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Time Series Analysis for Stock Price in Main Market Bursa Malaysia using ARIMA and Artificial Neural Networks

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Abstract

Stocks are a vital part of financial markets because they allow people and organizations to invest in company stock and also make significant contributions to stability and growth in the economy. For investors, financial analysts, and policymakers, accurate stock price forecasting is essential because it facilitates well-informed decision-making and efficient risk management in stock investment. This study investigates the performance of different time series models in forecasting the stock prices of a company listed on the Main Market of Bursa Malaysia such as Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average (ARIMA) models. The objective of the study is to identify the most appropriate approach for stock price prediction among both ARIMA and ANN models. The historical monthly stock price data were obtained from Yahoo Finance from 2015 to 2024. The dataset was separated into training and testing sets for the purpose of developing and validating the model. To evaluate the accuracy of the model, evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used. The findings suggest that the ANN model demonstrated consistent performance with low error values and achieved higher accuracy compared to ARIMA. The MAPE of ANN in both testing and training sets is less than 10% which demonstrates high accuracy of forecasting. In conclusion, the results offered insightful information for stock prediction besides improving investment strategies and enhancing financial market stability.

1. Introduction

The stock market is often considered the core of a financial system in a country, and it is strongly correlated with various macroeconomic factors [1]. By investing in the ownership of companies, the stock market provides a framework for economic growth and wealth generation [2]. In recent years, the stock market has experienced a significant increase in popularity as more individuals turn to it not only as an additional source of income but also a form of entertainment. Globalization, technological developments [3], and the growing accessibility of financial data have all influenced the evolution of the stock market. From experienced institutional investors to individual retail traders, these advancements have greatly increased the accessibility of stock market investment for a wide range of participants.

However, the attraction of high returns comes with some inherent difficulties, because stock values are impacted by a number of variables, including political changes, company-specific advancements, and macroeconomic indicators. These factors contribute to the volatility and unpredictability of the stock market, which frequently causes analysts and investors to struggle with uncertainty [4]. Accurately predicting stock prices is crucial in this dynamic market for risk management, portfolio performance optimization, and making well-informed investing decisions.

In Malaysia, Bursa Malaysia is the most prominent exchange holding company, and it plays an important role in the country's economy. It provides a broad variety of investment products and services, including equities, bonds, derivatives, offshore and Islamic bonds. The variety of markets available in Bursa Malaysia is one of its advantages compared to other stock markets. For example, there are three markets such as the Main Market, the ACE Market, and the LEAP Market, with each catering to different types of companies. The Main Market is the prime market for well-established large-cap enterprises with a track record of profitability or minimal market capitalization. It includes diverse sectors, including industrial products and services, healthcare, and technology [5], which reflects the diversity of the economy in Malaysia. The stock data selected for this study is obtained from a company listed on the Main Market which provide a rich dataset for stock price forecasting.

Many studies have been carried out over time to enhance stock price forecasting methods. It is well known that traditional statistical methods, such as the Autoregressive Integrated Moving Average (ARIMA) model, may accurately represent linear relationships and trends in time series data [6]. At the same time, modern techniques such as Artificial Neural Networks (ANN) use machine learning to capture complex nonlinear patterns in the data [7]. For stationary data, ARIMA appears in simplicity and consistency, whereas ANN provides an adaptable technique for modelling dynamic and nonlinear relationships. However, each method has its limitations. For example, the assumption of data stationarity in ARIMA and overfitting in ANN, allow for a comparative study to determine the effectiveness of each in particular applications.

For instance, time series analysis such as the ARIMA model can be utilised to forecast future stock prices according to historical data. A study by Tri Wahyudi applied the ARIMA model was chosen to predict the Indonesia Composite Stock Price Index (CSPI) due to its simplicity [8]. Other than that, another study applied ANN in predicting the direction of the daily price of the Japanese stock market index [9]. The ANN model is then improved by Genetic Algorithms to improve the accuracy and reduce the bias of the ANN model. Besides, Wijesinghe & Rathnayaka applied the ARIMA model, ANN, and hybrid ARIMA-ANN model to forecast the stock price of Larsen and Turbo (L&T) company [10].

This study employs a dataset that spans over ten years, from 2015 to 2024, to forecast the stock prices of a company listed on the Main Market of Bursa Malaysia. This study focuses on developing forecasting models and assessing their performance using both ARIMA and ANN models. Specifically, it aims to build time series models for stock price forecasting using ARIMA and ANN, determine the best forecasting method by comparing the models' accuracy based on metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), and forecast the future stock price using the best-performing model.

2. Methodology

In this part, the summary of the dataset applied in this study is provided. The procedures for building the forecasting models which are ARIMA and Artificial Neural Networks (ANN) models are discussed. Additionally, it also discussed the forecast performance evaluation metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) that are used to evaluate the forecast accuracy of the models.

2.1 Data description

The historical stock data applied in this study is the historical stock price of a selected company in Main Market Bursa Malaysia. The data was obtained from Yahoo Finance which is one of the most popular financial websites. The data obtained was from January 2015 to February 2024 which consists of 110 observations. Then, the data was divided into two parts, which are the training set and the testing set. The training set is from January 2015 to February 2023 which consists of 98 observations for model training whereas the testing set is from March 2023 to February 2024 which consists of 12 observations for forecast evaluation. The analysis is carried out using software such as Microsoft Excel, Minitab, and R software.

2.2 Box-Jenkins model

The Box-Jenkins approach is also known as the Autoregressive Integrated Moving Average (ARIMA) model. In 1970, George Box and Gwilym Jenkins proposed a time series forecasting model called the ARIMA model [11]. The autoregressive (AR) model, differencing (I), and the moving average (MA) models are combined to produce the ARIMA model. The non-seasonal ARIMA model is shown in Eq. (1).

$$\varnothing_p(B)\,\nabla^d y_t = \theta_q(B)\,a_t \tag{1}$$

where∇
∇^d = order of differencing
B = backshift operator
ϕ_p = non-seasonal autoregressive parameter of order p
θ_q = non-seasonal moving average parameter of order q
a_t = random error at time t

Before carrying out the analysis, a time series plot is required to be generated. This is important to visualize the historical stock price data used. By displaying the value changes on a graph, the trends, seasonality, and other patterns of the data can be easily identified [12]. It was important to confirm that the time series data was stationary that is its mean and variance were constant over time before building the ARIMA model. In order to achieve stationarity, non-stationary data must undergo transformations to achieve stationarity. The Box-Cox transformation was used to stabilize the variance and ensure that the assumption of homoscedasticity of the variance is met, which means the variance remains constant over time [13]. On the other hand, by removing the level, trend, and seasonality from the data, differencing was utilized to stabilize the mean and ensure the time series' stationarity.

There were three phases in building the ARIMA model, including model identification, parameter estimation, and diagnostic checking. The values of the order of autoregressive (p), degree of differencing (d), and order of moving average (q) are determined during the first phase which is model identification. The selection of p and q is guided by the significant lags found in the ACF and PACF plots. Table 1 shows the features for the model identification.

Table 1 Model Identification

Model	ACF	PACF
AR (p)	Decay to zero with exponential pattern	Cuts off after lag p
MA (q)	Cuts off after lag q	Decay to zero with exponential pattern
ARMA (p,q)	Decay to zero with exponential pattern	Decay to zero with exponential pattern
ARMA (p,q)	Cuts off after lag q	Cuts off after lag p

After the potential models have been identified, the following step is parameter estimation. The significance of the parameters for each model was examined at a 0.05 level of significance. Therefore, if the p-value obtained is greater than 0.05, then we can conclude that the parameter is not significant to the model. The coefficients of the AR and MA components are often determined via maximum likelihood estimation to guarantee that the model adequately fits the data. The Akaike Information Criterion (AIC) and Mean Squared Error (MSE) were two measures used to assess the performance of various ARIMA models.

Diagnostic checking is done to make sure the chosen model is adequate after the model parameters have been estimated. The residuals were examined for autocorrelation using the Ljung-Box test. The test statistic is carried out at a 0.05 level of significance. Therefore, if the p-value obtained is greater than 0.05, then do not reject the null hypothesis. Then, we can conclude that the model is adequate. The residual plots are plotted to ensure that they follow a white noise pattern and that the adequacy of the selected model is met. For example, residual plots such as normal probability plot, residuals versus fits plot, histogram, and residuals versus order plot.

2.3 Artificial Neural Network

One of the most popular machine learning models for resolving complex pattern recognition issues is the artificial neural network (ANN). ANN was inspired by the structure of biological nervous systems (14). They are effective in capturing the complex non-linear relationship of the data (15).

Choosing the input for the ANN models was the first step in the procedure. Based on patterns found in preliminary investigations, including insights from ARIMA models which were determined from the ACF and PACF plots, lag observations such as lag 1 and lag 4, were chosen as input features in ANN model.

The input layer, hidden layers, and output layer are the three primary layers that make up the ANN architecture. The chosen lagged features, which act as the model's input data, are represented by nodes in the input layer. The hidden layer is made up of interconnected neurons that use activation functions and weighted connections to interpret these inputs, transforming the data to uncover complex patterns (16). Lastly, using the data that has been processed from the hidden layer, the output layer generates the anticipated stock price. An ANN's neurones are processing units that take in inputs, process them using activation and transfer functions, and then produce an output. Since R software is employed in this study, the transfer function that is used is "sigmoid" or logistic function which is specified within packages like "neuralnet". The procedure is displayed in Fig. 1.

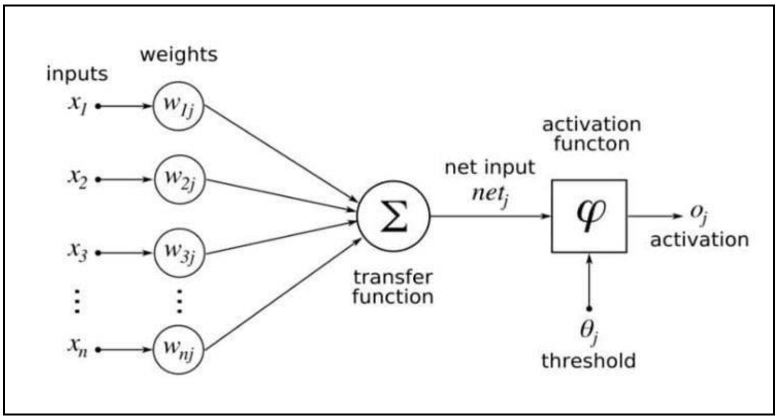


Fig. 1 Arithmetic process of neurons in ANN

The formula for the net input of the processing unit is shown in Eq. (2) while the formula for the output of the neuron is shown in Eq. (3).

$$z = \sum_{l=1}^{n} w_{ji} x_i + b \tag{2}$$

where

z = net input to the hidden layer
w_{ji} = weights form ith input to jth neurons in the hidden layer
x_i = ith input
b = bias added to the neurons in the hidden layer

$$\hat{y}_t = b_0 + \sum_{i=1}^{n} w_{0i} h_i \tag{3}$$

where

b_0 = bias added to the neuron in the output layer
w_{0i} = weight from ith neuron in hidden layer to 0th neuron in output layer
h_i = outputs from hidden layer used as output layer inputs

2.4 Forecast performance evaluation

Assessing forecast performance is crucial for determining the accuracy of forecast models generated by forecasting approaches (17). It helps in evaluating how well the forecast values generated by the forecasting model fit the actual values. The models' performance was evaluated using MAE, RMSE, and MAPE as forecast accuracy performance measures.

MAE measures the average absolute error between actual and forecasted values, with lower MAE indicating higher accuracy (18). RMSE, which measures the dispersion of residuals from the regression line, is the square root of the mean of squared errors. Higher accuracy is indicated by a lower RMSE, which represents mean forecasts. MAPE computes the average absolute percentage error, providing scale-independent results expressed as percentages, enabling comparisons across models (19). High accuracy is indicated by a MAPE ≤10%, good accuracy of 10–20%, fair accuracy of 20–50%, and inaccuracy of MAPE ≥50%. Eq. (4) to (6) display the formulas for determining MAE, RMSE, and MAPE, respectively.

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} \left| y_t - \hat{y}_t \right| \tag{4}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{n}} \tag{5}$$

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

3. Results and Discussion

The results of the forecasting models are provided in this part with an analysis of their performance. Evaluation measures such as MAE, RMSE, and MAPE are used to compare the results of ARIMA and Artificial Neural Network (ANN) models.

3.1 Time Series Plot

A time series plot is constructed to provide insights into the data's features. Fig. 2 illustrates the time series plot of the stock's monthly closing price from January 2015 to October 2024. The plot reveals an overall increasing trend over the ten-year period, with fluctuations in prices and a sharp increase observed after October 2023. No seasonality was detected, as the data does not exhibit repeating patterns at regular intervals. The time series is non-stationary, with both the mean and variance changing over time.

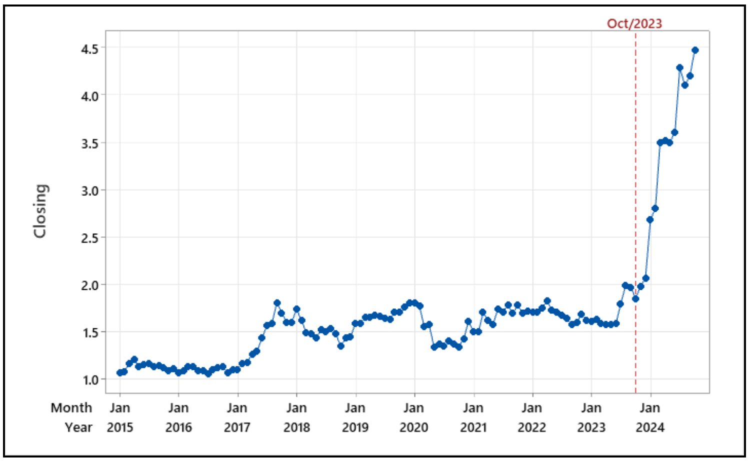


Fig. 2 Time series plot for stock's closing price

3.2 Box-Jenkins model

Before identifying the model for the Box-Jenkins model, it is essential to ensure the data is stationary and with constant variance and mean over time. Therefore, a Box-Cox plot is used to assess and stabilize the variance of data, which meets the homoscedasticity assumption required by ARIMA models. Fig. 3 shows the Box-Cox plot for the stock's closing price. The Box-Cox plot indicated that the lower and upper central limit ranges do not include 1 which means that variance is not constant. Therefore, transformation is required to achieve constant variance. The rounded result of -1.00 suggested applying a power transformation of -1, which is equivalent the inverse of the closing price.

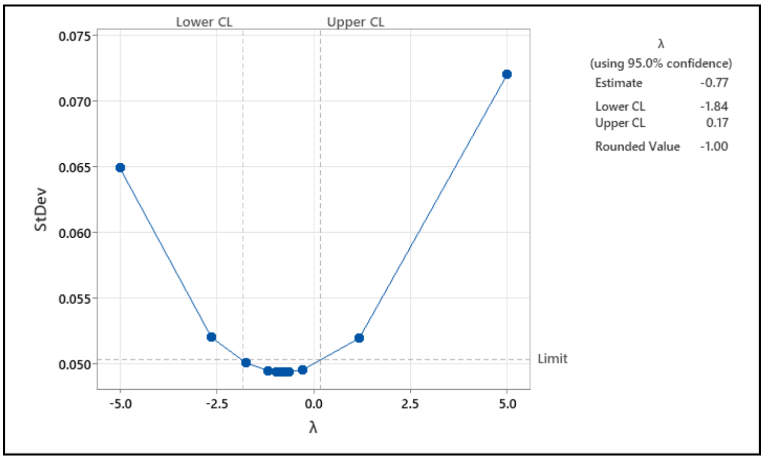
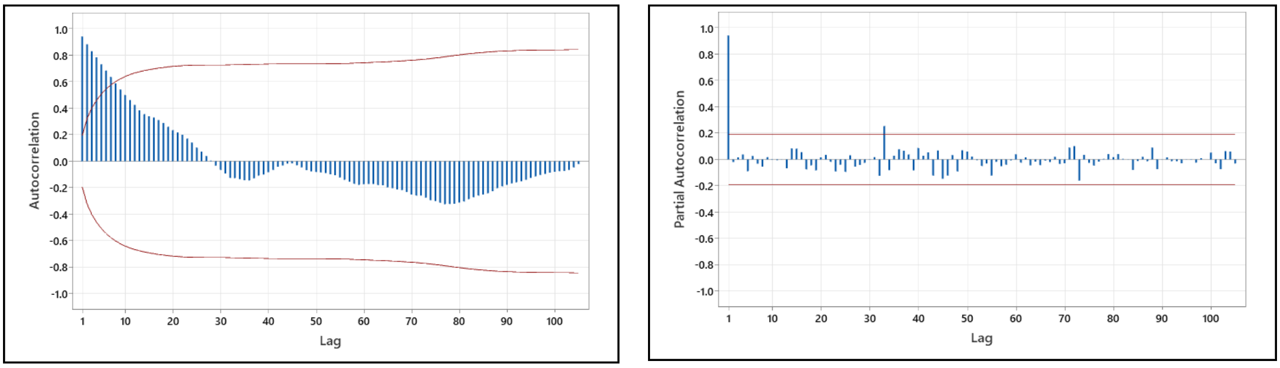


Fig. 3 Box-Cox plot for stock's closing price

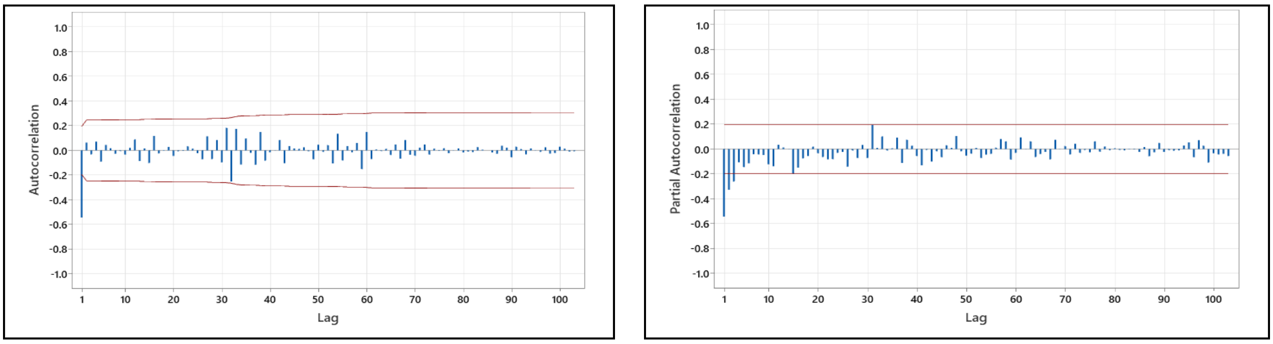
After achieving achieved constant variance, ACF and PACF plots are applied to check the stationarity of the time series by showing the presence of autocorrelation.



(a) (b)

Fig. 4 ACF and PACF plots of stock closing price (a) ACF plot; (b) PACF plot

Fig. 4(a) and Fig. (b) the ACF and PACF plots of stock's closing price. The ACF plot shows significant autocorrelation, with the first lag close to 1 and a slow decay, indicating non-stationarity. The PACF plot cuts off at lag 1, confirming the need for differencing. After differencing, the time series becomes stationary, with constant mean and variance over time.



(a) (b)

Fig. 5 ACF and PACF plots after second order differencing (a) ACF plot; (b) PACF plot

Fig. 5(a) and Fig. (b) shows the ACF and PACF plots of closing price after second order differencing. The ACF plot indicates autocorrelation cutting off at lag 1, suggesting a moving average of order 1, denoted as MA (1). Similarly, the PACF plot shows a die down at lag 4, suggesting an autoregressive order of 4, denoted as AR (4).

Table 2 Summary of the parameter estimation for the selected ARIMA models

Model	p-value of Estimated Parameters	p-value of Ljung-Box Test				AIC	MSE
		Lag 12	Lag 24	Lag 36	Lag 48		
ARIMA (4,2,1)	AR(1) 0.000 AR(2) 0.000 AR(3) 0.000 AR(4) 0.003 MA(1) 0.000	0.012	0.049	0.024	0.078	-313.830	0.0023
ARIMA (4,2,0)	AR(1) 0.000 AR(2) 0.000 AR(3) 0.000 AR(4) 0.000	0.000	0.000	0.000	0.001	-264.795	0.0039
ARIMA (3,2,1)	AR(1) 0.000 AR(2) 0.009 AR(3) 0.189 MA(1) 0.000	0.000	0.000	0.000	0.000	-251.448	0.0044

Table 2 summarizes the parameter estimation for the selected ARIMA models. According to the results, the *p*-value of the estimated parameters of all ARIMA models is less than 0.05 except for ARIMA (3,2,1). Therefore, we can conclude that the parameter of the ARIMA (3,2,1) model is not statistically significant to the models. The parameters of the ARIMA (4,2,1) and ARIMA (4,2,0) are significant to the model. After ensuring that the models have significant parameters, AIC is evaluated to determine how well a model fits the data. The AIC of ARIMA (4,2,1) is the smallest among the tentative models which are -313.830 followed by ARIMA (4,2,0) which is -264.795. Therefore, the most appropriate forecasting model is ARIMA (4,2,1).

After estimating the model parameters, the diagnostic checking phase evaluates model adequacy by examining residuals. The Ljung-Box test and residual plots are used to assess this. Table 2 shows the p-values of the Ljung-Box test for ARIMA (4,2,1) is greater than 0.05 at lag 12, 24, 36 and 48, respectively. Therefore, we can conclude that the model is adequate and there is no correlation between the residuals at 0.05 level of significance. This confirms the adequacy of the models. The equation of the ARIMA (4,2,1) model is expressed in Eq. (7).

$$\varnothing_4(B)\nabla^2 y_t = \theta_1(B)a_t \tag{7}$$

$$\left(1-\varnothing_1 B-\varnothing_2 B^2-\varnothing_3 B^3-\varnothing_4 B^4\right)\left(1-2B+B^2\right)y_t=\left(1+\theta_1 B\right)a_t$$

$$y_t = 2y_{t-1}-y_{t-2}+\varnothing_1\left(y_{t-1}-2y_{t-2}+y_{t-3}\right)+\varnothing_2\left(y_{t-2}-2y_{t-3}+y_{t-4}\right)+\varnothing_3\left(y_{t-3}-2y_{t-4}+y_{t-5}\right)+\varnothing_4\left(y_{t-4}-2y_{t-5}+y_{t-6}\right)+a_t+\theta_1 a_{t-1}$$

Considering all criteria, ARIMA (4,2,1) is considered the most appropriate forecasting model due to its lower AIC and MSE values compared to the other models. Residual plots also confirm that the residuals exhibit a white noise pattern, further validating the model's adequacy.

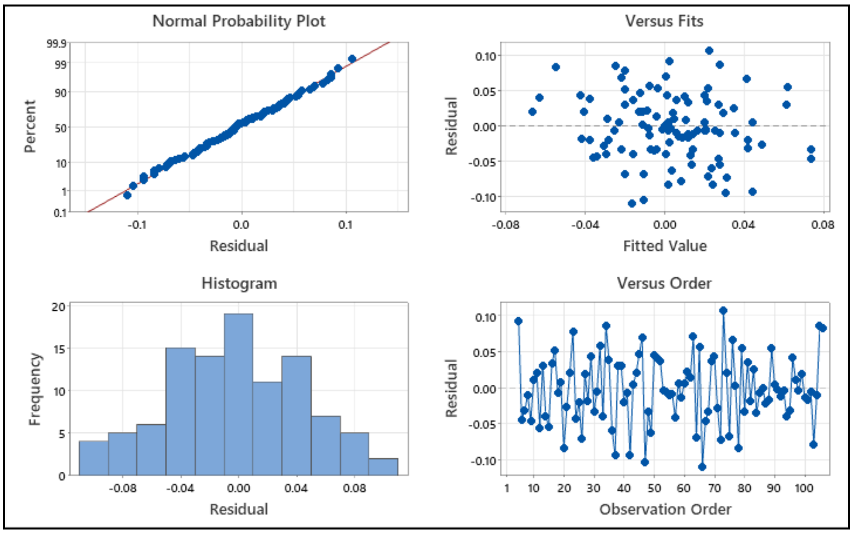


Fig. 6 Residual plots of ARIMA (4,2,1)

The residual plots of ARIMA (4,2,1) shown in Figure 6 consist of four plots that are normal probability plot, residuals versus fits plot, histogram, and residuals versus order plot. The normal probability plot shows that the residuals are normally distributed as the points lie approximately along the straight line. Next, the residuals versus fits plot shows that the residuals are randomly distributed around zero and have constant variance, indicating the homoscedasticity assumption is met. The histogram of residuals appears bell-shaped, indicating that the residuals are approximately normally distributed. Additionally, the residual versus order plot shows that the residuals are independent over time as the residuals fluctuate randomly around zero.

3.3 Artificial Neural Network

The Artificial Neural Network (ANN) approach is another method applied in this study to forecast the stock's closing price of the selected company. ANN has been identified as one of the most appropriate methods for stock market prediction as it considers complex and non-linear relationships in the data. During the training process, the artificial neural network (ANN) model discovered the relationships between the closing price of the stock and the lagged features which are lag 1 and lag 4. The selection of these lags which are suitable for forecasting the closing price of the stock is determined by the study of ARIMA (4,2,1) model.

The moving average (MA) term in ARIMA (4,2,1) suggests that the present observation depends on the value from the previous observation (lag 1). This indicates that present observation plays a critical role in predicting the next value, making lag 1 a suitable choice. Therefore, lag 1 is important for capturing the immediate dependencies in the time series. On the other hand, lag 4 is included in the input features. The autoregressive (AR) term in ARIMA (4,2,1) suggests that the current observation depends on the value from four steps back (lag 4). As a result, the ARIMA (4,2,1) model suggests that both lag 1 and lag 4 are statistically significant in explaining the variation in the closing price. By incorporating both lag 1 and lag 4, the ANN model can capture sufficient information to make accurate predictions.

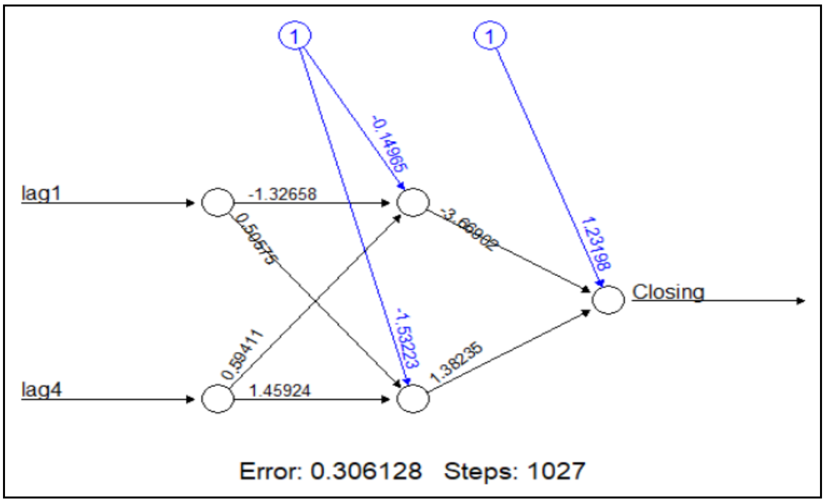


Fig. 7 Artificial neural network model architecture

Fig. 7 shows the architecture of the artificial neural network model. The input layer of the artificial neural network (ANN) model has two nodes, lag 1 and lag 4 of the historical stock's closing price. Two neurons in the hidden layer are each linked to the input nodes via weighted connections, such as -1.32658 and 0.59411. The weight affects the inputs' contribution. In the hidden layer, bias nodes are included to enhance the model's adaptability and capture complex patterns. With connections from the hidden layer, the output layer's single neurone is in charge of forecasting the closing price of the stock. After 1027 training steps, the model achieved an error value of 0.3061 which means that the model has high accuracy in forecasting.

3.4 Forecast performance evaluation

In training and testing datasets, MAE, RMSE, and MAPE were used to assess the forecast performance of the ARIMA and ANN models. These measures allow comparison between both forecasting models and evaluate the accuracy of predictions. Table 3 shows the performance results of the final model selected, which are ARIMA (4,2,1) and ANN model.

Table 3 Forecast performance evaluation for ARIMA (4,2,1) and ANN models

Model	Forecast Performance Evaluation					
	Training set			Testing set		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
ARIMA (4,2,1)	0.14891	0.20433	9.75346	0.58868	0.63549	16.52795
ANN	0.05718	0.07748	3.77572	0.25938	0.29858	7.25657

Based on Table 3, the ANN model demonstrated a consistent performance with low error values across both training and testing sets. The ANN model has a relatively low MAE of 0.05718, an RMSE of 0.07748, and a MAPE of 3.77572 during the training set. The ANN model, on the other hand, also shows high forecast accuracy for the testing set with a low MAE of 0.25938, an RMSE of 0.29858, and a MAPE of 7.25657. The low MSE indicates that the error between the predictions and actual values is small. The low MAPE in both training and testing sets which is less than 10% indicates that the prediction accuracy level is high. Therefore, these results conclude that ANN could capture the patterns in the data effectively and make accurate predictions.

In contrast, the ARIMA (4,2,1) model displayed a mixed performance. The ARIMA (4,2,1) model performed slightly better in the training set, with an MAE of 0.14891, an RMSE of 0.20433, and a MAPE of 9.75346.

However, its testing set performance deteriorated, with an MAE of 0.58868, an RMSE of 0.63549, and a MAPE of 16.52795. The high MAPE value in the testing set which falls within the range of 10% and 20% suggests a good prediction accuracy level compared to the training set which has a high prediction accuracy level. The ARIMA (4,2,1) model performs well during the training phase, but its forecast performance declines during the testing phase.

Based on the forecast performance evaluation, the ANN model is identified as the best forecasting model in this study. This is because the ANN model demonstrates consistent and better performance with low error metrics across both training and testing sets. The ANN model has high accuracy of prediction, as proved by its significantly low MAE, RMSE, and MAPE values.

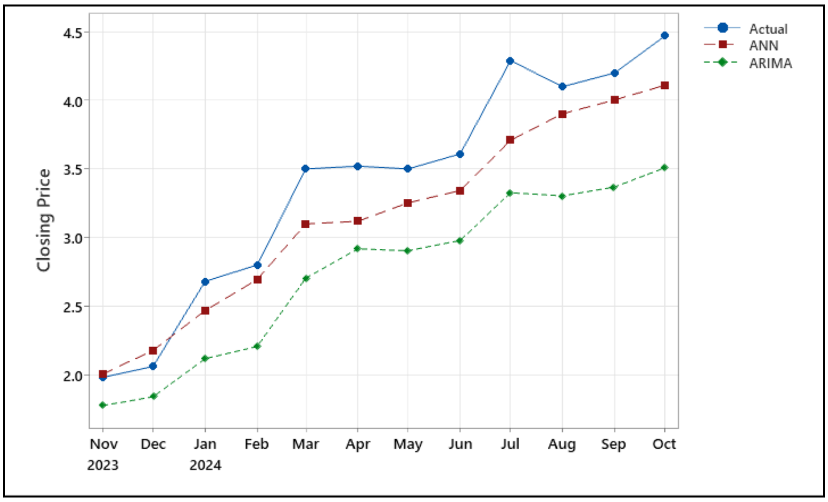


Fig. 8 Time series plot of actual closing price, ARIMA, and ANN models

Fig. 8 illustrates the time series plot of the actual closing price along with the predictions stock's price made by ARIMA, and ANN models from November 2023 to October 2024. The ANN model's predicted values align closely with the actual closing price whereas the ARIMA model's predicted values deviate significantly from the actual closing price particularly during the early months and across the period of forecasting.

4. Conclusion

This study successfully achieved its three research objectives. First, time series models for stock price forecasting were developed using ARIMA (4,2,1) and an Artificial Neural Network (ANN). The ARIMA model followed a systematic process involving stationarity checks, differencing, parameter selection using AIC, and residual diagnostics, while the ANN model was constructed through input selection, network architecture design, and training with historical stock prices. Next, this study determined the best forecasting method among ANN and ARIMA by evaluating the model using MAPE, MAE, and RMSE. The ANN model outperformed the ARIMA model because it had low error values in both the training and testing phases. The ANN had a low MAPE of 3.77572 during the training phase and a MAPE of 7.25657 during the testing phase. Meanwhile, the ARIMA model had a low MAPE of 9.75346, which proved that the ARIMA performed well in the training phase. However, it had a high MAPE of 16.52795 on the testing phase where its performance declined significantly. Lastly, the study employed the ANN model to successfully predict the closing price of the stock on the Main Market Bursa Malaysia from November 2023 to October 2024. For both the training and testing phases, the ARIMA model demonstrates its effectiveness in forecasting stock prices and making accurate predictions.

For future studies, one approach for improving the forecasting models is to apply the hybrid models, which combine the advantages of ARIMA and ANN. This method can leverage both linear and non-linear patterns in the time series and improve the forecast accuracy of the stock's closing price. Additionally, Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNNs) are two advanced machine learning techniques that can be used to improve forecast accuracy because they excel in managing complex relationships in time series forecasting. Furthermore, it is recommended to use a larger dataset or high-frequency data such as weekly or daily data when constructing an ANN model. By using a larger dataset, the model would capture the complex patterns more effectively and improve the accuracy of prediction.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm their contribution to the paper as follows: ***study conception and design:*** *Hong Wai Xiang, Kamil Khalid;* ***data collection:*** *Hong Wai Xiang;* ***analysis and interpretation of results:*** *Hong Wai Xiang, Kamil Khalid;* ***draft manuscript preparation:*** *Hong Wai Xiang, Kamil Khalid. All authors reviewed the results and approved the final version of the manuscript.*

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