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UNILEVER STOCK PRICES FORECASTING WITH ENSEMBLE AVERAGING APPROACH ARIMA-GARCH AND SUPPORT VECTOR REGRESSION

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ABSTRACT

Investment, mainly in stock prices, plays a significant role in the Indonesian economy. Accurate stock price forecasting can help investors make informed decisions. Unilever Indonesia Tbk (UNVR) exhibits high volatility in its closing stock prices, making it crucial to develop a reliable forecasting model. This study applies an ensemble averaging method that integrates the ARIMA-GARCH model and Support Vector Regression (SVR) to predict UNVR's closing stock prices from January 6, 2019, to November 5, 2023. The results indicate that the data can be modeled using ARIMA (0,2,1). However, the squared residuals of the model show heteroscedasticity, necessitating variance modeling using the ARCH-GARCH approach. The best combination of mean and variance modeling is achieved with ARIMA (0,2,1) – GARCH (1,1), yielding a Mean Absolute Percentage Error (MAPE) of 2.865%. Additionally, a nonparametric SVR model with parameters C = 4 and ε = 0 is applied, resulting in a MAPE of 2.94%. An ensemble averaging approach is implemented to optimize forecasting accuracy further, combining ARIMA-GARCH and SVR models. This ensemble approach improves predictive performance, achieving a final MAPE of 1.682%. These findings demonstrate that ensemble averaging effectively enhances stock price forecasting accuracy by leveraging linear and nonlinear modeling techniques.

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1. INTRODUCTION

Stock price analysis plays a crucial role in the investment decision-making process, as it enables investors to determine the optimal steps to take when buying and selling stocks [1]. Ideally, investors seek stocks with stable price trends that tend to increase over time. However, in reality, the market often exhibits high volatility and unexpected price fluctuations [2]. This situation underscores the importance of accurate stock price forecasting as a strategic tool for managing investment risk and improving the quality of decision-making. Stock price forecasting has gained increasing attention in both academic research and financial practice, driving the development of various statistical and computational approaches. Among the most commonly used methods are time series models such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH), which can capture temporal dependencies and model volatility in financial data

Unilever Indonesia Tbk. (UNVR), a company that distributes consumer products in Indonesia, is a multinational company and one of the suppliers of care and beauty products. According to disclosure information by the Indonesian Stock Exchange (IDX) at the end of 2022, UNVR owned 32,424,387,500 shares, accounting for around 84.99% [3].The closing value of UNVR's share price has very high volatility, requiring investors to consider future stock price movements to profit from their investment transactions [4]. Ilma in [5] analyzed the comparison of the results of the prediction of the closing price of PT—Unilever Indonesia Tbk. using the fuzzy time series Chen and Lee's fuzzy time series (FTS). The results of this study showed that the predictions produced by Chen and Lee's FTS methods showed good prediction results with MAPE below 10% and low MAE values. Permatasari in [6] analyzed the closing price of UNVR shares by taking the period from 2012 to 2021 using the decomposition method. This study's best decomposition model is an additive decomposition model with a MAPE of 0.1349. Irawan in [7] predicted UNVR's share price using the ARIMA model for data from 24 May 2010 to 26 May 2014. The results of this study obtained the best ARIMA model, namely ARIMA (1,1,1), but heteroscedasticity symptoms occurred, so the ARCH-GARCH approach was carried out. Forecasting using the ARIMA model (1,1,1) managed to approximate the actual stock price value, and the impact of residual volatility of the ARCH model was minimal, so the addition of these effects did not significantly affect the results of stock price forecasting.

To support the achievement of the eighth point of the Sustainable Development Goal (SDG), which relates to inclusive and sustainable economic growth and the creation of decent jobs, analyzing the financial performance of well-known companies, such as PT Unilever Indonesia Tbk (UNVR), plays a strategic role. UNVR is one of the companies classified as a blue-chip stock, characterized by a market capitalization exceeding 40 trillion rupiah, being a market leader in its industry, having high liquidity, and possessing strong fundamentals [8]. As a leading company in the consumer goods sector, UNVR's stock performance reflects not only investor sentiment but also the stability of the domestic consumer market. This study focuses on forecasting the closing price of UNVR shares from January 6, 2019, to November 5, 2023, to provide insights for investors, portfolio managers, and policymakers in anticipating market fluctuations. In the face of increasingly uncertain market conditions, forecasting has become an essential tool in risk management and investment decision-making [9], [10]. The high volatility in UNVR's closing stock prices serves as the basis for selecting the appropriate predictive method to enhance the accuracy of estimates and the resilience of investment strategies.

To address these issues, this study proposes an ensemble averaging approach that combines ARIMA-GARCH and Support Vector Regression (SVR) models. ARIMA-GARCH is effective in capturing linear patterns and volatility dynamics [11], while SVR is capable of recognizing nonlinear relationships in complex stock market data [12]. Previous studies have demonstrated the strengths of each approach separately, such as the study by Dalimunthe et al. in predicting inflation using the ARCH-GARCH method [13] and by Soewignjo et al. in predicting the exchange rate of the Yuan against the Rupiah using SVR with high accuracy (MAPE <10%) [14]. By combining both, this ensemble model is expected to address the irregularity of variance in time series data while improving prediction accuracy. The simple averaging technique (equal-weight averages) was chosen due to its efficiency, stability, and ease of implementation [15]. The main novelty of this research lies in the integration of statistical and machine learning models in the context of consumer sector stocks in Indonesia, as well as in the explicit evaluation of the performance of individual and combined models. The results of this research are expected to provide empirical contributions that support investment strategies, strengthen risk assessment, and enhance supervision in the Indonesian capital market.

2. RESEARCH METHODS

2.1 Autoregressive Integrated Moving Average (ARIMA)

ARIMA is an Autoregressive Moving Average (ARMA) model that handles non-stationary data. In overcoming the non-stationary nature of this data, a differencing process is carried out so that the data becomes stationary, and the amount of differencing is noted with d. In addition to stationary in the mean, the data to be analyzed should also satisfy the assumption of stationarity in variance. Stationary identification in variance can be known through the Box-Cox plot, so if the data is not stationary, the Box-Cox transformation must be carried out as follows.

$$Z_t^{(\lambda)} = \frac{Z_t^{(\lambda)} - 1}{\lambda}, \quad -1 < \lambda < 1, \tag{1}$$

by declaring the data Z_t at the time t and symbolizing the value of the transformation parameter λ. The following is the form of Box-Cox transformation on the data presented in Table 1.

Table 1. Transformation Forms Box-Cox

Transformation parameters values	-1	-0.5	0	0.5	1
Transformation Forms	$\frac{1}{Z_t}$	$\frac{1}{\sqrt{Z_t}}$	$\ln Z_t$	$\sqrt{Z_t}$	Z_t

Basis differencing is subtracting between today's observations (Z_t) and previous observations Z_{t-k} [16]. The general form of the autoregressive model is denoted as ARIMA (p, d, q) as follows [17].

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)\varepsilon_t, \tag{2}$$

where the AR operator is defined by

$$\phi_p(B) = \left(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\right), \tag{3}$$

and the MA operator is defined by

$$\theta_q(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right), \tag{4}$$

by being a B backward shift operator and $(1-B)^d Z_t$ expressing a stationary time series at the d^{th} differencing. This process is denoted by ARIMA (p, d, q). How to choose the order of the ARIMA model (p, q) is using the pattern of autocorrelation function (ACF) and partial autocorrelation function (PACF) concerning Table 2 as follows.

Table 2. ARIMA Models

Type	**ACF**	**PACF**
ARIMA$(\boldsymbol{p}, \boldsymbol{d}, \boldsymbol{0})$	Heading gradually or wavily	Towards zero after the q^{th} lag
ARIMA$(\boldsymbol{0}, \boldsymbol{d}, \boldsymbol{q})$	Towards zero after the q^{th} lag	Gradual decline or wavy
ARIMA$(\boldsymbol{p}, \boldsymbol{d}, \boldsymbol{q})$	Gradually decreasing or wavy (until the q^{th} lag is still different from zero)	Gradually decreased/wavy (until the q^{th} lag is still different from zero)

2.2 ARCH-GARCH

ARCH (Autoregressive Conditional Heteroscedastic) is used to handle heteroscedasticity in data. The general form of the ARCH model is as follows [18].

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-1}^2 ; \quad \alpha_0 > 0, \alpha_i \geq 0, i = 1,2, \dots, m \tag{5}$$

where σ_t and ε_t mutually independent.

GARCH (Generalized Autoregressive Conditional Heteroscedastic) is a development of ARCH that reduces the number of high orders in the ARCH model. The general form of the GARCH model is as follows.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_2 \varepsilon_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \lambda_q \sigma_{t-q}^2 \tag{6}$$

ARCH-GARCH influence testing was carried out after obtaining the ARIMA model by testing the quadratic residual from the best model obtained to detect the effect of heteroscedasticity using the Q-Ljung Box test with the following hypotheses [18].

$H_O: \rho(1) = \rho(2) = \cdots = \rho(k) = 0$ ((Model does not have the effect of heteroscedasticity)
H_1: there is at least one $k \epsilon 1, 2, \ldots, m$ with $\rho(k) \neq 0$ (There is an effect of heteroscedasticity in the model)

The test statistics used is

$$Q = (n+2)\sum_{i=1}^{m} \frac{p_i}{n-1}; i = \text{number of lags}, \quad (7)$$

where reject H_0 if $Q > \chi^2_{(1)}$, accept H_0 if $Q < \chi^2_{(1)}$.

The Lagrange Multiplier (LM) test for ARCH tests the presence or absence of conditional heteroscedasticity against the ARCH model. This test is carried out by progressing the t^{th} residual square against the constant and the value coefficients of $t-1$ lag to $t-k$ lag as below.

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_k a_{t-k}^2 \quad (8)$$

where k is the maximum lag. The test hypothesis for detecting the presence of ARCH/GARCH elements in the residual mean model is as follows.

$H_0: \alpha_1 = \cdots = \alpha_k = 0;$
H_1: There is at least one $\alpha_q \neq 0$ for $q = 1, 2, \ldots, k$.

The statistics of the ARCH-LM test $LM = TR^2$ where T is the coefficient of the number of observations and R^2 is the coefficient of determination in the regression results Eq. (8). With the critical area of reject H_0 if $TR^2 > \chi^2_{\frac{\alpha}{2},k}$, thus indicating the presence of symptoms of heteroscedasticity and ARCH-GARCH modeling can be done.

If there is an ARCH-GARCH effect, the next step is the determination of the order ARCH-GARCH based on the PACF plot of residuals σ_t^2 . If the residual σ_t^2 exhibits a pattern of autoregressive behavior AR(p), then the residual follows an ARCH(p) model. The determination of the order ARCH-GARCH uses the Akaike Information Criterion (AIC) value with the following formulas [18].

$$\boldsymbol{AIC = -2loglikelihood + 2(q+1)\left(\frac{N}{N-q-2}\right)}, \text{ not constant,}$$
$$\boldsymbol{AIC = -2loglikelohood + 2(q+1)\left(\frac{N}{N-q-3}\right)}, \text{ constant.} \quad \textbf{(9)}$$

2.3 Support Vector Regression

The SVR method can be used to determine the hyperplane best as a regression function, minimizing the chance of error by maximizing limits. The concept of the SVR method is to have training data $(x_1, y_1), (x_2, y_2), \ldots, (x_i, y_i)$ with $x_i \epsilon \mathbb{R}^2$ is the to-i vector where $i = 1,2, \ldots, n$, d is the dimension and y_i is the value of the goal or target. The general equation of the SVR model is written as follows [19].

$$f(x) = w'\phi(x) + b, \quad (10)$$

where w is a n dimension of weighting vector, $\phi(x)$ is a function that maps x in n dimensional space, and b expresses bias. The next step is to minimize w to obtain a suitable generalization of the regression function $f(x)$. Based on this, the solution to the optimization problem is as follows.

$$min_w \frac{1}{2}||w||^2 \begin{cases} y_i - w'x_i - b \leq \varepsilon; \\ w'x_i + b - y_i. \end{cases} \quad (11)$$

In the regression function $f(x)$, all points within the interval $f(x) \pm \varepsilon$ are considered qualified, while points outside this interval are considered unqualified. Therefore, slack variables ξ and ξ^* are added to address inappropriate constraints in optimization issues. Consequently, Eq. (11) can be converted into the following form.

$$min_w \frac{1}{2}||w||^2 + C(\xi_i + \xi_i^*). \tag{12}$$

The following constraint functions are used to overcome optimization problems.

$$\begin{cases} y_i - w'x_i - b \leq \varepsilon + \xi_i; \\ w'x_i + b - y_i \leq \varepsilon + \xi_i^*; \\ \xi_i, \xi_i^* \geq 0. \end{cases} \tag{13}$$

By solving optimization problems Eq. (13), it is obtained that

$$w = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i)\, \phi(x_i). \tag{14}$$

The information contained in the vector $\boldsymbol{x}$ from the input space can be transformed into a higher-dimensional feature space using functions ϕ that approximate kernel functions. With this approach, the functions can be defined as follows.

$$f(x) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i)\, K(x_i, x) + b \tag{15}$$

In SVR, several kernel functions are used to address problems in high-dimensional, nonlinear spaces by transforming the multiplication of x_i and x, as presented in Table 3.

Table 3. Kernel Functions

Kernel Type	Formula
Linear	$K(x_i, x) = (x_i', x)$
Polynomials	$K(x_i, x) = (\gamma(x_i', x) + r)^p, \quad p = 1,2, \ldots$
Radial Basic Function	$K(x_i, x) = \exp\left(-\lambda\left\|x_i - x\right\|^2\right)$
Sigmoid	$K(x_i, x) = \tanh(\gamma(x_i', x) + r)$

The kernel function used in this study is the Linear kernel, which requires the determination of two parameters, namely cost (C) and epsilon (ε). To search for the optimal parameter values, one possible method is the grid search methods.

2.4 Nonlinearity Test

A nonlinearity test, consisting of the White Test and the Terasvirta Test, is necessary to determine whether the data follows a linear or nonlinear pattern. The Terasvirta nonlinearity test is recognized as the most effective method for identifying the presence of nonlinearity in data derived from neural network model development, including the Lagrange Multiplier (LM) test developed by Taylor [20]. The nonlinear neural network model is presented in Eq. (16) as follows.

$$Z_t = \phi(\gamma' w_t) + \beta' w_t + \varepsilon_t \tag{16}$$

with $\beta' w$ represent the linier component, while $\phi(\gamma' w)$ denotes the non-linier component, γ' is weight in the neural network model from the input layer to output layer for the linear components, and ϕ represent the sigmoid activation function. Eq. (16) also can be expressed as

$$Z_t = \beta' w_t + \sum_{j=1}^{q} \theta_{0j} \left(\phi(\gamma' w_t) - \frac{1}{2}\right) + \varepsilon_t \tag{17}$$

with θ_{0j} represent the weight in the neural network model from the hidden layer to the output layer for nonlinear elements. If the number of nonlinear elements is zero, the data is considered to follow a linear pattern. The hypothesis tested in the Terasvirta test can be defined as follows.

H_0 : $\theta_{01} = \theta_{02} = \cdots = \theta_{0q}$ (data contains linear patterns);
H_1 : There is at least one $\theta_{0q} \neq 0$ (data contains nonlinear patterns).

By applying Taylor series to develop the parameter values of the neural network in the Terasvirta test, the time series model is defined as follows.

$$Z_t = \beta' w_t + \sum_{i=1}^{p}\sum_{j=1}^{p} \delta_{ij} Z_{t-1} Z_{t-j} + \sum_{i=1}^{p}\sum_{j=1}^{p}\sum_{k=1}^{p} \delta_{ijk} Z_{t-1} Z_{t-j} Z_{t-k} + \varepsilon_t \quad (18)$$

If the values of the quadratic and cubic components are zero, then accept the H_0, indicating that the resulting model is a linear. The Terasvirta test can be performed using chi-square and F distributions, similar to that White Test. The detailed steps for conducting the Terasvirta test with the chi-squared distribution are described as follows [20].

1. Regress Z_t on $1, Z_{t-1}, \dots, Z_{t-p}$ and calculate the residual values $\hat{\varepsilon}_t$.
2. Regress $\hat{\varepsilon}_t$ on $1, Z_{t-1}, \dots, Z_{t-p}$ and m additional predictors, then calculate the coefficient of determination (R^2).
3. Compute $\chi^2 = nR^2$, where n is the number of observations. If $nR^2 > \chi^2_m$, then reject H_0.

2.5 Ensemble Averaging

According to [21], forecasting in time series using the ensemble method or combination method, is a prediction technique that combines output values from multiple prediction models to obtain final predictive values. The ensemble approach integrates the forecasting results of two or more individual models. Thus, to construct an ensemble model, the best model from each method is first selected. Then, each of the n model produces a predicted value $\hat{Z}_t^{(i)}$, which is subsequently combined using an averaging approach. In this study, the combination method employed is the simple average method, with the forecasting combination equation defined as follows.

$$\hat{Z}_t = \frac{1}{n}\sum_{i=1}^{n} \hat{Z}_t^{(i)}, i = 1,2,\dots,n \quad (19)$$

Simple average is the most consistent and stable method, even compared to adaptive and more complex weighting methods, especially when dealing with extreme data such as during the COVID-19 period [22].

2.6 Model Goodness of Fit

MAPE (Mean Absolute Percentage Error) is a metric used to evaluate the accuracy of a model. It can be calculated using the following formula.

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{Z_t - \hat{Z}_t}{Z_t} \right| \times 100}{n} \quad (20)$$

with Z_t represents actual data, $\hat{Z}_t$ is the forecasted data, and n denotes the total number of data. The MAPE forecasting categories are presented in Table 4 are as follows.

Table 4. MAPE Categories

MAPE Range	Information
$\mathbf{MAPE < 10\%}$	Excellent forecasting model
$\mathbf{10\% \le MAPE < 20\%}$	Good forecasting model
$\mathbf{20\% \le MAPE < 50\%}$	Decent forecasting model
$\mathbf{MAPE \ge 50\%}$	Bad forecasting model

Root Mean Squared Error (RMSE) is a commonly used metric for evaluating how well forecasted values approximate actual values by calculating the square root of the average squared errors. A lower RMSE, or one close to zero, indicates that the forecasted results closely match the actual data, making it a reliable measure for future forecasting calculations.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (Z_t - \hat{Z}_t)^2}{n}} \quad (21)$$

R-Squared (R^2) is a statistical measure that evaluates how well model fits the data or how effectively the model explains the variance in the dependent variable.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_{t=1}^{n}(Z_t - \hat{Z}_t)^2}{\sum_{t=1}^{n}(Z_t - \bar{Z}_t)^2} \tag{22}$$

with n represents the number of data points, Z_t denotes the actual data at time t, $\hat{Z}_t$ denotes the predicted data at time t, and $\bar{Z}_t$ represents the average of the actual data.

2.7 Research Method

This study employs a quantitative approach, focusing on time series analysis. The data used in this research consists of Unilever Tbk (UNVR) stock prices obtained from the Investing.com website. The dataset includes weekly stock prices from January 6, 2019, to November 5, 2023. The study is divided into two phases: training and testing. The training data, spanning January 6, 2019, to July 30, 2023, is used to develop the model, while the testing data, covering August 6, 2023, to November 5, 2023, is used to evaluate the model's accuracy. The research variable analyzed is the closing price of Unilever stock. The procedures and stages of the analysis method are systematically presented in the flowchart shown in Fig. 1.

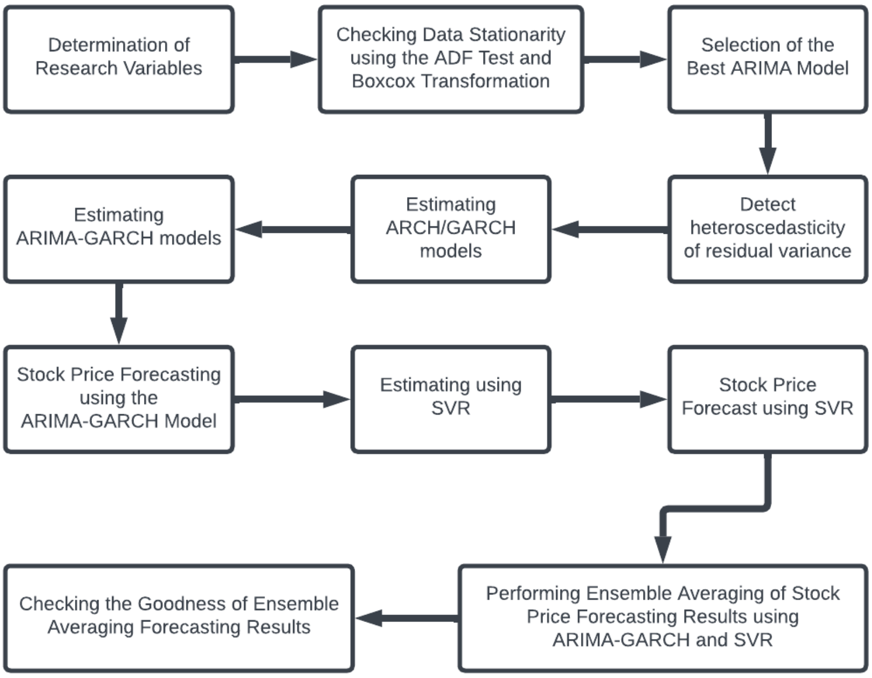


Figure 1. Analysis Flowchart

3. RESULTS AND DISCUSSION

Based on the research methodology, the results obtained and discussed in detail in the Results and Discussion section are as follows.

3.1 Time Series Plot and Descriptive Statistics

Descriptive statistics provide an initial observation to understand the characteristics of the variables. Fig. 2 presents a time series plot of daily Unilever stock prices from January 6, 2019, to November 5, 2023.

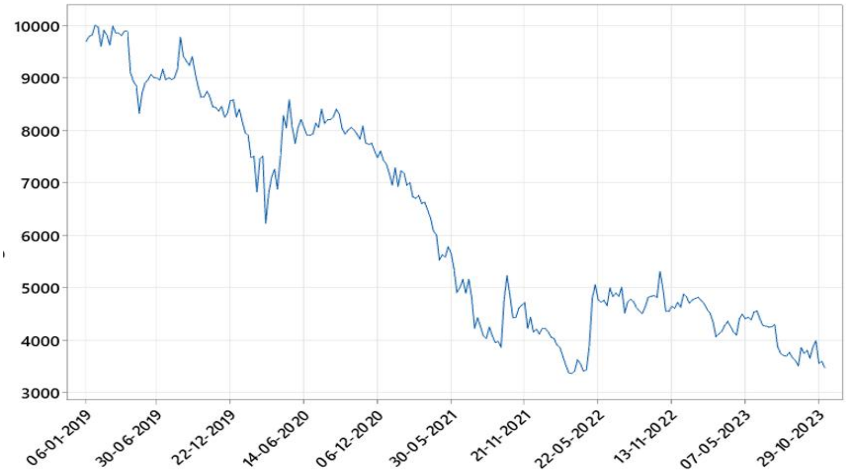


Figure 2. Time Series Plot UNVR Share Price
(Source: SAS Output)

Based on Fig. 2, the time series plot indicates fluctuations in Unilever's stock price, showing both declines and increases over time. The initial stock price on January 6, 2019, was IDR 9,690.00, while the final price at the end of the period was IDR 3,470.00. Table 5 presents a summary of the descriptive statistics for the variable.

Table 5. Descriptive Statistics

Variable	N	Mean	Variance	Standard Deviance	Median	Min	Max
Unilever's Stock Price	252	6219	4311497	2076	5325	3360	10000

3.2 Data Stationarity

Stationarity is important in classical time series modeling, such as ARIMA, because it ensures that the data has a constant mean and covariance over time. Non-stationary data tends to fluctuate in a way that violates this assumption. The Augmented Dickey-Fuller (ADF) test and the Box-Cox transformation are commonly used to assess stationarity.

If the ADF test gives a p-value below 0.05, the data is considered stationary. On the other hand, the Box-Cox transformation is used to address non-stationarity in variance. If the λ (lambda) value is not equal to 1, the data must undergo further transformation. Based on the Box-Cox result from the actual data shown in Fig. 3, a rounded lambda value of 0.5 was obtained, so the data needs to be transformed using $\sqrt{Z_t}$ to bring it closer to $\lambda = 1$ before continuing with further testing. The ADF test result on the actual data shows a p-value of 0.4964, indicating that the data is not yet stationary and further steps, such as differencing, are still necessary.

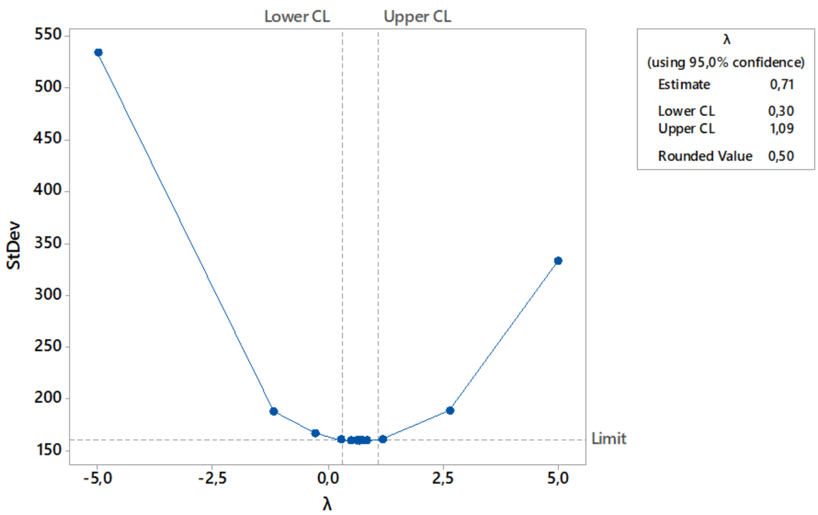
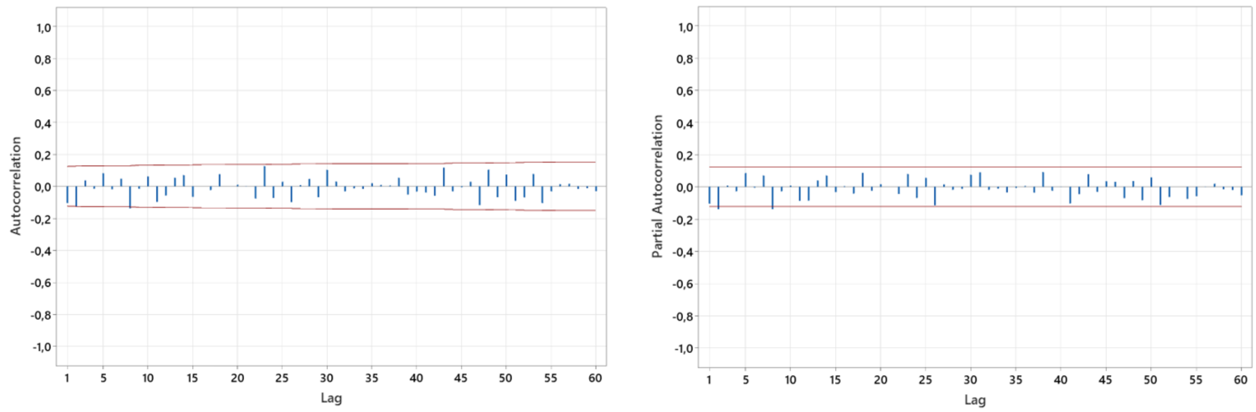


Figure 3. Box-Cox Plot for Original Data

Next, first-order differencing was applied to the actual data, followed by plotting the autocorrelation function (ACF) and partial autocorrelation function (PACF). The Autocorrelation Function (ACF) measures the correlation between current and past observations, helping to determine the appropriate Moving Average (MA) order. Meanwhile, the Partial Autocorrelation Function (PACF) captures the direct relationship between observations while controlling for the influence of intermediate lags, which helps identify the Auto-Regressive (AR) order.

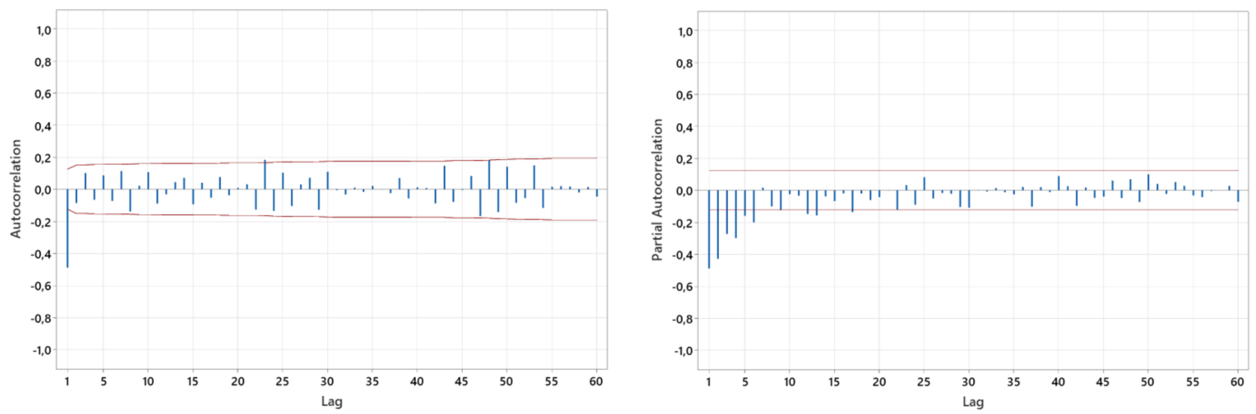
Fig. 4 shows the ACF and PACF plots of Unilever's stock price data after the first differencing. The ADF test on this differenced data produced a p-value of 0.0100, indicating that the data is now stationary. However, based on the ACF and PACF plots, there appears to be no significant lag observed in either plot, which suggests that the AR and MA terms are minimal or unnecessary in the model.



(a) (b)

Figure 4. (a) The ACF Plot of the First Differencing, (b) The PACF Plot of the First Differencing

Therefore, a second differencing was applied to identify emerging lag patterns better, as illustrated in Fig. 5, which displays the updated ACF and PACF plots with more visible lag significance. It is further supported by the ADF test result, which shows a p-value of 0.0100, indicating that the data is now stationary. Based on the ACF and PACF plots, several potential ARIMA models were considered, including ARIMA(1,2,0), ARIMA(6,2,1), and ARIMA(0,2,1). To determine the best-fitting model, further evaluation was conducted using parameter significance tests, white noise checks, residual normality tests, and a comparison of Akaike Information Criterion (AIC) scores.



(a) (b)

Figure 5. (a) The ACF Plot of the Second Differencing, (b) The PACF Plot of the Second Differencing

3.3 Selection of the Best ARIMA Model

In the ACF and PACF plots shown in Fig. 5, several potential ARIMA models can be identified for estimation. Table 6 is a summary of the best ARIMA model selection.

Table 6. Descriptive Statistics

Model	Parameters Significances	White Noise	Residual Normality	AIC Score
ARIMA (1, 2, 0)	Yes	No	Yes	3396.95
ARIMA (2, 2, 0)	Yes	No	No	3351.12
ARIMA (3, 2, 0)	Yes	No	Yes	3335.76
ARIMA (4, 2, 0)	Yes	No	No	3316.35
ARIMA (5, 2, 0)	**Yes**	**Yes**	**No**	**3311.92**
ARIMA (6, 2, 0)	Yes	No	Yes	3304.23
ARIMA (1, 2, 1)	No	Yes	No	3281.05
ARIMA (2, 2, 1)	No	Yes	No	3278.53
ARIMA (3, 2, 1)	No	Yes	No	3280.45
ARIMA (4, 2, 1)	No	Yes	No	3282.28
ARIMA (5, 2, 1)	No	Yes	No	3282.56
ARIMA (6, 2, 1)	No	Yes	No	3284.55
ARIMA (0, 2, 1)	**Yes**	**Yes**	**No**	**3281.09**

The model diagnostic tests revealed that none of the models fully met the requirements, with only ARIMA(5,2,0) and ARIMA(0,2,1) passing the four key evaluation criteria: parameter significances, white noise residuals, residual normality, and relatively lower AIC scores. Next, we examined the ACF and PACF plots after applying second differencing. As shown in Fig. 5, the ACF peaks at the first lag, while the PACF declines exponentially. According to [23] in Table 2, if the ACF returns to zero after the q-th lag and the PACF decreases gradually, ARIMA(0,2,1) is recommended. Although ARIMA(0,2,1) can be interpreted as a simple moving average (MA(1)) process applied to second-differenced data, its selection is supported by both diagnostic performance and theoretical pattern alignment. This model reflects short-term shock dependencies without autoregressive persistence, which is consistent with the stochastic nature of the series. To further explore why the residuals of this model do not satisfy the normality assumption, a residual histogram was analyzed, as shown in Fig. 6.

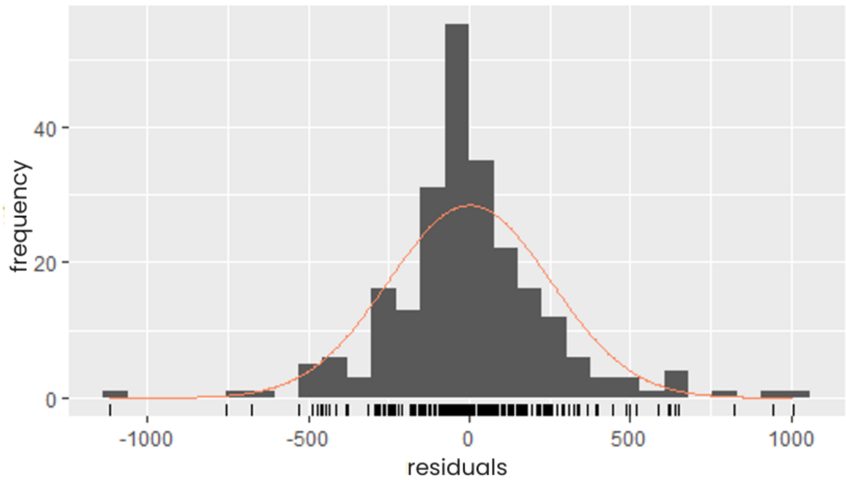


Figure 6. The Histogram of Residuals of ARIMA (0, 2, 1)
(Source: SAS Output)

Fig. 6 illustrates that the histogram of the ARIMA (0,2,1) model exhibits residual abnormalities due to an excess of zero values, resulting in a high peak and positive kurtosis (leptokurtic). This suggests that the residuals fluctuate around zero, indicating that the model's predictions closely align with the actual values. Consequently, the diagnostics for the ARIMA (0,2,1) model are considered satisfactory for period t. Fig. 7 presents a comparison between the actual Unilever stock price and the estimated price derived from the ARIMA (0,2,1) model. It show the results are very close to the original data.

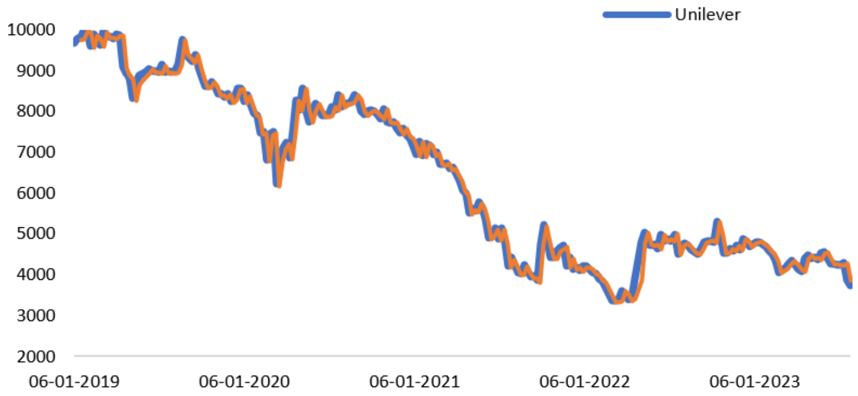


Figure 7. Comparison Chart of Actual Stock Price with Stock Price Estimation of ARIMA Model (0,2,1)

3.4 ARIMA Model

Based on Table 6, the ARIMA (0,2,1) model is identified as the one that meets the required assumptions. Table 7 presents the complete estimates for the ARIMA (0,2,1) model.

Table 7. The Estimated Model of ARIMA (0, 2, 1)

Parameter	Coefficient	Standard Error	p-Value	AIC	MSE
MA (1)	-0.9999	0.012511	0.000	3281.09	254.3628

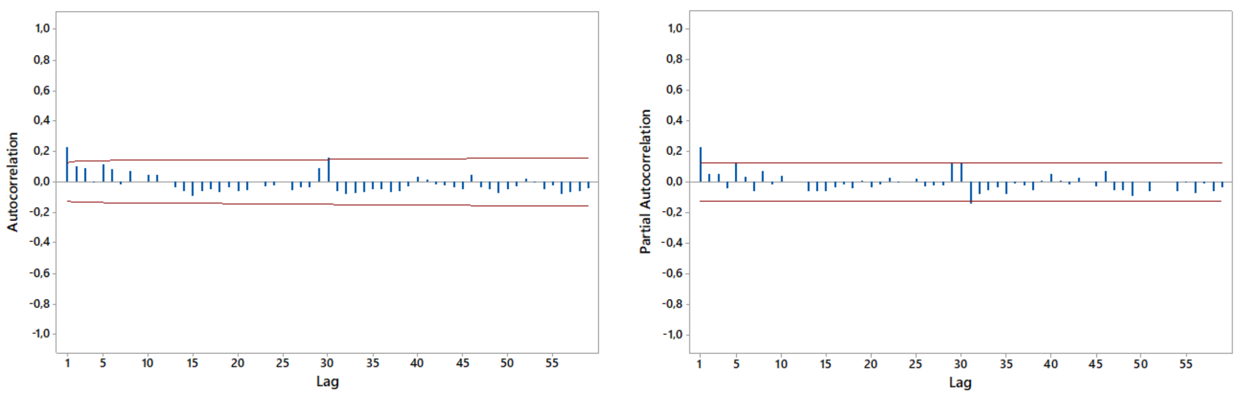
Therefore, the ARIMA (0, 2, 1) model estimation will be used for ARIMA-GARCH estimation. The mathematical equation for the transformed ARIMA (0, 2, 1) model is written as follows.

$$Z_t^* = 2Z_{t-1}^* - Z_{t-2}^* + \varepsilon_t + 0.9999\varepsilon_{t-1} \quad (23)$$

with $Z_t^* = \sqrt{Z_t}$ where Z_t represents the value of Unilever's stock price in the UNVR closing stock price data.

3.5 Heteroscedasticity Detection of Residual Variance

In the ARIMA model, residuals are assumed to follow a normal distribution with a mean of $\mu = 0$ and a homogeneous variance σ^2. However, economic data, such as exchange rates and stock prices, often exhibit high volatility, violating this assumption. To address this issue, a heteroscedasticity test was conducted on the squared residuals from the ARIMA (0, 2, 1) model estimation, which were used to estimate residual variance. The ACF and PACF plots for the squared residuals are presented below.



(a) (b)

Figure 8. (a) The ACF Plot of Squared Residual of ARIMA (0,2,1), (b) The PACF Plot of Squared Residual of ARIMA (0,2,1)

There is a significance lag in the ACF and PACF plots in Fig. 8, indicating autocorrelation. This suggest that the squared residuals are correlated with previous data and residual, implying that the variance of the residuals is not homogeneous and that heteroscedasticity may be present. In addition to using ACF and PACF plots, heteroscedasticity can be tested with the ARCH-LM test (Autoregressive Conditional

Heteroskedasticity - Lagrange Multiplier), where the null hypothesis states that there is no heteroscedasticity in the ARIMA model residuals.

Table 8. ARCH-LM Test of ARIMA (0, 2, 1) Residual

Orders	LM Test Statistics	Significances
1	7.5252	0.0061
2	10.8186	0.0045
3	14.8422	0.0020
4	15.2453	0.0040
5	17.9237	0.0030
6	20.3538	0.0024
7	21.0259	0.0037

The results in Table 8 show that for the first seven lags, all p-values are significant (less than the 5% significance level, α=0.05 indicating the presence of autocorrelation in the squared residuals of the ARIMA (0, 2, 1) model. Further modeling is required to address the detected heteroscedasticity.

3.6 ARCH-GARCH Model Estimation

The ARIMA (0, 2, 1) model exhibited heteroscedasticity in its residuals, necessitating variance modeling using ARCH-GARCH approach. The appropriate ARCH model was identified based on the ACF plot in Fig. 8, suggesting an ARCH (1) process. Meanwhile, the PACF plot guided the selection of GARCH models, leading to the identification of GARCH (1, 0) and GARCH (1, 1) for variance estimation.

Table 9. ARCH-GARCH Model Estimation

Models	Parameters	Coefficient Estimation	Significances	AIC Score
GARCH (1, 0)	ω	2.0777	< 0.0001	890.201533
	α_1	0.2395	0.0030	
GARCH (1, 1)	ω	0.8864	0.0007	883.361187
	α_1	0.2173	0.0011	
	γ_1	0.4599	0.0006	

The selection of the ARCH-GARCH model is based on parameter significance and the AIC, where a lower AIC value indicates a better model. Table 9 shows that both models have significant parameters. However, based on the AIC value, the GARCH (1, 1) model is selected as the optimal model. Therefore, the variance model equation for the ARIMA (0, 2, 1) is as follows.

$$\sigma_t^2 = 0.8864 + 0.2173\varepsilon_{t-1}^2 + 0.4599\sigma_{t-1}^2 \tag{24}$$

$$\varepsilon_t = \gamma_t \sigma_t \tag{25}$$

where γ_t represents the standardized ARIMA residual (0, 2, 1), assumed to follow a normal distribution $N(0, 1)$. Fig. 9 presents the residual estimation of the ARIMA model using the GARCH (1, 1) model.

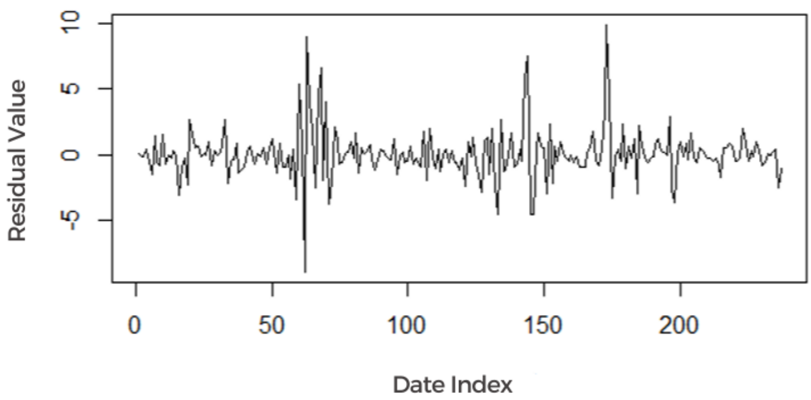


Figure 9. The Plot of Residual Estimation of ARIMA (0, 2, 1) Based on GARCH (1, 1)
(Source: SAS Output)

3.7 ARIMA-GARCH Model Estimation

By combining Eqs. (23) and (24), it obtains a unified equation that integrates the ARIMA mean model and the GARCH variance model. Thus, the ARIMA (0, 2, 1) – GARCH (1, 1) model can be expressed as follows.

$$Z_t^* = 2Z_{t-1}^* - Z_{t-2}^* + \varepsilon_t + \theta_1\varepsilon_{t-1} \quad (26)$$

with $\varepsilon_t = \gamma_t\sqrt{0.8864 + 0.2173\varepsilon_{t-1}^2 + 0.4599\sigma_{t-1}^2}$ and Z_t^* represents the square root-transformed stock price for UNVR with ARIMA (0, 2, 1) – GARCH (1, 1) model. Below is a comparison of the actual stock prices and the model estimates.

The UNVR stock price modeling results in Fig. 10 exhibit a fluctuating pattern, closely following the actual data.

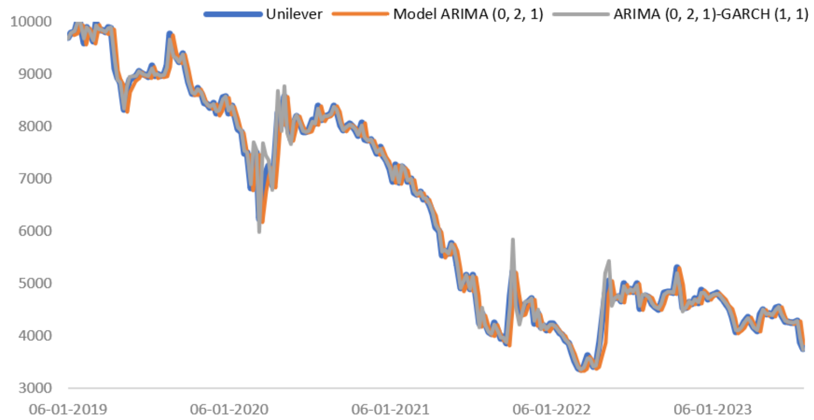


Figure 10. Comparative Plot of Actual Data and Estimated Values of ARIMA and ARIMA – GARCH Model

The ARIMA-GARCH model's performance is evaluated using three criteria. For in the in-sample data, the R^2 value is 0.998, categorizing the model as very good. The RMSE value is 100.26, considered unfavorable. The MAPE value is 0.712%, placing it in the very good category.

The forecasting results for UNVR's stock price exhibit a highly volatile pattern that aligns with actual data. Although some predictions exceed the observed stock prices, they remain within the upper and lower prediction limits, making them reasonable. For the out-sample data, the ARIMA (0, 2, 1) - GARCH (1, 1) model is assessed using the same three criteria. The R^2 value is 0.382, indicating a less favorable fit. The RMSE value is 107.6 categorized as poor. However, the MAPE value for the out-sample data is 2.865%, which falls within the excellent category. Since the out-sample MAPE is classified as very good, the ARIMA (0, 2, 1) - GARCH (1, 1) model provides a reliable interpretation of UNVR's stock price prediction for the upcoming periods. Fig. 11 presents the forecasted results for the out-sample data.

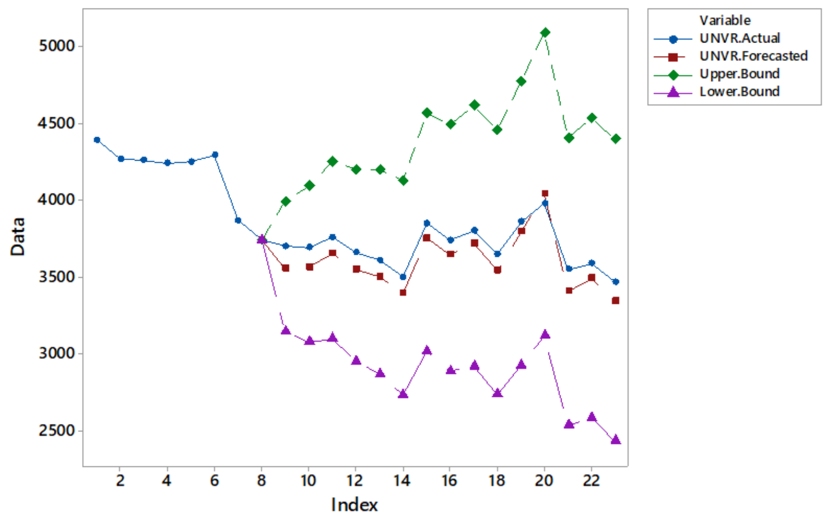


Figure 11. UNVR Stock Price Prediction Plot of ARIMA (0, 2, 1) - GARCH (1, 1)

3.8 Support Vector Regression (SVR)

The initial stage in analyzing data using SVR is to determine whether the research data follows a linear or non-linear functions using the White Tests and the Terasvirta Tests.

Table 10. Linearity Test Results

Linear Test	X-Squares	df	p-value
White Test	2.2208	2	0.3294
Terasvirta Test	1.969	2	0.3736

Table 10 indicates that the p-value is less than the significance level ($\alpha = 5\%$), suggesting that the data follows a linear pattern. Prior to modeling, the data must be transformed into a time-lagged format for input. The appropriate time lag can be determined from the PACF plot in Fig. 12.

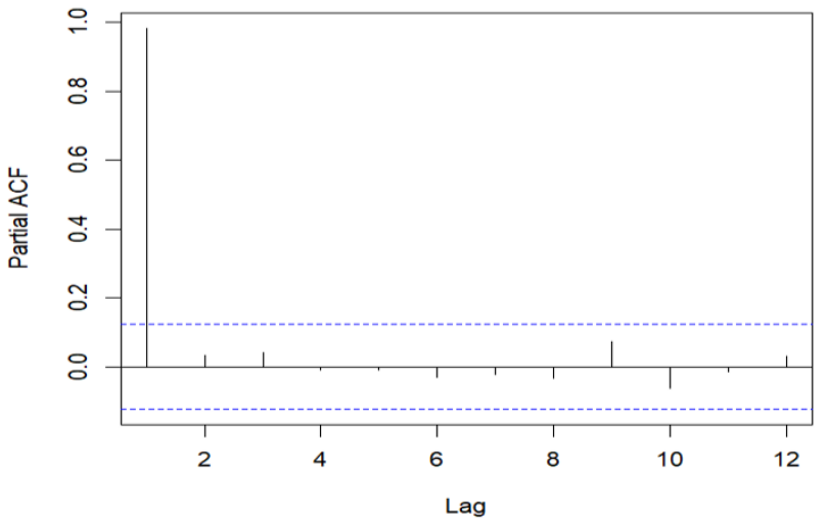
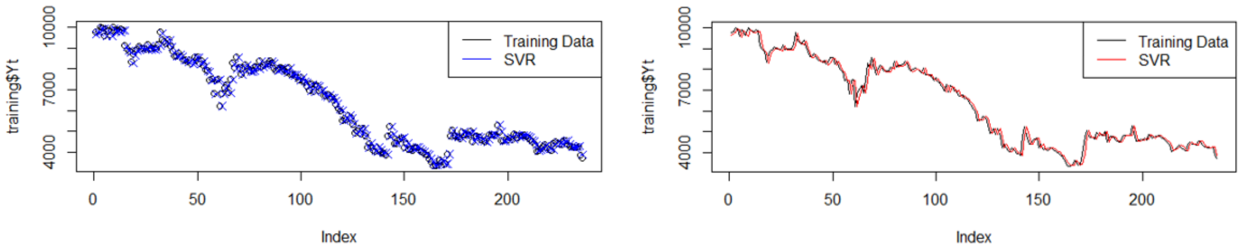


Figure 12. PACF Plot of SVR Analysis
(Source: RStudio Output)

Based on Fig. 12, a significant lag is observed: at lag 1, which is used as the input. The initial modeling of SVR was performed using a linear kernel function with parameter $C = 1$ and $\varepsilon = 0.1$. The results show that this model configuration, yield a RMSE of 255.0733 and MAPE 3.03%. Since MAPE value is below 10%, the model is considered highly accurate for in-sample data or training data. The results of the actual data plot and the predicted values using SVR model are illustrated in Fig. 13.



(a) (b)

Figure 13. (a) The Training Data Plot Using Linear Kernel Functions, (b) The Predicted Value Plot Using Linear Kernel Functions
(Source: RStudio Output)

After constructing the initial model using the optimal linear kernel function, SVR parameter tuning is performed through a two-stage grid search. The first stage applies a coarse grid search to identify a broad optimal range, followed by a finer grid search to refine parameter selection. According to [24] the range of parameter values used for the loose grid stage in Table 11 is as follows.

Table 11. Parameter Value Range of Loose Grid Method

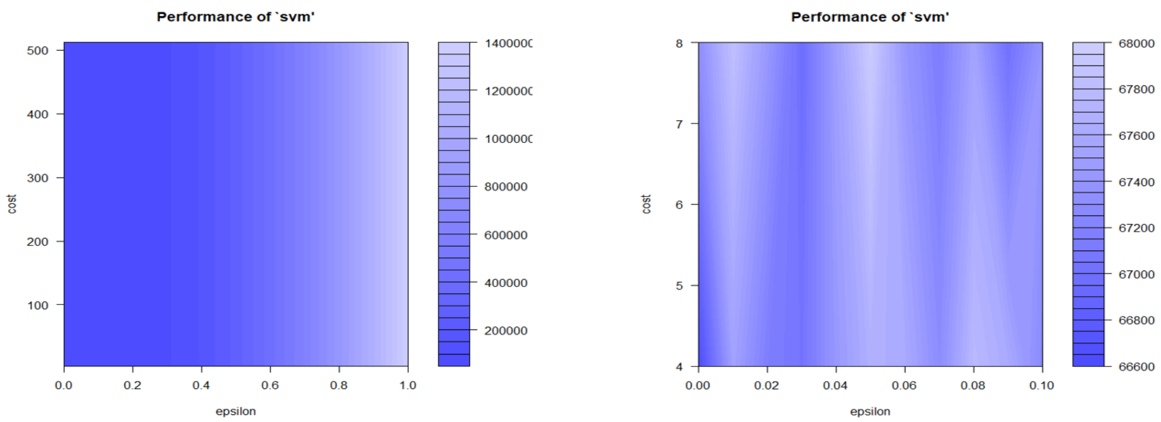
Parameter	Range Value
Cost (C)	$2^{-5}, 2^{-4}, \ldots, 2^{6}, 2^{7}$
Epsilon (ε)	$0;\ 0{,}01, \ldots, 0;\ 0{,}09;\ 0{,}1$

Therefore, to determine the optimal parameter values, this research employs a two-stage grid search. The optimal parameter is the parameter that produces the best accuracy with the lowest error value. The results of both the coarse and fine grid searches are presented in Table 12.

Table 12. Grid Search Methods Comparison

Grid Search Method	Optimal Combination of Parameters	
	Coat (C)	Epsilon (ε)
Loose Grid	4	0.1
Finer Grid	4	0

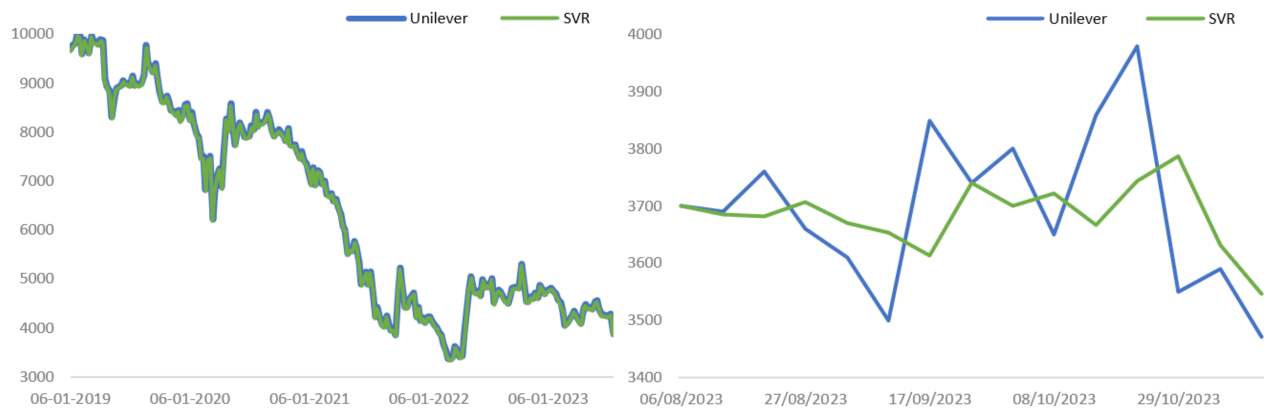
The optimal grid search method was achieved using the finer grid technique, with parameters $C = 4$ and $\varepsilon = 0$, as shown in Table 12. Fig. 14 illustrates the tuning results, highlighting optimal performance in the dark area. After parameter tuning, the SVR model was applied to predict Unilever's stock price, leveraging these optimized parameters for improved accuracy.



(a) (b)

Figure 14. (a) Loose Grid Plot, and (b) Finner Grid Plot
(Source: RStudio Output)

The comparison of RMSE and MAPE for kernel functions in training data resulted in an RMSE of 255.6638 and a MAPE of 2.99%. Meanwhile, for testing data, the RMSE was 138.7148, with a MAPE of 2.94%. The predicted results of applying the SVR model to training and testing data are visualized on the plot, which shows that the prediction results are similar to the actual data. Furthermore, the accuracy level of MAPE training and testing data is either less than 10% or classified as very accurate. The prediction plot alongside actual data for both training and testing is presented in Fig. 15.



(a) (b)

Figure 15. (a) Plot Prediction Data Training Using the SVR Method, (b) Plot Prediction Data Testing Using the SVR Method

Although the possibility of overfitting is a valid concern in SVR models, the slight difference between training and testing MAPE values suggests that the model generalizes well. In typical overfitting scenarios, testing errors would be substantially higher than training errors. Furthermore, the close alignment between actual and predicted values in both training and testing plots in Fig. 15 supports the model's robustness. Therefore, the SVR model is not only accurate but also reliable in terms of generalization performance.

3.9 Ensemble Averaging Forecasting GARCH-SVR

The forecast results using the GARCH and SVR methods presented in Table 13 as follows.

Table 13. ARIMA-GARCH and SVR Method Forecast Results

Forecast	ARIMA-GARCH	SVR	Average	APE
1	3556.366	3700	3628.183	0.019
2	3567.160	3685.455	3626.307	0.017
3	3651.348	3681.818	3666.583	0.025
4	3548.903	3707.273	3628.088	0.009
5	3502.406	3670.909	3586.657	0.006
6	3394.299	3652.727	3523.513	0.007
7	3751.914	3612.727	3682.320	0.044
8	3645.720	3740	3692.860	0.013
9	3719.604	3700	3709.802	0.024
10	3543.592	3721.818	3632.705	0.005
11	3793.462	3667.273	3730.367	0.034
12	4042.200	3743.636	3892.918	0.022
13	3406.770	3787.273	3597.021	0.013
14	3491.072	3630.909	3560.991	0.008
15	3342.852	3545.454	3444.153	0.007

Table 13 presents the predicted UNVR stock prices for the next 15 periods. The model's performance for out-sample data can be assessed based on these predictions. The ensemble averaging model is evaluated using three criteria: the R^2 value is 0.69, categorized as good; the RMSE value is 76.13, categorized as poor; and the MAPE value for out-sample data is 1.682%, categorized as excellent. Therefore, the ARIMA (0,2,1) – GARCH (1,1) ensemble model provides an excellent interpretation for forecasting UNVR's stock price over the next 15 periods.

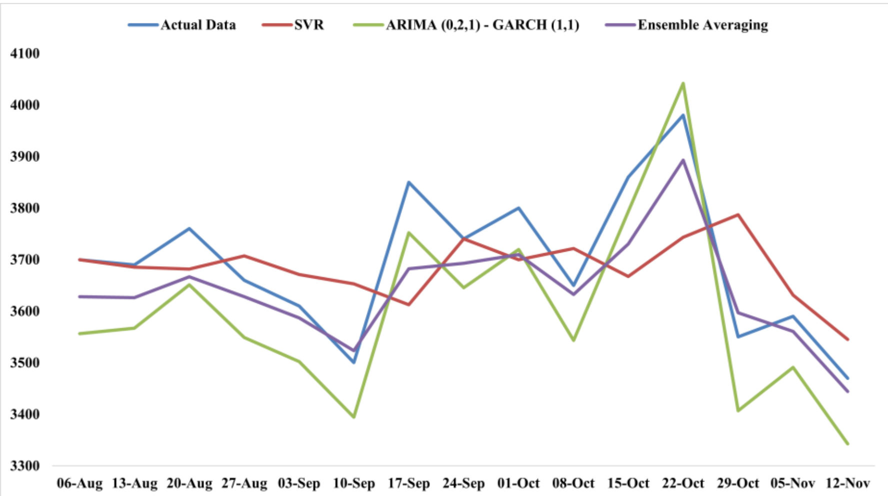


Figure 16. Comparison Graph of Data Forecasting Three Methods

Data visualization facilitates comparing forecasting results from different methods with actual data is presented in Fig. 16. It presents the forecasting outcomes of ARIMA (0, 2, 1) - GARCH (1, 1), SVR, and ensemble averaging. The ARIMA-GARCH model closely follows the data pattern, albeit with some discrepancies. The SVR model produces values relatively close to the actual data but captures the underlying pattern less effectively, making it less optimal. In contrast, the ensemble model closely aligns with the data, demonstrating strong forecasting performance.

4. CONCLUSION

Based on the analysis of Unilever Tbk (UNVR) 's daily stock price data from January 6, 2019, to November 5, 2023, it was found that the data can be modeled using an ARIMA (0,2,1) model. However, the squared residuals of the model indicated heteroscedasticity, necessitating variance modeling with the ARCH-GARCH method. The best-combined model was determined to be ARIMA (0, 2, 1) - GARCH (1, 1), which achieved a MAPE of 2.865%, classified as very good. Additionally, independent modeling using the Support Vector Regression (SVR) method with parameters $C = 4$ and $\varepsilon = 0$ resulted in a MAPE of 2.94%. To further optimize prediction accuracy, an ensemble averaging approach combining ARIMA-GARCH and SVR models was employed, yielding a MAPE of 1.682%, which is also classified as very good. These results indicate that short-term investors may benefit from the SVR model for capturing short-term price patterns, while medium- to long-term investors should consider the ARIMA-GARCH model due to its sensitivity to volatility. Meanwhile, the ensemble approach offers the best predictive performance and is recommended as the primary strategy for designing UNVR stock price forecasting systems. Furthermore, for policymakers, strategic decision-making is crucial to minimizing adverse impacts on both the company and its employees. For future research, it is recommended to add parameter variations and combine other methods to improve prediction accuracy.

Author Contributions

Elly Pusporani: Conceptualization, Methodology, Validation. Alfi Nur Nitasari: Data Curation, Project Administration, Writing-Original Draft. Fatiha Nadia Salsabila: Software, Visualization, Writing-Original Draft. Irma Ayu Indrasta: Software, Visualization, Writing-Review and Editing. M.Fariz FadillahMardianto: Validation, Writing-Review and Editing, Supervision. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no competing interest.

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