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An Explainable Machine Learning Framework for Inflation Forecasting in Nigeria: A Comparative Study of XGBoost, SARIMAX, and Hybrid SARIMAX-XGBoost

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Abstract
Inflation forecasting is essential for monetary policy formulation, business planning, and economic resilience. Accurate and interpretable forecasting models can support evidence-based economic decision-making in developing economies such as Nigeria. This study develops and evaluates an explainable inflation-forecasting framework for Nigeria using monthly inflation, broad Money Supply (M2), and exchange rate data spanning January 2004 to April 2021. Three forecasting approaches were compared: SARIMAX, XGBoost, and a Hybrid SARIMAX-XGBoost model. The model performance was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Directional Accuracy, and the Diebold-Mariano test. SHAP explainability analysis and an ablation study were also conducted to identify the most influential predictors. XGBoost achieved the best forecasting performance, with an RMSE of 0.7253 and MAPE of 5.16%, outperforming both SARIMAX and the Hybrid model. The Hybrid model performed similarly to SARIMAX, which indicates limited benefit from residual correction. SHAP analysis showed that the lagged inflation variables were the strongest predictors, while money supply (M2) was the most influential macroeconomic factor. Removing lagged inflation variables increased the RMSE from 0.7253 to 4.6507 and the MAPE from 5.16% to 36.15%. The findings show that explainable machine learning provides accurate short-term inflation forecasts and meaningful insights into inflation dynamics. Inflation persistence is the dominant driver of forecasting performance, while money supply contributes to predictive accuracy, supporting economic planning and policy decision-making in Nigeria.

Keywords: Inflation; XGBoost; SARIMAX; explainability.

1. Introduction

Inflation remains one of the major economic challenges facing Nigeria. Rising prices affect households, businesses, investments, and government planning by increasing the cost of living, raising production costs, and creating uncertainty in economic activities. Recent reports also show that inflation continues to affect poverty reduction and household welfare in Nigeria (World Bank, 2024). Inflation in Nigeria has been influenced by several economic factors, including exchange rate fluctuations, fuel price adjustments, food supply challenges, insecurity in farming communities, and monetary policy decisions. Recent reforms such as the removal of fuel subsidies and the liberalisation of the foreign exchange market have further increased inflationary pressures despite their long-term economic objectives (IMF, 2024).

Reliable inflation forecasting is therefore important for monetary policy, business planning, and economic decision-making. The Central Bank of Nigeria relies on inflation forecasts when making decisions on interest rates, money supply, and inflation control, while businesses use these forecasts for pricing, production planning, investment, and inventory management (CBN, 2022). However, forecasting inflation remains difficult because inflation is influenced by multiple economic factors whose relationships are often dynamic and nonlinear (Naghi *et al*., 2024; Liu, 2024).

Several forecasting approaches have been applied to inflation prediction. Statistical models such as ARIMA, SARIMA, and SARIMAX have remained widely used because they effectively model trends, seasonality, and time-series relationships. SARIMAX extends SARIMA by incorporating external variables such as the exchange rate and money supply, making it more suitable for macroeconomic forecasting (Box *et al.*, 2015). Doguwa and Alade (2013) demonstrated that SARIMAX produced better short-term inflation forecasts for Nigeria than SARIMA by incorporating relevant macroeconomic variables. Despite their effectiveness, these statistical models mainly assume linear relationships, which may reduce their performance when inflation is affected by policy reforms, external shocks, and other nonlinear economic interactions.

Machine learning methods, including Random Forest, Gradient Boosting, and Extreme Gradient Boosting (XGBoost), have gained attention because they can learn complex nonlinear relationships without relying on strict statistical assumptions. XGBoost, introduced by Chen and Guestrin (2016), has demonstrated strong forecasting performance across many economic forecasting applications. Recent studies also reported that machine learning models frequently outperform traditional statistical approaches when forecasting complex economic behaviour (Makridakis *et al.*, 2022; Naghi *et al*., 2024; Liu, 2024; Schnorrenberger *et al*., 2024). Hybrid forecasting models have also been proposed to combine the strengths of statistical and machine learning approaches. Zhang (2003) and Khashei and Bijari (2011) showed that hybrid models can improve forecasting accuracy when both linear and nonlinear patterns exist in the data, although their effectiveness depends on the characteristics of the dataset.

Although machine learning models often provide higher forecasting accuracy, many operate as black-box systems, making it difficult to understand how individual variables contribute to their predictions. This limits their usefulness in economic policy, where decision-makers require both accurate forecasts and transparent explanations. Explainable

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Artificial Intelligence (XAI) addresses this challenge by providing techniques for interpreting machine learning models. Ribeiro *et al*. (2016) introduced Local Interpretable Model-Agnostic Explanations (LIME), while Lundberg and Lee (2017) developed Shapley Additive exPlanations (SHAP), which quantifies the contribution of each variable to model predictions. Aras (2022) further demonstrated that explainable machine learning can provide both accurate and interpretable inflation forecasts.

Previous studies have applied statistical, machine learning, and hybrid models to inflation forecasting, with many reporting improvements in forecasting accuracy. However, most studies focused primarily on predictive performance, while limited attention was given to explaining the factors driving model predictions. Furthermore, few studies separately examined the contribution of inflation persistence and macroeconomic variables to forecasting performance, and explainable machine learning has received limited application in inflation forecasting within the Nigerian context. These limitations reduce the practical value of forecasting models for monetary policy and economic planning.

To address these gaps, this study develops and evaluates an explainable inflation forecasting framework for Nigeria by comparing SARIMAX, XGBoost, and a Hybrid SARIMAX–XGBoost model using monthly inflation, money supply, and exchange rate data. Forecasting performance is evaluated using standard forecasting metrics, while SHAP analysis is applied to explain the contribution of individual variables. An ablation study is further conducted to assess the relative importance of inflation persistence and macroeconomic variables. The proposed framework aims to provide both accurate inflation forecasts and interpretable insights that can support evidence-based economic planning and monetary policy in Nigeria.

2. Materials and Methods

2.1 Research Design

A quantitative research design was used in this study to develop and evaluate an explainable framework for short-term inflation forecasting in Nigeria. The study combined statistical, machine learning, and hybrid forecasting models to compare their performance in predicting inflation. Monthly inflation and selected macroeconomic data were obtained from official sources. The data were cleaned and prepared before exploratory analysis was carried out. SARIMAX, XGBoost, and a Hybrid SARIMAX-XGBoost model were then developed and evaluated using the same dataset. SHAP explainability analysis was later applied to identify the variables with the greatest influence on the model predictions. The methodology focused on two main objectives. The first was to compare the forecasting performance of the developed models. The second was to explain the factors influencing the inflation forecasts.

2.2 Research Framework

Figure 1 shows the overall research framework used in this study. The framework starts with the collection of inflation and macroeconomic data from official sources. The data are cleaned and explored before developing the forecasting models. Three forecasting approaches are considered in this study: SARIMAX, XGBoost, and the Hybrid SARIMAX-XGBoost model. Their forecasting performance is compared using standard evaluation metrics. SHAP explainability analysis and an ablation study are then used to identify the variables that

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contribute most to the inflation forecasts and to explain the model results from an economic perspective.

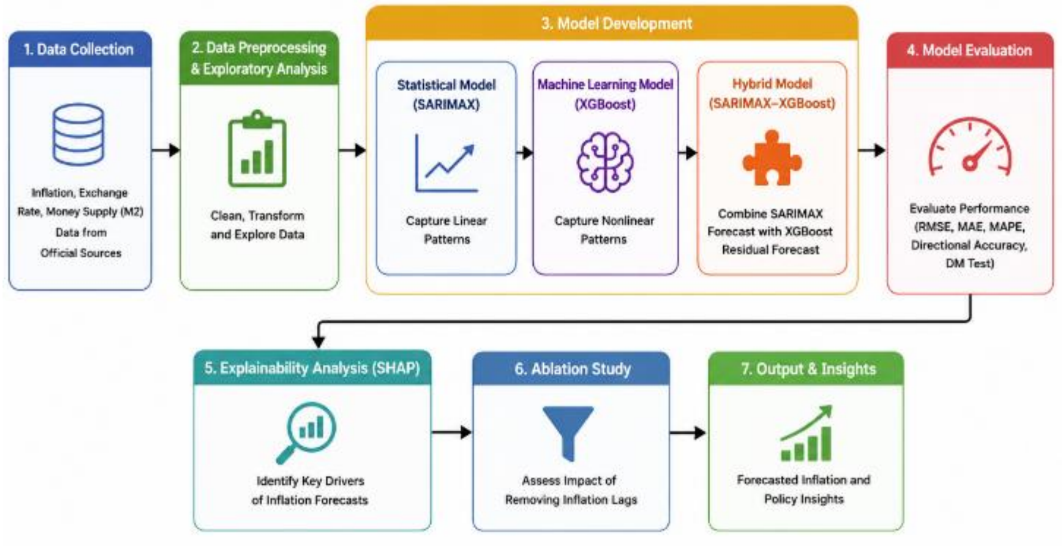

Figure 1. Proposed Explainable Hybrid SARIMAX-XGBoost Inflation Forecasting Framework

2.3 Data Sources and Data Description

Secondary data from reliable public sources were used in this study. Monthly inflation data were obtained from the National Bureau of Statistics (NBS), while exchange rate and broad money supply (M2) data were collected from the Central Bank of Nigeria (CBN). The monthly headline inflation rate was used as the target variable. The exchange rate and broad money supply (M2) were selected as explanatory variables because previous studies have identified them as important factors influencing inflation. The dataset contains monthly observations from January 2004 to April 2021. This period includes major economic events in Nigeria, such as exchange rate adjustments, oil price fluctuations, monetary policy changes, recession periods, and episodes of high inflation. These events make the dataset suitable for evaluating inflation forecasting models. Table 1 presents the variables used in this study.

Table 1. Description of Variables

Variable	Description	Source
Inflation	Monthly Headline Inflation Rate (%)	NBS
Exchange Rate	Monthly Naira-US Dollar Exchange Rate	CBN
Money Supply (M2)	Broad Money Supply	CBN

2.4 Data Preprocessing

Data preprocessing was carried out before model development to improve the quality and consistency of the dataset. Monthly inflation, exchange rate, and money supply data were merged using their timestamps to form a single dataset. Missing values were handled with interpolation where necessary, while duplicate records and inconsistent entries were removed. Descriptive statistics, including the mean, median, standard deviation, minimum, and maximum values, were calculated to summarise the dataset. Time-series plots were also examined to observe inflation trends and identify possible structural changes. An Augmented Dickey-Fuller (ADF) test was performed to check whether the data were stationary. Series that were not stationary were differenced before modelling. Lagged variables for inflation, exchange rate, and money supply were then created using three lag periods to capture delayed effects and historical relationships among the variables. The processed dataset was arranged according to time and divided into training and testing sets using an 80:20 ratio to preserve the time sequence.

2.5 Exploratory Data Analysis

Exploratory Data Analysis (EDA) was carried out to understand the behaviour of inflation and its relationship with the selected macroeconomic variables. Line charts were used to examine inflation trends over the study period. Correlation analysis was performed to measure the relationship between inflation, exchange rate, and money supply. Scatter plots, box plots, and correlation heatmaps were also generated to identify patterns, unusual observations, and possible relationships in the data before model development.

2.6 Development of Statistical Forecasting Models

SARIMA and SARIMAX were used as the statistical forecasting models in this study. SARIMA models the autoregressive, differencing, moving average, and seasonal components of time-series data. The general SARIMAX formulation used in this study is expressed as:

$$\Phi_{\mathrm{p}}(B^{\mathrm{s}})\varphi_{\mathrm{p}}(B)(1-B)^{\mathrm{d}}(1-B^{\mathrm{s}})^{\mathrm{D}}y_{\mathrm{t}} = \beta X_{\mathrm{t}} + \Theta Q(B^{\mathrm{s}})\theta q(B)\varepsilon_{\mathrm{t}} \tag{1}$$

where $\mathrm{y_t}$ represents inflation at time t, B is the backshift operator, $\mathrm{X_t}$ represents the exogenous variables, and β represents their coefficients. The parameters p, d, and q represent the non-seasonal autoregressive, differencing, and moving-average orders, respectively, while P, D, and Q represent the corresponding seasonal orders, and s is the seasonal period.

In this study, the exogenous variables were money supply (M2) and exchange rate. Model parameters were selected using an automated search based on the Akaike Information Criterion (AIC). The model with the lowest AIC value was selected, and residual diagnostic tests were performed to confirm that the model satisfied the required assumptions.

2.7 Development of Machine Learning Models

XGBoost was used as the machine learning model for inflation forecasting. The model builds decision trees sequentially, with each new tree reducing the errors made by the previous trees. It also includes regularisation techniques that help reduce overfitting and improve prediction performance.

The general XGBoost prediction can be expressed as:

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$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), \; f_k \in \mathcal{F} \tag{2}$$

where $\hat{y}_i$ is the predicted inflation value for observation i, K is the number of trees, x_i represents the input features, and f_k represents the prediction from the k-th decision tree.

The XGBoost objective function is expressed as:

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{3}$$

where $l(y_i, \hat{y}_i)$ represents the prediction loss between the actual and predicted values, while $\Omega(f_k)$ represents the regularisation used to control model complexity.

In this study, Grid Search Cross Validation (GridSearchCV) together with TimeSeriesSplit was used to determine the best model parameters. The optimisation considered tree depth, learning rate, number of estimators, subsampling ratio, and column sampling ratio. The final model was trained with the training dataset and evaluated using the testing dataset.

2.8 Development of the Hybrid SARIMAX-XGBoost Model

The Hybrid SARIMAX-XGBoost model combines statistical and machine learning forecasting. SARIMAX was first used to generate inflation forecasts and the corresponding residual errors. These residuals contain information that was not explained by the statistical model. XGBoost was then trained to learn the remaining patterns in the residual series. The final forecast was obtained by adding the SARIMAX forecast to the residual forecast produced by XGBoost.

The SARIMAX residual is defined as:

$$e_t = y_t - \hat{y}_t^{SARIMAx} \tag{4}$$

where e_t is the residual at time t, y_t is the observed inflation value, and $\hat{y}_t^{SARIMAx}$ is the inflation forecast produced by SARIMAX.

XGBoost is then used to estimate the residual component:

$$\hat{e}_t = XGBoost(X_t) \tag{5}$$

where $\hat{e}_t$ represents the residual forecast produced by XGBoost based on the input features X_t.

The final hybrid forecast is obtained as:

$$\hat{y}_t^{Hybrid} = \hat{y}_t^{SARIMAx} + \hat{e}_t \tag{6}$$

This approach allows the hybrid model to combine the time-series and exogenous-variable modelling capability of SARIMAX with the nonlinear pattern-learning capability of XGBoost. In the present study, the hybrid model was evaluated against the individual SARIMAX and XGBoost models rather than assuming that combining the two models would necessarily improve forecasting accuracy.

2.9 Explainability Analysis Using SHAP

Forecast accuracy alone is not enough for economic policy decisions. It is also important to understand the factors influencing each prediction. SHapley Additive exPlanations (SHAP) was used to measure the contribution of each predictor variable to the forecasting results. SHAP provides both global and local explanations. Global explanations identify the variables that have the greatest influence across the entire dataset, while local explanations explain the factors responsible for individual predictions. SHAP analysis was applied to both the complete forecasting model and the economic-only model used in the ablation study. This made it possible to compare the contribution of each predictor under both experimental settings.

2.10 Ablation Study

An ablation study was carried out to examine the contribution of inflation persistence to forecasting performance. The first experiment included lagged inflation together with exchange rate and money supply variables. The second experiment removed the lagged inflation variables and used only exchange rate and money supply as predictors. The forecasting results from both experiments were compared using RMSE and MAPE. The ablation study also helped explain the SHAP results by showing whether forecasting performance depended mainly on past inflation values or on the selected macroeconomic variables.

2.11 Model Evaluation

The forecasting models are evaluated using standard forecasting performance measures.

2.11.1 Mean Absolute Error (MAE)

The Mean Absolute Error measures the average magnitude of forecasting errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{7}$$

where y_i is the observed inflation value, $\hat{y}_i$ is the predicted value, and n is the total number of observations.

2.11.2 Root Mean Square Error (RMSE)

The Root Mean Square Error gives greater weight to larger forecasting errors.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

where y_i is the observed value, $\hat{y}_i$ is the forecast value, and n is the number of observations.

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2.11.3 Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error measures forecasting error in percentage terms.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{9}$$

where y_i represents the observed inflation value and $\hat{y}_i$ represents the predicted inflation value.

2.11.4 Directional Accuracy (DA)

Directional Accuracy measures the ability of the forecasting model to predict whether inflation will increase or decrease.

$$DA = \frac{1}{n}\sum_{i=1}^{n} I[(y_i - y_{i-1})(\hat{y}_i - \hat{y}_{i-1}) > 0] \times 100 \tag{10}$$

where *I* is an indicator function that takes a value of 1 when the predicted and actual inflation movements have the same direction and 0 otherwise. The Diebold-Mariano (DM) test is conducted to determine whether the performance differences between forecasting models are significant. The test compares forecast errors from competing models, and it determines whether one model provides better forecasts than another.

2.12 Experimental Environment

Python was used to develop and evaluate the forecasting models, while PyCharm served as the development environment. Data preprocessing and analysis were carried out using Pandas and NumPy. SARIMAX was implemented with the Statsmodels library, while XGBoost and model optimisation were implemented using Scikit-learn and the XGBoost library. SHAP analysis was performed with the SHAP library, and Matplotlib was used to generate the figures. The experiments were carried out on a standard personal computer with enough computing resources for data preprocessing, model training, model evaluation, SHAP analysis, and result visualisation.

Data were drawn from LMS activity logs and examination records for 405 second-year undergraduate students enrolled in an introductory statistics course across three faculties during the 2025/2026 session. Weekly engagement hours were computed as the mean number of hours logged per week over the fourteen-week semester. Prior academic standing was measured using cumulative grade point average (CGPA) at the start of the semester, and tutorial attendance was recorded as the proportion of scheduled tutorial sessions attended.

The relationship between examination performance and the predictor variables was modelled using ordinary least squares multiple regression, specified as:

$$Yi = \beta 0 + \beta 1Ei + \beta 2Ci + \beta 3Ai + \varepsilon i \tag{1}$$

where Yi is the examination score for student i; Ei is average weekly engagement hours; Ci is prior CGPA; Ai is tutorial attendance proportion; β0 is the intercept; β1, β2, and β3 are regression coefficients; and εi is the error term. Statistical significance was assessed at the

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0.05 level, and model diagnostics included tests for heteroscedasticity and multicollinearity (variance inflation factor < 5 for all predictors).

3. Results and Discussions

This section discusses the results obtained from the forecasting models developed in this study. Three models were evaluated: SARIMAX, XGBoost, and the Hybrid SARIMAX-XGBoost model. Monthly inflation, exchange rate, and money supply (M2) data for Nigeria were used in the evaluation. The models were compared using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). SHAP analysis was also used to explain the contribution of each variable to the forecasts. An ablation study was further carried out to examine the effect of lagged inflation variables on model performance.

3.1 Forecasting Performance Evaluation

The forecasting performance of SARIMAX, XGBoost, and the Hybrid SARIMAX-XGBoost model was compared using four evaluation metrics. MAE measures the average forecasting error, RMSE gives more weight to larger errors, MAPE expresses the error as a percentage, and Directional Accuracy (DA) measures how well each model predicts the direction of inflation changes. The results are presented in Table 2.

Table 2. Forecasting Performance of the Models

Model	MAE	RMSE	MAPE (%)	Directional Accuracy (%)
SARIMAX	3.3604	3.6384	28.12	72.50
XGBoost	0.6523	0.7253	5.16	45.00
Hybrid SARIMAX–XGBoost	3.4064	3.6914	28.51	70.00

The results presented in Table 2 show that XGBoost produced the best forecasting performance among the three models. It recorded the lowest MAE, RMSE, and MAPE values, indicating that its forecasts were closer to the actual inflation values than those generated by SARIMAX and the Hybrid SARIMAX-XGBoost model. The Hybrid model performed almost the same as SARIMAX, suggesting that adding the residual learning stage did not produce any noticeable improvement in forecasting accuracy.

3.2 Mean Absolute Error Analysis

Mean Absolute Error (MAE) measures the average difference between the predicted and the actual inflation values, with lower values indicating better forecasting performance. As shown in Table 2, XGBoost achieved the lowest MAE of 0.6523, whereas SARIMAX and the Hybrid model recorded values above 3.3. This shows that the average forecasting error of XGBoost was much lower than that of the other two models, making it the most accurate model based on the MAE metric. The comparison of MAE values is presented in Figure 2.

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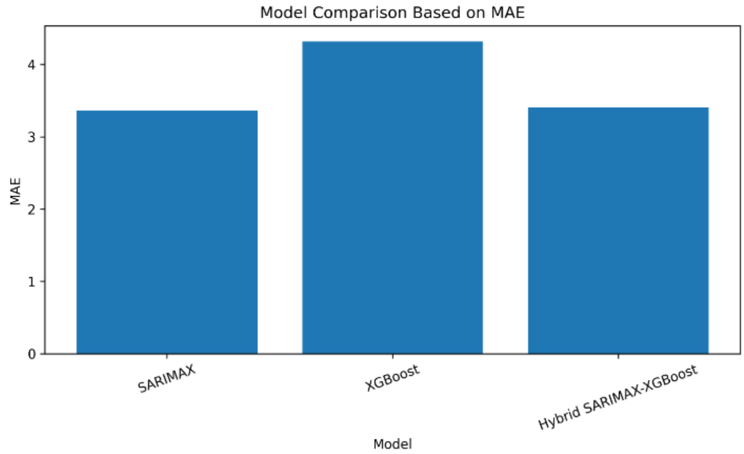

Figure 2. MAE Comparison

Figure 2 also shows the clear difference in MAE among the three models. XGBoost recorded a much lower error than SARIMAX and the Hybrid model, indicating that it learned the inflation pattern more effectively and produced more accurate forecasts.

3.2.1 Root Mean Square Error Analysis

Root Mean Square Error (RMSE) gives more weight to larger forecasting errors, making it useful for assessing model performance during periods of sharp inflation changes. The values in Table 2 show that XGBoost achieved the lowest RMSE of 0.7253, while SARIMAX and the Hybrid model recorded 3.6384 and 3.6914, respectively. These results further confirm that XGBoost produced more accurate forecasts and handled larger prediction errors better than the other models. The comparison of RMSE values is presented in Figure 3.

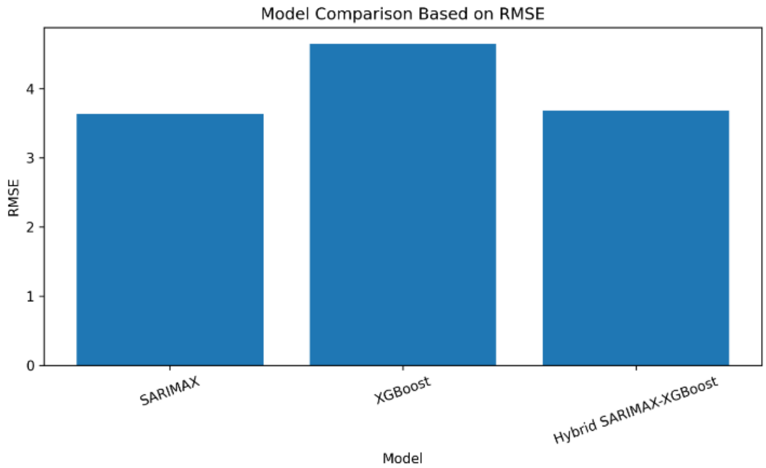

Figure 3. RMSE Comparison

The RMSE comparison in Figure 3 supports the results in Table 2. XGBoost produced much smaller forecasting errors than SARIMAX and the Hybrid model, showing that it handled changes in inflation more effectively than the statistical approaches.

3.2.2 Mean Absolute Percentage Error Analysis

Mean Absolute Percentage Error (MAPE) expresses forecasting error as a percentage, which makes it easier to compare the accuracy of the models. As shown in Table 2, XGBoost recorded the lowest MAPE of 5.16%, while SARIMAX and the Hybrid model recorded 28.12% and 28.51%, respectively. These results indicate that the predictions generated by XGBoost were much closer to the actual inflation values. The percentage error for each model is presented in Figure 4.

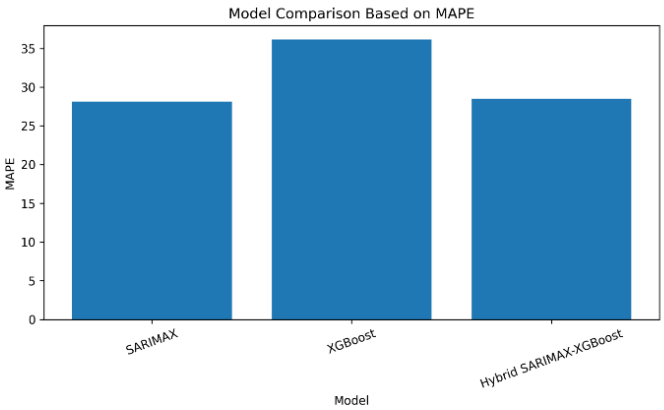

Figure 4. MAPE Comparison

The comparison in Figure 4 agrees with the MAPE values reported in Table 2. XGBoost maintained the lowest percentage error among the three models, confirming its higher forecasting accuracy. This result suggests that the model was better able to learn the nonlinear patterns present in the inflation data.

3.2.3 Directional Accuracy Analysis

Directional Accuracy (DA) measures how well a model predicts whether inflation will increase or decrease. The values in Table 2 show that SARIMAX recorded the highest Directional Accuracy of 72.5%, followed by the Hybrid model with 70.0%, while XGBoost recorded 45.0%. Although XGBoost achieved the lowest forecasting errors based on MAE, RMSE, and MAPE, it was less accurate in predicting the direction of inflation changes. The comparison of Directional Accuracy is presented in Figure 5.

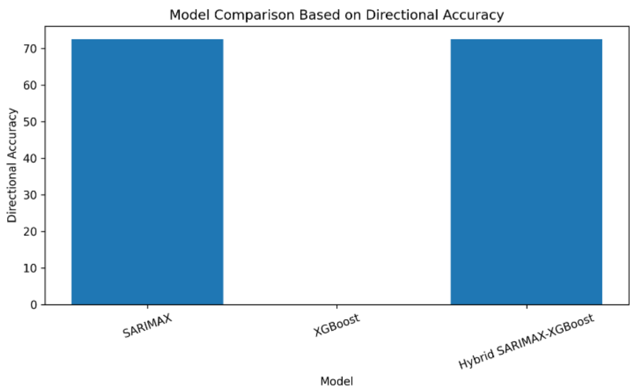

Figure 5. Directional Accuracy Comparison

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Figure 5 shows a clear trade-off between forecasting accuracy and directional prediction. SARIMAX performed better at predicting whether inflation would rise or fall, even though XGBoost achieved lower forecasting errors. This indicates that a model can produce more accurate forecasts without necessarily giving the best prediction of the direction of inflation movement.

3.3 Comparative Forecast Analysis

The evaluation metrics provide a numerical comparison of the forecasting models, but examining the forecast curves also helps to understand how each model followed changes in inflation over time. Figure 6 compares the actual inflation values with the forecasts produced by SARIMAX, XGBoost, and the Hybrid SARIMAX-XGBoost model.

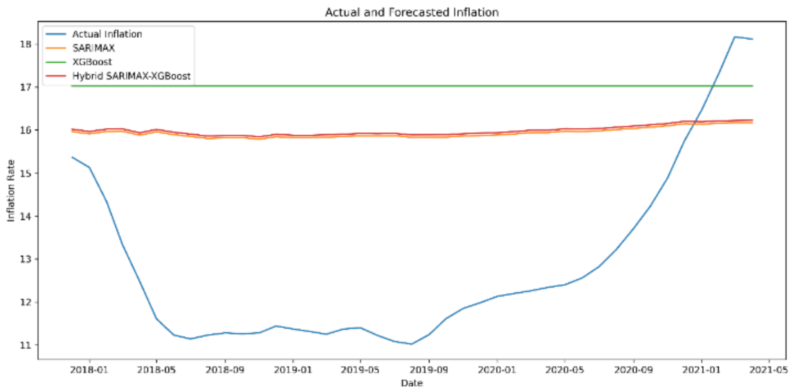

Figure 6. Actual and Forecasted Inflation

The actual inflation trend can be divided into three periods. Inflation first declined from about 15.4% to 11.0% between 2018 and 2019. It then increased gradually during 2020 before rising sharply to above 18% in early 2021. SARIMAX produced relatively smooth forecasts that stayed close to the average inflation level throughout the period. Although the model followed the overall trend, it did not fully capture the size of the changes observed in the actual inflation data. The Hybrid SARIMAX-XGBoost model produced almost the same forecast pattern as SARIMAX, which explains why both models recorded similar evaluation results. XGBoost also generated a smoother forecast than the actual inflation series, but it achieved the lowest forecasting errors across all the evaluation metrics. This indicates that the model learned the main inflation patterns in the data more effectively than the other forecasting approaches.

3.4 Statistical Significance of Forecast Differences

The Diebold-Mariano (DM) test was carried out to examine whether the differences in forecasting performance among the models were statistically significant. The results are presented in Table 3.

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Table 3. Diebold-Mariano Test Results

Comparison	DM Statistic
SARIMAX vs Hybrid	-7.8718
XGBoost vs Hybrid	-10.0787
SARIMAX vs XGBoost	10.1341

The large Diebold-Mariano (DM) statistics confirm that the differences in forecasting performance were statistically significant. The comparison between SARIMAX and XGBoost shows that XGBoost produced more accurate forecasts than the statistical model. A similar result was observed when XGBoost was compared with the Hybrid model, indicating that the additional residual learning stage did not improve forecasting accuracy. Overall, the DM test supports the better performance of XGBoost.

3.5 Explainability Analysis of the Full Model

Forecast accuracy alone does not explain why a model makes a particular prediction. SHAP analysis was therefore used to identify the variables that contributed most to the forecasts generated by XGBoost. The SHAP summary plot for the full model is presented in Figure 7.

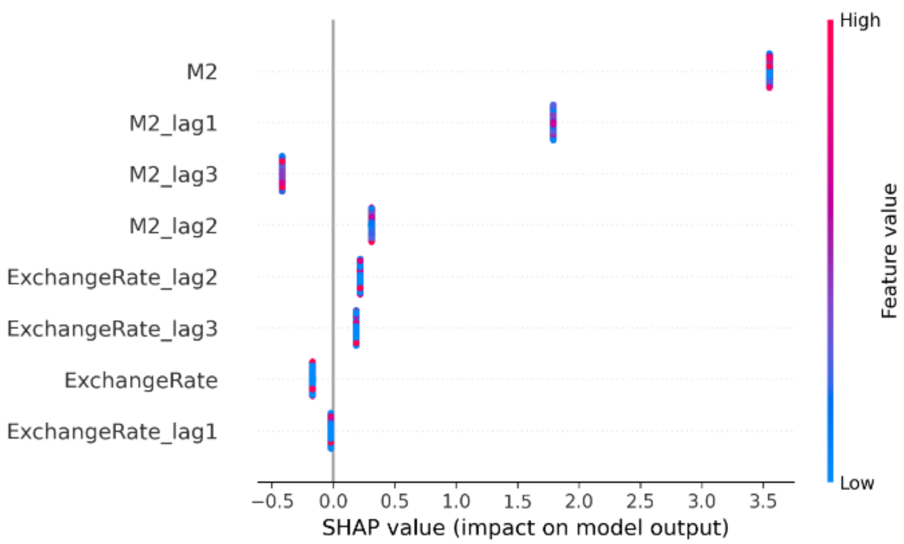

Figure 7. SHAP Summary Plot for the Full Model

3.6 Ablation Study

SHAP results indicated that the lagged inflation variables made a strong contribution to the forecasting performance. To better understand their importance, another experiment was carried out by removing all lagged inflation variables from the XGBoost model. The revised model used only exchange rate and money supply as predictor variables, making it possible to compare the contribution of inflation persistence with that of the selected macroeconomic variables.

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3.6.1 Economic-Only Forecasting Performance

Table 4 compares the forecasting performance of the full model with that of the economic-only model.

Table 4. Performance Before and After Removing Inflation Lags

Configuration	RMSE	MAPE (%)
Full Model	0.7253	5.16
Economic Variables Only	4.6507	36.15

Removing the lagged inflation variables reduced the forecasting performance of the model. RMSE increased from 0.7253 to 4.6507, while MAPE increased from 5.16% to 36.15%. These changes indicate that past inflation values contain important information for predicting future inflation and make a major contribution to the overall forecasting accuracy.

3.6.2 Economic-Only Forecast Visualisation

The forecasts produced by the economic-only model were compared with the actual inflation values to show the effect of removing the lagged inflation variables, as shown in Figure 8.

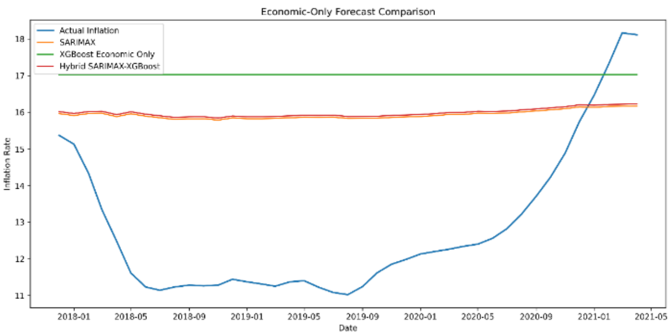

Figure 8. Economic-Only Forecast Comparison

Figure 8 compares the forecasts from the economic-only model with the actual inflation values. The model produced relatively flat forecasts and was unable to follow many of the changes observed in the inflation series. This explains the higher RMSE and MAPE values reported in Table 4 and shows that exchange rate and money supply alone were not enough to capture short-term inflation movements.

3.6.3 SHAP Analysis of the Economic-Only Model

The SHAP summary plot for the economic-only model is presented in Figure 9.

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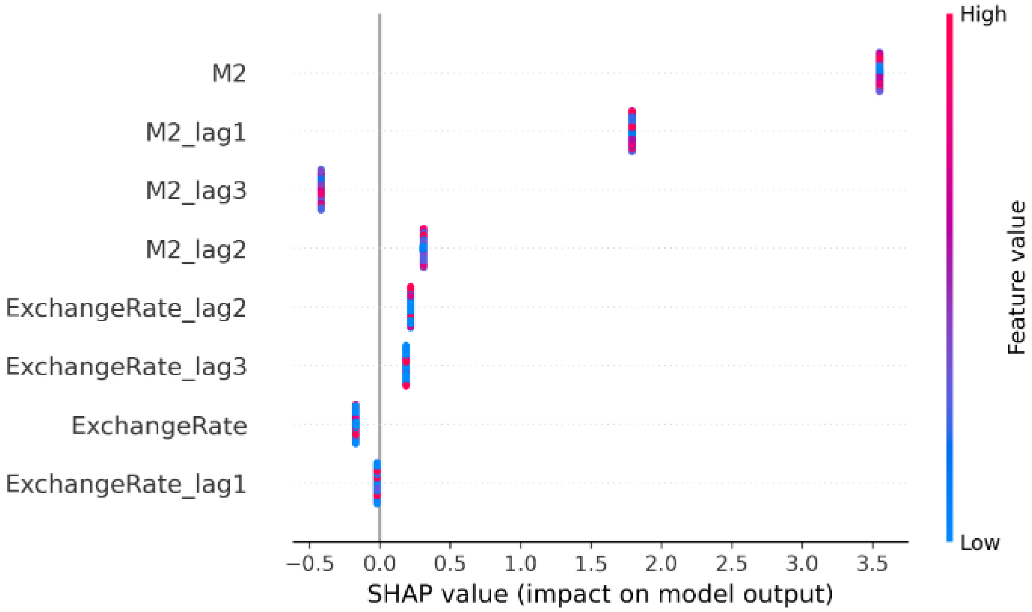

Figure 9. SHAP Summary Plot for Economic-Only Model

After removing the lagged inflation variables, M2 became the most important predictor in the model. M2 and its lagged values ranked highest in the feature importance results, while the exchange rate variables remained relevant but contributed less. This indicates that money supply contained stronger predictive information than exchange rate movements during the study period.

3.7 Discussion of Findings

XGBoost performed better than SARIMAX and the Hybrid SARIMAX-XGBoost model across most of the evaluation metrics. This shows that machine learning can capture the nonlinear behaviour of inflation better than the statistical models used in this study. The results also show that inflation persistence played an important role in forecasting future inflation. When the lagged inflation variables were removed, forecasting performance dropped considerably, indicating that past inflation values contain useful information for predicting future inflation. Money supply (M2) was the most important macroeconomic variable identified by both the full model and the economic-only model. Although the full XGBoost model achieved the best forecasting accuracy by including lagged inflation variables, those variables mainly reflect past inflation behaviour. The economic-only model produced lower forecasting accuracy, but it provided a clearer picture of how monetary variables influenced inflation forecasts.

3.8 Policy Implications

The findings from this study have useful implications for inflation management and monetary policy in Nigeria. The strong influence of inflation persistence suggests that inflationary pressure can remain for some time if policy action is delayed. Responding early may therefore help reduce the long-term effects of rising prices. Money supply also showed a strong influence on inflation forecasts. This means that changes in monetary aggregates can provide useful information for inflation monitoring and should be considered when making monetary policy decisions. The results also show that explainable machine learning models such as XGBoost can support inflation forecasting in Nigeria. Besides producing accurate forecasts, SHAP explanations help identify the variables responsible for each prediction, making the results easier for policymakers to understand and use.

3.9 Summary of Findings

This study developed and evaluated an explainable machine learning framework for forecasting inflation in Nigeria using monthly inflation, money supply (M2), and exchange rate data. SARIMAX, XGBoost, and the Hybrid SARIMAX-XGBoost model were developed and compared using MAE, RMSE, MAPE, and Directional Accuracy. SHAP analysis was also used to explain the contribution of each variable to the forecasting results. The results showed clear differences in the performance of the three models. XGBoost recorded the best forecasting accuracy with an RMSE of 0.7253 and a MAPE of 5.16%. SARIMAX produced moderate results after parameter tuning, while the Hybrid SARIMAX-XGBoost model performed almost the same as SARIMAX and did not provide any meaningful improvement. SHAP analysis identified the lagged inflation variables as the strongest contributors to the forecasts. Inflation_lag1 ranked first, followed by M2 and Inflation_lag2, showing that inflation persistence is an important factor in predicting future inflation in Nigeria. The ablation study further confirmed this result. Removing the lagged inflation variables caused RMSE to increase from 0.7253 to 4.6507, while MAPE increased from 5.16% to 36.15%. This shows that historical inflation contains important information that improves forecasting performance. The SHAP results for the economic-only model showed that M2 became the most important predictor after the lagged inflation variables were removed. The exchange rate also contributed to the forecasts, although its influence was lower than that of money supply. This suggests that money supply was the stronger macroeconomic predictor of inflation during the study period.

4. Conclusion

This study developed an explainable machine learning framework for short-term inflation forecasting in Nigeria using SARIMAX, XGBoost, and a Hybrid SARIMAX-XGBoost model. The results showed that XGBoost achieved the best forecasting performance, while SHAP analysis identified inflation persistence and money supply (M2) as the major factors influencing the forecasts. The study also showed that combining forecasting with explainability can produce accurate predictions and provide useful information for economic planning and policy decisions. The study contributes by comparing statistical, machine learning, and hybrid forecasting models within a single framework and by using SHAP and ablation analysis to explain the factors driving inflation forecasts. The findings provide additional evidence on the usefulness of explainable machine learning for inflation forecasting in Nigeria. Future studies can include more macroeconomic variables, evaluate advanced deep learning models such as LSTM, GRU, and Temporal Fusion Transformers (TFT), and develop real-time forecasting systems that update automatically as new economic data become available.

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