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# FORECASTING THE STOCK PRICE MOVEMENT OF BANK ALADIN SYARIAH USING THE ARIMA MODEL: A STUDY ON INDONESIA'S FIRST ISLAMIC DIGITAL BANK

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**ABSTRACT:** This study models the stock price movement of Bank Aladin Syariah (BANK), Indonesia's first Islamic digital bank, using the ARIMA method. As a pioneer in branchless, technology-driven sharia banking, Bank Aladin significantly contributes to enhancing financial inclusion and advancing Islamic finance. Its status as a first mover renders it particularly relevant to investors and market analysts, as its stock performance reflects broader sentiment toward technological adoption in the Islamic financial sector. The dataset comprises 694 daily closing prices sourced from Yahoo Finance, spanning the period from May 18, 2022, to March 27, 2025. Given the non-stationary nature of the data, first-order differencing was applied to attain stationarity. The ARIMA(1,1,1) model was identified as the most appropriate, producing nine-step-ahead forecasts ranging from 804.9910 to 804.9836 with gradually increasing standard errors. The model yields stable and conservative projections, offering valuable insights for investors and stakeholders in the Islamic digital banking sector.

**Keyword:** ARIMA, Islamic Digital Bank, Stock Price, Forecasting

## INTRODUCTION

The rapid advancement of digital technology has profoundly reshaped various sectors, including the banking industry. In Indonesia, the digitalization of the banking sector has given rise to digital banks that deliver financial services without relying on physical branch offices. This transformation is intended to improve operational efficiency and expand access to financial services, particularly for segments of the population that have been underserved by the traditional financial system. (Andrian et al., n.d.; Fraderic et al., 2024). One of the most notable innovations within this evolving landscape is the establishment of Bank Aladin Syariah, recognized as Indonesia's first fully digital Islamic bank. Among the four Islamic banks listed on the Indonesia Stock Exchange—PT Bank

Syariah Indonesia Tbk (BRIS), PT Bank BTPN Syariah Tbk (BTPS), PT Bank Panin Dubai Syariah Tbk (PNBS), and PT Bank Aladin Syariah Tbk (BANK)—only Bank Aladin has fully implemented a digital operational model. Its existence exemplifies the integration of Sharia-compliant financial principles with advanced digital technology, positioning the bank as a key player in promoting financial inclusion in Indonesia.

In response to the rising interest in digital financial services, the stock performance of digital banks such as Bank Aladin has emerged as a critical area of study. Stock prices not only reflect market sentiment regarding a company's performance and future prospects but also capture broader macroeconomic trends and investor expectations. In the context of Sharia-compliant stocks, previous research has indicated that stock prices often display significant volatility and non-linear movement patterns, which present challenges for traditional forecasting approaches(Gunaryati et al., 2025).

Stock price movements are influenced by various factors, including internal factors such as company performance, and external factors such as fiscal and monetary policies (Sukartaatmadja et al., 2023). To effectively capture and project these dynamics, a suitable quantitative approach is essential. One of the most widely utilized and empirically validated methods in time series analysis is the Autoregressive Integrated Moving Average (ARIMA) model. This model is well known for its ability to handle non-stationary data and accurately identify short-term trends and patterns.

Despite the development of hybrid models that combine ARIMA with machine learning methods such as LSTM to capture non-linear patterns, ARIMA remains highly relevant, particularly for analyzing linear or stationary data. Research findings indicate that ARIMA is capable of providing consistent and reasonably accurate forecasts, especially in the context of banking indices and financial sector stock prices (Armagan, 2023; Ayoub et al., 2023). Therefore, the use of ARIMA as the primary method in this study remains well-justified and relevant, particularly in the context of digital Islamic banking such as Bank Aladin. Moreover, the distinct characteristics between Islamic and conventional stocks represent a critical aspect to consider in the forecasting process. A study conducted by Yahya, Majid, and Hafasnuddin indicates that the Islamic stock market in Indonesia has the potential to serve as a hedging instrument against inflation, in contrast to the conventional stock market, which tends to be more vulnerable to the influence of macroeconomic variables(Yahya et al., 2021). Furthermore, several empirical studies reinforce the reliability of ARIMA in Islamic financial contexts. For instance, Anityaloka & Ambarwati (2013) successfully utilized ARIMA (1,0,0) to forecast the Jakarta Islamic Index, showing a clear linear relationship between current and past index values. Muthahharah (2019) applied a similar ARIMA model to the Indonesian Sharia Stock Index (ISSI), concluding that past stock behavior could serve as a strong predictor for short-term movement. Likewise, P. R. Fadhilah (2021)demonstrated the effectiveness of ARIMA in modeling ISSI data for annual forecasting. In a more comparative framework, Gunawan & Darwin (2023) analyzed the stock price of PT Unilever Indonesia Tbk—classified as a sharia-compliant stock—using both ARIMA and GARCH models. They found ARIMA (1,1,1) to be suitable for trend analysis, but ultimately selected GARCH (1,1) due to the presence of heteroskedasticity. In a multi-stock analysis, Nisa (2022) applied ARIMA models across various Islamic stocks and identified ARIMA (0,1,4) as the best fit for ACES stock, further confirming that ARIMA remains effective when applied to short-term, non-seasonal financial data. These cumulative findings underscore the methodological strength and continued applicability of ARIMA in the Islamic capital market sector, particularly when forecasting assets with relatively stable linear properties.

Considering these aspects, the present study holds substantial academic and practical significance. From an academic standpoint, it enriches the existing body of literature on stock price forecasting within the context of digital Islamic banking. Practically, the findings offer valuable insights for investors, financial analysts, and policymakers in formulating more targeted and sustainable investment strategies. This research aims to forecast the stock price movements of Bank Aladin Syariah by employing the ARIMA model and to evaluate its effectiveness in projecting future price trends. The results are expected to serve as a valuable reference for investment decision-making processes and to contribute to the enhancement of Islamic capital market literacy amidst ongoing digital transformation.

## LITERATURE REVIEW

### Islamic Digital Bank

Digital banking represents a significant innovation in the financial services industry, relying heavily on information technology to deliver banking services online without the need for physical branch offices(Hidayat & Kassim, 2023). This development has led to the emergence of fully digital banks that operate exclusively through internet platforms and mobile applications, often referred to as neobank (Citterio et al., 2024). The transformation is driven by shifting consumer preferences, with increasing demand for services that are faster, more convenient, and efficient (Tanuwijaya & Oktavia, 2023; Temelkov, 2020).

Digital banks offer several advantages over traditional banks, including lower operational costs, faster service delivery, and high accessibility due to the 24/7 availability of services via digital devices (Shin, 2022; Shin et al., 2020). Furthermore, the integration of technologies such as big data and artificial intelligence enables more personalized services and improved risk management capabilities(Zouari & Abdelhedi, 2021). Amid the global acceleration of digital technology adoption, a McKinsey report noted a substantial increase in consumer engagement with digital banking services in recent years

(Kurniawan & Vionita, 2024).

In the context of Islamic banking, digitalization is viewed not only as a necessary adaptation to technological advancements but also as a strategic effort to reinforce institutional identity. The Financial Services Authority of Indonesia (Otoritas Jasa Keuangan, OJK) identifies digital acceleration as one of the four key pillars in the development of the Islamic banking sector (OJK, 2020). The implementation of digital technologies in Islamic banks enhances service efficiency while providing added value in customer interactions, all while maintaining strict adherence to Sharia principles. The rapid growth of digital banks in Indonesia is also supported by high internet penetration rates and the increasing level of digital literacy among the population (Marlina Wijayanti et al., 2024).

**ARIMA Model in Stock Price Forecasting of Banks**

The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely used statistical methods in time series analysis, particularly for forecasting stock prices. This model relies on historical patterns of past data to predict future values by incorporating autoregressive, differencing, and moving average components. Its capability to handle non-stationary data makes ARIMA a relevant approach for modeling the dynamic and often random nature of stock price fluctuations(Fitriani et al., 2024).

In practice, ARIMA has been extensively applied in the banking sector, both conventional and Islamic. A study on the stock of PT Bank Central Asia Tbk demonstrated that ARIMA can provide an accurate depiction of short-term stock price trends, with predictions indicating upward movements over specific periods. Similar findings were observed for Bank Syariah Indonesia (BSI), where ARIMA effectively captured the positive trend in stock prices over the years ( (Ariadi & Herlinawati, 2024; Auliah et al., 2023).

Other research also supports the precision of ARIMA in forecasting the stock prices of major banks such as BBRI and BMRI, reporting relatively low forecasting errors, with Mean Absolute Percentage Error (MAPE) values below 10% (Sudipa et al., 2023)**.** Even in the post-COVID-19 context, ARIMA has been employed to re-map the stock price movements of the largest market-cap banks in Indonesia, demonstrating continued effectiveness in anticipating economic recovery trends(Hijrah, 2023)**.** However, ARIMA's accuracy tends to decline in long-term forecasts due to its reliance on historical data patterns, which may not fully reflect evolving market conditions. To address this limitation, ARIMA is often combined with other models, such as GARCH or LSTM, to enhance forecasting of volatility and capture nonlinear patterns. For instance, hybrid ARIMA-GARCH models have proven effective in forecasting returns and volatility of banking sub-sector stocks, as demonstrated in research on BBRI shares(D. N. Fadhilah et al., 2024)**.** Combined models have also been applied to Islamic stocks, such as BTPN

Syariah, with results indicating that the ARIMA-GARCH integration produces predictions that are closer to actual data and reduces the risk of error in investment decision-making (Iqbal & Ningsih, 2021)**.** Overall, ARIMA remains a robust foundational method for stock price forecasting, especially in the short term. Its advantages lie in the simplicity of its structure and its efficiency in capturing historical trends.

**RESEARCH METHODS**

In response to the existing gap concerning forecasting accuracy and the appropriateness of models for digital Islamic banking stock analysis, this study employs the ARIMA (Autoregressive Integrated Moving Average) model, which is widely acknowledged as a reliable and effective approach for time series forecasting.

**Autoregresiive Integrated Moving Average (ARIMA)**

The Autoregressive Integrated Moving Average (ARIMA) model is a statistical method used for analyzing and forecasting time series data. This method integrates three key components: Autoregressive (AR), Integrated (I), and Moving Average (MA). The combination of these components enables ARIMA to effectively capture and model complex patterns within time series data. The ARIMA model can be expressed using the following general equation:

$$Y_t = c + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (1)$$

Where:

$Y_t$ represents the value of the time series at period t

c represents the constant (intercept) of the model

$\emptyset_1, \emptyset_2, \ldots \emptyset_p$ are the parameters of the autoregressive (AR) component

$\theta_1, \theta_2, \ldots \theta_q$ are the parameters of moving average (MA)

$\varepsilon_t$ refers to error term (white noise) at time t

The ARIMA model consists of the following components:

**Autoregressive (AR)**

Autoregressive (AR) is a method within time series analysis that describes the relationship between the current value of a series and its previous values. In simple terms, the AR model posits that the current value depends on a weighted combination of past values. In other words, the series uses its own historical data as a predictor for future values. This component reflects the dependency of data on its past observations within the time series. The AR model assumes that the present value is a linear combination of its previous values, and the autoregressive order is determined by the parameter p. The autoregressive order (p) indicates how many past time periods should be considered when predicting the current value. A higher p value suggests a greater dependency on observations further in the past. The general form of the AR model is given as follows:

$$Y_t = c + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t \quad (2)$$

Where:
$Y_t$ represents the value of the time series at period t
c represents the constant (intercept) of the model
$\emptyset_1, \emptyset_2, \ldots \emptyset_p$ are the autoregressive (AR) parameters,
$\varepsilon_t$ refers to error term (white noise) at time t

Advantages of Using the Autoregressive (AR) Model:

1. Identification of Autocorrelation Patterns
   The AR model is useful in identifying autocorrelation patterns in time series data. Autocorrelation occurs when the values in a time series are correlated with their past values. Detecting such patterns is crucial for understanding the temporal structure of the data.
2. Forecasting Trends and Behavioral Patterns
   By using AR models, analysts can generate forecasts of future trends and behavioral patterns in the data. This capability is especially valuable for prediction and strategic planning in various fields, including finance and economics.
3. Handling Stationary and Non-Stationary Data
   The AR model is effective for analyzing stationary data. In cases where the data are non-stationary, differencing techniques can be applied to transform the data into a stationary form, thus enabling the AR model to be effectively implemented.

**Integrated (I)**

In Time Series Analysis, Data Integrity Plays a Critical Role in Deriving Accurate Insights and Making Reliable Predictions. Within the ARIMA (Autoregressive Integrated Moving Average) framework, the Integrated (I) component plays a crucial role in transforming a non-stationary time series into a stationary one. This component involves the application of differencing—a statistical technique used to reduce or eliminate trends and structural patterns in the data. The degree of differencing is denoted by d, indicating how many times the differencing process is applied to achieve stationarity. In the context of ARIMA, Integrated refers to this differencing procedure. Differencing transforms the original time series into a new series by computing the changes between consecutive observations. Conceptually, this is similar to taking the derivative of a mathematical function. The general equation for first-order differencing (d = 1) is:

$$Y'_T = Y_T - Y_{T-1} \quad (3)$$

Where:
$Y'_T$ is the differenced (integrated) value at time t,

$Y_T$ is the original time series value at time t.

Stationarity is a condition in which the statistical properties of a time series—such as mean and variance—remain constant over time. Without stationarity, statistical inferences can become invalid, and forecasting models may yield unreliable results. Differencing helps address this issue by removing trends or seasonality from the data, thereby stabilizing the mean of the time series.

Advantages of Using the Integrated Component:

1. Removal of Non-Stationary Trends
   The integrated component is highly effective in eliminating non-stationary trends from time series data, thereby enhancing the accuracy and reliability of subsequent analyses.
2. Broad Applicability
   The differencing approach is widely applied across various disciplines, including economics, finance, and meteorology, making it a versatile tool in time series forecasting.

**Moving Average (MA)**

The Moving Average (MA) is a statistical technique used to smooth out values in a time series in order to identify underlying trends or fluctuation patterns. The MA model provides an overview of how values evolve or fluctuate over time by incorporating the average of a specified number of past observations. This component involves filtering the time series through moving averages to detect fluctuation patterns. The order of the moving average, denoted by q, indicates how many past error terms are considered when estimating the current value. A higher q value implies that more previous error terms are included in the moving average calculation. The general equation for the MA model is as follows:

$$Y_t = c + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (4)$$

Where:

$Y_t$ represents the value of the time series at period t

c represents the constant (intercept) of the model

$\theta_1, \theta_2, \ldots \theta_q$ are the parameters of moving average (MA)

$\varepsilon_t$ refers to error term (white noise) at time t

q is the order of the moving average, indicating how far back in time past error terms are used to make the forecast.

Advantages of Using the Moving Average (MA) Model:

1. Data Smoothing

MA helps to smooth out random fluctuations or noise in time series data, thereby making the underlying patterns or trends more visible and interpretable.

2. Trend Pattern Identification
   By averaging previous values, MA facilitates the identification of trend patterns that may otherwise be obscured by short-term volatility.
3. Forecasting and Prediction
   The MA model can be used to forecast future values based on the detected fluctuation patterns in past error terms, making it a valuable tool in time series forecasting.

This study utilizes the daily closing price data of Bank Aladin Syariah's stock (ticker symbol: BANK), obtained from Yahoo Finance. The observation period spans from May 18, 2022, to March 27, 2025, comprising a total of 694 observations, and the data were processed using R Studio software. The selection of this period was based on the availability and consistency of the data. Prior to May 18, 2022, the data exhibited numerous inconsistencies, which can be attributed to the historical background of BANK's stock. Formerly known as Bank Net Syariah, the institution officially transformed into Bank Aladin Syariah on June 3, 2021. Although the stock had been listed on the Indonesia Stock Exchange prior to the transformation, its trading activity during that time still reflected the characteristics of the former entity. Additionally, potential historical adjustments by data providers such as Yahoo Finance may have affected the accuracy of price data during that period. Considering that the ARIMA model used in this study relies heavily on consistent data patterns and the assumption of stationarity, data prior to May 18, 2022, were excluded from the analysis to ensure more accurate and representative estimation results.

The ARIMA modeling procedure generally consists of four main stages: model identification, parameter estimation, model diagnostics, and forecasting (Ariadi & Herlinawati, 2024). The steps undertaken to forecast Bank Aladin Syariah's stock price using the ARIMA model are as follows:

1. Data Collection and Preliminary Assessment
   The stock price data of Bank Aladin Syariah (BANK) were collected from Yahoo Finance. The model was then formulated, followed by testing for stationarity in variance. If the test yields a rounded value of 1, the data can be considered stationary. Otherwise, a transformation process is applied to achieve stationarity.
2. Stationarity Test in Mean
   Once variance stationarity is confirmed, the next step is to test for stationarity in the mean using the Augmented Dickey-Fuller (ADF) test and visual inspection of the time

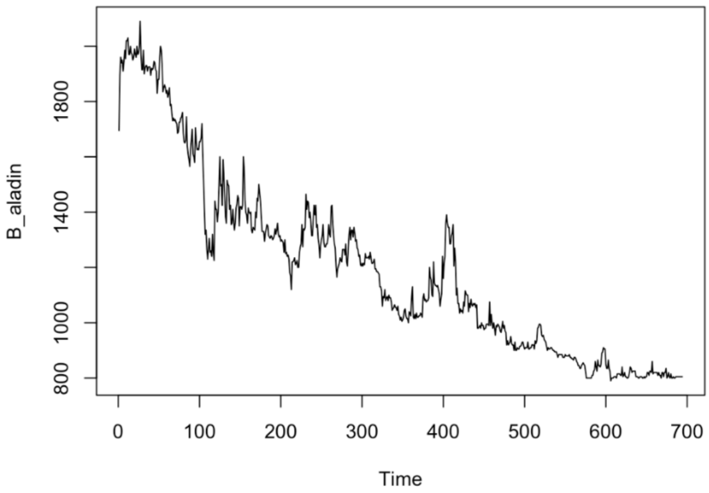
series plot. If lags appear outside the confidence bands in the plot, the data are not stationary in the mean, and differencing must be applied.

3. Identification of ACF and PACF
   The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are analyzed to assist in determining the appropriate order of the ARIMA model.
4. Parameter Estimation
   The parameters of the selected ARIMA models are estimated by identifying the optimal combination of model orders. The Moving Average (MA) order q is determined based on the ACF plot, while the Autoregressive (AR) order p is based on the PACF plot.
5. Model Diagnostics
   Diagnostic checking is conducted to assess the adequacy of the ARIMA models. If the models satisfy the necessary criteria, forecasting can proceed. If not, the ACF and PACF plots are re-examined for re-identification.
6. Forecasting and Error Evaluation
   The chosen ARIMA model is applied to forecast values, and the Squared Error (SE) is calculated for model performance evaluation.
7. Model Selection
   The model with the lowest SE is selected as the best-performing model and is subsequently used for forecasting purposes.
8. Forecasting and Simulation
   The selected ARIMA model is used to generate forecasts and simulate the future stock price movements of BANK.

## RESULT AND DISCUSSION

This study investigates the daily closing price movement of Bank Aladin Syariah (stock code: BANK). The data were obtained from Yahoo Finance, covering the period from May 18, 2022, to March 27, 2025. A total of 694 observations of daily closing stock prices were collected and processed using R Studio software.

**Figure 1 Plot of Bank Aladin Syariah's Daily Closing Stock Prices**




The data presented in Figure 1 reflect the stock price movements over the designated observation period, spanning from May 18, 2022, to March 27, 2025. The time series visualization reveals a gradual downward trend in stock prices, accompanied by short-term fluctuations that indicate market volatility. This graph provides an initial overview of the stock price movement patterns.

An initial stationarity test was conducted using the Augmented Dickey-Fuller (ADF) Test. The test result showed a p-value of 0.08328, which is above the 0.05 significance level. This indicates that the data are non-stationary, and further transformation is required. To address this, first-order differencing (diff order = 1) was applied to eliminate the trend and achieve stationarity. Following the differencing process, the ADF test yielded a p-value of 0.01, which is below the 0.05 threshold. Thus, it can be concluded that the data meet the stationarity assumption and are ready for further analysis using the ARIMA model.

**Figure 2 Closing Price Plot of Bank Aladin Syariah After First Differencing**

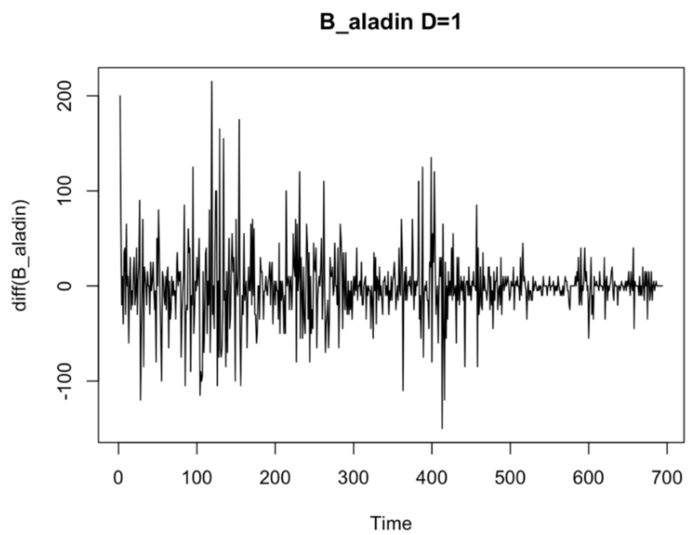
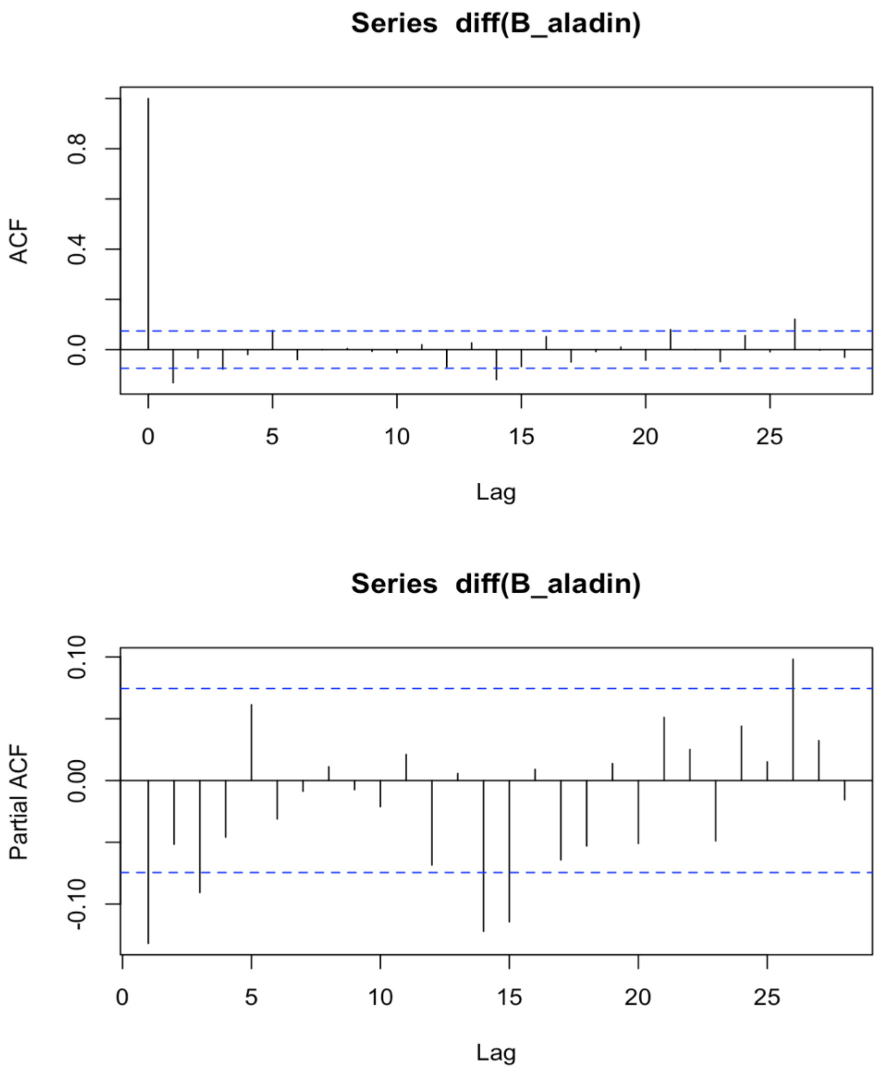


Figure 2 displays the results of the first-order differencing, where the fluctuations appear more stable and oscillate around zero. This condition indicates that the long-term trend present in the original data has been successfully removed, rendering the series closer to stationarity. Based on these results, the first differencing process (D=1) is considered sufficient for building the ARIMA model in this study.

**Figure 3. ACF and PACF Plots**



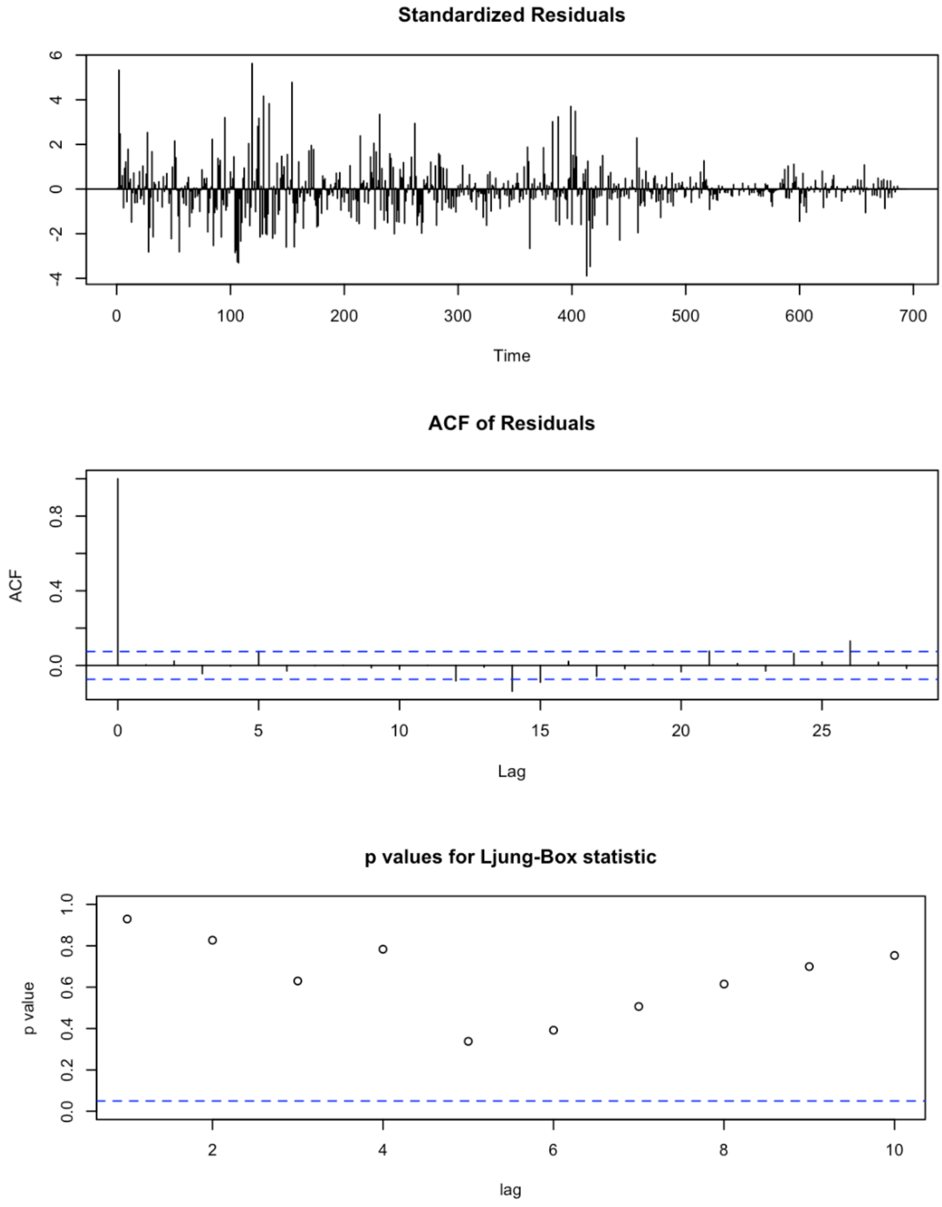

Following the first-order differencing transformation of Bank Aladin Syariah's stock closing price data, the next step involves analyzing the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots to identify patterns and determine appropriate parameters for ARIMA model construction. Figure 3 displays the ACF and PACF plots of the differenced data. Based on the ACF plot, there is a significant spike at lag 1 exceeding the significance threshold, followed by a sharp decline and random movements around zero at subsequent lags. This pattern indicates that the Moving Average (MA) component is likely of order one, suggesting that the parameter q in the ARIMA model may be equal to one. Meanwhile, the PACF plot does not show a clear cutoff, with several scattered negative spikes that are not statistically significant after lag 1. Although some fluctuations appear at lags such as lag 5, the pattern is not strong enough to indicate a high-order Autoregressive (AR) component. Therefore, it is estimated that the parameter p in the ARIMA model may be of order zero or one. The final model selection will be based on parameter estimation, evaluation using information criteria such as AIC and BIC, and residual diagnostics.

**Figure 4. ARIMA Model Evaluation**

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Saham_Bank_Aladin_Syariah | | | | |
| | (1)<br>ARIMA 1<br>ARIMA(1,1,1) | (2)<br>ARIMA 2<br>ARIMA(1,1,2) | (3)<br>ARIMA 3<br>ARIMA (2,1,1) | (4)<br>ARIMA 4<br>ARIMA(2,1,2) | (5)<br>ARIMA 5<br>ARIMA(3,1,1) |
| ar1 | $0.45^{**}$ | 0.52 | 0.50 | 0.49 | 0.07 |
| | (0.18) | (0.54) | (0.47) | (0.61) | (0.27) |
| ar2 | | | 0.01 | 0.26 | -0.04 |
| | | | (0.11) | (0.44) | (0.06) |
| ar3 | | | | | $-0.08^{*}$ |
| | | | | | (0.04) |
| ma1 | $-0.60^{***}$ | -0.67 | -0.65 | -0.64 | -0.22 |
| | (0.16) | (0.53) | (0.47) | (0.62) | (0.27) |
| ma2 | | 0.02 | | -0.22 | |
| | | (0.11) | | (0.52) | |
| Observations | 693 | 693 | 693 | 693 | 693 |
| Log Likelihood | -3,486.24 | -3,486.23 | -3,486.22 | -3,485.74 | -3,484.99 |
| $sigma^2$ | 1,371.10 | 1,371.03 | 1,371.00 | 1,369.02 | 1,366.14 |
| Akaike Inf. Crit. | 6,978.49 | 6,980.45 | 6,980.44 | 6,981.48 | 6,979.98 |
| *Note:* | | | | | $^{*}p^{**}p^{***}p<0.01$ |

The analysis of five ARIMA models in Figure 4 highlights differences in parameter significance and statistical performance. In ARIMA Model 1 (1,1,1), the autoregressive parameter AR(1) is statistically significant at the 5% level, while the moving average parameter MA(1) is significant at the 1% level. These findings suggest that past values have a meaningful influence on current values, and the moving average component plays a critical role in capturing the data pattern. In contrast, Models ARIMA 2 (1,1,2) through ARIMA 4 (2,1,2) exhibit non-significant results for additional parameters such as MA(2) and AR(2). This lack of statistical significance may be attributed to multicollinearity or model overfitting, which can reduce estimation efficiency. ARIMA Model 5 (3,1,1) shows that only the AR(3) parameter is marginally significant at the 10% level, while the remaining parameters remain statistically insignificant. This suggests that although lag-three values contribute to the model, their overall impact is limited. From a performance standpoint, the increase in log-likelihood values from ARIMA 1 to ARIMA 5 indicates an improvement in model fit. Moreover, the decrease in sigma² (residual variance) suggests enhanced predictive accuracy. However, the Akaike Information Criterion (AIC)—which balances model fit and complexity—reaches its lowest point in ARIMA 1, indicating superior model efficiency. Considering parameter significance, model selection criteria (AIC), and structural simplicity, ARIMA(1,1,1) emerges as the most optimal model for forecasting purposes.

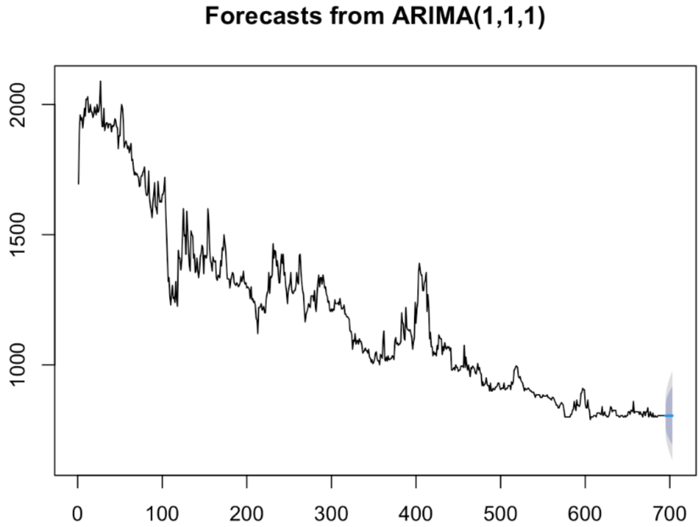
**Figure 5. Diagnostic Evaluation**



A diagnostic evaluation of the ARIMA(1,1,1) model was conducted to ensure that the model satisfies key assumptions in time series analysis, such as randomness of residuals, absence of autocorrelation, and residual distribution centered around zero. Figure 5 presents three key components of diagnostic checking: standardized residuals over time, residual autocorrelation through the ACF plot, and p-values from the Ljung-Box test at various lags.

The plot of standardized residuals shows a random dispersion around the zero line, with no discernible pattern that would suggest unmodeled structure. The ACF plot of the residuals indicates that nearly all autocorrelations fall within the 95% confidence bounds, suggesting no significant autocorrelation remains in the residuals. This is further supported by the Ljung-Box test, where all p-values across different lags exceed the 0.05 significance threshold. Therefore, there is insufficient evidence to reject the null hypothesis of no autocorrelation among residuals. In addition, a One-Sample t-test was performed to assess whether the mean of the residuals significantly differs from zero. The resulting p-value of 0.2047 indicates no statistically significant difference between the residual mean and zero. This finding reinforces the conclusion that the residuals are random and symmetrically distributed around the center. Based on these diagnostic results, it can be concluded that the ARIMA(1,1,1) model fulfills the necessary statistical assumptions and is deemed appropriate for both forecasting and inferential purposes.

**Figure 6. Forecasting**




The ARIMA(1,1,1) model was applied to forecast the stock prices for the next nine periods, yielding the following predicted values: 804.9910, 804.9870, 804.9851, 804.9843, 804.9839, 804.9838, 804.9837, 804.9837, and 804.9836. Each predicted value is accompanied by a progressively increasing standard error, recorded at 37.02838, 48.58693, 56.55652, 63.02678, 68.68777, 73.83191, 78.60468, 83.08866, and 87.33627, respectively. The forecasting results are visualized in Figure 6, where the black line represents the historical stock price data, and the blue line at the end of the graph indicates the model's predicted values for the upcoming nine periods. The shaded gray area denotes the confidence intervals of the forecasts, reflecting the model's level of uncertainty in predicting future values. From the graph, it can be observed that the stock price is expected to remain relatively stable with minimal fluctuations during the forecast period. This suggests that the ARIMA(1,1,1) model provides a conservative and realistic estimation of future price movements, aligning with historical trends. Therefore, the forecasting results may serve as a basis for strategic decision-making, both for investors and bank management, in anticipating future market dynamics.

## CONCLUSION

This study aims to model the daily stock price movement of Bank Aladin Syariah (BANK), the first Islamic digital bank in Indonesia, using an ARIMA approach based on historical data from May 18, 2022, to March 27, 2025. As a pioneer in branchless Sharia-compliant banking services powered by digital technology, Bank Aladin plays a strategic role in promoting national Islamic financial inclusion. Consequently, the movement of BANK's stock serves as a key indicator of market perception regarding the digital transformation within the Islamic finance sector. Since its initial public offering in 2021, BANK's stock price has shown a gradual downward trend. This decline may reflect the market's adjustment to the company's performance realization, the challenges of expanding its digital customer base, and investor sentiment regarding the sustainability of the Islamic digital banking business model.

Through a series of tests on five ARIMA models, the ARIMA(1,1,1) model was selected as the most optimal, demonstrating superior performance in terms of parameter significance, the lowest Akaike Information Criterion (AIC) value, and satisfactory residual diagnostics. This model effectively captures the historical patterns of BANK's stock price movement and provides a stable projection for the next nine periods. The forecasting results suggest a leveling-off trend at a certain price range, potentially indicating a market consolidation phase following a medium-term decline. Thus, the model offers a reliable tool to support strategic decision-making by both investors and corporate management in responding to stock market dynamics. However, since this study is limited to a single stock within a single sector, future research is recommended to include a broader range of stocks to generate more comprehensive insights.

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