Forecasting Weekly Stock Price of Apple Inc by using ARIMA model

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***Abstract*— Stock price forecasting remains a critical field in financial research, offering practical benefits for portfolio optimization and risk management. This study focuses on forecasting the weekly closing prices of Apple Inc. (AAPL) from March to April 2025 using the Autoregressive Integrated Moving Average (ARIMA) model. The objective is twofold: to assess the forecasting accuracy and to validate the statistical adequacy of the model. Employing the Box-Jenkins methodology, the process includes stationarity testing via the Augmented Dickey-Fuller test, model identification through ACF and PACF plots, parameter estimation, and residual diagnostics using the Shapiro-Wilk and Ljung-Box tests. ARIMA(6,1,0) was selected based on the lowest AIC and BIC values and diagnostic compliance. The model achieved a low Mean Absolute Percentage Error (MAPE) of 2.6%, indicating strong predictive accuracy. Forecasts were accompanied by 95% confidence intervals, enhancing interpretability. The results confirm that the ARIMA model is suitable for short-term financial forecasting where model transparency and statistical validity are essential.*

Keywords— Forecasting, Apple, ARIMA, Ljung Box-Jenkins method,

I. INTRODUCTION

The stock market is a dynamic system in which price movement will typically reflect a variety of economic, financial, and psychological factors. stock price forecasting has been a special concern to investors, analysts, and researchers, given its potential to optimize portfolio planning, manage financial risk, and guide decisions.

Among other statistical methods, the Autoregressive Integrated Moving Average (ARIMA) model remains a trusted giant that continues to be very pertinent in financial time series forecasting. ARIMA, introduced through the Box-Jenkins methodology, offers a framework for modeling time series data that exhibits autocorrelation and non-stationarity by combining autoregressive (AR), differencing (I), and moving average (MA) components to capture trend and stochastic properties in data [1].

Compared to more complex approaches such as neural networks or hybrid models, ARIMA models are more easy to understand and fast it runs on a computer. These traits make ARIMA particularly valuable in scenarios with limited data points and where model transparency is necessary for stakeholders [2]. For example, the ARIMA(3,1,0) model yielded satisfactory predictive accuracy for the weekly stock prices of PT Aneka Tambang Tbk (ANTM), achieving a low Mean Absolute Percentage Error (MAPE) of 7.68%. This lends support to the applicability of the ARIMA model to real-world forecasting, particularly in volatile financial markets [3]

The present study targets Apple Inc. (AAPL), a most traded and most valuable company in the world. The stock's high liquidity combined with the demand for investors across the world makes it a most appropriate candidate for studies in time series forecasting. Academics have explored Apple stock projections based on ARIMA. [4] demonstrated that ARIMA models can produce effective forecasts of Apple's weekly prices with moderate accuracy, and ARIMA provided better results compared to regression smoothing methods for short-term forecasting of Apple stock [4].

Several previous research studies have applied the ARIMA method to forecast stock prices and other investments. For example, it has been used ARIMA to predict TSMC stock price with a Mean Absolute Percentage Error (MAPE) of 3.2% [5], as well as PT Aneka Tambang Tbk [3]. Though ARIMA has been useful, most of the research puts great importance on short-run forecast accuracy with little regard for diagnostic checking, such as heavy stationarity testing, residual autocorrelation tests, or residual normality assumptions tests.

Additionally, trend and seasonality plots are often overlooked even though they can help in gaining further understanding of the data. This study is attempting to bridge these gaps by applying ARIMA in a more comprehensive manner via diagnostic testing and plots that confirm the results of the forecasting.Addressing these limitations, this research adopts an integrated ARIMA modeling approach to forecast Apple Inc.'s weekly closing stock prices from January 2024 to April 2025. The approach involves a complete Box-Jenkins process: stationarity testing (ADF test and visual examination), model identification using ACF and PACF plots, parameter estimation, and residual checking using the Shapiro-Wilk and Ljung-Box tests. The final prediction includes a confidence interval to make the results easier to understand and more useful in practice.

The objective of this study is twofold: (1) to evaluate the accuracy of the ARIMA modeling in forecasting Apple Inc.'s weekly stock prices on a recent time period, and (2) to verify the model's validity through strict checks testing and validation methods. The goal is to offer a reliable but simple model that can help both individual and professional inverstors make better decisions.

II. METHODOLOGY

This research adopts the Box-Jenkins methodology to implement the ARIMA (Autoregressive Integrated Moving Average) model, which combines three core components: Autoregressive (AR), Moving Average (MA), and Integration (I). This structured approach ensures a systematic process for time series forecasting.

A. *Box-Jenkins Method*

The Box-Jenkins method is a systematic approach to analyzing and forecasting time series data using ARIMA models. The goal is to build a model that best fits the historical data and can accurately forecast future values. This method relies on transforming non-stationary data into a stationary form, then using autocorrelation patterns to select the most appropriate ARIMA(p,d,q) model, where *p* is the autoregressive order, *d* is the number of differencing steps, and *q* is the moving average order.

1. *Autoregressive (AR) :*

The AR part of a time series makes the assumption of the current values (Y_t) effect on the previous value (Y_{t-p}) of a time series. An AR(p) model is the current value expressed as a linear combination of the past p observations. For example, today's price of stocks can be predicted by looking at prices from previous weeks. The equation of AR model can be written as [1]:

$$Yt = \phi 1Yt - 1 + \phi 2Yt - 2 + \cdots + \phi pYt - p + e_t$$

Where $\phi 1,\ \phi 2, .., \phi p$ are the autoregressive parameters and e_t is white noise [1].

2. *Moving Average (MA) :*

The MA (Moving Average) component expresses the present value (Y_t) in terms of past errors of prediction. A MA model of order *q* assumes that the movement in the series are determined by random errors or shocks from the previous *q* periods (e_{t-q}) as well as the present data (e_t). The equation of an MA model can be written as [1]:

$$Yt = et - \theta 1et - 1 - \theta 2e_{t-2} - \cdots - \theta qet - q$$

3. Autoregressive Integrated Moving Average (ARIMA):

AR and MA equation can be combined and written as the ARMA (p,q):

$$Yt = \phi 1Yt - 1 + \phi 2Yt - 2 + \cdots + \phi pYt - p + et - \theta 1et - 1 - \theta 2et - 2 - \cdots - \theta qet - q$$

ARIMA combines the AR and MA models, with the addition of an integration step (I) in order to transform a non-stationary series into a stationary series. It is typically achieved by differencing the series $Wt = \nabla^d Yt$, where every observation is replaced by the difference between itself and its previous value. ARIMA(p,d,q) consists of:

- p : Number of autoregressive terms
- d : Number of times the data has been differenced to achieve stationarity
- q : Number of moving average terms

ARIMA equation can be written as [1]:

$$Wt = \phi 1Wt - 1 + \phi 2Wt - 2 + \cdots + \phi pWt - p + et - \theta 1et - 1 - \theta 2et - 2 - \cdots - \theta qet - q$$

To perform forecasting using the ARIMA method, these are the steps :

1. Data Stationary Check
   The first step in ARIMA forecasting is to make sure the time series data is stationary. This is typically done using the Augmented Dickey-Fuller (ADF) test.
2. Differencing the data
   If the ADF test indicates the data is non-stationary, differencing is applied. This process is repeated until the data becomes stationary.
3. Model identification
   Once the data is stationary, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are analyzed. These plots help identify the potential AR (Autoregressive) and MA (Moving Average) orders for the candidate ARIMA models.
4. Parameter Estimation
   The parameters for each identified model are then estimated using the stationary data.
5. Diagnostic checking
   Before finalizing the model for forecasting, diagnostic test must be conducted to validate its adequacy:
   - Shapiro-wilk test: checks whether the residuals are normally distributed
   - Ljung-Box test: Assesses whether residuals are free from autocorrelation

   Both test should yield p-values greater than 0.05 to indicate that the assumptions are satisfied

6. Model selection
   From the estimated models, the best-fitting model is selected using evaluation metrics such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model with the lowest AIC or BIC value is generally preferred.
7. Forecasting
   Once the optimal ARIMA model is selected and validated, it can be used to forecast future values. The model generates point forecasts and confidence intervals (95%) for the future time periods. The forecasted values can be visualized alongside historical data to interpret trends and make decisions.

B. *Metric Evaluations*

1. The mean absolute percentage error (MAPE)
   Average value of the absolute forecasting errors as a percentage of the respective data value.

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

   Where, $\hat{y}_t$: Actual value
   y_t : Prediction value
   MAPE values can be interpreted into four categories, namely: <10% highly accurate, 10%-20% good, 20%-50% reasonable, >50% inaccurate [6].
2. The mean squared error (MSE)
   The mean squared error (MSE) defined as:

$$MSE = \sum_{t=1}^{n}\frac{(y' - y)^2}{n}$$

   Where, y': Prediction value
   y : Actual value
   n : Total data
   MSE is the measure most used when optimal forecasting models are being sought.
3. The mean absolute error (MAE)

$$MAE = \sum_{t=1}^{n} \frac{|y' - y|}{n}$$

4. The root mean square error

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(y' - y)^2}{n}}$$

C. *Information Criterion*

$$AIC = -2\log(maximum\ likelihood) + 2k$$

The value of k is given by $k = p + q + 1$ if the model includes an intercept (constant term), and $k = p + q$ if the intercept is excluded [7][8].

III. RESULT AND DISCUSSION

A. Data preparation

The data used in this study is Apple Inc. (AAPL) Stock historical price, recorded globally by Kaggle and Yahoo Finance from January 2024 to April 2025, totaling 53 data points. The dataset contains one observation per week or four observation per month. The dataset is processed using R studio and visualised in figure 1 below.

TABLE 1
Data of the AAPL stock price

Date	Close Price	Date	Close Price
26/04/2024	16930	01/11/2024	22291
03/05/2024	18338	08/11/2024	22696
10/05/2024	18305	15/11/2024	22500
17/05/2024	18987	22/11/2024	22987
24/05/2024	18998	29/11/2024	23733
31/05/2024	19225	06/12/2024	24284
07/06/2024	19689	13/12/2024	24813
14/06/2024	21249	20/12/2024	25449
21/06/2024	20749	27/12/2024	25559
28/06/2024	21062	03/01/2025	24336
05/07/2024	22634	10/01/2025	23685
12/07/2024	23054	17/01/2025	22998
19/07/2024	22431	24/01/2025	22278
26/07/2024	21796	31/01/2025	23600
02/08/2024	21986	07/02/2025	22763
09/08/2024	21624	14/02/2025	24460
16/08/2024	22605	21/02/2025	24555
23/08/2024	22684	28/02/2025	24184
30/08/2024	22900	07/03/2025	23907
06/09/2024	22082	14/03/2025	21349
13/09/2024	22250	21/03/2025	21827
20/09/2024	22820	28/03/2025	21790
27/09/2024	22779	04/04/2025	18838
04/10/2024	22680	11/04/2025	19815
11/10/2024	22755	18/04/2025	19698
18/10/2024	23500	25/04/2025	20928
25/10/2024	23141		

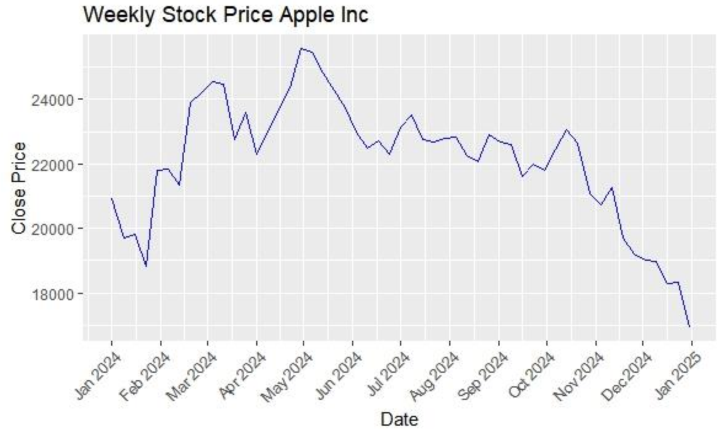

Figure 2. Graph of weekly AAPL stock price

B. Stationary Check

Before modeling, it is essential to test whether the time series is stationary using the **Augmented Dickey-Fuller (ADF) Test**. The result of the ADF test on the original data returned a **p-value is 0.122**, indicating that the data is **not stationary** which shown in figure 3. Figure 4 shows a clear upward trend, which supports this conclusion. To make the data stationary, **first-order differencing** was applied using the diff(data.ts) function in R Studio. After differencing with p-value obtained from the Augmented Dickey Fuller Test is 0.01084, the ADF test resulted in a **p-value < 0.05**, confirming that the data has become stationary. This implies that the **d (differencing order) = 1** in the ARIMA model.

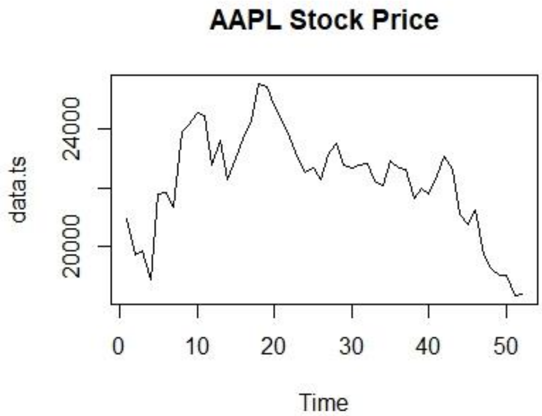

Figure 3. Plot of weekly AAPL Stock Price

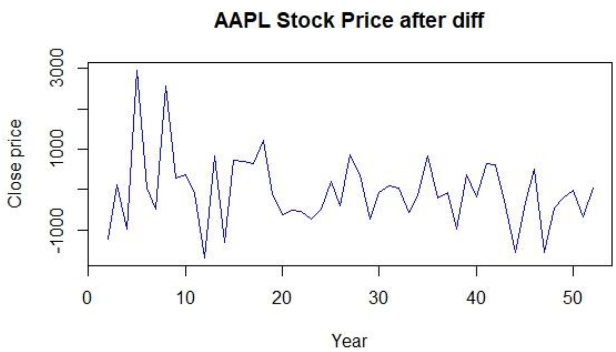

Figure 4. Plot of First Difference Weekly Stock Price of AAPL

C. Model Specification

The next step is to determine the values of **p (AR order)** and **q (MA order)** using the **Auto-Correlation Function (ACF)** and **Partial Auto-Correlation Function (PACF)** plots. Figure 5 shows the ACF and PACF after the first differencing.

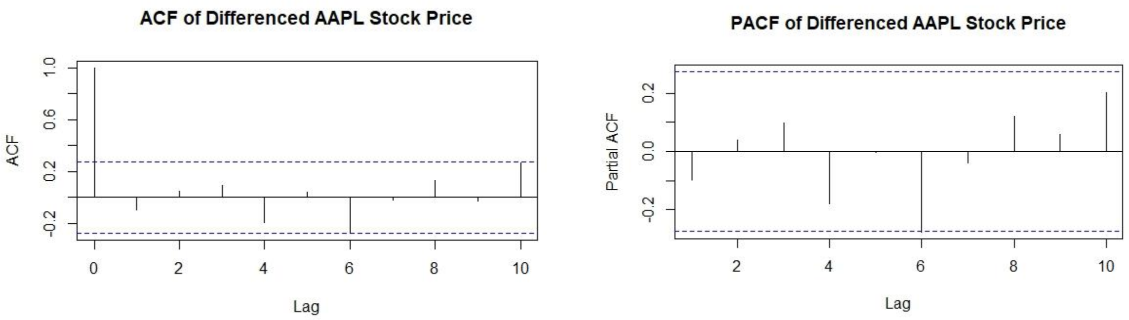

Figure 5. Plot of ACF and PACF First Difference of AAPL Weekly Stock Price

Based on the information provided by Figure 5, it can be observed that the PACF cuts off at lag 6, indicating the presence of an AR(6) component. Meanwhile, the ACF tails off gradually, supporting the choice of an autoregressive model. In table 2, All models are considered with p=6, d=1 and q=0 based on differencing and autocorrelation behavior.

TABLE 2
ARIMA Model Specification

No	ARIMA Model	p	d	q
1	ARIMA(0,1,0)	0	1	0
2	ARIMA(1,1,0)	1	1	0
3	ARIMA(2,1,0)	2	1	0
4	ARIMA(3,1,0)	3	1	0
5	ARIMA(4,1,0)	4	1	0
6	ARIMA(5,1,0)	5	1	0
7	ARIMA(6,1,0)	6	1	0

D. Parameter Distribution

The parameters of the Autoregressive (AR) formula are denoted as φ with order p. While the parameters of the Moving average (MA) formula are denoted as θ with order q. TABLE 3 shows that by using the summary(model) code, the value of each parameter as well as Log Likelihood and Akaike Information Criteration (AIC) can be obtained.

TABLE 3
Parameter Estimation for ARIMA Model

Model ARIMA	AR1	AR2	AR3	AR4	AR5	AR6	Log Likelihood	AIC
(0,1,0)							-417.83	837.65

(1,1,0)	-0.0965						-417.59	839.18
(2,1,0)	-0.0927	0.0399					-417.55	841.1
(3,1,0)	-0.0938	0.0490	0.0973				-417.31	842.63
(4,1,0)	-0.0489	0.0544	0.0924	-0.2279			-416.29	842.58
(5,1,0)	-0.0444	0.0506	0.0917	-0.2281	0.0222		-416.28	844.56
(6,1,0)	-0.0433	-0.0409	0.1554	-0.2057	0.0174	-0.4020	-413.1	840.2

E. *Residual Analysis*

Determining the best ARIMA model is performed using the Shapiro Test and the Ljung-Box Test. Through these tests, the ARIMA model with a p-value that exceeds 0.05 will be selected. TABLE 4 shows the results of the Shapiro Test and Ljung-Box Test and the ARIMA models that satisfy the condition. Models that passed the residual test will be forecasted and the error of each model will be calculated.

TABLE 4
Result of Residual Analysis

No	Model ARIMA	Shapiro Test	Ljung-Box Test	AIC	Result
1	(0,1,0)	0.004156461	0.6604875	841.1030	Not Passed
2	(1,1,0)	0.008043633	0.6627579	837.6518	Not Passed
3	(2,1,0)	0.008612706	0.7034365	839.1834	Not Passed
4	(3,1,0)	0.02306194	0.6688126	842.6251	Not Passed
5	(4,1,0)	0.03844299	0.9208532	842.5753	Not Passed
6	(5,1,0)	0.04013401	0.9178578	844.559	Not Passed
7	(6,1,0)	0.07717013	0.9877648	840.2002	Passed

F. *Forecast*

Using the ARIMA(6,1,0) model, we forecasted **8 weeks** of weekly AAPL stock price. The forecast results are shown in Table 5

TABLE 5
Forecasting Value of the ARIMA (6,1,0)

Date	Actual Data	Predicted Data	Lower Bound	Upper Bound
07-03-2025	23907	23352.54	23312.17	23392.90
14-03-2025	21349	21215.08	21167.47	21262.68
21-03-2025	21827	22206.86	22157.68	22256.04
28-03-2025	21790	22026.40	21973.12	22079.68
04-04-2025	18838	17954.78	17901.33	18008.23
11-04-2025	19825	19888.57	19829.07	19948.07
17-04-2025	19698	20829.32	20768.93	20889.71
25-04-2025	20928	20107.56	20043.22	20171.90

Based on forecasting value on TABLE 5, the best model for forecasting using ARIMA method can be determined by comparing the error. However, since the forecasting value only one, the error models shown below.

TABLE 6
Error Measured from ARIMA Model

Model ARIMA	MSE	RMSE	MAE	MAPE
ARIMA (6,1,0)	407833,1	638,6181	525,39875	2,6%

TABLE 6 shows that the ARIMA (6,1,0) is the effective model for forecasting the stock price of Apple Inc, the best model that is ARIMA (6,1,0) can be expressed in the form of equation as shown below.

$$w_t = -0{,}0433w_{t-1} - 0{,}0409w_{t-2} + 0{,}1554w_{t-3} - 0{,}2057w_{t-4} + 0{,}0174w_{t-5} - 0{,}4020w_{t-6} + e_t$$

Let,

$$w_t = Y_t - Y_{t-1}$$

Then the equation become

$$Y_t - Y_{t-1} = -0{,}0433(Y_{t-1} - Y_{t-2}) - 0{,}0409(Y_{t-2} - Y_{t-3}) + 0{,}1554(Y_{t-3} - Y_{t-4}) - 0{,}2057(Y_{t-4} - Y_{t-5}) + 0{,}0174(Y_{t-5} - Y_{t-6}) - 0{,}4020(Y_{t-6} - Y_{t-7}) + e_t$$

$$Y_t = Y_{t-1} - 0{,}0433(Y_{t-1} - Y_{t-2}) - 0{,}0409(Y_{t-2} - Y_{t-3}) + 0{,}1554(Y_{t-3} - Y_{t-4}) - 0{,}2057(Y_{t-4} - Y_{t-5}) + 0{,}0174(Y_{t-5} - Y_{t-6}) - 0{,}4020(Y_{t-6} - Y_{t-7}) + e_t$$

$$\boldsymbol{Y_t = 0,9567Y_{t-1} + 0{,}0024Y_{t-2} + 0,1963Y_{t-3} - 0,3611Y_{t-4} + 0,2231Y_{t-5} - 0,4194Y_{t-6} + 0,4020Y_{t-7} + e_t}$$

The accuracy of this model, as evidenced by an extremely low Mean Absolute Percentage Error (MAPE) of 2.6%, highlights the very good predictive stability of the model [6]. With such minimal forecast error, the model is an excellent tool for investors seeking to make fully informed buy or sell decisions. By accurately forecasting stock price direction, investors can optimize their portfolios more efficiently, better minimize risks, and boost overall investment performance. Further, organizations are able to incorporate these forecasts into financial planning and strategic initiatives, providing more responsive and fact-based responses to anticipated marketplace development. Figure 6 below shows the visualization plot of forecasting from ARIMA(6,1,0) of weekly stock price Apple Inc from 2024 to 2025.

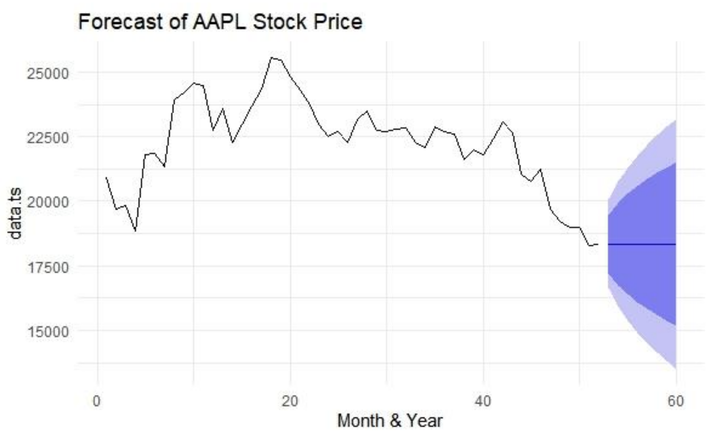

Figure 6. Forecasting Plot from ARIMA (6,1,0)

IV. CONCLUSION

This study explored the application of the ARIMA model, specifically ARIMA (6,1,0), in forecasting the weekly closing prices of Apple Inc. (AAPL) eight weeks ahead based on historical data of March to April 2025. The ARIMA approach was selected since it has been found to be effective in time series data modeling that has trends and autocorrelation. The model development followed the standard Box-Jenkins methodology, such as testing for stationarity, model identification through ACF and PACF plots, parameter estimation, and residual diagnostics. Among the several ARIMA models tested, ARIMA(6,1,0) was selected based on its passing of the Shapiro-Wilk and Ljung-Box tests, indicating that the residuals were normally distributed and not autocorrelated. The model also provided reasonable confidence intervals and stable forecas values throughout the forecasting period.

The forecasting ability shows that ARIMA(6,1,0) is able to capture short-term dynamic in Apple's weekly stock price, and thus is an effective tool for short-period financial forecasting. Although the model lacks external variables or volatility terms, its simplicity and interpretability are a benefit in situations where rapid and interpretable forecasting is required. This study confirms that the ARIMA model remains a sound and applicable methodology in financial time series analysis, especially where interpretability and statistical strength are prioritized above other factors.

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