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Evaluating multiple time series models for consumer price index forecasting to support national defense decision-making

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Abstract

Price stability, as reflected in the Consumer Price Index (CPI), plays a crucial role in supporting economic resilience and national defense readiness. This study evaluates multiple time series forecasting models, including Error-Trend-Seasonal (ETS), Holt, Holt–Winter, SARIMA, SARIMAX with exogenous variables, and hybrid approaches combining Holt/Holt–Winter with SARIMA, to identify the most accurate method for predicting Indonesia's CPI. Monthly data from 2017–2022 were analyzed using a training–testing split, and forecasting accuracy was assessed based on RMSE. The results show that the Holt–Winter model outperforms all other approaches, achieving the lowest RMSE value of 1.9159. Residual diagnostics confirm that the Holt–Winter model effectively captures trend and seasonal patterns, with errors behaving close to white noise. These findings highlight the superiority of Holt–Winter in providing reliable CPI forecasts, offering significant implications for economic policy formulation and strategic planning in the context of national resilience.

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INTRODUCTION

National resilience is a multifaceted concept encompassing political, social, military, and economic dimensions (Ballada et al., 2022; Goodwin et al., 2023). Among these pillars, economic resilience plays a crucial role as the foundation for stability and defense readiness. A robust economy ensures the availability of resources, smooth logistics, and the government's ability to respond to crises or external threats without compromising defense functions (Li et al., 2020). One of the primary indicators for assessing economic resilience is price stability, reflected through the Consumer Price Index (CPI) (Mohamed, 2020; Shinkarenko et al., 2021). Significant fluctuations in the CPI can affect household purchasing power, government budget allocations, and strategic planning within the context of national defense.

Research by (Nguyen et al., 2023) highlights the importance of forecasting the CPI, showing that accurate predictions can effectively support economic policy formulation and national development. However, CPI is influenced by long-term trends, seasonal fluctuations, and external factors such as trade conditions, exchange rates, and fiscal policies, making its behavior complex and often non-linear. Traditional forecasting methods, such as Autoregressive Integrated Moving Average (ARIMA) have limitations in capturing non-linear patterns and the simultaneous effects of external factors (Huang et al., 2020; Thiruchelvam et al., 2021; Xiao & Su, 2022). This underscores the need for more advanced approaches to improve prediction accuracy. Therefore, this research

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aims to evaluate various CPI forecasting methods—both traditional and hybrid—focusing on improving prediction accuracy to better support economic and national defense decision-making.

Exponential Smoothing approaches, such as Error-Trend-Seasonal (ETS) (Khan et al., 2022; Wang et al., 2020), are widely applied in time series forecasting due to their ability to adaptively capture level, trend, and seasonal patterns. ETS variants, including Holt's linear trend method, efficiently model linear trends, while Holt–Winters extends this capability to capture recurring seasonal fluctuations. These methods have proven effective for short- to medium-term forecasting when data exhibit relatively stable seasonal patterns (Ahmar et al., 2023; Trull et al., 2020). In addition to exponential smoothing, ARIMA models are commonly employed in time series analysis. While ARIMA effectively captures autocorrelations in different data, it does not explicitly account for seasonality. Seasonal Autoregressive Integrated Moving Average (SARIMA) was developed to address this limitation by incorporating seasonal components, enabling simultaneous modeling of long-term trends and seasonal variations (Wanjuki et al., 2022). Wanjuki et al. (2022) demonstrated that SARIMA can accurately forecast food and beverage price indices, although prediction errors tend to increase over longer horizons. SARIMA can be further extended to Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX), which integrates external factors—such as economic indicators, trade conditions, or fiscal policies—to improve predictive accuracy (Banaś & Utnik-Banaś, 2021). Banaś & Utnik-Banaś (2021) showed that SARIMAX can capture seasonal fluctuations and business cycles, thereby enhancing short-term forecasts of commodity prices. Despite its flexibility, SARIMAX still has limitations in capturing rapidly changing short-term patterns and adaptive seasonal trends. Therefore, hybrid approaches combining exponential smoothing with SARIMA, such as Holt–SARIMA and Holt–Winters–SARIMA, have been developed. These hybrid models leverage the adaptive trend and seasonal capture of Holt/Holt–Winters together with SARIMA's strength in modeling residual autocorrelations and stationary seasonal structures, thereby significantly enhancing CPI forecasting accuracy.

This study aims to evaluate and compare various CPI forecasting methods, including traditional models such as SARIMA and SARIMAX, as well as hybrid approaches like Holt-SARIMA and Holt–Winters–SARIMA. By conducting a comparative assessment of prediction accuracy, the study is expected to contribute to the development of more precise CPI forecasting methods while supporting economic and national defense decision-making. The following sections present the dataset and methodology for calculating the CPI, along with explanations of ETS, Holt's linear trend, Holt–Winters, SARIMAX, and hybrid models such as Holt–SARIMA and Holt–Winters–SARIMA in Section 2. Section 3 presents the forecasting results, and Section 4 provides the conclusions and implications of the study.

METHOD

This study employs a quantitative approach with a time series forecasting design to predict Indonesia's CPI, using monthly data for the period 2017–2022 obtained from https://id.tradingeconomics.com/. The dataset was divided into training (80%) and testing (20%) subsets, and preprocessing included checking for missing values. Various forecasting models were then developed, starting with ETS and its variants Holt and Holt–Winters to adaptively capture trend and seasonal patterns, followed by SARIMA to model long-term trends and seasonal fluctuations, and SARIMAX to incorporate external or exogenous variables for improved predictive accuracy. Hybrid approaches, including Holt–SARIMA and Holt–Winters–SARIMA, were also implemented to combine the adaptive capabilities of exponential smoothing with SARIMA's strength in modeling residual autocorrelations and stationary seasonal structures. Each model was used to forecast 14 months ahead, corresponding to the entire testing period. Prediction accuracy was evaluated using the Root Mean Square Error (RMSE), and the results were compared to identify the most suitable model for CPI forecasting, providing a basis for economic policy formulation and national defense decision-making.

Dataset

This study uses one dependent variable and three independent variables. The dependent variable (Y) is the CPI, which reflects the price level of goods and services consumed by households and serves as a key indicator of economic stability. The independent variables are: (1) Crude oil price

(X_{oil}), which can affect production and distribution costs and, consequently, inflation; (2) Exports (X_{exp}), as an indicator of foreign trade performance that may influence domestic demand and prices; and (3) Gasoline price (X_{gas}), which directly impacts transportation costs and household purchasing power. All variables are measured monthly and obtained from the official source https://id.tradingeconomics.com/. These variables are employed to build SARIMA, SARIMAX, and hybrid forecasting models, as well as to analyze the influence of external factors on CPI movements.

Consumer Price Index

The CPI measures the average change in prices of goods and services consumed by households over time (Blundell et al., 2020; Pournaras et al., 2022). CPI can be calculated using the following formula:

$$CPI_t = \frac{B_t}{B_0} \times 100 \tag{1}$$

where,
CPI_t = CPI at the current period
B_t = Cost of the market basket in the current period
B_0 = Cost of the market basket in the base period

This formula indicates the relative change in prices compared to the base period, based on the cost of goods and services consumed by households. CPI is commonly used to assess inflation, purchasing power, and overall economic stability, and serves as the dependent variable in this forecasting study.

Error-Trend-Seasonal

ETS is a general framework for exponential smoothing in time series forecasting that models the data based on three components: Error (E), Trend (T), and Seasonal (S) (Punyapornwithaya et al., 2021). The error component can be additive or multiplicative, the trend can be none, additive, or additive damped, and the seasonal component can be none, additive, or multiplicative. ETS allows the model to adaptively capture level, trend, and seasonal patterns, making it suitable for datasets with clear trend and/or seasonal fluctuations. This flexibility makes ETS a widely used baseline method before applying more complex models like SARIMA or hybrid approaches. The ETS model with a trend component can be expressed mathematically as:

a. Level update

$$\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{2}$$

b. Trend update

$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{3}$$

c. Forecast h-step

$$\hat{y}_{t+h} = \ell_t + hb_t \tag{4}$$

where,
y_t = Observed value at time t
ℓ_t = Estimated level at time t
b_t = Estimated trend at time t
α, β = Smoothing parameters

Holt Linear and Holt-Winter

Holt's linear trend method and Holt–Winters exponential smoothing extend the basic ETS framework by explicitly modeling trends and seasonality in time series data (Majid & Dzikria, 2023;

Yonar et al., 2020). Holt's method adds a trend component to the level, enabling the model to adapt to linear changes over time, making it suitable for datasets exhibiting a clear trend but no strong seasonal patterns (Hendri & Fadhila, 2024). Holt–Winters further incorporates a seasonal component, which can be additive or multiplicative, allowing the model to capture recurring seasonal fluctuations in addition to the trend. For Holt–Winters with additive seasonality, the seasonal component is updated as:

$$s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \tag{5}$$

where, y_t is the observed value, ℓ_t the level, b_t the trend, s_t the seasonal component, mmm the seasonal period, and α, β, γ are smoothing parameters. Holt and Holt–Winters methods are particularly effective for short- to medium-term forecasting when the data exhibit trends and seasonal patterns, providing a robust foundation before applying more complex models like SARIMA or hybrid approaches.

Seasonal Autoregressive Integrated Moving Average (SARIMA) with Exogenous Variables

SARIMA is an extension of the ARIMA model designed to handle seasonal patterns in time series data (Falatouri et al., 2022; Manigandan et al., 2021). This model combines Autoregressive (AR), Integrated (I), and Moving Average (MA) components with additional seasonal components: Seasonal AR (SAR), Seasonal MA (SMA), and Seasonal differencing (SI). SARIMA is generally denoted as:

$$SARIMA(p,d,q)(P,D,Q)_s \tag{6}$$

where,

p = non-seasonal autoregressive order
d = non-seasonal differencing
q = non-seasonal moving average order
P = seasonal autoregressive order
D = seasonal differencing
Q = seasonal moving average order
s = length of the seasonal period (e.g., 12 for monthly data with annual seasonality)

The general SARIMA model can be expressed as:

$$\Phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t \tag{7}$$

where,

B = lag operator
$\phi_p(B)$ dan $\Phi_p(B^s)$ = AR coefficients for non-seasonal and seasonal parts
$\Theta_Q(B^s)$ dan $\theta_q(B)\varepsilon_t$ = MA coefficients for non-seasonal and seasonal parts
ε_t = residual error

The SARIMAX model is a seasonal time series model that incorporates exogenous variables (X), which are external factors expected to have a significant influence on the data (Alharbi & Csala, 2022; Ampountolas, 2021; Elshewey et al., 2023). By including these exogenous variables, SARIMAX aims to improve the accuracy of forecasts, allowing the model to capture both seasonal patterns and the effects of external factors on the target variable. The SARIMAX model is as follows:

$$\Phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t + \alpha_1 X_{1t} + \cdots + \alpha_k X_{kt} \tag{8}$$

where,

X_{kt} = Exogenous variable k at time t
α_k = Coefficient of exogenous variable k

Exogenous variables (X) are chosen based on their economic relevance and potential impact on Y, enhancing the model's predictive power.

RESULTS AND DISCUSSION

Descriptive Analysis

Figure 1 illustrates the time series patterns of all research variables, consisting of the CPI (X_{cpi}) as the dependent variable and three independent variables: crude oil price (X_{oil}), exports (X_{exp}), and gasoline price (X_{gas}) for the period 2017–2022. The CPI shows a clear and consistent upward trend, indicating a non-stationary long-term pattern driven by persistent inflationary pressures in Indonesia. This justifies the application of models that can capture trend and level components, such as ETS and the Holt Linear Trend model. Crude oil production exhibits a declining trend with high volatility, exports display cyclical and partly seasonal fluctuations, and gasoline prices show level shifts and irregular variations resulting from domestic policy interventions and changes in global oil markets. These behaviors indicate the presence of trend, seasonality, and short-term irregularity across the observed variables.

Therefore, this study employs a variety of time series forecasting models that reflect these characteristics, including ETS, Holt Linear Trend, Holt–Winter, SARIMA, and SARIMAX. In addition, two hybrid models (Holt–SARIMA and Holt–Winter–SARIMA) are developed to integrate the strengths of trend- and seasonality-based methods within a unified forecasting framework. This multi-model approach provides a strong empirical foundation for selecting the most reliable CPI forecasting model.

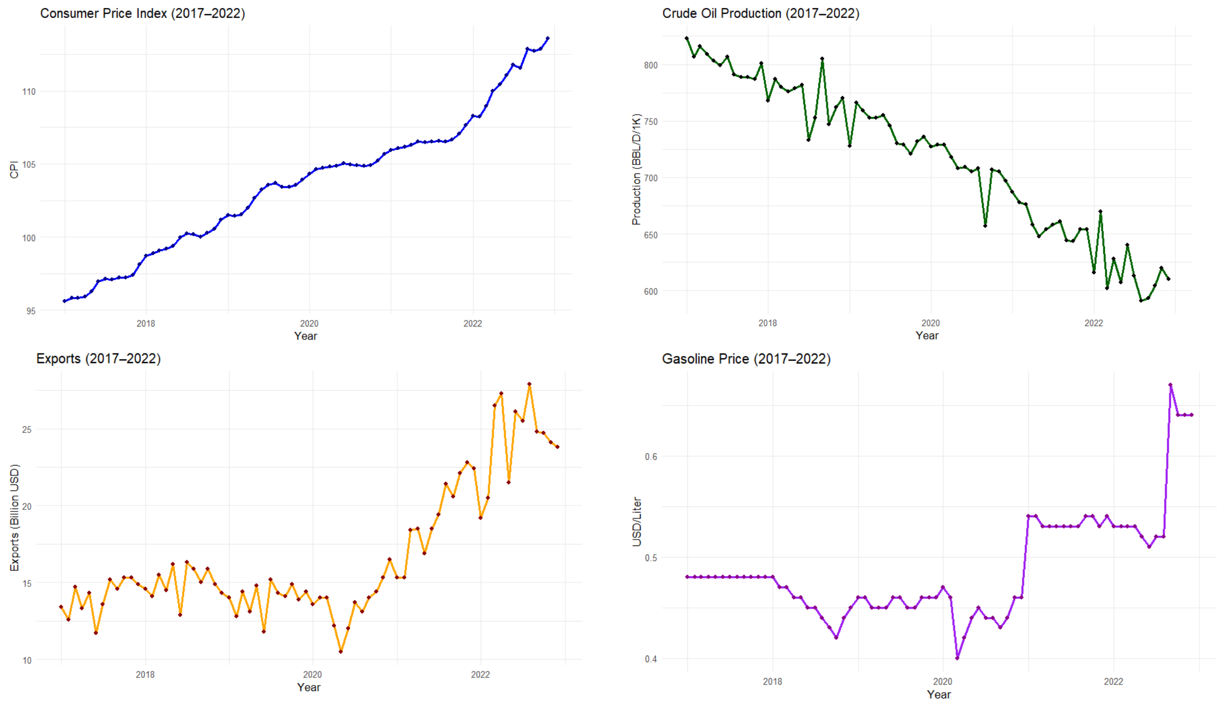


Figure 1. Trends of CPI, crude oil price, exports, and gasoline price in Indonesia (2017–2022)

Furthermore, the Spearman correlation analysis presented in Figure 2 shows the strength and direction of the relationships among the variables. CPI demonstrates a very strong negative correlation with crude oil production (ρ = –0.957***), indicating that higher oil output is generally associated with lower inflationary pressures. In contrast, CPI exhibits strong positive correlations with exports (ρ = 0.747***) and gasoline prices (ρ = 0.626***), suggesting that increases in trade activity and fuel costs contribute to rising consumer prices. Crude oil production is also negatively correlated with both exports (ρ = –0.796***) and gasoline prices (ρ = –0.663***), while exports and gasoline prices share a strong positive association (ρ = 0.751***). These findings highlight the interconnectedness of energy, trade, and inflation dynamics in Indonesia, where fluctuations in global oil markets and export demand play a substantial role in shaping domestic price stability.

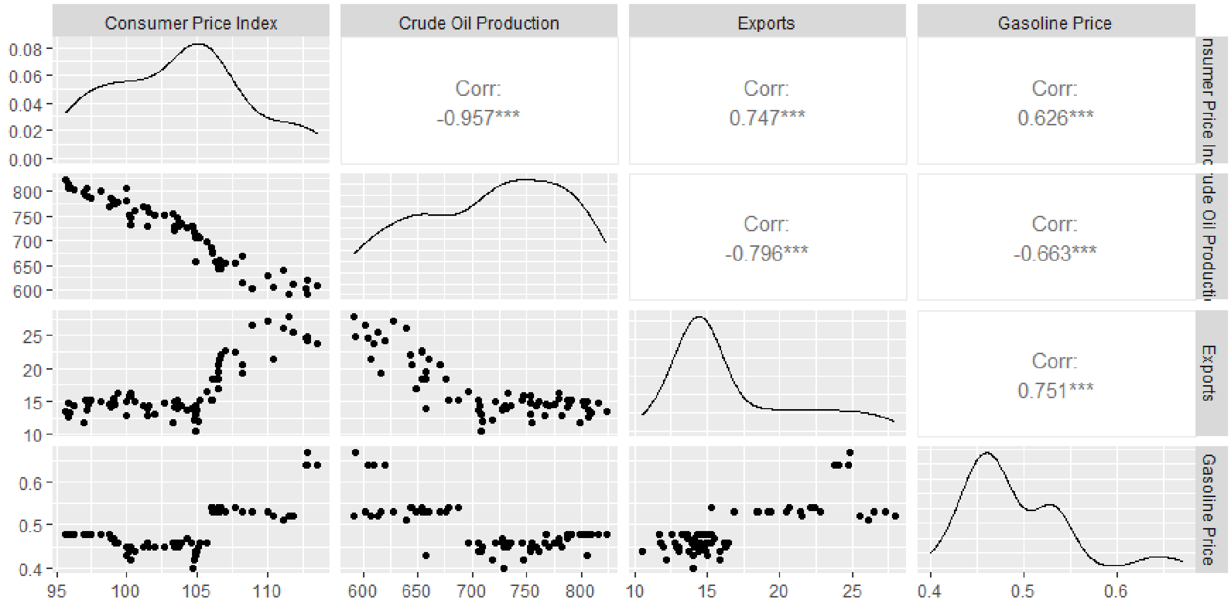


Figure 2. Spearman Correlation Matrix of Research Variables

Figure 3 presents the additive decomposition of the CPI time series for the period 2017–2022, which separates the observed series into trend, seasonal, and random components. The trend component shows a consistent upward movement, confirming the long-term inflationary pressure in Indonesia during the observed period. The seasonal component exhibits a clear cyclical pattern that repeats annually, indicating the presence of recurring fluctuations in consumer prices due to periodic factors such as festive seasons or commodity cycles. Meanwhile, the random component captures short-term irregular variations that are not explained by the trend or seasonality, reflecting temporary shocks such as global economic disruptions or policy adjustments. This decomposition highlights that CPI dynamics are jointly shaped by structural trends, recurring seasonal effects, and irregular external shocks.

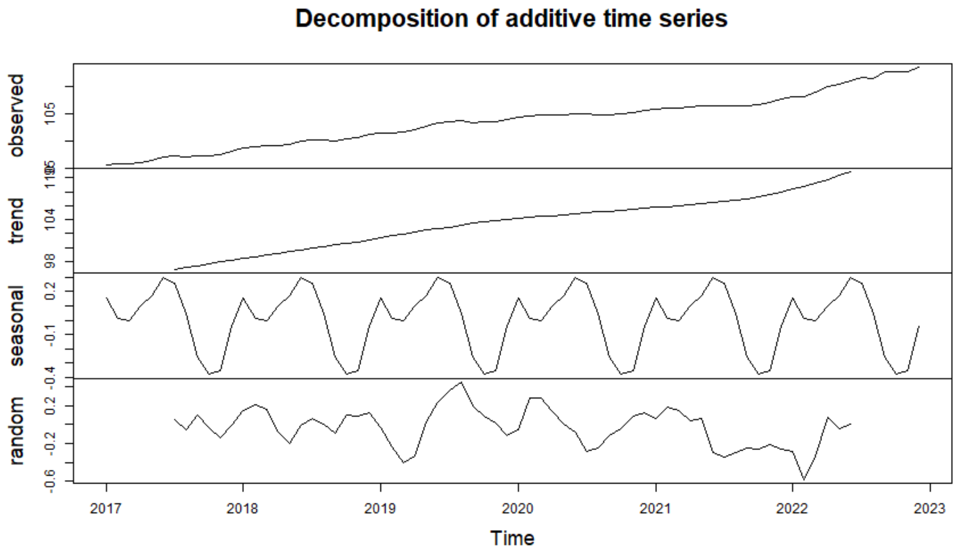


Figure 3. Additive Decomposition of the CPI Time Series in Indonesia

ETS Modelling

The ETS modeling resulted in the ETS(A, A, A) specification, indicating that the error, trend, and seasonal components follow an additive form. The estimated smoothing parameters are α =

0.9999, β = 0.1339, and γ = 0.0001. The value of α close to 1 implies that the model is highly responsive to the most recent observations, while the relatively small β reflects a stable yet adaptive trend component. Meanwhile, the near-zero γ suggests that the seasonal pattern is relatively consistent across years. The forecast results are shown in Figure 4, where the blue line represents the point forecasts and the shaded areas denote prediction intervals. The model successfully captures the upward trend of CPI and projects continued inflationary pressures in the forecast horizon. The narrow prediction interval at the beginning indicates reliable short-term accuracy, while the widening interval towards the end reflects greater uncertainty in longer-term projections. Overall, the ETS model proves effective in providing dependable CPI forecasts to support policy analysis.

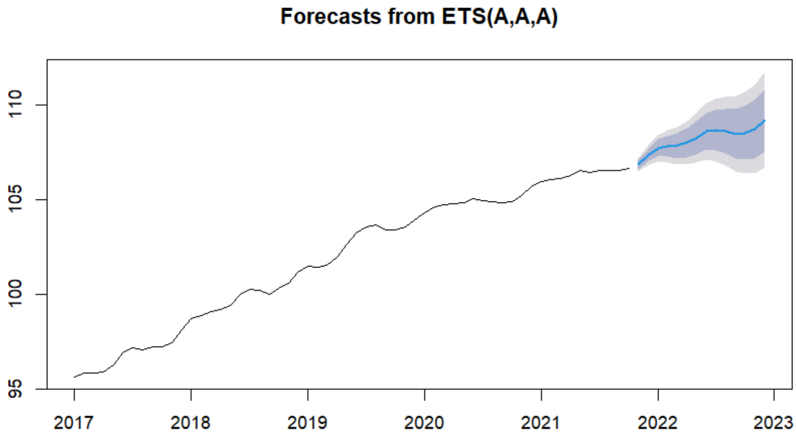


Figure 4. CPI Forecast using ETS(A, A, A) Model, 2017–2022

Holt Linear Trend Modelling

The Holt Linear Trend model produced smoothing parameters of α = 0.9999 and β = 0.0001, with an initial level of 95.4044 and an initial slope of 0.1939. The very high α indicates that the model places almost full weight on the most recent observations, while the very small β suggests a stable trend throughout the observation period. Model performance evaluation yielded AIC = 71.1305, demonstrating that the model adequately captures the CPI growth pattern. The forecast results are presented in Figure 5, where the blue line represents the predicted values and the shaded area denotes the prediction intervals. The Holt Linear Trend model projects a consistent increase in CPI over the next 14 months, in line with the identified historical trend.

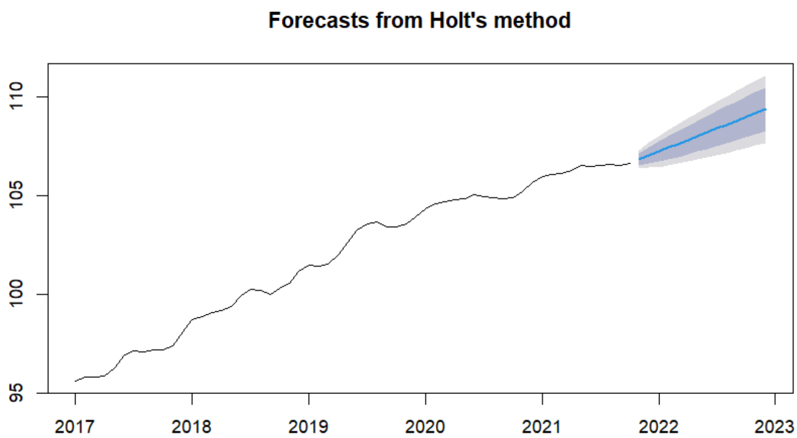


Figure 5. CPI Forecast Using Holt Linear Trend Model, 2017–2022

Holt-Winter Modelling

The Holt–Winters model was estimated using an additive seasonal component with smoothing parameters of α = 1.0000, β = 0.0000, and γ = 0.0984. The value of α = 1.0000 indicates that the model gives full weight to the most recent observations, while β = 0.0000 suggests no adaptive adjustment to the trend, and γ = 0.0984 reflects the moderate role of seasonality in shaping the CPI pattern. The model's sum of squared errors (SSE) was 4.6127, showing a reasonable fit in capturing both the level and seasonal fluctuations of the data. Figure 6 presents the 14-month forecast generated by the Holt–Winters method, where the predicted CPI continues to follow a rising trend with seasonal variation, consistent with the historical movement observed in the training dataset.

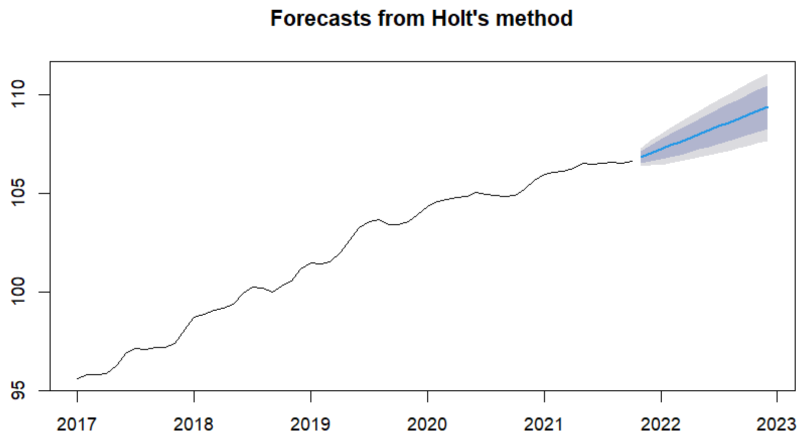


Figure 6. CPI Forecast Using Holt–Winters Model, 2017–2022

SARIMA Modelling

The SARIMA model selected for Indonesia's CPI was identified as ARIMA(2,1,0)(1,0,0)[12] with drift, indicating two autoregressive terms in the non-seasonal component, first-order differencing, and a single seasonal autoregressive term with a period of 12 months. The estimated coefficients were ar1 = 0.5783, ar2 = −0.3731, sar1 = 0.3522, and drift = 0.1993. Results from the coefficient significance test confirmed that all parameters (ar1, ar2, sar1, and drift) were statistically significant at the 5% level ($p < 0.05$), demonstrating that each component contributes meaningfully to the model.

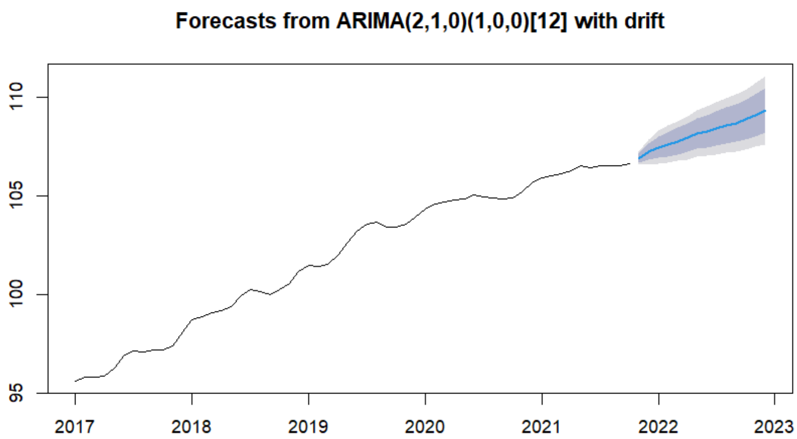
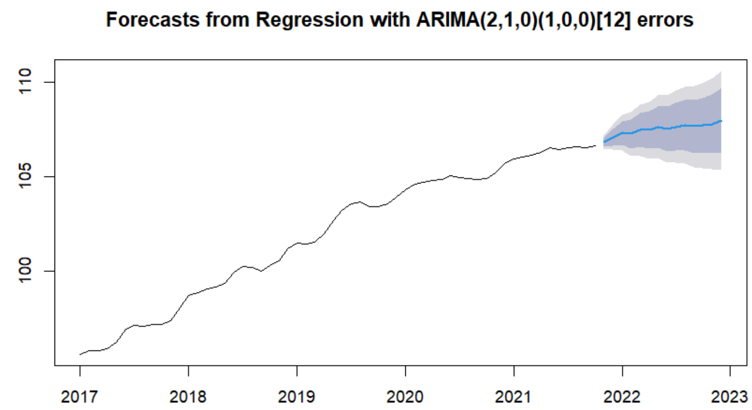


Figure 7. CPI Forecast Using SARIMA(2,1,0)(1,0,0)[12] Model, 2017–2022

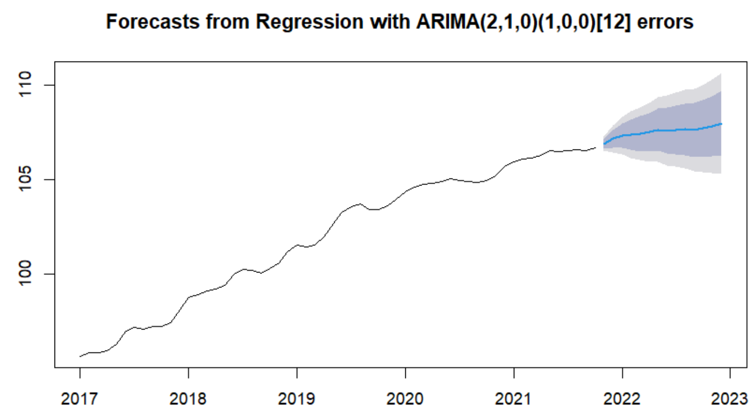
This strengthens the robustness of the SARIMA specification in capturing both autoregressive and seasonal dependencies. The model achieved a log-likelihood of 20.07, with information criteria values of AIC = −30.14, AICc = −28.97, and BIC = −19.93, reflecting its efficiency in balancing fit and complexity. Figure 7 illustrates the 14-month ahead forecast generated by the SARIMA model, effectively capturing long-term trend dynamics and recurring seasonal patterns in the CPI.

SARIMAX Modelling

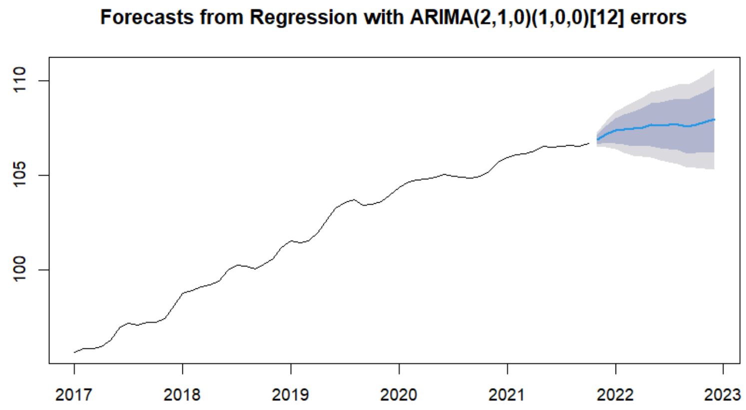
The SARIMAX models with three external variables—crude oil price (X_{oil}), exports (X_{exp}), and gasoline price (X_{gas})—were estimated using the same structure, ARIMA(2,1,0)(1,0,0)[12]. The estimation results indicate that while the autoregressive and seasonal parameters remain consistent across models, the contribution of each external variable differs. The model with crude oil price (X_{oil}) demonstrates the best performance, as reflected in the lowest information criteria (AIC = −25.32; BIC = −15.11). This suggests that fluctuations in crude oil prices are closely related to movements in the CPI in Indonesia, mainly through production and distribution costs that are highly sensitive to energy prices. The model incorporating exports (X_{exp}) produces a positive coefficient, indicating that higher exports may contribute to inflation through increased domestic demand, although its forecasting accuracy is relatively weaker. Meanwhile, the gasoline price (X_{gas}) variable shows a negative coefficient, but with large standard errors, suggesting that its effect on CPI is less conclusive. Overall, although all three variables are related to inflation, crude oil price appears to provide the most stable contribution to improving the explanatory power of the model, while exports and gasoline price exert weaker and less consistent effects. The comparison of forecasts from the three SARIMAX models against the actual CPI is illustrated in Figure 8.



(a)



(b)



(c)

Figure 8. Comparison of SARIMAX Forecasts with External Variables: Crude Oil Price (a), Exports (b), and Gasoline Price (c) on Indonesia's CPI

Hybrid Holt-SARIMA

The hybrid Holt–SARIMA model was constructed by first modeling the CPI series with Holt's exponential smoothing to capture the trend component, followed by applying a SARIMA model to the residuals to address the remaining autocorrelation structure. The residuals were best fitted with an ARIMA(0,0,1)(1,0,0)[12] specification, consisting of one non-seasonal moving average term (ma1 = 0.5400) and one seasonal autoregressive term (sar1 = 0.3723). Both coefficients were statistically significant, confirming the ability of the model to effectively account for short-term shocks and seasonal dependencies left unexplained by Holt's model. The hybrid specification achieved a relatively low residual variance (σ^2 = 0.0307) and favorable information criteria values (AIC = –31.32), indicating a parsimonious yet robust fit. By combining the strengths of Holt's trend-capturing capability with SARIMA's effectiveness in modeling autocorrelation, the hybrid Holt–SARIMA model enhances forecast accuracy for Indonesia's CPI.

Hybrid Holt-Winter-SARIMA

The hybrid Holt–Winter SARIMA model was constructed by first applying the Holt–Winter method to capture the trend and seasonal components of the CPI data, followed by modeling the residuals with SARIMA to address any remaining autocorrelation. The residual estimation yielded an ARIMA(0,1,1) specification with a statistically significant moving average component (ma1 = –0.8708). This result indicates that short-term shocks in the residuals can be effectively captured through the moving average process. However, the residual variance (σ^2 = 0.1043) and information criteria (AIC = 30.39) are relatively higher compared to the hybrid Holt–SARIMA model, suggesting weaker performance. Nevertheless, this hybrid specification still provides a reasonable representation of dependency patterns not fully explained by Holt–Winter alone, thereby contributing to the accuracy of CPI forecasting, albeit less effectively than the Holt–SARIMA approach.

Model Comparison

The comparison of forecasting models is summarized in Table 1, which presents the values of error metrics RMSE. Based on Table 1, it can be observed that the best model is Holt-Winter model with RMSE = 1.9159, followed by the Hybrid HW-SARIMA model with RMSE = 1.9933. This indicates that the explicit seasonal component captured by the Holt-Winter method provides the most accurate forecasts compared to other models. Meanwhile, the integration of Holt-Winter with SARIMA also maintains strong performance, although slightly less accurate than Holt-Winter alone. Figure 9 presents the residual diagnostics of the Holt-Winter model, which are used to evaluate whether the model assumptions are satisfied.

Table 1. Comparison of Forecasting Model Performance Based on RMSE

Model	RMSE
ETS	2.7712
Holt	2.7378
Holt-Winter*	**1.9159***
SARIMA	2.7160
Hybrid Holt-SARIMA	2.7594
Hybrid HW-SARIMA	1.9933
SARIMAX1	3.5161
SARIMAX2	3.5160
SARIMAX3	3.5104

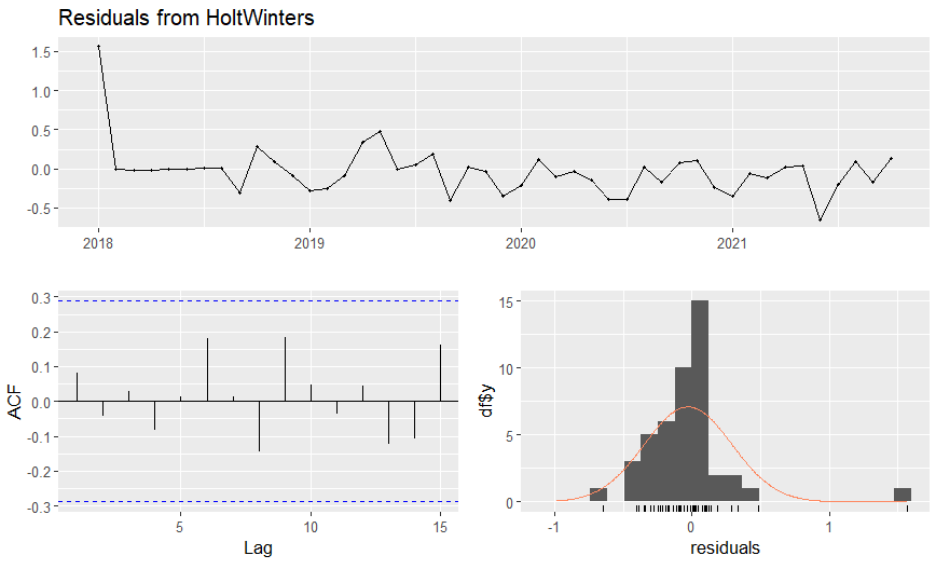


Figure 9. Residual Diagnostics of the Holt-Winter Model

The residual plot (top) shows that the residuals fluctuate randomly around zero without forming a clear trend or systematic pattern, indicating that the model captures the main structure of the data well. The ACF plot (bottom left) demonstrates that most autocorrelation values fall within the confidence bounds, suggesting no significant autocorrelation remains in the residuals. This implies that the residuals behave like white noise. Finally, the histogram with a density curve (bottom right) shows that the residual distribution is approximately symmetric and centered around zero, although a few extreme values are present.

A related study by Shinkarenko et al. (2021) compared the Holt–Winters and ARIMA models to analyze the CPI dynamics in Ukraine from 2010 to 2020. Its usefulness for predicting inflation with both trend and seasonal components was confirmed by their investigation, which showed that the Holt–Winters approach had the lowest forecasting error. This result is in line with the current study's findings, which also show that the Holt–Winter model is the most accurate at predicting Indonesia's CPI because it exhibits comparable long-term and seasonal inflationary patterns.

The ability of the Holt–Winter model to accurately forecast Indonesia's CPI has important implications for national economic resilience. Precise inflation forecasting allows policymakers to anticipate price volatility that can affect household purchasing power, production costs, and fiscal stability. Persistent inflation shocks may threaten social stability and undermine the economic foundations essential for national defense and resilience. Therefore, the application of reliable time series models such as Holt–Winter supports early warning systems for economic disturbances and strengthens evidence-based strategies in maintaining price stability, safeguarding welfare, and ensuring sustainable resource allocation for national resilience. Yaacob et al. (2020) emphasized that fluctuations in the CPI play a critical role in assessing a country's economic vulnerability and resilience, particularly during the Covid-19 pandemic. Their study found that CPI movements significantly influenced Brunei's economic stability, reinforcing the importance of accurate inflation modeling in supporting economic recovery and resilience strategies.

CONCLUSION

The decomposition of Indonesia's CPI from 2017–2022 highlights three main components: a steadily increasing long-term trend, recurring seasonal fluctuations that repeat annually, and irregular variations driven by external shocks such as global energy price changes and trade dynamics. This confirms that CPI behavior is shaped by both structural and cyclical factors that require models capable of capturing complex patterns.

Among the models tested, the Holt–Winter method achieved the best performance with the lowest RMSE of 1.9159, outperforming ETS, Holt, SARIMA, SARIMAX, and hybrid approaches. The model effectively captured the upward trend and seasonal behavior of CPI, producing forecasts that closely align with historical patterns. This demonstrates the strength of exponential smoothing with explicit seasonal components in handling data with recurring fluctuations.

Residual diagnostics further validate the suitability of Holt–Winter. The residuals fluctuate randomly around zero without systematic patterns, the ACF shows no significant autocorrelation, and the residual distribution is approximately symmetric. These findings indicate that the model has adequately explained the trend and seasonality of CPI and that the remaining errors behave like white noise. Therefore, the Holt–Winter model can be considered the most reliable tool for CPI forecasting, providing valuable support for economic policy formulation and national defense decision-making.

However, this study has several limitations. The Holt–Winter model assumes that the historical trend and seasonal structures remain stable over time, which may limit its accuracy during structural economic changes or policy shocks. In addition, the model does not explicitly account for spatial dependencies or external macroeconomic variables, such as crude oil prices or exchange rates, that could affect CPI dynamics. Future research could address these limitations by integrating Holt–Winter with models that include exogenous and spatial–temporal factors, such as GSTARIMA, GSTARIMAX, GST-SARIMA, or GST-SARIMAX, to enhance the adaptability and robustness of CPI forecasting in complex economic environments.

AUTHOR CONTRIBUTIONS

M.Y.A.: Data curation, formal analysis, visualization, writing – original draft. R.N.R.: Conceptualization, methodology, funding acquisition, supervision, validation. J.S.: Validation, supervision, writing – review & editing.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

Ahmar, A. S., Singh, P. K., Ruliana, R., Pandey, A. K., & Gupta, S. (2023). Comparison of ARIMA, SutteARIMA, and Holt-Winters, and NNAR Models to Predict Food Grain in India. *Forecasting*, *5*(1). https://doi.org/10.3390/forecast5010006

Alharbi, F. R., & Csala, D. (2022). A Seasonal Autoregressive Integrated Moving Average with Exogenous Factors (SARIMAX) Forecasting Model-Based Time Series Approach. *Inventions*, *7*(4). https://doi.org/10.3390/inventions7040094

Ampountolas, A. (2021). Modeling and Forecasting Daily Hotel Demand: A Comparison Based on SARIMAX, Neural Networks, and GARCH Models. *Forecasting*, *3*(3). https://doi.org/10.3390/forecast3030037

Ballada, C. J. A., Aruta, J. J. B. R., Callueng, C. M., Antazo, B. G., Kimhi, S., Reinert, M., Eshel, Y., Marciano, H., Adini, B., da Silva, J. D., & Verdu, F. C. (2022). Bouncing back from COVID-19: Individual and ecological factors influence national resilience in adults from Israel, the Philippines, and Brazil. *Journal of Community and Applied Social Psychology*, *32*(3). https://doi.org/10.1002/casp.2569

Banaś, J., & Utnik-Banaś, K. (2021). Evaluating a seasonal autoregressive moving average model with an exogenous variable for short-term timber price forecasting. *Forest Policy and Economics*, *131*. https://doi.org/10.1016/j.forpol.2021.102564

Blundell, R., Griffith, R., Levell, P., & O'Connell, M. (2020). Could COVID-19 Infect the Consumer Prices Index?*. *Fiscal Studies*, *41*(2). https://doi.org/10.1111/1475-5890.12229

Elshewey, A. M., Shams, M. Y., Elhady, A. M., Shohieb, S. M., Abdelhamid, A. A., Ibrahim, A., & Tarek, Z. (2023). A Novel WD-SARIMAX Model for Temperature Forecasting Using Daily Delhi Climate Dataset. *Sustainability (Switzerland)*, *15*(1). https://doi.org/10.3390/su15010757

Falatouri, T., Darbanian, F., Brandtner, P., & Udokwu, C. (2022). Predictive Analytics for Demand Forecasting - A Comparison of SARIMA and LSTM in Retail SCM. *Procedia Computer Science*, *200*. https://doi.org/10.1016/j.procs.2022.01.298

Goodwin, R., Hamama-Raz, Y., Leshem, E., & Ben-Ezra, M. (2023). National resilience in Ukraine following the 2022 Russian invasion. *International Journal of Disaster Risk Reduction*, *85*. https://doi.org/10.1016/j.ijdrr.2022.103487

Hendri, E.P., & Fadhlia, S. (2024). Times series data analysis: holt-winters model for rainfall prediction in West Java. *International Journal of Applied Mathematics, Sciences, and Technology for National Defense*, 2(1), 1-8. https://doi.org/10.58524/app.sci.def.v2i1.325

Huang, Y., Xu, C., Ji, M., Xiang, W., & He, D. (2020). Medical service demand forecasting using a hybrid model based on ARIMA and self-adaptive filtering method. *BMC Medical Informatics and Decision Making*, *20*(1). https://doi.org/10.1186/s12911-020-01256-1

Khan, D. M., Ali, M., Iqbal, N., Khalil, U., Aljohani, H. M., Alharthi, A. S., & Afify, A. Z. (2022). Short-Term Prediction of COVID-19 Using Novel Hybrid Ensemble Empirical Mode Decomposition and Error Trend Seasonal Model. *Frontiers in Public Health*, *10*. https://doi.org/10.3389/fpubh.2022.922795

Li, A., Wei, X., & He, Z. (2020). Robust proof of stake: A new consensus protocol for sustainable blockchain systems. *Sustainability (Switzerland)*, *12*(7). https://doi.org/10.3390/su12072824

Majid, W. K., & Dzikria, I. (2023). Comparison of Multiple Linear Regression and Holt-Winter Exponential Smoothing in the Gold Jewelry Pricing Prediction. *Procedia of Engineering and Life Science*, *4*. https://doi.org/10.21070/pels.v4i0.1390

Manigandan, P., Alam, M. S., Alharthi, M., Khan, U., Alagirisamy, K., Pachiyappan, D., & Rehman, A. (2021). Forecasting natural gas production and consumption in united states-evidence from sarima and sarimax models. *Energies*, *14*(19). https://doi.org/10.3390/en14196021

Mohamed, J. (2020). Time Series Modeling and Forecasting of Somaliland Consumer Price Index: A Comparison of ARIMA and Regression with ARIMA Errors. *American Journal of Theoretical and Applied Statistics*, *9*(4). https://doi.org/10.11648/j.ajtas.20200904.18

Nguyen, T. T., Nguyen, H. G., Lee, J. Y., Wang, Y. L., & Tsai, C. S. (2023). The consumer price index prediction using machine learning approaches: Evidence from the United States. *Heliyon*, *9*(10). https://doi.org/10.1016/j.heliyon.2023.e20730

Pournaras, E., Haqqoni, M. G. Al, & Pramana, S. (2022). Implementation of marketplace data in the production of Consumer Price Index in Indonesia. *Data Science*, *5*(2). https://doi.org/10.3233/DS-210037

Punyapornwithaya, V., Jampachaisri, K., Klaharn, K., & Sansamur, C. (2021). Forecasting of Milk Production in Northern Thailand Using Seasonal Autoregressive Integrated Moving Average, Error Trend Seasonality, and Hybrid Models. *Frontiers in Veterinary Science*, *8*. https://doi.org/10.3389/fvets.2021.775114

Shinkarenko, V., Hostryk, A., Shynkarenko, L., & Dolinskyi, L. (2021). A forecasting the consumer price index using time series model. *SHS Web of Conferences*, *107*. https://doi.org/10.1051/shsconf/202110710002

Thiruchelvam, L., Dass, S. C., Asirvadam, V. S., Daud, H., & Gill, B. S. (2021). Determine neighboring region spatial effect on dengue cases using ensemble ARIMA models. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-84176-y

Trull, O., García-Díaz, J. C., & Troncoso, A. (2020). Initialization methods for multiple seasonal holt-winters forecasting models. *Mathematics*, *8*(2). https://doi.org/10.3390/math8020268

Wang, Y., Xu, C., Ren, J., Wu, W., Zhao, X., Chao, L., Liang, W., & Yao, S. (2020). Secular seasonality and trend forecasting of tuberculosis incidence rate in China using the advanced error-trend-seasonal framework. *Infection and Drug Resistance*, *13*. https://doi.org/10.2147/IDR.S238225

Wanjuki, T. M., Wagala, A., & Muriithi, D. K. (2022). Evaluating the Predictive Ability of Seasonal Autoregressive Integrated Moving Average (SARIMA) Models using Food and Beverages Price Index in Kenya. *European Journal of Mathematics and Statistics*, *3*(2). https://doi.org/10.24018/ejmath.2022.3.2.100

Xiao, D., & Su, J. (2022). Research on Stock Price Time Series Prediction Based on Deep Learning and Autoregressive Integrated Moving Average. *Scientific Programming*, *2022*. https://doi.org/10.1155/2022/4758698

Yaacob, H., Ali, Q., Sarbini, N. A., Rani, A. N., & Zaini, Z. (2020). Resilience of Bruneian economy amidst Covid-19 based on the United Nations Disaster Risk Reduction (UNDRR) framework. Problems and Perspectives in Management, 19(1). https://doi.org/10.21511/ppm.19(1).2021.08

Yonar, H., Yonar, A., Tekindal, M. A., & Tekindal, M. (2020). Modeling and Forecasting for the number of cases of the COVID-19 pandemic with the Curve Estimation Models, the Box-Jenkins and Exponential Smoothing Methods. *Eurasian Journal of Medicine and Oncology*, *4*(2). https://doi.org/10.14744/ejmo.2020.28273