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Comparison of SARIMA Method, Holt-Winters Exponential Smoothing Method and Prophet Method in Inflation Data Forecasting

Desty Mayang Pratiwi[1], Atika Ratna Dewi[2*], Aina Latifa Riyana Putri[3]

[1,2,3] Data Science Study Program, Telkom University, Purwokerto Campus
Jl. D.I Panjaitan No.128, South Purwokerto, 53147, Central Java, Indonesia

E-mail Correspondence Author: *atikad@telkomuniversity.ac.id*

Abstract

This study aims to forecast inflation in Indonesia using three time series methods: SARIMA, Holt-Winters Exponential Smoothing, and Prophet, based on monthly inflation data from January 2014 to October 2024 obtained from Bank Indonesia. The research process included exploratory analysis, data preprocessing, model development, and accuracy evaluation using Mean Absolute Percentage Error (MAPE). The results show that the SARIMA(2,1,2)(1,0,1)$_6$ model achieved the best performance with a MAPE of 8.11%, outperforming Holt-Winters Exponential Smoothing (11.75%) and Prophet (52.85%). Therefore, SARIMA was selected as the optimal model for forecasting Indonesian inflation from November 2024 to April 2025. The forecasted inflation rates were 6.19%, 5.40%, 4.96%, 4.94%, 4.57%, and 4.58%, respectively. These findings indicate that the SARIMA model can provide reliable inflation forecasts to support economic policy and decision making. .

Keywords: *Forecasting, Holt-Winters Exponential Smoothing, Inflation, Prophet, SARIMA.*

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1. INTRODUCTION

Indonesia as a developing country with a large population, the majority of whom are in the productive and consumer age group, faces challenges in maintaining economic stability. One of the main challenges is controlling inflation, which has a broad impact on people's purchasing power and national economic stability. Bank Indonesia, as the monetary authority, implements an inflation targeting policy to prevent price spikes that can disrupt the economy, based on legal basis and long-term strategy[1].

Inflation is an important indicator in economic analysis because it affects the flow of funds, both in formal financial institutions such as banks and insurance companies, as well as in informal financial practices. Therefore, inflation forecasting is crucial in formulating effective monetary policy[2]. The Consumer Price Index (CPI) is the main indicator for measuring inflation in Indonesia, which is calculated based on changes in the average price of household goods and services using the COICOP classification[3]. External factors such as the weakening of the rupiah exchange rate against foreign currencies, especially the US dollar, often cause an increase in the price of imported goods and raw materials. This condition drives up domestic production costs and creates inflationary pressures. However, exchange rate depreciation also has the potential to increase export competitiveness, which can ultimately trigger inflation from the demand side[4].

Accurate inflation forecasting not only helps the central bank and government in formulating price control policies, but also benefits the business world and society in managing costs, wages, and investment[5]. Forecasting techniques are divided into two main categories, namely subjective qualitative methods and quantitative methods based on historical data. One of the widely used quantitative approaches is time series forecasting, which considers seasonal patterns, trends, and data stationarity[6].

Commonly used time series forecasting models include autoregressive, moving average, exponential smoothing, and SARIMA (Seasonal Autoregressive Integrated Moving Average) [7]. In addition, the Holt-Winters Exponential Smoothing method is also popular because of its ability to capture seasonal components and trends by giving more weight to the latest data[8]. Several previous studies have shown that the SARIMA model is effective for data with short-term seasonal patterns, while Holt-Winters Exponential Smoothing can be refined with optimization techniques such as golden section search to improve prediction accuracy[9].

In addition to these two methods, one of the modern methods that is starting to be widely used for time series forecasting is Prophet, developed by Facebook. Prophet is designed to handle data with strong seasonal patterns and long-term trends, and provides flexibility in handling missing data and trend changes automatically. Prophet also allows intuitive visualization and explicit annual seasonal modeling without having to perform complex data transformations. Prophet's ease of implementation and ability to handle non-stationary economic data make it a worthy alternative model to be compared with conventional methods in this study, with the novelty of this research being the comprehensive comparison of Prophet, SARIMA, and Holt-Winters Exponential Smoothing additive models for forecasting Indonesia's monthly inflation from January 2014 to October 2024 a combination of forecasting models and time period that, to the best of the authors' knowledge, has not been addressed in previous studies [10].

The novelty of this research lies in the comparative analysis of three time series forecasting methods from different paradigms, namely SARIMA, Holt-Winters Exponential Smoothing, and Prophet, for predicting Indonesian inflation using monthly data from January 2014 to October 2024. This study introduces an alternative six-month seasonal period in the SARIMA model, which reveals a seasonal structure that is rarely explored in previous studies that commonly apply a twelve-month period. In addition, the Holt-Winters model parameters were systematically optimized through 1000 combinations of α, β, and γ to improve forecasting accuracy. The inclusion of Prophet also provides insight into the performance of modern decomposable models on long-term macroeconomic data. Overall, this research contributes to the development of inflation forecasting methodology through cross-model comparison, alternative seasonal analysis, and evaluation of classical and modern forecasting approaches.

2. RESEARCH METHODS

2.1. Data Sources

This study employs a quantitative approach with a deductive framework by analyzing numerical data to explain and forecast inflation trends in Indonesia. The study uses secondary data consisting of monthly inflation rates in Indonesia from January 2014 to October 2024, obtained from the official website of Bank Indonesia. The dataset contains 130 observations representing monthly inflation percentages, where each observation corresponds to the inflation rate recorded in a particular month, while the values ranging from 1 to 130 represent the time index used for data sequencing and modeling purposes, not the inflation values themselves.

2.2. SARIMA (Seasonal Autoregressive Integrated Moving Average)

SARIMA is an approach in time series data analysis. SARIMA was developed as an extension of the ARIMA method. Seasonal patterns refer to the tendency of data to exhibit repetitive behavior over a period of time, usually annually in monthly data. SARIMA is specifically designed to handle time series data that has a seasonal pattern, by combining two main components: a non-seasonal component that uses the ARIMA model, and a seasonal component that is adjusted for a specific period[11]. In general, the general form of this model is stated as seasonal ARIMA or ARIMA(p, d, q)(P, D, Q)s.

$$\emptyset_p(B)\Phi_p(B^S)(1-B)^d(1-B^S)^D X_t = \theta_q(B)\,\Theta_q(B^S)_{e_t} \tag{1}$$

with:

e_t	: error
X_t	: Observation Value at Time-
$(1 - B)^d$:	: Mathematical operations of non-seasonal differencing
$\emptyset_p(B^s)^D$	: Mathematical Operations of Seasonal Differentencing
$\emptyset_p(B)$	: Autoregressive Operator = $(1 - \emptyset_1 B - \emptyset_2 B^2 - \ldots - \emptyset_p B^p)$
$\Phi_p(B^s)$:	: Seasonal Autogressive Operator = $(1 - \emptyset_1 B^s - \emptyset_2 B^{2s} - \ldots - \emptyset_q B^{Pq})$
$\Theta_q(B)$	: Moving Average Operator = $(1 + \Theta_1 B - \Theta_2 B^2 - \ldots - \Theta_q B^q)$
$\Theta_Q(B^s)$:	: Seasonal Moving Average Operator = $(1 - \emptyset_1 B^s - \emptyset_2 B^{2s} - \ldots - \emptyset_q B^{Qs})$

2.3. Holt Winters Exponential Smoothing

Holt-Winters Exponential Smoothing is a combination of Holt and Winters models, specifically designed to handle data with trend and seasonal patterns. This model combines exponential smoothing for levels, trends, and seasonality in time series data, so that it can predict more accurately for data that has seasonal variations and long-term trends. This method is applied to non-stationary data. The weighting in Holt-Winters Exponential Smoothing consists of three parameters: alpha, beta, and gamma (y), where alpha is used for the overall data parameter, beta for the trend parameter and gamma for the seasonal parameter[12].

$$\hat{S}_t = \gamma.\left(\frac{y_t}{\hat{L}_t}\right) + (1-y).\hat{S}_{t-m} \tag{2}$$

with:

$\hat{S}_t$: Estimated seasonality in period t

y_t : Actual value at period t

$\hat{L}_t$: Estimated level at period t

$\hat{S}_{t-m}$: Seasonality in the previous period is estimated by the seasonal cycle m

γ is a smoothing parameter for seasonality, which controls how quickly seasonality adjusts to changes in the data. The closer γ is to 1, the more seasonality is responsive to changes in the data and the closer it is to 0, the more stable the seasonality is.

2.4. Prophet

Prophet is a time series modeling method developed by Facebook and designed to handle non-linear trends that contain seasonal components, holidays, and sudden changes. Prophet is suitable for data with strong seasonal patterns, long-term trends, missing data, and outliers, and can work without the need for complex transformations or stationarity assumptions. The Prophet model is expressed in the form of an additive equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t) \tag{3}$$

with:

y = Forecast

g = Growth Trend

s = Seasonal Trend

h = Holiday Effect

ε = error

a. Trend Components

For data with a logistic trend (approaching the upper limit), Prophet uses the formula:

$$g(t) = \frac{c}{1+exp(-k(t-m))} \tag{4}$$

with:

c = Maximum Capacity

k = Growth Rate

m = Offset Parameter (time value when significant change occurs)

t = Time t

If the trend is linear, Prophet simply uses piecewise linear regression as an approximation to the trend. Seasonal Component

b. Prophet uses a Fourier series approach to capture annual seasonal patterns, which is formulated as follows:

$$s(t) = \sum_{n=1}^{N}(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n sin\left(\frac{2\pi nt}{P}\right)) \tag{5}$$

with:
P = Seasonal Period (e.g. 365.25 for annual)
N = Number of Fourier Components
a_n, b_n = Fourier Coefficients

The seasonality used can be annual, weekly, or daily, depending on the data and model configuration.

c. Holiday Effect

Prophet also allows for the manual addition of a holiday effect (h(t)) based on a set of important dates:

$$h(t) = \text{holiday effect for date } t, \text{ if } t \in D \tag{6}$$

with
D = set of past and future holiday dates
This effect is optional and is only used if the data is prone to spikes during holidays.

2.5. Evaluation

MAPE is a measure used to assess the level of error in data forecasting. MAPE calculates the average percentage error between the predicted value and the actual value, giving an idea of how much difference there is between the forecast and the actual value in percentage terms[13].

$$MAPE = 100 \times \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{7}$$

With:
$\hat{y}_i$: Forecasting value
y_i : Actual value
n : Amount of data

2.6. Research Flow

This research began with a literature review to gather various theories, concepts, and previous research findings relevant to time series forecasting and inflation analysis. Data collection included monthly Indonesian inflation data, which was then analyzed through preliminary data exploration to understand patterns, trends, and seasonal structures within the data. The next stage was preprocessing, which involved cleaning, transforming, and formatting the data to prepare it for use in modeling.

This research employed three forecasting methods: SARIMA, Holt-Winters Exponential Smoothing, and Prophet. In the SARIMA method, the process begins with identifying time series patterns through analysis of ACF and PACF plots. A stationarity test is then performed to determine whether the data requires differencing. If the data is non-stationary, transformation and differencing are performed until the stationarity requirement is met. The SARIMA model parameters are then determined based on the smallest AIC value, followed by parameter estimation and significance testing. The next stage involves checking residual assumptions to ensure the model's suitability, before finally verifying the model.

For the Holt-Winters Exponential Smoothing method, the modeling process begins with determining the initialization values for the level, trend, and seasonality. Then, the smoothing parameters, alpha, beta, and gamma, are determined. These values are then used to calculate the overall smoothing level and to perform parameter estimation and significance testing before the model is used in the forecasting process.

In the Prophet method, the first step is data cleaning and validation, followed by the construction of a Prophet model that includes trend, seasonality, and error components. Once the model is successfully constructed, the forecasting process can be performed based on the specified time horizon.

The three methods are then evaluated using MAPE values to determine the accuracy of each model. The model with the smallest MAPE value is selected as the best model, which is then used to formulate the final equation and perform the inflation forecasting process. The research concludes with the stage of compiling the forecasting results based on the best model obtained.

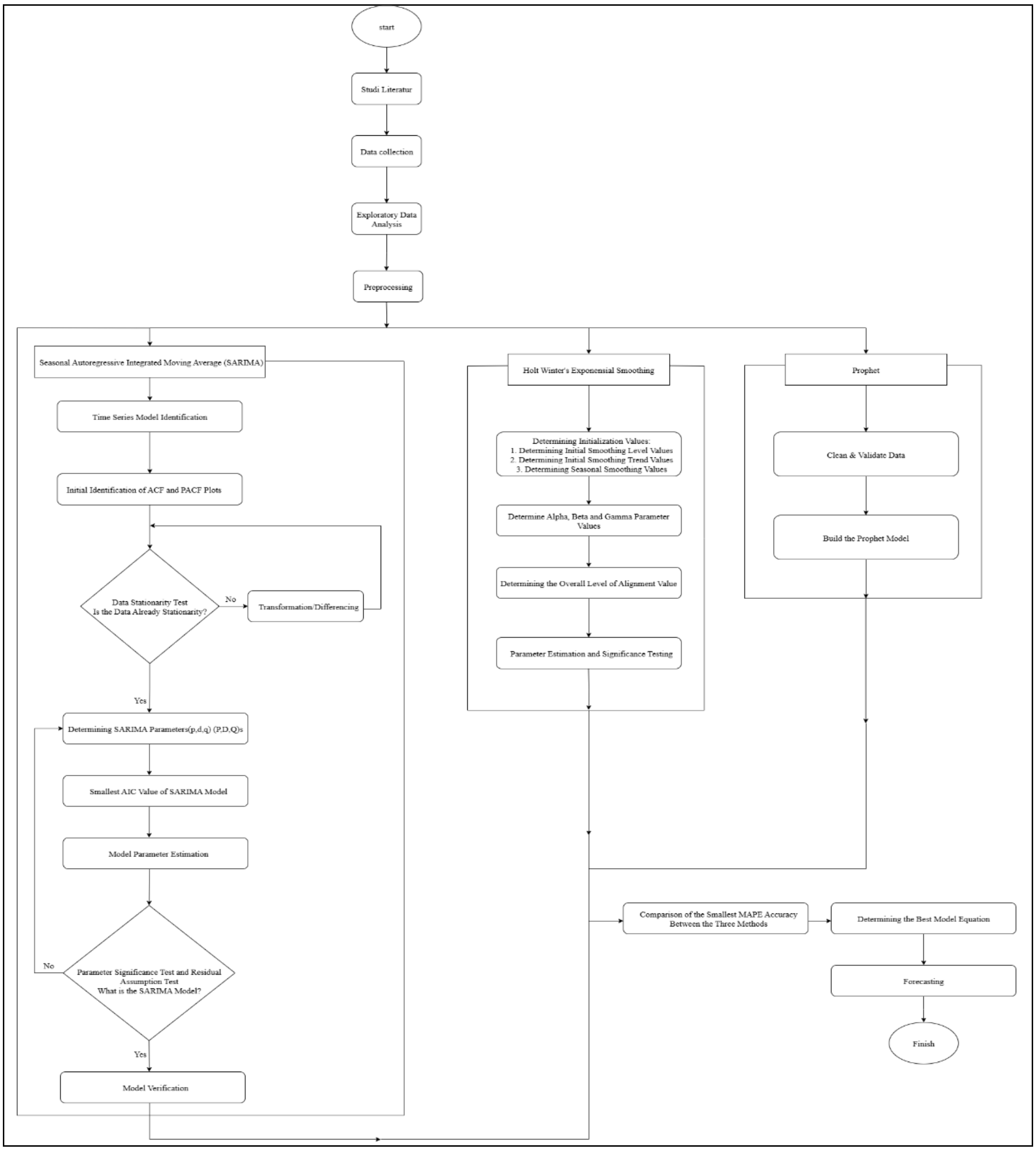

Figure 1. Research Flow Chart

Figure 1. shows the research flow comparing the SARIMA, Holt-Winters Exponential Smoothing, and Prophet methods. The research begins with a literature review, data collection, analysis, and preprocessing. The SARIMA method involves model identification, stationarity testing, parameter determination based on AIC, estimation, and model verification. The Holt-Winters method involves determining initialization values, alpha, beta, and gamma parameters, as well as estimation and significance testing.

The Prophet method includes model cleaning, validation, and building. The final stage is comparing the smallest MAPE values to determine the best model for forecasting.

The research process is carried out in several stages as follows:

1. Collection of monthly inflation data for Indonesia from January 2014 to October 2024 through the official website of Bank Indonesia.
2. Exploration of initial data through visualization of time series graphs and descriptive statistical analysis to see trends and seasonal patterns in the data.
3. Application of the SARIMA method, which includesv[14]:
    - The stationarity of the data is assessed using the Augmented Dickey-Fuller (ADF) test to determine whether differencing is necessary.
    - Model parameters are identified through the analysis of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.
    - The optimal combination of parameters (p,d,q)(P,D,Q) is selected based on the lowest Akaike Information Criterion (AIC) value.
    - Model estimation and parameter significance test.
    - Residual diagnostic test with Ljung-Box Test to ensure that the residuals do not have autocorrelation.
    - Forecasting inflation data for the next period using the SARIMA model.
    - Application of the additive Holt-Winters Exponential Smoothing (HWES) method[15], which consists of:
    - Determine the smoothing parameters alpha (α) for level, beta (β) for trend, and gamma (γ) for seasonality through the optimization process.
    - Initialize the initial values:
        a. Initial level (L_0) is calculated from the average value in the first seasonal cycle.
        b. Initial trend (T_0) from the average difference between periods in the cycle.
        c. nitial seasonal index (S_0) from the difference between the actual data and the initial level value per season.
    - Calculate the level, trend, and seasonality of each period iteratively using the additive Holt-Winters Exponential Smoothing formula.
    - Forecast for the next period.
4. Implementation of the Prophet method, consisting of:

    • Data pre-processing includes converting Indonesian month names to English format, removing invalid symbols or characters, and transforming time columns to Date format.

    • Creating a Prophet model by utilizing trend components (g), seasonality (s), and holiday effects (h) (if necessary), using an additive regression approach.

    • Adjusting seasonality settings according to data characteristics, such as activating annual seasonality and deactivating weekly and daily because the data is monthly.

    • Creating a future data horizon (forecasting window) for the next 6 months (November 2024 - April 2025).

    • Forecasting is done using the predict() function and the results are visualized with a trend graph and Prophet component decomposition

5. Evaluate the forecasting results of both methods using MAPE to assess the accuracy of the model. The model with the smallest MAPE value will be considered the best forecasting model.

3. RESULTS AND DISCUSSION

3.1. Identify Data Patterns

Analysis of time series data obtained from various points in time in the past to the present aims to make predictions based on patterns that can be recognized from historical trends. In this study, Indonesia's monthly inflation data from January 2014 to October 2024 was analyzed using an exploratory approach and time series modeling techniques. Four important components in identifying time series patterns include long-term trends, seasonal patterns, cyclical fluctuations, and random components. The initial step is carried out with an exploratory analysis using descriptive statistics to understand the basic characteristics of the data. Table 1 shows measures of central and dispersion of data such as minimum, maximum, mean, median, quartiles, and standard deviation. The mean value of 65.50 and the standard deviation of 37.67 indicate that the data variation is relatively large but still within a reasonable range. The minimum value of 1.00 and the maximum of 130.00 reflect a fairly wide range of data distribution.

Table 1. Descriptive Statistics

Descriptive Statistical Analysis	
Minimum Value	1.00
Maximum Value	130.00
Mean	65.50
Quartil 1	33.25
Median	65.50
Quartil 3	97.75
Standar Deviasi	37.6718286

Next, missing values were identified in the dataset. Based on the results of the examination, all data entries were filled in completely, so that the analysis process could be continued without the need for data imputation. Table 2 shows that all values have a FALSE status, which means that there is no empty or unfilled data. Inflation data that was originally a character type was converted to numeric form to facilitate further statistical analysis. The percentage symbol (%) was removed, then the data was converted to decimal by dividing it by 100. After the data was cleaned, the extraction process into time series format was carried out for the purposes of time series modeling. This data was then analyzed in monthly time series format starting in January 2014.

Table 2. Identify Missing Value

Data To -	Data Inflasi
1	False
2	False
3	False
4	False
5	False
.	.
.	.
.	.
128	False
129	False

The actual data visualization is presented in **Figure 2**, which shows the inflation fluctuations from year to year. There is a significant tendency for inflation to increase towards 2024, which is likely to be influenced by macroeconomic dynamics such as rising commodity prices, monetary policy, and global external factors.

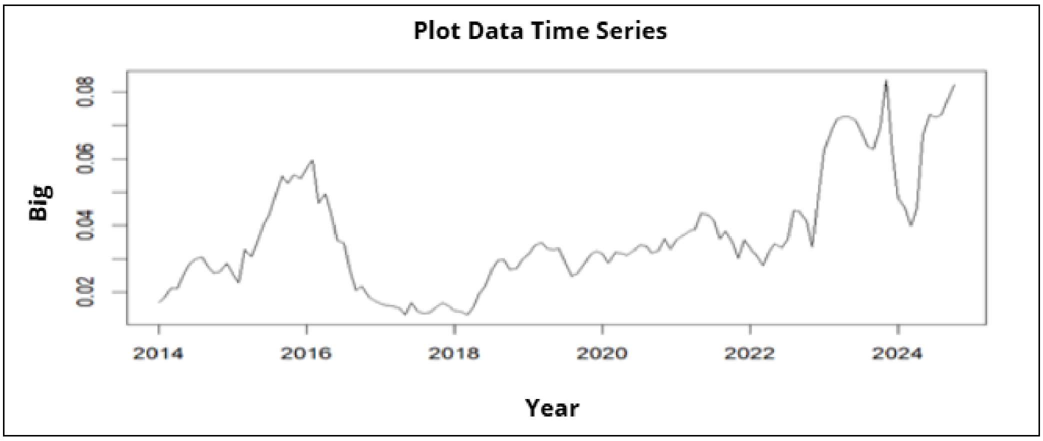

Figure 2. **Time Series Data Plot**

To identify the component structure in the data, time series decomposition was performed using the STL (Seasonal-Trend Decomposition using Loess) method. The decomposition results show that the inflation data has a long-term trend that changes gradually and a seasonal pattern that repeats every year. Figure 2 shows that inflation increased from 2015 to mid-2016, declined steadily until 2018, and increased again from 2022 to 2024. The remainder component shows relatively small random fluctuations, indicating that the model can capture the data structure well.

With clear seasonal patterns and trends, this monthly inflation data is suitable for analysis using time series methods that consider both components, such as Holt-Winters Exponential Smoothing (HWES) and Seasonal ARIMA (SARIMA).

3.2. Analysis Using the SARIMA Method (Seasonal Autoregressive Integrated Moving Average)

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is used in this study to model and forecast Indonesia's monthly inflation data from January 2014 to October 2024. The SARIMA model is chosen because of its ability to capture seasonal patterns and trends in time series data.

3.2.1. Identification of Data Patterns and Stationarity

Initial visualization of inflation data shows quite significant fluctuations with an annual seasonal pattern and a sharp upward trend since 2022. Initial tests using Augmented Dickey-Fuller (ADF) indicate that the data is not stationary (p-*value* = 0.5921). Therefore, a log transformation is carried out based on the Box-Cox estimation results (λ = -0.02743), followed by a two-time seasonal differencing process and one-time non-seasonal differencing.

Table 3. **Stationarity Test**

Test Type	Result	Description
Test ADF	Statistics = -1.9626 p-value = 0.5921	The data is not stationary on average (because p-value > 0.05)
Box-Cox Lambda Estimation	$\lambda = -0.02743$	Approaching zero, so the logarithmic transformation is considered the most appropriate

After transformation and differencing, the results of the ADF and Phillips-Perron tests showed a p-value < 0.05, which indicates that the data has met the stationarity assumption and is ready to be further processed using the SARIMA model.

3.2.2. Model Estimation and Selection

A total of 13 SARIMA models with various combinations of test parameters. The evaluation was carried out based on three main criteria, namely:

a. Parameter significance (p-value < 0.05)
b. Residual diagnostics (Ljung-Box test and Kolmogorov–Smirnov test)
c. Residual diagnostics (Ljung-Box test and Kolmogorov–Smirnov test)

Table 4. **Evaluation of SARIMA Model**

SARIMA Model	AIC	MAPE (%)	Description
(2,1,2)(1,0,1)6	-178.1972	8.11	All parameters are significant

The SARIMA$(2,1,2)(1,0,1)_6$ model was selected as the best forecasting model because all parameters were statistically significant (p-value < 0.05), the residuals satisfied the white noise and normality assumptions, and the model achieved the lowest MAPE with a competitive AIC value. In contrast, the Prophet model produced a substantially higher MAPE compared to SARIMA and Holt-Winters Exponential Smoothing. This result indicates that Prophet was less effective in capturing the relatively stable and limited seasonal patterns of Indonesian monthly inflation data. Although Prophet is designed to handle nonlinear trends and multiple seasonal components, its flexible decomposable structure may lead to overfitting or inaccurate trend estimation when applied to macroeconomic data with weak seasonal fluctuations and limited observations. Consequently, classical statistical models such as SARIMA were more suitable for modeling the characteristics of Indonesian inflation data in this study.

3.2.3. Residual Diagnostics

The Ljung-Box test was applied to the residuals of each model, with all resulting p-values exceeding 0.05, suggesting that the residuals exhibit white noise characteristics. Furthermore, the Kolmogorov-Smirnov test confirmed the normality of the residuals for all models, as indicated by p-values greater than 0.05. These findings imply that the evaluated models satisfy the fundamental assumptions required for time series analysis.

3.2.4. Model Evaluation

The accuracy of the model is tested using the Mean Absolute Percentage Error (MAPE) value. The best model, namely SARIMA(2,1,2)(1,0,1)$_6$, has a MAPE of 8.11%, which is considered very good because it is below the 10% threshold. This shows that the model is able to produce monthly inflation predictions with a low and consistent error rate. The SARIMA(2,1,2)(1,0,1)$_6$ model obtained in the form of the following operator:

$$(1-\emptyset_1 B - \emptyset_2 B^2)(1-\Phi_1 B^6)(1-B)Y_t = (1+\theta_1 B + \theta_2 B^2)(1+\Theta_1 B^6)\varepsilon_t$$

$$(1+9.4919B - 12.8118B^2)(1-2.6221B^6)(1-B)Y_t = (1+17.4820B + 17.7620B^2)(1+4.8970B^6)\varepsilon_t$$

3.3. Analysis Using Holt-Winters Exponential Smoothing Method

The additive Holt Winters Exponential Smoothing (HWES) method is used to forecast time series data that have constant trend and seasonal patterns from year to year. This model consists of three main components: level, trend, and seasonality, each of which is influenced by smoothing parameters α (alpha), β (beta), and γ (gamma).

3.3.1. Determination of Parameter Values α, β, and γ

To obtain the optimal parameter combination, an exploration of 1000 combinations of α, β, and γ values ranging from 0 to 1 was carried out. This procedure was implemented using automated looping in R Studio, with each parameter combination evaluated based on its Mean Absolute Percentage Error (MAPE) value.

Table 5. Parameters α, β and γ

Combination To	α	β	γ	MAPE (%)
908	0.8	0.1	1.0	11.75

Of all the combinations tested, the 908th combination with values α = 0.8, β = 0.1, and γ = 1 produced the smallest MAPE, namely 11.75371%, and was selected as the optimal parameters.

3.3.2. Model Evaluation and Overall Smoothing Value

Based on the best parameter combination, the final smoothing value for each model component is obtained as follows:

Table 6. Level, Trend and Seasonal Smoothing Values

Component	Mark
Level (St)	7.852963
Tren (bt)	1.595538
Seasonality (It)	$It_1 = 3.452479$, $It_2 = -1.305160$, ..., $It_{12} = 3.670372$

The smoothing value is entered into the following Holt-Winters Exponential Smoothing Additive prediction formula:

$$F_{(t+6)} = 0.07852963 + (0.001595538 \text{ x } 6) + (-1.888724)$$
$$F_{(t+6)} = 0.07852963 + 0.009573228 - 1.888724$$
$$F_{(t+6)} = -1.800621142$$

3.4. Analysis Using the Prophet Method

This study also applies the Prophet method as a comparison in forecasting monthly inflation in Indonesia. Prophet is an additive model based on trend, seasonal, and error decomposition, designed to handle time series data with nonlinear trends and annual seasonal patterns.

3..4.1. Data Pre-Processing

The initial step involves converting the time column to match the format recognized by Prophet. This process includes removing spaces, normalizing capitalization, and translating month names from Indonesian to English. Next, the parse_date_time() function from the lubridate package is used to convert the time data into Date format, and the results are stored in the ds column.

3.4.2. Modeling

The Prophet model is built using the prophet() function with two main components: ds (date) and y (inflation value). Because the data is monthly, the daily and weekly seasonal components are disabled (daily.seasonality = FALSE, weekly.seasonality = FALSE). Prophet automatically captures long-term trends and annual seasonal patterns without requiring explicit definition of seasonal patterns.

3.4.3. Forecasting and Visualization

Forecasting is done for the next six months (November 2024 – April 2025) using make_future_dataframe() with periods = 6 and freq = "month". The prediction results are obtained through the predict() function and visualized in a graph that depicts historical trends, future projections, and uncertainty intervals.

3.5. Selection of the Best Model

After all stages of evaluation are carried out, the selection of the best model is carried out based on the MAPE value. The following table presents a comparison of the MAPE values of the two models:

Table 7. Best Model Selection

Model	Parameter	MAPE (%)
SARIMA	(2,1,2)(1,0,1)6	8.107
Holt-Winters Exponential Smoothing	$\alpha = 0.8, \beta = 0.1, \gamma = 1$	11.754
Prophet	-	52.85

Based on the table above, the SARIMA(2,1,2)(1,0,1)$_6$ model shows the lowest MAPE value, which is 8.10%, compared to the additive Holt-Winters Exponential Smoothing model which has a MAPE value of 11.75%. This indicates that the SARIMA model has a better level of accuracy in forecasting monthly inflation. Meanwhile, the Prophet method produces a MAPE value of 52.85%, which indicates a higher level of prediction error. Thus, the SARIMA model is considered the most optimal model in this study, while Holt-Winters and Prophet are used as comparative methods to strengthen the analysis of the forecasting results.

3.6. Forecasting

The best SARIMA model is used to forecast inflation values for the period November 2024 to April 2025. The model parameters consist of:

a. Non-seasonal components: p = 2, d = 1, q = 2
b. Seasonal components: P = 1, D = 0, Q = 1

c. Seasonal period: s = 6

The forecasting process is carried out by data differentiation, the use of seasonal/non-seasonal AR and MA parameters, logarithmic scale back transformation, and iterative prediction. The forecasting results are presented in the following table:

Table 8. Inflation Forecasting

Month	Year	Forecast Results (%)
November	2024	6.19
Desember	2024	5.40
January	2025	4.96
February	2025	4.94
March	2025	4.57
April	2025	4.58

Forecasts show a downward trend in inflation from late 2024 to early 2025, with the highest value predicted in November 2024 at 6.19%.

3.7. Comparison Visualization

To strengthen the analysis of the prediction results, a visualization comparing the actual data with the predictions using the best model was performed. This visualization aims to demonstrate the model's ability to follow historical inflation patterns over time. The comparison graph demonstrates whether the model produces predictions that closely approximate the actual values, particularly in areas with high data levels, rising trends, and seasonal changes. Furthermore, this visualization helps assess the model's consistency in capturing dynamic data, providing additional evidence that the selected model is appropriate based on quantitative evaluation criteria such as MAPE and AIC. The following graph presents a comparison between actual data and forecast results to demonstrate the model's ability to replicate Indonesia's historical inflation patterns.

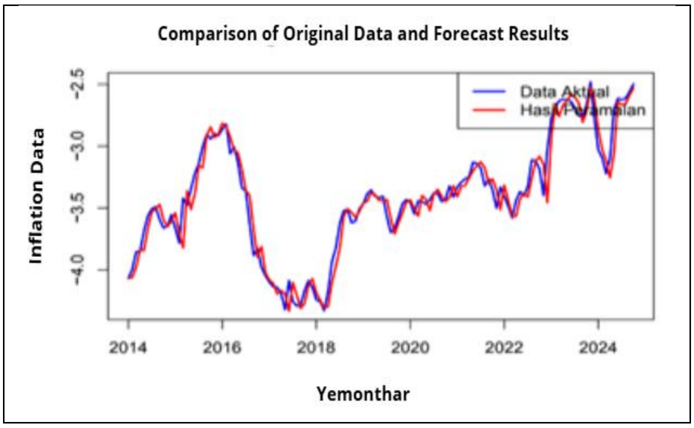

Figure 3. Comparison Chart

The graph shows that the SARIMA model is able to follow the historical data trend pattern and provide consistent predictions during the forecasting period. This finding aligns with previous studies, as reported by Azzahrah et al. [9] and Dewi et al. [15], which also found that SARIMA outperformed other time series models in capturing seasonal patterns and achieving lower forecasting errors for economic indicators. Similar to the results obtained by Muslihin and Ruchjana [5], the SARIMA model in this study demonstrated strong adaptability to short-term seasonal variations and fluctuating trends, resulting in a low MAPE value (8.11%). These consistent findings across different datasets and application domains reinforce the robustness of SARIMA as a reliable method for forecasting economic time series data.

4. CONCLUSION

This study compares three time series forecasting methods, namely SARIMA, Holt-Winters Exponential Smoothing (additive), and Prophet, to predict monthly inflation in Indonesia. The results of the analysis show that the SARIMA$(2,1,2)(1,0,1)_6$ model is the most superior model based on parameter significance, adequate residual diagnostic test results, and low AIC values. This model is able to capture seasonal patterns and fluctuating trends in inflation data with a high level of accuracy, as indicated by the MAPE value of 8.11%. On the other hand, although the additive Holt-Winters Exponential Smoothing method produces optimal smoothing parameters ($\alpha = 0.8$; $\beta = 0.1$; $\gamma = 1$), the MAPE value of 11.75% indicates lower accuracy compared to the SARIMA model. Thus, SARIMA is considered more effective for forecasting monthly inflation in Indonesia. In addition to the two methods, this study also applies the Prophet method as an alternative to the additive decomposition-based approach. Prophet automatically models annual trends and seasonality from historical data. However, the evaluation results show that Prophet produces a MAPE of 52.85%, indicating that its accuracy is much lower than SARIMA and Holt-Winters Exponential Smoothing. Therefore, although not used as the main model, Prophet still plays a role as a comparison in enriching the analysis and providing additional insights related to inflation trend modeling. Forecasting using the SARIMA model for the period November 2024 to April 2025 produces estimated inflation rates of 6.19%, 5.40%, 4.96%, 4.94%, 4.57%, and 4.58%, respectively. With a higher level of accuracy, this model can be used as a reliable tool in supporting fiscal and monetary policy making to maintain price stability and national economic growth.

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