abrupt changes in the actual closing price. Investors and analysts should therefore combine the model's output with additional information, such as trading volume, technical indicators, company announcements, financial performance, interest-rate changes, relevant economic news, and broader market conditions.

The findings also have implications for model developers and financial researchers. Training performance alone should not be used to support claims about forecasting quality. Training and testing metrics should be reported separately, and actual-versus-predicted plots should be presented for both datasets. These practices make it easier to identify performance deterioration on new observations and assess possible overfitting.

From a policy perspective, the findings underscore the importance of access to consistent, accurate, and well-documented historical financial data. Market authorities, stock exchanges, and financial-data providers may support responsible model development by improving data availability and maintaining consistent definitions of price variables, trading dates, corporate actions, and missing observations.

Investor education should also emphasize that machine-learning forecasts contain uncertainty and should not be interpreted as guaranteed future prices. The results of this study should not be regarded as a recommendation to buy, sell, or hold PGEO shares.

5.4. Limitations of the Study

This study has several limitations. First, the analysis used 233 daily closing-price observations from a relatively short period. A longer period may encompass more varied market conditions and provide a stronger basis for assessing model stability.

Second, the study focused only on PGEO. Company-specific characteristics and conditions in the renewable-energy sector may influence the observed price pattern. Therefore, the findings should not be generalized directly to other companies, sectors, or stock markets.

Third, the model used historical closing prices as its primary input. The analysis did not include opening prices, high and low prices, trading volume, technical indicators, company fundamentals, interest rates, inflation, exchange rates, market indices, investor sentiment, company announcements, or financial news. Excluding these variables may limit the model's ability to capture sudden price changes driven by new market information.

Fourth, the model was evaluated using a single chronological 80:20 split. This procedure preserved time order and reduced the risk of future information entering the model-training process. However, a single split may not fully represent model performance across different periods and market conditions.

Fifth, this study did not directly compare LSTM with alternative forecasting methods using the same dataset, observation period, forecast horizon, and evaluation procedure. Therefore, the results do not establish that LSTM performs better than ARIMA, ARCH-GARCH, Support Vector Regression, Random

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Forest, GRU, Transformer-based models, or other forecasting approaches.

Sixth, the study did not conduct an extensive comparison of alternative model architectures and hyperparameters. Different look-back windows, numbers of layers, units, dropout rates, learning rates, batch sizes, optimizers, and numbers of epochs may produce different results.

Seventh, the five-step forecast occurred beyond the final historical observation on March 31, 2026. Actual closing prices for these forecast steps were not available at the time of the analysis. Therefore, we did not evaluate the five-step forecast using MAE, MSE, RMSE, or MAPE.

Finally, we assessed possible overfitting based on a single chronological split. The moderate difference between training and testing performance did not indicate a large performance gap in this model run. However, this finding is not sufficient to conclude that the model will remain free from overfitting under different observation periods or market conditions.

5.5. Directions for Future Research

Future research should use longer observation periods and larger datasets that span diverse market conditions. A longer dataset may capture periods of price increases, declines, relative stability, and sudden market changes, enabling a more comprehensive evaluation of model stability.

Future studies should also examine other companies in the renewable-energy sector or in other sectors listed on the Indonesia Stock Exchange. A multi-company analysis would provide a stronger basis for determining whether the model performance observed for PGEO also appears in other stocks.

Consider additional variables, including opening price, highest price, lowest price, closing price, trading volume, technical indicators, company fundamentals, interest rates, inflation, exchange rates, market indices, and other macroeconomic variables. Unstructured information, such as company announcements, financial news, and market sentiment, may also be incorporated using systematic and transparent measurement procedures.

Use rolling-window or walk-forward validation to evaluate model performance across multiple periods. These procedures would provide stronger evidence of the model's stability and reduce dependence on a single chronological data split.

Future studies should compare LSTM with statistical, machine-learning, and deep-learning models using the same dataset, forecast horizon, and evaluation metrics. Models to consider include ARIMA, ARCH-GARCH, Support Vector Regression, Random Forest, GRU, and Transformer-based models.

Systematic hyperparameter tuning should also evaluate different look-back windows, numbers of layers, numbers of units, dropout rates, learning rates, batch sizes, optimizers, and numbers of epochs. Early stopping and other regularization methods may be used to reduce the risk of overfitting.

Finally, future research should conduct an ex-post evaluation of the five-step forecast after the corresponding actual closing prices become available. This evaluation would allow MAE, MSE, RMSE, and MAPE to be calculated for the forecast horizon and would provide stronger evidence regarding the model's practical short-term forecasting performance.

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