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Stock Price Prediction of PT Kalbe Farma Tbk Using the Extreme Gradient Boosting (XGBOOST)

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ABSTRACT: Stock price prediction is crucial in investment decision - making due to its dynamic and volatile nature. Fluctuations in stock prices are influenced by macroeconomic indicators, market sentiment, and global financial conditions, resulting in complex and non-linear patterns that traditional models struggle to capture. PT Kalbe Farma Tbk shares are among the leading stocks in the pharmaceutical sector listed on the Indonesia Stock Exchange. This study employs Extreme Gradient Boosting (XGBoost) to predict PT Kalbe Farma Tbk closing stock price. XGBoost was leveraging its ability to process time series data and model intricate dependencies. XGBoost was chosen for its efficiency in handling large datasets, managing missing values, and applying regularization to prevent overfitting. To enhance model performance ensuring accuracy, robustness, and generalization Particle Swarm Optimization (PSO) and GridSearchCV. PSO and GridSearchCV are used for hyperparameter tuning. PSO is a swarm intelligence-based algorithm, mimics collective behaviors in nature, refining parameters through individual and group adaptation. Meanwhile, GridSearchCV systematically explores parameter spaces via cross-validation to select optimal configurations. The model was evaluated using Mean Absolute Percentage Error (MAPE). Based on the analysis result, it shows that XGBoost without optimization has a MAPE of 1.78, while optimization with PSO, the MAPE is reduced to 1.46, and GridSearchCV, the MAPE achieved 1.58. These results confirm that PSO and GridSearchCV improve XGBoost's predictive accuracy, making it a reliable method for financial market forecasting

KEYWORDS: PT Kalbe Farma Tbk; Particle Swarm Optimization; GridSearchCV; XGBoost

1. INTRODUCTION

The capital market plays a crucial role in channeling funds from investors to business actors, enabling better economic growth. However, the fluctuating nature of stock prices makes this investment inherently high-risk. Therefore, accurate analytical methods are required to assist investors in making more informed decisions. Traditional approaches to stock analysis are generally divided into two main categories: fundamental analysis and technical analysis. Fundamental analysis focuses on evaluating a company's financial condition to determine the intrinsic value of its stock, while technical analysis examines historical price movement patterns to forecast future trends. Alongside technological advancements, Machine Learning approaches have gained popularity in stock price prediction due to their ability to identify complex and dynamic data patterns.

Extreme Gradient Boosting (XGBoost) is a tree-based Machine Learning algorithm widely used in stock price prediction. This algorithm has advantages in handling large-scale data and nonlinear patterns that are difficult to address using traditional methods such as ARIMA and GARCH. However, the prediction accuracy of XGBoost heavily depends on the selection of optimal parameters, thus requiring parameter optimization methods such as Particle Swarm Optimization (PSO) and GridSearchCV to enhance model performance. PSO is a swarm intelligence-based algorithm that mimics the social behavior of a flock to find the best parameter combination, while GridSearchCV performs a systematic parameter search through cross-validation. Several previous studies have demonstrated that combining XGBoost with parameter optimization can significantly improve prediction accuracy. Uhunmwangho (2024) predicted the direction of Microsoft's stock price changes, with conclusion that the XGBoost model outperformed the LSTM in terms of accuracy. Yang, et.al (2021) combined two boosting algoritms, namely XGBoost and LightGBM to predict stock prices, concluding that the stock price prediction performance was better than using each model

In this study, PT Kalbe Farma Tbk (KLBF) was selected as the object of analysis due to the pharmaceutical sector's strong resilience to economic shocks. In the second quarter of 2020, Indonesia's chemical and pharmaceutical industry recorded a growth of 8.65%, driven by increased demand for medications during the Covid-19 pandemic. As one of the largest pharmaceutical issuers listed on the Indonesia Stock Exchange (IDX), KLBF's stock price is of interest for analysis using the XGBoost method optimized with PSO and GridSearchCV. This research aims to analyze the prediction of KLBF's stock price using XGBoost, both without parameter optimization and with optimization employing PSO and GridSearchCV. The novelty of this research lies in the combination of optimization methods to improve XGBoost's accuracy in forecasting pharmaceutical sector stocks, as well as the development of a Python GUI as a visualization aid. The results of this study are expected to serve as a reference for investors and capital market practitioners in utilizing Machine Learning-based prediction models to enhance accuracy in investment decision-making.

2. LITERATURE REVIEW

The capital market plays a crucial role in the economy by providing a means for the government and private companies to obtain capital through trading securities such as stocks and bonds. Besides serving as a source of funding, the capital market also functions in income distribution, enhancing production capacity, creating employment opportunities, and acting as an economic indicator (UUPM, 1995). Stocks, as instruments of company ownership, grant rights to profits in the form of dividends and potential capital gains (Kasmir, 2009), and are influenced by various factors such as operational performance and macroeconomic conditions (Cahyani et al., 2021). One issuer that attracts investor attention is PT Kalbe Farma Tbk, which is listed in the LQ45 index with high stock trading liquidity.

Machine Learning (ML) is a branch of Artificial Intelligence that enables computers to learn from data to make predictions or decisions without explicit programming (Alzubi et al., 2018). In the capital market, machine learning is used to predict stock price movements, including those of PT Kalbe Farma Tbk, using algorithms such as Artificial Neural Networks (ANN) and Extreme Gradient Boosting (XGBoost), as well as parameter optimization techniques like GridSearchCV and Particle Swarm Optimization (PSO) to enhance prediction accuracy. Supervised learning is employed for classification and regression, whereas unsupervised learning is used for clustering and feature reduction, with the primary goal of improving prediction accuracy and supporting investment decision-making .

The data preprocessing stage is a crucial step in data mining to ensure high-quality data before analysis. Data cleaning is used to address issues such as missing values and noise, while data imputation techniques replace missing values using methods such as linear interpolation, regression, or machine learning (Moritz & Beielstein, 2017). In time series analysis, the Partial Autocorrelation Function (PACF) technique is employed to identify inter-period relationships within stock data, aiding in the selection of the most relevant input variables for stock price prediction (Hyndman & Athanasopoulos, 2018). Splitting the data into training and testing sets, commonly in an 80:20 ratio, is also important to prevent overfitting and to ensure the model's ability to generalize (Kuhn & Johnson, 2013).

Extreme Gradient Boosting (XGBoost) is an advancement of the Gradient Boosting Decision Tree (GBDT) algorithm developed by Tianqi Chen in 2016, featuring improved computational efficiency and superior prediction accuracy compared to other boosting methods (Chen & Guestrin, 2016). XGBoost operates by building the model in a sequential manner using an additive modeling approach, where the final prediction is obtained by summing the contributions of each decision tree in the ensemble learning, as formulated in Equation (1):

$$F_k(x_i) = \sum_{k=1}^{K} f_{k(x_i)}, \quad f_k \in F \tag{1}$$

The challenge of finding an optimal algorithm can be addressed by employing a novel classification approach to minimize the objective function (Liu & Liu, 2022). The objective function is defined in Equation (*2*).

$$L^{(k)} = \sum_i l\big(y_i, F_k(x_i)\big) + \sum_k \Omega(f_k) \tag{2}$$

A commonly used loss function for binary classification problems is the cross-entropy loss, which is shown in Equation (3).

$$Loss\ function = -\frac{1}{n}\sum_{i=1}^{n}[y_i log(p_i) + (1 - y_i) log(1 - p_i)] \tag{3}$$

With n representing the number of samples, y_i denoting the actual value of the i-th sample and p_i the predicted probability of the i-th observation. the regularization term $\Omega(f_k)$ in Equation (4) is calculated to reduce model complexity and improve its generalizability to other datasets.

$$\Omega(\mathrm{f_k}) = \gamma \mathrm{T_k} + \frac{1}{2}\lambda\|\mathrm{w_j}\|^2 \tag{4}$$

where γT serves as a penalty based on the number of leaf nodes, and $\lambda\|\omega_j\|^2$ is the regularization term on the leaf node weights to prevent the model from becoming overly complex. With its advantages in computational speed and high accuracy, XGBoost has become a widely used algorithm in stock price prediction, including in the analysis of PT Kalbe Farma Tbk's stock movements, to enhance estimation accuracy and support investment decision-making (Liu & Liu, 2022).

In the optimization process, the objective function is further simplified by evaluating candidate splits in the decision tree using Equation (6), which calculates the gain from the split by assessing the gradient and Hessian scores at each leaf node. The first three terms in Equation (5) represent the scores for the left child, right child, and the original leaf, respectively (Chen & Guestrin, 2016).

$$Gain = \frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{G}{H + \lambda} \tag{5}$$

Particle Swarm Optimization (PSO) is a population-based optimization algorithm that mimics the flocking behavior of birds to find optimal solutions within a search space using collective intelligence. Particles move in a hyperdimensional space based on their personal best-known solution (local best) and the overall best-known solution (global best) (Eberhart & Kennedy, 1995). The algorithm implements five main steps in the search for an optimal solution, beginning with the initialization of particle velocities and population, followed by the evaluation of particle fitness and updating of positions based on new velocities calculated using Equation (6):

$$\begin{gathered} v_j^{i+1} = wv_j^{(i)} + \left(c_1 \times r_1 \times \left(local\ best_j - x_j^{(i)}\right)\right) \\ + \left(c_2 \times r_2 \times \left(global\ best_j - x_j^{(i)}\right)\right), \\ v_{min} \leq v_j^{(i)} \leq v_{max} \end{gathered} \tag{6}$$

where $v_j^{(i)}$ is the velocity of the j-th particle at iteration i, and c_1, c_2 are acceleration coefficients that drive the particle toward the best solutions. After the velocity is updated, the particle's position is calculated using Equation (7):

$$x_j^{i+1} = x_j^{(i)} + v_j^{(i+1)} \tag{7}$$

where $x_j^{(i+1)}$ is the new position of the particle after the next iteration. PSO repeats this process until the best solution is found, with particle fitness evaluated using appropriate functions such as the Mean Absolute Percentage Error (MAPE), and terminates when no significant improvement is observed (Sanyal, 2023). PSO is employed for efficient optimization in various problems, including stock price prediction, where XGBoost and PSO collaborate to enhance the accuracy of prediction models by searching for optimal solutions within the parameter space.

GridSearchCV is a systematic hyperparameter optimization technique widely used in machine learning to find the best parameter combination by exhaustively searching the predefined parameter space (Bergstra et al., 2012). The process begins by defining the parameter space $\theta = \{\theta_1, \theta_2, \ldots, \theta_n\}$. Each parameter combination $\theta_i \, \epsilon \, \theta$ is evaluated using an objective function $f(\theta_i)$, and the optimal parameter θ^* is selected by minimizing or maximizing the objective function, as formulated in Equation (8).

$$\theta^* = \underset{\theta i \epsilon \theta}{argmin}\, f(\theta_i) \tag{8}$$

This process involves evaluating various parameter combinations using cross-validation techniques to ensure optimal results. However, GridSearchCV has computational intensity drawbacks when the hyperparameter space is large or the model is complex, which can be mitigated by variants such as randomized search (Pramudhyta & Rohman, 2024). Despite the emergence of more advanced optimization methods like Bayesian optimization, GridSearchCV remains a popular choice due to its ability to deliver optimal results and good interpretability (Snoek et al., 2012).

Model evaluation is a crucial stage in machine learning to assess the model's performance in predicting new data, using evaluation metrics appropriate to the prediction problem type (regression, classification, ranking, etc.) such as accuracy, precision, recall, and F1-score for classification, as well as MSE, RMSE, and MAE for regression (Sokolova & Lapalme, 2009; Chai & Draxler, 2014). In numerical prediction cases like stock price forecasting, the metric used is the Mean Absolute Percentage Error (MAPE), which measures the model's prediction error relative to actual values, with better models having lower MAPE values (Hyndman & Athanasopoulos, 2021). The MAPE value is calculated using Equation (9).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{9}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of data points.

3. DATA AND METHODOLOGY

This study utilizes secondary data in the form of historical stock prices of PT Kalbe Farma Tbk (KLBF) obtained from Yahoo Finance, with the closing price attribute and 1,473 daily data points during the period from 1st January 2019, to 1st January 1, 2025. The data is divided into two sets: the training data set consisting of 1,178 data points (from 1st January 2019, to 12th October 2023), and the testing data set consisting of 295 data points (from 13th October 2023, to 1st January 2025), with an 80%:20% ratio. The variables used are the stock closing price as the dependent variable, and the stock closing price from the previous period as the independent variable. The analysis is conducted using the Extreme Gradient Boosting (XGBoost) model, optimized using Particle Swarm Optimization (PSO) and GridSearchCV to find the best parameter combination, which is then evaluated using the MAPE metric. The modeling is carried out in Python using Google Colaboratory or Jupyter Notebook, with steps including data input, data cleaning, descriptive analysis, data splitting, model training, parameter optimization, and model performance evaluation.

The data analysis process begins with inputting the historical stock price dataset of PT Kalbe Farma Tbk (KLBF) obtained from Yahoo Finance, covering the daily closing prices from 1st January 2019, to 1st January 2025. After the data is imported, the next step is data cleaning, which involves identifying and handling missing values, removing duplicate data, and detecting and handling outliers. Once the data is prepared, descriptive analysis is conducted to understand the data characteristics through statistical calculations such as mean, median, and standard deviation, as well as data visualization in the form of time series graphs to observe stock price trends. The variables are then divided into input (independent variables) and output (dependent variables), with the closing stock price from the previous period used as input and the closing stock price at time ttt as output. The data is then split into two sets: the training data set (80%) to train the model and the testing data set (20%) to evaluate the model. The XGBoost model is first trained without parameter optimization to obtain the baseline performance, followed by parameter optimization using Particle Swarm Optimization (PSO) and GridSearchCV to find the best parameter combination that enhances the model's accuracy. The model's performance is evaluated using the MAPE metric, and the model with the smallest MAPE value is selected as the best model for predicting KLBF’s future stock prices.

4. RESULTS AND DISCUSSION

In this study, descriptive analysis was performed to describe the characteristics of the stock closing price data of PT Kalbe Farma Tbk (KLBF) from 1st January 2019, to 1st January 2025. The data used includes 1,473 daily data points, with an average closing price of IDR 1,529.01 per share and a standard deviation of IDR 238.64 per share. The highest stock price recorded was IDR 2,271.54 per share on 10th February 2023, while the lowest price was IDR 784.91 per share on 24th March 2020. The stock price movement graph shows significant fluctuations, with a sharp decline in March 2020 due to the impact of the Covid-19 pandemic, followed by a recovery in stock prices in 2021, driven by the operational stability of the company and market optimism toward the pharmaceutical sector.

In determining the input and output variables for the Extreme Gradient Boosting (XGBoost) model, the daily closing stock price data of KLBF was used as the output variable, while the input variables were derived from modified closing price data using the Partial Autocorrelation Function (PACF) analysis. From the PACF plot, significant first, second, and third lags were obtained, which were used as inputs for the model. This reflects that the current stock price is influenced by the stock prices of previous periods, and these lags are considered relevant for predicting future stock prices.

The normalized data was then divided into two parts: the training data and the testing data with an 80%:20% ratio. The training data, consisting of 1,174 data points, was used to train the XGBoost model, while the testing data, consisting of 294 data points, was used to evaluate the model’s performance. This division was made to ensure that the model could generalize well and avoid overfitting. The process was conducted using Google Colaboratoryto ensure proper data splitting before proceeding to the modeling and evaluation stages.

Modeling with the Extreme Gradient Boosting (XGBoost) algorithm showed that the XGBoost-Default model, which uses default parameters without optimization, produced relatively optimal performance with a MAPE value of 0.34 for the training data and 1.78 for the testing data. However, it still needs to be compared with optimized models such as XGBoost-PSO and XGBoost-GridSearchCV to improve the accuracy of stock price predictions for PT Kalbe Farma Tbk (KLBF). The stock price prediction results using the XGBoost-Default model showed relatively small errors and met the criteria for good prediction evaluation, with a comparison of the actual and predicted prices shown in Table 1 and the stock price movement graph in Figure 1.

Table 1. Comparison of Actual and Predicted Stock Prices using the XGBoost-Default Model

Date	Actual Closing Price	Prediction
10-09-2023	1,719.9000	1,724.8259
10-10-2023	1,715.0000	1,738.2982
10-11-2023	1,705.2001	1,710.9208
10-12-2023	1,715.0000	1,720.6525
10-13-2023	1,724.8000	1,721.0336
...	...	...

12-19-2024	1,275.0000	1,275.7533
12-20-2024	1,330.0000	1,294.1497
12-23-2024	1,400.0000	1,324.9495
12-24-2024	1,355.0000	1,393.3500
12-27-2024	1,360.0000	1,359.5468

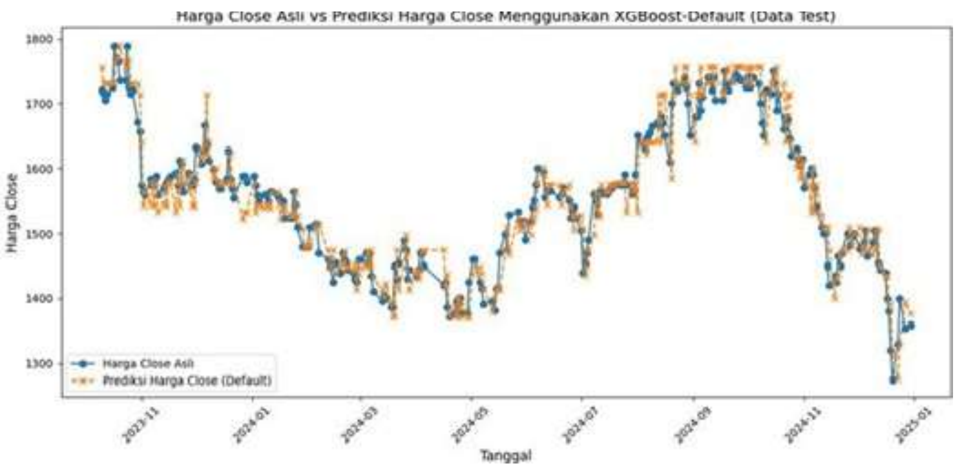

Figure 1. Comparison of Actual and Predicted Stock Prices using the XGBoost-Default Model

Modeling with parameter optimization using Particle Swarm Optimization (PSO) on the XGBoost model showed more optimal results compared to the XGBoost model without optimization, with a MAPE value of 1.25 for the training data and 1.46 for the testing data. These values are lower than those of the XGBoost-Default model, resulting in more accurate stock price predictions, as seen in the comparison of actual and predicted prices presented in Table 2 and the stock price movement graph in Figure 2.

Table 2. Comparison of Actual and Predicted Stock Prices using the XGBoost-PSO Model

Date	Actual Closing Price	Prediction
10-09-2023	1,719.9000	1,759.5297
10-10-2023	1,715.0000	1,734.8926
10-11-2023	1,705.2001	1,715.9756
10-12-2023	1,715.0000	1,718.6469
10-13-2023	1,724.8000	1,717.1652
...	...	...
12-19-2024	1,275.0000	1,325.8229
12-20-2024	1,330.0000	1,298.1051
12-23-2024	1,400.0000	1,323.0653
12-24-2024	1,355.0000	1,387.1937
12-27-2024	1,360.0000	1,356.8811

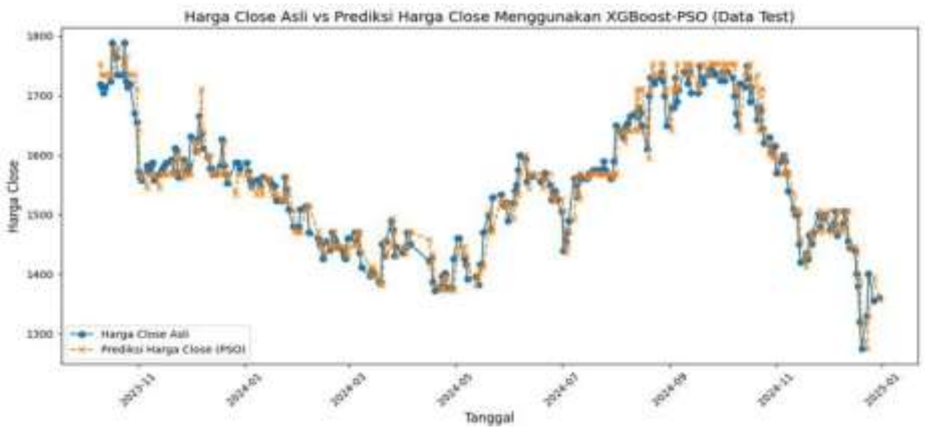

Figure 2. Comparison of Actual and Predicted Stock Prices using the XGBoost-PSO Model

Modeling with parameter optimization using GridSearchCV on the XGBoost model resulted in good performance, with a MAPE value of 1.11 for the training data and 1.58 for the testing data. These values are lower than those of the XGBoost-Default model but slightly higher than the XGBoost-PSO model, resulting in accurate stock price predictions, as seen in the comparison of actual and predicted prices presented in Table 3 and the stock price movement graph in Figure 3.

Table 3. Comparison of Actual and Predicted Stock Prices using the XGBoost-GridSearchCV Model

Date	Actual Closing Price	Prediction
10-09-2023	1,719.9000	1,7473958
10-10-2023	1,715.0000	1,738.2052
10-12-2023	1,705.2001	1,723.2893
10-12-2023	1,715.0000	1,722.4935
10-13-2023	1,724.8000	1,720.0758
...	...	...
12-19-2024	1,275.0000	1,311.8887
12-20-2024	1,330.0000	1,292.6669
12-23-2024	1,400.0000	1,326.0874
12-24-2024	1,355.0000	1,368.3980
12-27-2024	1,360.0000	1,356.5636

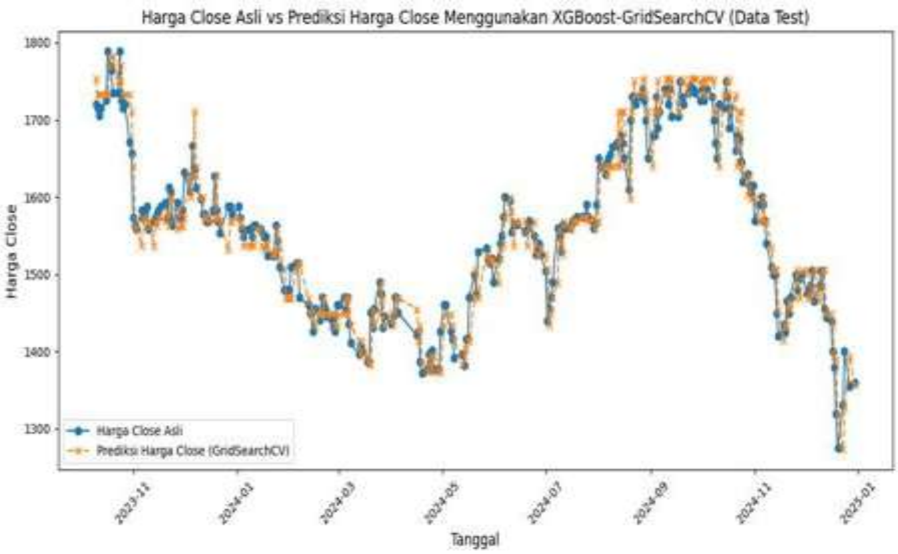

Figure 3. Comparison of Actual and Prediction Stock Price Using the XGBoost- GridSearchCV Model

Based on the model evaluation results using the regression metric MAPE (Mean Absolute Percentage Error), the XGBoost-PSO model showed better performance compared to the XGBoost-Default and XGBoost-GridSearchCV models. The XGBoost-PSO model had a lower MAPE value on the testing data, specifically 1.46, indicating more accurate stock price predictions. This evaluation is also reflected in the comparison of actual and predicted prices presented in Table 4, where the stock price predictions from the XGBoost-PSO model are closer to the actual stock prices compared to the other two models, reinforcing that parameter optimization using PSO provides a significant performance improvement. Additionally, Figure 4 shows the comparison of actual and predicted stock prices for all XGBoost models.

Table 4. Selection of the Best XGBoost Model

Model	Evaluation Metric Values	
	Training	***Testing***
	MAPE	**MAPE**
XGBoost-Default	0.34	1.78
XGBoost-PSO	1.25	1.46
XGBoost-GridSearchCV	1.11	1.58

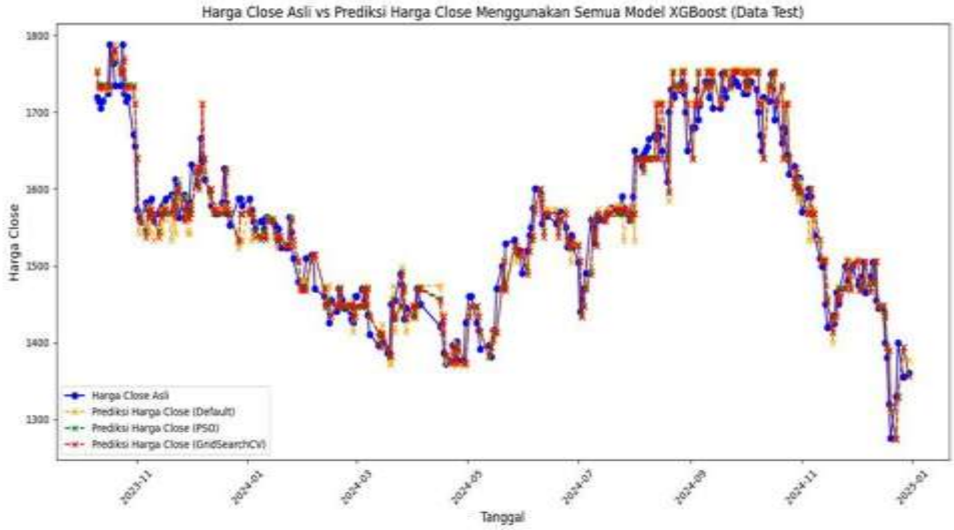

Figure 4. Comparison of Actual and Predicted Stock Prices using All XGBoost Models

Based on the parameters obtained from the XGBoost-PSO model, the closing stock price of PT Kalbe Farma Tbk (KLBF) for the next 30 periods was predicted. The daily stock price predictions, presented in Table 6, show more stable fluctuations, with prices estimated to range from IDR 1,356 to IDR 1,664 per share during the prediction period. These predictions are expected to assist investors in making more informed investment decisions based on more accurate stock price projections. The predicted stock price movement is also visualized in Figure 5 for easier further analysis.

Table 5. Daily Closing Stock Price Predictions for KLBF

Date	Prediction
12-31-2024	IDR 1,358.9400 per share
01-01-2025	IDR 1,361.5667 per share
01-02-2025	IDR 1,376.7263 per share
01-03-2025	IDR 1,374.9573 per share
01-06-2025	IDR 1,370.2603 per share
...	...
02-04-2025	IDR 1,514.4342 per share
02-05-2025	IDR 1,542.7339 per share
02-06-2025	IDR 1,563.5245 per share
02-07-2025	IDR 1,562.6795 per share
02-10-2025	IDR 1,551.9892 per share

(a)

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(b)

Figure 5. Daily Stock Price Predictions for KLBF for the Entire Data Set (a); for the Predicted Trend for the Next 30 Periods (b)

5. CONCLUSIONS

This study successfully analyzed the stock price prediction of PT Kalbe Farma Tbk (KLBF) using the Extreme Gradient Boosting (XGBoost) model with and without parameter optimization, and implemented the prediction results in a Python-based GUI interface for interactive use. The results show that the XGBoost model without parameter optimization provided reasonably good predictions, with a MAPE of 1.78, indicating that XGBoost by default is already capable of capturing stock price movement patterns with a low error rate. Parameter optimization using Particle Swarm Optimization (PSO) and GridSearchCV successfully improved the model's prediction accuracy, with XGBoost-PSO achieving a MAPE of 1.46, outperforming the XGBoost-GridSearchCV model, which resulted in a MAPE of 1.58. Based on the evaluation results, the XGBoost model with PSO optimization showed the highest prediction accuracy and was more effective in finding the optimal parameter combination compared to GridSearchCV. Additionally, the Python-based GUI developed with Streamlit allows users to select the prediction model and perform stock price analysis interactively, which is expected to assist investors in making more accurate investment decisions.

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