Daily Stock Price Forecasting of PT Astra Agro Lestari (AALI) Using Arima and Arch-Garch Models

Azizah Rizki Amelia[1]*, Siti Nurhaliza[2], Zhakira Cantika Dewi[3], Agus Rifai[4]

[1,2,3,4] Islamic Economics Study Program, Bina Cipta Madani Islamic Economics College, Indonesia
*Corresponding Author:
Email:yulianti@stei-bcm.ac.id

Abstract.

The capital market serves as a vital investment channel where stock prices exhibit dynamic fluctuations influenced by macroeconomic factors and market sentiments. This study estimates daily stock prices of PT Astra Agro Lestari Tbk (AALI), a leading palm oil company, using hybrid ARIMA-ARCH-GARCH models. Employing quantitative time series analysis, the population comprises all daily AALI stock prices from January 1, 2021, to June 30, 2025 (1,145 observations), sampled purposively via Investing.com data. Analysis techniques include ADF stationarity tests, ACF-PACF correlograms, AIC/SC/HQ model selection, ARCH-LM heteroskedasticity tests, and forecasting accuracy evaluation. Results identify ARIMA(1,1,1) as optimal for mean modeling and GARCH(2,1) for volatility, achieving 53% average forecasting accuracy for July 31-August 5, 2025. The hybrid model effectively captures price patterns despite external influences.

Keywords: *Arch-Garch; Arima; Forecasting; Stock Price and Time Series.*

I. INTRODUCTION

Capital markets play a crucial role in the modern economy as a vehicle for investment and a channel for corporate funding. Stock prices, the primary instrument in the capital market, are dynamic and fluctuating, influenced by macroeconomic factors, issuer performance, and global market sentiment.PT Astra Agro Lestari Tbk (AALI), a leading palm oil plantation company listed on the Indonesia Stock Exchange, exhibited high volatility due to changes in commodity prices, government policies, and global economic conditions. These fluctuations created a volatility clustering pattern, where periods of high volatility are followed by similar periods, challenging the accuracy of daily stock price predictions.Although the ARIMA model is effective for modeling non-stationary time series averages through autoregressive, integrated, and moving averages, it fails to address heteroscedasticity in financial data.

ARIMA assumes constant residual variance, even though stock prices exhibit non-constant time-conditional volatility. [Briliantya, 2022] Previous studies, such as Junaid et al. (2020), compared ARIMA and GARCH on mining stocks, while Trimono and Agista (2021) focused on AALI's VaR without direct price prediction. These limitations include the lack of model integration for volatility and broad accuracy evaluation, necessitating a more comprehensive hybrid approach. [Junaid et al., 2020][Astra & Lestari, 2021] This study aims to forecast AALI's daily stock price for the 2021-2025 period using a combination of ARIMA and ARCH-GARCH to capture mean and volatility. Its urgency supports investment decisions in the volatile agribusiness sector, while its novelty lies in AALI's specific application with a comprehensive accuracy evaluation, surpassing previous studies that were limited to sectors or solely focused on risk. [Zili et al., 2022]

II. LITERATURE REVIEW

Theoretical Study

PartThe theoretical study aims to provide the scientific basis and concepts used in this research. Through theoretical study, researchers can understand relevant models for analyzing and predicting stock prices, particularly in the context of time series data. This section explains the main theories underlying the research, namely the ARIMA, ARCH, and GARCH models, as well as supporting tests such as the stationarity test, ARCH-LM, and Ljung-Box. The following is an explanation:

ARIMA (Autoregressive Integrated Moving Average) model

The Autoregressive Integrated Moving Average (ARIMA) model is a time series model developed by Box and Jenkins. This model is used to model non-stationary data by converting it to stationary through a differencing process. In general, the ARIMA model is expressed as:

$$ARIMA(p, d, q)$$

with the following information:

p : Autoregressive (AR) order

d : level of differencing

q : Moving Average (MA) order

The ARIMA model is used to model the mean of a time series. However, ARIMA assumes that the residual variance is constant (homoscedasticity). In reality, financial data actually exhibits heteroscedasticity, which is a variable residual variance. Therefore, a complementary model is needed to model volatility.

ARCH Model (Autoregressive Conditional Heteroskedasticity)

The Autoregressive Conditional Heteroskedasticity (ARCH) model was developed by Engle (1982) to model residual variance that depends on past errors.

Main features of the ARCH model:

a. the variance of the error in the current period is influenced by the square of the error in the previous period,
b. suitable for financial data that has dynamic volatility,
c. used to model risk/uncertainty.

The ARCH model can depict short-term volatility.

GARCH (Generalized ARCH) Model

Bollerslev then developed the ARCH model into GARCH (Generalized ARCH). The GARCH model includes:

a. previous period error, and
b. previous period variance

into the variance equation. The most commonly used GARCH models are:

$$GARCH(1,1)$$

Advantages of the GARCH model:

a. more efficient than ARCH,
b. able to describe long-term volatility,
c. very suitable for financial market data.

Stationarity and Diagnostic Tests

In time series modeling, several initial and diagnostic tests are required, including: the ADF (Augmented Dickey-Fuller) test, used to test for data stationarity. The ARCH-LM test, used to test for heteroscedasticity in the residuals of the ARIMA model.

Previous Research

This section summarizes several previous studies relevant to the topic of stock price forecasting using ARIMA, ARCH, GARCH, and their variants. The following table presents a comparison of the results of previous studies, the methods used, and their advantages and disadvantages.

Table 1. Previous research

No	Researcher & Year	Research Title	Method	Excess	Lack
1	Muhammad Tharmizi Junaid, Ahmad Juliana, and Hardianti Sabrina (2020)	Comparative Study of ARIMA and GARCH Models for Predicting Stock Prices in Mining Companies in Indonesia.	This research uses a quantitative method with time series analysis. The models used are ARIMA and GARCH.	This study directly compares the performance of ARIMA and GARCH models and uses historical data with a long enough observation period so that the analysis results are relatively stable.	This study focuses solely on the mining sector and does not examine stocks in the agribusiness sector, such as PT Astra Agro Lestari Tbk. Furthermore, the study does not combine ARIMA and GARCH

					models into a single, integrated forecasting framework.(Junaid et al., 2020)
2	Aisyah Putri Utami, Supriyanto, and Najmah Istikaanah	Stock Price Forecasting Model Using the ARIMA–GARCH Method (Case Study of PT Unilever Indonesia Stocks)	This study uses the ARIMA–GARCH method with secondary data in the form of daily stock price data for PT Unilever Indonesia for the period January 31, 2011–January 19, 2021.	The advantage of this paper is the use of the ARIMA–GARCH model, which is able to overcome the problem of heteroscedasticity in stock return data, resulting in more accurate forecasting results. Furthermore, this study uses daily data over a fairly long period and performs a comprehensive model testing process, from stationarity testing and diagnostic testing to accuracy evaluation using MAPE.	This research isn't limited to a single issuer, making the results more general and comparable across stocks. Furthermore, this study focuses not only on short-term forecasting but also evaluates the model's accuracy more broadly.(Math & Mathematics, 2023)
3	Arman Haqqi, Anna Zili, Derick Hendri, and Selly Anastassia Amellia Kharis. (2022)	Stock Price Forecasting with the Hybrid ARIMA-GARCH Model and the Walk Forward Method.	This study uses a quantitative method with time series analysis using the ARIMA-GARCH hybrid model and the Walk Forward method on LQ45 stocks.	Research Strengths The use of the ARIMA–GARCH hybrid model and the Walk Forward method makes the forecasting results more adaptive to data changes and is able to handle high volatility.	The research was limited to LQ45 stocks and did not specifically examine stocks in the agribusiness sector. Furthermore, the study focused on hybrid methods without an in-depth discussion of the characteristics of stationarity and heteroscedasticity in stages.(Zili et al., 2022)
4	Sofalina nodra Briliantya (2022)	Egarch and Tagrach model to measure symmetric volatility of stock returns	EGARCH & TGARCH	- Using a symmetric volatility model -Focus on stock return pattern analysis	- No price forecast accuracy test - Limited model use(Briliantya, 2022)
5	Trimono and Fira Agista (2021)	ARMA-GARCH Model Predicts Value-at-Risk on PT Astra Agro Lestari Tbk Shares	The quantitative time series method uses the ARMA–GARCH model with the Value-at-Risk (VaR) approach to measure the risk of loss of AALI shares.	This study is able to measure stock investment risk quantitatively through a combination of ARMA-GARCH and VaR, so it is useful in market risk analysis.	This research focuses more on risk measurement (VaR) and has not focused on direct stock price forecasting.(Astra & Lestari, 2021)

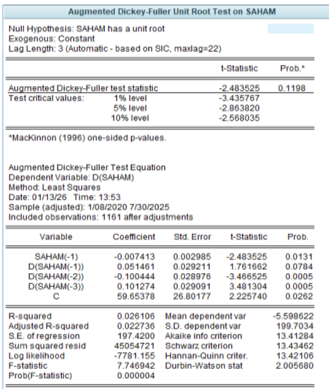
III. METHODS

This study uses a quantitative approach with time series analysis to forecast the daily stock price of PT Astra Agro Lestari Tbk (AALI). This approach is suitable for time-series financial data, where the ARIMA model handles non-stationarity and the ARCH-GARCH model models heteroscedastic volatility. Sugiyono (2023) emphasizes the effectiveness of quantitative time series methods for economic forecasting, while Creswell and Creswell (2023) define quantitative design as hypothesis testing through structured numerical data.The main instrument is secondary data of AALI daily stock prices from January 1, 2021 to June 30, 2025, taken from the Investing.com website. Analysis techniques include the Augmented Dickey-Fuller (ADF) stationarity test, ACF-PACF correlogram analysis, ARIMA model selection based on AIC/SC/HQ, ARCH-LM test for heteroscedasticity, and optimal GARCH selection, followed by forecasting and accuracy evaluation. [Junaid et al., 2020] Sudaryono (2022) recommends ADF and ARCH-LM for financial time series diagnostics, while Emzir (2021) highlights model selection based on the smallest information criterion in quantitative economic research.The study population comprised all daily AALI stock price data during the period, with a total sample of 1,145 daily observations (calculated over 4.5 years x approximately 255 trading days). The sampling technique used was non-probability purposive sampling, selecting the post-pandemic period to capture recent volatility. [Trimono & Agista, 2021] The research procedure follows systematic stages: (1) data collection from Investing.com; (2) ADF stationarity test until stationary at first differentiation; (3) parameter identification via correlogram; (4) estimation of the ARIMA(1,1,1) model as the best; (5) ARCH-LM test confirming heteroscedasticity; (6) optimal GARCH(2,1) modeling; (7) 3-day forecasting (July 31-August 5, 2025) and calculating the average accuracy of 53%. [Briliantya, 2022] This procedure is in line with Box-Jenkins for ARIMA-GARCH.

III. RESULT AND DISCUSSION

Stationary Testing

The stationarity test is the initial step in time series analysis to ensure that the data has a constant mean and variance over time. The test is performed using the Augmented Dickey-Fuller (ADF) test.



Augmented Dickey-Fuller Unit Root Test on SAHAM

Null Hypothesis: SAHAM has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.483525	0.1198
Test critical values:	1% level	-3.435767	
	5% level	-2.863820	
	10% level	-2.568035	

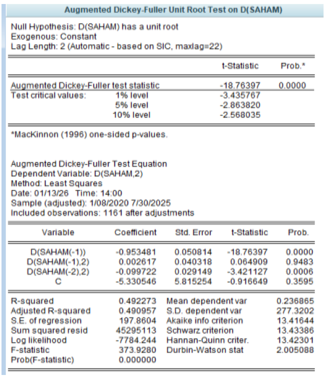
*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SAHAM)
Method: Least Squares
Date: 01/13/26 Time: 13:53
Sample (adjusted): 1/08/2020 7/30/2025
Included observations: 1161 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SAHAM(-1)	-0.007413	0.002985	-2.483525	0.0131
D(SAHAM(-1))	0.051461	0.029211	1.761662	0.0784
D(SAHAM(-2))	-0.100444	0.028976	-3.466525	0.0005
D(SAHAM(-3))	0.101274	0.029091	3.481304	0.0005
C	59.65378	26.80177	2.225740	0.0262

R-squared	0.026106	Mean dependent var	-5.598622
Adjusted R-squared	0.022736	S.D. dependent var	199.7034
S.E. of regression	197.4200	Akaike info criterion	13.41284
Sum squared resid	45054721	Schwarz criterion	13.43462
Log likelihood	-7781.155	Hannan-Quinn criter.	13.42106
F-statistic	7.746942	Durbin-Watson stat	2.005680
Prob(F-statistic)	0.000004		

Fig 1. Level data



Augmented Dickey-Fuller Unit Root Test on D(SAHAM)

Null Hypothesis: D(SAHAM) has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.76397	0.0000
Test critical values:	1% level	-3.435767	
	5% level	-2.863820	
	10% level	-2.568035	

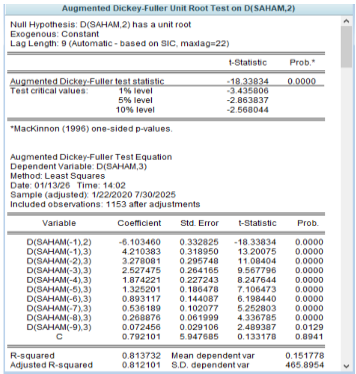
*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SAHAM,2)
Method: Least Squares
Date: 01/13/26 Time: 14:00
Sample (adjusted): 1/08/2020 7/30/2025
Included observations: 1161 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SAHAM(-1))	-0.953481	0.050814	-18.76397	0.0000
D(SAHAM(-1),2)	0.002617	0.040318	0.064909	0.9483
D(SAHAM(-2),2)	-0.099722	0.029149	-3.421127	0.0006
C	-5.330546	5.815254	-0.916649	0.3595

R-squared	0.492273	Mean dependent var	0.236865
Adjusted R-squared	0.490957	S.D. dependent var	277.3202
S.E. of regression	197.8604	Akaike info criterion	13.41644
Sum squared resid	45295113	Schwarz criterion	13.43386
Log likelihood	-7784.244	Hannan-Quinn criter.	13.42301
F-statistic	373.9280	Durbin-Watson stat	2.005088
Prob(F-statistic)	0.000000		

Fig 2. st different



Augmented Dickey-Fuller Unit Root Test on D(SAHAM,2)

Null Hypothesis: D(SAHAM,2) has a unit root
Exogenous: Constant
Lag Length: 9 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.33834	0.0000
Test critical values:	1% level	-3.435806	
	5% level	-2.863837	
	10% level	-2.568044	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SAHAM,3)
Method: Least Squares
Date: 01/13/26 Time: 14:02
Sample (adjusted): 1/22/2020 7/30/2025
Included observations: 1153 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SAHAM(-1),2)	-6.103460	0.332825	-18.33834	0.0000
D(SAHAM(-1),3)	4.210383	0.318950	13.20075	0.0000
D(SAHAM(-2),3)	3.278081	0.295748	11.08404	0.0000
D(SAHAM(-3),3)	2.527475	0.264165	9.567796	0.0000
D(SAHAM(-4),3)	1.874221	0.227243	8.247644	0.0000
D(SAHAM(-5),3)	1.325201	0.186478	7.106473	0.0000
D(SAHAM(-6),3)	0.893117	0.144087	6.198440	0.0000
D(SAHAM(-7),3)	0.536189	0.102077	5.252803	0.0000
D(SAHAM(-8),3)	0.268876	0.061999	4.336785	0.0000
D(SAHAM(-9),3)	0.072456	0.029106	2.489387	0.0129
C	0.792101	5.947685	0.133178	0.8941

R-squared	0.813732	Mean dependent var	0.151778
Adjusted R-squared	0.812101	S.D. dependent var	465.8954

Fig 3. nd difference

The results in the figure show the stationarity test using Augmented Dickey-Fuller (ADF). At the level, the data is not stationary because the probability value (Prob.) is greater than 0.05, so it still contains a unit root. After differentiation (first difference), the probability value is less than 0.05, which means the data is stationary. Thus, it can be concluded that the time series data is stationary at the first difference and can be used for further analysis such as ARIMA or other time series models.

Correlogram Testing

Correlogram analysis is used to see autocorrelation patterns in data, in order to determine the parameter values p (AR) and q (MA).

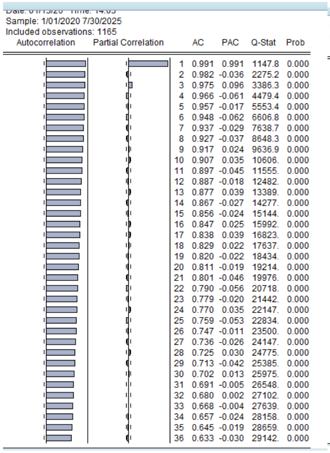


Fig 4. Level data

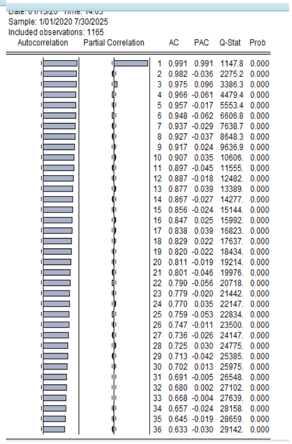


Fig 5. t difference

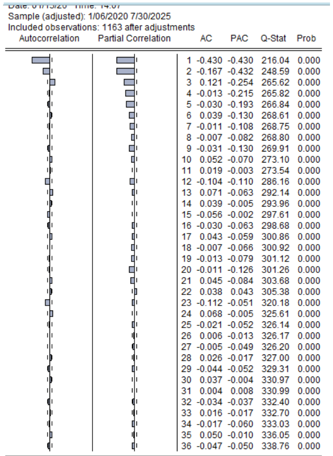


Fig 6. nd difference

At this stage, a correlogram analysis is performed, which involves testing the correlogram to observe autocorrelation patterns using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The results of this test identify the most appropriate AR (p) and MA (q) model orders.

Testing and determining the best ARIMA

The results of the ARIMA test analysis obtained from the data testing are as follows:

Table 2. Best Arima Results

Variables	Model	ARIMA	AIC	SC	HQ
share		110	13.43993	13.45297	13.44485
Share		011	13.43961	13.45265	13.44453
share		111	13.43222	13.44960	13.43878

Based on the results of the ARIMA model selection test, it can be seen that the AIC, SC, and HQ values of ARIMA (1,1,1) are smaller than those of ARIMA (1,1,0) and ARIMA (0,1,1). Lower AIC, SC, and HQ values indicate that the model is more efficient in explaining the data with a smaller error rate. Therefore, ARIMA (1,1,1) is the best model for forecasting stock data, because it is able to better capture data patterns and provide more accurate prediction results than the other two models.

Heteroscedasticity Testing

After the best ARIMA model is determined, the ARCH-LM Test is carried out to detect heteroscedasticity (changes in residual variance).

Heteroskedasticity Test: ARCH

F-statistic	33.89313	Prob. F(1,1161)	0.0000
Obs*R-squared	32.98848	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/13/26 Time: 14:29
Sample (adjusted): 1/06/2020 7/30/2025
Included observations: 1163 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	32986.73	3304.171	9.983361	0.0000
RESID^2(-1)	0.168413	0.028928	5.821781	0.0000

R-squared	0.028365	Mean dependent var	39662.73
Adjusted R-squared	0.027528	S.D. dependent var	107163.0
S.E. of regression	105677.7	Akaike info criterion	25.97589
Sum squared resid	1.30E+13	Schwarz criterion	25.98459
Log likelihood	-15102.98	Hannan-Quinn criter.	25.97918
F-statistic	33.89313	Durbin-Watson stat	2.025580
Prob(F-statistic)	0.000000		

Fig 7. Heteroscedasticity test results

At this stage, a heteroscedasticity test is performed on the residuals from the selected ARIMA model. This test is performed to determine whether there are any symptoms of non-constant residual variance, or heteroscedasticity. The test results indicate that heteroscedasticity is still present, requiring further modeling using ARCH or GARCH methods to better model stock price volatility.

Testing and determining the best Garch

Table 3. Best Garch Results

Variable	D(BNSI)-ARIMA(1,1,1)				
	GARCH (1,0)	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)
AIC	13.29298	13.01123	13.00615	12.99332	12.99490
SC	13.31473	13.03732	13.03660	13.02377	13.02969
HQ	13.30119	13.02107	13.01764	13.00481	13.00803

The selection of the best model again refers to the smallest AIC, SC, and HQ values. Based on the results from the table above, it shows that Garch (2,1) is the best model because it provides the lowest information criterion value.

LM arch test

The results of the ARCH (Lagrange Multiplier Test) heteroscedasticity test are in the image below.

Fig 9. LM arch test

Heteroskedasticity Test: ARCH

F-statistic	0.269140	Prob. F(1,1160)	0.6040
Obs*R-squared	0.269541	Prob. Chi-Square(1)	0.6036

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 01/13/26 Time: 14:53
Sample (adjusted): 1/07/2020 7/30/2025
Included observations: 1162 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.022415	0.077588	13.17754	0.0000
WGT_RESID^2(-1)	-0.015233	0.029363	-0.518787	0.6040

R-squared	0.000232	Mean dependent var	1.007090
Adjusted R-squared	-0.000630	S.D. dependent var	2.444878
S.E. of regression	2.445648	Akaike info criterion	4.628217
Sum squared resid	6938.184	Schwarz criterion	4.636922
Log likelihood	-2686.994	Hannan-Quinn criter.	4.631501
F-statistic	0.269140	Durbin-Watson stat	1.999192
Prob(F-statistic)	0.604008		

Forecasting

In this study, forecasting was carried out to predict stock prices atPT Astra Agro Lestari. Forecasting was conducted for three days, from July 31 to August 5, 2025.On several days determined by ARIMA and GARCH modeling, the following are the predicted results for PT Astra Agro shares.sustainable

7/31/2025	12775.58	12775.58	8982.177	37067.78
8/04/2025	12774.57	12774.57	8986.230	37064.98
8/05/2025	12773.56	12773.56	8990.283	37062.18

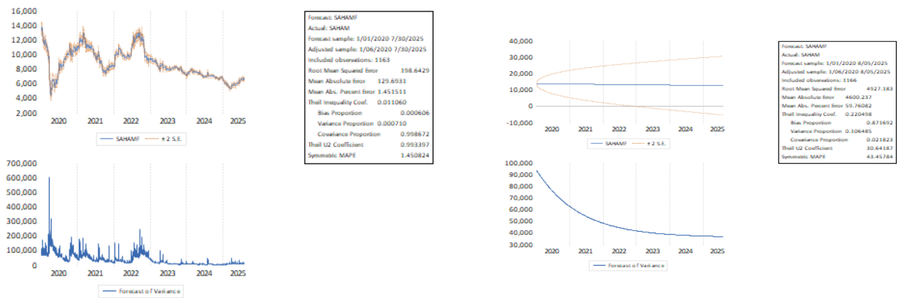


Table 4. Accuracy Results

No	Year	Stock price prediction	Actual stock price	Accuracy
1	07/31/2025	12775.58	6,800	53%
2	04/08/2025	12774.57	6,750	52%
3	05/08/2025	12773.56	6,900	54%
Average: 53%				

Based on the calculations, the stock price forecasting accuracy of PT Astra Agro Lestari Tbk was 53%. This value indicates that although the forecasting model was able to follow stock price movement patterns, there was still a significant difference between the predicted and actual prices. This was due to stock price fluctuations influenced by various external factors outside the model.

IV. CONCLUSION

This study concludes that the daily stock price data of PT Astra Agro Lestari Tbk (AALI) is not stationary at the initial level, but becomes stationary after the first differentiation, with the ARIMA(1,1,1) model as the best based on the smallest AIC, SC, and HQ criteria. The ARCH-LM test confirms the heteroscedasticity of the ARIMA residuals, so the GARCH(2,1) model is selected to model volatility, resulting in an average forecasting accuracy of 53% for the period July 31 to August 5, 2025. This finding confirms the ability of the ARIMA-ARCH-GARCH hybrid in capturing the mean pattern and dynamics of stock price volatility in the agribusiness sector.However, a major limitation is the 53% accuracy, which indicates the influence of external factors such as global commodity fluctuations and economic policies beyond the historical model. Suggestions for future research include integrating exogenous variables (ARIMAX) or hybrid machine learning models for more accurate long-term forecasting. Practically, these results provide implications for Islamic investors in managing AALI risk, supporting diversification strategies, and contributing to decision-making in the Indonesian capital market.

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