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# Predicting Monthly Inflation Trends in Indonesia: An ARIMA Approach

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***ABSTRACT***

Inflation is the decline in the value of paper money due to the rapid increase in the amount of money in circulation, which leads to rising prices of goods. Inflation is a key indicator in a country's economy. Inflation instability can disrupt the economic decisions of businesses and the public, making accurate predictions essential. Monthly inflation data from January 2021 to October 2024, obtained from Bank Indonesia, is analyzed using the ARIMA model. This model is chosen for its statistical efficiency in forecasting time series data. The aim of this study is to predict Indonesia's inflation rate from November 2024 to May 2025 using the ARIMA (Autoregressive Integrated Moving Average) method.

**Keywords:** forecasting; inflation rate; ARIMA

## INTRODUCTION

According to the KBBI (Indonesian Dictionary), inflation refers to the decrease in the value of money (currency) due to the rapid circulation of money (currency), leading to an increase in the prices of goods. Inflation is a key indicator in a nation's economy, where stable and controlled inflation rates are essential for maintaining economic and financial stability. It remains a common issue faced by developing countries (Dinureja *et al.*, 2024). Inflation negatively impacts the majority of the population. To mitigate and anticipate these losses, society and all economic actors must be capable of recognizing the signs and trends of past inflation events (Suparmono, 2018). High and unstable inflation reflects economic instability, characterized by continuous increases in the prices of goods and services, which can ultimately elevate poverty levels. As inflation rises, it becomes increasingly challenging for people to meet their daily needs due to escalating prices, contributing to the growing poverty rate. According to data from data.worldbank.org, inflation in Indonesia has fluctuated year by year.

In 2021, inflation stood at 1.6%, a relatively stable figure. The low inflation rate in 2021 was linked to domestic demand (total consumption plus gross domestic investment) during the first three quarters, although it was higher than in 2020, it remained lower than in 2019. Weak domestic demand led to underutilization of economic capacity, resulting in stable or declining prices (Ikhsan, 2021).

The sharp rise in inflation in 2022 was influenced by several factors, including shortages of cooking oil and the implementation of a fixed price policy for cooking oil in January 2022, increased demand during the Eid al-Fitr holiday, and extreme weather anomalies in some regions in June 2022 that resulted in crop failures in horticulture producing centers. The adjustment of subsidized fuel prices in September 2022 also contributed to this, with Pertalite increasing by 30.72%, subsidized diesel by 32.04%, and Pertamax by 16%. The Christmas and New Year holidays further exacerbated the rise in commodity and transportation prices (Prima, 2023). The decrease in inflation to 3.7% in 2023 reflects the effectiveness of government policies in controlling prices. However, it is important to note that excessively low inflation is often seen as an indication of weakened consumer spending. Although inflation plays a role in economic growth, overly low inflation can signal problems within the economy, such as declining consumption activity (Damayanti, 2024).

Previous research conducted by Ayu Nurjannah titled "Monthly Inflation Rate Projection in DIY Using ARIMA Model" concluded that forecasting with ARIMA is a viable short-term prediction alternative, yielding fairly good and accurate results. The output forecasting indicated a tendency for stable positive increases, albeit relatively gradual (Nurjannah, 2024). Additionally, research conducted by Melyani *et al.* in the journal "Inflation Forecasting in Indonesia Using Autoregressive Moving Average (ARMA) Method" found that this model produced inflation forecasts for May to December 2021, ranging from 0.1% to 0.3%. The graphical pattern of the predictions aligned with actual data patterns, indicating that the model is suitable for use (Melyani *et al.*, 2021). Therefore, the author is interested in conducting research titled "Predicting Monthly Inflation Trends in Indonesia: An ARIMA Approach." This study aims to predict Indonesia's inflation rate from November 2024 to May 2025.

## METHOD

The method employed for this prediction is the ARIMA (Autoregressive Integrated Moving Average) model. Commonly known as the Box-Jenkins method, ARIMA is used for short-term forecasting with the assumption that the time series data must be stationary, meaning that the average variation of the data remains constant (Yunita, 2020). The ARIMA method utilizes an iterative approach to identify the existing model. The data used consists of Indonesia's inflation data from January 2021 to October 2024 (monthly data), obtained from the Bank Indonesia website (bi.go.id). This data is expected to facilitate the prediction of inflation rates in Indonesia for the period from November 2024 to May 2025.

Once the inflation data is collected, several analytical steps are necessary to forecast the inflation rate using Stata software. Stata is a comprehensive and integrated statistical software that provides tools for data processing, analysis, and graphical representation (Basri *et al.*, 2024). The initial step involves determining the stationarity of the data. Data stationarity is a crucial assumption that must be satisfied in forecasting. Stationarity can be classified into two categories: stationary data and non-stationary data (Salwa *et al.*, 2018).

Time series data often exhibit certain patterns, including trends that can influence the analysis results. If these trends are not properly addressed, the analysis risks producing biased forecasts (Prasada, Dhamira, & Nugroho, 2021). Therefore, it is essential to ensure that the data is stationary before proceeding to the forecasting analysis, as non-stationary data properties can impact the validity of the model used and diminish prediction accuracy. If the stationarity condition is not met in the mean, differencing is applied (Landa *et al.*, 2024). This step is critical to ensure that inflation rate predictions can be made more accurately and reliably.

Stationarity testing is conducted using the Augmented Dickey-Fuller (ADF) unit root test. The ADF test is used to check the stationarity of data (Naya *et al.*, 2024). If the data is found to be stationary based on the results of this test, it can then be analyzed further in the forecasting process. The mathematical representation of the ADF stationarity test is as follows:

$\Delta P$t = a0 + $\gamma P$t-1 + $\sum j\ i$=1 $a1\Delta P$t-i+1 + $\varepsilon$t

Description:

| | |
|---|---|
| Pt | : The first difference of inflation at time ( t ). |
| $P$t-1 | : The inflation value in the previous month or period ( t-1 ). |
| $\sum j\ i$=1 $a1\Delta P$t-I | : The sum of the lagged first differences of inflation data, utilized to address the autoregressive effects within the data. |

The ADF test is crucial for ensuring that the data to be used meets the necessary criteria for analysis with forecasting models. Once the data is confirmed to be stationary, the next step is to conduct the forecasting analysis to achieve better and more reliable results. This study utilizes the ARIMA (Autoregressive Integrated Moving Average) technique for forecasting. This model combines the AR (Autoregressive) and MA (Moving Average) components (Nugroho, *et al.*, 2022). Mathematically, the ARIMA formula can be expressed as follows:

$$Z_t = \delta + \Phi_1 Z_{t-1} + \Phi_2 Z_{t-2} + \varepsilon_t - \Theta_1 \varepsilon_{t-1} - \Theta_2 \varepsilon_{t-2}$$

Description:

| | |
|---|---|
| $Z_t$ | : The inflation value in month ( t ). |
| $Z_{t-1}$ , $Z_{t-2}$ | : The inflation values in the previous months. |
| $\varepsilon_t$ | : The residual for month ( t ). |
| $\varepsilon_{t-1}$ , $\varepsilon_{t-2}$ | : The residuals from the previous months. |
| $\Phi1,\Phi2$ | : AR coefficient. |
| $\Theta1,\Theta2$ | : MA coefficient. |

Following the confirmation of stationarity, the optimal ARIMA model was determined. Various models were considered, with their orders (p, d, q) selected based on the analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots (Figures 2 and 3). Model selection was then based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which penalize models for excessive complexity. Lower AIC and BIC values indicate a better fit to the data, considering both the model's explanatory power and its parsimony. After evaluating several candidate models, the ARIMA (2,1,2) model was selected due to its lowest AIC and BIC values, implying a superior balance between model fit and complexity. Further details on the model selection process and criteria values are provided in Table 3.

## RESULT AND DISCUSSION

The inflation data displays the monthly inflation rates from January 2021 to October 2024, with a noticeable increase in inflation during 2022, peaking at 5.95% in September 2022, before declining in the following years. The sharp rise in inflation in 2022 can likely be attributed to several factors, including the shortage of cooking oil, the implementation of a fixed price policy for cooking oil in January 2022, increased demand during the Eid al-Fitr holiday which raised food commodity prices, and adverse weather conditions in some regions in June 2022 that led to crop failures in key horticultural production areas. Additionally, adjustments to subsidized fuel prices may have contributed (Prima, 2023). The decrease in inflation observed in 2023 and 2024 may be influenced by tighter monetary policies and stabilization of energy prices, which have helped alleviate inflationary pressures.


Source: Data processed (2024)

**Figure 1.** Inflation in Indonesia

**Table 1.** Inflation Rate in Indonesia

| Month | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|
| January | 1,55 | 2,18 | 5,28 | 2,57 |
| February | 1,38 | 2,06 | 5,47 | 2,75 |
| March | 1,37 | 2,64 | 4,97 | 3,05 |
| April | 1,42 | 3,47 | 4,33 | 3,00 |
| May | 1,68 | 3,55 | 4,00 | 2,84 |
| June | 1,33 | 4,35 | 3,52 | 2,51 |
| July | 1,52 | 4,94 | 3,08 | 2,13 |
| August | 1,59 | 4,69 | 3,27 | 2,12 |
| September | 1,60 | 5,95 | 2,28 | 1,84 |
| October | 1,66 | 5,71 | 2,56 | 1,71 |
| November | 1,75 | 5,42 | 2,86 | - |
| December | 1,87 | 5,51 | 2,61 | - |

Source: Data processed (2024)

Inflation fluctuates monthly, showing a sharp increase in 2022 compared to 2021, followed by a gradual decline in 2023 and 2024. In 2022, inflation rose significantly from 2.18% in January to 5.95% in September. However, this trend reversed in 2023 and 2024, with a consistent decrease, particularly in the second half of 2024.

**Table 2.** Results of Stationarity Test for Inflation Variables (DI)

| Variable | Stage | Test-Statistic | P-value | Interpolated Dickey-Fuller | | |
|---|---|---|---|---|---|---|
| | | | | 1% | 5% | 10% |
| Inflation (DI) | Level | -1.019 | 0,7641 | -3.61 | -2.99 | -2.60 |
| Inflation (DI) | 1st Difference | -5.927 | 0,0000 | -3.62 | -2.94 | -2.60 |

Source: Data processed (2024)

The data above presents the results of the stationarity test using the Dickey-Fuller test on the inflation variable (DI) in two stages: at level and first difference. At the level, the test statistic

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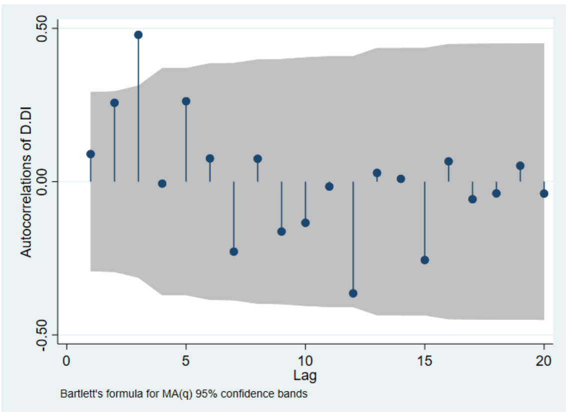
value is -1.019, while at the first difference, the test statistic value is -5.927. The inflation variable is non-stationary at the level because it tends to follow a trend pattern or exhibits variability that changes over time. However, after applying the first difference, the inflation data becomes stationary.

Stationarity is crucial in time series analysis to ensure that the relationships between the variables in the model are stable and that the estimation results are not biased or inefficient. At the level stage, the test statistic value (-1.019) is greater than the critical values at the 1%, 5%, and 10% significance levels (which are -3.61, -2.99, and -2.60, respectively). This indicates that at the level, the inflation variable is non-stationary. However, after applying the first difference, the test statistic value becomes -5.927, which is less than the critical values at all significance levels. This shows that after differencing, the inflation variable becomes stationary, meaning that the Dickey-Fuller test indicates stationarity at the first difference.

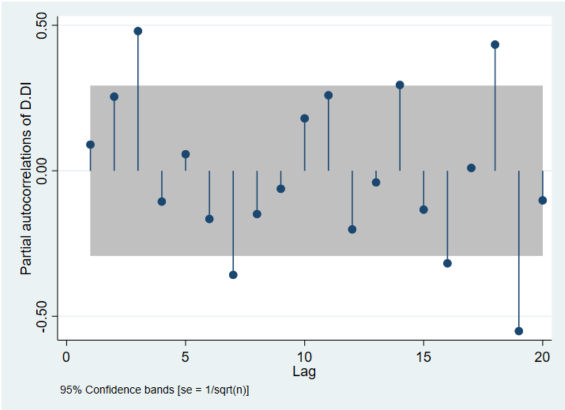
Once the stationarity of the inflation variable (DI) is well established, the next step is to determine the AR and MA orders to construct an appropriate ARIMA model. The process of determining the AR and MA orders will lead to the emergence of alternative ARIMA models that can be utilized. The AR order (p) can be identified from the autoregressive (AR) process, while the MA order (q) is determined from the moving average (MA) process. The analysis results indicate that several alternative ARIMA models arise from this process. The appropriate ARIMA model can be identified using several indicators, namely BIC (Bayesian Information Criterion), AIC (Akaike's Information Criterion), ACF (Autocorrelation Function), and PACF (Partial Autocorrelation Function) (Nugroho *et al.*, 2022).




Source: Data processed (2024)

**Figure 2.** ACF Plot for Inflation in Indonesia

Autocorrelation Function (ACF) plot of the differenced inflation rate. Significant autocorrelation at lags 1 and 2 suggests a potential autoregressive component of order 2 (AR(2)). The decay in autocorrelations beyond these lags supports the selection of the ARIMA(2,1,2) model.




Source: Data processed (2024)

**Figure 3.** PACF Plot for Inflation in Indonesia

Partial Autocorrelation Function (PACF) plot of the differenced inflation rate. The significant partial autocorrelation at lag 2, coupled with a rapid decay thereafter, further supports the selection of an autoregressive component of order 2 (AR(2)) for the ARIMA(2,1,2) model.

The Autocorrelation Function (ACF) describes the relationship of each observation with its previous values across various lags (Fadhilah *et al.*, 2024). The Partial Autocorrelation Function (PACF) serves to identify the correlation between two observation values at different lags after removing the influences of previous lags (Fadhilah *et al.*, 2024). Furthermore, among the several alternative models available for forecasting, it is essential to determine the best model to ensure robust predictions. Based on the four available indicators—BIC (Bayesian Information Criterion), AIC (Akaike's Information Criterion), ACF (Autocorrelation Function), and PACF (Partial Autocorrelation Function)—the ARIMA (2,1,2) model has been identified as the optimal choice.

**Table 3.** Results of AIC and BIC Tests

| Model | df | AIC | BIC |
|---|---|---|---|
| ARIMA(2,1,2) | 6 | 41.17 | 52.01 |
| ARIMA(2,1,1) | 5 | 45.81 | 54.73 |
| ARIMA(1,2,0) | 3 | 58.94 | 64..29 |
| ARIMA(2,0,1) | 4 | 53.68 | 60.99 |

Source: Data processed (2024)

The Akaike's Information Criterion (AIC) is utilized to select the best model by considering the number of parameters within the model. A lower AIC value indicates a better and more suitable model (Machmudin and Ulama, 2012). Similarly, the smallest value of the Bayesian Information Criterion (BIC) also indicates the best model (Muzaki, Agustina, and Timur, 2024). The ARIMA (2, 1, 2) model is chosen as the optimal model due to its lower AIC and BIC values compared to other models, such as ARIMA (2, 1, 1), ARIMA (2, 0, 1), and ARIMA (1, 2, 0).

Moreover, the analysis of the ACF curve shows that the residuals from the ARIMA (2, 1, 2) model are stable and fall within the 5% confidence interval. A similar observation can be noted in the PACF curve, where the residuals from the ARIMA (2, 1, 1) model also exhibit stability within the same confidence limits. Table 4 presents the significance of the parameters for the ARIMA (2, 1, 1) model, which further reinforces these findings.

**Table 4.** ARIMA Model for Inflation in Indonesia

| Variable | Coefficient | Std.Error | t-Statistic | Prob. |
|---|---|---|---|---|
| Constant | -0.004 | 0.122 | -0.04 | 0.969 |
| AR(1) | 1.157 | 0.192 | 6.02 | 0.000 |
| AR(2) | -0.386 | 0.184 | -2.10 | 0.036 |
| MA(1) | -1.345 | 0.135 | -9.90 | 0.000 |
| MA(2) | 0.869 | 0.145 | 5.99 | 0.000 |
| Sigma | 0.326 | 0.039 | 8.25 | 0.000 |
| Log likelihood | -14.585 | | | |
| F-Statistic | 274.93 | | | |
| Prob.(F-Statistik) | 0.0000 | | | |

Source: Data processed (2024)

Once the ARIMA model is established, the next step is to forecast inflation in Indonesia. The results of this forecasting can be seen in Table 5 as follows.

**Table 5.** Forecast Results of Inflation in Indonesia

| Periode | Inflation Forecast |
|---|---|
| November 2024 | 1.47% |
| December2024 | 1.38% |
| January 2025 | 1.36% |
| February 2025 | 1.38% |
| March 2025 | 1.40% |
| April 2025 | 1.42% |
| May 2025 | 1.43% |

Source: Data processed (2024)

The monthly inflation forecast from November to May indicates relatively stable figures, ranging from 1.36% to 1.47%. The highest inflation is expected in November at 1.47%, while the lowest is projected for January at 1.36%. This projection is likely influenced by various factors, including historical patterns, seasonal trends, and both domestic and global economic developments.

The period from November to May typically reflects seasonal dynamics, such as a surge in consumption leading up to the end of the year and potential fluctuations in food prices. Additionally, monetary policy and movements in international commodity prices can also play a role in shaping these projections. After peaking in November, inflation is anticipated to decrease slightly in December (1.38%) and continue to decline until reaching its lowest point in January. However, beginning in February, inflation is predicted to gradually increase until May. Despite minor variations, this forecast suggests that inflation will remain controlled within a relatively narrow range, indicating a degree of stability throughout this period.

## CONCLUSION

Based on the analysis of inflation data in Indonesia from January 2021 to October 2024 and projections for the period from November 2024 to May 2025 using the ARIMA (2, 1, 2) model, it can be concluded that Indonesian inflation exhibits a fluctuating trend, with a significant increase in 2022 due to both global and domestic factors such as supply chain disruptions and rising energy prices. However, inflation began to stabilize and decline in 2023 and 2024, aided by tighter monetary policies and a recovery in economic conditions.

The inflation forecast for November 2024 to May 2025 indicates relatively stable figures within the range of 1.36% to 1.47%, with the highest inflation predicted for November 2024 at 1.47% and the lowest in January 2025 at 1.36%. This projection suggests that inflation during this period is expected to be well-controlled, with minimal variability. Such stability is crucial for supporting sustainable economic growth.

Table 3 presents a comparison of the AIC and BIC values for several candidate ARIMA models. The ARIMA(2,1,2) model demonstrates substantially lower AIC (41.17) and BIC (52.01) values than alternative specifications such as ARIMA(2,1,1), ARIMA(2,0,1), and ARIMA(1,2,0), confirming its selection as the optimal model. The lower values for these information criteria indicate the ARIMA(2,1,2) provides the best balance between a satisfactory model fit and parsimony. The significant parameters of the ARIMA(2,1,2) model (shown in Table 4) further support its appropriateness.

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