ICDSOS
The 3rd International Conference on Data Science and Official Statistics
November 27 - 28, 2025

"From Data to Impact: Leveraging Innovation in Data Science and Official Statistics for Data-Driven Policy Making and Global Competitiveness"

Forecasting Composite Stock Price Index on Indonesia Stock Exchange Using Extreme Learning Machine

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Abstract. Technological advances have driven active participation in digital economic activities, including capital market investment. Stocks remain a dominant instrument, with the Composite Stock Price Index or Indeks Harga Saham Gabungan (IHSG) serving as a primary benchmark for investment decisions in Indonesia. However, its high volatility—driven by economic, political, global, and market sentiment factors—demands accurate forecasting methods. Traditional approaches such as ARIMA and linear regression are limited in capturing the non-linear and complex patterns of stock market data. This study proposes the use of the Extreme Learning Machine (ELM), an artificial intelligence method considered more adaptive to market dynamics. To enhance prediction accuracy, hyperparameter optimization was performed using the grid search method. The research forecasts IHSG performance by incorporating exogenous variables, namely gold prices, the US dollar to rupiah exchange rate, and a COVID-19 dummy variable. The optimal model utilized a hidden layer configuration of nine neurons. Evaluation results indicate that the ELM models effectively perform multi-horizon forecasting (t+1 to t+5), as evidenced by low MAE, MAPE, and RMSE values across horizons. The five-day IHSG forecasts are 7,242.28, 7,228.42, 7,211.02, 7,192.67, and 7,174.06, demonstrating the model's potential in supporting investment decision-making with high accuracy.

Keyword: ELM, grid search, hyperparameter optimization, IHSG.

1. Introduction

Current technological advances have had a significant impact on people's lives. People can now more easily engage in activities that are beneficial in terms of economics and employment. For example, in financial terms, people can easily make money using the internet, one of which is through investing. Investing is the act of postponing consumption and allocating funds to productive assets for a certain period of time with the expectation of gaining profits in the future. Investing in stocks is a common practice. Many Indonesian and foreign investors invest and trade stocks in Indonesia. Stocks represent ownership in a company. Purchasing stocks means that shareholders, as part owners of the company, have the right to receive the company's profits in the form of dividends [1].

The capital market plays a very important role in supporting a country's economic growth. One of the main indicators used to measure the performance of the capital market in Indonesia is the IDX Composite (IHSG). In other words, it represents the movement of indicators that show whether the market is active or weak [2]. The IHSG reflects the price movements of all shares listed on the Indonesia Stock Exchange (IDX) and is used as a reference in investment decision-making, both by institutional and retail investors. Therefore, the ability to predict the direction of the IHSG is crucial in managing investment risk and designing the right strategy for stock market transactions.

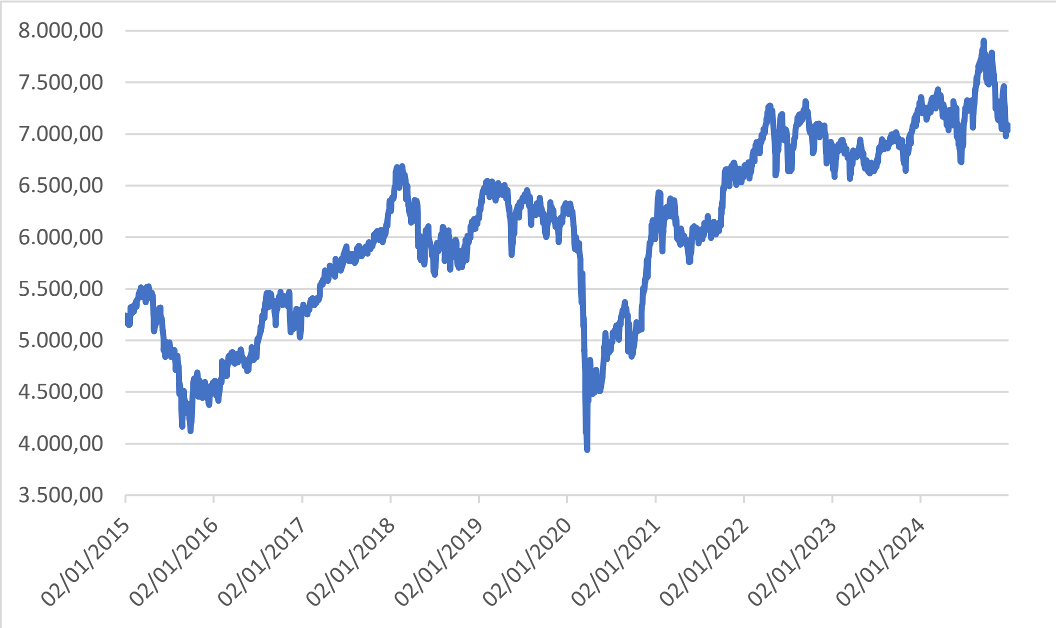

Figure 1. IHSG data period from January 2, 2015 to December 30, 2024

Figure 1 shows the significant dynamics of the IHSG in recent years. At the end of 2023, the IHSG stood at 7,272.8. At the end of 2024, the IHSG stood at 7,079.90, with the highest level reaching 7,905.39 on September 19, 2024 [3]. However, in the last 10 years, the IHSG hit its lowest point at 3,937.63 on March 24, 2020. The movement of the IHSG shows high daily volatility, medium-term trends, and sudden changes (shocks) that arise due to global and domestic economic events. This also supports the fact that the IHSG has non-linear, fluctuating time-series properties and is influenced by various external factors.

In this context, the ability to accurately predict IHSG movements has become increasingly crucial for various stakeholders in the capital market. Traditional methods such as ARIMA have the basic assumption that data is linear and stationary, so this model is less capable of capturing complex and dynamic patterns such as those that occur in the stock market [4]. Traditional models also tend to be sensitive to noise and outliers, which often appear in market data due to sudden fluctuations, market speculation, or unexpected external factors. When data contains random disturbances, the performance of ARIMA and linear regression becomes unstable [5]. Meanwhile, conventional artificial neural network (ANN) approaches require intensive computation and are prone to overfitting [6].Extreme Learning Machine (ELM) is a method that works based on the concept of single-layer feedforward network (SLFN). This method was created to overcome the weaknesses of feedforward neural network methods, especially in the learning rate process [6]. The superiority of the proposed Extreme Learning Machine (ELM) model over classical time series models such as ARIMA is theoretically and empirically supported by recent studies. Kontopoulou et al. [7] reviewed over 50 comparative studies and concluded that AI-based models generally outperform ARIMA across financial, energy, and economic forecasting tasks. Furthermore, Zhang et al. [8] demonstrated that Kernel ELM significantly improves forecasting accuracy in nonlinear and volatile datasets compared to traditional statistical models. ELM offers potential with several advantages, such as superior learning speed compared to conventional neural network methods, good generalization capabilities, minimal human intervention in the training process, and the ability to handle non-linear data effectively [9]. This method is suitable for overcoming the weaknesses of conventional methods, namely accommodating the complexity and non-linearity of stock market data.

Arbitrage Pricing Theory (APT) emphasizes that systemic risks such as interest rate changes, inflation, exchange rates, and global economic dynamics are major factors that affect almost all financial assets and cannot be eliminated through diversification. Previous studies have developed research related to IHSG forecasting with exogenous variables. Gold prices affect almost all stock sectors in the long and short term [10]. This is reinforced by the findings of Prasada & Pangestuti [11], that gold prices have a positive and significant effect on the IHSG in the short term. Volatility in currency exchange rates can have a negative effect on trading activity and equity index performance, proving that the composite stock price index is partially influenced by exchange rates [12] . Other studies also show that, in part, nominal exchange rate growth has a significant negative effect on composite stock price index growth in the short and long term [13]. Junaedi [14] also mentions that policies to address COVID-19, such as WFH and PSBB, have a negative impact on the movement of the IHSG. In addition, Putranto [15] in his research mentions that there was a significant change between the IHSG in December 2019 and March 2020.

To improve stock price forecasting capabilities, this study applies a hyperparameter tuning process to the ELM model using grid search tuning [15]. The purpose of this stage is to find the best combination of hyperparameters that can produce a model with the highest forecasting accuracy [16]. The main focus of this study is to forecast the closing price of the IHSG by utilizing exogenous variables as additional features in the model [17].However, to date, there have been few studies conducting ELM by applying hyperparameter tuning to the Indonesian capital market, particularly in daily IHSG forecasting. An understanding of the effectiveness of this method is urgently needed in order to select the most accurate and efficient approach for use by market analysts and investors. Considering the complexity of IHSG data and the importance of forecasting accuracy in decision-making, a comparative study is needed to empirically evaluate the performance of both models in the context of daily IHSG forecasting. This research is expected to provide a real contribution to the selection of the appropriate forecasting method for the capital market in Indonesia.

2. Research Method

This study uses secondary data in the form of daily closing prices of the IHSG, gold prices, and USD/IDR exchange rates from investing.com, as well as a COVID-19 dummy variable with a value of 1 for the period March 31, 2020–June 21, 2023, in accordance with Presidential Decrees No. 11/2020 and No. 17/2023 [18][19]. Descriptive analysis was conducted through time series visualization and correlation tests, using Pearson's correlation for continuous variables and Point-Biserial correlation for binary variables. The preprocessing stage includes cleaning missing values due to differences in trading days, dividing the data into training (80%), validation (10%), and testing (10%), and normalization using Min-Max Scaler. Modeling was performed using Extreme Learning Machine (ELM) with tuning of the number of neurons (1–100) through grid search tuning. Model training utilizes training data, while testing uses testing data. Accuracy evaluation is performed using MAE, MAPE, and RMSE.

2.1. Data and Data Sources

The data used in this study is secondary data in the form of daily closing price time series data from the Composite Stock Price Index (IHSG), gold prices, and the US dollar exchange rate against the rupiah, which can be accessed on the investing.com website. IHSG data is generally not recorded on Saturdays, Sundays, national holidays, and other days designated by the government as holidays, so gold prices, the US dollar exchange rate against the rupiah, and the COVID-19 dummy variable adjust the series of IHSG data.

The COVID-19 dummy variable is used to distinguish between the COVID-19 pandemic period and non-pandemic periods. The COVID-19 dummy variable has a value of 1 during the COVID-19 pandemic period and a value of 0 for other periods. Based on Presidential Decree No. 11 of 2020 declaring the Public Health Emergency for Coronavirus Disease 2019 (COVID-19) effective March 31, 2020, and Presidential Decree No. 17 of 2023 declaring the end of the COVID-19 pandemic status on June 21, 2023 [18][19]. Table 1 below explains the variables, descriptions, and data sources used in the study.

Table 1. Variables, Descriptions, and Data Sources Used

Variables	Descriptions	Data Sources	References
IHSG	Daily closing price of the IDX Composite	investing.com	Prabowo et al. [20]; Darmawan & Haq [21]
Gold Price	Daily closing price of Gold Futures	investing.com	Asrif'ah & Wahyudin [10]; Prasada & Pangestuti [11]
Exchange Rate	Daily closing price of the US dollar exchange rate against the rupiah	investing.com	Sara [12]; Pramesthi et al. [13]
Dummy COVID-19	Valued at 1 during the COVID-19 pandemic period		Junaedi [14]; Putranto [22]

2.2. *Data Exploration*

Data exploration is a general description of a phenomenon through existing data in a simple manner with the aim of seeing distribution patterns and gaining visual insights into the data. Descriptive analysis is applied to the general description of the IHSG, gold prices, and the US dollar exchange rate against the rupiah. To observe the movements of the IHSG, gold prices, and the US dollar exchange rate against the rupiah, data visualization in the form of time series graphs was conducted.

In addition to time series graphs, the data exploration method used was correlation. Correlation was performed to determine the relationship between the variables of gold prices, the US dollar exchange rate against the rupiah, and the COVID-19 dummy variable with the IHSG variable. In this study, the correlation measure used is Pearson's correlation for gold prices and the US dollar exchange rate against the rupiah because all the data used are on an interval and ratio scale. Meanwhile, for the COVID-19 dummy variable against the IHSG use Point-Biserial correlation.

2.3. *Data Preprocessing*

In the preprocessing stage, several research steps are carried out, such as data cleaning, data normalization, and data division. Data cleaning involves checking the completeness of the data. If there are missing values, they will be cleaned up. Missing values are caused by differences in working days between the stock exchange, gold prices, and exchange rates on certain days. Missing values will be cleaned up by deleting the rows on those days.

After data cleaning, all data will be divided into three parts, namely training data, validation data, and testing data. Zheng and Casari [23] state that testing data should only be used after modeling is complete to estimate the error of the model's predictions and should not be used during the model training process to avoid data leakage. The training data, which accounts for 80% of the total dataset, will be used to train the model. The validation data, comprising 10% of the dataset, will be used to tune and validate the model's hyperparameters to prevent overfitting. The remaining 10% will be allocated as testing data to evaluate the model's performance on unseen data. The selection of this 80%–10%–10% data division is supported by the findings of Rácz et al. [24] who reported that increasing the proportion of training data up to 80% improves classification performance, especially for large datasets. Their study also revealed that a ratio of 70%–80% yielded better performance than lower ratios, with only minor differences between the testing and cross-validation results. These findings indicate that an 80% allocation for training and 20% for validation and testing provides an optimal balance between the model's learning capacity and its generalization ability.

Then, perform data normalization using Min-Max Scaler. Min-Max Scaler is a technique for transforming data into a range of 0 to 1 for each variable. Before entering the modeling stage, a metric change is required to adjust to the modeling metric.

2.4. Modeling

After going through the preprocessing stage, modeling is then carried out using the ELM model. ELM is a new method for training artificial neural networks (ANN) that works based on the concept of a single-layer feedforward network (SLFN) [25]. In the ELM algorithm, the input layer weights are set randomly, and the output layer weights are obtained using the generalized inverse of the hidden layer output matrix [26]. After that, the output from the hidden layer matrix is used in the final weight calculation. The final weights are calculated using the Moore-Penrose Generalized Inverse [25].

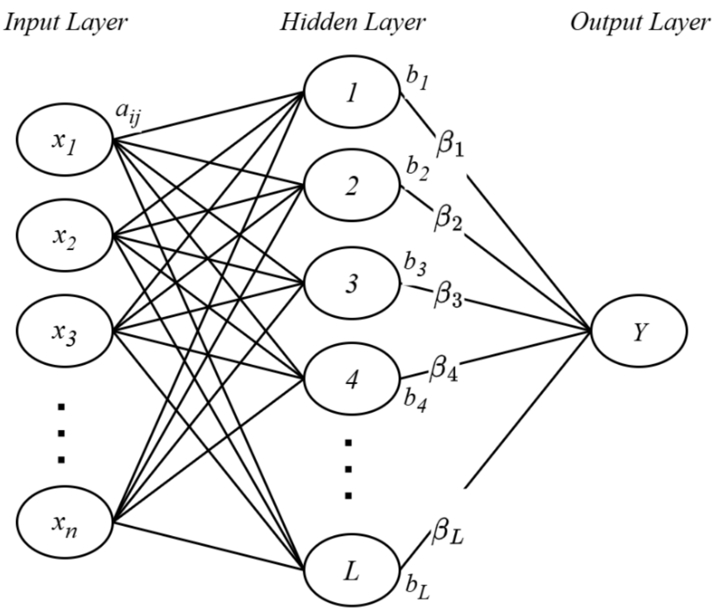

Figure 2. Architecture Extreme Learning Machine (ELM)

Based on Figure 2, the stages of learning the ELM model are as follows.

1. Input the normalized training data as input nodes $(x_1, \dots, x_n)$ and determine the activation function and number of neurons in the hidden layer.
2. Initialize input weights (a_i) and biases b_j randomly.

3. Calculate each output from the nodes in the hidden layer and denote it by $\boldsymbol{G}(a_{*j}, b_j, x_*)$. Then determine a matrix $\boldsymbol{H}$ consisting of all outputs from the nodes in the hidden layer.
4. Calculate the final weight (β) of the hidden layer and output using the equation:

$$\beta = \boldsymbol{H}^{+}\boldsymbol{T} \tag{1}$$

Explanation:
$\boldsymbol{H}^{+}$: Moore-Penrose Generalized Inverse matrix $\boldsymbol{H}$
$\boldsymbol{T}$: Target vector
5. Calculate all output nodes in the output layer.
6. Calculate the error value at each node in the output layer.

2.5. Evaluation
After the model has been trained and tested, the next step is to evaluate the forecasting results. The prediction results on the testing data will be compared with the actual IHSG values to assess the model's accuracy. The evaluation metrics used are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). The best model is the one with the smallest MAE, MAPE, and RMSE values [27].

3. Result and Discussion

3.1. Data Exploration
This study conducts modeling for IHSG forecasting. The IHSG is used as the dependent variable, while gold prices, the US dollar exchange rate against the rupiah, and the COVID-19 dummy variable are used as exogenous variables. The data period for this study spans from January 2, 2015, to December 30, 2024. Daily data was collected from the Investing.com website. Investing.com provides daily data with Open, Close, High, Low, Volume, and Change for the IHSG, gold prices, and the US dollar exchange rate against the rupiah. However, in this study, only the Close is used to represent the price for each variable. Figures 3 to 5 sequentially show the graphs of the IHSG, gold prices, and the US dollar exchange rate against the rupiah.

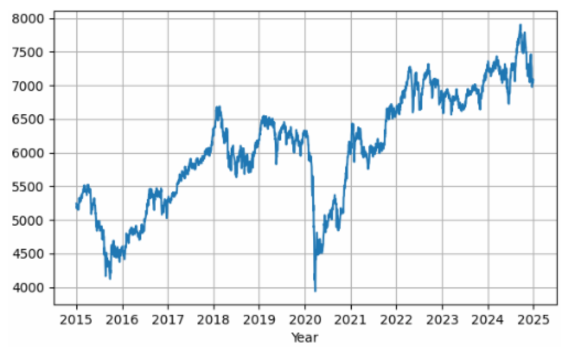

Figure 3. IHSG 2015-2024 (Point)

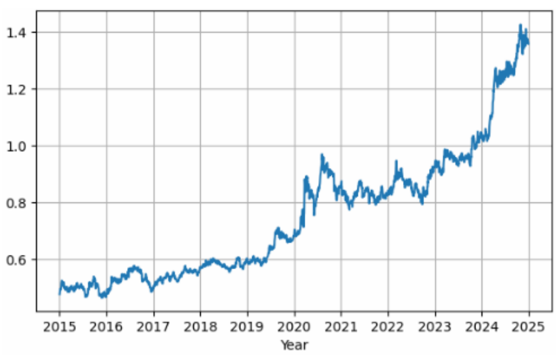

Figure 4. Gold Price 2015-2024 (Million Rupiah)

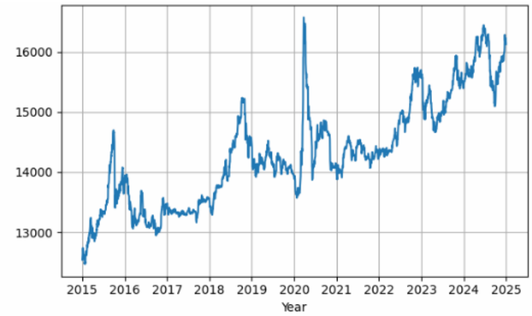

Figure 5. Exchange Rate 2015-2024 (Rupiah)

Figure 3 shows that the movement of the IHSG from 2015 to 2024 has been volatile. In particular, there was a significant decline in 2020. The decline in the IHSG was caused by the spread of COVID-19, which began to widen and entered a pandemic phase [28]. Unlike the IHSG, Figure 4 shows that gold prices are trending upward. This is because gold is considered a safe haven [29]. Figure 5 shows that the exchange rate has been trending upward, but there was a significant increase in 2020, which was during the COVID-19 pandemic.

Table 2. Descriptive Statistics

	IHSG	Gold Price	Exchange Rate	Dummy COVID-19
Mean	6,063.93	751,632.6	14,318.75	0.32
Median	6,107.38	694,585.9	14,250.00	0
Standard Deviation	844.27	227,441.5	883.44	0.47
Minimal	3,937.63	466,187.2	12,472.50	0
Maximal	7,905.39	1,425,411	16,575.00	1

Table 2 shows the descriptive statistics of the IHSG, Gold Price, Exchange Rate, and COVID-19 Dummy data from 2015 to 2024. The IHSG has an average of 6,063.93 with a standard deviation of 844.27. This value indicates a fairly high degree of variability, suggesting moderate fluctuations in the average IHSG value throughout the period. The highest IHSG was recorded at 7,905.39, while the lowest IHSG was at 3,937.63. The average gold price was 751,632.6 with a standard deviation of 227,441.5. This indicates significant volatility in gold prices. The highest gold price was recorded at 1,425,411, while the lowest gold price was 466,187.2. The US Dollar to Rupiah exchange rate showed an average of 14,318.75 with a standard deviation of 883.44. This figure indicates moderate exchange rate variation. The highest exchange rate reached 16,575.00, while the lowest exchange rate was 12,472.50. The COVID-19 dummy variable has an average of 0.32 with a standard deviation of 0.47. Since the COVID-19 dummy variable indicates the COVID-19 pandemic period, approximately 32% of the observation period was during the COVID-19 pandemic.

Table 3. Correlation

Variable	IHSG	Gold Price	Exchange Rate	Dummy COVID-19
IHSG	1	0.7030	0.6207	0.1756
Gold Price	0.7030	1	0.8480	0.3441
Exchange Rate	0.6207	0.8480	1	0.2657
Dummy COVID-19	0.1756	0.3441	0.2657	1

Table 3 shows the correlation between variables. Calculating correlations using Pearson's correlation for continuous variables and point-biserial correlations for dummy variables [30]. The correlation value between the IHSG and the price of gold is 0.7030, while that between the IHSG and the US dollar exchange rate against the rupiah is 0.6207, indicating a strong positive relationship. This indicates that movements in the price of gold and exchange rates tend to be in line with movements in the IHSG, where an increase in the price of gold or an appreciation in the exchange rate is generally followed by an increase in the IHSG. Meanwhile, the COVID-19 dummy variable has a weak correlation with the IHSG of 0.1756, the exchange rate of 0.2657, and the price of gold of 0.3441. The dummy variable only has two categories, so the correlation does not reflect a linear relationship, but rather the difference in the average values of the three variables between the two periods. These low correlation values indicate that the COVID-19 pandemic has a statistically limited direct effect on the fluctuations of the three variables, although economically, the pandemic can still have an indirect impact through market volatility. The highest correlation was recorded between the price of gold and the exchange rate at 0.8480, where there is an indication of multicollinearity between the price of gold and the exchange rate [30]. Therefore, a VIF test needs to be conducted to assess multicollinearity.

Table 4. VIF Values

Variable	VIF
IHSG	2.0050
Gold Price	4.6687
Exchange Rate	3.5840
Dummy COVID-19	1.1499

Based on Table 4, which shows the VIF test, there is no indication of multicollinearity in any of the variables. This is indicated by VIF values below 10 [30]. The price of gold has the highest VIF value of 4.6687, followed by the exchange rate at 3.5840 and the IHSG at 2.0050, all of which are still within reasonable and acceptable limits. Meanwhile, the COVID-19 dummy variable has the lowest VIF value, namely 1.1499, which indicates that this variable is not strongly correlated with other independent variables and contributes unique information to the model. The low VIF value also reinforces the previous correlation results, which show a weak relationship between the COVID-19 dummy and other macroeconomic variables.

3.2. *Data Preprocessing*

Before modeling, the collected data is processed first to check data completeness, divide the data into training, validation, and testing data, normalize the data, and adjust the data matrix to the modeling matrix

Table 5. Missing Value

Variable	Missing Value
IHSG	0
Gold Price	18
Exchange Rate	0
Dummy COVID-19	0

Table 5 shows that there are 18 missing values in the gold price data. The method used to address missing values is to delete rows with missing values. This is because the number of missing values is small and there is still sufficient data to conduct the study [31].

After addressing missing values, the next step is to divide the data into three parts: training data, validation data, and testing data. The training data will be used to train the model using 80% of the total data, the validation data will be used to evaluate the tuning results using 10% of the total data, and the testing data will be used to test the model using 10% of the total data. Next, standardize the data using the Min-Max Scaler. The Min-Max Scaler is a technique for transforming data into a range of 0 to 1 for each variable. Finally, the last step before training the model is to adjust the data metric format to match the metric used in the modeling process.

3.3. *Modeling*

The ELM model constructed is a Multi-Output ELM model capable of predicting the IHSG for the next five days (t+1 to t+5). The ELM model is constructed using hyperparameter optimization to produce the best model for predicting the IHSG. Hyperparameters will be optimized using hyperband tuning, grid search tuning, and Bayesian optimization to obtain the optimal hyperparameters for the ELM model. Table 6 illustrates the comparison of hyperparameters prior to and following the optimization process using grid search tuning.

Table 6. ELM Hyperparameter Combination

Hyperparameter	Combination Before Grid Search Tuning	Combination After Grid Search Tuning
Hidden layer	1 – 100	9

After obtaining the best hyperparameter combination from the grid search tuning results, it is then applied to the training data to build the ELM model. The built model is then applied to the testing data to be evaluated by comparing it with the actual data. The evaluation metrics used are MAE, MAPE, and RMSE to assess its effectiveness in predicting IHSG movements. The following are the ELM evaluation metrics with grid search tuning from t+1 to t+5.

Table 7. Evaluating ELM with Grid Search Tuning

Evaluation metrics	t+1	t+2	t+3	t+4	t+5
MAE	74.9162	80.2978	90.8107	103.6286	115.6987
MAPE	1.03%	1.10%	1.25%	1.42%	1.58%
RMSE	88.2441	101.5874	114.6406	126.1370	138.8425

Based on Table 8, the results of hyperparameter tuning and ELM model performance evaluation with grid search tuning, it can be concluded that the best configuration with 9 hidden layers obtained through grid search tuning provides excellent IHSG forecasting performance with a consistent average error rate below 1.6% for all forecasting periods (days 1 to 5). The model shows a predictable and manageable pattern of accuracy decline, where the best accuracy is achieved in one-day-ahead forecasting with an average absolute error of 74.9162 and a percentage error of 1.03%. followed by a gradual decline to an average absolute error of 115.6987 and a percentage error of 1.58% for five-day forecasts, which is still considered very good according to financial forecasting industry standards. The combination of the grid search tuning method with ELM has proven effective in achieving an optimal balance between model complexity and forecasting performance, resulting in a robust framework for trading strategies of various time frames with significant competitive advantages over traditional forecasting methods, as well as providing a solid foundation for practical application in daily trading, medium-term trading, and portfolio management with measurable and manageable risk levels. This is supported by the research results of Janad et al. [32], which shows that the evaluation of the ELM model in predicting the IHSG produced an RMSE value of 1 x 10^{-16}. This means that the model's forecasting performance in estimating actual values is excellent. In addition, research results of Zhang [33], also show that ELM forecasting results are generally consistent with actual data trends.

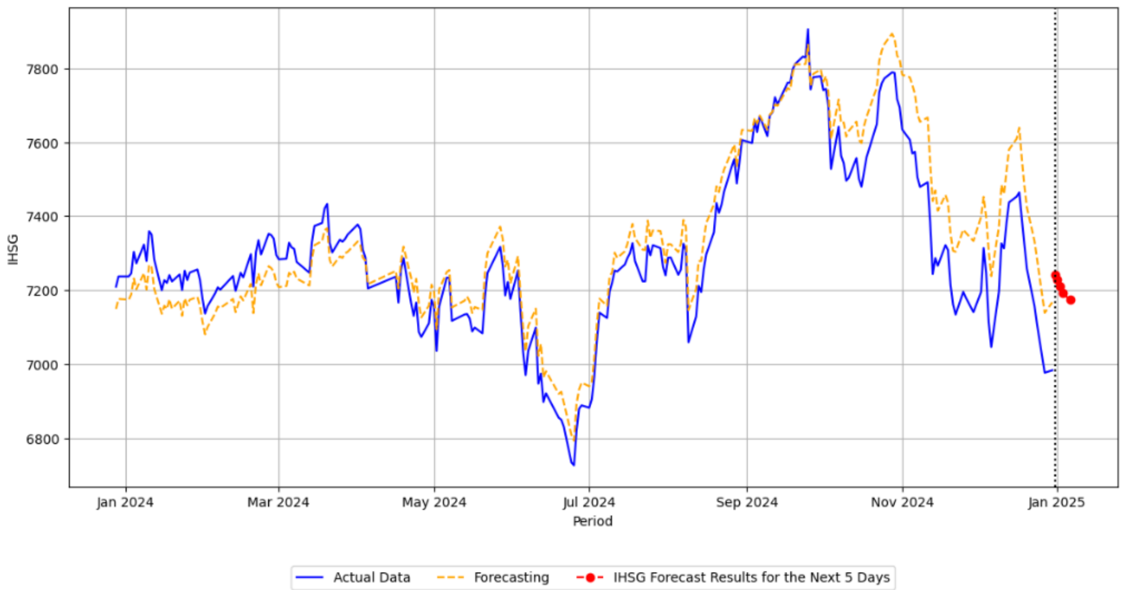

Figure 6. Comparison of Forecast and Actual Results of the IHSG ELM with Grid Search Tuning December 21, 2023 to January 8, 2025

Figure 6 shows the results of testing data forecasting using the ELM model with grid search tuning. The blue line shows the actual data, while the orange dotted line shows the results of the ELM model forecasting with grid search tuning using the testing data. It can be seen that there is no significant difference between the prediction results and the actual data. The black dotted line shows the boundary between the testing data and the prediction, while the red dotted line shows the forecasting results for the next five days. The ELM model with grid search tuning indicates that the IHSG will fluctuate over the next five days. Below are the IHSG prediction results from the ELM model with grid search tuning.

Table 8. IHSG Forecasting Results Using the ELM Model with Grid Search Tuning

Day	IHSG
January 2, 2025	7,242.28
January 3, 2025	7,228.42
January 6, 2025	7,211.02
January 7, 2025	7,192.67
January 8, 2025	7,174.06

4. Conclusion

This study forecast the movement of the IHSG using an Extreme Learning Machine (ELM) model with multi-horizon forecasting and exogenous variables such as gold prices, the USD/IDR exchange rate, and a COVID-19 dummy. The model also applies grid search tuning to find the optimal number of hidden layers, resulting in a total of 9 hidden layers. Evaluation results show that both ELM models are capable of multi-horizon forecasting (t+1 to t+5). This is demonstrated by the very small values of MAE, MAPE, and RMSE at each horizon. The IHSG forecasts for the next five days are 7,242.28, 7,228.42, 7,211.02, 7,192.67, and 7,174.06. The findings confirm that ELM effectively captures nonlinear dependencies among macroeconomic indicators and stock market movements. In conclusion, this research strengthens the empirical evidence supporting the application of neural-based models in stock market forecasting and extends prior work by incorporating exogenous macroeconomic variables and pandemic indicators.

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