



Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943



Comparative Analysis of Forecasting: A Case Study of Malaysia's Inflation

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ARTICLE INFO

Article history:

Received 26 July 2026
Received in revised form 30 September 2026
Accepted 30 September 2026
Available online 9 October 2026

Keywords:

Inflation forecasting; Consumer Price Index; Artificial Neural Network (ANN); Random Forest (RF); ARIMAX

ABSTRACT

An accurate forecast of inflation is important for the stability of the economy, shaping the monetary policy and making business and investment decisions. Despite its importance, forecasting inflation remains challenging due to the complex and dynamic relationships among economic variables. There are limited studies in Malaysia that have investigated the predictive capability of Consumer Price Index (CPI) using both traditional and machine learning methods. The objective of this study is to forecast the inflation rate of Malaysia using three CPI components, namely Food, Health and Insurance Services, which were obtained from the Department of Statistics Malaysia (DOSM) from January 2016 to December 2025. A comparative forecasting framework is developed in this study using three models: Artificial Neural Network (ANN), Random Forest (RF), and ARIMAX. Data preprocessing, exploratory data analysis, and stationarity tests are performed to ensure data suitability and model robustness. Four training-testing data ratios (60:40, 70:30, 80:20, and 90:10) are examined systematically to determine the optimal training-testing data ratio for each forecasting model. The best forecasting model is determined by the lowest forecasting errors in forecasting performance measured by Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The findings show that ARIMAX (1,0,2) model with a 90:10 training-testing ratio has outperformed the other models by achieving the lowest error. Thus, ARIMAX (1,0,2) is selected as the best model to forecast the inflation rate of Malaysia for the next 24 months. The forecasting results indicate an overall increasing trend in Malaysia's inflation rate throughout the forecast period. These results indicate that ARIMAX is effective in modelling the relationship between inflation and selected CPI components, providing useful information for the policymakers and economic planners in anticipating future inflation movements.

1. Introduction

1.1 Inflation in Malaysia

Inflation is the average rate of price change in the average of goods and services in an economy. According to Lucas [1], the purchasing power of money will decrease when the prices increase. Consumer Price Index (CPI) is the key measure of inflation in Malaysia, which is compiled by Department of Statistics Malaysia (DOSM). The annual percentage change in the CPI, which is also known as headline inflation, is used to make monetary policy decisions or assess the health of the household [2].

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Malaysia has experienced periods of relatively calm and larger economic shocks which impact on its inflation rates. Compared to the period between 2011 and 2017, the inflation level was rather moderate and in 2020, coinciding with the worldwide outbreak of COVID-19, the inflation rate was even negative. Subsequently, inflation began to rise and hit its peak in 2022, causing effects of disruption of commodity value chains and commodity prices, although it began to moderate in 2024. Headline inflation can provide a broad picture of overall price trends, but this does not imply that the inflation movement will be the same for all components of the CPI [3]. Therefore, illustrations of CPI components may then provide a closer look at the inflationary dynamics.

The CPI components observed in this study are Food, Health and Insurance Services, which is closely related to basic expenditure of household and domestic cost pressures. These components are affected by wages, health care expenses, insurance claims, regulation, production expenses and other economic elements. Food prices are highly sensitive to climate change, exchange rates, commodity prices and international trade, whereas healthcare and insurance prices show higher persistence and more sluggish adjustment in prices [4,5]. Hence, headline CPI does not necessarily indicate the inflation behavior at the component level.

The level of inflation is also affected by both the domestic and external economies. Money supply, GDP, exchange rate, unemployment and foreign direct investment (FDI) are some of the significant factors identified which are associated to the Malaysian inflation [6,7]. The economic orientation of Malaysia towards international markets also allows the commodity prices to respond quickly to the changes in international markets and importation of inflation from other countries [8]. Thus, an accurate forecast of the inflation rate is vital to monetary policy, household financial planning and business decisions as well as financial risk management.

Forecast for inflation has been studied in the literature based on traditional statistical methods and Machine Learning (ML) method. Simple methods such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA), classical econometric models, such as the Exponential Smoothing model, have been widely used due to their simplicity and capacity of modeling the trends and temporalities. However, these traditional models might not be able to deal with nonlinearities and abrupt structural shifts. Therefore, the ML approaches will be flexible to model the complex and nonlinear relationship, hence increasingly being utilized [9].

Although the literature on inflation forecasting is wide, there are still gaps in the literature. One of the limitations is that the training-testing split is performed without systematic analysis indicated whether the split selected is best suited to a particular forecasting models in a number of the studies. For example, Muhammad *et al.*, [10] determined the split of training-testing data to 70:30 when forecasting Malaysia's inflation, while Nhat [11] used a 65:20:15 split for training, validation, and testing ratio in his inflation forecasting for Vietnam without comparing on other potential splits. The split ratio between observations in training and testing is regarded as a procedural decision that can impact generalization of the model and the accuracy of the forecasts, therefore setting a split ration may lead to misleading conclusions.

Second, a number of the studies of inflation forecasting investigated have relatively short forecast horizons. For example, the study by Muhammad *et al.*, [10] is used to predict the inflation rate for Malaysia for the next 6 months through the use of Artificial Neural Network (ANN). If the time horizon of the forecasts is short, the results may be limited for medium-term planning, because the forecasting errors may accumulate over time with longer time horizons of the forecasts [12]. Third, the studies are often conducted with only one model or on specific comparative models and it is not always easy to find a model for comparison among the different modelling paradigms [13].

1.2 Disaggregated CPI Components and Inflation Forecasting

CPI consists of various components and the price changes in these components depending on several factors in each sector. The significance of food in nutritional security is extremely important, as it is a significant portion of household expenditure and affects cost of living. The food prices are extremely volatile as it is dependent on agricultural production, weather conditions, transport costs, international market price, exchange rates and trade regulations [4,14]. Such characteristics make food CPI as one of the important but challenging factors for forecasting inflation.

The monetary expenditure of the household on health products and services is Health CPI. In general, the price volatility and its persistence of healthcare goods are small because price is regulated and it has a long-term contract due to the institutional characteristics [15]. The reasons that influencing health inflation include labour costs, health care utilisation, the price change of pharmaceutical and supply-chain products, demographic change, exchange rates and the prices of medical equipment [16,17].

In addition, Insurance services is a special category in the CPI because insurance tickets are not only a reflection of the number of expected claims, but also the insurance administrative costs, capital requirements and investment returns [5]. Conversely, when it does occur, inflation will increase insurers claims, operating costs and premiums. Moreover, even if the cost of insurance has risen due to inflation or other shocks, many publications or regulation due to long-term contracts may take a while for a gradual temporary adjustment to occur [18].

This provides additional evidence in support of the use of disaggregated CPI components, as opposed to just headline CPI. The short-term shocks in individual sectors of the economy are part of the factors that makes it impossible for the headline to capture underlying trends in inflation [19], thus making it ideal to adopt a disaggregated set of inflation measures. In the same way, Ibarra [20] also showed that the disaggregated CPI data can be useful to identify common inflation patterns that can be obscured from aggregate data. Based on more recent results by Martínez-Rivera et al., [3] it was also found that relying on individual components of the CPI in a model forecast could lead to a reduction in forecast errors, where these individual components displayed differential persistency, seasonality and shock sensitivity. Thus, utilising Food, Health and Insurance Services can serve as the basis to accommodate all various conditions of inflation in Malaysia.

1.3 Inflation Forecasting Models

ANNs have been extensively used to forecast the inflation due to their ability to model complex and nonlinear relationship. Şengüler *et al.*, [21] indicated that they performed the best in predicting Turkish inflation compared to Support Vector Regression (SVR), Random Forest (RF) and Gradient Boosting Machine (GBM). Similarly, better performance of ANN over ARIMA were obtained by Oyewale *et al.*, [22] with another set of inflation indices for the United States. Besides, Muhammad *et al.*, [10] employed ANN to forecast inflation in Malaysia based on the Malaysian macroeconomic indicators and demonstrated that the model was able to predict inflation satisfactory. The results presented here show the ANN is a good model for nonlinear relationship of inflation.

Another method of machine learning that can identify nonlinear relationships while making few parametric assumptions is Random Forest (RF). Breiman [23] uses the ensemble of decision trees to make it more stable and avoid overfitting problem. Mueller [24] used an empirical approach to determine the relative performance of the ARIMA, Random Walk models and RF in predicting the CPI in Sweden with three, six and 12 months horizons and concluded that the ARIMA and Random walk models' relative performance was less than RF. Additionally, Boaretto *et al.*, [25] showed that RF is

not only useful in disaggregated forecasting for central bankers but also applicable in the presence of structural changes. However, RF does not necessarily provide the best performance in all the forecasting horizons, and hence the empirical comparison of the models is crucial.

An ARIMAX model is the extension of ARIMA model with exogenous data added, which allows modelling inflation that moves both inwards and outwards [26]. Based on the criteria of MAPE, Coker [27] found ARIMAX to be the best model for predicting Sierra Leone's inflation rate than ARIMA and VAR. Similarly, if applied in the country of Indonesia, the forecast results carried out by Oktavia et al., [28] revealed that the ARIMAX is more superior than ARIMA for forecasting when using money supply and exchange rate as factors. Even though there is some evidence which have pointed to mixed results when employing ARIMA and ARIMAX, both models are potentially useful, since ARIMAX has the benefit of being able to include economic interpretability and forecasting power.

It can be observed that ANNs, RF and ARIMAX can model various aspects about the inflation based on the result of the previous studies. ANN is suitable for a non-linear relationship; RF are suitable for modelling complex interaction and high dimensional data and ARIMAX is suitable for modelling the inflationary phenomena based on their historical properties as well as relevant exogenous factors. In this way, it is possible to observe the performances of inflation forecasting in each paradigm by comparing these three models' inflation forecasting.

1.4 Training-Testing Data Split

The training-testing split is important because it obviously determines the size of the set of available required information to learn, and the size of the set of hidden required information to evaluate generalization, which are important methodological factors. However, Muraina [29] found that the ratio of the training to testing sets could affect the prediction performance of the model and this ratio should be determined case by case. Sivakumar *et al.*, [30] also noted a compromise in using these data sets, as using more data may increase learning capacity while using less data may reduce the confidence in evaluating the performance. Another study by Genç *et al.*, [31] showed that the spatial coverage of the training and testing data can introduce a model performance stabilization and bias among the models used.

There is also evidence from economic forecasting that could potentially impact the results of forecasting: split ratios. Septiarini *et al.*, [32] compared the following chronological splits: 80:20, 75:25 and concluded that there was not much difference in the performance of the models but that the impact of using a model was greater in the chronological splits. They, however, only focused on agricultural exports, one economic series that is univariate, and two split ratios. There are a few investigations into training-testing ratios, but for the most part these have been in non-economic settings. The use of 50:50, 60:40, 70:30 or 90:10 ratio of historical training period has been examined by some studies [29] and it was suggested that further increase of the historical training period does not further increase the degree of forecasting accuracy [33].

The above results show that the best training to test data ratio is dependent on the characteristics of the data set and model. However, training – testing studies in the context of CPI inflation forecasting are still quite limited particularly for the Malaysian CPI data. The present study is aimed at comparing both the training and testing procedures methodologically through empirical testing and implementing the forecasting model for the generation of 24 months inflation forecast. Overall, the objective of this study is to determine the optimal split ratio between the training and testing set for the Malaysian inflation rate forecasting, the best model that gives the best performance among ANN, Random Forest and ARIMAX, and forecast the Malaysian inflation rate for the next 24 months using the best model and the optimum split ratio. The data used in this study was obtained from

DOSM, which covers the monthly data for Food, Health and Insurance Services from January 2016 to December 2025. This will assist policymakers, businesses and financial institutions and households, in better decision-making concerning the future inflation environment and economic circumstances.

While there exists an increasing number of studies on inflation forecasts, not many studies have investigated the impact of various training-testing splits on forecasting efficacy, especially in regard to CPI inflation prediction in Malaysia. Also, very few studies have compared various forecasting techniques that follow various modelling approaches as advocated in the same dataset and using multiple splits. Thus, the objective of this paper is to find out the optimal ratio of training and testing splits, select the best method of inflation forecasting from ANN, RF and ARIMAX, and provide a 24-month prediction of Malaysia's inflation. The results derived from the research should prove to be useful for the existing body of knowledge by delivering empirical proof regarding the effect of data-split choices and modelling approaches on inflation forecasting. The paper also serves practical purpose as it gives ideas about inflation forecasts which can help various stakeholders make more informed decisions in the context of possible inflation.

2. Methodology

2.1 Data Collection and Pre-processing

The data used in this study is the Consumer Price Index (CPI) and inflation monthly data for January 2016 to December 2025 from the Department of Statistics Malaysia (DOSM). Inflation rate of Malaysia is forecasting using the selected CPI components: Food, Health, and Insurance services as explanatory variables.

First, the data is indicative of whether any observations are missing. If there are any missing values, the continuity of the time series has to be considered and their values are specified using interpolation due to the lessen of the effect of the missing values on the models, if they are not, this may negatively affect the models' estimations and the reliability of training [34]. Outliers are identified using the z score as follows:

$$Z = \frac{x - \bar{x}}{s} \quad (1)$$

where x is the observation, $\bar{x}$ is the mean, and s is the standard deviation. The ± 3 is chosen as threshold value in order to detect possible outliers as described by Yaro *et al.*, [35]. However, extreme observations which are identified are not automatically rejected since unusual observations may be economic features and not data errors. Such observations made in an incorrect manner can result in an incorrect estimation of the parameters and forecast.

Since ANN is scale dependent, the variables chosen from CPI are normalized by using min-max normalization [36]:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

where X' is the normalized value, X is the original value, X_{min} is the minimum value and X_{max} is the maximum value. In order to make the ANN training stable, the resulting values are scaled between 0 and 1.

2.2 Exploratory Data Analysis

Exploratory Data analysis (EDA) is conducted for the inflation series and selected inflation components to identify the features and behavior of inflation series before building model. The time-series plots are examined to check for trend and data movement over the duration of the study and descriptive statistics are used to summarize the distribution of the variables. Correlation analysis is also carried out to analyze the relationship between inflation and analyzed selected components of CPI data. The Pearson correlation coefficient is positive for positive relationships, negative for negative relationships and lies between -1 and +1 [37]. Correlation values that range from 0.00 to 0.19 indicate a very weak correlation, 0.20 to 0.39 shows a weak correlation, 0.40 to 0.59 shows a moderate correlation, 0.60 to 0.79 shows a strong correlation, and 0.80 to 1.00 shows a very strong correlation. Both positive and negative correlations are assigned to the same strength classification, based on the absolute value of correlation coefficient.

The Augmented Dickey-Fuller (ADF) test is used for testing stationarity of inflation series. The ADF regression is defined as [38]:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^p \delta_i \Delta y_{t-i} + \varepsilon_t \quad (3)$$

where y_t is the time-series variable at time t , Δy_t is the first difference of the time-series, α is the constant, βt is the deterministic time trend, γ is the coefficient used to test for a unit root, p is the number of lagged difference terms, δ_i is the coefficients of the lagged differences and ε_t is the error term. The null hypothesis of ADF test suggests that the series has a unit root, thus it is non-stationary. While the alternative hypothesis of ADF test indicates that there is no unit root in the series, and therefore it is stationary series. If the p value from the ADF test is less than significance level, then the null hypothesis of the test is rejected, and it means that the data is stationary [39].

2.3 Training-Testing Data Split

Instead of adopting a single predetermined data ratio, four chronological training-testing splits are examined: 60:40, 70:30, 80:20 and 90:10 as previous studies [10-11], [32]. The observations in the first ratio are used for training the model and the rest of the observations are kept as out-of-sample testing data. By this process, it is possible to find out how the performance of forecasting varies with different observation ratios between training and testing set for each forecasting model.

2.4 Forecasting Models

Three models are used to forecast: Artificial Neural Network (ANN), Random Forest (RF), and AutoRegressive Integrated Moving Average with eXogenous variables (ARIMAX). ANN is chosen due to its capability of capturing potential nonlinear association between CPI components and inflation, RF is preferred because of its complex nonlinear interaction capability using ensemble learning techniques and finally, ARIMAX offers the autoregressive nature of inflation and the selected CPI components as its exogenous variables.

2.4.1 Artificial Neural Network (ANN)

The Multi-Layer Perceptron (MLP) for feedforward with backpropagation learning is used. ANN is composed of three layers: input layer, hidden layer, and output layer, as shown in Figure 1 below. The three CPI components are fed into the input neurons, pass through the learned weights and nonlinear activation functions, then transformed into the estimated inflation rate.

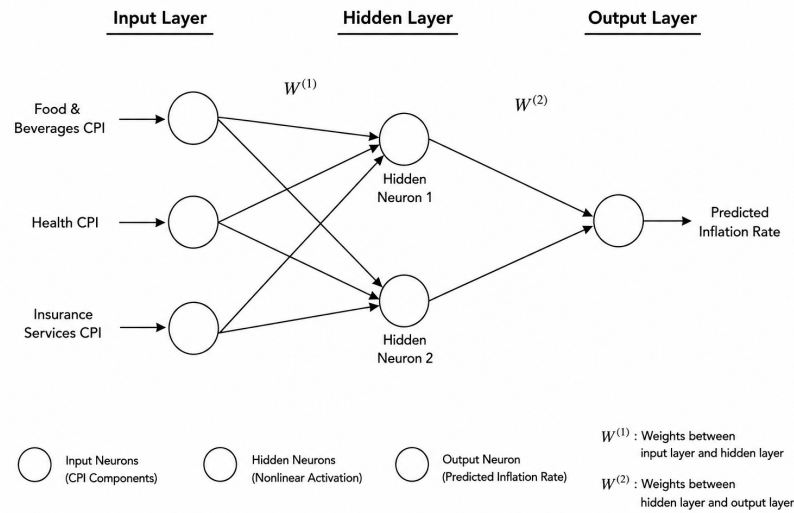


Fig. 1. The three-layer feed forward ANN architecture

The net input to a neuron is defined as [40]:

$$NET_j = \sum_{i=1}^p x_i w_{ij} + b_j \quad (4)$$

In Eq. (4), NET_j denotes the summation of the weighted input added with bias, x_i represents the input variables, w_{ij} is the connection weights, p is the number of input nodes, and the b_j is the bias term for neuron j . As a standard practice in the literature of inflation forecasting, a logistic sigmoid function is then applied [40]:

$$F(NET_j) = \frac{1}{1 + e^{-NET_j}} \quad (5)$$

Mean Squared Error (MSE) is used in determining the forecasting error when the ANN is trained:

$$MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2 \quad (6)$$

In Eq. (6), n is the number of observations in the testing dataset, y_t is the observed inflation rate at period t , and $\hat{y}_t$ represents the forecasted inflation rate at period t . Lastly, back propagation and gradient descent are then used to update the network weights [40]:

$$w_{new} = w_{old} - \eta \frac{\partial E}{\partial w} \quad (7)$$

In Eq. (7), w_{new} and w_{old} denoted as the new and old weight respectively, η is the learning rate and $\partial E / \partial w$ is the gradient of the error. The process of optimization is repeated until the error becomes small.

2.4.2 Random Forest (RF)

Random Forest (RF) is an ensemble learning method which has an ability to combine multiple decision trees to make more accurate predictions with lesser overfitting [41]. As Figure 2 below, a test sample is successively sent to all separated decision trees in the forest. The trees are built separately using bootstrap samples of the training data, and randomly chosen predictors at every split, which yields a variety of tree structures. Each of the decision trees has a specific sequence of decision rules, and the test sample is followed by the decision rule all the way to a terminal leaf node, resulting in a single prediction of inflation. These personal forecasts represent various elements of the connection between the CPI elements and inflation because each tree indicates different trends in the data. After getting all the trees to make predictions, the results of the RF model are determined by getting the average of the results of all individual trees.

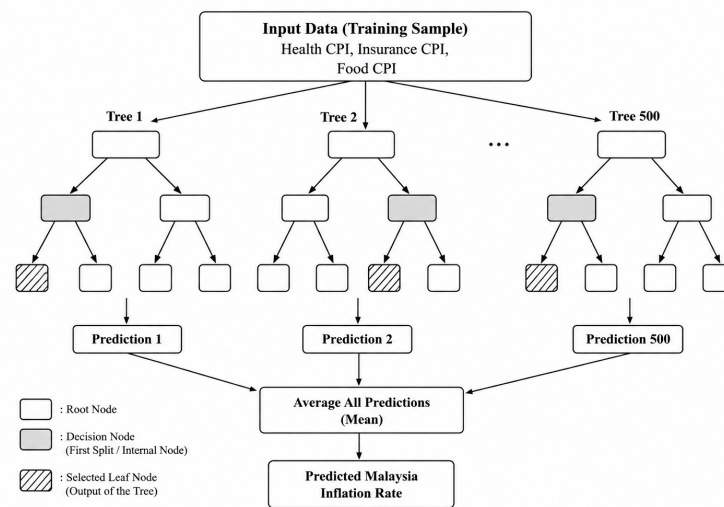


Fig. 2. The structure of random forest

In a regression problem, the RF prediction is expressed as [23]:

$$\hat{y}_t = \frac{1}{T} \sum_{t=1}^T f_t(x) \quad (8)$$

In Eq. (8), $\hat{y}_t$ represents the forecasted value, T is the total number of trees and $f_t(x)$ is the prediction made by the t -th tree. Number of trees, number of randomly selected variables at each split and minimum node size are the default values in R and kept fixed across the various training-testing ratios for a fair comparison.

2.4.3 Autoregressive integrated moving average with exogenous variables (ARIMAX)

The ARIMAX is an extension of the ARIMA framework that aims to include external explanatory variables. In this study, the exogenous variables used to represent inflation rate in Malaysia are Food, Health and Insurance services. The general ARIMAX specification is given as:

$$y_t = c + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \sum_{k=1}^{r=3} \beta_k X_{t,k} + \varepsilon_t \quad (9)$$

In Eq. (9), y_t is the observed inflation rate, c is the constant term, ϕ_i and θ_j are the autoregressive and moving-average coefficients and d is the degree of differencing, $X_{t,k}$ is the set

of exogenous variables of the CPI, β_k is the set of exogenous variables' coefficients, and ε_t is the error term.

The ADF test is used prior to the estimation of ARIMAX. When the inflation series is not stationary, it is differenced until it is stationary, and the number of times it is differenced is d . Next, the ACF and PACF plots are used to decide on orders for the AR and MA processes. Furthermore, the value of p , d and q is systematically tested using `auto.arima()`, and the primary statistical comparisons are done using the corrected AIC (AICc) and the maximum likelihood estimation [42].

The Ljung-Box test is then performed to check if there are significant residual autocorrelations in the ARIMAX fitted model [43]. The Ljung-Box test will follow the hypothesis: null hypothesis shows that the residual values are independent and have no autocorrelation, while alternative hypothesis indicates that the residuals have an autocorrelation. The decision will be made if p -value is larger than 0.05, null hypothesis is failed to reject and this indicates that the fitted model is adequate; if p -value is smaller or equal to 0.05, null hypothesis is rejected and this indicates that the fitted model is inadequate.

2.5 Forecast Accuracy Evaluation

The out-of-sample testing data is used to measure the model performance. Three accuracy measures are chosen in this study, which have been widely used in previous forecasting studies [9] [44-45].

The forecast error is defined as:

$$e_t = y_t - \hat{y}_t \quad (10)$$

In Eq. (10), e_t is the forecast error, while y_t and $\hat{y}_t$ represent the observed and forecasted inflation rate at period t respectively. When the error is positive, then the error is under-forecasting and when it is negative, the error is over-forecasting [46]. There are three measures of accuracy used in this study, namely:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n e_t^2} \quad (11)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |e_t| \quad (12)$$

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{e_t}{y_t} \right| \quad (13)$$

RMSE exponential weights larger forecasting errors [47], whereas MAE offers an easily interpretable average indicator of forecasting error [48]. Errors on the MAPE are presented as percentages but can be misleading when the actual values are close to zero, thus MAPE is reported with RMSE and MAE [49].

2.6 Optimal Ratio, Model Selection and Final Forecast

RMSE, MAE and MAPE are computed for each model with the four training-testing ratios. The ratio that gives the smallest forecasting error is chosen as the optimal training-testing ratio, where RMSE is used as the main criterion, and MAE and MAPE are used as the secondary criteria. Once the optimum ratio is found for each model, they are compared by using the optimum ratio for each model. The best model is chosen by analyzing the overall RMSE, MAE and MAPE performance but giving more weightage to RMSE. Lower values are an indicator of a better forecast performance. In the end, the chosen model is re-trained with entire data set from January 2016 to December 2025 to maximize information to be learned by the model. The retrained model is then employed to forecast the out-of-sample data from January 2026 onwards for 24 months using the R programming.

3. Results

3.1 Descriptive Statistics and Correlation Analysis of the Variables

The descriptive statistics of the inflation rate of Malaysia and three selected CPI components within the study period is shown in Table 1 below. The average value of Food CPI was the highest as recorded 2.88, followed by the inflation rate, Health CPI and Insurance CPI. This means that the food price had the highest average change in price for the study period out of the selected variables. As far as the variability is concerned, Food CPI showed highest standard deviation of 1.73, followed by Insurance CPI and the inflation rate which shows relatively more fluctuations during the study period. Standard deviation was the lowest for Health CPI, indicating that it was the most stable variable of those selected. The minimum and maximum values also show differences in the behaviour of the variables. Inflation ranged from -2.9% to 4.9%, while Food CPI ranged from 0.4% to 7.3%, Health CPI ranged from -0.5% to 4.39%, and Insurance CPI ranged from -2.5% to 5.41%. As a result, the inflation, Health CPI and Insurance CPI showed positive and negative changes in the study period while the Food CPI was positive with significant fluctuations. Overall, the descriptive statistics suggest that the chosen variables have varying degrees of variation and price change, which gave enough variation for further forecasting analysis.

Table 1
Descriptive statistics of the variables

Variable	Mean	Standard deviation	Minimum	Maximum
Inflation	1.8	1.62	-2.9	4.9
Food CPI	2.88	1.73	0.4	7.3
Health CPI	1.42	0.98	-0.5	4.39
Insurance CPI	0.51	1.60	-2.5	5.41

After that, correlation analysis was performed to investigate the linear relationship among the chosen components of the CPI and the inflation rate in Malaysia and the correlation analysis is concluded in the Table 2 below. Food CPI had the highest positive correlation with inflation with a correlation coefficient of 0.687, followed by Health CPI of 0.3629 and Insurance CPI of 0.1785. This indicates that the inflation rate in Malaysia was the most linearly associated amongst the selected explanatory variables with Food CPI. These findings suggest that the selected CPI components can give different information for the forecasting models.

Table 2
Correlation analysis of the variables

	Inflation	Food CPI	Health CPI	Insurance CPI
Inflation	1.0000	0.6870	0.3629	0.1785
Food CPI	0.6870	1.0000	0.3985	0.1651
Health CPI	0.3629	0.3985	1.0000	0.4716
Insurance CPI	0.1785	0.1651	0.4716	1.0000

3.2 Forecasting Performance of ANN

Four different chronological training-testing ratios: 60:40, 70:30, 80:20, and 90:10 were used to test the ANN model. The forecasting performance was calculated using the RMSE, MAE, and MAPE, which are indicators of the forecasting accuracy with lower value showing better forecasting performance. The forecasting results of the ANN model in the four training-testing ratios are displayed in Table 3 below. From Table 3, the 90:10 ratio produced the lowest RMSE, MAE and MAPE, with values of 0.4722, 0.4271 and 32.52%, respectively. Thus, 90:10 was chosen as the optimum training-testing ratio of ANN. The predicted inflation series also reflected the general trend of the inflation series during the testing period, but larger differences were observed when there were periods of sharp fluctuations. The residual analysis shown in Table 4 below also revealed that ANN tended to overestimate inflation with mean residual of -0.4157, and the range of -0.6839 to 0.0682. However, there were no significant large forecasting errors.

Table 3
Forecasting performance of ANNs model

Training ratio	Testing ratio	Forecast accuracy metrics		
		RMSE	MAE	MAPE (%)
60	40	1.2521	1.1290	58.7542
70	30	1.3266	1.2183	67.5948
80	20	1.2818	1.1246	69.1112
90	10	0.4722	0.4271	32.5226

Table 4
Residual summary of ANNs model

Statistics	Value
Minimum residual	-0.6839
Maximum residual	0.0682
Mean residual	-0.4157
Standard deviation	0.2339

3.3 Forecasting Performance of Random Forest

To make sure the model is comparable, the RF model was tested with the same four training-testing ratios. The forecasting results are shown in Table 5 below. Forecasting performance was significantly better with more observations in the training set, with the 60:40 ratio returning the highest RMSE and MAE. The 90:10 ratio achieved the lowest RMSE of 0.3720 and MAE of 0.3192. Thus, the ratio of 90:10 was chosen as an optimum ratio for RF. From the residual summary shown in Table 6 below, the mean residual was -0.2563 and the standard deviation was 0.2816, which was quite close to the zero line, reflecting fairly consistent prediction errors.

Table 5
Forecasting performance of RF model

Training ratio	Testing ratio	Forecast accuracy metrics		
		RMSE	MAE	MAPE (%)
60	40	1.0153	0.7954	32.8653
70	30	0.5470	0.4580	27.3657
80	20	0.4138	0.3480	22.3951
90	10	0.3720	0.3192	23.8191

Table 6
Residual summary of RF model

Statistics	Value
Minimum residual	-0.6265
Maximum residual	0.1946
Mean residual	-0.2563
Standard deviation	0.2816

Results of the actual versus the predicted plot shown in Figure 3 indicated that RF has the ability to capture the overall direction of inflation during the testing period with some differences between predicted and actual inflation values. Another result obtained from the RF variable-importance technique shown in Table 7 below highlighted that the most important predictor was Food CPI followed by Health CPI and Insurance CPI. The importance values of %IncMSE and IncNodePurity were highest for Food CPI. The result confirms the results in the previous studies that the CPI components selected are not equally important for forecasting inflation, and the Food CPI is the most important component in the RF model.

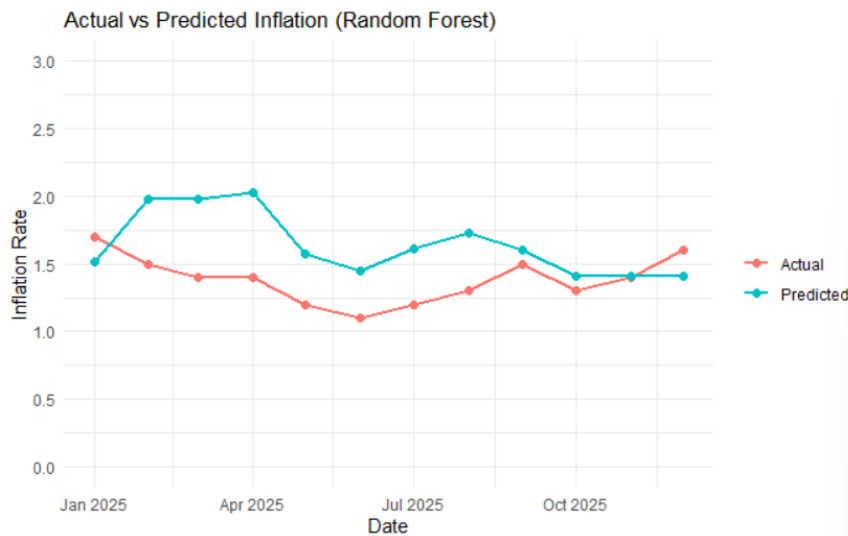


Fig. 3. Comparison between the actual and predicted inflation rate by random forest model using 90:10 training-testing ratio

Table 7
Variable importance summary of RF model

Variable	%IncMSE (%)	IncNodePurity (%)
Food CPI	32.6037	126.2704
Health CPI	29.1115	90.9589
Insurance CPI	24.8348	57.8700

3.4 Forecasting Performance of ARIMAX

Three ARIMAX specifications were tested for the four training-testing ratios: ARIMAX(1,1,1), ARIMAX(2,1,1) and ARIMAX(1,0,2). The ARIMAX(1,1,1) model achieved its lowest RMSE of 0.5157, MAE of 0.4611 and MAPE of 34.89% under the 90:10 ratio. While ARIMAX(2,1,1) achieved its best performance under the 80:20 ratio, with an RMSE of 0.5002, MAE of 0.4345 and MAPE of 26.92%. Conversely, the errors for ARIMAX(2,1,1) for the 90:10 ratio were larger than 80:20, suggesting that not every model specification would necessarily be improved by increasing the number of training observations.

Among the three ARIMAX specifications, the best performed model is ARIMAX(1,0,2). As shown in Table 8 below, the forecasting error was reduced continuously with the training percentage of 60% to 90%. The 90:10 ratio had the smallest RMSE of 0.3388, which is about 16% lower than the RMSE at the 80:20 ratio. It also obtained the minimum value of MAE and MAPE which is 0.2956 and 22.69%. Thus, the 90:10 ratio was chosen as the best ratio in ARIMAX(1,0,2).

Table 8

Forecasting performance of ARIMAX(1,0,2) model

Training ratio	Testing ratio	Forecast accuracy metrics		
		RMSE	MAE	MAPE (%)
60	40	0.8125	0.7346	34.6906
70	30	0.5420	0.4556	24.4734
80	20	0.4963	0.4073	24.4124
90	10	0.3388	0.2956	22.6892

From Figure 4, the selected ARIMAX(1,0,2) was also found to have a good fit between the actual and predicted inflation trend within the testing period. The model generally over-predicted inflation in part of the test period, but the model results were closer to the actual results during the latter stages of the test. The mean residual shown in Table 9 was -0.2738 and the standard deviation was 0.2084. The forecasting errors were fairly consistent, with most residuals falling within a fairly narrow range, although the negative mean suggests that there was a slight tendency to overestimate.

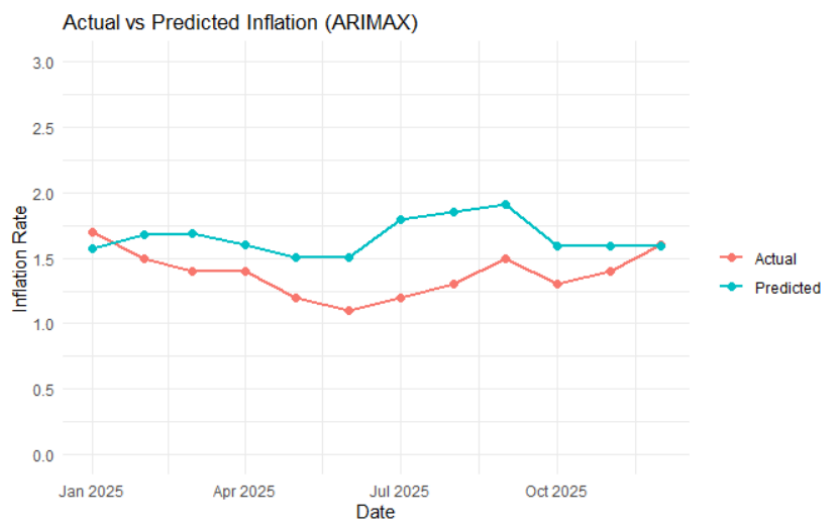


Fig. 4. Comparison between the actual and predicted inflation rate by ARIMAX(1,0,2) model using 90:10 training-testing ratio

Table 9

Residual summary of ARIMAX(1,0,2) model

Statistics	Value
Minimum residual	-0.5971
Maximum residual	0.1273
Mean residual	-0.2738
Standard deviation	0.2084

3.5 Optimal Training-Testing Ratio and Model Comparison

From the results above, it shows that training-testing ratio is affecting the forecasting performance. In the case of ANN and RF, the 90:10 ratio resulted in the lowest RMSE. The ARIMAX(1,1,1) also turned out to perform best for the 90:10 and ARIMAX(2,1,1) perform best for 80:20 cases, among the ARIMAX specifications. However, the ARIMAX(1,0,2) selected in this study had the optimal performance at 90:10 training-testing ratio.

Since three final models have the best overall configuration for the 90:10 ratio, so it is possible to compare their performance under the same conditions. Based on the Table 10 below, the model ARIMAX(1,0,2) resulted in the lowest values for all the evaluation metrics, with an RMSE of 0.3388, an MAE of 0.2956 and a MAPE of 22.69%. RF performed the second best with RMSE value of 0.3720, while ANN had the highest forecasting errors with an RMSE value of 0.4722. Hence, ARIMAX(1,0,2) model with the training-testing split of 90:10 was chosen as the final forecasting model. This may be explained by its better performance due to the inclusion of the historical dynamics of inflation and the information in the Food, Health and Insurance CPI as exogenous variables.

Table 10
Optimal training-testing ratio of each model

Model	Training-testing ratio	RMSE	MAE	MAPE (%)
ANN	90:10	0.4722	0.4271	32.5226
Random forest	90:10	0.3720	0.3192	23.8191
ARIMAX(1,0,2)	90:10	0.3388	0.2956	22.6892

3.6 24-Month inflation forecast

After selecting the model, the ARIMAX(1,0,2) model was retrained with the complete 120 monthly observations from January 2016 to December 2025. As it was not possible to have future values of Food CPI, Health CPI and Insurance CPI, the forecast results of these CPIs from Auto ARIMA were used as explanatory variables and fed into the retrained ARIMAX model as future external regressors. This last model was then applied to predict the inflation rate of Malaysia from January 2026 to December 2027.

Based on the forecasted inflation rate, the forecast starts around 1.81% in January of 2026 with a slight dip to the lowest level of 1.64% in March of 2026. Inflation then slowly rises to be around 2.08% in December 2026 and 2.49% in December 2027. The descriptive statistics shown in Table 11 below also align with the observed forecast pattern. The average predicted inflation rate during the 24-month period is 2.093% with a standard deviation of 0.279, which is relatively low. The lowest forecast is 1.644% and the highest is 2.487%, which is less than one percentage point throughout the entire two-year period. This implies that the ARIMAX model forecasts a gradual rise in inflation, rather than a sharp rise and fall, which indicates a relatively stable inflation rate, given the historical patterns and changes of the independent variables.

Table 11
Descriptive statistics summary of 24-month inflation forecast

Statistics	Value
Minimum	1.644%
Median	2.122%
Maximum	2.487%
Mean	2.093%
Standard deviation	0.2789

The original inflation and the 24-month ARIMAX(1,0,2) forecast of inflation are plotted in Figure 5 below. As illustrated, the forecast is running smoothly from the end of the historical series, and is not making any abrupt or unrealistic changes. Although the historical inflation rate was irregular and experienced a few sharp peaks and troughs over the ten-year observation period, the forecasted values present a smoother pattern. This behavior is normal as the ARIMAX model tries to explain the overall long-term relationship between inflation and the CPI components, rather than capturing every fluctuation in the historical inflation data. Consequently, this has led to a more stable forecast for future inflation, while at the same time capturing the underlying trend observed from past history.

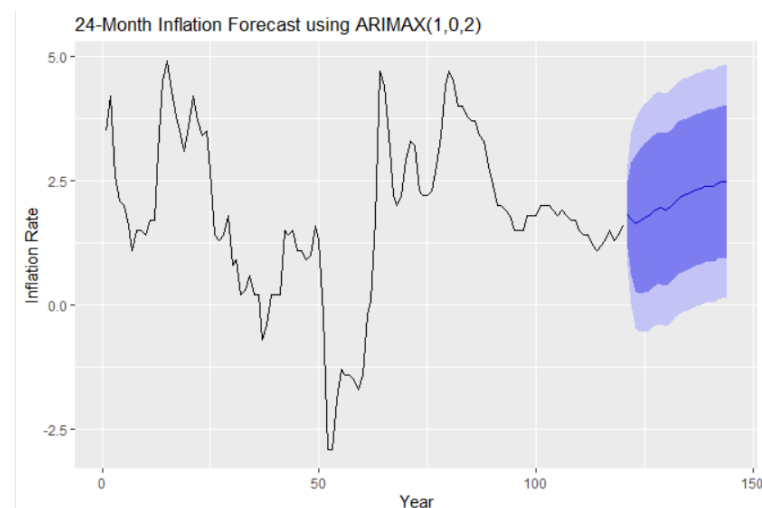


Fig. 5. 24-month inflation forecast using ARIMAX(1,0,2) model

Overall, the model projects a relatively stable inflation forecast, with inflation rising slightly, but not significantly, over the two-year forecasting horizon. The widening prediction intervals also suggest that the later predictions should be exercised with more caution, due to the increase in uncertainty over the longer forecasting horizon.

4. Conclusions

The aim of this study was to examine the forecasting of Malaysia's monthly inflation rate using selected Consumer Price Index (CPI) components such as Food, Health and Insurance CPI in three forecasting methods: Artificial Neural Network (ANN), Random Forest (RF) and AutoRegressive Integrated Moving Average with eXogenous variables (ARIMAX). Four ratios of chronological training-testing such as 60:40, 70:30, 80:20, and 90:10 were tested using RMSE, MAE, and MAPE, with RMSE as the main evaluation criterion. The results met all three research objectives very well.

The first objective of this study is the optimal training-testing ratio to be used for forecasting inflation. Results indicated that there was no single best ratio for each model specifications. Nevertheless, the ratio of 90:10 was determined as the optimal ratio for the final forecasting method, with ANN, RF and ARIMAX(1,0,2) performing the best with this ratio. On the other hand,

ARIMAX(2,1,1) had the minimum RMSE with the ratio of 80:20. Therefore, the results show that ratio of training to testing does not have a universal optimum, but depends on the model and the data set. The results reinforce the need for testing various data split ratios, instead of relying on the common ratios of 70:30 or 80:20. This finding is in line with Muraina [29] who found that a higher ratio of training observations can yield better prediction accuracy in relatively small datasets with the optimum ratio being dependent on the data set and the model. It further supported by Medar et al., [33] who discovered that there is no linear improvement in forecasting accuracy as the training period is extended.

Second, the forecasting capability of the ANN, RF and the three ARIMAX specifications was compared, with optimal training-testing ratio for each. The model with the lowest RMSE, MAE and MAPE was identified as ARIMAX(1,0,2) with the ratio 90:10 of which RMSE was 0.3388, MAE 0.2956 and MAPE 22.69%. This result is in line with the finding of Eksiandayani *et al.*, [50] who showed that ARIMAX is effective in forecasting inflation compared to neural network models. Similarly, Doguwa *et al.*, [51] discovered the dimension of incorporating CPI components as external variables could lead to better performance in forecasting inflation. The two features of ARIMAX that allow for incorporation of both internal time-series dynamics and external variables were also pointed out by Hyndman *et al.*, [52].

Third, the ARIMAX model selected was retrained with all the 120 monthly data for Malaysia from January 2016 to December 2025 and then applied to predict the inflation rate for the next 24 months, from January 2026 to December 2027. Forecasts of inflation ranged from 1.64% to 2.49%, with the average forecast being about 2.09% and the standard deviation being 0.28 percentage points. The forecast for inflation was to rise to around 1.81% in January 2026, then slowly fall to 1.64% in March 2026, and then gradually increasing to an estimated 2.08% in December 2026 and 2.49% in December 2027. The overall picture from the model is a relatively stable inflation outlook with gradual increases in the rate of inflation, without significant inflationary peaks and troughs.

Although the objectives of the research were met, there are a number of limitations that need to be taken into account when interpreting the findings. For instance, the models such as ANN and RF are not able to learn the complex nonlinear relationships, due to the limited 120 observations used in this study. This might be one of the reasons why the statistical ARIMAX forecasting model is suitable for this study and in agreement with Cerqueira *et al.*, [53] who noted that in situations of limited historical data, statistical forecasting techniques outperform forecasting techniques that use machine learning. Besides that, all the models only include three CPI components as explanatory variables. There were other macroeconomic variables that were not included such as exchange rates, crude oil prices, unemployment, money supply, interest rates, GDP, and relevant information particularly during periods of economic change or uncertainty. This restriction is in line with that found by Coker [27], Ibarra [20] and Bermingham *et al.*, [54] who pointed out the merits of using more macroeconomic indicators for inflation forecasting.

The current model could be expanded to include a greater number of macroeconomic and CPI-related variables and a historical time series for a longer period for model estimation in future studies. Other forecasting methods and combinations of models could be explored to assess if forecasting accuracy can be further improved. Moreover, the prediction intervals have expanded over the 24-month prediction period, reflecting the greater uncertainty in longer-term forecasts, thus suggesting that future research could explore forecasting methods that are more suitable to capture uncertainty on longer time horizons. However, this study has shown that it is possible to use a more informed approach to selecting an appropriate model for forecasting inflation in Malaysia by systematically investigating training-testing ratios and comparing the various forecasting methods.

Acknowledgement

This research was funded by any grant.

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