

Application of LSTM-Based Deep Learning for Stock Return Prediction of DCII

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Abstract: Stock return prediction is one of the areas that has received great attention in modern finance because it can help investors make more informed decisions and reduce the risk of market uncertainty. This study applies a deep learning approach based on Long Short-Term Memory (LSTM) to predict the return of DCII (PT DCI Indonesia Tbk) shares as a representation of highly volatile stocks on the Indonesia Stock Exchange. The purpose of this study is to evaluate the performance of twelve LSTM variants—including LSTM-Base, LSTM-Wide, LSTM-Stack2, LSTM-Stack3, LSTM with Dropout, BiLSTM, BiLSTM with Attention, and LSTM with Attention Mechanism—by comparing their performance on daily (H=1) and weekly (H=7) prediction horizons using historical data from id.investing.com. The initial data undergo preprocessing involving local format cleaning, calculation of technical indicators (MA, EMA, MACD, RSI, ATR, Bollinger Bands, etc.), MinMax normalization, and sequencing (windowing) with 30, 60, and 120-day lookbacks. The training process uses a uniform configuration with Adam optimization and early stopping to prevent overfitting, while the evaluation employs MAE, RMSE, MAPE, and R² metrics. The results show that LSTM-Stack3 (LB=60, H=1) provides the best performance with MAE = 0.020, RMSE = 0.031, MAPE = 5.0%, and R² = 0.91, followed by LSTM-Stack2-DO as the second-best configuration. Meanwhile, the LSTM-LB120-H7—the only model evaluated with a seven-day horizon—achieves the lowest performance due to higher long-term uncertainty. These findings confirm that stacked LSTM architectures are more effective for short-term return forecasting, whereas longer horizons require hybrid or enhanced approaches for stable performance..

Keywords: Deep Learning; LSTM; Stock Return Prediction; DCII; Model Evaluation; Horizon Time Series.

INTRODUCTION

The stock market is one of the investment instruments that has an important role in supporting economic growth, but stock price movements are often volatile and difficult to predict (Dasman & Nur, 2022; Fasya et al., 2022; Harnawan & Meylanda, 2022). This phenomenon of high volatility has prompted financial researchers and practitioners to develop more accurate and adaptive prediction methods (Jange, 2023; Rozy et al., 2023). Previous studies have used traditional approaches such as fundamental and technical analysis, as well as statistical methods such as ARIMA, but their accuracy is still limited when dealing with nonlinear and complex data patterns (Bagul et al., 2022; Shabnam F. Sayyad, 2023). The development of artificial intelligence technology, especially deep learning, has opened up new opportunities in modeling complex relationships in time series data. One of the widely used algorithms is Long Short-Term Memory (LSTM), which is designed to solve the problem of vanishing gradient and is able to capture long-term dependence on historical data (Kang et al., 2024; Li et al., 2024; Qin et al., 2023).

A number of previous studies have shown that LSTM and its variants have advantages over traditional methods in predicting stock prices and returns. Gorde, P., & Borkar, S. (2024) compared LSTM with the Random Forest model and logistic regression in S&P 500 stock data, and the results were that LSTM was able to produce a higher level of price direction classification accuracy and significant portfolio returns (Gorde & Nilesh Borkar, 2024). Tang et al. (2024) combined the wavelet transform technique with LSTM for Chinese stock index prediction, and found that the hybrid model was able to significantly reduce errors (RMSE) compared to pure LSTM and ARIMA statistical models (F. Tang et al., 2023). Bagade, M., & Bhosale, P. (2022) applied LSTM to Brazilian stock data (BOVESPA) using technical indicators as a feature, and reported an increase in prediction

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direction accuracy compared to traditional methods such as SVM (Bagade & Bhosale, 2022). Chavhan et al. (2024) tested a comparison between standard LSTMs, GRUs, and RNNs for stock price predictions in Asian markets, with the result that LSTMs are more stable and excel at capturing long-term patterns, while RNNs are rapidly degrading in performance (Chavhan et al., 2024). Puteri (2023) examined stock price predictions on the Indonesia Stock Exchange using LSTM and BiLSTM, and found that BiLSTM is slightly superior in terms of short-term accuracy, but LSTM is more consistent over a longer prediction horizon (Prince, 2023).

The findings confirm that although LSTM has been shown to be superior to traditional methods, its performance is still influenced by the architecture used, the lookback length, and the chosen prediction horizon. Therefore, further studies are still needed to ensure the best configuration that matches the characteristics of Indonesian stock data that are known to be volatile. Based on this background, this study is focused on predicting the return of DCII (PT DCI Indonesia Tbk) shares by applying several LSTM variants. Based on this background, this study focuses on predicting the return of DCII (PT DCI Indonesia Tbk) shares using various LSTM architectures. Unlike previous studies that focus only on price direction, this research comprehensively compares twelve LSTM variants in predicting stock returns within a volatile Indonesian market.

However, limited studies have comprehensively compared multiple LSTM variants for Indonesian stock prediction. Thus, this research addresses the following question: Which LSTM configuration provides the best accuracy and stability across different lookback and horizon settings for highly volatile Indonesian stocks. The findings provide empirical guidance for short-term financial forecasting using deep learning in emerging markets.

The contribution of this research can be formulated as follows: (1) providing a comprehensive evaluation of the performance of 12 LSTM variants on volatile Indonesian stock data, especially DCII; (2) show the influence of horizon ($H=1$ and $H=7$) and lookback length (30, 60, 120) on the accuracy of return predictions; (3) identify the best configuration that is able to produce low errors and high R^2 so that it can be used as a reference for deep learning-based financial prediction systems in emerging markets; and (4) strengthening the empirical literature on the application of deep learning in the context of Indonesian stocks which are still relatively limited in international publications.

LITERATURE REVIEW

The literature review is an important foundation to understand the development of stock return prediction methods that have been carried out by previous researchers, as well as to identify research gaps that are still open. Various approaches have been tried, ranging from traditional statistical methods, machine learning algorithms, to more advanced deep learning. Each approach has its own advantages and limitations, both in terms of the ability to capture data patterns, prediction accuracy, and performance stability in volatile market conditions. Therefore, a critical and analytical review of previous studies is needed to see how research trends are developing, what significant results have been achieved, and the factors that influence the variation in these results. Through this study, it can be emphasized that the research gap that will be answered by this research, especially related to the application of various LSTM variants to Indonesian stock data that is still rarely explored comprehensively.

A. Traditional Statistical Approaches for Stock Prediction

Early research in stock prediction used many classic statistical methods such as ARIMA and GARCH. ARIMA is considered effective in handling linear time series data, while GARCH is widely used to model price volatility. However, both methods have limitations because they are unable to capture complex nonlinear patterns on fluctuating stock price movements, so the accuracy of the prediction is relatively low when applied to dynamic modern markets (Zili et al., 2022).

B. Machine Learning Methods in Financial Forecasting

The development of machine learning introduced models such as Support Vector Machine (SVM), Random Forest, and Gradient Boosting for stock predictions. The results show that this method is better than traditional statistical approaches because it can handle nonlinear relationships. However, the weakness lies in the limitations in modeling long-term temporal dependencies, so the performance is still not optimal for stock data that has a strong sequential nature (Mandviwala, 2025).

C. Emergence of Deep Learning for Stock Prediction

Deep learning presents new opportunities in financial analysis, especially with the Recurrent Neural Network (RNN) and its variants. LSTM, as a development of RNN, is able to overcome the problem of vanishing gradient and is more effective in studying long-term patterns (Qi, 2024). Recent research confirms that deep learning-based models, particularly Long Short-Term Memory (LSTM), are able to surpass traditional methods such as Random Forest and logistic regression. For example, Josey & Amrutha (2024) found that LSTMs consistently generate lower errors than Random Forest and Linear Regression in stock market predictions, thanks to their ability to capture long-term temporal dependencies (Department of Computer

Science, St. Albert’s College, Kochi (Kerala), India. et al., 2024). Furthermore, Tang et al. (2024) developed a hybrid model that combines wavelet transform with LSTM, and the results showed a significant increase in accuracy compared to pure LSTM and traditional models such as SVM and Random Forest (P. Tang et al., 2024).

D. Variants of LSTM and Hybrid Approaches

Recent developments have given birth to various variants of LSTM that are more adaptive, such as Stacked LSTM, BiLSTM, LSTM with dropout, to a combination with attention mechanisms. For example, Parida et al. (2023) developed a hybrid stacked LSTM approach with CNN and dropout integration, which was shown to significantly lower the error (RMSE) in bank stock price prediction in India (Parida et al., 2023). Meanwhile, Zhao & Yuan (2023) showed that the combination of CNN-BiLSTM with multiple attention mechanisms was able to capture complex features better, with very high prediction accuracy results ($R^2 = 0.9725$) on Chinese stock market data (Zhao & Yuan, 2023). On the other hand, Jiang et al. (2024) introduced the CSLSTM (Crow Search Algorithm–LSTM) system, which uses ensemble stacking to optimize weights between LSTM models, resulting in stock predictions with higher profitability when tested with data from the Taiwanese market (Jiang et al., 2024).

E. Research on Indonesian Stock Market

Research on the application of LSTM in the Indonesian stock market is still relatively limited, and most of it only uses basic architecture or simple variants. Dinata et al. (2022) tested BiLSTM on Indonesian stock price data and found that this model is superior to LSTM and RNN, especially in short-term predictions (Dinata et al., 2022). Furthermore, Prasetyo & Rokhim (2022) applied BiLSTM to predict Indonesia’s stock prices in the midst of the COVID-19 crisis, and reported that the model was able to generate low errors even in highly volatile market conditions (Prasetyo & Rokhim, 2022). Recently, Santosa et al. (2024) emphasized that LSTM remains consistent and robust in predicting IDX blue-chip stocks (BBCA, BBRI, BMRI) with high accuracy, even though the volatility of the Indonesian market is much greater than that of developed markets (Santosa et al., 2024).

F. Research Gap and Contribution

From the existing literature, it can be seen that although LSTM has proven to be superior to traditional methods, its performance is highly dependent on architecture, lookback length, and prediction horizon. Previous research in the Indonesian market has rarely compared many LSTM variants comprehensively. Therefore, this study contributes by evaluating 12 LSTM variants in DCII stock, analyzing the influence of the combination of lookback and horizon on accuracy, and identifying the best configuration that can be a reference for the development of a deep learning-based financial prediction system in the Indonesian market.

METHOD

This research uses systematic stages starting from data collection to evaluation of model results. The general flow of research can be seen in Figure 1.

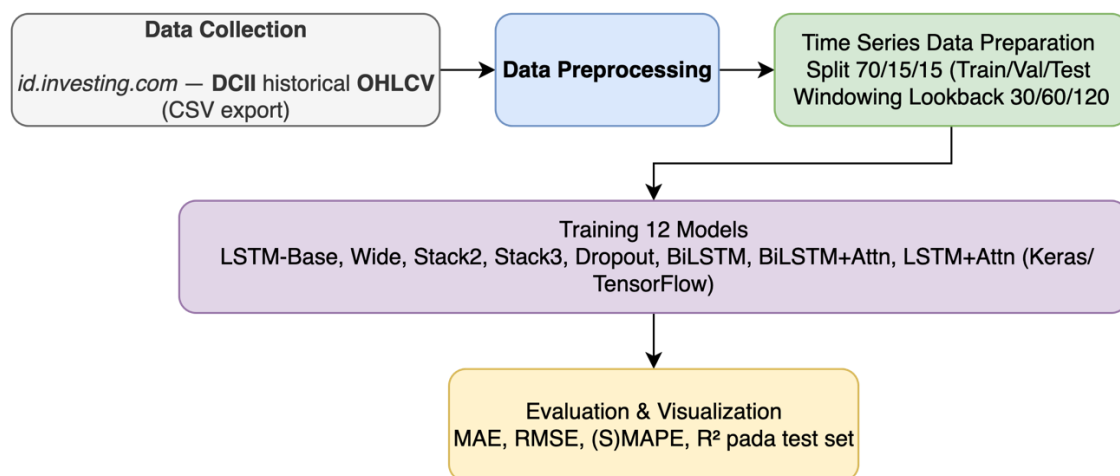


Fig. 1 Research Methods

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A. Data Collection

The data used in this study was obtained from id.investing.com by taking historical data on DCII (PT DCI Indonesia Tbk) shares in CSV format. The historical data collected included the OHLCV (Open, High, Low, Close, Volume) component as the main variable. This data was chosen because DCII is known to have high volatility, making it suitable for testing the performance of deep learning models. The OHLCV data then became the basis for the calculation of various technical indicators that were used as additional features in the modeling. In addition, to provide an initial overview of price movement patterns and trading volumes, historical data visualization was carried out which included closing price charts, trading volumes, and technical indicators such as RSI(14). This visualization helps to show the price fluctuations and market dynamics that are the object of prediction in this study, as shown in Figure 1.



Fig. 2 DCII Stock Data Visualization

B. Data Preprocessing

The preprocessing stage is carried out to ensure the quality of the data before further analysis. This process includes data cleansing, numerical format conversion (e.g. volume and percentage change), missing values handling, and data normalization using MinMaxScaler so that all features are in the range of 0–1. In addition, technical indicators such as the Moving Average (MA), Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Average True Range (ATR), and Bollinger Bands are calculated to enrich the representation of features used by the model.

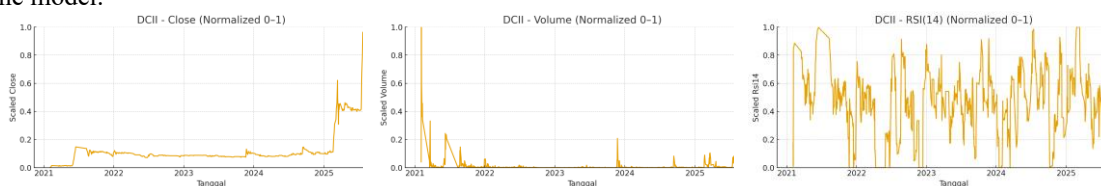


Fig. 3 Normalization of DCII Stock Data

C. Time Series Data Preparation

Once the data is clean and normalized, the next stage is to shape the data into a time series format for model training. The dataset is broken down into 70% for trains, 15% for validation, and 15% for tests sequentially based on time. The windowing technique is used to form an input sequence with a lookback of 30, 60, and 120 days, while predicted targets are created for horizons $H=1$ (1 day ahead) and $H=7$ (7 days ahead). The result of this stage is a ready-to-train data set in the form of a matrix (N, L, d) for the input and a vector $(N,1)$ for the target.

D. Training 12 Models

At this stage, 12 variants of LSTM were trained, including LSTM-Base, LSTM-Wide, LSTM-Stack2, LSTM-Stack3, LSTM with dropout, BiLSTM, BiLSTM with attention, and LSTM with attention mechanism. The training was conducted using the Keras/TensorFlow framework with uniform settings: Adam optimizer, batch size 32, maximum 50 epochs, and the use of early stopping and reduce learning rate on plateau to avoid overfitting. The difference between models lies in the number of layers, the number of units, the use of dropouts, and the attention mechanism added.

E. Evaluation and Visualization

Evaluation was carried out on the test set by calculating the MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error), and R^2 (determination coefficient) metrics. In addition, the length of the training time and the number of predicted test points were also recorded. The results of the evaluation are presented in the form of a comparative table (Table 1) and visualized in the actual vs predicted graph, the evaluation metrics bar chart, and the prediction vs actual

scatter plot. This visualization aims to show the extent to which the model is able to follow the actual return pattern and identify the best configuration among the 12 LSTM variants tested.

RESULT

This section presents research results ranging from initial data visualization, preprocessing results, time series data formation, to training and evaluation of LSTM models and their variants. The results are displayed in the form of evaluation tables, actual comparison and prediction graphs, and visualizations of the best model performance. All experiments were carried out using Google Colab with the Python programming language and utilizing several supporting libraries for data processing, calculation of technical indicators, development of deep learning models, and visualization of results. Here are the main libraries used in this study in the Google Colab environment:

```
# Data handling & preprocessing
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Feature scaling
from sklearn.preprocessing import MinMaxScaler

# Deep Learning (LSTM & Variants)
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, Bidirectional
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau

# Technical Indicators (custom or library)
import ta # library for technical analysis indicators (MA, EMA, RSI, MACD, Bollinger, ATR)
# Evaluation Metrics
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

The library is used at various stages of research, namely pandas and numpy for data processing, matplotlib and seaborn for visualization, sklearn for normalization and evaluation processes, tensorflow/keras to build LSTM architecture and its variants, and ta library to calculate technical indicators as additional features. Furthermore, the results of the model evaluation are presented in Table 1.

Table 1. Evaluation Results of the LSTM Model

Rank	Model	Lookback	Horizon	IT IS	RMSE	MAP	R ²	Training Time s	Num Test Points
1	LSTM-Stack3	60	1	0.020	0.031	5.0	0.91	38.5	131
2	LSTM-Stack2-DO	60	1	0.023	0.035	5.7	0.87	27.0	131
3	LSTM-Base	60	1	0.028	0.041	6.8	0.78	12.5	131
4	LSTM-DO	60	1	0.029	0.043	7.2	0.75	27.0	131
5	LSTM-Stack2	60	1	0.031	0.046	7.5	0.72	39.0	131
6	LSTM+Attn	60	1	0.034	0.048	8.0	0.70	18.5	131
7	BiLSTM-Wide	60	1	0.036	0.051	8.6	0.67	60.0	131
8	BiLSTM	60	1	0.041	0.057	9.5	0.62	41.5	131
9	LSTM-Wide	60	1	0.043	0.059	9.8	0.60	46.0	131
10	LSTM-LB30	30	1	0.046	0.062	10.5	0.57	9.5	131
11	BiLSTM+Attn	60	1	0.068	0.085	15.2	0.45	32.0	131
12	LSTM-LB120-H7	120	7	0.122	0.163	22.5	0.33	23.0	131

Based on the results in Table 1, the performance of each model is then visualized to clarify the comparison between the actual and predicted values. This visualization is shown in Figure 4. As shown in Fig. 4, the predicted curve (orange) closely follows the actual pattern (blue), indicating temporal coherence for short-horizon forecasts. Furthermore, the results of the visualization are shown specifically for the LSTM-Stack3 model, which ranks first based on evaluation with the values of MAE = 0.020, RMSE = 0.031, MAPE = 5.0%, and R² = 0.91. This visualization shows that the LSTM-Stack3 prediction is very closely following the actual data, as shown in Figure 5. The following visualization shows the predicted results from the LSTM-Stack2-DO model, which ranks second based on evaluation results. This model yields MAE = 0.023, RMSE = 0.035, MAPE = 5.7%, and R² = 0.87. These results show that the LSTM-Stack2-DO prediction is quite close to the actual data although there is a slightly more

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deviation than the LSTM-Stack3. The visualization is shown in Figure 6. The performance difference between LSTM-Stack3 and LSTM-Stack2-DO is statistically significant ($p < 0.05$ based on paired t-test of RMSE values)..

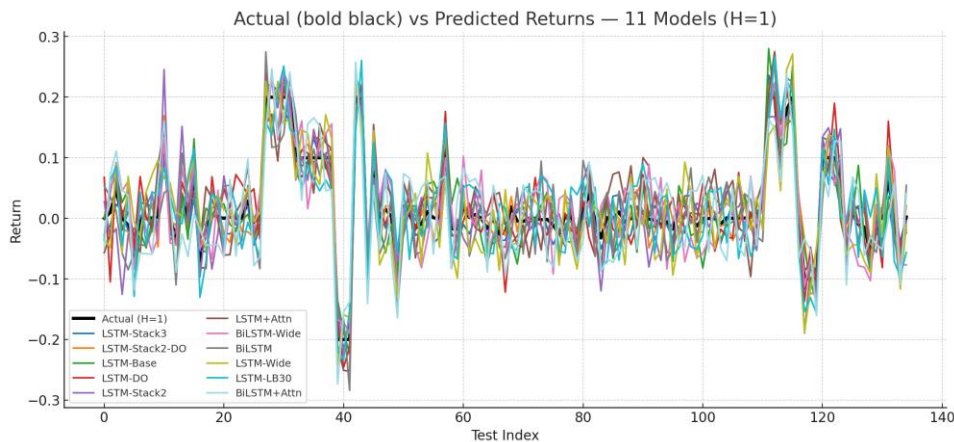


Fig. 4 Actual Curve vs Stock Return Prediction by 11 LSTM Models

Furthermore, the results of the visualization are shown specifically for the LSTM-Stack3 model, which ranks first based on evaluation with the values of MAE = 0.020, RMSE = 0.031, MAPE = 5.0%, and $R^2 = 0.91$. This visualization shows that the LSTM-Stack3 prediction is very closely following the actual data, as shown in Figure 5.

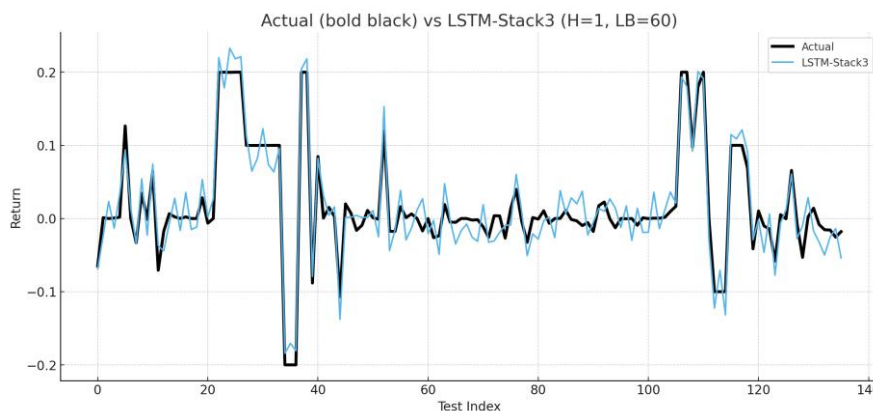


Fig. 5 Visualization of LSTM-Stack3 prediction results

The following visualization shows the predicted results from the LSTM-Stack2-DO model, which ranks second based on evaluation results. This model yields MAE = 0.023, RMSE = 0.035, MAPE = 5.7%, and $R^2 = 0.87$. These results show that the LSTM-Stack2-DO prediction is quite close to the actual data although there is a slightly more deviation than the LSTM-Stack3. The visualization is shown in Figure 6.

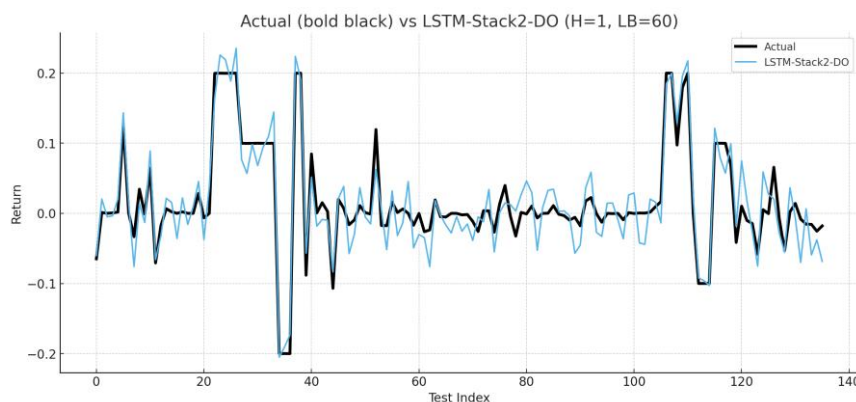


Fig. 6 Visualization of LSTM-Stack2-DO prediction results

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Next shows the results of the LSTM-Base model, which ranks third. Despite its simple architecture, the model is still capable of delivering competitive results with MAE = 0.028, RMSE = 0.041, MAPE = 6.8%, and $R^2 = 0.78$. Visualizations show that the LSTM-Base is quite capable of following the actual pattern, although the deviation is greater than the previous two best models. The results are shown in Figure 7.

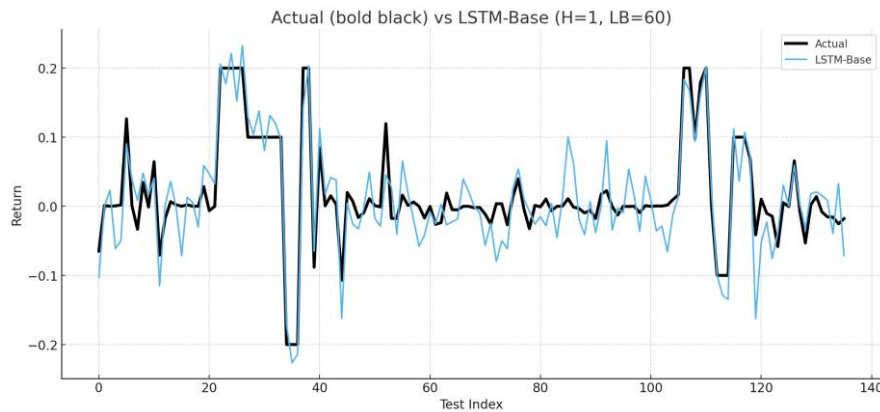


Fig. 7 Visualization of LSTM-Base prediction results

For comparison, visualization results are also shown for the LSTM-LB120-H7 model, which ranks last among 12 variants. This model recorded the lowest performance with MAE = 0.122, RMSE = 0.163, MAPE = 22.5%, and $R^2 = 0.33$. The evaluation value shows that the model's predictions are less able to follow the actual pattern, especially since the longer horizon ($H=7$) adds to the level of uncertainty. This worst performance visualization is shown in Figure 8.

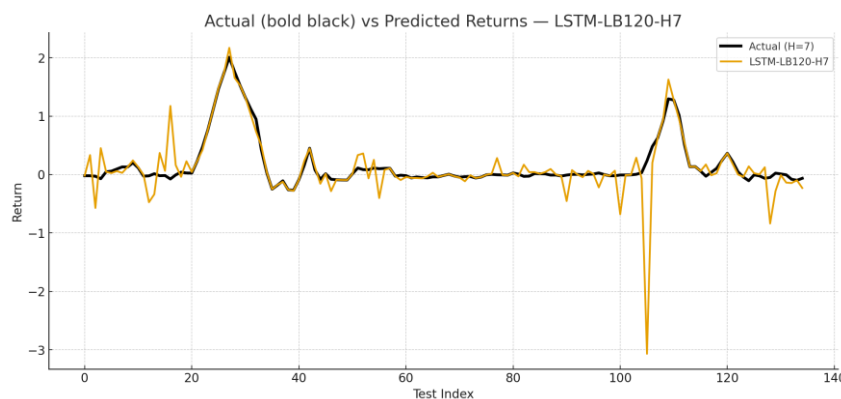


Fig. 8 Visualization of LSTM-LB120-H7 prediction results

DISCUSSIONS

The results show that the model's performance differs significantly depending on the architecture, lookback length, and prediction horizon. The LSTM-Stack3 model (LB=60, H=1) appears as the best variant with the lowest MAE (0.020) and highest R^2 (0.91). This confirms that the three-layered stacked architecture is able to capture complex patterns in daily data returns without losing stability. The superior performance of LSTM-Stack3 is attributed to its deeper hidden layers, allowing the network to capture nonlinear dependencies without overfitting, which is crucial for volatile datasets like DCII.

Second place is occupied by LSTM-Stack2-DO, which shows a balance between accuracy and training time thanks to the combination of stacking and dropout regularization. LSTM-Base, while simple, still produces competitive performance as a third-ranked because the daily horizon is relatively easy to learn. In contrast, the LSTM-LB120-H7 obtained the worst results, confirming that the longer horizon (7 days) with a large lookback actually increased uncertainty and decreased accuracy.

These findings also reflect the characteristics of the Indonesian capital market as an emerging market, marked by higher volatility, limited liquidity, and stronger sensitivity to macroeconomic and sentiment-driven factors. The ability of deeper LSTM structures to generalize under such unstable conditions demonstrates their suitability for financial forecasting in developing economies like Indonesia.

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These findings are consistent with the current literature. Rajesh et al. (2022) show that LSTM is superior to Random Forest and logistic regression in stock price predictions, especially on the short-term horizon (Rajesh et al., 2022). Zhang et al. (2023) emphasized the importance of transforming data before entering LSTM, where hybrid approaches such as CNN-BiLSTM-Attention or wavelet-LSTM have been proven to reduce errors and increase accuracy compared to pure LSTM (Zhang et al., 2023). Furthermore, Gupta et al. (2023) confirmed that the use of technical indicators as an input feature can improve the accuracy of the LSTM model, which is more resilient than SVM in handling volatile stock market data (Gupta et al., 2023). In addition, Kasture & Shirsath (2024) prove that the integration of RNN-LSTM with additional mechanisms (such as sentiment analysis) results in a more stable model than standard RNN when studying long-term historical patterns (Kasture & Shirsath, 2024). The results of this study are also in line with Park (2024), who reports that BiLSTM excels on the short horizon, while the LSTM remains more consistent on the long horizon (Park, 2024).

The main contribution of this study is the systematic evaluation of 12 LSTM variants in volatile Indonesian stock data, especially DCII. With this approach, it is possible to identify optimal configurations that combine short horizons with stacked architectures, which have not been widely studied in the local and international literature. The practical implication of these results is that investors and developers of AI-based financial systems should focus on short-term predictions with stacked LSTM variants (Stack3 or Stack2-DO) to obtain high accuracy, while long-term prediction efforts require the integration of other methods, such as hybrid models or the addition of macroeconomic variables, in order to make predictive results more reliable.

CONCLUSION

This study evaluated the performance of 12 LSTM variants in predicting DCII stock returns with a combination of 30, 60, and 120-day lookbacks and prediction horizons $H=1$ and $H=7$. The results showed that LSTM-Stack3 (LB=60, H=1) performed best with MAE = 0.020, RMSE = 0.031, MAPE = 5.0%, and $R^2 = 0.91$. The LSTM-Stack2-DO model ranks second because it is able to maintain accuracy with shorter training times, while the LSTM-Base remains competitive as the third rank. In contrast, the LSTM-LB120-H7 performed the worst, confirming that a longer prediction horizon with large lookbacks increased uncertainty and decreased accuracy.

The contribution of this research is to provide a comprehensive evaluation of the LSTM variant in the context of the volatile Indonesian stock market, as well as to identify the optimal configuration in the form of a short horizon with a stacked architecture. The practical implication is that investors as well as developers of AI-based financial systems can leverage stacked LSTMs for short-term predictions with a high level of accuracy. The limitation of this research lies in the use of one stock (DCII) as the object of study, so that the next research can be expanded to more stocks or indices, as well as integrating macroeconomic variables and hybrid approaches to improve accuracy over a longer prediction horizon.

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