Forecasting Weekly Stock Price of Jakarta Stock Exchange Composite Index (IHSG) Using ARIMA Box-Jenkins Method

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Abstract— Stock price movements in the capital market reflect investor sentiment and economic trends, requiring accurate forecasting methods to support decision-making. One method that can be used for forecasting is the Autoregressive Integrated Moving Average (ARIMA). The application of the ARIMA method to the weekly stock price data of the Jakarta Stock Exchange Composite Index (IHSG) from November 2023 to April 2025 produces the equation $\boldsymbol{Y_t = 0.874Y_{t-1} - 0.5359Y_{t-2} + 0.6619Y_{t-3} + 0.0416e_{t-1} + 0.9721e_{t-2} + 0.189e_{t-3} + e_t}$ which is obtained from ARIMA(2,1,3) as the best model based on the lowest error values (MAE, MSE, RMSE, and MAPE). This model passed residual diagnostics and demonstrates strong potential in forecasting IHSG stock prices.

Keywords— ARIMA; Jakarta Stock Exchange Composite Index; IHSG; Forecasting

I. INTRODUCTION

The capital market plays a vital role in a country's economic development, acting as a barometer of financial health and investor sentiment. In Indonesia, the Composite Stock Price Index (IHSG) serves as the leading indicator of overall stock market performance, reflecting the movement of all stocks listed on the Indonesia Stock Exchange [1].

Forecasting IHSG is very important for investors, policymakers, and analysts to support strategic decision-making and risk management [2]. Stock price can be understood as the price charged in transactions per share in the capital market [3]. The ability to accurately predict stock price index movements has a significant impact on investment decision-making, risk management, and financial planning [4].

However, predicting stock price indexes remains a challenging task due to the inherent volatility and non-linear patterns of financial time series data [5]. This challenge requires the use of robust statistical models that are able to capture the underlying data patterns [6].

Among the available forecasting models, the Autoregressive Integrated Moving Average (ARIMA) model introduced by Box and Jenkins in 1976 is one of the most widely adopted techniques [7]. This model is effective in capturing linear dependence of time series data through a combination of autoregressive (AR), differencing(I), and moving average (MA) components, making it suitable for non-stationary financial time series [8].

Several studies have applied ARIMA in forecasting stock indices in various markets. [9] used monthly IHSG data. However, these studies often lack comprehensive model diagnostics or do not use weekly data with higher frequencies. Furthermore, a recent study by Haerani and Nugraha [10] predicted the IHSG using daily data from June to December 2019, selecting ARIMA(21,1,2) as the best model based on AIC and RMSE. Although the study showed the potential of ARIMA forecasting, it did not discuss post-pandemic market behavior or use residual validation techniques.

This indicates a gap in existing research: there are limited studies that specifically focus on weekly IHSG data, which are processed with strict model selection, validation techniques (e.g., ADF, AIC, Shapiro and Ljung-Box tests), and comprehensive forecast error analysis (e.g., MSE, MAE, RMSE, and MAPE). In addition, many previous studies do not consider the post-pandemic period and current geopolitical conditions that affect the global capital market and the IHSG in particular [11].

This study addresses this gap by developing a weekly stock price forecasting model for the Jakarta Composite Index using ARIMA. The purpose of this study is to identify the most accurate ARIMA model through a systematic approach involving data stationarity checks, model identification, parameter estimation, residual diagnostics, and forecast accuracy evaluation [12]. The results of this study aim to improve predictive accuracy and provide valuable insights for financial forecasting in the Indonesian stock market.

By using the latest IHSG data and a rigorous methodology, this study is expected to make a significant contribution to the financial forecasting literature and provide a practical tool for market players and investment decision makers in Indonesia.

II. LITERATURE REVIEW

A. *Time Series Analysis*

Time series data represents a sequence of observations recorded at regular time intervals (daily, weekly, monthly) where previous values influence subsequent measurements. Time series analysis examines these temporal relationships to uncover patterns, trends, and seasonal variations in chronological data, enabling an understanding of historical data behavior for accurate future value prediction. Among various analytical techniques available, Autoregressive Integrated Moving Average (ARIMA) stands as one of the most effective and widely used frameworks due to its ability to capture complex temporal dependencies through a combination of autoregressive components, differencing operations, and moving averages.

B. *Stasionary and Diffferencing*

In ARIMA (Autoregressive Integrated Moving Average) time series modeling, stationarity and differencing are fundamental concepts for developing accurate predictive models. A stationary time series maintains consistent statistical properties—particularly a constant mean—across time, which is essential for reliable forecasting [13]. Before implementing ARIMA, analysts must verify stationarity, typically using the Augmented Dickey-Fuller (ADF) Test in statistical software like R Studio, where a p-value below 0.05 indicates stationary characteristics. When time series data exhibits non-stationary behavior, differencing techniques are employed to transform the data into a stationary form. This transformation creates a new series representing the changes between consecutive observations rather than absolute values. The differencing process, which can be iteratively applied until stationarity is achieved, removes trend components and stabilizes the series variance, preparing the data for effective ARIMA parameter estimation. The mathematical representation of this differencing operation follows a specific formula that calculates the difference between sequential observations[13].

$$W_t = \Delta^d Y_t \tag{1}$$

$$W_t = \Delta Y_t = Y_t - Y_{t-1} \tag{2}$$

$$W_t = \Delta^2 Y_t = \Delta(\Delta Y_t) = Y_t - 2Y_{t-1} + Y_{t-2} \tag{3}$$

$$W_t = \Delta^3 Y_t = \Delta(\Delta^2 Y_t) = \Delta(Y_t - 2Y_{t-1} + Y_{t-2}) \tag{4}$$

C. *Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF)*

The Autocorrelation Function (ACF) serves as a fundamental tool in time series analysis to assess the degree of correlation between current observations and their lagged counterparts. Specifically, ACF helps in identifying the appropriate order of the Moving Average (MA) component in the ARIMA (AutoRegressive Integrated Moving Average) model by detecting where the autocorrelation significantly diminishes, often referred to as the cutoff point at lag k. Conversely, the Partial Autocorrelation Function (PACF) is employed to determine the order of the Autoregressive (AR) component by quantifying the direct correlation between a value and its lagged values, after removing the influence of intermediate lags. By analyzing the patterns observed in the ACF and PACF plots, researchers can make informed decisions in specifying candidate ARIMA models. This step is essential in ensuring model accuracy, interpretability, and forecasting performance[14].

D. *Error Estimation*

Error estimation plays a critical role in assessing the performance and reliability of ARIMA models within time series forecasting. This process involves quantifying the accuracy of the model's predictions in capturing the true behavior of historical data. Several commonly used error metrics for evaluating ARIMA model performance include Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). MAE calculates the average of the absolute differences between actual and predicted values, offering a straightforward interpretation of prediction accuracy. MAPE, on the other hand, expresses these errors as a percentage, allowing for comparison across datasets with different scales. MSE measures the mean of the squared differences, placing greater weight on larger errors, and is particularly useful in penalizing significant deviations. RMSE, derived as the square root of MSE, provides an error estimate in the same unit as the original data, making it more interpretable in practical applications [15]. In the next part, the error estimation will be presented in more detail. Here, n denote number of observations, y_i represent actual values, $\hat{y}_i$ represent predicted values and i refer to the i-th observation.

a) Mean Square Error (MSE)
MSE calculates the average of the squared differences between the predicted and actual values. A lower MSE indicates better model performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^\wedge 2 \tag{5}$$

b) Root Mean Square Error (RMSE**)**
RMSE is the square root of MSE and estimates the magnitude of the prediction error in the original units of the data. It is commonly used to compare model performance across different models.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^\wedge 2} \tag{6}$$

c) Mean Absolute Error (MAE)
MAE calculates the average of the absolute differences between the predicted and actual values. It provides a straightforward measure of how well the predictions align with the true values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

d) Mean Absolute Percentage Error (MAPE)
MAPE measures the average absolute percentage difference between predicted and actual values, providing a scale-independent measure of prediction accuracy. where *h* denotes the number of test data and *i* denotes the forecast data point [16]. MAPE values can be interpreted into four categories, namely: < 10% = very accurate, 10 – 20% = good, 20 – 50% = reasonable, and > 50%[16].

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

e) Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)
AIC and BIC are used to assess the relative quality of statistical models. Models with lower AIC or BIC values are considered superior.

$$AIC = -2\ln(L) + 2k$$
$$BIC = -2\ln(L) + k * \ln(L) \tag{9}$$

III. METHODOLOGY

A. Box-Jenkins Method

The ARIMA (Autoregressive Integrated Moving Average) model, originally introduced by George Box and Gwilym Jenkins, remains one of the most widely adopted techniques for time series forecasting, particularly in applications such as stock price prediction [17]. This model integrates the Autoregressive (AR) and Moving Average (MA) components, along with a differencing step to account for non-stationarity, in order to effectively capture underlying patterns, trends, and dependencies in time series data. A fundamental requirement in applying the ARIMA model is that the data must be stationary, meaning its statistical properties such as mean and variance are constant over time. When working with nonstationary time series, this condition can be addressed by applying differencing techniques, which transform the original data into a stationary form, thus enabling the ARIMA model to be properly specified and used for accurate forecasting[18].

1. *Autoregressive (AR)*

   The Autoregressive (AR) model show that current data (Yt) depends on data from the previous period (Yt-p). The equation of AR model can be written as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t \tag{5}$$

2. *Moving Average (MA)*

   The Moving Average (MA) model show that current data (Y_t) depends on the error in the present data (e_t) and past data (e_{t-q}). The equation of MA model can be written as:

$$Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{6}$$

3. *Autoregressive Integrated Moving Average (ARIMA)*

   Autoregressive (AR) model and Moving Average (MA) equation can be combined and written as the ARMA (p,q):

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{7}$$

   Forecasting nonstationary data can be done with the ARIMA (p,d,q) method by combining the AR and MA methods and using differencing $W_t = \nabla^d Y_t$ ARIMA equation can be written as:

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots + \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{8}$$

To apply the ARIMA method for forecasting, a series of procedures must be followed, as illustrated in Figure 1. The time series data must first be examined for stationarity using the Augmented Dickey-Fuller (ADF) test. If the data is found to be non-stationary, differencing should be applied until stationarity is achieved. Once the data is stationary, potential ARIMA models can be identified by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) at lag k. The parameters for each candidate model are then estimated. Before proceeding with forecasting, it is essential to perform diagnostic checks to ensure the adequacy and validity of the selected model[19].

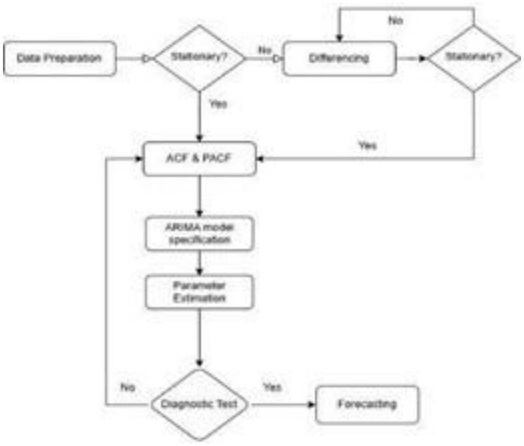

Figure. 6 ARIMA forecasting steps

IV. RESULT AND DISCUSSION

A. Data Preparation

The data used in this analysis is Jakarta Stock Exchange Composite Index (IHSG) weekly stock price data from November 05, 2023 to April 27, 2025 with a total of 76 data. 76 data as data training and 4 data as data test. Data shown in TABLE 1 and Figure 7 as graph. The data is taken from Investing com website and is processed using R Studio.

TABLE 1

Data of Jakarta Stock Exchange Composite Index (IHSG)

Date	Close	Date	Close	Date	Close	Date	Close
11/5/2023	6,809.26	3/17/2024	7,350.15	8/4/2024	7,257.00	12/15/2024	6,983.87
11/12/2023	6,977.67	3/24/2024	7,288.81	8/11/2024	7,432.09	12/22/2024	7,036.57
11/19/2023	7,009.63	3/31/2024	7,286.88	8/18/2024	7,544.30	12/29/2024	7,164.43
11/26/2023	7,059.91	4/14/2024	7,087.32	8/25/2024	7,670.73	1/5/2025	7,088.87
12/3/2023	7,159.60	4/21/2024	7,036.08	9/1/2024	7,721.85	1/12/2025	7,154.66
12/10/2023	7,190.99	4/28/2024	7,134.72	9/8/2024	7,812.13	1/19/2025	7,166.06
12/17/2023	7,237.52	5/5/2024	7,088.79	9/15/2024	7,743.00	1/26/2025	7,109.20
12/24/2023	7,272.80	5/12/2024	7,317.24	9/22/2024	7,696.92	2/2/2025	6,742.58
12/31/2023	7,350.62	5/19/2024	7,221.04	9/29/2024	7,496.09	2/9/2025	6,638.46
1/7/2024	7,241.14	5/26/2024	6,970.74	10/6/2024	7,520.60	2/16/2025	6,803.00
1/14/2024	7,227.40	6/2/2024	6,897.95	10/13/2024	7,760.06	2/23/2025	6,270.60
1/21/2024	7,137.09	6/9/2024	6,734.83	10/20/2024	7,694.66	3/2/2025	6,636.00
1/28/2024	7,238.79	6/16/2024	6,879.98	10/27/2024	7,505.26	3/9/2025	6,515.63
2/4/2024	7,235.15	6/23/2024	7,063.58	11/3/2024	7,287.19	3/16/2025	6,258.18
2/11/2024	7,335.54	6/30/2024	7,253.37	11/10/2024	7,161.26	3/23/2025	6,510.62
2/18/2024	7,295.10	7/7/2024	7,327.58	11/17/2024	7,195.56	4/6/2025	6,262.23
2/25/2024	7,311.91	7/14/2024	7,264.45	11/24/2024	7,114.27	4/13/2025	6,438.27
3/3/2024	7,381.91	7/21/2024	7,288.17	12/1/2024	7,382.79	4/20/2025	6,678.92
3/10/2024	7,328.05	7/28/2024	7,308.12	12/8/2024	7,324.79	4/27/2025	6,719.31

Figure. 7 Graph of Jakarta Stock Exchange Composite Index

B. Stationary Check

Before processing the data, the data must be confirmed to be stationary using the Augmented Dickey-Fuller Test method in R Studio. If the data has a p-value below 0.05, then the data can be considered stationary. In Figure 8, it is shown the plot of Jakarta Stock Exchange Composite Index (IHSG) with p-value obtained from the Augmented Dickey-Fuller Test is 0.9836. This value exceeds the significance level of 0.05, which indicates that the data is not stationary.

Figure. 8 Plot of Jakarta Stock Exchange Composite Index

To make the data stationary, differencing is required using the "diff(data)" code in R Studio. In Figure 9, it is shown the plot of first difference of Jakarta Stock Exchange Composite Index (IHSG) after performing first differencing with p-value obtained from the Augmented Dickey-Fuller Test is 0.01. The p-value after first differencing is less than 0.05 indicates that the data is stationary and order d used in ARIMA model is 1.

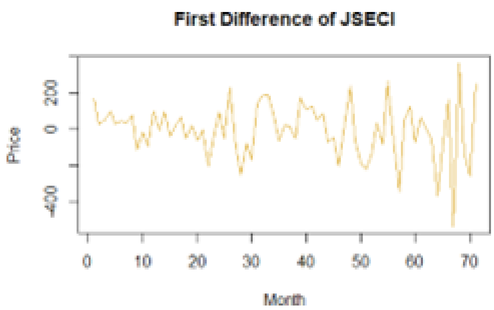

Figure. 9 Plot of First Difference Jakarta Stock Exchange Composite Index

C. Model Specification

The ARIMA model can be specified from the Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) plot of the data. Figure 10 shows the ACF and PACF plot for Jakarta Stock Exchange Composite Index (IHSG) after the first differencing.

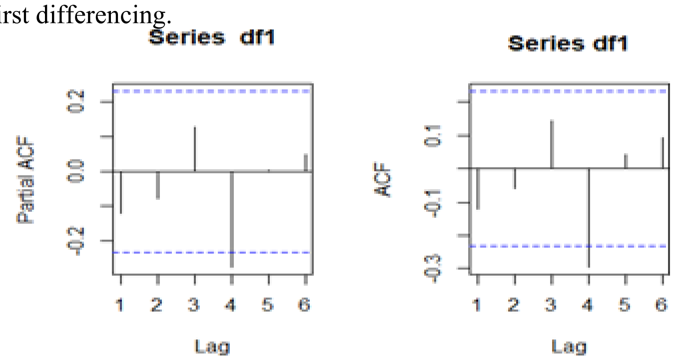

Figure. 10 Plot of ACF and PACF First Difference of Jakarta Stock Exchange Composite Index

Based on the information provided by Figure 10, it is known that PACF cuts off at a lag time of 4 and ACF cuts off at a lag time of 4. Thus, the order of p is determined as 4 and order of q is determined as 4. TABLE 2 shows the ARIMA model arranged based on these parameters.

TABLE 2
ARIMA Model Specification

No	ARIMA Model	p	d	q
1	ARIMA (0,1,0)	0	1	0
2	ARIMA (0,1,1)	0	1	1
3	ARIMA (0,1,2)	0	1	2
4	ARIMA (0,1,3)	0	1	3
5	ARIMA (0,1,4)	0	1	4
6	ARIMA (1,1,0)	1	1	0
7	ARIMA (1,1,1)	1	1	1
8	ARIMA (1,1,2)	1	1	2
9	ARIMA (1,1,3)	1	1	3
10	ARIMA (1,1,4)	1	1	4
11	ARIMA (2,1,0)	2	1	0
12	ARIMA (2,1,1)	2	1	1
13	ARIMA (2,1,2)	2	1	2

14	ARIMA (2,1,3)	2	1	3
15	ARIMA (2,1,4)	2	1	4
16	ARIMA (3,1,0)	3	1	0
17	ARIMA (3,1,1)	3	1	1
18	ARIMA (3,1,2)	3	1	2
19	ARIMA (3,1,3)	3	1	3
20	ARIMA (3,1,4)	3	1	4
21	ARIMA (4,1,0)	4	1	0
22	ARIMA (4,1,1)	4	1	1
23	ARIMA (4,1,2)	4	1	2
24	ARIMA (4,1,3)	4	1	3
25	ARIMA (4,1,4)	4	1	4

D. *Parameter Estimation*

The parameters of the Autoregressive (AR) formula are denoted as φ with order p. While the parameters of the Moving Average (MA) formula are denoted as θ with order q. TABLE 3 shows that by using the summary(model) code, the value of each parameter as well as Log Likelihood and Akaike Information Criterion (AIC) can be obtained.

TABLE 3
Parameter Estimation for Arima Model

Model ARIMA	AR1	AR2	AR3	AR4	MA1	MA2	MA3	MA4	Log Likelihood	AIC
(0,1,0)									-457.98	917.97
(0,1,1)					-0.1353				-457.4	918.81
(0,1,2)					-0.1125	-0.0819			-457.31	920.61
(0,1,3)					-0.0496	-0.1802	0.1188		-456.84	921.68
(0,1,4)					-0.0634	0.1466	0.2605	-0.5287	-450.07	910.14
(1,1,0)	-0.1231								-457.46	918.93
(1,1,1)	0.3229				-0.4509				-457.35	920.71
(1,1,2)	-0.8011				0.7591	-0.2129			-454.98	917.97
(1,1,3)	-0.7009				0.6743	-0.0973	0.1499		-454.72	919.43
(1,1,4)	-0.0134				-0.0546	0.147	0.2639	-0.5276	-450.07	912.14
(2,1,0)	-0.13	-0.0759							-457.27	920.54
(2,1,1)	-1.0009	-0.2423			0.9235				-454.72	917.44
(2,1,2)	-1.4485	-0.7773			1.3743	0.5691			-453.8	917.59
(2,1,3)	-0.126	-0.6619			0.0416	0.9721	0.189		-451.89	915.77

(2,1,4)	-0.0704	-0.3806			-0.0072	0.4781	0.2388	-0.4488	-448.78	911.56
(3,1,0)	-0.1212	-0.0591	0.1396						-456.61	921.23
(3,1,1)	-0.8612	-0.1256	0.1731		0.799				-454.09	918.18
(3,1,2)	-0.2065	0.5434	0.2135		0.1294	-0.7104			-454.69	921.39
(3,1,3)	-0.6711	0.3457	0.6083		0.5983	-0.4906	-0.442		-453.79	921.59
(3,1,4)	-0.3062	-0.4117	-0.222		0.2096	0.5094	0.4686	-0.419	-448.39	912.78
(4,1,0)	-0.0938	-0.058	0.1115	-0.3183					-453.26	916.53
(4,1,1)	-0.5756	-0.1022	0.0918	-0.2402	0.5227				-453.15	918.31
(4,1,2)	0.054	-0.7967	0.042	-0.2677	-0.1864	0.95			-449.82	913.63
(4,1,3)	-0.7307	-0.7386	-0.481	-0.1779	0.6571	0.8484	0.838		-448.85	913.69
(4,1,4)	-0.2927	-0.386	-0.2117	0.0237	0.1973	0.4867	0.4591	-0.4446	-448.39	914.77

E. Residual Analysis

Determining the best ARIMA model is performed using the Shapiro Test and the Ljung-Box Test. Through these tests, the ARIMA model with a p-value that exceeds 0.05 will be selected. TABLE 4 shows the results of the Shapiro Test and Ljung-Box Test and the ARIMA models that satisfy the condition. Models that passed the residual test will be forcasted and the error of each models will be calculated.

TABLE 4
Result of Residual Analysis

No	Model ARIMA	Shapiro Test	Ljung-Box Test	Result
1	(0,1,0)	0.1161	0.3033	Passed
2	(0,1,1)	0.06066	0.9738	Passed
3	(0,1,2)	0.08352	0.9388	Passed
4	(0,1,3)	0.3023	0.7704	Passed
5	(0,1,4)	0.009823	0.9953	Not Passed
6	(1,1,0)	0.05979	0.9342	Passed
7	(1,1,1)	0.05734	0.9891	Passed
8	(1,1,2)	0.1975	0.942	Passed
9	(1,1,3)	0.2998	0.8761	Passed
10	(1,1,4)	0.00973	0.9787	Not Passed
11	(2,1,0)	0.09316	0.9356	Passed
12	(2,1,1)	0.218	0.8424	Passed
13	(2,1,2)	0.1261	0.8094	Passed
14	(2,1,3)	0.06933	0.8141	Passed
15	(2,1,4)	0.005716	0.906	Not Passed
16	(3,1,0)	0.3224	0.7399	Passed
17	(3,1,1)	0.1423	0.8666	Passed
18	(3,1,2)	0.2951	0.8416	Passed
19	(3,1,3)	0.1289	0.8175	Passed
20	(3,1,4)	0.005356	0.9532	Not Passed
21	(4,1,0)	0.005937	0.902	Not Passed

22	(4,1,1)	0.01577	0.918	Not Passed
23	(4,1,2)	0.01174	0.9899	Not Passed
24	(4,1,3)	0.01985	0.9571	Not Passed
25	(4,1,4)	0.005318	0.9556	Not Passed

F. Forecast

TABLE 5
Forecasting Value of The ARIMA (0,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6510.62	6258.679	6762.561
4/13/2025	6,438.27	6510.62	6154.322	6866.918
4/20/2025	6,678.92	6510.62	6074.245	6946.995
4/27/2025	6,719.31	6510.62	6006.738	7014.502

TABLE 6
Forecasting Value of The ARIMA (0,1,1)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6481.377	6231.519	6731.234
4/13/2025	6,438.27	6481.377	6151.063	6811.69
4/20/2025	6,678.92	6481.377	6086.68	6876.073
4/27/2025	6,719.31	6481.377	6031.417	6931.336

TABLE 7
Forecasting Value of The ARIMA (0,1,2)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6506.682	6257.188	6756.176
4/13/2025	6,438.27	6489.127	6155.546	6822.708
4/20/2025	6,678.92	6489.127	6050.878	6927.377
4/27/2025	6,719.31	6489.127	6050.878	6927.377

TABLE 8
Forecasting Value of The ARIMA (0,1,3)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6503.461	6255.737	6751.186
4/13/2025	6,438.27	6457.173	6115.424	6798.922
4/20/2025	6,678.92	6476.708	6085.306	6868.11
4/27/2025	6,719.31	6476.708	6027.599	6925.816

TABLE 9

Forecasting Value of The ARIMA (1,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6479.533	6229.458	6729.608
4/13/2025	6,438.27	6483.361	6150.764	6815.958
4/20/2025	6,678.92	6482.89	6082.413	6883.367
4/27/2025	6,719.31	6482.948	6024.762	6941.134

TABLE 10

Forecasting Value of The ARIMA (1,1,1)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6494.728	6245.056	6744.4
4/13/2025	6,438.27	6489.597	6158.343	6820.851
4/20/2025	6,678.92	6487.941	6097.128	6878.753
4/27/2025	6,719.31	6487.406	6046.533	6928.278

TABLE 11

Forecasting Value of The ARIMA (1,1,2)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6464.467	6224.558	6704.375
4/13/2025	6,438.27	6468.577	6136.521	6800.634
4/20/2025	6,678.92	6465.285	6084.28	6846.289
4/27/2025	6,719.31	6467.922	6027.426	6908.419

TABLE 12

Forecasting Value of The ARIMA (1,1,3)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6415.199	6175.691	6654.706
4/13/2025	6,438.27	6445.36	6111.119	6779.601
4/20/2025	6,678.92	6442.956	6045.916	6839.997
4/27/2025	6,719.31	6444.641	5968.175	6921.108

TABLE 13

Forecasting Value of The ARIMA (2,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6414.91	6175.23	6654.59
4/13/2025	6,438.27	6449.55	6123.46	6775.65
4/20/2025	6,678.92	6438.06	6064.8	6811.33
4/27/2025	6,719.31	6441.17	6005	6877.34

TABLE 14
Forecasting Value of The ARIMA (2,1,1)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6497.359	6247.981	6746.737
4/13/2025	6,438.27	6479.918	6149.365	6810.471
4/20/2025	6,678.92	6483.191	6095.673	6870.71
4/27/2025	6,719.31	6484.09	6044.927	6923.252

TABLE 15
Forecasting Value of The ARIMA (2,1,2)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6316.781	6080.301	6553.261
4/13/2025	6,438.27	6416.805	6094.542	6739.068
4/20/2025	6,678.92	6422.594	6045.87	6799.318
4/27/2025	6,719.31	6336.46	5888.025	6784.895

TABLE 16
Forecasting Value of The ARIMA (2,1,3)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6448.389	6222.141	6674.637
4/13/2025	6,438.27	6397.043	6090.057	6704.03
4/20/2025	6,678.92	6473.134	6061.399	6884.87
4/27/2025	6,719.31	6497.533	5976.039	7019.027

TABLE 17
Forecasting Value of The ARIMA (3,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6478.438	6231.46	6725.416
4/13/2025	6,438.27	6431.468	6102.676	6760.261
4/20/2025	6,678.92	6474.309	6086.279	6862.339
4/27/2025	6,719.31	6467.4	6009.217	6925.583

TABLE 18
Forecasting Value of The ARIMA (3,1,1)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6339.108	6101.47	6576.746
4/13/2025	6,438.27	6410.548	6084.764	6736.331
4/20/2025	6,678.92	6414.256	6028.947	6799.565
4/27/2025	6,719.31	6372.407	5905.636	6839.177

TABLE 19

Forecasting Value of The ARIMA (3,1,2)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6401.407	6161.752	6641.062
4/13/2025	6,438.27	6435.796	6109.678	6761.914
4/20/2025	6,678.92	6423.243	6048.327	6798.158
4/27/2025	6,719.31	6421.206	5979.493	6862.919

TABLE 20

Forecasting Value of The ARIMA (3,1,3)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
4/6/2025	6,262.23	6314.934	6078.469	6551.399
4/13/2025	6,438.27	6413.936	6091.463	6736.408
4/20/2025	6,678.92	6421.129	6043.479	6798.78
4/27/2025	6,719.31	6331.496	5881.253	6781.739

Based on forecasting value on TABLE 5, TABLE 6, TABLE 7, TABLE 8, TABLE 9, TABLE 10, TABLE 11, TABLE 12, TABLE 13, TABLE 14, TABLE 15, TABLE 16, TABLE 17, TABLE 18, TABLE 19, and TABLE 20, it best model for forecasting using ARIMA method can be determined by comparing the error among models as shown below.

TABLE 21

Error Measured From ARIMA Models

Model ARIMA	MAE	MSE	RMSE	MAPE(%)
ARIMA(0,1,0)	174.4325	34702.13	186.29	2.679
ARIMA(0,1,1)	174.4325	36379.74	190.73	2.6669
ARIMA(0,1,2)	178.8213	37837.2	194.52	2.7402
ARIMA(0,1,3)	176.237	39573.79	198.93	2.696
ARIMA(1,1,0)	173.6965	35887.14	189.44	2.6558
ARIMA(1,1,1)	176.677	36735.56	191.67	2.7052
ARIMA(1,1,2)	174.3918	37663.54	194.07	2.66
ARIMA(1,1,3)	167.673	38642.96	196.58	2.5434
ARIMA(2,1,0)	170.74	39703.46	199.26	2.5897
ARIMA(2,1,1)	176.9315	37664.62	194.07	2.7082
ARIMA(2,1,2)	178.798	53928.42	232.22	2.685

ARIMA(2,1,3)	163.7373	31971.94	178.81	2.4987
ARIMA(3,1,0)	169.8828	38029.12	195.01	2.5927
ARIMA(3,1,1)	179.0418	49266.87	221.96	2.6959
ARIMA(3,1,2)	173.858	43403.27	208.33	2.6314
ARIMA(3,1,3)	180.6608	55056.44	234.64	2.7127

TABLE 21 above shown the error measured from ARIMA (2,1,3) as the lowest error among ARIMA models considered. Thus, it can be stated that ARIMA (2,1,3) is the best model for forecasting the stock price of Jakarta Stock Exchange Composite Index.

$$W_t = -0.126W_{t-1} - 0.6619W_{t-2} + 0.0416e_{t-1} + 0.9721e_{t-2} + 0.189e_{t-3} + e_t \tag{9}$$

Let

$$W_t = Y_t - Y_{t-1}$$

Then the equation become

$$Y_t - Y_{t-1} = -0.126(Y_{t-1} - Y_{t-2}) - 0.6619(Y_{t-2} - Y_{t-3}) + 0.0416e_{t-1} + 0.9721e_{t-2} + 0.189e_{t-3} + e_t$$
$$Y_t = Y_{t-1} - 0.126Y_{t-1} + 0.126Y_{t-2} - 0.6619Y_{t-2} + 0.6619Y_{t-3} + 0.0416e_{t-1} + 0.9721e_{t-2} + 0.189e_{t-3} + e_t$$
$$\boldsymbol{Y_t = 0.874Y_{t-1} - 0.5359Y_{t-2} + 0.6619Y_{t-3} + 0.0416e_{t-1} + 0.9721e_{t-2} + 0.189e_{t-3} + e_t} \tag{10}$$

Figure 11 below shows the visualization plot of forecasting from ARIMA (2,1,3) of Jakarta Stock Exchange Composite Index stock price forecasting from November 05, 2023 to April 27, 2025.

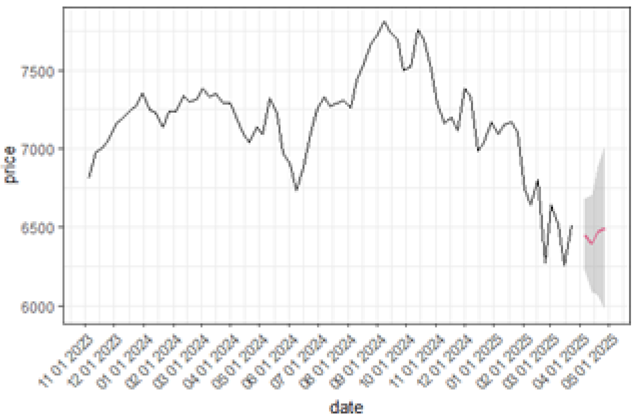

Figure. 11 Forecasting Plot from ARIMA (2,1,3)

V. **CONCLUSION**

Stock price forecasting has been conducted for the Jakarta Stock Exchange Composite Index (IHSG) for the next 4 weeks from April 6, 2025 to April 27, 2025 using historical weekly data from November 5, 2023 to March 30, 2025 with a total of 76 observations, obtained from the Investing.com website. By applying the Box-Jenkins method and processing the data using R Studio, it was found that the ARIMA (2,1,3) model passed the residual tests (Shapiro and Ljung-Box) and produced the smallest forecasting error among 25 evaluated models. The ARIMA (2,1,3) model can be used to forecast stock price and is expressed in the following equation:

$$\boldsymbol{Y_t = 0.874Y_{t-1} - 0.5359Y_{t-2} + 0.6619Y_{t-3} + 0.0416e_{t-1} + 0.9721e_{t-2} + 0.189e_{t-3} + e_t}$$

This study is limited to using the ARIMA model for weekly IHSG data. In the future, research can be extended by trying other models such as SARIMA or ARIMA-GARCH, which can capture seasonal patterns and more complex volatility. It is also possible to use daily or monthly data to obtain more detailed forecasting results. Future studies may also include other economic variables, such as inflation, exchange rates, or interest rates, to see whether these factors affect prediction accuracy. Finally, machine learning methods such as LSTM (Long Short-Term Memory) could also be tested and compared with the linear ARIMA model.

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