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LQ45 Stock Price Forecasting: A Comparison Study of Arima(p,d,q) and Holt-Winter Method

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Abstract
The Holt-Winter method and ARIMA(p,d,q) are two frequently used forecasting techniques. When using ARIMA, errors are expected to be connected with earlier errors because it is based on data correlation with prior data (autoregressive) (moving average). The Holt-Winter model comes in two forms: Multiplicative and Additive Holt-Winter. No one has ever attempted to compare combined time series and cross-section data, despite many prior studies on ARIMA and Holt-Winter. This study will compare the Holt-Winter and ARIMA accuracy rates (p,d,q) in a combined time-series and cross-section dataset. LQ45 stock prices are used because they track the performance of 45 stocks with substantial liquidity, sizable market caps, and solid underlying businesses. We use dataset LQ45 stocks as training data in the range 2016–2021. We use data from January - February 2022 for the testing. In terms of time series data analysis, the terms indata are used for training data and outdata for forecasting test data. Daily stock closing data is used in this case: indata of 1458 and outdata of 39. The Mean Absolute Percentage Error (MAPE) method is used to gauge accuracy. This study contributes to MAPE exploration using a Boxplot diagram from cross-sectional data. The Boxplot diagram shows the MAPE spread, the MAPE's center point, and the presence of outliers from the MAPE of LQ45 stock. According to the findings of this empirical study, the average error rate for predicting LQ45 stock prices using ARIMA is 7,0390%, with a standard deviation of 7,7441%; for multiplying Holt-Winter, it is 29,3919%, with a standard deviation of 25,7571%; and for additive Holt-Winter, it is 18,0463%, with a standard deviation of 18,3504%. Apart from numerical comparisons, based on the Boxplot diagram, it can also be seen visually that the ARIMA MAPE (p,d,q) is more focused than Holt-Winter. In addition, in terms of accuracy distribution, it can be seen that the MAPE accuracy of the ARIMA method produces four outliers. Based on the MAPE accuracy rate, we conclude that Holt-Winter has a bigger error based on the MAPE value than ARIMA(p,d,q) at forecasting LQ45 stock prices.

Keywords— ARIMA(p,d,q), boxplot, Holt-Winter, LQ45, time-series

1 Introduction

A market for different long-term financial products is referred to as a capital market. They could be derivative instruments, equities, debentures, or other instruments. The capital market is crucial because it serves as a venue for individuals to engage in investment activities and organizations to obtain financial or capital support. Stock is one of the traded commodities. A company's stock might be viewed as evidence of ownership of its worth.

From an investment point of view, some popular investment instruments include gold, property, obligation, business unit, etc. Stock is also considered an investment instrument since it can give benefits [1]. In a developing country, stocks have an essential role in the nation's development [2]. The Indonesian index (IHSG) is a stock market exchange index used by BEI. It started to operate on 10 August 1982, with base prices of 100 and 13 stocks. More than 700 stocks are listed, and the number keeps growing.

Stock price forecasting is an essential activity for investors in the stock market. By utilizing a proper forecasting process, investors will have better input and support to decide and finalize transactions in the market. Regarding the LQ45 Minor Evaluation Index Announcement No. Peng-00315/BEI.POP/10-2020, we previously explored LQ45 equities using ARIMA [3]. According to a press release dated 25 January 2022, with the number Peng-00023/BEI.POP/01-2022, we will concentrate on LQ45 equities for the duration of this research, which spans August 2021 to January 2022. The criteria used to select the period (January to February 2022) as the forecasting period because that period is two consecutive months after six years of training data. January and February were also included in the training data, with L=12 months in that period.

ARIMA(p,d,q) and Holt-Winter are two forecasting techniques that are compared in this paper. This study wants to answer the following research question: Which method performs best compared to the accuracy rates of Holt-Winter and ARIMA(p,d,q), especially *In a combined time-series and cross-section dataset*? We then observed whether the approach is more suited for predicting the price of LQ45 stock after achieving the accuracy rate.

The Holt-Winter method and the ARIMA(p,d,q) model are two forecasting methods that are often used in forecasting problems. These two methods have exciting characteristics and are different in their use. There are three characteristics of the ARIMA model, namely:

- ARIMA is very good for non-stationary time series data but can be made stationary through a differencing process. It handles trends well but does not explicitly handle seasonality unless using the SARIMA model.
- The ARIMA(p,d,q) model offers flexibility through parameters p, d, and q, which can be tuned to handle autocorrelation and specific patterns in time series data.
- The ARIMA(p,d,q) model requires testing stationarity and autocorrelation assumptions, which can be more complex than Holt-Winters.

Meanwhile, the Holt-Winter method has the following characteristics:

- The Holt-Winter method is specifically designed for data that has consistent seasonal patterns. It handles level, trend, and seasonal components explicitly.
- Holt-Winters is more accessible to implement and interpret than ARIMA, especially for data with clear seasonal patterns.
- Holt-Winters typically has fewer parameters to estimate compared to ARIMA, so the model can be faster and easier to adjust

This study uses two approaches, namely a numerical approach, by comparing the average prediction accuracy in the dataset. Meanwhile, the second approach uses a Boxplot diagram to visually view the accuracy distribution from the ARIMA(p,d,q) model and two Holt-Winter methods (Additive H-W and Multiplicative H-W).

Some previous studies tried to compare Exponential Smoothing Holt-Winter and ARIMA(p,d,q) with all their values. Nowadays, those two methods are still often used in forecasting since they are easy and effective. Some of the previous research and objects used in past research will be outlined as follows:

- In 2017, Dwidayati, Sugiman, and Safitri researched the best forecasting model using Holt-Winter and ARIMA exponential smoothing. Because the Holt-Winter approach has a lower error rate than ARIMA (MAPE=9,40981%), they concluded that it performs better than the latter [4]. Fitria, Alam, and Subchan employed ARIMA and Double Exponential Smoothing to make a forecasting comparison in the same year. Again, this study found that ARIMA is inferior to exponential smoothing [5].
- Munarsih and Saluza did a new study in 2019 to predict the number of dengue fever cases in Palembang. They used Autoregressive Integrated Moving Average and Exponential Smoothing (ARIMA). ARIMA's MSE and MAE were the least in contrast to Exponential Smoothing (108077.877 and 172.424, respectively), making it better suitable to forecast the number of dengue fever cases in Palembang. [6]. Similar research on PT Indofood CBP Sukses Makmur Tbk (ICBP) and PT Indofood Sukses Makmur Tbk in 2020 by Malik, Juliana, and Widyasella (INDF). RIMA is better suited for INDF, while Double Exponential Smoothing is better suited for ICBP [7]. Using Amazon Sagemaker and Amazon Forecast to forecast rice prices in the Cipinang rice market [8] and the consumer index price in Ambon in 2022 were further instances where ARIMA outperformed other methods [9].

In additional studies, we discovered that Holt-Winter outperformed ARIMA [10] when it was used to predict the line of poverty in Central Java, Indonesia, patients with acute respiratory infection in Malang from 2017 until 2020 [11], the unemployment rate in Indonesia [12], white pepper prices in Pangkalpinang, Bangka Belitung [13], consumer price index in Tegal (Efrilia, 2021, number of consumers PT. AIA FINANCIAL LGP Sunrise Agency in 2022 [14], and forecasting in PT Suzuki Indomobil Motor [15].

We also found cases where Holt-Winter and ARIMA had similar performance when they were used to forecast the total population of Banyumas [21] and daily stocks in the health industry [16]. In most cases, previous work tried to compare ARIMA(p,d,q) and Holt-Winter to forecast one object, while in this research, we attempted to compare LQ45 stocks and other favorite stocks in BEI. Some contributions from this publication are:

(1) We use 45 different stocks that have other characteristics. This will allow us to see how well both methods are applied in each stock.
(2) This research compared the accuracy rate between ARIMA(p,d,q), multiplicative Holt-Winter, and additive Holt-Winter applied to LQ45 stocks using Kruskal-Wallis Rank Sum tests and MAPE as accuracy measurement displayed in the Boxplot diagram.
(3) Previous research usually uses time-series data, but this research tries to combine time-series data with cross-sectional data. Apart from looking at the MAPE comparison numerically (by looking at the average and median), this research also visually looks at the MAPE distribution based on the Boxplot diagram. With Boxplot, we can see the data center, data distribution, and data outliers.

1.1 Arima and Holt-Winter Model

Time-series data are frequently used in business or present decision-making, forecasting, and long-term planning [17]. Processes for making forecasts frequently make use of time-series data. The ARIMA model is a forecasting model that does not consider the independent variable. Only dependent variable values from the past and present are used by ARIMA to produce precise short-term forecasts [18]. A technique for forecasting that uses exponentially dropping weighting compared to historical observation values is known as exponential smoothing. Compared to earlier values, newer values are given a substantially higher weight. For the upcoming prediction, the forecasting procedure does not keep much data. Single exponential, double exponential, and triple exponential are the three varieties of exponential smoothing. Single exponential smoothing is used for data with a stable fluctuation (typical) pattern. Double exponential smoothing is used for data with a pattern (trend). Triple exponential smoothing is used for data with a cyclical repeating pattern. [19].

1.2 Arima(p,d,q)

Model identification, parameter estimation, and residual testing are the main ARIMA(p,d,q) phases [20]. Based on an autoregressive integrated moving average, or ARIMA, ARIMA(p,d,q) is referred to as the Box-Jenkins formula. [18]. Time-series data from ARIMA are converted into stationary using the AR(p), MA(q), and differencing processes up to d times. The Box-Cox transformation is then used to obtain stability in variance. The change is demonstrated in Formula 1.

$$yt = \begin{cases} \log(z_t) & , if\ \lambda = 0 \\ \frac{sign(z_t)(|z_t|^{\lambda}-1)}{\lambda}, & if\ not\ 0 \end{cases} \quad (1)$$

We used the inverse transformation to do forecasting, as shown in Formula 2.

$$zt = \begin{cases} \exp(y_t) & , if\ \lambda = 0 \\ sign(\lambda y_t + 1)(\lambda y_t + 1)^{1/\lambda} & if\ not\ 0 \end{cases} \quad (2)$$

The steps of this ARIMA(p,d,q) modeling are based on earlier work [3]. An ARIMA(p,d,q) model can be found by analyzing the ACF and PACF from the existing time-series data.

Moving Average (MA) model results indicate a relationship between residual values from the preceding time $at-k$ and y_t. θ_i is a coefficient that ranges from -1 to 1. MA (q) can be written as formula 3:

$$yt = \varepsilon t-\theta 1\varepsilon t-1-\theta 2\varepsilon t-2-\cdots-\theta q\varepsilon t-q \quad (3)$$

The Autoregressive (AR) model demonstrates a correlation between the values at time y_t and time y_{t-k} where $k = 1,2,3,..,n$, and where is ϕ is an AR coefficient model and ε_t is the residual at time t. AR (p) is written as formula (4):

$$yt=\phi 1yt-1+\phi 2yt-2+\cdots+\phi pyt-p+\varepsilon t \quad (4)$$

Differencing can be done by using the operator (1-B).

With operator Backshift (B):

$By_t = y_{t-1}$, $B(By_t) = y_{t-2}$, ...$y'_t = y_t - y_{t-1} = y_t - By_t = (1- B)\, y_t$ is called differencing 1

$y''_t = y_t - 2y_{t-1} + y_{t-2} = (1 -2B + B2)\, y_t = (1-B)^2 y_t$ is called differencing 2.

The notation for d in a differencing order is $(1-B)^d y_t$. The Kwatkowski-Phillips-Schmidt-Shin (KPSS) test is used to make series data stationary [21].

Autoregressive *Moving Average* ARMA (*p,q*) combines AR and MA models. In ARMA (*p,q*), ϕp represents an AR coefficient model, θ_q represents the MA coefficient, and ε_t represents a residual at time *t*. The following is a formula for the AR(*p)* and MA*(q*) mixed model in formulas 5, 6, and 7:

$$\phi p(B) yt = \theta q(B) \varepsilon t \quad (5)$$

Where:

$$\phi p(B) = 1 - \phi 1 B - \cdots - \phi p B p \quad (6)$$

$$\theta q(B) = 1 - \theta 1 B - \cdots - \theta q B q \quad (7)$$

Autoregressive *Integrated Moving Average* ARIMA(p,d,q) is a time series model that is not stationary to mean values and requires executing a differencing step to get stationery. Equation $(1-B)^d y_t$ is differentiated and applied to ARMA (*p,q*) to follow the ARIMA (*p,d,q*) stationary model. yt is the current time, ϕp is coefficient AR, B is the deviation order of *d,* θq is the coefficient of MA, while ε_t is residual on time *t*. ARIMA (*p,d,q*) can be written as formula 8.

$$\phi p(B)\, (1-B)d\ yt = \theta q(B) \varepsilon t \quad (8)$$

Table I [20] displays the AR(p) and MA(q) identification models based on ACF and PACF functions [3].

Table I. Ar(P) And Ma(Q) Identification Model

Model	**ACF**	**PACF**
MA (q)	Fast downtrend after lag q	Exponentially down / damped sinusoidal
AR (p)	Exponentially down / damped sinusoidal	Fast downtrend after lag p
ARMA (p,*q*)	Exponentially down / damped sinusoidal	Exponentially down / damped sinusoidal

We employ the Maximum Likelihood Estimator or least square estimator to estimate the parameters ϕ and θ. Such calculations are carried out automatically by software like Minitab, SAS, SPSS [19], and R [22]. In this research, we utilize an auto ARIMA packet modeled by Hyndman-Khandakar [23], while the residual test is conducted with residual data, which is the difference between the real data and predicted data as in Formula 9 [20].

$$\hat{\varepsilon}_t = y_t - \left(\hat{\delta} + \sum_{i=1}^{p} \hat{\varphi}_i\, y_{t-i} + \sum_{i=1}^{q} \hat{\theta}_i\, \hat{\varepsilon}_{t-i}\right) \quad (9)$$

We forecast using the expected value of $y_{T+\tau}$ with known previously known observation values of y_T , y_{T-1} , y_{T-2} … after receiving the model as shown in formula 10.

$$\hat{y}_{T+\tau}(T) = E[y_{T+\tau}: y_T\ , y_{T-1}\ , y_{T-2}\ , \dots] = \mu + \sum_{i=\tau}^{\infty} \Psi_i\, \varepsilon_{T+\tau-i} \quad (10)$$

Ψ is coefficient from AR and MA stated as a linear combination. Because $E[e_T(\tau)] = 0$ and $Var[e_T(\tau)] = \sigma^2 \sum_{i=0}^{\tau-1} \Psi_i{}^2 = \sigma^2(\tau)$, Using that variance, a confidence interval (1-α)% for prediction points may be created [21] [20].

1.3 Multiplicative and Additive Holt-Winter

Multiplicative Exponential Holt-Winter can be written as follows in formula 11 until formula 19 [24] [18]:

Typical/Average:

$$S_t = \alpha \frac{X_t}{I_{t-L}} + (1-\alpha)(S_{t-1} + b_{t-1}) \quad (11)$$

Slope (trend) over time:

$$b_t = \beta(S_t - S_{t-1}) + (1-\beta) b_{t-1} \quad (12)$$

Cyclical repeating (seasonality):

$$I_t = \gamma \frac{X_t}{S_t} + (1-\gamma) I_{t-L+m} \quad (13)$$

Forecasting:

$$F_{t+m}^{Multiplicative} = (S_t + b_t m) I_{t-L+m} \quad (14)$$

Multiplicative Holt-Winter is looking for value (α,β,γ), assume (α*,β*,γ *) that will minimize MAPE(α,β,γ) function with the following form:

$$MAPE_{(\alpha,\beta,\gamma)}^{Multiplicative} = \sum_{i=1}^{n} \left| \frac{A_i - F_{i,(\alpha,\beta,\gamma)}}{A_i} \right| \quad (15)$$

Value of (α*,β*,γ *) is used for the forecasting process, while for additive exponential Holt-Winter can be written as follows: [24] [18]:

Typical/Average:

$$S_t = \alpha(X_t - I_{t-L}) + (1-\alpha)(S_{t-1} + b_{t-1}) \quad (16)$$

Slope (trend) over time:

$$b_t = \beta(S_{t-1} - S_t) + (1-\beta) b_{t-1} \quad (17)$$

Cyclical repeating (seasonality):

$$I_t = \gamma(X_t - S_t) + (1-\gamma) I_{t-L} \quad (18)$$

Forecasting:

$$F_{t+m}^{Additive} = S_t + b_t m + I_{t-L+m} \quad (19)$$

where:
X_t= actual value for period t
α = smoothing constant for data (0 < α < 1)
β = smoothing constant for trend (0 < β < 1)
γ = smoothing constant for seasonal (0 < γ < 1)
S_t = smoothing value at period t
bt = trend smoothing value at period t
It = seasonal smoothing value at period t
L =length of a season
Ft+m = forecasting for m period since t.

In this paper, we use L=12, so 12 initial values for I are as follows:

$$I1 = \frac{X_1}{Avg(X_1, X_2, X_3, \ldots, X_{12})}, I2 = \frac{X_2}{Avg(X_1, X_2, X_3, \ldots, X_{12})}, I3 = \frac{X_3}{Avg(X_1, X_2, X_3, \ldots, X_{12})} \ldots, I12 = \frac{X_{12}}{Avg(X_1, X_2, X_3, \ldots, X_{12})}$$

Additive Holt-Winter is looking for value (α,β,γ), assume (α*,β*,γ *) that will minimize MAPE(α,β,γ) function with the following form as seen in formula 20:

$$MAPE_{(\alpha,\beta,\gamma)}^{Additive} = \sum_{i=1}^{n} \left| \frac{A_i - F_{i,(\alpha,\beta,\gamma)}}{A_i} \right| \quad (20)$$

Value of (α*,β*,γ *) is used for the forecasting process.

1.4 Forecasting Accuracy

We measure predicting accuracy using MAPE (Mean Absolute Percentage Error). A prediction scale for forecasting techniques in statistics, MAPE is often referred to as MAPD (Mean Absolute Percentage Deviation). In MAPE, accuracy is displayed as a ratio, as seen in Formula 21.

$$MAPE = \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right| \quad (21)$$

Where A_i represents the actual value, and F_i is the predicted value. In this study, we employ 34 data points collected over two months (January - February 2022). Because MAPE is sometimes represented as a percentage, we multiply the calculation above by 100%. The difference splits the actual value of Ai between Ai and F_i.

Finally, this paper is written as follows: firstly, in the introduction, this paper presents the research problems and questions that need to be solved. Secondly, in the literature review, this paper explains some of the state-of-the-art research about the methods we used and also writes the theoretical foundation we used in this paper. After that, we introduced the research methodology that we proposed. In the results and discussion, we state and discuss the research results. Finally, we give the conclusion in the final section.

2 Research methods

This study is being conducted using data from BEI (Indonesian's Stocks Exchange) via a securities company to produce meaningful interpretations for future science and capital markets. These two forecasting methods have different assumptions, so the preprocessing process is also different. Data preprocessing steps to increase productivity in the ARIMA model are: Collecting Data, handling Missing Values, dealing with Outliers, data standardization, Data transformation (Box-Cox), Trend detection and Removal, Stationarity Check with the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, splitting data into indata and outdata. Meanwhile, data preprocessing in the Holt-Winter method is Collecting Data, handling Missing Values, dealing with Outliers, data standardization, data decomposition, separating data components into trends, seasonality, and residuals using decomposition methods (additive or multiplicative), splitting data into indata and outdata.

The steps being used in this research are the following:

1. As a dataset or collection of training data for modeling, we retrieved LQ45 stocks for the previous six years (2016–2021). We used data from January and February 2022 for the testing.
2. For each LQ45 stock, the ARIMA(p,d,q) model was constructed (there are 45 LQ45 stocks). The following are the stages for creating the ARIMA model:
    a. Utilize Box-Cox transformation and differencing to validate stationary training data and resolve non-stationary training data..
    b. Choose the best ARIMA model by examining the ACF and PACF graphs in the training data set.
    c. Determine model parameters using information gathered from practice sets.
    d. Apply the Shapiro-Wilk test to residual analysis tests on training data.
    e. Select the model with the smallest AICc to use.
3. Create a useful ARIMA(p,d,q) model based on the options.
4. Apply ARIMA(p,d,q) for forecasting and base the accuracy rate calculation on the MAPE result (MAPE_1).
5. Create a multiplicative Holt-Winter model. This method was developed using parameter values ($\alpha^*,\beta^*,\gamma^*$) that will reduce MAPE _M from the model.
6. Make an additive Holt-Winter model. The creation of this model is based on parameter values ($\alpha^*,\beta^*,\gamma^*$) that will minimize MAPE_A from the model.
7. Begin forecasting with the multiplicative Holt-Winter technique and calculate the accuracy rate with MAPE. (MAPE_2) followed by additive Holt-Winter technique with MAPE (MAPE_3).
8. Create a boxplot to illustrate the precision of three forecasting techniques using the MAPE description. Perform the Kruskal-Wallis Rank Sum test to confirm the average similarity from the MAPE accuracy from the three approaches.

3 Results and Discussion

From modeling results and LQ45 stock forecasting, we can achieve several results.

The parameter adjustment process in the ARIMA model is:

1. Identify Integration Factors (d): First, determine the amount of differencing needed to make the data stationary. The stationarity test can be carried out using Kwiatkowski-Phillips-Schmidt-Shin (KPSS). If the data is not stationary, do differencing once (d=1) and test again. Repeat this process until the data becomes stationary.
2. Identify AR(p) and MA(q): After the data becomes stationary, identify the parameters p (autoregressive) and q (moving average) using the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots. The parameter p is identified from the PACF plot by looking for the lag where the PACF cuts off (becomes zero or approaches zero). The parameter q is identified from the ACF plot by finding the lag where the ACF cuts off.
3. Model Estimation: Use previously identified combinations of p, d, and q parameters to build multiple ARIMA models.

4. Model Evaluation: Evaluate each model using information criteria such as AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion). Choose the model with the lowest AIC or BIC value.
5. Iteration: Iterate by trying different variations of the parameters p, d, and q to find the best combination. Numerical computing methods such as grids or other parameter search techniques are used to simplify this process.

Finding lambda in the Box-Cox transformation is the first step in stabilizing variance from the entire data set. Each stock's Lambda value for the Box-Cox transformation is listed in Table I.

Table I. Box-Cox Transformation Value For LQ45 Stocks From 2016 – 2021

Stock Code	**Lambda Value**	**No**	**Stock Code**	**Lambda Value**
ADRO	0,3505583	24	INTP	0,8470147
AMRT	-0,2029994	25	ITMG	0,06121064
ANTM	-0.09419162	26	JPFA	0,1287421
ASII	0,919035	27	KLBF	1,999924
BBCA	-0,5795557	28	MDKA	-0,9999242
BBNI	1,092007	29	MEDC	-0,07062299
BBRI	0,322906	30	MIKA	1,020545
BBTN	0,7015581	31	MNCN	0,1742018
BFIN	0,4911407	32	PGAS	0,4097003
BMRI	1,031648	33	PTBA	0,14723
BRPT	-0,05377114	34	PTPP	0,4301648
BUKA	0,1234286	35	SMGR	1,232573
CPIN	-0,2178353	36	TBIG	-0,1947626
EMTK	-0,9999242	37	TINS	-0,1633053
ERAA	-0,7623531	38	TKIM	-0,1220211
EXCL	1,279385	39	TLKM	1,464463
GGRM	0,6287337	40	TOWR	-0,01857672
HMSP	0,384775	41	TPIA	0,2723973
HRUM	-0,2626412	42	UNTR	0,6066393
ICBP	-0,4448302	43	UNVR	0,9539936
INCO	0,009922585	44	WIKA	0,6735463
INDF	1,570633	45.	WSKT	0,5703537
INKP	-0,06689875			

The lambda value from Table I will be used to make ARIMA(p,d,q) modeling for LQ45, while Box-Cox inverse transformation is used for forecasting. We will use the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test in data stationary analysis. In this test, our first hypothesis is that the data will be stationary, and we will prove that the first hypothesis is wrong. The results are displayed in Table II.

Table II. KPPS value for LQ45 Stocks from 2016 – 2021

No.	**Stock code**	**KPPS Value**	**No.**	**Stock code**	**KPPS Value**
1.	ADRO	2.0198	24.	INTP	7.7023
2.	AMRT	12.9041	25.	ITMG	2.5284
3.	ANTM	8.6285	26.	JPFA	2.4400
4.	ASII	11.1044	27.	KLBF	0.9060
5.	BBCA	16.3603	28.	MDKA	0.9988
6.	BBNI	3.0307	29.	MEDC	12.2226
7.	BBRI	11.8263	30.	MIKA	2.7370
8.	BBTN	5.3741	31.	MNCN	11.0889
9.	BFIN	5.6816	32.	PGAS	12.3091
10.	BMRI	3.0602	33.	PTBA	3.5371
11.	BRPT	2.7113	34.	PTPP	15.8619
12.	BUKA	1.9369	35.	SMGR	1.2558
13.	CPIN	13.5926	36.	TBIG	6.8328
14.	EMTK	7.2037	37.	TINS	3.7621
15.	ERAA	16.538	38.	TKIM	12.7835

No.	Stock code	KPPS Value	No.	Stock code	KPPS Value
16.	EXCL	4.4497	39.	TLKM	5.5828
17.	GGRM	11.1552	40.	TOWR	7.4878
18.	HMSP	15.9567	41.	TPIA	12.2182
19.	HRUM	5.6511	42.	UNTR	2.9925
20.	ICBP	5.1523	43.	UNVR	9.6223
21.	INCO	10.6851	44.	WIKA	10.5584
22.	INDF	5.3529	45.	WSKT	13.6782
23.	INKP	10.9926			

The ARIMA(p,d,q) modeling for LQ45 will be performed using the lambda value from Table II and the Box-Cox inverse transformation. We performed the Kwatkowski-Phillips-Schmidt-Shin (KPSS) test for data stationary analysis. We will disprove the first hypothesis in this test, which states that the data will not be stationary. High test results for KPPS indicate that Ho is rejected or the data is not steady. LQ45 stocks, therefore, require a differencing method [3].

For each stock in LQ45, a functional ARIMA(p,d,q) model can be written as shown in Table III. We applied the Shapiro-Wilk test for the residual test. This test will determine whether or not the residual has a normal distribution.

Table III. Functional ARIMA(P, D, Q) Model For Forecasting After Differencing Process

No.	Stock Code	ARIMA Model
1.	ADRO	ARIMA(3,0,0)
	with AR coeficient : Φ1 = 0.0025, Φ2 =-0,0122 , Φ3= 0.0682 and there is no MA coeficient	
2.	AMRT	ARIMA(0,0,4)
	there is no AR coeficient and with MA coeficient : Θ1= -0.2097, Θ2=– 0.0545 , Θ3= 0.0275, Θ4=-0.0610	
3.	ANTM	ARIMA(3,0,1)
	with AR coeficient : Φ1 = 0.5149, Φ2 = – 0.0269 , Φ3 = 0.0887 and with MA coeficient : Θ1= - 0.4920	
4.	ASII	ARIMA(2,0,2)
	with AR coeficient : Φ1 = 1.2361, Φ2 = – 0.7171 and with MA coeficient : Θ1= – 1.2843 , Θ2 = 0.7089	
5.	BBCA	ARIMA(2,0,3)
	with AR coeficient : Φ1 =-1.4627, Φ2 = – 0.8225 and with MA coeficient : Θ1= 1.4077, Θ2 = 0.7114, Θ3= - 0.0455	
6.	BBNI	ARIMA(1,0,1)
	with AR coeficient : Φ1 =-0.6738 and with MA coeficient : Θ1= 0.7161	
7.	BBRI	ARIMA(2,0,1)
	with AR coeficient : Φ1 =-0.5148 , Φ2 = – 0.0706 and with MA coeficient : Θ1= 0.5607	
8.	BBTN	ARIMA(0,0,3)
	there is no AR coeficient and with MA coeficient : Θ1= 0.0377, Θ2 =- 0.0539 , Θ3=- 0.0958	
9.	BFIN	ARIMA(4,0,0)
	with AR coeficient : Φ1 =-0.0478 , Φ2= -0.0329, Φ3=-0.0763 , Φ4= -0.0424 and there is no MA coeficient	
10.	BMRI	ARIMA(5,0,0)
	with AR coeficient : Φ1 = 0.0196, Φ2 =-0.0796 , Φ3= 0.0042, Φ4=-0.0596 Φ5=0.0672 and there is no MA coeficient	
11.	BRPT	ARIMA(5,1,0)
	with AR coeficient : Φ1 = -0.7848 , Φ2 =-0.6409 , Φ3=-0.4745 , Φ4=-0.3261 , Φ5= -0,1608 and there is no MA coeficient	
12.	BUKA	ARIMA(0,0,0)
	there is no AR and MA coeficient	
13.	CPIN	ARIMA(2,0,0)
	with AR coeficient : Φ1 =-0.0123, Φ2 =-0.0759 and there is no MA coeficient	
14.	EMTK	ARIMA(4,0,0)
	with AR coeficient : Φ1 =-0.0485 , Φ2 =-0.0428 , Φ3= 0.0607, Φ4= -0.0699 and there is no MA coeficient	
15.	ERAA	ARIMA(0,0,0)
	there is no AR and MA coeficient	
16.	EXCL	ARIMA(0,0,2)
	there is no AR coeficient and with MA coeficient : Θ1= 0.0181, Θ2 =- 0.0662	
17.	GGRM	ARIMA(2,0,0)
	with AR coeficient : Φ1 = -0.0049 , Φ2 = -0.0605 and there is no MA coeficient	
18.	HMSP	ARIMA(0,0,2)
	there is no AR coeficient and nwith MA coeficient : Θ1= - 0.0401, Θ2 = - 0.1162	

19.	HRUM	ARIMA(1,0,3)
	with AR coeficient : Φ1 = 0,8500 and with MA coeficient : Θ1=– 0.7674 , Θ2 = - 0.0810,Θ3= 0.0477	
20.	ICBP	ARIMA(1,0,1)
	with AR coeficient : Φ1 = 0.7690 and with MA coeficient : Θ1= – 0.8534	
21.	INCO	ARIMA(4,0,1)
	with AR coeficient : Φ1 =-0.7539 , Φ2 = 0.0296, Φ3=-0.0071 , Φ4=- 0.0711 and with MA coeficient : Θ1= 0.8467	
22.	INDF	ARIMA(3,0,2)
	with AR coeficient : Φ1 =0.9891 , Φ2 =- 0.5546 , Φ3=- 0.0512 and with MA coeficient : Θ1= – 1.0590 , Θ2 = 0.5606	
23.	INKP	ARIMA(0,0,1)
	there is no AR coeficient and with MA coeficient : Θ1= 0.0520	
24.	INTP	ARIMA(0,0,0)
	there is no AR and MA coeficient	
25.	ITMG	ARIMA(4,0,0)
	with AR coeficient : Φ1 = 0.0752, Φ2 =-0.0054 , Φ3=-0.0607 , Φ4=-0.0586 and there is no MA coeficient	
26.	JPFA	ARIMA(1,0,1)
	with AR coeficient : Φ1 =-0.8921 and with MA coeficient : Θ1= 0.9178	
27.	KLBF	ARIMA(0,0,2)
	there is no AR coeficient and with MA coeficient : Θ1= - 0.1056, Θ2 =- 0.0864	
28.	MDKA	ARIMA(0,0,0)
	there is no AR and MA coeficient	
29.	MEDC	ARIMA(1,0,0)
	with AR coeficient : Φ1 =0.0524 and with there is no MA coeficient	
30.	MIKA	ARIMA(0,0,1)
	there is no AR coeficient and with MA coeficient : Θ1=- 0.1409	
31.	MNCN	ARIMA(0,0,0)
	there is no AR and MA coeficient	
32.	PGAS	ARIMA(0,0,0)
	there is no AR and MA coeficient	
33.	PTBA	ARIMA(4,0,0)
	with AR coeficient : Φ1 =-0.0197 , Φ2 =-0.0370 , Φ3= 0.0531, Φ4= 0.0565 and with there is no MA coeficient	
34.	PTPP	ARIMA(0,0,5)
	there is no AR coeficient and with MA coeficient : Θ1= 0.0920, Θ2 =-0.0361 , Θ3=- 0.0304, Θ4=-0.0056 , Θ5 =0.0738	
35.	SMGR	ARIMA(2,0,2)
	with AR coeficient : Φ1 = -1.1747 , Φ2 =- 0.9627 and with MA coeficient : Θ1=- 1.1665 , Θ2 = 0.9383	
36.	TBIG	ARIMA(1,0,0)
	y't = y't-1 + εt with AR coeficient : Φ1 = -0.115 and there is no MA coeficient	
37.	TINS	ARIMA(3,0,0)
	with AR coeficient : Φ1 = 0.0215, Φ2 =-0.0065 , Φ3=-0.0725 and there is no MA coeficient	
38.	TKIM	ARIMA(5,1,0)
	with AR coeficient : Φ1 =-0.7314 , Φ2 =-0.624 , Φ3=- 0.4639, Φ4= - 0.3268 , Φ5=-0.1764 and there is no MA coeficient	
39.	TLKM	ARIMA(0,0,2)
	there is no AR coeficient and with MA coeficient : Θ1= - 0.0735, Θ2 =- 0.1246	
40.	TOWR	ARIMA(0,0,1)
	there is no AR coeficient and with MA coeficient : Θ1= - 0.1582	
41.	TPIA	ARIMA(1,0,1)
	with AR coeficient : Φ1 = 0.8561 and with MA coeficient : Θ1=- 0.7952	
42.	UNTR	ARIMA(2,0,2)
	with AR coeficient : Φ1 = 1.1432, Φ2 = - 0.6044 and with MA coeficient : Θ1=- 1.2294 , Θ2 = 0.6450	
43.	UNVR	ARIMA(0,0,2)
	there is no AR coeficient and with MA coeficient : Θ1= - 0,0628, Θ2 =- 0,0840	
44.	WIKA	ARIMA(0,0,5)
	there is no AR coeficient and with MA coeficient : Θ1= 0,0352, Θ2 =- 0,0159 , Θ3= 0,0222, Θ4=0,0351, Θ5=0,0659	
45.	WSKT	ARIMA(1,0,1)
	with AR coeficient : Φ1 = -0,8142 and with MA coeficient : Θ1= 0,8544	

The p-value from the W Shapiro-Wilk test tends to be very small. A small p-value will bring us to H_o rejection. Based on this p-value, the residuals from each LQ45 stocks' ARIMA(p,d,q) model are generally not distributed. The results from MAPE of the ARIMA(p,d,q) model for LQ45 stocks are listed in Table IV.

Table IV. MAPE From LQ45 Stocks For Forecasting With ARIMA(P,D,Q) From January – February 2022

No	Stock code	MAPE_1 (%)	No	Stock code	MAPE_1 (%)
1	ADRO	2,4891	24	INTP	10,2056
2	AMRT	6,1157	25	ITMG	6,4557
3	ANTM	19,3077	26	JPFA	4,6945
4	ASII	2,5578	27	KLBF	2,9452
5	BBCA	4,1152	28	MDKA	3,5422
6	BBNI	8,1963	29	MEDC	11,6382
7	BBRI	3,6441	30	MIKA	3,4373
8	BBTN	2,9459	31	MNCN	4,3438404
9	BFIN	7,9614	32	PGAS	3,1555
10	BMRI	5.4917	33	PTBA	4,8828
11	BRPT	35,2175	34	PTPP	4,1644
12	BUKA	9,8937	35	SMGR	3,2376
13	CPIN	3,371	36	TBIG	3,0329
14	EMTK	16,351	37	TINS	4,5742
15.	ERAA	40.5597	38	TKIM	11,7987
16.	EXCL	5,2402	39	TLKM	4,9261
17.	GGRM	1,7965	40	TOWR	7,6566
18.	HMSP	2,7013	41	TPIA	11,9424
19.	HRUM	4.2328	42	UNTR	4,0235
20	ICBP	1,1542	43	UNVR	3,7997
21	INCO	3,0907	44	WIKA	3,8092
22	INDF	1,2108	45	WSKT	5,4738
23	INKP	5,3700			
	Averag				7.0390
	Stan. Dev.				7.7441
	Minimum				1.1542
	Maximum				40.5597
	Median				4.3438

The average predicting error rate for the LQ45 stock market is 7,0390%, with a standard deviation of 7,7441%, according to Table IV. The stock with the lowest forecasting error rate is ICBP, at 1,1542%. ERAA has the highest mistake rate, at 40,5597%.

Meanwhile, the parameter adjustment process in the Holt-Winter method is:

a. Level Components (St): This is the primary value of the time series over a certain period.
b. Trend Component (bt): It reflects base-level changes over time. Trends can be linear or exponential, depending on the model used.
c. Seasonal Component (It): It reflects recurring periodic patterns in the data. The seasonal component can capture fluctuations at fixed intervals, such as months, quarters, or years.

There is two Seasonal Component Types.

1. Seasonal Additives: used when the amplitude of the seasonal pattern does not change with changes in the level of the time series. The additive seasonal model is formulated using formula (19)
   a. Here, L is the seasonal period (in this case L=12).
   b. Multiplicative Seasonality: Used when the amplitude of the seasonal pattern changes with changes in the level of the time series. Typically used when seasonal variations increase or decrease in proportion to the data level. The multiplicative seasonal model is formulated in formula (14)
2. Update Equations: to update these components, the Holt-Winters method uses the following update equation:
   a. Levels: For the additive model, use formula (16), and for the multiplicative model, use formula (11)
   b. Trends: For the additive model using formula (17) and for the multiplicative model using formula (12)
   c. Seasonal: For the additive model using formula (18) and For multiplicative models using formula (13)
3. Here, α, β, and γ are smoothing parameters for level, trend, and seasonality whose values lie between 0 and 1.

Table V. MAPE From LQ45 Stocks Forecasting With Multiplicative Holt Winter (Three Parameters)

No	Stock code	MAPE_M	Alpha*	Beta*	Gamma*	MAPE_2
1	ADRO	0.213316	0.845154	0.567561	0.947116	0.701089
2	AMRT	0.064701	0.996327	0.404219	0.963305	0.07457
3	ANTM	0.291831	0.945983	0.34049	0.983805	0.622315
4	ASII	0.116846	0.828078	0.190731	1	0.181688
5	BBCA	0.060567	0.943174	0.21827	1	0.139268
6	BBNI	0.08167	0.939639	0.111494	1	0.132765
7	BBRI	0.064316	1	0.139931	1	0.026526
8	BBTN	0.146513	0.919976	0.225273	1	0.165632
9	BFIN	0.104938	0.953797	0.203993	1	0.348461
10	BMRI	0.08722	0.932521	0.173723	1	0.152146
11	BRPT	0.7194782	0.285438	0.732296	0.918305	0.7202829
12	BUKA	-	-	-	-	-
13	CPIN	0.100518	0.951087	0.036808	1	0.080856
14	EMTK	0.146823	1	0.050088	1	0.193269
15	ERAA	0.166873	0.826309	0.027428	1	0.127045
16	EXCL	0.155864	1	0.417165	1	0.868939
17	GGRM	0.085598	0.847692	0.122114	1	0.134332
18	HMSP	0.064609	0.813985	0.105718	1	0.093560
19	HRUM	0.287494	0.792108	0.319205	1	0.625383
20	ICBP	0.065276	0.886665	0.938446	1	0.105395
21	INCO	0.19762	0.860073	0.461496	1	0.536881
22	INDF	0.099904	0.848059	0.328466	1	0.224744
23	INKP	0.133942	0.98537	0	1	0.046197
24	INTP	0.110972	0.982915	0.203098	1	0.366563
25.	ITMG	0.230784	0.920641	0.421696	1	0.730655
26	JPFA	0.21897	0.935377	0.862827	1	0.572572
27	KLBF	0.073743	0.81383	0.762785	1	0.046837
28	MDKA	0.148499	1	1	0.6	0.106988
29	MEDC	0.272279	0.888576	0.171828	1	0.480080
30	MIKA	0.09484	1	0.173511	1	0.128144
31	MNCN	0.142246	0.990094	0.226936	1	0.049077
32	PGAS	0.133096	0.918125	0.094697	1	0.050641
33	PTBA	0.225956	0.920906	0.448911	1	0.673267
34	PTPP	0.118762	1	0.064307	1	0.059479
35	SMGR	0.094707	0.858018	0.230313	1	0.153583
36	TBIG	0.095125	1	0.116904	0	0.265652
37	TINS	0.273552	1	0.324257	0	0.623982
38	TKIM	0.208142	1	0.307968	0	0.378857
39	TLKM	0.074263	1	0.743141	0	0.076130
40	TOWR	0.081399	0.84485	0.380556	1	0.216716
41	TPIA	0.340231	0.999469	0.477791	1	0.921035
42	UNTR	0.101043	0.873607	0.365131	1	0.347587
43	UNVR	0.067357	0.823323	0.245346	1	0.071547
44	WIKA	0.117142	0.935809	0.096566	1	0.124987
45	WSKT	0.186199	0.922352	0.291782	1	0.186709
				Average		0.293919
				Stan. Dev.		0.257571
				Minimum		0.026526
				Maximum		0.921035
				Median		0.17366

Table V shows that the average error rate for LQ45 stock forecasting with multiplicative Holt-Winter is 29,3919% with a standard deviation of 25,7571%. The stock with the lowest forecasting error rate is BBRI, with 2,6526%, and the highest is TPIA, with 92,1035%. Stocks with code BUKA have no data since there are not enough data points to utilize the Holt-Winter method to examine them. The reason for that is that this issue has only recently begun its public sale.

Table VI. MAPE from LQ45 stocks for Forecasting with Additive Holt's Winter

No.	Stock code	MAPE_A	Alpha*	Beta*	Gamma*	MAPE_3
1.	ADRO	0.51681	0.998615	0.999243	0.929541	0.356037
2.	AMRT	0.078531	0.996327	0.404219	0.963305	0.057295
3.	ANTM	0.469717	1	1	0.98149	0.152867
4.	ASII	0.153808	1	0.128964	1	0.020360
5.	BBCA	0.09297	1	0.057645	0	0.083975
6.	BBNI	0.109617	1	0.328514	0.716185	0.069861
7.	BBRI	0.075632	0.997659	0	0.877319	0.023236
8.	BBTN	0.17169	1	0.284198	0.894098	0.087779
9.	BFIN	0.149985	1	0.137877	0.459011	0.302492
10.	BMRI	0.114792	1	0.065887	0.710885	0.089268
11.	BRPT	0.7138493	1	0.89828	0.716172	0.570583
12.	BUKA	-	-	-	-	-
13.	CPIN	0.100872	1	0.026227	0.371127	0.126400
14.	EMTK	0.135216	1	0.050777	0.461344	0.146575
15.	ERAA	0.165999	0.894904	0.046784	1	0.214206
16.	EXCL	0.256842	1	0.080842	0	0.537546
17.	GGRM	0.090966	1	0.068038	0	0.026512
18.	HMSP	0.062709	1	0.068353	0	0.038978
19.	HRUM	0.528493	1	0.293407	0	0.497907
20.	ICBP	0.111212	1	0.872769	0	0.051669
21.	INCO	0.378952	1	0.115802	0	0.333855
22.	INDF	0.133114	1	0.43437	0	0.016799
23.	INKP	0.13530	1	0.303016	0	0.038293
24.	INTP	0.107521	0.724879	0.180125	0.233924	0.211915
25.	ITMG	0.502274	1	0.209915	0.133982	0.465093
26.	JPFA	0.497734	1	0.172467	0.133982	0.301188
27.	KLBF	0.124731	1	0.029629	0.133982	0.026115
28.	MDKA	0.13138	0.967642	0.0144	0.128319	0.048563
29.	MEDC	0.345106	1	0.140636	0.136109	0.107358
30.	MIKA	0.107369	1	0.117131	0.136109	0.049534
31.	MNCN	0.154398	0.983381	0.10632	0.131327	0.205286
32.	PGAS	0.326437	0.203258	1	0	0.124197
33.	PTBA	0.45799	1	0.666032	0	0.364477
34.	PTPP	0.126474	1	0.069538	0	0.071132
35.	SMGR	0.086695	0.752819	0.266549	1	0.079208
36.	TBIG	0.094141	0.978392	0.091599	1	0.271617
37.	TINS	0.326472	1	0.222884	1	0.391288
38.	TKIM	0.249663	1	0	1	0.053835
39.	TLKM	0.121229	1	0.139124	1	0.021963
40.	TOWR	0.0877	0.789782	0.726943	1	0.057866
41.	TPIA	1.114483	1	0.150693	0.3692	0.830783
42.	UNTR	0.155473	0.312481	0.223841	0.151409	0.142438
43.	UNVR	0.068925	1	0.115226	0.144564	0.059078
44.	WIKA	0.149889	1	1	0.144563	0.074562
45.	WSKT	0.248583	1	1	0.144564	0.140402
		Averag				0.180463
		Stand. dev.				0.183504
		Minimum				0.016799
		Maximum				0.830783
		Median				0.098313

Table VI shows that the average error rate for LQ45 stock forecasting with additive Holt-Winter is 18,0463% with a standard deviation of 18,3504%. The stock with the lowest forecasting error rate is INDF, with 1,6799%, and the highest is TPIA, with 83,0783%. Tables IV, V, and Table VI summarize the results from three different MAPEs from three other forecasting methods in Table VII.

Table VII. Summary of MAPE for Three Forecasting Methods

Measurement	**ARIMA(p,d,q)**	**Multiplicative H-W**	**Additive H-W**
Average	0.070390	0.293919	0.180463
Stan. Dev.	0.077441	0.257571	0.183504
Minimum	0.011542	0.026526	0.016799
Maximum	0.405597	0.921035	0.830783
Median	0.043438	0.17366	0.098313

Based on VII, we can see that ARIMA(p,d,q) is the best method according to MAPE values to forecast LQ45 stocks—the three MAPE values visualization on a boxplot diagram in Figure 1. Figure 1 shows that ARIMA(p,d,q) and additive Holt-Winter give outlier MAPEs. Four MAPE outliers exist for ARIMA(p,d,q) and one outlier for additive Holt-Winter. Looking at the distribution, MAPE for ARIMA(p,d,q) tends to be centered, while multiplicative Holt-Winter spreads out. From the concentration size, ARIMA(p,d,q) has the lowest median with 0.042883, while multiplicative Holt-Winter has the highest median with 0.17366.
We use the Kruskal-Wallis test to test the similarity of the MAPE average from the three methods. Using R, we get a result of Kruskal-Wallis chi-squared = 38.118, df = 2, p-value = 5.282e-09**.** If we assume a significance level α = 0.05, the most suitable method is ARIMA(p,d,q), while multiplicative Holt-Winter performs the worst in accuracy based on MAPE values. Several factors may contribute to the suboptimal performance of the Holt-Winters model, viz inconsistent seasonal patterns, non-linear trends, seasonal increases or decreases, and the presence of outliers in the Data.

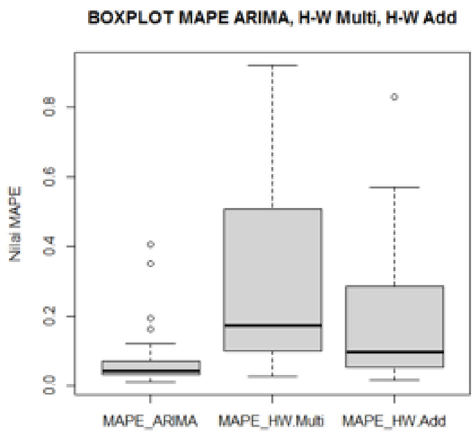

Figure. 1. MAPE Boxplot Diagram from 3 Forecasting Methods

Several limitations can affect the prediction results from examining the specific characteristics of LQ45 shares for forecasting purposes. Some of the main limitations may be encountered: high volatility, external factors, market liquidity, seasonal factors, economic cycles, and model assumptions.

Findings from research on forecasting methods, particularly in the context of LQ45 shares, have several important implications for practitioners and investors. Here are some of the deeper impact: There are several implications for practitioners, namely selecting the suitable model, handling volatile data with transformation and integration of external factors, and sentiment analysis and risk management. There are several implications for investors, namely more informed decision-making and better investment strategies

4 Conclusion

From this work, we can conclude:

1. The average error rate for LQ45 stock forecasting with ARIMA is 7,0390%, with a standard deviation of 7,7441%. The stock with the lowest forecasting error rate is ICBP, with 1,1542%, and the highest error rate is ERAA, with 40,5597%. This occurs because this stock tends to stay flat while the prediction leans up.
2. The average error rate for LQ45 stock forecasting with multiplicative Holt-Winter is 29,3919% with a standard deviation of 25,7571 %; the stock with the lowest forecasting error rate is BBRI with 2,6526 %, and the highest error rate is TPIA with 92,1035%.
3. The average error rate for LQ45 stock forecasting with additive Holt-Winter is 18,0463% with a standard deviation of 18,3504 %; the stock with the lowest forecasting error rate is INDF with 1,6799%, and the highest error rate is TPIA with 83,0783 %.
4. Based on the MAPE accuracy rate from two different forecasting methods, we conclude that Holt-Winter is less effective than ARIMA(p,d,q) at forecasting LQ45 stock prices.
5. For future research aimed at improving stock forecasting methods and overcoming existing limitations, the following suggestions can be considered namely: exploring other forecasting methods (Non-Linear Models, Deep Learning, Hybrid Models, or Bayesian Models), expanding the period and Stock Index, and External alternative Data Integration (with Sentiment Analysis or Natural Language Processing) and using Tool and Platform Development (software tools or automation for real-time stock forecasting)
6. Based on research findings on stock forecasting methods, especially in the context of LQ45 stocks, here are some practical applications and recommendations for investors: evaluate and adjust the strategy of the two models periodically and implement automatic procedures to update the dataset and model periodically with the latest data.

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