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Gold Price Forecasting Using Hybrid ARIMA-IGARCH

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ABSTRACT

Gold is an important investment and hedging instrument, with highly volatile price movements that are difficult to accurately predict. Previous studies have generally used ARIMA-GARCH models to forecast financial time series, but these models have not fully captured the persistent volatility of gold prices. Therefore, this study proposes an ARIMA-IGARCH approach to simultaneously model the mean and persistent volatility patterns of gold price movements. Daily gold closing price data from November 2022 to August 2025 was analyzed using Python, with 90% used for training and 10% for testing. The ARIMA model was used to capture the mean structure, while the IGARCH model was used to represent the long-term volatility persistence. The results showed that the proposed model achieved high forecasting accuracy, with a MAPE of 9,38%, indicating strong predictive performance. These findings indicate that the ARIMA-IGARCH model can serve as an alternative approach for gold price forecasting and financial market volatility analysis.

INTRODUCTION

One precious metal with qualities of a monetary asset is gold. Gold has been used as an investment tool, a store of wealth, and a medium of exchange throughout history. Furthermore, gold plays a crucial role in portfolio diversification by reducing investment risk (Hoang et al., 2015) Gold's use extends beyond the investment sector to include the industrial and jewelry sectors, influencing demand for gold by the needs of these various sectors (Grynberg et al., 2018). Gold prices are highly volatile and reflect uncertainty in global economic conditions. These fluctuations are influenced by various factors, such as inflation, interest rates, monetary policy, geopolitical conditions, and market demand, making gold prices an important indicator in economic and financial analysis (Victor, 2021). Gold price volatility increases the risks faced by investors, underscoring the importance of accurate forecasting methods to support investment decision-making (Bentes, 2015).

Forecasting is a crucial component of the decision-making process because accurate forecasting results can reduce prediction errors and improve planning effectiveness

(Hyndman, 2025). In quantitative forecasting, time series analysis is commonly used to predict future events based on historical observations (Malik, 2023). Financial time series data, including gold prices, generally exhibit volatility clustering and heteroscedasticity, conditions in which variance changes over time. One of the most widely used methods for modeling time series data is the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA is effective for modeling the mean structure and short-term forecasting of stationary time series data (Jadhav et al., 2017). However, ARIMA has limitations for representing fluctuating volatility patterns, as its forecasts tend to remain relatively constant over long-term prediction horizons (Ospina et al., 2023).

To address heteroscedasticity in financial time series data, the Autoregressive Conditional Heteroscedasticity (ARCH) model was introduced by Engle in 1982 and later developed into the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model by Bollerslev in 1986. These models can capture changes in variance and volatility clustering in time series data (Burak & Emrah, 2025). Compared to ARCH, the GARCH model provides a more efficient representation of volatility with fewer parameters and has been widely applied in financial forecasting research (Samuel & Chimedza, 2023) . However, the GARCH model still has limitations in modeling volatility persistence, especially when the data exhibit unit-root characteristics in variance (Sidik & Badriyah, 2017). To address these limitations, (Francq & Zakoian, 2019) introduced the Integrated Generalized Autoregressive Conditional Heteroscedasticity (IGARCH) model, which integrates variance components and captures persistent volatility. These characteristics make the IGARCH model relevant for use with gold price data, which often exhibits long-term volatility persistence.

Several previous studies have applied volatility-based forecasting models to financial and commodity data analysis. (Setyowibowo et al., 2021) used a hybrid ARIMA-GARCH model to forecast daily gold prices and demonstrated that the combination of these models produced good accuracy on highly volatile data. In an international study, (Yaziza et al., 2013) developed a hybrid ARIMA-GARCH model for gold price forecasting and found that combining ARIMA and GARCH improved estimation and forecasting accuracy compared to either method alone. The study demonstrated that ARIMA effectively captured linear patterns, whereas GARCH accommodated volatility and risk in financial time series. Furthermore, (Dritsaki, 2018) demonstrated that the ARIMA-GARCH model is effective for highly volatile data, including world oil prices and other financial data. This finding reinforces the view that the volatility-based hybrid model has a strong capability to capture the dynamics of financial markets.

(Mani and Thoppan, 2023) compared the ARIMA and GARCH models. The findings demonstrated that, especially when it came to capturing non-constant volatility changes, the volatility-based model outperformed a single ARIMA model in representing market swings. Additionally, (Khan, 2024) discovered that the Saudi Arabian market's gold price volatility is quite persistent, necessitating a modeling strategy that can account for long-term variations in variance. Previous research has compared statistical and machine-learning approaches for financial forecasting. (Xing et al., 2024) compared ARIMA, ARIMA-GARCH, and deep learning models in stock price forecasting and found that volatility-based models were more effective in capturing volatile financial market behavior. (Chen et al., 2020) also explained that the combination of ARIMA and GARCH can handle volatility clustering and fat-tail distributions common in modern financial data. (Villar et al., 2023) explain that financial time-series data generally exhibit asymmetric volatility, underscoring the importance of volatility modeling for understanding market dynamics. Furthermore, (Bentes, 2015) emphasizes that volatility analysis in gold prices is becoming increasingly important due to unstable market conditions and irregular price movement patterns. (Beeg et al., 2024) also report that combining mean and volatility forecasting models yields more accurate predictions than a single-model approach, particularly for financial and commodity time series.

Although previous research has extensively discussed ARIMA, ARCH, and GARCH models, research on the application of the ARIMA-IGARCH model to gold price forecasting using current data remains limited. Most studies still focus on the ARIMA-GARCH approach, whereas the persistent characteristics of gold price volatility require a model that can better accommodate unit-root behavior in variance. Although the GARCH model is widely used to capture volatility clustering in financial time series, it assumes that the persistence of volatility is stationary, where the sum of the ARCH and GARCH parameters is less than one. In contrast, financial assets such as gold often exhibit highly persistent volatility, with shocks having long-lasting effects on future variance. Under such conditions, the sum of the ARCH and GARCH coefficients is frequently found to be close to one, indicating the presence of a unit root in the variance process. The IGARCH (Integrated GARCH) model is specifically designed to accommodate this behavior by imposing the constraint that the persistence parameter equals one, allowing volatility shocks to decay much more slowly and remain influential over a longer period. (Bentes, 2015). Therefore, IGARCH is considered more appropriate than conventional GARCH for modeling gold price volatility when empirical evidence suggests near-integrated variance dynamics and strong volatility persistence.Therefore, this study proposes an ARIMA-IGARCH approach to simultaneously model the persistent volatility of gold price movements. This study aims to evaluate the forecasting performance of the ARIMA-IGARCH model using gold closing prices for the period November 2022 to August 2025 and to provide an alternative approach for analyzing gold price volatility and forecasting financial market behavior. The main contribution of this study is the application of the ARIMA-IGARCH model to capture the highly persistent volatility of gold prices using recent data. Unlike previous studies that predominantly employ ARIMA-GARCH models, this research demonstrates the usefulness of IGARCH in modeling long-lasting volatility effects and provides empirical evidence of its forecasting capability in the gold market.

METHODS

This study proposes an ARIMA-IGARCH approach to modeling and forecasting gold price movements with persistent volatility. This study's goal is to assess the ARIMA-IGARCH models' forecasting performance in order to offer a different method for examining the volatility of gold prices and the behavior of financial markets.

Data Collection for Gold Prices

The data used in this study consists of secondary time-series data, specifically daily gold price data covering the period from November 8, 2022, to August 30, 2025. The data was obtained from the official website www.logammulia.com which is managed by PT.ANTAM with a daily observation interval. The gold prices analyzed are expressed in grams. The data were analyzed as time series data and processed using Python software. For the purpose of evaluating forecasting performance, the data were divided into two parts: a 90% training set and a 10% test set.

ARIMA Model

One well-liked statistical technique for predicting gold prices is ARIMA. Because ARIMA models are good at capturing the trend and dynamic features of prices, they are frequently employed in gold price forecasting. Numerous academics have effectively used ARIMA models to forecast gold prices over various time periods and geographical areas (Rubio, 2022). The research process began with a descriptive analysis of the data to identify general patterns in gold price movements. Next, stationarity tests were conducted on the mean and variance of the data . If the data were not stationary with respect to the mean, a differencing process was performed until the stationarity assumption was met. Model identification was based on the autocorrelation function and partial autocorrelation function patterns to determine a tentative model (Alsuwaylimi, 2023). The ARIMA model is an extension of the ARMA model introduced by Gwilyn Jenkins and George Box in 1970. The ARIMA model is used to handle non-stationary time series data through the application of a differencing process, thereby making the data stationary. The equation is as follows:

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)\alpha_t \quad (1)$$

After the mean model is obtained, a test for heteroscedasticity effects on the residuals is performed (Tong et al., 2026). If the residuals show heteroscedasticity, modeling of volatility proceeds using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach.

GARCH Model

When modeling time series data with persistent volatility, the GARCH model works well.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j a_{t-j}^2 \quad (2)$$

IGARCH Model

If the AR polynomial of the GARCH representation has a unit root, it is determined by the following conditions (Ekananda, 2016):

$$\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j = 1 \quad (3)$$

Thus, the IGARCH model is a unit root GARCH model. The IGARCH equation can be written as follows:

$$\alpha_t = \sigma_t x_t \quad (4)$$

$$\sigma_t^2 = \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (5)$$

ARIMA-IGARCH

The data analysis model applied in this study uses a statistical modeling approach, specifically the ARIMA-IGARCH model, in which the ARIMA component accounts for heteroscedasticity in the gold price data. Gold price fluctuations not only exhibit short-term trends but also high and non-stationary volatility. This volatility can spike suddenly due to market sentiment or external shocks, making gold price forecasting a unique challenge (Villar et al., 2023). The use of a single model such as ARIMA is effective only in modeling trend patterns and temporal dependence on the mean, but it assumes constant residual variance and thus fails to capture high and persistent changes in volatility. Conversely, applying a volatility model without adequate mean modeling also has the potential to produce inaccurate estimates. Combining these two models makes it possible to generate more accurate forecasts and understand the dynamics of volatility associated with gold prices (Bunnag, 2024).

The ARIMA(p,d,q)-IGARCH model is defined by:

$$\phi_p(B)(1-B)^d Z_t = \theta_p(B)\alpha_t \quad (6)$$

$$\alpha_t = \sigma_t x_t \quad (7)$$

$$\sigma_t^2 = \sum_{i=1}^{p} \alpha_{i-1}\varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{8}$$

Evaluation Metrics

Akaike's Information Criterion (AIC), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE), and Root Mean Square Error (RMSE) are used to assess the accuracy of forecasting models. By weighing a model's complexity and goodness of fit, the Akaike Information Criterion (AIC) is used to assess and choose the optimum model. The AIC value helps determine the most efficient model for explaining the data without overfitting. SMAPE measures the average absolute difference between predicted and actual values, while RMSE measures the magnitude of the deviation from the predicted data using the root mean square error. The smaller the AIC, MAE, and RMSE values, the better the model's forecasting ability. These three metrics are commonly used to evaluate forecasting models, including ARIMA models and their variants.

The AIC formula can be written as follows (Wei, 2006):

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

where k is the estimated number of parameters and L is the likelihood function.

The MAE formula can be written as follows (Wei, 2006):

$$(MAE) = \frac{1}{n}\sum_{t=1}^{n} Z_t - \hat{Z}_t \tag{10}$$

where Z_t means actual data at time t, $\hat{Z}_t$ means the predicted data at time t, and n is number of forecasting periods.

The RMSE formula can be written as follows(Wang & Lu, 2018):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(\hat{Z}_t - Z_t\right)^2}{n}} \tag{11}$$

where Z_t means actual data at time t, $\hat{Z}_t$ means the predicted data at time t, and n is number of forecasting periods.

The MAPE formula can be written as follows (Wei, 2006):

$$MAPE = 100\% \times \frac{\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right|}{n} \tag{12}$$

where Z_t means actual data at time t, $\hat{Z}_t$ means the predicted data at time t, and n is number of forecasting periods.

The SMAPE formula can be written as follows (Chicco et al., 2021):

$$SMAPE = \frac{100\%}{n} \times \sum_{t=1}^{n} \frac{\frac{|\hat{Z}_t - Z_t|}{|\hat{Z}_t| + |Z_t|}}{2} \tag{13}$$

where Z_t means actual data at time t, $\hat{Z}_t$ means the predicted data at time t, and n is number of forecasting periods.

The steps in determining the ARIMA-IGARCH model can be illustrated through the following flowchart

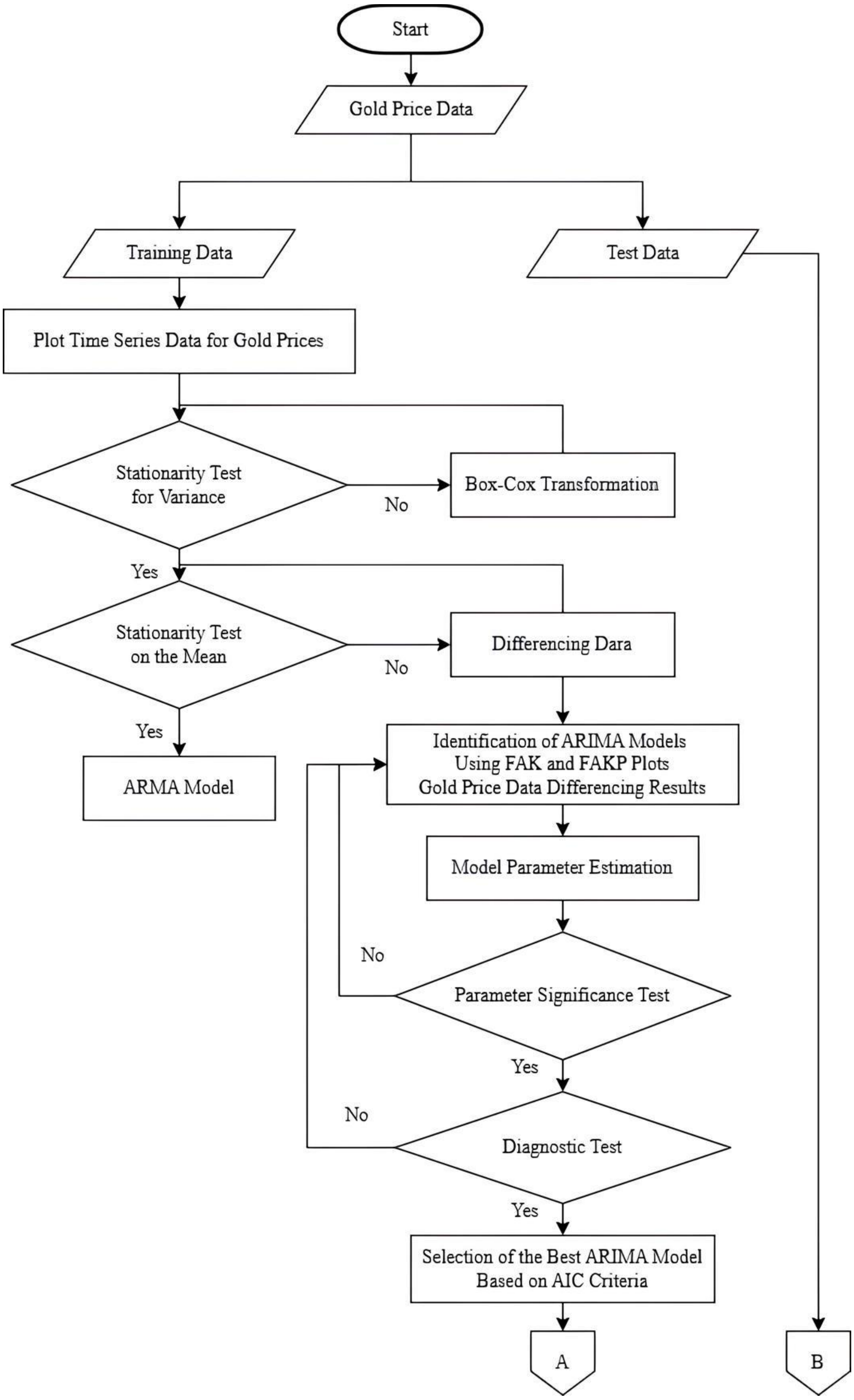

Figure 1. Research Flowchart (a)

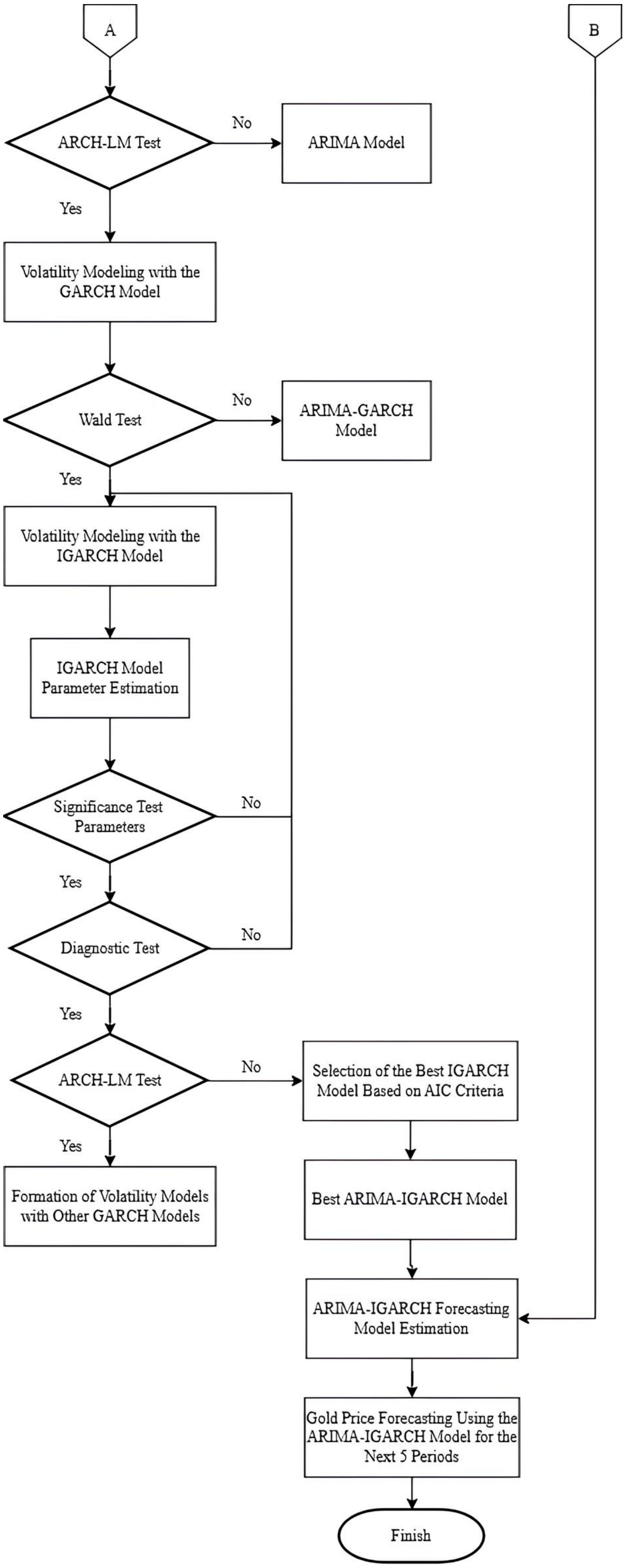

Figure 2. Research Flowchart (b)

RESULT AND DISCUSSIONS

Initial analysis shows that gold price data indicates a fairly stable upward trend until early 2024, then moves more fluctuatively with a fairly sharp increase towards early 2025. The peak gold price occurred around April 2025 at Rp2,039,000 per gram. After reaching its peak, the price of gold experienced a significant decline, then fluctuated again in the range of Rp1,800,000 to Rp1,900,000 until mid-2025. Thus, the data is suspected to be non-stationary.

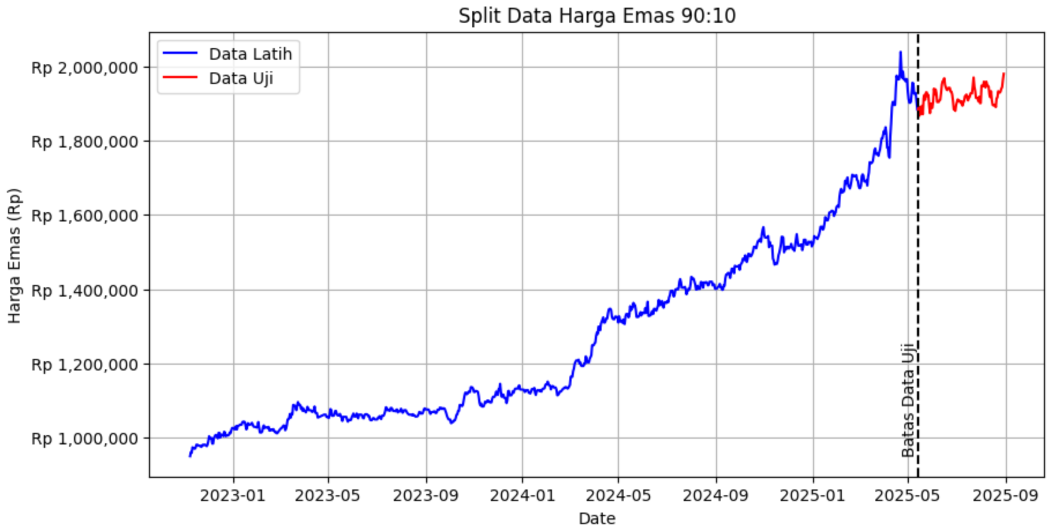

Figure 3. Gold Price Data Plot(90:10)

Formulation of ARIMA Models

There are two types of stationarity requirements in time series analysis: stationarity in variance and stationarity in mean. While stationarity in variance denotes that the distribution or variance of the data stays constant over time, stationarity in mean denotes that the average value of the data does not change over time. Testing for stationarity in mean is done using the ADF method (Ivanovski, 2024).

Table 1. ADF Test Results

	ADF Test after 0 differencing(s)	**ADF Test after 1 differencing(s)**
p-value	0,9729	0,0000
Description	Data is not yet stationary	The data is stationary

The stationarity test results are presented in Table 1. As shown in Table 1 that the data is not stationary with respect to the mean, so it is differentiated once. After the differentiation process, the data meets the stationarity assumption and can proceed to the modeling stage.

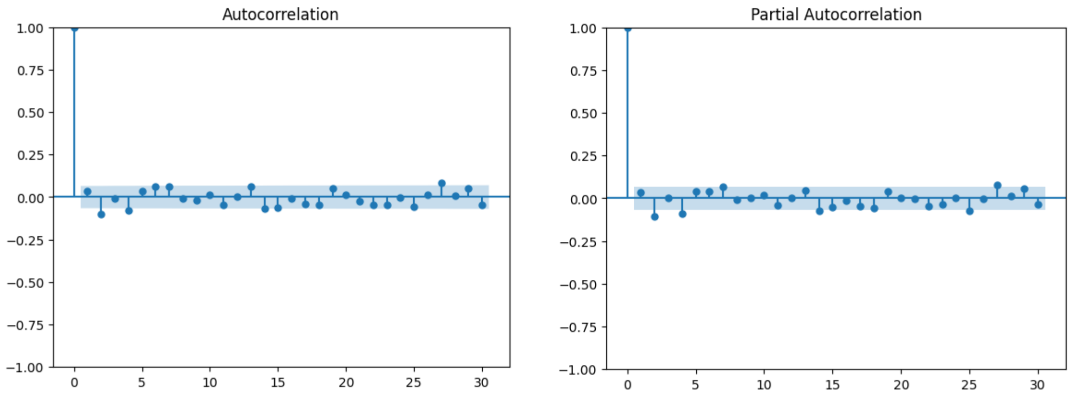

Figure 4. Plot ACF and PACF

Several preliminary ARIMA models were derived based on the autocorrelation function pattern and partial autocorrelation function in the differentiated data, specifically:

ARIMA(0, 1, 2), ARIMA(0, 1, 4), ARIMA(2, 1, 0), ARIMA (4, 1, 0), ARIMA(2, 1, 2), ARIMA(4, 1, 2), ARIMA(2, 1, 4), ARIMA(4, 1, 4). The tentative models obtained were then analyzed through the estimation stage and statistical significance testing of each parameter. Table 2 displays the results of the parameter estimation.

Table 2. Parameter Estimation and Significance Testing of ARIMA Model Parameters

ARIMA (p,d,q) Model	Parameter Estimation	*p-value*	Significance Test Results
ARIMA (0, 1, 2)	$\theta_1 = 0{,}0646$	0,000	Significant
	$\theta_2 = -0{,}1043$	0,000	Significant
ARIMA (0, 1, 4)	$\theta_1 = 0{,}0555$	0,000	Significant
	$\theta_2 = -0{,}1101$	0,000	Significant
	$\theta_3 = 0{,}0204$	0,000	Significant
	$\theta_4 = -0{,}0655$	0,000	Significant
ARIMA (2, 1, 0)	$\phi_1 = 0{,}0515$	0,000	Significant
	$\phi_2 = -0{,}0908$	0,000	Significant
ARIMA (4, 1, 0)	$\phi_1 = 0{,}0588$	0,000	Significant
	$\phi_2 = -0{,}1083$	0,000	Significant
	$\phi_3 = 0{,}0217$	0,000	Significant
	$\phi_4 = -0{,}0768$	0,000	Significant
ARIMA (2, 1, 2)	$\phi_1 = -0{,}3773$	0,000	Significant
	$\phi_2 = 0{,}0403$	0,000	Significant
	$\theta_1 = 0{,}4421$	0,000	Significant
	$\theta_2 = -0{,}1223$	0,000	Significant
ARIMA (4, 1, 2)	$\phi_1 = -0{,}8882$	0,000	Significant
	$\phi_2 = -0{,}7524$	0,000	Significant
	$\phi_3 = -0{,}0320$	0,000	Significant
	$\phi_4 = -0{,}1319$	0,000	Significant
	$\theta_1 = 0{,}9493$	0,000	Significant

ARIMA (p,d,q) Model	Parameter Estimation	*p-value*	Significance Test Results
	$\theta_2 = 0{,}7006$	0,000	Significant
ARIMA (2, 1, 4)	$\phi_1 = 0{,}3570$	0,000	Significant
	$\phi_2 = -0{,}0635$	0,000	Significant
	$\theta_1 = -0{,}3016$	0,000	Significant
	$\theta_2 = -0{,}0666$	0,000	Significant
	$\theta_3 = 0{,}0629$	0,000	Significant
	$\theta_4 = -0{,}0806$	0,000	Significant
ARIMA (4, 1, 4)	$\phi_1 = 0{,}4437$	0,000	Significant
	$\phi_2 = -0{,}0481$	0,000	Significant
	$\phi_3 = -0{,}2991$	0,000	Significant
	$\phi_4 = -0{,}0147$	0,000	Significant
	$\theta_1 = -0{,}3877$	0,000	Significant
	$\theta_2 = -0{,}0867$	0,000	Significant
	$\theta_3 = 0{,}3708$	0,000	Significant
	$\theta_4 = -0{,}0494$	0,000	Significant

Based on diagnostic tests in Table 2, the Ljung-Box test results show $p{-}value$ > 0.05 at lag 10, thus concluding that the residuals are white noise. Therefore, the selected model is suitable for analysis and forecasting. The best ARIMA model to be used for forecasting was selected based on the AIC criterion. This criterion is used to assess the quality of a model's fit. The best model is the one with the smallest AIC value. Based on Table 3, the best ARIMA model is the ARIMA(4, 1, 0) model because it has the smallest AIC value.

Table 3. Selecting the Best ARIMA Model

Model ARIMA (p,d,q)	AIC
ARIMA (0, 1, 2)	-22484,134
ARIMA (0, 1, 4)	-22897,023
ARIMA (2, 1, 0)	-22130,656
ARIMA (4, 1, 0)	-23026,910
ARIMA (2, 1, 2)	-22269,281
ARIMA (4, 1, 2)	-22953,993
ARIMA (2, 1, 4)	-22895,913
ARIMA (4, 1, 4)	-22870,524

After evaluating the models, the best model selected was ARIMA(4, 1, 0), with the following estimated parameters:

$\phi_1 = 0{,}0588$; $\phi_2 = -0{,}1083$; $\phi_3 = 0{,}0217$; $\phi_4 = -0{,}0768$

Thus, the ARIMA(4,1,0) model based on Equation 1 is obtained as follows:

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)\alpha_t$$

With:

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p \quad (14)$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q \quad (15)$$

Since $q = 0$ then: $\theta_q(B) = 1$

$$(1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3 - \phi_4 B^4)Y_t = \alpha_t \quad (16)$$

$$Y_t - \phi_1 B(Y_t) - \phi_2 B^2(Y_t) - \phi_3 B^3(Y_t) - \phi_4 B^4(Y_t) = \alpha_t \quad (17)$$

$$Y_t - 0{,}0588Y_{t-1} - 0{,}1083Y_{t-2} + 0{,}0217Y_{t-3} - 0{,}0768Y_{t-4} = \alpha_t \quad (18)$$

$$Y_t = 0{,}0588Y_{t-1} + 0{,}1083Y_{t-2} - 0{,}0217Y_{t-3} + 0{,}0768Y_{t-4} + \alpha_t \quad (19)$$

Formulation of IGARCH Models

Table 4. ARCH-LM Best ARIMA Model

Best ARIMA Model	***p-value***	***Lag***	**ARCH-LM Test Results**
ARIMA(4, 1, 0)	0,000	5	There is an ARCH effect

Table 4 shows that the residuals of the best ARIMA model have an ARCH impact, with a p-value below the significance level α=0.05. Consequently, GARCH modelling is employed to overcome the inadequacy of the ARIMA model in modeling the training data(Bunnag, 2024). The lowest AIC value for the GARCH (1,1) model is -30872.3.

Number of GARCH (1,1) model coefficients:

$$\alpha_0 + \alpha_1 + \alpha_2 = 0.0000 + 0.7800 + 0.2000$$
$$\alpha_0 + \alpha_1 + \alpha_2 = 0.9800 \quad (20)$$

The sum of the parameters in the GARCH(1,1) model shows a value close to one. This condition indicates the presence of unit roots in the model, so the GARCH modeling needs to be further developed using the IGARCH model (Mursetya & Dwipa, 2016).

Table 5. Parameter Estimation and Significance Test of IGARCH Model Parameters

IGARCH(r,s) Model	**Parameter Estimation**	***p-value***	**Significance Test Results**	**AIC**
IGARCH(1,1)	$\alpha_1 = 0{,}2000$	0,000	Yes	-30791,5
	$\beta_1 = 0{,}8000$	0,000	Yes	

Several IGARCH models were tested, and the estimation results showed that the IGARCH(1,1) model provided the best results in capturing the dynamics of gold price volatility. The volatility parameters obtained showed a high level of persistence, indicating that shocks to the gold price have a long-term impact on variance(Jiang, 2020). These findings reinforce the characteristics of gold prices as an asset with persistent volatility.

Table 6. Ljung–Box Test Results for Residuals of the IGARCH Model

IGARCH Model	***Lag***	***p-value***	**Description**
IGARCH(1,1)	10	0,214	*White Noise*

The results of the Ljung–Box diagnostic test for the selected IGARCH model are presented in Table 6. As shown in Table 6, the p-values at lag 10 are greater than 0.05, indicating that no significant autocorrelation remains in the residuals. Therefore, the residuals can be considered white noise, suggesting that the model has adequately captured the underlying structure of the gold price series. Consequently, the selected model satisfies the diagnostic requirements and is appropriate for forecasting and further analysis.

Table 7. ARCH-LM Best IGARCH Model

IGARCH Model	***p-value***	***Lag***	**ARCH-LM Test Results**
IGARCH(1,1)	0,664	5	There is no ARCH effect.

Based on diagnostic tests in Table 7, the ARCH-LM test results gave $p{-}value$ > 0.05 at lag 5, so it was concluded that the selected model was suitable for analysis and forecasting.

Through data processing, the best forecasting model for PT.ANTAM's gold price is ARIMA(4,1,0)-IGARCH(1,1). The following are the parameters of this model:

ARIMA (4,1,0) Model:

$$Y_t = 0.0588Y_{t-1} + 0.1083Y_{t-2} - 0.0217Y_{t-3} + 0.0768Y_{t-4} + \alpha_t \quad (21)$$

IGARCH (1,1) Model :

$$\sigma_t^2 = \alpha_i \varepsilon_{t-1}^2 + \beta_j \sigma_{t-1}^2$$
$$\sigma_t^2 = 0{,}2000\varepsilon_{t-1}^2 + 0{,}8000\sigma_{t-1}^2 \quad (22)$$

Forecasting Performance Evaluation

Table 8. Results of Forecasting Model Evaluation on Training Data

Best Model	**MAE**	**MAPE**	**SMAPE**	**RMSE**
ARIMA(4,1,0)-IGARCH(1,1)	24269,47	1,89%	1,93%	32189

Based on the results of the MAE, MAPE, SMAPE, and RMSE calculations are presented in Table 8, it was found that the ARIMA(4,1,0)-IGARCH(1,1) model provided excellent forecasting results on the training data.

Table 9. Results of Forecasting Model Evaluation on Test Data

Best Model	**MAE**	**MAPE**	**SMAPE**	**RMSE**
ARIMA(4,1,0)-IGARCH(1,1)	151256,37	7,8554%	8,2111%	158968,99

Based on the results of MAE, MAPE, SMAPE, and RMSE calculations are presented in Table 9, it was found that the ARIMA(4,1,0)-IGARCH(1,1) model provided good forecasting results on the test data.

Table 10. Results of Forecasting Model Evaluation on Forecasting

Best Model	MAE	MAPE	SMAPE	RMSE
ARIMA(4,1,0)	55653,54	2,74%	2,78%	58345,93
ARIMA(4,1,0)-IGARCH(1,1)	190335,31	9,38%	9,84%	191232,27

Based on the results of MAE, MAPE, SMAPE, and RMSE calculations are presented in Table 10, it was found that the ARIMA(4,1,0)-IGARCH(1,1) model provided good forecasting results on forecasting.

Table 11. Forecasting Results

Model	Period-	Date	Forecasting Results	Current Price
ARIMA(4,1,0)	1	01/09/2025	Rp1.976.751,36	Rp2.011.000
	2	02/09/2025	Rp1.974.031,16	Rp2.009.000
	3	03/09/2025	Rp1.971.384,49	Rp2.035.000
	4	04/09/2025	Rp1.970.081,17	Rp2.044.000
	5	05/09/2025	Rp1.970.484,11	Rp2.042.000
ARIMA(4,1,0)-IGARCH(1,1)	1	01/09/2025	Rp1.935.452.12	Rp2.011.000
	2	02/09/2025	Rp1.929.469.26	Rp2.009.000
	3	03/09/2025	Rp1.923.887.36	Rp2.035.000
	4	04/09/2025	Rp1.919.849.36	Rp2.044.000
	5	05/09/2025	Rp1.917.644.26	Rp2.042.000

In financial time series forecasting, short forecasting horizons are commonly used because the accuracy of volatility-based models tends to decline as the forecast horizon increases. Since gold prices are influenced by rapidly evolving economic and geopolitical factors, a five-day horizon was chosen to provide a realistic evaluation of the model's predictive ability under short-term market conditions. Based on the results of the forecast as shown in Table 11, it was found that the price of PT. ANTAM gold in the next 5 periods will experience a decline in price to the lowest price on September 5, 2025, of IDR 1,917,644.26 and the highest price on September 1, 2025, of IDR 1,935,452.12

CONCLUSIONS AND SUGGESTIONS

Based on the results of analysis and evaluation, the best model for forecasting PT.ANTAM gold prices using the ARIMA-IGARCH model is ARIMA(4,1,0)-IGARCH(1,1). Furthermore, the forecast results from the best ARIMA and IGARCH models for PT.ANTAM's gold price for the next five periods will experience a decline in price to a low of Rp1,917,644.26 on September 5, 2025, with the actual gold price at Rp2,042,000.

The forecasting results obtained are expected to be useful for investors who need them and can serve as a basis for short-term risk management. To improve this study, there are several suggestions that could be considered. Future research is recommended to use the ARIMA-IGARCH model with the addition of exogenous variables (ARIMAX-IGARCH), such as the exchange rate of the rupiah against the U.S. dollar or the price of gold

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