Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 2, Desember 2025
e-ISSN 2685-998X
DOI 10.30865/json.v7i2.8925
Hal: 239−248

LQ45 Index Stock Market Prediction: A Deep Learning Approach using LSTM with Bayesian Optimization

Putu Devi Novayanti[1*], Padma Nyoman Crisnapati[1], Dian Pramana[2]

[1] Computer System,Faculty of Informatics and Computer, ITB STIKOM Bali, Denpasar, Indonesia
[2] Infromation System, Faculty of Informatics and Computer, ITB STIKOM Bali, Denpasar, Indonesia
Email: [1,*]devinovayanti@stikom-bali.ac.id, [2]crisnapati@@stikom-bali.ac.id, [3]dian@@stikom-bali.ac.id
Correspondence Author Email: devinovayanti@stikom-bali.ac.id*
Submitted: **23/07/2025**; Accepted: **12/09/2025**; Published: **31/12/2025**

Abstract− This study investigates the application of Long Short-Term Memory (LSTM) models with Bayesian Optimization for predicting stock price movements in the LQ45 Index, a collection of the 45 most liquid stocks on the Indonesia Stock Exchange. The primary objective is to enhance prediction accuracy by addressing the challenges of volatile stock markets and inefficient hyperparameter tuning. Historical data, including daily closing prices from January 2020 to October 2024, was processed using Min-Max Scaling and transformed into time-series input features with a 60-time-step window. Bayesian Optimization was employed to fine-tune key hyperparameters such as LSTM units, dropout rate, and learning rate, optimizing the model's performance. The results revealed that the LSTM model accurately captured trends for stocks with stable price patterns, such as ACES, ASII, and MTEL, achieving low Mean Absolute Percentage Error (MAPE) and Root Mean Square Percentage Error (RMSPE). However, stocks with high volatility, like AMMN and ITMG, exhibited higher prediction errors, indicating limitations in modeling complex patterns. The study highlights that while LSTM with Bayesian Optimization is highly effective for stable stocks, additional preprocessing and advanced modeling techniques are required for volatile stocks. This research demonstrates the potential of machine learning in supporting stock market decision-making, contributing to the development of more robust and efficient financial prediction tools for investors navigating dynamic markets.

Keywords: Long Short-Term Memory (LSTM); Bayesian Optimizatio; Stock Price Prediction; Machine Learning; Financial Technology

1. INTRODUCTION

The development of machine learning and deep learning has significantly impacted various fields, including finance. Traditional models like K-Nearest Neighbors (KNN) are commonly used for simple classification and regression tasks [1]. However, more advanced models like Long Short-Term Memory (LSTM), a subset of Recurrent Neural Networks (RNN) in deep learning, excel in analyzing sequential data, such as stock prices [2]. LSTM's ability to retain long-term information makes it suitable for predicting complex stock price movements [3]. Additionally, the use of hyperparameter tuning with Bayesian Optimization further enhances model performance, enabling more accurate predictions with efficient optimization, which is crucial for understanding the high volatility of stock markets [4].

Predicting stock movements in the LQ45 index is of high strategic value for investors, especially in highly volatile markets [5]. High volatility often leads to sharp price fluctuations, making stock price prediction particularly challenging [6]. This situation necessitates more effective approaches to assist investors in making informed and strategic decisions [7]. Furthermore, an initial survey using search engines with the keyword "LQ45 stock price recommendation" yielded tens of thousands of results, indicating strong investor interest in stock analysis and prediction. This also underscores the need for well-considered decision-making in investments, including through technology-driven stock prediction applications [8].

The Long Short-Term Memory (LSTM) method is one of the most advanced deep learning techniques proven effective for handling time-series data, including stock prices [9], [10], [11]. LSTM is designed to overcome the vanishing gradient problem commonly found in traditional neural networks [12]. With its ability to store long-term information and identify complex patterns in data, LSTM offers more accurate predictions for stock price movements [13]. While widely adopted in various studies for time-series forecasting, optimizing LSTM's performance remains a challenge, particularly in selecting the right hyperparameters [14], [15]. Previous studies often relied on traditional methods like Grid Search and Random Search for hyperparameter tuning. For instance, [16] explored high-frequency financial time series forecasting using an LSTM model combined with a Sub-step Grid Search (SGS) technique, demonstrating the model's high efficiency and accuracy for datasets with clear trends. [17] investigated hyperparameter optimization for Deep Neural Networks (DNNs) through a twofold Genetic Algorithm (GA) approach. The results showed that the GA-based method effectively enhances the DNN process by optimizing hyperparameters and selecting relevant data subsets. Similarly, [18] assessed the impact of hyperparameter tuning on stock price prediction models, including Support Vector Regression (SVR), Kernel Ridge Regression (KRR), Decision Tree, and K-Nearest Neighbor (KNN). They found that tuning hyperparameters significantly boosts the performance of these models, with SVR benefiting the most. Finally, [19] compared Bitcoin price prediction models, specifically GRU (Gated Recurrent Unit), RNN (Recurrent Neural Network), and LSTM, using Grid Search and Random Search for hyperparameter optimization. Their findings

Jurnal Sistem Komputer dan Informatika (JSON) Hal: 239−248
Volume 7, Nomor 2, Desember 2025
e-ISSN 2685-998X
DOI 10.30865/json.v7i2.8925

underscored the effectiveness of these approaches in forecasting Bitcoin prices. Among the insights presented, some of these methods have limitations due to their inefficiency in exploring large hyperparameter spaces.

Hyperparameter tuning significantly influences the performance of LSTM models [20], [21], [22], [23]. The tuning process is time-consuming and requires multiple iterations. Suboptimal hyperparameter combinations can result in low model accuracy, which is detrimental for investors relying on such predictions [24]. To address this, this study adopts Bayesian Optimization as a method for hyperparameter tuning. This approach provides a systematic and efficient way to find the best hyperparameter combinations, significantly enhancing the model's performance [25], [26]. Using Bayesian Optimization, the hyperparameter search space is explored more efficiently, allowing faster tuning processes and significantly improved prediction accuracy [27]. This study aims to optimize LSTM models for predicting LQ45 stock movements with Bayesian Optimization. The findings are expected to contribute significantly to helping investors manage risks and maximize profits in a volatile market.

This research offers several novelties that make it unique and relevant to stock prediction and financial technology. One primary novelty is the use of Bayesian Optimization for hyperparameter tuning in LSTM models. This approach, though less commonly applied in stock prediction, has been proven more efficient than traditional methods like Grid Search or Random Search. Bayesian Optimization directs the hyperparameter search to promising areas based on prior evaluations, reducing computational time and increasing the likelihood of finding optimal hyperparameter combinations. Additionally, this study provides specific contributions to local capital market analysis through its application to the LQ45 index. Comprising the 45 most liquid stocks on the Indonesia Stock Exchange, the LQ45 index holds strategic value for investors in a volatile market [28]. Previous studies rarely focused on LQ45 stock predictions using LSTM models optimized with Bayesian Optimization. Therefore, this research not only offers an advanced approach but also delivers relevant insights for the Indonesian capital market, which differs significantly from other markets.

Key findings reveal that the model's performance varies based on stock characteristics. The model performed exceptionally well on stocks with stable price patterns and low volatility, such as ACES, ASII, BBTN, and CPIN, achieving low error rates across Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Percentage Error (RMSPE). Conversely, stocks with high volatility or complex patterns, such as AMMN and ITMG, exhibited significant errors, indicating challenges in capturing unstable temporal patterns. The model development process involved systematic steps, starting with historical stock data collection using Yahoo Finance, data preprocessing through Min-Max Scaler normalization, and input-output dataset creation using a sliding window approach. The dataset was split into 80% training and 20% testing data. The LSTM model consisted of two LSTM layers with dropout layers to prevent overfitting. Bayesian Optimization was applied for hyperparameter tuning, and the best model was trained using 50 epochs and a batch size of 32.

The results demonstrate that the LSTM model with Bayesian Optimization provides accurate trend predictions for certain LQ45 stocks. However, the model faces limitations with highly volatile stocks, which require advanced data preprocessing or alternative models. Future discussions recommend evaluating additional features or ensemble techniques to improve accuracy for less stable stocks. This study aims to contribute to the development of decision-support systems in stock investments using machine learning technology. By integrating deep learning and probabilistic optimization, this research offers an innovative solution to help investors manage risks and maximize returns in the capital market. The proposed solution not only enhances stock movement prediction accuracy but also establishes a relevant technological foundation for developing future FinTech applications. Thus, this research is not only academically significant but also has practical implications for the investment world.

2. RESEARCH METHODOLOGY

2.1 Research Stages

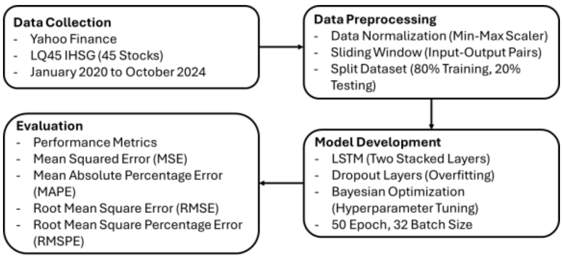


Figure 1. Stages of LSTM Model Development for LQ45 Stock Prediction

Figure 1 illustrates the stages of developing a Long Short-Term Memory (LSTM) model for predicting stock prices in the LQ45 index. The process includes four main steps: data collection, data preprocessing, model development, and evaluation, carried out systematically to ensure prediction accuracy.

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 2, Desember 2025
e-ISSN 2685-998X
DOI 10.30865/json.v7i2.8925

2.1 Data Collection

This study utilizes historical data consisting of daily closing prices from 45 stocks included in the LQ45 Index. The LQ45 Index represents the 45 most liquid stocks on the Indonesia Stock Exchange (IDX) and is evaluated every six months. The dataset includes various elements such as opening price, closing price, highest price, lowest price, and trading volume. Data was collected from January 2020 to October 2024 to encompass broader market fluctuations, resulting in over 1,000 data points per stock.

2.2 Data Preprocessing

After data collection, preprocessing was performed to prepare the data for use in the Long Short-Term Memory (LSTM) model [29]. The first step was data cleaning, which involved removing incomplete or missing data and handling missing values using techniques such as interpolation or forward-fill. The data was then normalized using the Min-Max Scaling method to ensure that all values fall within the range of 0 to 1, as LSTM models are sensitive to data scale. Normalization was performed using the Equation 1, where x is the original value, x_{min} is the minimum observed value, and x_{max} is the maximum observed value. The dataset was then split into 80% training data and 20% testing data to ensure objective evaluation of the model on unseen data during training [30].

2.3 Model Development

The LSTM model was used in this study to capture long-term patterns in time-series data. The model was designed with several key layers: an input layer to receive historical stock data, an LSTM layer to capture temporal relationships in the data, and a dense layer to generate the next day's stock price prediction. The model predicts the next day's closing price based on historical data from the previous 60 days. The forward pass in the LSTM layer is formulated as Equation 2, where h_t s the output of the LSTM cell at time *t*, W_h , U_h, and b_h are the weights and bias for the input and hidden state, x_t is the input at time t, σ is the activation function (typically sigmoid or tanh) [31].

To optimize the model, Bayesian Optimization was used for hyperparameter tuning. This method identifies the optimal combination of hyperparameters, such as the number of neurons in the LSTM layer, learning rate, batch size, and the number of epochs. Bayesian Optimization builds a probabilistic model based on previous evaluations and guides the search toward hyperparameter combinations with the highest potential. The formula for Bayesian Optimization is expressed as Equation 3, where $f(\theta)$ is the objective function measuring the model's performance based on the hyperparameter set θ [32].

2.4 Evaluation

Once the model was trained using optimized hyperparameters, evaluation was conducted using metrics such as Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). The formulas for these metrics are Equation 4 and 5, where y_i represents the actual value, and $\hat{y}_i$ represents the predicted value. The evaluation results were analyzed to determine the extent to which Bayesian Optimization improved prediction accuracy. A comparison graph between actual stock prices and predictions was presented to visualize the model's performance [33].

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

$$h_t = \sigma(W_h x_t + U_h h_{t-1} + b_h) \quad (2)$$

$$Next\ parameter\ set = arg \min_{\theta} E[f(\theta)] \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (4)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (5)$$

3. RESULT AND DISCUSSION

Table 1 describes the key parameters used in this study. The Ticker represents the stock symbols within the LQ45 Index downloaded for historical data, as the selection of LQ45 stocks is relevant to the Indonesian stock market. The Start and End parameters specify the time range for downloading historical data, which is essential to capture trend patterns over several years. The Time Step is used to create LSTM input features, where 60 time

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 2, Desember 2025
e-ISSN 2685-998X
DOI 10.30865/json.v7i2.8925

steps (3 months of daily data) are considered sufficient for stock analysis as they help capture temporal relationships.

The Split Ratio parameter determines the division of data into training and testing datasets, with an 80:20 ratio as the standard to ensure the model has enough data for learning and testing. The range of LSTM Units tested during Bayesian optimization affects the model's capacity to capture patterns, while the Dropout Rate range is used to prevent overfitting by randomly ignoring units during training. The Learning Rate, set within a logarithmic range, influences the model's training speed and stability. For efficiency, the number of Max Trials during Bayesian tuning is limited to 10 experiments.

The number of Epochs varies between the tuning process (10 epochs) and final training (50 epochs) to ensure the model converges optimally. A Batch Size of 32 is used during training as it balances efficiency and training stability. The Loss Function employs Mean Squared Error (MSE) as it is suitable for regression tasks such as stock price prediction. The Adam Optimizer is chosen for its efficiency in optimizing neural network model parameters. Finally, a Validation Split of 20% is used to monitor the model's performance on unseen data during training, helping to detect overfitting. All these parameters are designed to ensure flexibility and accuracy in building and optimizing the LSTM model.

Table 1. Parameters and Descriptions for LSTM Model Optimization

Parameter	Value	Description
Ticker	BBRI.JK … UNTR.JK	Stock ticker symbol for downloading data (45 LQ45 IHSG Stocks).
Start	2020-01-01	Start date for downloading historical data.
End	2024-10-01	End date for downloading historical data.
Time Step	60	Number of time steps for creating LSTM input features.
Split Ratio	0.8	Ratio for splitting training and testing datasets.
Units	[50, 100, 150, 200]	Range of LSTM units for Bayesian Optimization.
Dropout Rate	[0.1, 0.2, 0.3, 0.4, 0.5]	Range of dropout rates for Bayesian Optimization.
Learning Rate	[1e-4, 1e-2]	Range of learning rates for Bayesian Optimization (log-scaled).
Max Trials	10	Maximum number of trials for Bayesian Optimization.
Epochs	10 (tuner), 50 (best model)	Number of epochs for training during hyperparameter tuning and final model training.
Batch Size	32	Batch size used for training.
Loss	Mean Squared Error	Loss function for the LSTM model.
Optimizer	Adam	Optimizer used for compiling the model.
Validation Split	0.2	Ratio of data used for validation during training.

After the explanation of the parameters and descriptions in the previous table, the implementation of the LSTM model was conducted using the following pseudocode, executed in Google Colab Python. This pseudocode outlines a comprehensive process from data collection to the evaluation and visualization of the stock prediction model results. It ensures that the steps for building the LSTM model are carried out systematically using Python and various supporting libraries, including numpy (1.26.4), pandas (2.2.2), yfinance (0.2.50), tensorflow (2.17.1), kerastuner (1.4.7), and matplotlib (3.8.0).

The first step is data collection, where historical stock data is downloaded using the yfinance library with specified stock symbols (e.g., "UNVR.JK") and time ranges. Only the closing prices are extracted from the dataset for modeling purposes. Next, data preprocessing is performed by applying MinMaxScaler to normalize the closing prices to a range of 0 to 1. A function create_dataset is defined to split the dataset into features (X) and targets (Y) based on the specified time step, which is set to 60 steps.

The processed data is then divided into training (80%) and testing (20%) datasets. This data is reshaped into a three-dimensional format [samples,time steps,features], which aligns with the input requirements of the LSTM model. The next step is LSTM model development, where a build_model function is designed to create a Sequential model with LSTM, dropout, and dense layers. This function incorporates hyperparameter (hp) values, such as the number of LSTM units and dropout rates, which are optimized using Bayesian Optimization through kerastuner. The tuning process identifies the best model configuration based on the val_loss metric.

Once the tuning process is complete, the best model is trained on the training data for 50 epochs using a batch size of 32, and its performance is validated using the testing data. During the evaluation stage, the model generates stock price predictions, which are then reverted to their original scale. The evaluation metrics, including Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Root Mean Square Percentage Error (RMSPE), are computed to compare the actual and predicted values.

The final step is visualization, where graphs comparing the actual and predicted stock prices are created using matplotlib. These graphs are labeled and include legends to provide clear interpretations of the model's performance. Overall, this pseudocode reflects a structured approach to building and optimizing the LSTM model for accurately predicting stock price movements.

In general, the performance of the LSTM model shows variation in its ability to predict trends and absolute prices for stocks in the LQ45 index, as presented in Table 2. Stocks such as AMRT, ASII, and MTEL demonstrate exceptional performance in trend prediction, with very low MAPE and RMSPE values, indicating high accuracy in capturing price patterns. However, certain stocks, such as AMMN and ITMG, face challenges in absolute predictions, reflected in their very high MSE and RMSE values, likely caused by high volatility or noisy data.

Stocks with strong trend predictions but weaker absolute accuracy, such as BBCA, BMRI, and UNTR, suggest that the model can identify price movement patterns effectively, even if it struggles at the granular price level. Conversely, stocks like BUKA and GOTO excel in absolute accuracy, as shown by their very low MSE and RMSE values, but their relatively high MAPE and RMSPE indicate difficulty in following trend patterns.

Certain stocks, such as ESSA, KLBF, and UNVR, exhibit reliable performance with a balance between trend and absolute accuracy, making them good examples of the model's ability to handle relatively stable stock data. On the other hand, stocks such as INKP, INTP, and ITMG exhibit weaknesses in both aspects, highlighting the need for improved preprocessing or hyperparameter tuning to enhance the model's performance.

Stocks like MBMA, MTEL, and PGAS stand out as examples of the model's success in producing highly accurate predictions for both trends and absolute prices. Conversely, stocks like AMMN and ITMG display significant weaknesses, with high error rates across all metrics, indicating challenges in modeling high volatility or unstable data patterns.

Overall, the LSTM model's performance varies depending on the characteristics of each stock. Strong trends can be identified in most stocks, but absolute price accuracy is often disrupted by data volatility. Based on this analysis, Table III presents a list of LQ45 stocks recommended as support for decision-making in stock purchases.

Table 2. LQ45 Stock Recommendations Based on LSTM Model Performance with Bayesian Optimization

Recommended	Not Recommended
ACES, AMRT, ANTM, ASII, BBTN, CPIN, ESSA, EXCL, INDF, ISAT, KLBF, MBMA, MTEL, PGAS, PGEO, SIDO, TLKM, UNVR	BBRI, ADMR, ADRO, AKRA, AMMN, ARTO, BBCA, BBNI, BMRI, BRIS, BRPT, BUKA, GOTO, ICBP, INCO, INKP, INTP, ITMG, JSMR, MAPI, MDKA, MEDC, PTBA, SMGR, SMRA, TOWR, UNTR

In Figure 2, for the recommended stocks (Figure 2 (a)), the LSTM model demonstrates strong performance in predicting stock price movements. The prediction line (red) consistently follows the actual price pattern (blue), both for upward and downward trends. Stocks such as ACES, ASII, BBTN, CPIN, UNVR, and SIDO exhibit a high level of alignment between predictions and actual prices, reflecting the model's ability to capture temporal patterns and price fluctuations with adequate accuracy. This indicates that these stocks have stable data characteristics and trend patterns that the model can effectively learn.

Conversely, the charts for non-recommended stocks (Figure 2 (b)) reveal that the LSTM model struggles to predict price movements accurately. For stocks such as BUKA, TOWR, ITMG, and GOTO, significant discrepancies are observed between predictions and actual prices, especially during large fluctuations or trend changes. The model's predictions often appear overly smooth or deviate from the actual price patterns, as seen in ADMR and AMMN. This indicates that high volatility, unstable patterns, or noise in the data can hinder the model's ability to deliver accurate predictions as shwon in Figure 2.

In general, the recommended stocks exhibit more stable data patterns with price fluctuations that the LSTM model can predict effectively. On the other hand, non-recommended stocks tend to show higher volatility, sharper trend changes, or more complex price patterns. For these stocks, additional methods such as improved data preprocessing, the inclusion of additional features, or alternative models better suited for handling high volatility are required. In conclusion, the LSTM model with Bayesian Optimization is more effective for stocks with stable trend patterns and less fluctuating price characteristics. Stocks with high volatility require more complex modeling strategies to enhance prediction accuracy.

Table 3. Performance Analysis of LSTM Model and Bayesian Optimization for Lq45 Stocks Based on Insights, Strengths, and Weaknesses

\	Insights	Strengths	Weaknesses
BBRI	Moderate performance with decent trend prediction.	MAPE (2.28%) and RMSPE (3.05%) indicate good trend accuracy.	High MSE (23,373.14) and RMSE (152.88) show difficulty in absolute predictions.

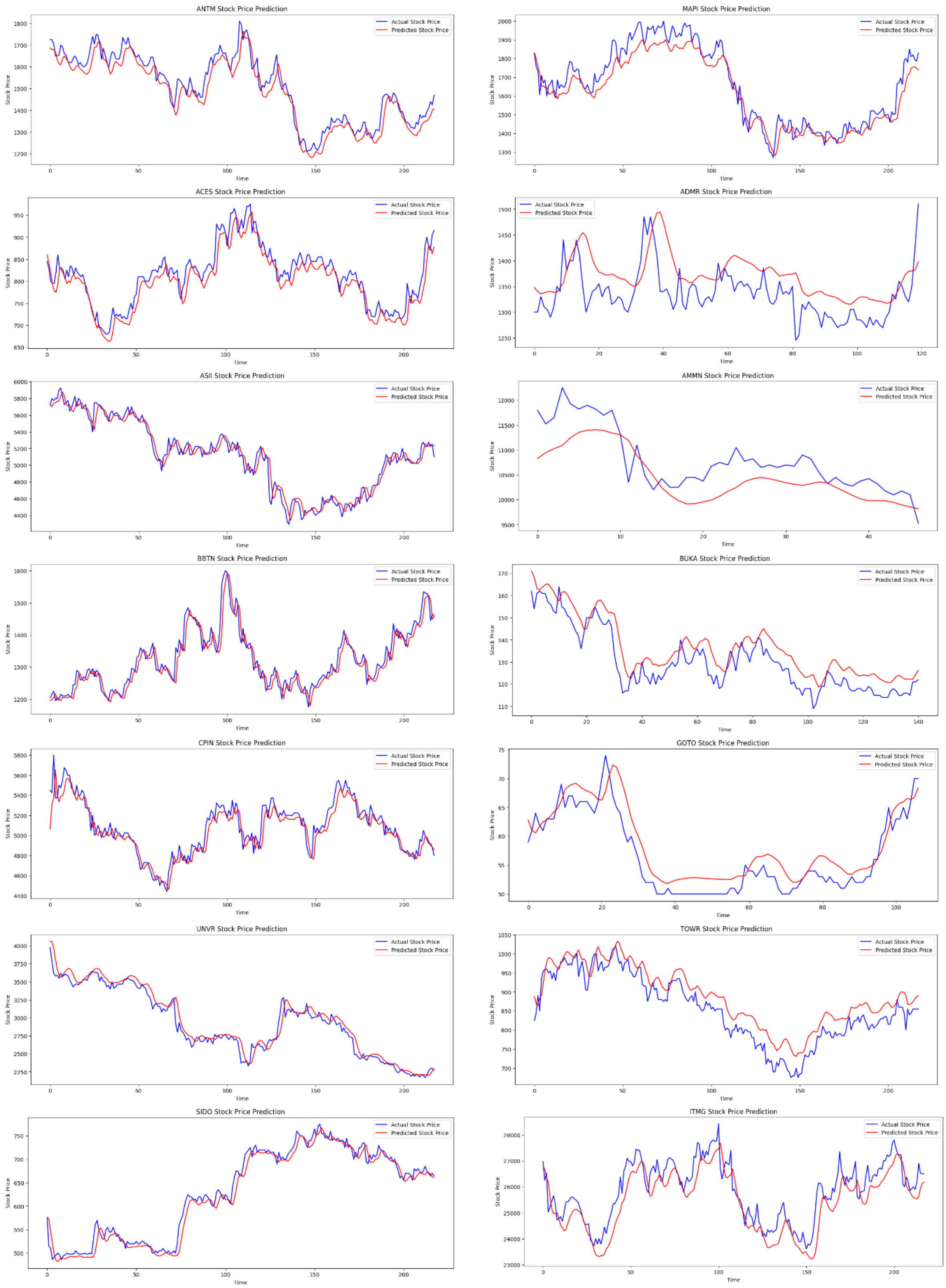
Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 2, Desember 2025
e-ISSN 2685-998X
DOI 10.30865/json.v7i2.8925

\	Insights	Strengths	Weaknesses
ACES	Good accuracy for absolute and trend predictions.	Low MSE (692.46) and RMSE (26.31). MAPE (2.48%) is acceptable.	Slightly higher percentage errors compared to peers with similar MSE.
ADMR	Performs moderately for both trend and absolute predictions.	MAPE (3.32%) is reasonable for stock volatility.	Higher RMSPE (4.04%) and moderate RMSE (53.64).
ADRO	Moderate performance for trend prediction.	MAPE (2.89%) and RMSPE (3.38%) are reasonable.	High MSE (10,423.06) and RMSE (102.09).
AKRA	Good trend prediction but overfitting issues.	MAPE (2.33%) and RMSPE (2.89%) are acceptable.	High val_loss (0.02897) and MSE (2,202.16).
AMMN	Poor performance overall due to high volatility.	No significant strengths as the high MSE (218,625.14), RMSE (467.57), MAPE (3.69%), and RMSPE (4.21%) indicate substantial errors.	Struggles with both trend prediction and absolute accuracy, possibly due to high stock volatility or noise in the data.
AMRT	Excellent trend prediction and reasonable absolute accuracy.	Very low MAPE (1.56%) and RMSPE (2.09%) indicate excellent trend accuracy.	Moderate MSE (3,730.04) and RMSE (61.07) show room for improvement in absolute predictions.
ANTM	Consistent performance across metrics.	Low MAPE (2.57%) and RMSE (48.76).	Moderate MSE (2,377.87).
ARTO	Strong absolute prediction but weaker trend accuracy.	Very low val_loss (6.7998e-05) and good RMSE (127.39).	Higher MAPE (3.44%) and RMSPE (4.72%).
ASII	Excellent trend prediction with low errors.	Very low MAPE (1.35%) and RMSPE (1.83%).	Moderate MSE (8,165.92).
BBCA	Strong trend prediction but struggles with absolute accuracy.	Low MAPE (1.26%) and RMSPE (1.59%).	High MSE (24,098.53).
BBNI	Moderate performance but high absolute errors.	Moderate MAPE (2.90%).	High MSE (31,817.72) and RMSE (178.38).
BBTN	Reliable performance across all metrics.	Low MAPE (1.62%) and RMSPE (2.22%).	Moderate MSE (934.17).
BMRI	Strong trend prediction but moderate absolute accuracy.	Low MAPE (1.58%) and RMSPE (2.11%).	High MSE (18,421.24) and RMSE (135.72).
BRIS	Moderate performance with consistent metrics.	MAPE (2.41%) and RMSPE (3.18%).	Errors higher compared to peers with similar volatility.
BRPT	Good absolute accuracy but weaker trend prediction.	Moderate MSE (3,434.91) and RMSE (58.61).	Higher MAPE (3.39%) and RMSPE (4.91%).
BUKA	Excellent absolute prediction but weaker trend accuracy.	Very low MSE (60.36) and RMSE (7.77).	High MAPE (5.34%) and RMSPE (6.16%).
CPIN	Strong trend prediction and reasonable absolute accuracy.	Very low MAPE (1.41%) and RMSPE (1.93%).	High MSE (10,078.42).
ESSA	Reliable performance across all metrics.	Low MSE (484.05) and RMSE (22.00).	Moderate MAPE (2.55%) and RMSPE (3.26%).
EXCL	Good overall performance.	Low MAPE (1.65%) and RMSPE (2.31%).	Moderate MSE (2,718.48) and RMSE (52.14).
GOTO	Strong absolute prediction with low errors.	Very low MSE (8.74) and RMSE (2.96).	Higher percentage errors: MAPE (4.53%), RMSPE (5.21%).
ICBP	Excellent trend prediction but poor absolute accuracy.	Very low MAPE (1.28%) and RMSPE (1.87%).	High MSE (41,791.53) and RMSE (204.43).
INCO	Moderate trend prediction and weaker absolute accuracy.	Moderate MAPE (2.41%).	High MSE (17,317.80) and RMSE (131.60).

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 2, Desember 2025
e-ISSN 2685-998X
DOI 10.30865/json.v7i2.8925
Hal: 239−248

\	Insights	Strengths	Weaknesses
INDF	Excellent trend prediction with consistent accuracy.	Very low MAPE (0.98%) and RMSPE (1.33%).	High MSE (7,045.74) and RMSE (83.94).
INKP	Moderate performance but struggles with absolute accuracy.	Low MAPE (2.15%) and RMSPE (2.94%).	High MSE (61,766.53) and RMSE (248.53).
INTP	Weaker performance with high errors across metrics.	MAPE (1.72%) and RMSPE (2.39%) indicate reasonable trend prediction capability.	High MSE (36,996.74) and RMSE (192.35) reflect significant errors in absolute price predictions.
ISAT	Reliable performance with low trend errors.	Low MAPE (1.67%) and RMSPE (2.16%).	Moderate MSE (3,347.48).
ITMG	Poor performance overall with high absolute errors.	MAPE (2.03%) and RMSPE (2.45%) indicate acceptable trend prediction for this stock.	Very high MSE (407,105.92) and RMSE (638.05) suggest the model fails to capture accurate price levels, possibly due to high volatility or noise in the data.
JSMR	Moderate performance with consistent trend accuracy.	Low MAPE (1.65%) and RMSPE (2.06%).	High MSE (10,761.44) and RMSE (103.74).
KLBF	Reliable overall performance.	Low MAPE (1.59%) and RMSPE (2.06%).	Moderate MSE (1,028.03).
MAPI	Moderate performance with slightly higher errors.	Moderate MSE (4,442.46) and RMSE (66.65).	High MAPE (3.14%) and RMSPE (3.84%).
MBMA	Excellent trend prediction and absolute accuracy.	Low MSE (197.18), RMSE (14.04), and reasonable MAPE (1.94%) and RMSPE (2.41%).	Slightly higher RMSPE (2.41%).
MDKA	Struggles with trend accuracy despite moderate absolute metrics.	Moderate MSE (10,689.49).	High MAPE (3.20%) and RMSPE (4.20%).
MEDC	Struggles across all metrics.	MSE (3,291.88) and RMSE (57.37).	High MAPE (3.77%) and RMSPE (4.34%).
MTEL	Excellent trend prediction and strong absolute accuracy.	Extremely low MSE (122.46), RMSE (11.07), MAPE (1.19%), and RMSPE (1.72%).	Slightly higher val_loss (0.00285).
PGAS	Good performance overall.	Low MAPE (1.75%) and RMSPE (2.48%).	Moderate MSE (1,183.26).
PGEO	Reliable predictions across all metrics.	Low MAPE (2.09%) and RMSE (31.29).	Moderate MSE (979.03).
PTBA	Moderate trend prediction and weaker absolute accuracy.	MAPE (2.88%) and RMSPE (3.33%).	High MSE (8,125.69).
SIDO	Strong trend prediction and moderate absolute accuracy.	Low MAPE (1.86%) and RMSE (16.09).	Moderate MSE (258.75).
SMGR	Consistent trend prediction with moderate accuracy.	MAPE (2.36%) and RMSPE (3.13%).	High MSE (19,247.31).
SMRA	Reliable overall predictions.	Moderate MSE (495.74) and RMSE (22.27).	Higher MAPE (3.47%) and RMSPE (4.11%).
TLKM	Strong trend prediction but moderate absolute accuracy.	Low MAPE (1.47%) and RMSPE (2.09%).	Moderate MSE (4,456.37) and RMSE (66.76).
TOWR	Weaker performance with high percentage errors.	Moderate MSE (1,643.24) and RMSE (40.54).	High MAPE (4.37%) and RMSPE (5.07%).
UNTR	Excellent trend prediction but poor absolute accuracy.	Very low MAPE (1.23%) and RMSPE (1.70%).	Very high MSE (163,359.95).
UNVR	Reliable performance across all metrics.	Low MAPE (2.40%) and RMSPE (3.34%).	Moderate MSE (9,598.69).

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 2, Desember 2025
e-ISSN 2685-998X
DOI 10.30865/json.v7i2.8925



(a) (b)

Figure 2. Comparative Data Visualization of LSTM Model Performance for (a) Recommended and (b) Non-Recommended Stocks

4. CONCLUSION

This study demonstrates the capability of Long Short-Term Memory (LSTM) models combined with Bayesian Optimization in predicting stock movements within the LQ45 Index. The results indicate that the performance of the LSTM model varies significantly depending on the characteristics of individual stocks. Stocks with stable price patterns and lower volatility, such as ACES, ASII, and MTEL, exhibited excellent trend prediction accuracy, highlighting the model's ability to capture temporal patterns effectively. In contrast, stocks with high volatility or complex patterns, such as AMMN and ITMG, showed significant prediction errors, emphasizing the challenges in modeling unstable temporal patterns. The integration of Bayesian Optimization proved beneficial for hyperparameter tuning, enabling systematic exploration of the hyperparameter space and improving the model's overall performance. The optimization process significantly enhanced the LSTM model's ability to balance between accurate trend predictions and reliable absolute price estimations for most stocks. However, the study also revealed limitations in handling highly volatile stocks, suggesting the need for further enhancements, such as improved data preprocessing, additional feature engineering, or the application of ensemble models. Recommended stocks, such as ESSA, KLBF, and UNVR, exhibited balanced performance across all evaluation metrics, making them suitable for supporting decision-making in stock investments. Conversely, non-recommended stocks, including ADMR, TOWR, and GOTO, require alternative approaches to achieve meaningful prediction accuracy. In conclusion, the LSTM model with Bayesian Optimization is an effective approach for predicting stock movements in relatively stable and liquid markets, such as those represented by the LQ45 Index. However, for highly volatile or noisy data, more advanced modeling strategies are necessary. This research contributes to the development of decision-support tools for stock market investments, offering a foundation for further exploration in financial technology and machine learning applications.

REFERENCES

[1] R. Hadi, N. Luh, G. Pivin, I. G. Ngurah, and A. Kusuma, “Implementasi Metode Normalisasi dan Seleksi Fitur dalam Optimasi Algoritma K-Nearest Neighbor (KNN) untuk Klasifikasi Data Bank,” vol. 7, no. 5, pp. 1064–1071, 2024.

[2] M. Bansal, A. Goyal, and A. Choudhary, “Stock Market Prediction with High Accuracy using Machine Learning Techniques,” in *Procedia Computer Science*, Elsevier B.V., 2022, pp. 247–265. doi: 10.1016/j.procs.2022.12.028.

[3] Melina, H. Napitupulu, A. Sambas, A. Murniati, and V. Adimurti Kusumaningtyas, “Artificial Neural Network-Based Machine Learning Approach to Stock Market Prediction Model on the Indonesia Stock Exchange During the COVID-19,” *Engineering Letters*, vol. 30, no. 3, pp. 1–14, 2022, [Online]. Available: https://www.researchgate.net/publication/362983602

[4] K. Liu, J. Cheng, and J. Yi, “Copper price forecasted by hybrid neural network with Bayesian Optimization and wavelet transform,” *Resources Policy*, vol. 75, Mar. 2022, doi: 10.1016/j.resourpol.2021.102520.

[5] N. A. Savitri and D. Saepudin, “Deep Learning Implementation for Portfolio Optimization Index Tracking LQ45,” in *2022 1st International Conference on Software Engineering and Information Technology, ICoSEIT 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 12–17. doi: 10.1109/ICoSEIT55604.2022.10029954.

[6] A. Syukur and D. Istiawan, “Prediction of LQ45 Index in Indonesia Stock Exchange: A Comparative Study of Machine Learning Techniques,” *International Journal of Intelligent Engineering and Systems*, vol. 14, no. 1, pp. 453–463, 2020, doi: 10.22266/IJIES2021.0228.42.

[7] F. Alkaraan, M. Elmarzouky, K. Hussainey, and V. G. Venkatesh, “Sustainable strategic investment decision-making practices in UK companies: The influence of governance mechanisms on synergy between industry 4.0 and circular economy,” *Technol Forecast Soc Change*, vol. 187, Feb. 2023, doi: 10.1016/j.techfore.2022.122187.

[8] T. Ignatius Ijomah, O. Gloria Eyieyien, C. Idemudia, and P. Okpeke Paul, “The Impact of ICT Projects on Community Development and Promoting Social Inclusion,” 2024. [Online]. Available: www.ijerd.com

[9] E. Doğan, “LSTM training set analysis and clustering model development for short-term traffic flow prediction,” *Neural Comput Appl*, vol. 33, no. 17, pp. 11175–11188, Sep. 2021, doi: 10.1007/s00521-020-05564-5.

[10] S. Zaheer *et al.*, “A Multi Parameter Forecasting for Stock Time Series Data Using LSTM and Deep Learning Model,” *Mathematics*, vol. 11, no. 3, Feb. 2023, doi: 10.3390/math11030590.

[11] J. Q. Wang, Y. Du, and J. Wang, “LSTM based long-term energy consumption prediction with periodicity,” *Energy*, vol. 197, Apr. 2020, doi: 10.1016/j.energy.2020.117197.

[12] I. E. Livieris, N. Kiriakidou, S. Stavroyiannis, and P. Pintelas, “An Advanced CNN-LSTM Model for Cryptocurrency Forecasting,” *Electronics (Basel)*, vol. 10, no. 287, 2021, doi: 10.3390/electronics.

[13] A. Thakkar and K. Chaudhari, “A comprehensive survey on deep neural networks for stock market: The need, challenges, and future directions,” Sep. 01, 2021, *Elsevier Ltd*. doi: 10.1016/j.eswa.2021.114800.

[14] B. Jiang, H. Gong, H. Qin, and M. Zhu, “Attention-LSTM architecture combined with Bayesian hyperparameter optimization for indoor temperature prediction,” *Build Environ*, vol. 224, Oct. 2022, doi: 10.1016/j.buildenv.2022.109536.

[15] W. Li, W. W. Wing, T. Wang, M. Pelillo, and S. Kwong, “HELP: An LSTM-based approach to hyperparameter exploration in neural network learning,” *Neurocomputing*, vol. 442, pp. 161–172, Jun. 2021, doi: 10.1016/j.neucom.2020.12.133.

[16] S. Luo and C. Tian, “Financial high-frequency time series forecasting based on sub-step grid search long short-term memory network,” *IEEE Access*, vol. 8, pp. 203183–203189, 2020, doi: 10.1109/ACCESS.2020.3037102.

Volume 7, Nomor 2, Desember 2025
e-ISSN 2685-998X
DOI 10.30865/json.v7i2.8925

[17] P. Kumar, S. Batra, and B. Raman, “Deep neural network hyper-parameter tuning through twofold genetic approach,” *Soft comput*, vol. 25, no. 13, pp. 8747–8771, Jul. 2021, doi: 10.1007/s00500-021-05770-w.

[18] K. E. Hoque and H. Aljamaan, “Impact of hyperparameter tuning on machine learning models in stock price forecasting,” *IEEE Access*, vol. 9, pp. 163815–163830, 2021, doi: 10.1109/ACCESS.2021.3134138.

[19] N. Buslim, I. L. Rahmatullah, B. A. Setyawan, and A. Alamsyah, “Comparing Bitcoin’s Prediction Model Using GRU, RNN, and LSTM by Hyperparameter Optimization Grid Search and Random Search,” in *2021 9th International Conference on Cyber and IT Service Management, CITSM 2021*, Institute of Electrical and Electronics Engineers Inc., 2021. doi: 10.1109/CITSM52892.2021.9588947.

[20] st Muhammad Nizar Yoga Pratama, “Multilayer Perceptron and Long Short-Term Memory for Predicting Indonesian Composite Stock Price Index Using Macroeconomic Factors,” in *2019 Fourth International Conference on Informatics and Computing (ICIC) 2019* , 2019, pp. 1–5.

[21] Z. Rustam and P. Kintandani, “Application of Support Vector Regression in Indonesian Stock Price Prediction with Feature Selection Using Particle Swarm Optimisation,” *Modelling and Simulation in Engineering*, vol. 2019, 2019, doi: 10.1155/2019/8962717.

[22] W. Budiharto, “Data science approach to stock prices forecasting in Indonesia during Covid-19 using Long Short-Term Memory (LSTM),” *J Big Data*, vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00430-0.

[23] A. Lawi, H. Mesra, and S. Amir, “Implementation of Long Short-Term Memory and Gated Recurrent Units on grouped time-series data to predict stock prices accurately,” *J Big Data*, vol. 9, no. 1, Dec. 2022, doi: 10.1186/s40537-022-00597-0.

[24] C. Alzaman, “Forecasting and optimization stock predictions: Varying asset profile, time window, and hyperparameter factors,” *Systems and Soft Computing*, vol. 5, Dec. 2023, doi: 10.1016/j.sasc.2023.200052.

[25] X. Du, H. Xu, and F. Zhu, “Understanding the Effect of Hyperparameter Optimization on Machine Learning Models for Structure Design Problems,” *CAD Computer Aided Design*, vol. 135, Jun. 2021, doi: 10.1016/j.cad.2021.103013.

[26] Y. A. Ali, E. M. Awwad, M. Al-Razgan, and A. Maarouf, “Hyperparameter Search for Machine Learning Algorithms for Optimizing the Computational Complexity,” *Processes*, vol. 11, no. 2, Feb. 2023, doi: 10.3390/pr11020349.

[27] K. Yang, L. Liu, and Y. Wen, “The impact of Bayesian optimization on feature selection,” *Sci Rep*, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024-54515-w.

[28] B. Usman, M. G. Hasnam, R. Nurazi, Baihaqi, and S. Aujirapongpan, “Exploring investor attention in Shariah markets, macroeconomic influences, and corporate performance: Insights from Indonesia,” *Social Sciences and Humanities Open*, vol. 10, Jan. 2024, doi: 10.1016/j.ssaho.2024.101015.

[29] J. Krohkaew, P. Nilaphruek, N. Witthayawiroj, S. Uapipatanakul, Y. Thwe, and P. N. Crisnapati, “Thailand Raw Water Quality Dataset Analysis and Evaluation,” *Data (Basel)*, vol. 8, no. 9, Sep. 2023, doi: 10.3390/data8090141.

[30] K. Wang, C. Ma, Y. Qiao, X. Lu, W. Hao, and S. Dong, “A hybrid deep learning model with 1DCNN-LSTM-Attention networks for short-term traffic flow prediction,” *Physica A: Statistical Mechanics and its Applications*, vol. 583, Dec. 2021, doi: 10.1016/j.physa.2021.126293.

[31] D. G. da Silva and A. A. de M. Meneses, “Comparing Long Short-Term Memory (LSTM) and bidirectional LSTM deep neural networks for power consumption prediction,” *Energy Reports*, vol. 10, pp. 3315–3334, Nov. 2023, doi: 10.1016/j.egyr.2023.09.175.

[32] M. Zulfiqar, K. A. A. Gamage, M. Kamran, and M. B. Rasheed, “Hyperparameter Optimization of Bayesian Neural Network Using Bayesian Optimization and Intelligent Feature Engineering for Load Forecasting,” *Sensors*, vol. 22, no. 12, Jun. 2022, doi: 10.3390/s22124446.

[33] Z. Chen, B. Wu, B. Li, and H. Ruan, “Expressway Exit Traffic Flow Prediction for ETC and MTC Charging System Based on Entry Traffic Flows and LSTM Model,” *IEEE Access*, vol. 9, pp. 54613–54624, 2021, doi: 10.1109/ACCESS.2021.3070625.