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ENHANCING LQ45 STOCK PRICE FORECASTING USING LSTM MODEL

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ABSTRACT

Stocks listed in the LQ45 index represent companies with high liquidity, large market capitalization, and strong fundamentals, making them pivotal to the movements of the Indonesian capital market. This study selects eight LQ45-listed stocks from the energy and mining sectors, as well as the banking sector. Historical data spanning a 10-year period from February 28, 2015, to February 28, 2025. This research aims to mitigate the impact of stock market dynamics, a significant challenge for investor decision-making. The Long Short-Term Memory (LSTM) method was employed to forecast stock prices using four variables: opening, highest, lowest, and closing prices. The LSTM architecture was chosen because its gated memory cells can effectively capture long-term dependencies and nonlinear patterns in financial time series, thereby aligning with the research objective of minimizing forecasting error under volatile market conditions. Evaluation results using the Mean Absolute Percentage Error (MAPE) showed prediction errors below 2.5%, indicating relatively low forecasting error. Root Mean Squared Error (RMSE) values varied depending on stock price volatility. Companies exhibiting higher stock prices, such as Indo Tambangraya Megah Tbk (ITMG), demonstrate larger RMSE values. For opening prices, predictive accuracy was notably strong, with MAPE values consistently below 1.26%. This suggests that opening prices, influenced by pre-market sentiment and historical data, are more stable and easier to predict compared to other price variables.

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1. INTRODUCTION

The stock market plays a strategic role in a country's economy, serving as a key indicator of economic health and investment attractiveness [1]. The LQ45 index comprises the 45 largest and most liquid stocks on the Indonesia Stock Exchange (IDX). Changes in LQ45 stock prices can impact the national economy through various mechanisms, including influencing both domestic and foreign investors' decisions to invest in Indonesia. The inflow of foreign investors is expected to enhance capital inflows into the country.

The highly volatile dynamics of the stock market pose significant challenges for investors in making timely investment decisions [2]. Investors require robust tools, techniques, and decision-making analyses. By employing stock price prediction algorithms, investors can obtain more accurate information on stock price movements, thereby facilitating more informed investment decisions. Technical indicators can also be used to identify patterns and trends in stock prices based on historical data, such as closing prices, trading volume, and moving averages [3].

In Indonesia, the dynamics of stock prices, especially those included in the LQ45 index, are increasingly becoming a concern, along with the increasing participation of retail investors and the influence of external factors such as global interest rate policies, geopolitics, and post-pandemic economic uncertainty. Therefore, an effective strategy for predicting stock prices is becoming an increasingly urgent necessity to support informed, data-driven investment decision-making. This need for robust predictive strategies has led to the exploration of advanced analytical techniques, including machine learning and artificial intelligence, which can analyze vast amounts of data to identify trends and patterns. As these technologies evolve, they hold the potential to significantly enhance the accuracy of stock price forecasts, ultimately benefiting both individual investors and the broader market [4].

Combining technical indicators with market sentiment analysis can provide deeper insights into understanding the complex dynamics of the stock market. Several previous studies [5]-[8] have developed stock prediction algorithms using technical indicators and sentiment analysis. The primary challenge in analyzing market sentiment with technical indicators lies in the large volume of data and the nonlinear relationships that are difficult to capture using traditional methods. Technology-based approaches, such as deep learning, offer a promising solution with their ability to process vast amounts of data, recognize intricate patterns, and produce more accurate predictions [9].

The energy and mining sectors have significant contributions to national exports and are highly sensitive to global commodity price fluctuations, while the banking sector is the backbone of the national financial system. Both sectors are strategic and have a major influence on the LQ45 index as a whole [10]. While technical indicators are able to capture historical patterns of price movements, this approach tends to ignore psychological factors and market expectations reflected in public opinion and financial news. Therefore, combining market sentiment analysis provides a more comprehensive picture, encompassing both technical and emotional aspects of market participants [11].

Long Short-Term Memory (LSTM) is widely employed in various applications such as time series forecasting, sentiment analysis, language translation, and speech recognition [12], owing to its ability to capture long-term dependencies in data. The primary advantage of LSTM over conventional RNNs is its capacity to learn from complex sequential data without losing crucial information over extended periods. Gupta et al. [1] developed an LSTM model utilizing sentiment analysis and historical stock data for stock price prediction. Hansun and Wahab [13]-[14] applied the LSTM model to forecast stocks listed in the LQ45 index, specifically within the financial sector, while [15] employed the LSTM model to support trading decisions by enhancing market prediction accuracy.

Based on the track record of previous studies, this research will develop a predictive model architecture using LSTM for stocks listed on the LQ45 index from the energy, mining, and banking sectors. The study will construct an LSTM model to forecast stock price trends or movements one month ahead, predicting closing, opening, highest, and lowest prices. Indicator calculations will be performed using the Python library pandas-ta. During the model training process, one-hot encoding is employed to represent company identities as additional features. This approach aims to enable the model to understand and distinguish the unique characteristics of each company analyzed.

2. RESEARCH METHODS

2.1 Data Collection and Study Area

This study selects eight Indonesian stock issuers listed on the LQ45 index, utilizing daily historical stock price data over a ten-year period sourced from Yahoo Finance, as presented in Table 1.

Table 1. Table of Stock Data

No	Name of Stock	Start	End
1	Alamtri Resources Indonesia Tbk (ADRO)	28/ 02/ 2015	28 /02 / 2025
2	Aneka Tambang Tbk (ANTM)	28/ 02/ 2015	28 /02 / 2025
3	Vale Indonesia Tbk (INCO)	28/ 02/ 2015	28 /02 / 2025
4	Indo Tambangraya Megah Tbk (ITMG)	28/ 02/ 2015	28 /02 / 2025
5	Medco Energi Internasional Tbk (MEDC)	28/ 02/ 2015	28 /02 / 2025
6	Perusahaan Gas Negara Tbk (PGAS)	28/ 02/ 2015	28 /02 / 2025
7	Bukit Asam Tbk (PTBA)	28/ 02/ 2015	28 /02 / 2025
8	Bank Tabungan Negara Tbk (BBTN)	28/ 02/ 2015	28 /02 / 2025

This study utilizes four price parameters: Open Price, High Price, Low Price, and Close Price. The technical indicators employed include the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Average True Range (ATR), Bollinger Bands (BB), Williams %R (W%R), Stochastic Oscillator (STOCH), and Rate of Change (ROC). By integrating momentum indicators (RSI, W%R, STOCH, ROC) that detect shifts in buying or selling pressure with trend and volatility measures (MACD, BB, ATR) that reveal trend strength, breakout potential, and risk magnitude, the LSTM model receives a rich, orthogonal feature set. This multifaceted input enables the network to learn complex, nonlinear temporal dependencies more effectively, thereby enhancing the accuracy and stability of multi-step price forecasts.

2.2 Step of Data Analysis

Based on [16], the research begins by defining the problem scope and objectives, followed by the collection of raw, domain-specific data tailored to the task requirements. The gathered data undergoes preprocessing to address missing values and inconsistencies, transforming it into a structured format suitable for sequential modeling. To balance generalizability and computational efficiency, the dataset is partitioned into training (70%), validation (10%), and test (20%) subsets. This partitioning strategy is critical for time-series data, as contiguous splits preserve temporal dependencies and minimize data leakage, ensuring reliable evaluation. Prior to training, normalization techniques such as Min-Max scaling are applied to standardize feature ranges, a step vital for stabilizing gradient updates in LSTM models.

The LSTM architecture is then designed, incorporating layers (e.g., input, LSTM, dense), activation functions, and regularization mechanisms like dropout. The model is trained using the Adam optimizer with a learning rate of 0.001, a configuration chosen for its ability to adaptively adjust learning rates and accelerate convergence in complex, noisy datasets. During training, the model processes the training data to iteratively adjust weights via backpropagation, while the validation set monitors intermediate performance to detect overfitting. If the training and validation loss curves diverge, indicating suboptimal generalization [17]. Once a satisfactory fit is achieved, the model's robustness is rigorously evaluated on the unseen test data using task-specific metrics (e.g., Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE)). Finally, the validated model is deployed to generate predictions on new data, with results contextualized within the original problem framework.

Subsequently, the training data is split into portions for model construction and model evaluation. The LSTM model architecture is established by determining the number of layers, neurons, and initial hyperparameters. When the model performance remains suboptimal, hyperparameter tuning is performed using the validation data. The detailed steps of the procedure in this study can be seen in Fig. 1.

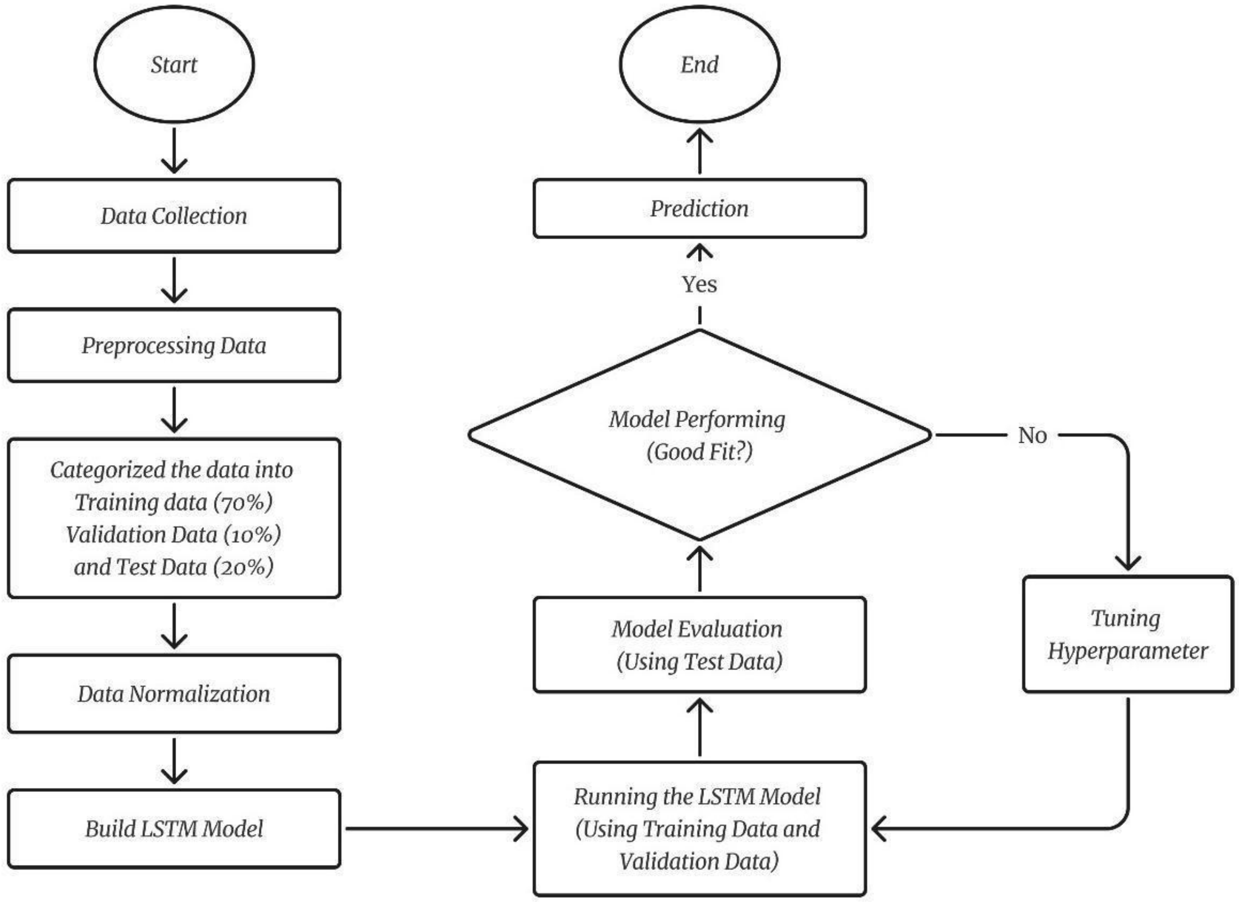


Figure 1. Flowchart

The overall process depicted in the workflow in Fig. 1 shows a systematic approach to building LSTM models for time series data processing. Each stage, from data preprocessing to model performance evaluation, is designed to ensure high prediction accuracy and good generalization to new data. By combining normalization techniques, temporal continuity-preserving data partitioning, and careful hyperparameter tuning, this study provides a robust framework for applying LSTM to sequential data-based predictive problems.

2.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a specialized type of Recurrent Neural Network (RNN) designed to deal with the vanishing gradient problem in sequential data processing [18]. The vanishing gradient issue arises when gradients become extremely small during backpropagation, hindering weight updates in the initial layers and making it challenging for the model to learn long-term patterns or dependencies [19]. LSTM has a unique architecture that includes a cell state and three primary gates, namely the input gate, forget gate, and output gate [20]:

1. Forget gate

$$f_t = \sigma\left(h_{t-1} \times R_f + x_t \times W_f + b_f\right). \tag{1}$$

Where h_{t-1} is the hidden state at time $t-1$, x_t is the input at time t, R_f represents the weights associated with h_{t-1}, W_f represents the weights associated with x_t, and b_f is the bias.

2. Input gate

$$i_t = \sigma(h_{t-1} \times R_i + x_t \times W_i + b_i). \tag{2}$$

Where R_i represents the weights associated with h_{t-1}, W_i represents the weights associated with x_t and b_i is the bias.

3. State Candidate gate

$$g_t = tanh(h_{t-1} \times R_g + x_t \times W_g + b_g). \quad (3)$$

Output gate

$$o_t = \sigma(h_{t-1} \times R_o + x_t \times W_o + b_o). \quad (4)$$

Where R_g and R_o represents the weights associated with h_{t-1}, W_g and W_o represents the weights associated with x_t, and b_g and b_o are the biases.

4. Cell State

$$C_t = f_t \times C_{t-1} + i_t \times g_t, \quad (5)$$

$$y_t = o_t \times tanh(C_t). \quad (6)$$

Where C_{t-1} is cell state at time $t-1$, and y_t is the output of the LSTM cell.

This structure enables the LSTM to selectively store, update, or delete information at each time step, thereby retaining relevant information from long data sequences [21]. The illustration that clearly illustrates the structure of the LSTM cell can be seen in Fig. 2.

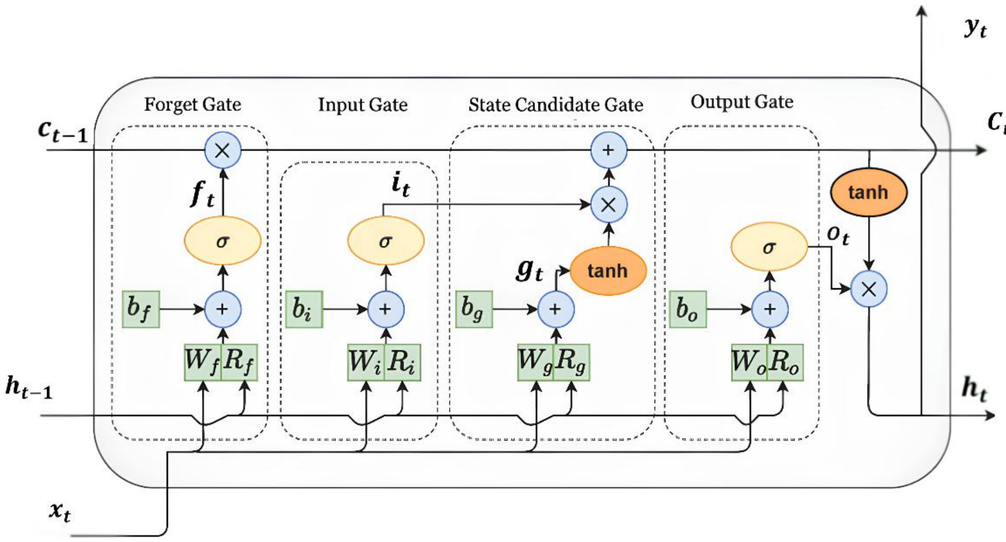


Figure 2. LSTM Cell Structure

The LSTM architecture shown in Fig. 2 provides an effective mechanism to overcome the limitations of conventional RNN models in capturing long-term dependencies in sequential data. Through a combination of inter-integrated gates and internal memory management (cell states), LSTM is able to retain important information while filtering out irrelevant data at each time step. Thus, LSTM is a very suitable choice for various applications that require an understanding of temporal context, such as time series prediction, natural language processing, and sequence-based pattern recognition.

2.4 Loss Function and Evaluation Metrics

The loss function is employed during model training to optimize parameters by minimizing errors, while the evaluation metric is used post-training to assess the model's predictive capabilities [22]. Both are utilized to evaluate the performance of the LSTM model, with different objectives, as follows:

1. Mean Squared Error (MSE) calculates the average of the squared differences between the predicted values and the actual values. Mathematically, this loss function can be defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (7)$$

Where y_i is the actual value at index i and $\hat{y}_i$ is the predicted value at index i.

2. Mean Absolute Error (MAE) measures the average absolute difference between the predicted and actual values. Mathematically, this loss function can be defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

3. Huber Loss is a loss function that combines the characteristics of both MSE and MAE, as follows:

$$L(y,\hat{y}) = \begin{cases} \frac{1}{2}((y_i - \hat{y}_i)^2), & for\ |y_i - \hat{y}_i| \le \delta, \\ \delta\left(|y_i - \hat{y}_i| - \frac{1}{2}\delta\right), & otherwise. \end{cases} \tag{9}$$

Where δ is the predetermined threshold, and Log-Cosh Loss.

$$L(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n} log(cosh(y_i - \hat{y}_i)). \tag{10}$$

3. RESULTS AND DISCUSSION

3.1 LSTM Model Architecture and Training

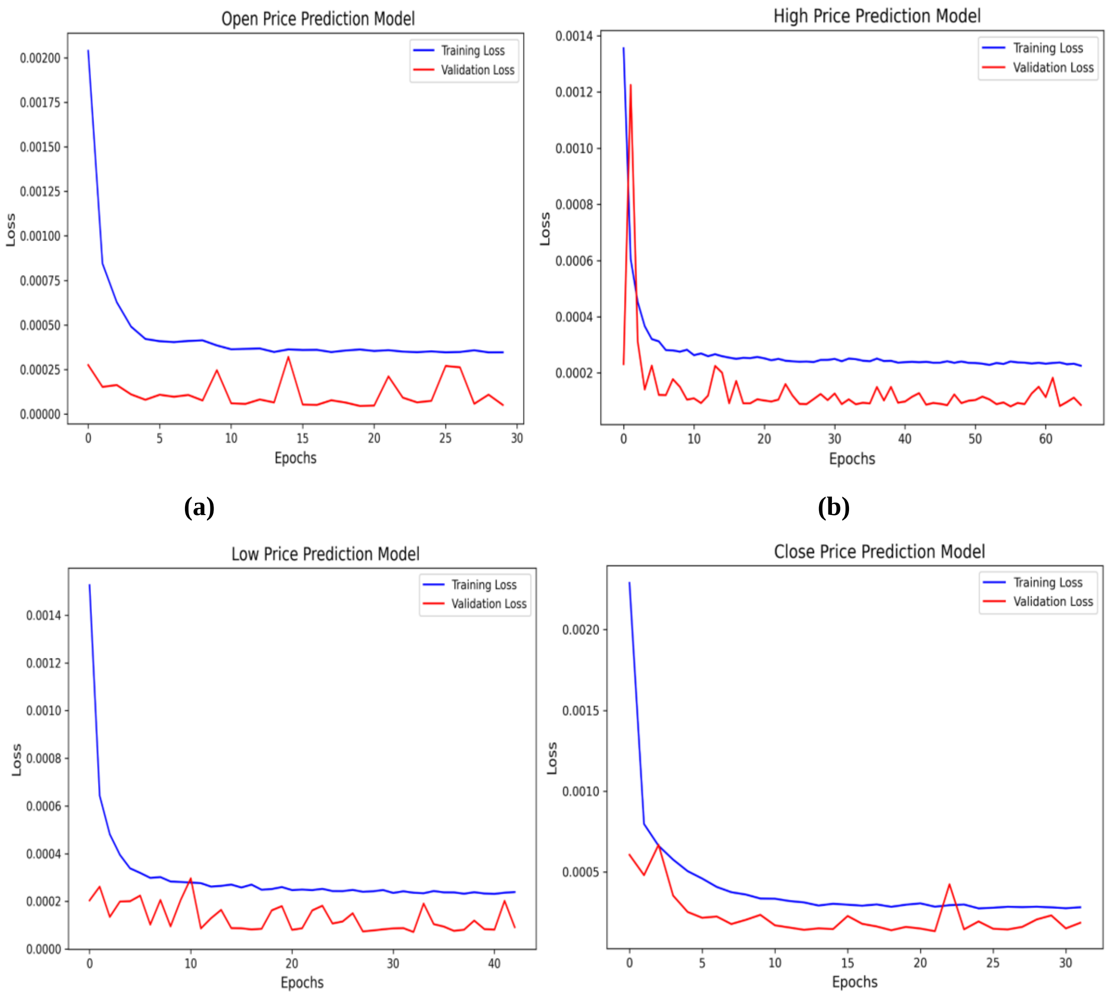
The model was trained with a maximum of 150 epochs and a batch size of 32. The selection of Loss Log-Cosh functions is carried out because it has a low sensitivity to outliers compared to MSE, making it suitable for financial data that has extreme fluctuations [23]. The use of two LSTM layers aims to capture short- and long-term patterns in sequential data. Dropout is used to reduce the risk of overfitting [24]. Due to time constraints in this study, iterations were halted if the validation loss did not decrease over the last 10 epochs, thereby improving efficiency.

Table 2. The Four Architectures of LSTM Models

No	Model	Layer (Type)	Output Shape	Parameter
1	Open Price	Lstm (LSTM)	(None, 14, 100)	50800
		Lstm_1 (LSTM)	(None,50)	30200
		Dropout (Dropout)	(None, 50)	0
		Dense (Dense)	(None, 1)	51
2	High Price	Lstm (LSTM)	(None, 14, 150)	106200
		Lstm_1 (LSTM)	(None,100)	100400
		Dropout (Dropout)	(None, 100)	0
		Dense (Dense)	(None, 1)	101
3	Low Price	Lstm (LSTM)	(None, 14, 120)	70560
		Lstm_1 (LSTM)	(None,80)	64320
		Dropout (Dropout)	(None, 80)	0
		Dense (Dense)	(None, 1)	851
4	Close Price	Lstm (LSTM)	(None, 14, 150)	106200

No	Model	Layer (Type)	Output Shape	Parameter
		Lstm_1 (LSTM)	(None,100)	100400
		Dropout (Dropout)	(None, 100)	0
		Dense (Dense)	(None, 1)	101

The final numbers of epochs for the Open Model, High Model, Low Model, and Close Model were 29, 37, 14, and 50, respectively. The model architecture consists of four layers: the first and second layers are LSTM layers that process the data in the forward and backward directions, respectively; the third layer is a Dropout layer; and the final layer is a Dense layer used to generate the output value, as shown in Table 2. The total number of parameters for the Open Model is 81.051, for the High Model is 206.701, for the Low Model is 134.961, and for the Close Model is 206.701. All models have 0 non-trainable parameters.



(a) (b)

(c) (d)

Figure 3. Training and Validation Loss of LSTM
(a) Open Price Model, (b) High Price Model, (c) Low Price Model, and (d) Close Price Model

The evolution of loss values over training epochs for each prediction model: open, high, low, and close prices are shown in Fig. 3. The model utilizes the Log-Cosh loss function in conjunction with the Adam optimizer to evaluate performance and stability by comparing loss values between the training and validation datasets.

The study's LSTM architecture and setup show good performance in identifying intricate patterns in stock price data while taking model stability and training efficiency into account. It has been demonstrated that the Log-Cosh loss function and dropout approach effectively reduce overfitting and that adaptively choosing the number of epochs preserves computing efficiency. Given the performance demonstrated by each model's loss curves, this strategy may serve as a solid basis for the creation of a more precise and trustworthy stock price prediction system when it is put into practice.

3.2 Evaluation Metrics

The model's performance was evaluated using RMSE and MAPE metrics, with the results presented in Table 3. For the open, high, low, and close prices, MAPE values for all models were below 2.5%, indicating that the employed models exhibit a high level of accuracy with relatively low prediction errors. RMSE values varied depending on the volatility of each company's stock prices, with companies that have higher stock prices tending to exhibit larger RMSE values, as observed in ITMG. The high RMSE in ITMG shares can be caused by the volatility of coal prices that are influenced by global geopolitical conditions and the dynamics of the export market.

Table 3. Metrics for Evaluating Model Predictions

Company Model	Open Price		High Price		Low Price		Close Price	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
ADRO	76.4633	1.04%	96.6040	1.56%	91.9330	1.70%	101.5169	2.04%
ANTM	13.9087	0.59%	41.1614	2.16%	38.0537	1.97%	39.9848	2.04%
INCO	36.60967	0.74%	98.227329	1.65%	79.351225	1.62%	102.161023	1.88%
ITMG	235.031250	0.59%	303.647762	0.85%	364.593783	1.09%	389.289101	1.09%
MEDC	16.753522	0.86%	26.381699	1.43%	25.118543	1.57%	31.183456	1.80%
PGAS	22.689398	1.26%	27.706178	1.39%	27.855775	1.45%	32.053966	1.56%
PTBA	36.732437	0.64%	43.641077	1.00%	58.842328	1.48%	55.522722	1.38%
BBTN	9.655753	0.55%	26.585817	1.74%	29.736249	1.69%	31.276495	1.89%

For open prices, the model demonstrated strong predictive accuracy, with MAPE consistently below 1.26% and RMSE ranging from 9.66 to 235.03. Open prices, influenced by pre-market sentiment and historical data, are more stable and easier to forecast. In contrast, high prices exhibited greater variability, with a significant increase in RMSE for volatile stocks such as ITMG (303.65) and INCO (98.23), although the MAPE remained moderate (0.82–2.16%). The RMSE for low price predictions also indicates relatively stable model performance, with the highest values observed in most stocks (e.g., ITMG at 364.59); however, MAPE stayed below 1.70%. Close prices recorded the highest RMSE values across all categories (e.g., ITMG at 389.29 and INCO at 102.16), which can be attributed to cumulative market noise, reactions to news, and end-of-session liquidity pressures. Nevertheless, the MAPE for close prices remained controlled, below 2.04% (e.g., BBTN at 1.89% and ADRO at 2.04%), indicating that the percentage error is well-contained despite the higher absolute deviation. From the prediction results, ADRO and PTBA shares show a moderate increasing trend, while INCO shows a tendency of sideways.

3.3 One-Month-Ahead Prediction

Based on the evaluation metrics, predictions were obtained for 8 issuers over 22 trading days, using the most recent stock data as of February 28, 2025, in a candlestick chart as shown in Fig. 4. The stock price prediction using a candlestick chart incorporates all essential price points, including opening, high, low, and closing prices. This candlestick chart can be utilized by investors to mitigate the impact of stock market dynamics, which is a significant challenge for investor decision-making. With the visualization of stock price predictions in the form of candlestick charts, investors not only get a comprehensive picture of historical and predictive price movements but can also identify technical patterns that are useful for short-term and long-term investment strategies. This prediction model, when combined with fundamental analysis and market sentiment, can be a reliable tool in making more informed investment decisions and responding to the rapidly changing dynamics of the stock market.

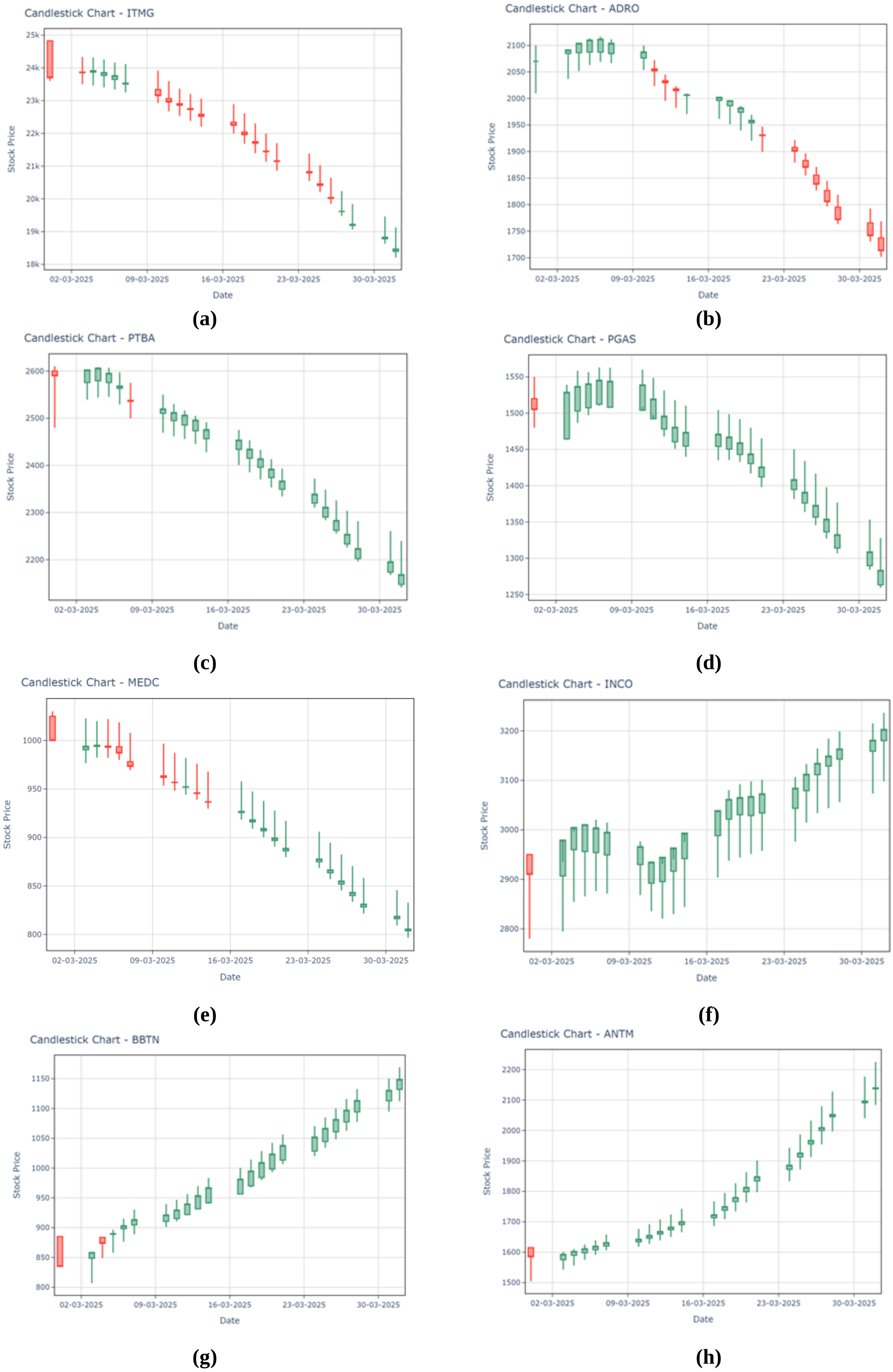


Figure 4. Predicted LQ45 Stock Results in Candlestick Chart
(a) ITMG, (b) ADRO, (c) PTBA, (d) PGAS, (e) MEDC, (f) INCO, (g) BBTN, and (h) ANTM

During the period from March 3, 2025, to April 10, 2025, our LSTM-based candlestick prediction model achieved its highest accuracy on ITMG, ADRO, and PTBA, successfully capturing the same downtrend patterns observed in the actual price series. The next-best performance was observed on PGAS:

from March 3 through March 19, 2025, the model's predictions closely matched the real prices, but after March 19, the model erroneously forecasted a breach below the established support level that held throughout the March 3-April 10 window.

For MEDC, the model consistently predicted a down-trend over the entire month, whereas the actual price action remained sideways. In the cases of INCO and BBTN, the model projected an uptrend, but both stocks in reality exhibited a downtrend during the forecast horizon. Finally, for BBTN, the model again forecasted an uptrend, while the actual price movement was sideways throughout the prediction period.

4. CONCLUSION

This study demonstrates the value of issuer identification representation as an extra feature and the efficacy of the multi-target LSTM strategy in forecasting OHLC prices for the key sector on LQ45. The developed LSTM model demonstrates varied performance in predicting stock prices. For some issuers, such as BBTN with a MAPE of 0.789% for the open price, the model achieves excellent accuracy (MAPE <1%), exceeding the 80% target. Although all MAPE values remain below the 20% threshold, the relatively higher error margins observed in some low-price forecasts underscore opportunities for further model optimization in those cases.

The model exhibits instability for certain issuers and price parameters, particularly for the low and close prices, with a notably high RMSE of 421.72 observed for INCO's close price. This indicates that the model is less robust in handling extreme fluctuations or complex data patterns in specific stocks. Early stopping between 26 and 35 epochs suggests that the model converges relatively quickly; however, further testing is necessary to determine whether increasing the number of epochs or adjusting the learning rate could enhance accuracy. Additionally, while the combination of seven technical indicators and historical data has the potential to provide comprehensive insights, further analysis is needed to ensure that there is no redundancy or noise among these features. In the future, this research can be expanded with the addition of macroeconomic variables (such as exchange rates and interest rates) and the integration of news-based sentiment analysis or social media.

Author Contributions

Marlina Setia Sinaga: Conceptualization, Funding Acquisition, Methodology, Project Administration. Said Iskandar: Formal Analysis, Software, Writing – Original Draft. Sudianto Manullang: Data Curation, Software. Arnita: Review, Software. Faridawaty Marpaung: Investigation, Visualization. Fatizanolo Buulolo: Writing and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare that no conflicts of interest exist in this study.

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