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FORECASTING THE INFLATION RATE IN INDONESIA USING ARIMA-GARCH MODEL

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ABSTRACT

Inflation is a key economic indicator that affects purchasing power, economic growth, and financial stability. Accurate forecasting is essential for policymakers to implement effective monetary and fiscal policies. However, traditional models like ARIMA (Autoregressive Integrated Moving Average) mainly capture general trends and often fail to address inflation volatility. This study enhances inflation forecasting accuracy by applying the ARIMA-GARCH hybrid model, which combines trend estimation with volatility modelling. Focusing on Indonesia's inflation patterns using recent data, it addresses a gap in existing research. This type of research uses quantitative methods, and the data were obtained from the official website of Bank Indonesia. The dataset consists of 240 monthly Indonesian inflation data points spanning from September 2004 to August 2024. The ARIMA (0,1,1)-GARCH (2,0) model is used to analyze inflation trends and volatility dynamics. The model evaluation shows strong predictive performance, with a Mean Absolute Percentage Error (MAPE) of 2.73% and Root Mean Squared Error (RMSE) of 0.74 for training data. Testing data results in a MAPE of 18.95% and RMSE of 0.702, which remains within an acceptable range. These findings highlight the importance of incorporating volatility modelling in inflation forecasting to enhance economic decision-making. A reliable forecast mitigates economic uncertainty, thereby providing a stronger foundation for achieving long-term economic growth. This study contributes by demonstrating the practical application of ARIMA-GARCH in Indonesia's inflation modelling, providing valuable insights for policymakers in managing inflation-related risks.

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1. INTRODUCTION

A nation's prosperity is reflected not only by economic growth but also by economic stability. Maintaining stability in an economic play a crucial role in ensuring a predictable environment for businesses, households, and policymakers to thrive. Economic stability is characterized by controlled inflation, stable exchange rates, and sustainable fiscal policies, all of which contribute to long-term growth and improved living standards [1]. This aligns with the Sustainable Development Goals (SDGs), especially Goal 8, which emphasizes fostering inclusive, sustained, and sustainable economic growth, as well as ensuring productive, full, and decent employment for everyone [2]. However, achieving and maintaining this stability is a complex challenge, as it can be disrupted by various factors. One of the most significant threats to economic stability is inflation, that can affects purchasing power, increases uncertainty, and distorts market efficiency [3].

Inflation refers to the rise in the prices of goods and services in an economy over a specific time frame [4]. When inflation persists, it results in a reduction in the market value of a country's produced goods and services. In essence, inflation indicates how much the cost of a selected group of goods and services has increased over time [5]. The country's economic growth is threatened by the persistent rise in inflation. Consequently, fluctuations in the inflation rate can cause price instability and changes in market value, which, in turn, impact the nation's gross domestic product [6]. This economic uncertainty can lead to reduced trade activity and slower economic growth.

In Indonesia, inflation is still a major concern for the government and economic stakeholders due to its significant impact on policy-making, market stability, and overall economic growth. Over the past few decades, inflation in Indonesia has often experienced significant fluctuations. In the last 5 years, the highest inflation in Indonesia reached 5.51% in 2022 and the lowest reached 1.68% in 2020 [7]. Such fluctuations can occur anytime and anywhere, even under the worst conditions that cannot be controlled. Therefore, forecasting future inflation rates is very important for the government and the business world as a basis for determining economic policies and strategies [8]. For this reason, an appropriate method is needed to analyze and manage inflation patterns, in order to forecast its future movements, thus enabling the formulation of preventive policies to maintain economic stability. The combined application of traditional statistical and econometric models, including the Autoregressive Integrated Moving Average (ARIMA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH), has been extensively utilized for inflation forecasting [9]. ARIMA captures trends and historical dependencies, while GARCH models volatility and dynamic variance changes. Thus, the ARIMA-GARCH model provides a more robust framework for analyzing inflation patterns and assessing risks [10].

Previous studies have examined the effectiveness of the ARIMA-GARCH hybrid model in forecasting inflation. For example, research by [11] found that the conventional ARIMA model provided a reasonably accurate estimation of monthly inflation in Nigeria, with ARIMA(1,2,1) identified as the best-performing model . Another study reported that the ARIMA model outperformed the ARIMA-GARCH hybrid, as indicated by lower RMSE, MAPE, MAE, Theil, and BIAS values in forecasting inflation in Kenya [12]. Similarly, Qasim et al. (2021) highlighted that the conventional ARIMA model still exhibited heteroskedasticity issues, as reflected in the significant lags observed in the ACF and PACF of squared ARIMA residuals. As a result, the GARCH model was applied to capture the error component within ARIMA, leading to improved predictive accuracy compared to the standalone ARIMA model [13]. These findings reinforce that the ARIMA-GARCH model can enhance inflation forecasting accuracy by addressing the heteroskedasticity issues commonly found in conventional ARIMA models.

While many studies have explored ARIMA-GARCH for inflation forecasting, none have specifically applied it to Indonesian inflation using recent data. This study fills the gap by analyzing Indonesian inflation using the most recent data, thus providing a more accurate picture of current economic conditions. This approach evaluates the effectiveness of the model in capturing inflation volatility which contributes to the advancement of knowledge on inflation prediction in the context of Indonesia's volatile economy. The results of this research have the potential to enhance the development of monetary policies, support better strategies for managing inflation risks, and promote the wider use of advanced forecasting methods in economic decision-making.

This study aims to analyze Indonesian inflation using a quantitative approach, utilizing data from the Bank Indonesia website covering September 2004 to August 2024. By employing RStudio and Minitab, the study applies descriptive statistics, ARIMA modelling, and GARCH model identification to capture inflation trends and volatility. The methodology involves stationarity testing, model selection based on AIC, and heteroscedasticity analysis to determine the most suitable forecasting approach. The effectiveness of the models is assessed using MAPE and RMSE, ensuring accurate and reliable inflation predictions. The findings contribute to financial forecasting techniques, supporting economic decision-making and policy formulation in Indonesia.

2. RESEARCH METHODS

2.1 Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is an extension of the Auto Regressive Moving Average (ARMA) model, specifically designed to handle non-stationary time series. While the conventional ARMA model assumes that the time series under analysis is stationary, ARIMA addresses non-stationary data by transforming it into a stationary series. This transformation is achieved through differencing denoted as (d), a process that eliminates trends and seasonality by computing the differences between consecutive data points [14].

A stationary time series can be conceptualized as a combination of signal (the underlying pattern) and noise (random fluctuations). The ARIMA model focuses on analyzing the signal component after separating it from the noise, and it generates predictions for future time. As the name implies, the ARIMA model has three main components, namely autoregressive, integration, and moving average, which are represented by the autoregressive order. The fundamental concept of time series analysis indicates that the present value of an observation (Y_t) is affected by one or more past observation values (Y_t). Typically, the autoregressive integrated moving average model is denoted as ARIMA (p, d, q) and is formulated as follows [15].

$$(1-B)^d Y_t = \mu + \Phi(B)(1-B)^d Y_t = \mu + \Phi(B)Z(t) + \Theta(B)\varepsilon_t, \tag{1}$$

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p, \tag{2}$$

$$\Theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q, \tag{3}$$

where $\Phi(B)$ is an autoregressive operator with order p, and $\Theta(B)$ is a moving average operator with order q.

ARIMA models are commonly estimated using either the Maximum Likelihood (MLE) method or the Conditional Sum of Squares (CSS) approach to derive parameter estimates [16]. Nevertheless, selecting the appropriate values for parameters p and q in an ARIMA model is guided by the patterns observed in the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

2.2 Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

ARCH (Autoregressive Conditional Heteroskedasticity) is a model designed to analyze volatility in time series data, especially when residual variance is not constant (heteroskedasticity). It was introduced to capture unstable price movements, where significant fluctuations are typically followed by further large shifts, and minor changes tend to be succeeded by similarly small ones. The fundamental equation for the ARCH model can be expressed as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2. \tag{4}$$

The data variance at time period t; σ_t^2 id modeled as a function of the coefficient α_0 ; the ARCH parameter α_1 ; and the squared error term from the previous period ϵ_{t-1}^2. The ARCH model only considers the squared residuals from the previous period, while the GARCH model adds an autoregressive component by considering the variance from the previous period. Thus, the GARCH model is more flexible and capable of handling more complex volatility compared to the ARCH model [17].

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) is a statistical model used to analyze and forecast volatility (variation) in time series data, especially within financial applications. This model was developed to address conditional heteroskedasticity, which refers to situations where the variance of errors in the model changes over time. GARCH is particularly useful in modeling the volatility of financial assets, such as stock prices, currencies, or commodities like gold, which often experience periods of both high and low volatility [18]. The general form of the GARCH (p, q) model is as follows.

$$\sigma_t^2 = \alpha_0 + \textstyle\sum_{i=1}^{p} \alpha_i \varepsilon_{t-p}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-q}^2, \tag{5}$$

where σ_t^2 is the conditional variance, α_0 is the constant, ε_{t-p}^2 is the residuals in period $t-p$, σ_{t-q}^2 is the conditional variance in period $t-q$, and α_i, β_i is the ARCH, GARCH parameter.

2.3 Mean Absolute Error (MAPE)

MAPE (Mean Absolute Percentage Error) is a performance metric widely used in regression models, valued for its clear interpretation in terms of relative error. It is particularly recommended for tasks where sensitivity to relative variations is more critical than sensitivity to absolute variations. However, MAPE also has several limitations. The most notable drawbacks are its restriction to strictly positive data by definition and its inherent bias toward lower forecasts. MAPE aims to minimize or reduce the level of error in the forecasting process. In forecasting, there is always a level of uncertainty that can leads to error value. The MAPE can be calculated as follows [19].

$$MAPE = \left(\frac{100}{n}\right)\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right|, \tag{6}$$

where y_t and $\hat{y}_t$ is the actual and predicted data at time t, and n is the number of data observations.

The characteristics of MAPE values that indicate prediction accuracy are as follow in Table 1 below.

Table 1. Interpretation of MAPE Values

MAPE	Interpretations
MAPE ≤ 10%	Model has a high degree of forecasting accuracy.
10% < MAPE ≤ 20%	Model's forecasting accuracy is good.
20% < MAPE ≤ 50%	Model has sufficient predictive power.
MAPE > 50%	Model demonstrates minimal predictive capability.

2.4 Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is a metric used to evaluate model performance by measuring the difference between observed values and model predictions, RMSE is calculated as the square root of the average of the squared errors between the observed values y_i and the predicted values $(\hat{y}_i)$. The formula used to calculate RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t-\hat{y}_t)^2}. \tag{7}$$

where y_t and $\hat{y}_t$ is the actual and predicted data at time t, and n is the number of data observations.

RMSE provides an indication of the magnitude of the average error produced by the model, with the same units as the observed data. This metric is optimal for errors that are normally distributed (Gaussian), as it minimizes the squared error, which aligns with the principle of maximum likelihood estimation (MLE) for normal distributions [20].

2.5 Research Methodology

This type of research uses quantitative research methods. The data used in this study was obtained from the Bank Indonesia website regarding inflation in Indonesia. The dataset consists of 240 monthly Indonesian inflation data points from September 2004 to August 2024. The training data consists of 216 observations covering the period from September 2004 to August 2022, while the testing data consists of 24 observations from September 2022 to August 2024. There are two types of variables in this study: independent and dependent variables. Based on the background and research objectives, the independent variable in this study is the period (time), while the dependent variable is the inflation rate in Indonesia, expressed as a percentage (%).

This research was conducted using RStudio [21] and Minitab. The analysis steps in this study include descriptive statistics, GARCH model identification, and accuracy evaluation. Descriptive statistics involve collecting data, creating descriptive statistics on the original data, and making a time series plot of the original data. In the GARCH model identification stage, the data is divided into training and testing sets with a ratio of 90%:10%. The stationarity of the training data in variance is identified, and if necessary, transformed according to the appropriate lambda value. The stationarity of the transformed training data in mean is then examined using ACF and PACF plots and the ADF test. The appropriate ARIMA model is identified based on differencing order (d) and model selection criteria such as the Akaike Information Criterion (AIC). The best ARIMA mathematical model is formulated, and the presence of heteroscedasticity in the residuals is tested using the ARCH-LM test. If heteroscedasticity is present, further ARCH/GARCH modelling is conducted using transformed data and the selected ARIMA order. The appropriate ARCH/GARCH order is determined, followed by significance testing, and the ARIMA variance model is formulated based on the GARCH model obtained. The accuracy of the GARCH model is evaluated by comparing the original data, ARIMA estimations, and ARIMA-GARCH estimations through visualization. The MAPE and RMSE values of the training data are calculated for both ARIMA and ARIMA-GARCH models. The model is then tested using the testing data, and the MAPE and RMSE values are calculated to assess its performance. The research methodology is illustrated in Fig. 1 to provide a clearer understanding of the analysis process.

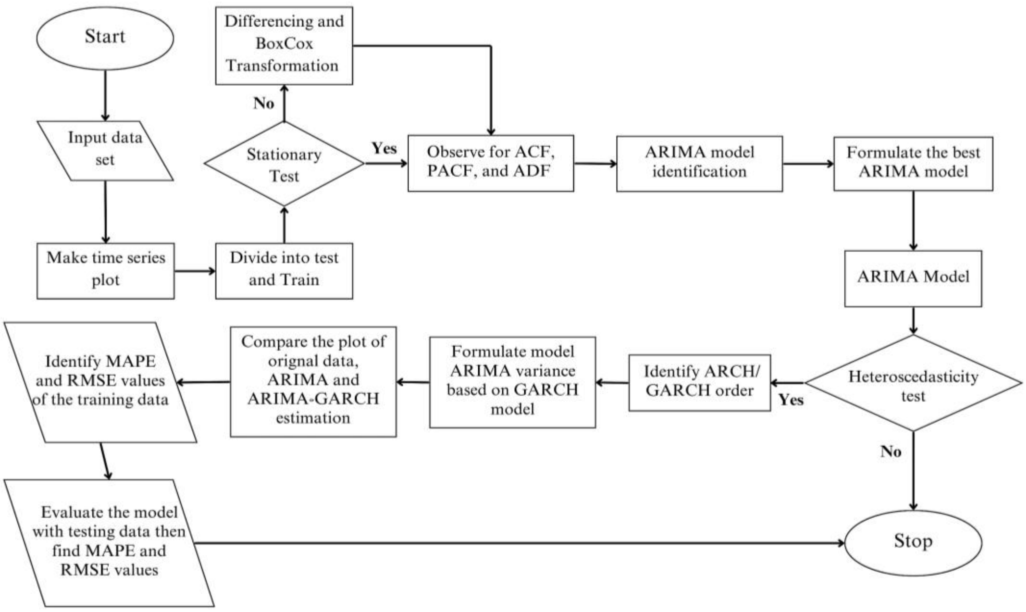


Figure 1. Flowchart of Research Methodological Process

3. RESULTS AND DISCUSSION

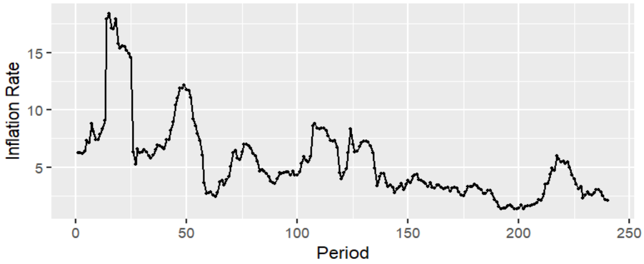
3.1 Descriptive Statistics

One of the initial observations to determine general characteristics of the dataset is through descriptive statistics. Table 2 below highlights these statistics for Indonesia's inflation rates on a monthly basis from September 2004 to August 2024.

Table 2. Summary Results of Descriptive Statistics Inflation Rate in Indonesia

Variable	N	Mean	Variance	Standard Deviation	Median	Minimum	Maximum
Inflation rate	240	5.44	11.59	3.4	4.52	1.32	18.38

The average inflation rate in Indonesia is 5.44%, with a variance of 11.59% and a standard deviation of 3.4%. Therefore, the highest inflation rate, recorded at 18.38% in November 2005, was attributed to a fuel price hike policy during Susilo Bambang Yudhoyono's presidency, leading to increased prices of goods and necessities. Conversely, the lowest rate, at 1.32%, occurred in August 2020, driven by the economic slowdown during the COVID-19 pandemic, which weakened purchasing power and suppressed inflation. Fig. 2 illustrates these inflation rate fluctuations.



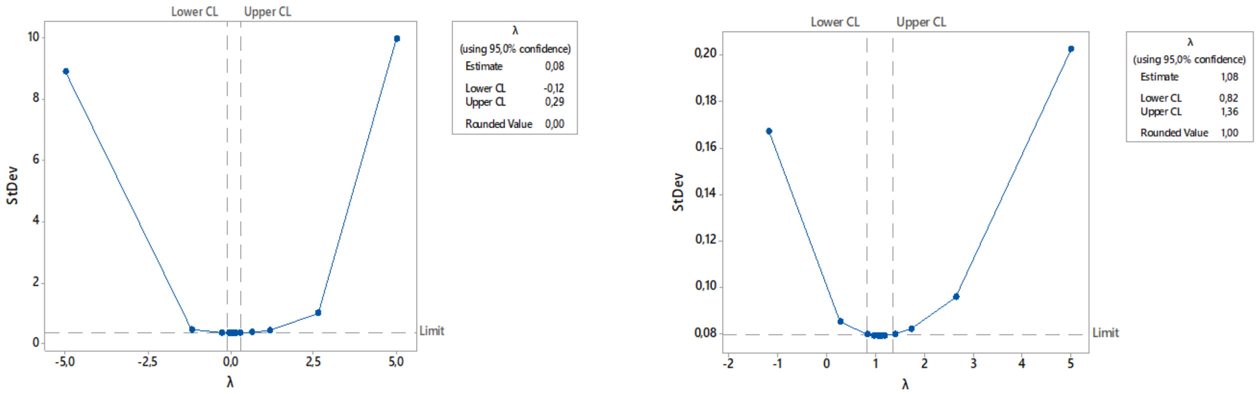
Source: R Output

Figure 2. Time Series Plot of Inflation Rate Data in Indonesia

The graph shown in Fig. 2 illustrates the monthly inflation rate in Indonesia across 240 time points from September 2004 to August 2024. The plot reveals no clear upward or downward trend, yet the series is notably non-stationary, with evident shifts in both mean and variance over time. Several sharp spikes are observed, particularly in the early periods, where inflation surpasses 15%, indicating episodes of extreme volatility. These fluctuations are not constant; periods of high variability alternate with more stable intervals, suggesting the presence of volatility clustering. Overall, the inflation series demonstrates complex dynamic behavior, with irregular movements and structural changes that evolve throughout the observed time frame.

3.2 Data Stationarity

The assumption of stationarity is fundamental in time series analysis, as it underpins the validity of numerous statistical tests and forecasting models. A non-stationary time series, characterized by trends and seasonal variations, can lead to biased parameter estimates and unreliable forecasts [22]. Therefore, ensuring stationarity is a prerequisite for model construction, as many time series methodologies assume constant statistical properties over time. To achieve this, appropriate transformations, such as detrending and seasonal adjustment, must be applied to remove time-dependent structures before conducting any statistical analysis or model estimation. The Box-Cox transformation is often applied to stabilize variance, particularly in cases where non-stationarity arises due to heteroscedasticity. This transformation is particularly effective when the estimated transformation parameter (λ) deviates from 1, indicating the necessity of variance stabilization.



(a) (b)

Source: Minitab Output

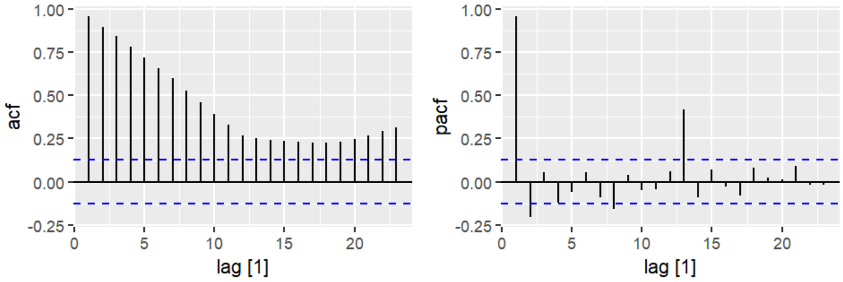
Figure 3. Box-Cox Plot (a) Before (b) After Logarithm Transformation

As presented in Fig. 3, the rounded lambda (λ) value is 0, indicating the necessity of a logarithmic transformation, represented as $log(Z_t)$. Following the application of this transformation, the results of the Box-Cox analysis yield a rounded lambda (λ) value of 1, suggesting that the transformation has appropriately adjusted the data distribution. This adjustment facilitates the application of subsequent statistical tests with greater reliability and interpretability. Table 3 presents the descriptive statistics of the data after the logarithmic transformation.

Table 3. Summary Results of Descriptive Statistics (Logarithm Transformation)

Variable	N	Mean	Variance	Standard Deviation	Median	Minimum	Maximum
Inflation rate	240	1.5275	0.3298	0.5743	1.5074	0.2776	2.9113

Subsequently, the stationarity of the mean is assessed using the Box-Cox transformed data by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. These plots serve as diagnostic tools to evaluate whether the time series data exhibit stationarity, thereby determining the suitability of the series for further model development.

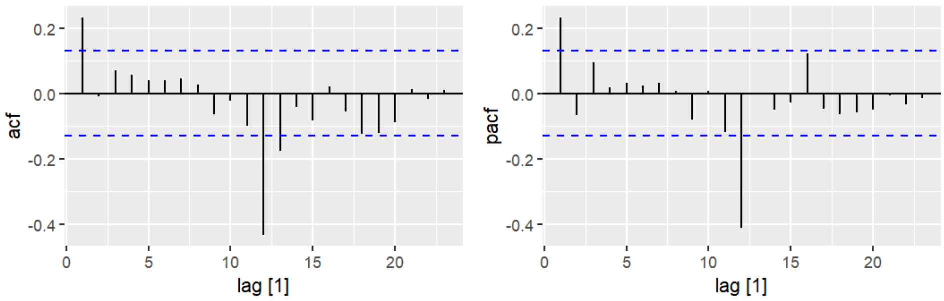


(a) (b)

Source: R Output

Figure 4. (a) ACF Plot of Training Data, (b) PACF Plot of Training Data

In Fig. 4, the ACF pattern of the data exhibits a "dies down" behaviour, indicating that the time series is non-stationary. Consequently, differencing is required to achieve stationarity. The ACF and PACF plots following the first differencing, presented in Fig. 5, serve as diagnostic tools to evaluate whether the series has attained stationarity after the transformation.



(a) (b)

Source: R Output

Figure 5. (a) ACF Plot for Differencing 1, (b) PACF Plot for Differencing 1

Based on Fig. 5, it is concluded that the data becomes stationary after applying first differencing to the Box-Cox transformed series. Additionally, the Augmented Dickey-Fuller (ADF) Test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Tests is widely utilized as a formal statistical method to asses stationarity. The ADF test is a unit root test commonly used to determine whether a time series is stationary by evaluating the presence of a unit root in the autoregressive model. A rejection of the null hypothesis, which assumes the presence of a unit root (non-stationarity), confirms that the series is stationary. In addition to the ADF test, the stationarity of the series is further examined using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. This approach is motivated by the findings of [22] which suggest that the KPSS test demonstrates superior performance compared to the ADF test for both small and large sample sizes. Unlike the ADF test, which assumes non-stationarity as the null hypothesis, the KPSS test assumes stationarity, providing a complementary perspective in stationarity analysis. The results of the ADF and KPSS test are presented in Table 4.

Table 4. ADF and KPSS Test

	Statistics	p-value	Conclusion
ADF Test	-5.1302	0.01	Reject H_0, the series is stationary
KPSS Test	0.0495	0.1	Failed to reject H_0, the series is stationary

Based on Table 4 the results of the Augmented Dickey-Fuller (ADF) test indicate a p-value < 0.05, providing statistical evidence that the series has achieved stationarity. The results of the KPSS test, presented in Table 4, indicate a p-value of 0.1, which is greater than the significance level, leading to a failure to reject the null hypothesis of stationarity. Consequently, both tests yield consistent conclusions, confirming that the data is stationary.

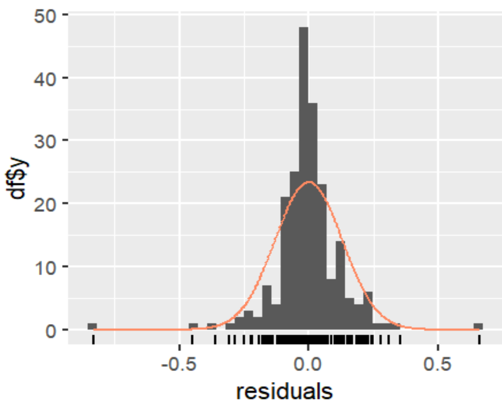
3.3 ARIMA Model Identification

The ARIMA model selection was carried out on the Box-Cox transformed data, which had been subjected to a logarithmic transformation followed by first differencing ($d = 1$) to ensure stationarity. The estimation results of the selected ARIMA model, including the optimal parameter specifications, are presented in Table 5.

Table 5. Selection of the Best ARIMA Model

Model	Parameters	*White Noise*	Residual Normality	AIC
ARIMA (1, 1, 0)	Significant	✓	×	-259.94
ARIMA (1, 1, 1)	Insignificant	✓	×	-261.74
ARIMA (1, 1, 2)	Insignificant	✓	×	-259.74
ARIMA (0, 1, 1)	**Significant**	**✓**	**×**	**-263.18**
ARIMA (2, 1, 1)	Insignificant	✓	×	-259.75
ARIMA (2, 1, 2)	Insignificant	✓	×	-257.98

As observed in Table 5, the ARIMA (0,1,1) model is identified as the optimal model based on the significance of its parameters, the white noise characteristics of its residuals, and the lowest Akaike Information Criterion (AIC) value. However, the assumption of residual normality is not satisfied, which is likely attributable to the presence of autocorrelation in the model's residuals. To further assess this issue, a detailed examination of the residual distribution is conducted using a histogram, as illustrated in Fig. 6.



Source: R Output

Figure 6. ARIMA (0,1,1) Residual Normality Chart

The histogram of the residuals from the ARIMA (0,1,1) model indicates that the observed non-normality can be attributed to an excessive concentration of values around zero, leading to a pronounced peak and increased kurtosis. This phenomenon, known as leptokurtic, occurs when a distribution exhibits higher kurtosis and more pronounced tails compared to a normal distribution. Despite this deviation from normality, the residuals oscillate around zero, suggesting that the model's predictions closely align with the actual values. Moreover, according to the Central Limit Theorem (CLT), the sampling distribution of the residuals can be approximated as normal when the sample size is sufficiently large. Given this statistical property, minor deviations from normality in the residuals do not necessarily undermine the validity of the model. Consequently, the diagnostic criteria for the ARIMA (0,1,1) model are deemed satisfactory, supporting its suitability for modelling Indonesia's inflation data. The parameters generated by the selected model, along with their significance levels, are presented in Table 6.

Table 6. Parameter Estimation Results of Selected Models

Parameter	Coefficient	Standard Error	p-value	AIC
MA (1)	0.315634	0.068273	0.0000	-263.18

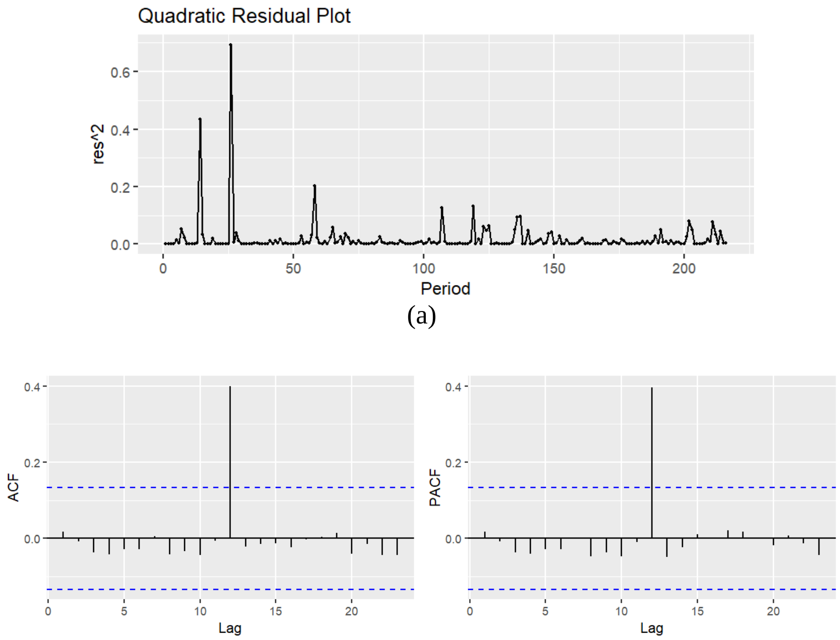
The mathematical equation for the estimation of the transformed ARIMA (0,1,1) model is represented in Eq. (8).

$$\hat{Z}_t^* = \hat{Z}_{t-1}^* + \hat{\varepsilon}_t - 0.315634\hat{\varepsilon}_{t-1}, \tag{8}$$

where $\hat{Z}_t^* = \ln(Z_t^*)$ (by λ Box-Cox transformation), and $\hat{\varepsilon}_t$ is error.

3.4 Heteroscedasticity Test

In the previously estimated ARIMA model, it is assumed that the residuals follow a normal distribution with a mean of $\mu = 0$ and a constant variance σ^2 (homoscedasticity). However, in economic time series data, such as exchange rates, inflation, and stock prices, periods of high volatility often result in violations of the homoscedasticity assumption. To assess the presence of heteroskedasticity, diagnostic testing is performed on the squared residuals derived from the ARIMA model. Specifically, the squared errors ($\hat{\varepsilon}_t^2$) obtained from the ARIMA (0,1,1) model estimates serve as an empirical proxy for σ^2. The time series plot, along with the ACF and PACF of these squared residuals, is presented in Fig. 7 to evaluate potential autoregressive dependencies in volatility dynamics.



(a)

(b) (c)

Source: R Output

Figure 7. Plot of (a) Residual Squares (b) Residual ACF and (c) Residual PACF from ARIMA (0,1,1)

As shown in Fig. 7, the presence of significant lags beyond the critical thresholds in both the ACF and PACF plots suggests autocorrelation in the squared residuals, indicating time-varying variance and potential heteroskedasticity. To formally assess this, the ARCH-LM (Autoregressive Conditional Heteroskedasticity – Lagrange Multiplier) test is applied. The null hypothesis of the ARCH-LM test states that no conditional heteroskedasticity is present in the residuals of the ARIMA model. If rejected, this confirms the presence of autoregressive volatility patterns, necessitating the incorporation of volatility modeling techniques. The results of the ARCH-LM test for the residuals of the ARIMA (0,1,1) model are presented in Table 7.

Table 7. Lagrange Multiplier Test Results

Lag Order	LM Test Statistics	p-value
4	558.9	0.0000
8	263.0	0.0000
12	155.7	0.0000
16	25.6	0.0427
20	19.4	0.4305
24	15.2	0.8887

The test results presented in Table 7 indicate that for lags 4 to 16, the p-values are lower than the predetermined significance level ($\alpha = 5\%$), leading to the rejection of the null hypothesis. This finding provides statistical evidence of autocorrelation in the squared residuals of the ARIMA (0,1,1) model, suggesting the presence of heteroskedasticity and necessitating further modelling to account for volatility effects. However, the non-significant p-values at lags 20 and 24 indicate that heteroskedasticity is not detected at these lags. This pattern is characteristic of financial and economic time series data, where volatility tends to fluctuate unevenly over time. Despite the presence of heteroskedasticity at certain lags, the analysis can proceed while considering appropriate adjustments for volatility modelling.

3.5 GARCH Model

The ARCH (Autoregressive Conditional Heteroskedasticity) model is a commonly used method to model variance in time series data that exhibits heteroscedasticity, assuming that the conditional variance is influenced by the squared past residuals. However, the standard ARCH model has a weakness in describing persistent volatility dynamics, as it only considers the squared past residuals without involving the conditional past variance. To overcome this weakness, the GARCH (Generalized ARCH) model was developed by adding the lagged conditional variance into the model, thus providing a more flexible and comprehensive view of the volatility clustering pattern. Given the presence of heteroskedasticity in the residuals of the ARIMA (0,1,1) model, the GARCH (1,0) and GARCH (1,1) specifications were selected based on the patterns observed in the ACF and PACF plots, ensuring an appropriate characterization of the time-varying variance structure.

Table 8. Parameter Estimation Results of GARCH (1,0) and (1,1) Models

Model	Parameters	Coefficient	p-value	ARCH LM Test	AIC
GARCH (1,0)	ω	0.015091	0.0002	Significant	0.23912
	α_1	0.920638	0.0000		
GARCH (1,1)	ω	0.004538	0.0791	Significant	0.17505
	α_1	0.553366	0.0000		
	β_1	0.432184	0.0002		

As shown in Table 8, the GARCH (1,1) model exhibits insignificant parameter estimates, indicating its limitations in capturing the volatility dynamics of the data. Furthermore, although the GARCH (1,0) model demonstrates statistically significant parameters, it fails to fully eliminate the heteroskedasticity present in the residuals of the ARIMA (0,1,1) model. Given these findings, alternative GARCH model specifications were explored to better accommodate the observed volatility structure. The results of these additional model evaluations are presented in Table 9.

Table 9. Parameter Estimation Results of GARCH (2,0) and (2,1) Models

Model	Parameters	Coefficient	p-value	ARCH LM Test	AIC
GARCH (2,0)	ω	0.010985	0.0018	Insignificant	0.064947
	α_1	0.125678	0.0387		
	α_2	0.757438	0.0000		
GARCH (2,1)	ω	0.010985	0.0011	Insignificant	0.074207
	α_1	0.125678	0.0001		
	α_2	0.757438	0.0000		
	β_1	0.000000	1.0000		

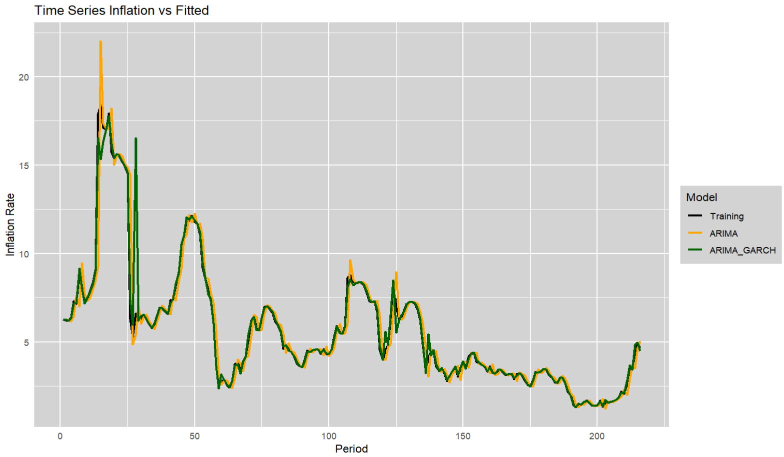
Based on the results in Table 9, the GARCH (2,0) model is identified as the most suitable specification for addressing the heteroskedasticity present in the residuals of the ARIMA (0,1,1) model. This selection is justified by the statistical significance of its parameter estimates, indicating its effectiveness in capturing volatility dynamics. Consequently, the variance equation for the error term of the ARIMA (0,1,1) model under the GARCH (2,0) specification is formulated in Eq. (9) as follows:

$$\hat{\sigma}_t^2 = 0.010985 + 0.125678\hat{\varepsilon}_{t-1}^2 + 0.757438\hat{\varepsilon}_{t-2}^2, \quad (9)$$

where $\hat{\sigma}_t^2$ is the estimated conditional variance, which accounts for time-varying volatility and addresses the presence of heteroskedasticity in the residuals. Additionally, $\hat{\varepsilon}_{t-1}^2$: the squared residual from the ARIMA (0,1,1) model lagged by one period, capturing the impact of past shocks on current volatility.

3.6 Evaluation of ARIMA-GARCH Model

The performance assessment of the ARIMA-GARCH model is conducted using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) metrics, which are derived from the model's estimation results on both the training and testing datasets. These evaluation criteria provide a quantitative measure of the model's predictive accuracy and error magnitude. To facilitate a comparative analysis, Fig. 8 presents the actual observations alongside the predictions generated by the ARIMA model and the ARIMA-GARCH model for the training dataset, allowing for a visual examination of their respective forecasting capabilities.



Source: R Output

Figure 8. Time Series Plot of Actual Vs Fitted Inflation Rate on Training Data

The graph shown in Fig. 8 provides empirical evidence that the ARIMA-GARCH model exhibits a superior fit to the actual values in the training dataset compared to the conventional ARIMA model. This improvement can be attributed to the GARCH component's ability to model time-dependent volatility, which the conventional ARIMA framework fails to capture. The enhanced predictive performance of the ARIMA-GARCH model is further substantiated by the MAPE and RMSE values presented in Table 10, reinforcing its efficacy in capturing the underlying data dynamics with greater precision.

Table 10. MAPE and RMSE Values in Training Data

	ARIMA	ARIMA-GARCH
MAPE (%)	8.52	2.73
RMSE	1.02	0.74

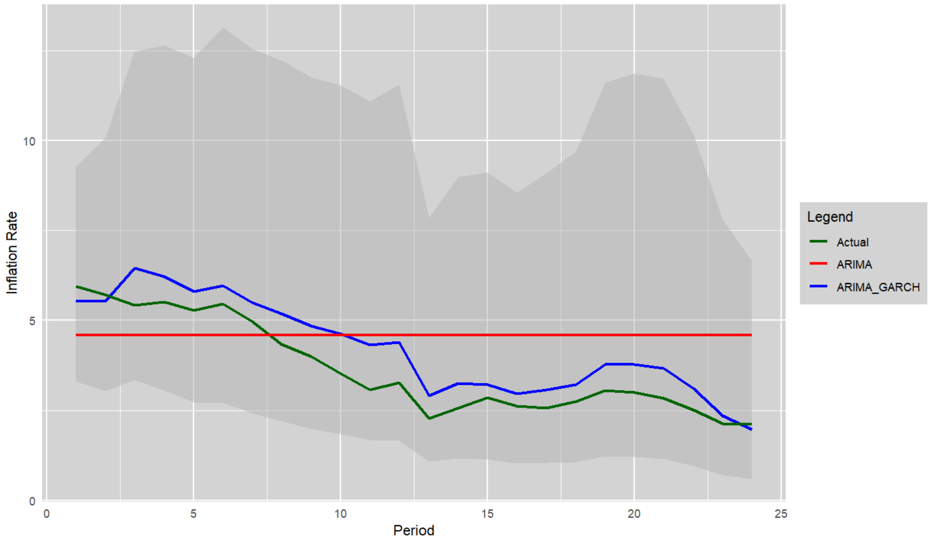
To further assess the predictive capability of ARIMA (0,1,1)-GARCH (2,0), its forecasting performance is evaluated using the testing dataset. This evaluation ensures the model's generalizability beyond the training data. The comparison between actual values and forecasted results is presented in Table 11, providing empirical insights into the model's effectiveness in capturing future observations.

Table 11. Forecasting Results

Period	Inflation Rate (%)			
	Actual	Forecast	Lower Bounds	Upper Bounds
Sep-22	5.95	5.54	3.31	9.27
Oct-22	5.71	5.53	3.04	10.09
Nov-22	5.42	6.45	3.33	12.49
Dec-22	5.51	6.23	3.06	12.66
Jan-23	5.28	5.80	2.73	12.30
Feb-23	5.47	5.97	2.71	13.15
Mar-23	4.97	5.51	2.41	12.57
Apr-23	4.33	5.19	2.20	12.23
May-23	4.00	4.84	1.99	11.77
Jun-23	3.52	4.62	1.85	11.55
Jul-23	3.08	4.32	1.68	11.09
Aug-23	3.27	4.38	1.66	11.56
Sep-23	2.28	2.90	1.07	7.84

Period	Inflation Rate (%)			
	Actual	Forecast	Lower Bounds	Upper Bounds
Oct-23	2.56	3.25	1.17	8.99
Nov-23	2.86	3.22	1.14	9.12
Dec-23	2.61	2.95	1.02	8.55
Jan-24	2.57	3.07	1.04	9.09
Feb-24	2.75	3.21	1.06	9.70
Mar-24	3.05	3.77	1.23	11.63
Apr-24	3.00	3.78	1.20	11.87
May-24	2.84	3.66	1.14	11.73
Jun-24	2.51	3.12	0.95	10.16
Jul-24	2.13	2.35	0.71	7.79
Aug-24	2.12	1.97	0.58	6.66

Based on the forecasting results, the Mean Absolute Percentage Error (MAPE) for the testing dataset is 18.95%, which falls within the range classified as "good" in predictive accuracy assessment. Furthermore, the Root Mean Squared Error (RMSE) is recorded at 0.702, indicating a reasonable level of precision in the model's forecasts. A visual representation of the testing data alongside the ARIMA-GARCH model estimates is provided in Fig. 9, offering a comparative analysis of the predicted and actual values.



Source: R Output

Figure 9. Time Series Plot of Actual Vs Forecast Inflation Rate with Confidence Interval on Testing Data

The graph shown in Fig. 9 presents the inflation rate forecasts using the ARIMA (0,1,2) and ARIMA (0,1,2)-GARCH (2,0) models, compared to the actual data. In general, the ARIMA (0,1,2) model produces relatively stable forecasts that tend to converge toward the long-term average. This characteristic is typical of ARIMA models, which do not account for volatility in the estimation process. Consequently, when the data exhibit high volatility, ARIMA forecasts appear excessively constant, as the model captures only linear patterns and struggles to adapt to dynamic variability in inflation rates. These findings are consistent with the study by [23] which identified similar forecasting patterns in Indonesia's export values using the ARIMA method. On the other hand, the ARIMA-GARCH (2,0) model is better equipped to capture fluctuations in volatility. By explicitly modelling heteroskedasticity, the GARCH component adjusts forecast uncertainty based on past fluctuations. As a result, the ARIMA-GARCH model (blue line) demonstrates greater flexibility in tracking actual inflation trends compared to the pure ARIMA model. Furthermore, the wider confidence intervals in certain periods indicate that the ARIMA-GARCH approach successfully accommodates high volatility, thereby reducing the risk of underestimating forecast errors.

In terms of forecast accuracy, the Mean Absolute Percentage Error (MAPE) is recorded at 18.95%, which is relatively high. This elevated MAPE is primarily attributed to the ARIMA model's overly constant forecasts, particularly during periods of substantial inflation volatility. Since ARIMA does not account for changes in variability, its forecasts tend to be less responsive, leading to increased errors in certain time periods. Therefore, the ARIMA-GARCH approach proves superior in handling high-volatility data due to its ability to capture evolving volatility patterns over time.

From the overall analysis, inflation is a key economic indicator that influences purchasing power, monetary policy decisions, and overall economic stability. Accurate inflation forecasting is crucial for policymakers, businesses, and investors, enabling them to anticipate economic trends and develop effective strategies. Given its fluctuating nature, inflation requires a robust forecasting approach to capture both short-term variations and long-term trends. Advanced time series models, such as ARIMA-GARCH, have been widely used to analyze inflation patterns, providing valuable insights for economic planning and financial stability.

Previous research findings indicate mixed results regarding the effectiveness of the ARIMA model in forecasting inflation. Study by [11] found that the conventional ARIMA model provides a reasonably accurate estimation of monthly inflation in Nigeria, with ARIMA(1,2,1) identified as the best model based on forecast errors ranging between -0.24 and 3.77. However, other studies have highlighted the limitations of ARIMA in handling volatility. Study by [13] on inflation in Pakistan, revealed that the conventional ARIMA model still faces heteroskedasticity issues, as indicated by significant lags in the ACF and PACF of squared ARIMA residuals. Consequently, the GARCH approach was employed to model the error component within ARIMA, demonstrating improved predictive accuracy compared to the conventional ARIMA model. Nevertheless, a contrasting finding was reported by Uwilingiyimana et.al (2015) in her study on inflation in Kenya, where the conventional ARIMA model outperformed the ARIMA-GARCH hybrid, as evidenced by lower RMSE, MAPE, MAE, Theil, and BIAS values. These discrepancies suggest that the effectiveness of the ARIMA-GARCH approach is highly dependent on data characteristics and the degree of inflation volatility in each country [12].

In line with [13], the findings of this study indicate that the ARIMA-GARCH model is superior to the conventional ARIMA model in modeling inflation in Indonesia. The ARIMA (0,1,1)-GARCH (2,0) model applied in this study effectively addresses heteroskedasticity, produces more stable forecasts, and enhances accuracy compared to ARIMA without GARCH. This model suggests that a 1-unit shock to current inflation (ε_t) results in a 1-unit increase in the log-transformed inflation variable (Z_t^*). Conversely, a shock from the previous period (ε_{t-1}) leads to a 0.315634-unit decline in inflation, indicating that past shocks continue to exert an influence, albeit in the opposite direction. Additionally, inflation volatility is affected by previous shocks, where a 1-unit increase in past-period volatility ($\hat{\varepsilon}_{t-1}^2$) leads to a 0.125678-unit rise in uncertainty, while two-period lagged volatility ($\hat{\varepsilon}_{t-2}^2$) has a larger impact of 0.757438 units. Thus, this model not only captures inflationary patterns over time but also accounts for the economic shocks that influence inflation movements in Indonesia.

Forecast accuracy is commonly evaluated using the Mean Absolute Percentage Error (MAPE), with lower values indicating better predictive performance. Although the ARIMA-GARCH model proves effective in capturing volatility, the main challenge remains minimizing MAPE, particularly during the testing phase. Moreover, the computational complexity of this model must be considered, especially for real-time forecasting applications. One potential solution is to optimize model selection to balance accuracy and computational efficiency, ensuring that the model remains practical without compromising predictive performance. Previous studies, [24] demonstrated that increasing the alpha parameter while proportionally reducing beta improves the accuracy of information criteria in selecting the optimal model with high probability and performance.

Furthermore, in this study, the inflation forecasting model does not incorporate exogenous variables, in accordance with the established research limitations, meaning that predictions rely solely on historical inflation patterns in Indonesia. However, prior research, such as that conducted by [25] suggests that external macroeconomic factors, such as exchange rates and interest rates, significantly influence inflation dynamics. Additionally, while the ARIMA-GARCH framework effectively captures inflation volatility, it is still based on linear assumptions, which may not adequately represent the complex nonlinear patterns inherent in macroeconomic data. Therefore, future research may consider incorporating exogenous variables and exploring machine learning-based time series models.

4. CONCLUSION

The ARIMA (0,1,1)-GARCH (2,0) model demonstrates strong performance in predicting inflation rates in Indonesia. Evaluation on training data yielded a MAPE of 2.73% and an RMSE of 0.74, while testing data recorded a MAPE of 18.95% and an RMSE of 0.702. However, the relatively high MAPE of 18.95% on the test data suggests limitations in generalization and highlights the need for improvement. This discrepancy may be due to unmodeled nonlinearities or the absence of exogenous variables that influence inflation. Future research could explore the integration of nonlinear models such as LSTM or the inclusion of external economic indicators to improve forecasting robustness. Additionally, comparative studies with alternative methods like Prophet or VAR would provide a broader perspective on model performance. Despite these limitations, the current model offers valuable insights for policymakers, supporting the formulation of responsive and data-driven monetary and fiscal policies aimed at maintaining inflation stability and promoting sustainable economic growth.

Author Contributions

Toha Saifudin: Conceptualization, Funding Acquisition, Supervision, Validation. Suliyanto: Methodology, Funding Acquisition, Investigation. Fitriana Nur Afifa: Methodology, Software, Formal Analysis, Writing - Original Draft. Aini Divayanti Arrofah: Formal Analysis, Data Curation, Writing - Original Draft. Doni Muhammad Fauzi: Formal Analysis, Data Curation, Writing - Review and Editing. Fachriza Yosa Pratama: Formal Analysis, Writing - Original Draft, Writing - Review and Editing. Irsyad Yoga Adyatama: Methodology, Writing - Original Draft, Writing - Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declares that he/she has no conflicts of interest to report study.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

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