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Foreign exchange rates, oils price, domestic economic policies, supply chain disruption and inflation rate in Nigeria: Evidence from ensemble learning algorithms

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Abstract This study investigates the drivers of inflation in Nigeria, focusing on the influence of foreign currencies, oil prices, domestic economic policies and supply chain disruption. With Nigeria experiencing an unprecedented inflation rate, the study employs five ensemble learning algorithms; Decision Tree, Random Forest, AdaBoost, Bagging, and Gradient Boosting regressions to uncover the relationships between inflation rates and its potential drivers. These drivers considered are exchange rates of foreign currencies, oil prices, domestic economic policies (the removal of oil subsidies and the floating of the Naira), and supply chain disruptions linked to the ongoing Russian-Ukrainian War. To better capture the effect of oil subsidy removal, floating of the Naira and Russia–Ukraine war, the continuous time-based variables which created a time counters that track the number of periods since these events occurred was used. The Exchange Rate Pass-Through (ERPT) Theory and Cost-Push Inflation Theory provided the theoretical framework for this study. Data from the Central Bank of Nigeria, covering January 2012 to September 2024, were used and the time series cross validation was used to ensure robustness against temporal dependencies while multicollinearity analysis was carried out using the Variance Inflation Factor (VIF) followed by PCA for dimensionality reduction. To estimate the possible effect of outliers the result was presented with and without robust scaler. Preprocessing was carried out, hyperparameters tuning were performed using Grid Search algorithm, and model performance was evaluated using metrics such as Mean Absolute Error, R-squared, Root Mean Square Error, Huber loss and adjusted R-squared using five-fold cross-validation. The results reveal a significant positive relationship between foreign currency exchange rates and inflation $p < .05$ with evidence of multicollinearity among features and hence the Principal Component Analysis (PCA) was used in dimensionality reduction. The use of robust scaler was found to improve the performance of the Machine Learning algorithms and the Gradient Boost algorithms outperformed other machine learning algorithms with the least RMSE (1.2990), MAE (0.8132) and Huber loss (0.5036) and the highest values of R^2 (0.9671) and adjusted R^2(0.9634). Additional analysis using feature importance, Shapley Additive exPlanations (SHAP) and Partial Dependence (PP) plots showed that domestic policies variables particularly the removal of fuel subsidy and the floating of the Naira policy had the most significant positive impact on inflation in Nigeria while exchange rate of CFA and other global currencies such as USD and Euro were found to have moderate impact on inflation. These findings underscore an urgent need to reinvest savings from the subsidy removal into developmental projects such as building of refineries while also providing incentives and financial support to cushion the effect of subsidy removal. The need to establish currency swap agreements with key trade partners particularly China will help stabilize the Naira and its exposure to foreign currency volatility. These strategies could help in improving external balances, support industrial growth, and promote long –term resilience of Nigerian economy.

Keywords Inflation Rate, Machine Learning, Foreign Currencies, algorithms

AMS 2010 subject classifications 91G70, 62M20, 62P05.

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1. Introduction

1.1. Overview

One of the major problems in Nigeria now is that of the high rate of inflation and exchange rate in Nigeria. At present, the inflation rate in Nigeria is the highest in the history of the country inflation rate stands in March 2024 stands at 33.2%from 31.70% in February and it is expected to be 38.50% at the end of the first quarter of 2024 (This is an all-time high in Nigeria history). The issue of Naira to foreign currencies has also become a topical issue with the government doing everything possible to strengthen the naira. Nigeria as a country has been observed to be overdollarized with over-reliant on foreign currencies as against the Naira which is an official legal tender in Nigeria. Exchange rate and inflation have remained one the most discourse issues in Nigeria Ewubare & Ushang [1]. Presently Nigeria is suffering badly from a high inflation rate. The rapid increase in the price level of the goods and services which are the daily needs of the households. The most famous indicator of inflation is the consumer price index, which measures the percentage change in the prices of services & goods consumed by households. The increasing rate of inflation reflects the turmoil in the political and economic situation in Nigeria. It was observed that some school fees including house rents are paid in dollars and the activities of some unscrupulous owners of Bureau De Change (those that specialize in changing currencies from Naira to other foreign currencies) The government agencies particularly the Central Bank of Nigeria (CBN) and Economic and Financial Crime Commission have stem into action by curbing with some of the unscrupulous practices and ensuring that the naira is strengthened some of which has been yielding positive results. One of the major obstacles to managing economic policy globally, especially in emerging nations like Nigeria, is the impact of fluctuating currency rates on inflation and, by extension, economic activity (Bada et al.[2]).

1.2. Review of Literature

Exchange rate as described by Bada et al.[2] is a veritable tool for achieving economic progress. Exchange rate misalignment has a well-documented detrimental impact on the economy, and governments frequently hesitate to modify exchange rates because they believe it will have a negative impact, primarily because of pass-through effects (Bade et al. [2]). A change in exchange rates and inflation has been observed to have an impact on economic development as well as the standard of living (Eke, Magaji, Obalemo, & Ezeigwe [3]; Odoh, Ugwoke, and Onyeanu [4]; Odoh & Edith, [5]. A lot of factors based on public discourse have been identified as responsible for the all time high inflation rate in Nigeria. One of the major factors that have been commented to drive inflation rate in Nigeria is that of the fact that Nigeria imports most of its goods which is usually done in foreign currencies. Of particular mention is of the abuse of USD as many of the transactions in Nigeria are carried out in dollars. When this is mere speculation to the best of the researchers as there are no adequate empirical studies on this. This study argues that instead of the government focusing more on the dollar, there are other foreign currencies in Nigeria such as Euros, Pound Sterling, and Yen among others that could also drive inflation in Nigeria other than the focus on Dollar. The review of empirical studies has also indicated that the majority of the studies on the nexus between the foreign exchange rate and inflation rate in Nigeria were done using models such as cointegration, Autoregressive Distributed Lag Stationarity model while this study intends to leverage the of Machine Learning algorithms in determining the major foreign currency that drives inflation in Nigeria. These Machine Learning algorithms have strength over the conventional model used as the result of the ability of these Machine Learning to capture non-linearity in data unlike the conventional models. The primary focus of the majority of the studies have been on the impact and not on the rating of foreign currencies drivers of inflation in Nigeria. The findings from this empirical study would provide a more innovative and focused policy that would help address inflation in Nigeria while also addressing the foreign exchange issue.

Umar & Umar [6] employed Nonlinear ARDL to examine the Impact of currency rate's consequence on inflation of food prices in Nigeria's. Findings from Cointegration show evidence of a long-run association among food inflation & exchange rate along with the Gross Domestic Product (GDP). Muhammad et al.[7] examined the impact of inflation on standard of living in Nigeria using the Autoregressive Distributed Lag [ARDL] and found that there are two type of relationship exists long-run & short-run between the standard of living and the inflation rate in

Nigeria within the period of study. Odoh & Edith [5] examined the nexus between exchange rate, inflation rate and economic growth in Nigeria. The short-run ARDL model was used in testing the hypotheses and the study found the adverse effect of exchange rate imbalances on economic growth in Nigeria. Similarly, Mordi[8] examined the link between exchange rate and domestic price level in Nigeria using Vector Autocorrelation (VAR) technique. Results of the VAR model revealed that exchange rate pass-through coefficients indicate that pass-through to price level in Nigeria is partial or incomplete. Factor analysis was used by John et al. [9] to examine the determinants of inflation in Nigeria. The results shows that the month of the year has a relationship with the various types of inflation in Nigeria. Other studies have also applied other modelling approaches other than Machine Learning algorithms (Alexander et al.,[10]; Mbagwu[11], Nnoli [12] ,Chinekwu[21]) in investigating the drivers of inflation. A review of related empirical studies shows that the Autoregressive Distributed Lag (ARDL) and Vector Autoregressive (VAR) models are among the most widely used forecasting tools. However, these models have notable limitations, including the underlying assumption of linear relationships between features. Another major weakness is the need to pre-specify lag lengths, where an incorrect choice can lead to misleading results. Additionally, ARDL and VAR models are prone to overfitting and have limited capacity to manage multicollinearity, particularly when dealing with large numbers of inter-related predictors as in this study. In contrast, machine learning algorithms offer a compelling alternative with the ability to capture both linear and nonlinear relationships, handle high-dimensional datasets effectively, and automatically manage complex feature interactions. Importantly, many of the limitations associated with ARDL and VAR models are some of the stylized properties of economic and financial variables.

1.3. Theoretical Framework

The theoretical framework for this study to understand the drivers of inflation in was hinged on Exchange Rate Pass-Through (ERPT) Theory and Cost-Push Inflation Theory. The ERPT highlights the influence of changes in the Naira's value against the US dollar impact of domestic inflation. The over reliance on foreign goods in Nigeria, the depreciation of the Naira increase imports costs and this translates into higher consumer prices. This implies that a high pass-through rate indicates that a small change in the exchange rate can result to significant increase in inflation. This therefore emphasizes the need for robust exchange rate management. This phenomenon is very crucial for Nigeria's economy, where currency volatility has the ability to destabilize price levels, making it difficult for policymakers to effectively control inflation. The Cost-Push Inflation Theory on the other hand emphasized how increase in production cost as a result of global oil price increases contribute to inflationary pressures. Nigeria as a major oil producer benefits from high oil revenues, nevertheless, this raises both transportation and operational cost domestically which in turn will be passed into the consumers. This will eventually lead to widespread price hikes and consequently intensifying inflation and making it very difficult to achieve economic stability. By combining ERPT and cost-push frameworks, we gain a clearer understanding of how currency devaluation, oil price shifts, domestic economic policy, and supply chain disruptions together fuel inflation in Nigeria. Recognizing these mechanisms allows policymakers to adopt targeted strategies such as exchange rate stabilization, diversified revenue streams, and improved supply chains to manage inflation and support economic resilience in challenging conditions.

1.4. Research highlights and contributions

The uniqueness of the study is based on the fact that there is dearth of research on the nexus between the exchange rate in Nigeria and the inflation rate despite the huge strength of the Machine learning approach over the conventional methods. The ability of Machine learning algorithms to learn intelligently from the data and capture both linear and non-linear patterns in the data could also be harnessed in determining the foreign currency drivers of inflation in Nigeria. The second major distinction of this study is that most of the speculation on the foreign currency that drives inflation in Nigeria has been only around USD dollars with less emphasis on the effect of other currencies such as the Euro, Pound Sterling, and the Yen among others which are also used in transactions in Nigeria. The effect of the domestic policies in Nigeria such as the removal of oil subsidy and the floating of the Naira introduced by the current administration in Nigeria also need to study. The supply chain distortion of some food items as a result of the ongoing Russian-Ukraine war on Nigeria inflation rate also need to be investigated. Proper understanding of the contribution of these multi-facet factors will help provide a more holistic assessment of the situation while also providing a more impactful policy decision that would help in addressing this serious challenge. These therefore serve as motivation for this study on foreign exchange rate and inflation in Nigeria with Machine Learning algorithms.

2. Methodology

This section describes the data set used in the analysis, the data preprocessing process as well as the machine learning algorithms and dataset used for this study. The data used in this study comprise monthly Naira exchange rates of ten foreign currencies in Nigeria (USD, Yen, WAUA, Yuan, SwisFranc, Euro, SDR, Pounds Sterling, CFA, and Danish Kroner) and crude oil price between January, 2013 and September, 2024. Other variables such as the removal of fuel subsidy, floating of the Naira and Russian Ukraine war were treated as dummy variable with value 1 for periods when the events occurred and 0 before the advent of these events. Data were taken from the Central Bank of Nigeria (CBN). The target variable is the inflation rate while the features were the exchange rate of these ten foreign currencies, removal of fuel subsidy, floating of the Naira and Russian Ukraine war. To better capture the effect of these policies and external shocks, we adopted the continuous time-based variables by creating a time counters that track the number of periods since these events occurred (Russia–Ukraine war, the floating of the Naira, and the removal of the oil subsidy). Employing this approach helps us capture not just the immediate impact, but also how the effects developed and changed over time, providing a clearer picture of their influence on the economy. As part of the data preprocessing process, missing values and duplicates were checked after importing the data into Python environment with the functions **data.isnull().sum()** for missing values and **data.duplicated().sum()** for duplicates and these function returned returned 0 indicating that there is no missing values and no duplicate. The Isolation Forest algorithm also in Python was used to detect outliers in the data set across all the features. The Isolation Forest algorithms shows evidence of presence of outliers though very few in the data set and hence to address this the data was scaled using robust scaler also in Python. The scikit-learn Python library offers RobustScaler, a preprocessing technique for scaling dataset features that is resilient to outliers. Compared to approaches like the StandardScaler that utilize the mean and standard deviation, the RobustScaler is less affected by outliers because it employs the median and Interquartile Range (IQR). The RobustScaler used the formula below in scaling the observation.

$$W_{\text{scale}} = \frac{W - \text{Median}(W)}{\text{IOR}} \tag{1}$$

where, W is the actual data, W_{scale} is the scaled data, Median(W) is the median of the feature and IOR is the interquartile range.

The following machine learning algorithms were considered in this study:

Decision tree regression: The decision tree regression is a supervised machine learning algorithms that is used to forecast numerical values. The focus of the machine learning algorithm is to reduce error in the target variable by dividing the data into subsets based on the values of the feature. This machine learning algorithms is very valuable due to its interpretability ability and its capacity to account for the intricate. The diagrammatical representation of the Decision Tree is presented in Figure 1.

Random Forest regression is another essential type of supervised machine learning. It is an ensemble learning technique that creates a final prediction by aggregating the predictions of several different individual models. It integrates the predictions of multiple decision trees in this instance. Regression using Random Forest can handle a high number of features and account for intricate interactions between them, making it less prone to overfitting. Figure 2 displays the Random Forest regression schematic model. A machine learning technique called bagging regression improves the stability and performance of algorithms, especially decision trees and other high-variance algorithms. By combining predictions from several models trained on bootstrap samples of the data, it is an effective method for enhancing the performance of regression models by lowering variance and boosting resilience. . In the Bagging regression, using the original data set, multiple bootstrap samples are generated. Each sample is created by randomly selecting data points with replacement, meaning some data points may appear multiple times in a single sample while others may be omitted. After this a separate model (often a decision tree) is trained on each bootstrap sample. Since each model is trained on a slightly different dataset, they will make different predictions. Then, the final prediction for a given input is obtained by averaging the predictions from all the individual models. This averaging helps to smooth out the predictions and reduce the model's variance (Figure 3). The base estimator for the Random Forest regression in this study is a decision tree regressor and this allows the model to account for non-linear relationship as well as maintaining robustness through averaging. This tool's versatility and ease of use

Figure 1. Schematic diagram of the Decision Tree

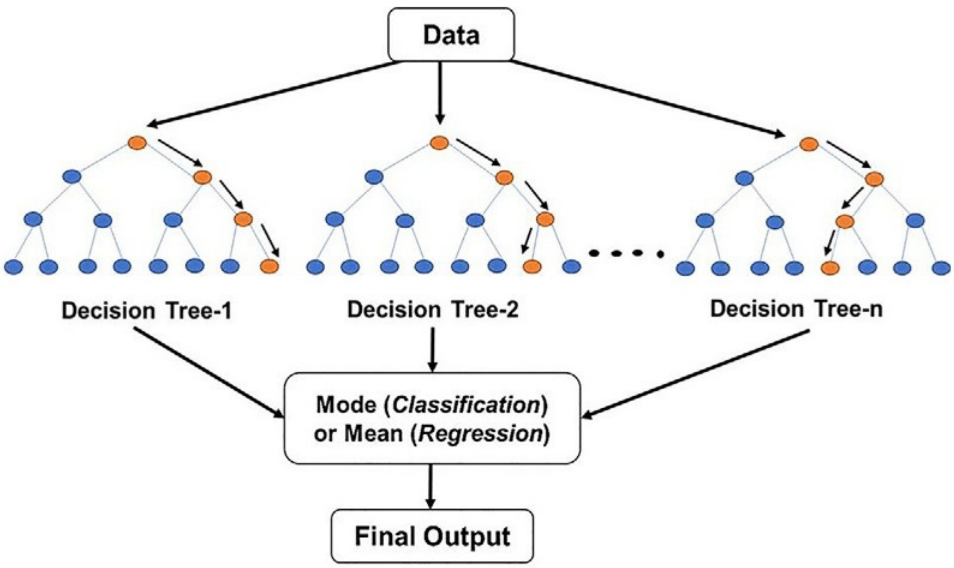

Figure 2. Schematic diagram of the Random forest. Source: Rani et al [14].

in solving regression and classification problems. This approach resolves the over fitting of the decision tree (Liu et al.,[15]).

Bagging regression is a meta-estimator method which is used for ensemble. It fits regressors separately on random subsets of the unique dataset, and then joins their predictions through voting method and generates the final predication. For the bagging regression, tree regression served as the base estimator and this provides flexible but strong learner capable of capturing complex non-linear relationships.

This approach is known as pasting as random subsets of the datasets are used as sample. This technique is called bagging when sample are drawn using replacement method.

AdaBoost is another machine learning technique used for regression and classification. AdaBoost is an extremely straightforward algorithm that is used as an ensemble technique to increase accuracy. In this study, the decision trees was used as the base learner for the AdaBoost algorithm thereby providing a balance between simplicity and expressive power.

Gradient Boosting (GB) is a machine learning boost model that can be applied to both regression and classification tasks.

Boosting created ensembles learning requires that each new model attempt to correct an existing model and the models must be trained consecutively. The square error loss function which minimizes the squared difference between the actual and predicted values was used in this study. This enable the model to adequately capture the continuous variable in the target feature (inflation rate) while also improving the performance of the regression. In order to prevent data leakage, the study adopted a walk- forward validation approach using TimeSeriesSplit from sklearn.model_selection in Python. This method trains the machine learning algorithms on a growing historical window and then assess its performance on the immediately following period. This was carried out to reflect

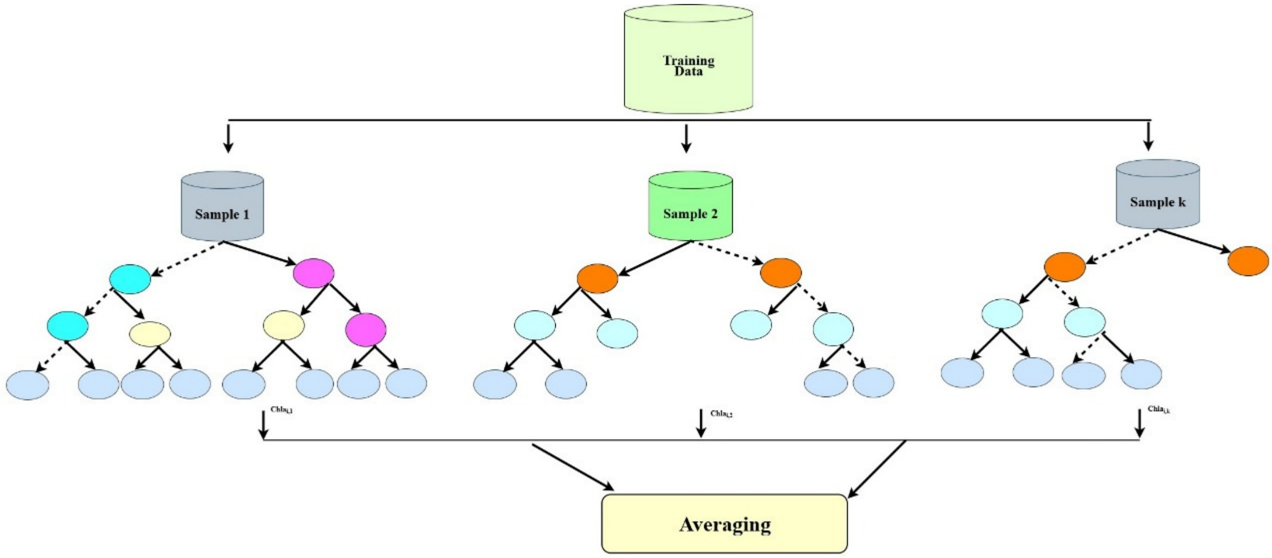

Figure 3. Schematic diagram of the Bagging regressor.

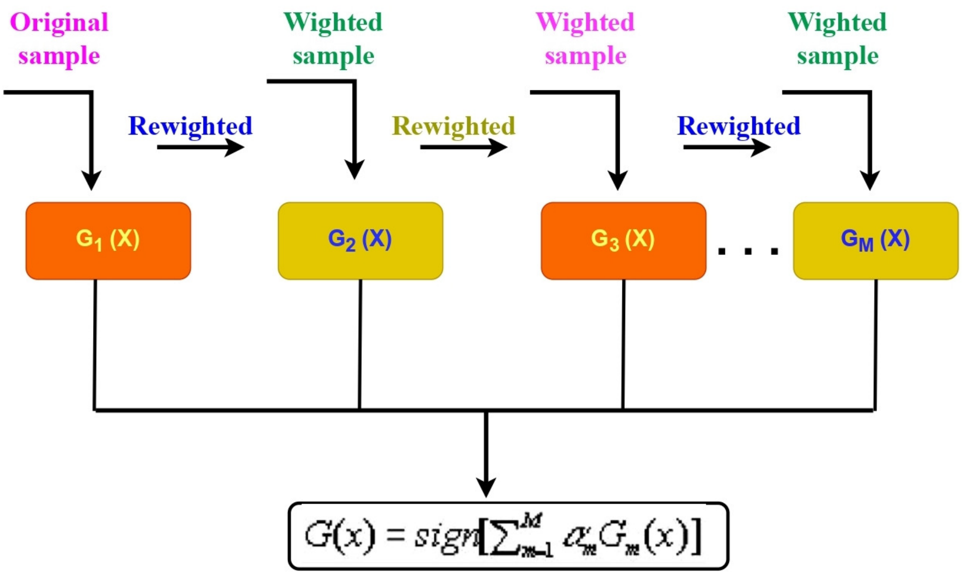

Figure 4. Schematic diagram of the AdaBoost.

the time dependent nature of the data set and below is the summary of the hyperparameter values and the best hyperparameter values for each of the machine learning algorithm (Table 1).

The performance of these ensemble learning algorithms were compared using the RMSE, R-squared, Mean Absolute Error and the adjusted R-Squared defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(IR_i - \hat{IR_i}\right)^2} \tag{2}$$

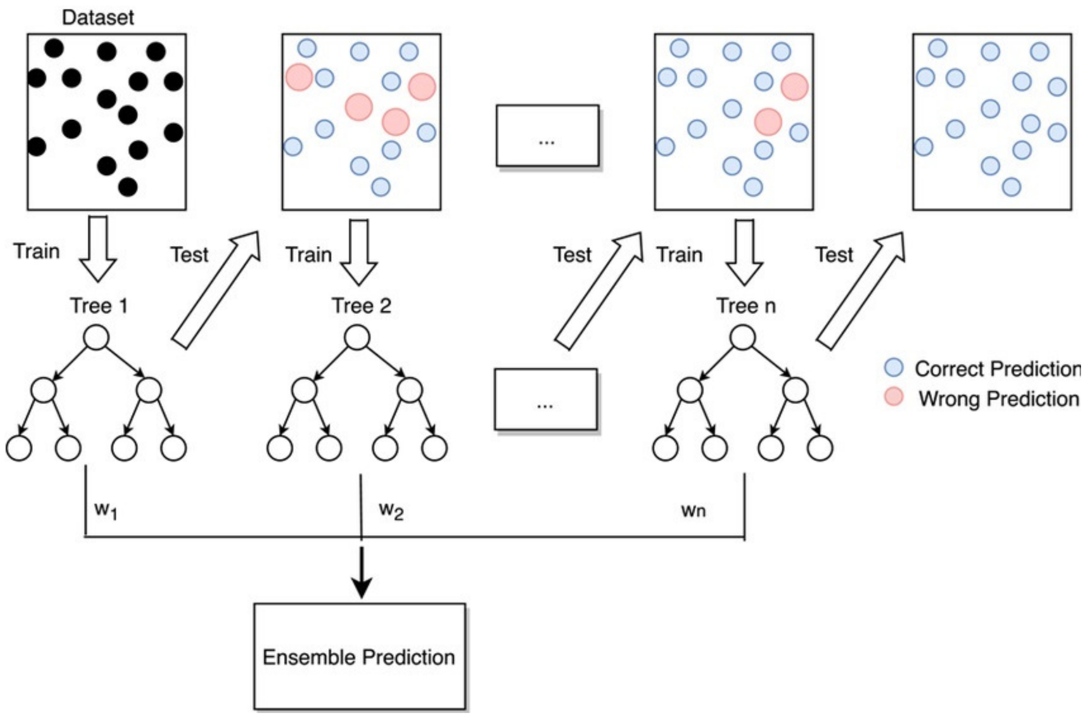

Figure 5. Schematic diagram of the Gradient Boosting (GB). Source: Zhang et al.[18].

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|IR_i - \hat{IR}_i\right| \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(IR_i - \hat{IR}_i)^2}{\sum_{i=1}^{n}(IR_i - \overline{IR})^2} \tag{4}$$

$$R_a^2 = 1 - \frac{(1-R^2)(n-1)}{n-p-1} \tag{5}$$

Also, because of the tradeoff between the Mean Square Error & Mean Absolute Error, the Huber Loss function was used. The Huber Loss function combines both the strengths of both the MSE and MAE and hence making it a more robust performance evaluation criteria. It is also robust against outliers and it can be defined as:

$$L_\delta(IR, \hat{IR}) = \begin{cases} \frac{1}{2}(IR - \hat{IR})^2, & \text{if } |IR - \hat{IR}| \le \lambda \\ \lambda|IR - \hat{IR}| - \frac{1}{2}\lambda^2, & \text{if } |IR - \hat{IR}| > \lambda \end{cases} \tag{6}$$

Where, p is the number of features, R^2 is the coefficient of determination, R_a^2 is the adjusted coefficient of determination, IR_i is the actual inflation rate at month i, $\hat{IR}_i$ is the estimated value of the inflation rate in Nigeria, and λ is the threshold parameter that determines the transition point between the squared error and the absolute error.

2.1. Model Interpretability Measures

In order to understand the underlying relationships between variables, three model interpretability measures were used and they are described below:

Table 1. Summary of the best hyperparameter values for each ML algorithm

Machine Learning Algorithm	Hyperparameter Grid	Best Hyperparameters
Decision Tree	max_depth = [3, 5, 7, 10, None], min_samples_split = [2, 5, 10], min_samples_leaf = [1, 2, 4], max_features = [None, 'sqrt', 'log2']	max_depth = None, max_features = None, min_samples_leaf = 1, min_samples_split = 2
Random Forest	n_estimators = [100, 200], max_depth = [3, 5, 7, 10, None], min_samples_split = [2, 5, 10], min_samples_leaf = [1, 2, 4], max_features = [None, 'sqrt', 'log2']	n_estimators = 100, max_depth = 10, max_features = None, min_samples_leaf = 1, min_samples_split = 2
AdaBoost	n_estimators = [50, 100, 200], learning_rate = [0.01, 0.1, 1.0], loss = ['linear', 'square', 'exponential']	n_estimators = 200, learning_rate = 0.1, loss = 'exponential'
Bagging	n_estimators = [10, 50, 100], max_samples = [0.5, 0.75, 1.0], bootstrap = [True, False], estimator__max_depth = [3, 5, 10]	n_estimators = 100, max_samples = 1.0, bootstrap = True, estimator__max_depth = 10
Gradient Boosting	n_estimators = [50, 100, 200], learning_rate = [0.01, 0.1, 0.2], max_depth = [3, 5, 7], subsample = [0.8, 1.0]	n_estimators = 100, learning_rate = 0.2, max_depth = 5, subsample = 0.8

(i) Feature importance: Additionally helpful for comprehending and explaining the ML model to other stakeholders is feature significance. The characteristics that contribute most to your model's predictive capacity may be identified by generating scores for each feature and using the feature significance.
(ii) Permutation Importance: This interpretability measure work by randomly rearranging the values of the feature so as to break the relationship with the target and then re-evaluate the performance of the model. A notable decline in performance indicate the importance of the feature. This measures computes how much each feature contributes to the performance of the model.
(iii) SHAP (SHapley Additive exPlanations): SHAP (SHapley Additive exPlanations) is the most popular interpretability measures for quantifying the contribution of each of the feature. The SHAP works based on the concept of cooperative game theory. This measure provide help to identify the feature that has the most impact on the target variable including the magnitude of the impact of each of feature to the target variable.
(iv) Partial Dependence Plot (PDP): Partial Dependence (PD) plot was used to substantiate results obtained from other model interpretability measuring by providing the relationship between inflation and specific original features. The PD plot provides how changes in given feature impact inflation while accounting for the average effect of other features.

Empirical results and discussion The findings presented in Table 2 provide descriptive statistics for foreign exchange rates and inflation rates in Nigeria. The analysis shows that an average inflation rate of 15.14%, indicating significant economic pressures in Nigeria. Notably, among the various foreign currencies considered, the West African United Dollar (WAUA) was found to have the highest standard deviation, suggesting substantial variability in its values of WAUA compared to the other foreign currencies. This variability indicates that the WAUA may experience more significant variation in prices and this could have implications for trade and investment. Also, the results illustrated in Figure 6 depict the distributions of inflation rates, various foreign currencies as well as the oil prices, showing a positively skewed distribution for the inflation rate and the majority of foreign currencies examined. This positive skewness implies that while most values cluster at lower levels, there are significant outliers on the higher end, suggesting occasional spikes in both foreign currency values and inflation rate in Nigeria. Figure 7 further elucidates the positive correlation between the inflation rate and all foreign currencies assessed, suggesting that as the value of these currencies rises, so too does the inflation rate in Nigeria. Specifically, the U.S. Dollar (USD), Chinese Yuan, and WAUA demonstrated the strongest positive correlations with inflation rates, each with a correlation coefficient of 0.89. Additionally, the analysis indicates that domestic policies such as the removal of fuel subsidies and the floating of the Naira are highly positively correlated with inflation rates. These policy changes have likely contributed to rising inflation by affecting the costs of goods and services. The study also observes a strong positive relationship among the foreign currencies, suggesting high multicollinearity between them. This multicollinearity could complicate model interpretations and hence Principal Component Analysis (PCA) was used to reduce dimensionality in the data and create uncorrelated component and five different machine learning algorithms: Bagging, Decision Tree, AdaBoost, Random Forest and Gradient Boosting regression were used to learn the patterns in the data and uncover the relationship between the target variable (inflation) and the features. The result of the multicollinearity using Variance Inflation Factor (VIF) as presented in Table 2 indicated that these foreign currencies such as Euros, Danish Kroner, Yuan, Pounds Sterling, and WAUA reported extremely high VIF values suggesting that they are highly correlated with each other. Similarly, policy variables were also found to have high VIF indicating that they are highly correlation which suggests that they are measuring an overlapping effects. In view of these the data was subjected to Principal Component Analysis (PCA) for dimensionality reduction and five PCAs were extracted accounted for 99.58% of the variation in the data set with PCA 1 accounting for 88.58% while PCA 2, 3,4 and 5 accounted for 5.95%, 3.28%, 1.05% and 0.72% respectively. This suggests that PCA 1 is the most importance PCA in the data (Figure 8).

Table 2. Descriptive statistics for foreign currencies and inflation rates in Nigeria

Variable	Mean	Std	Min	25%	50%	75%	Max
Euro	418.35	325.21	189.84	213.33	346.49	450.33	1796.11
CFA	0.67	0.83	0.27	0.32	0.51	0.68	8.86
SDR	512.50	399.41	223.63	271.47	424.82	553.79	2182.58
USD	370.13	304.89	154.86	189.07	305.56	409.66	1617.72
Danish Kroner	56.17	43.51	25.67	28.56	46.40	61.07	240.76
Yuan	54.33	41.28	24.40	29.93	44.60	61.48	227.90
Pound	491.14	377.65	234.04	275.44	396.43	516.64	2138.32
Yen	3.13	1.99	1.36	1.76	2.78	3.48	11.28
Swiss Franc	409.57	370.59	159.00	194.76	309.30	428.63	1906.14
WAUA	507.67	400.38	229.76	254.68	423.03	552.47	2175.29
Oil Price	76.76	25.90	14.28	56.85	74.72	98.24	130.10
Inflation Rate	15.14	6.62	7.70	11.10	12.86	17.74	34.19

The results summarized in Table 3 present a comprehensive analysis of the performance of various machine learning algorithms used for forecasting in this study with and without the robust scaler. The result reveals that using the robust scaler improved the performance of these machine learning algorithms. Notably, the Gradient Boosting demonstrated superior performance, achieving the lowest RMSE (1.2990), MAE (0.8132) and Huber loss (0.5036) and highest R^2 (0.9671) as well as the highest value of adjusted R^2(0.9634). The strength of Gradient Boosting over other ensemble methods considered in this study lies in its ability to build trees sequentially while correcting errors from previous models. This sequential learning process effectively reduces bias and variance, resulting in improved predictive accuracy and giving Gradient Boosting an edge over other algorithms. The plots of the features importance, SHAP values plot as well as Partial Dependence are in Figures 9, 10 and 11 respectively.

The feature importance analysis clearly illustrates that the local policy shift particularly the removal of oil subsidy and the floating of the Naira policy introduced by the present Administration in Nigeria have the most

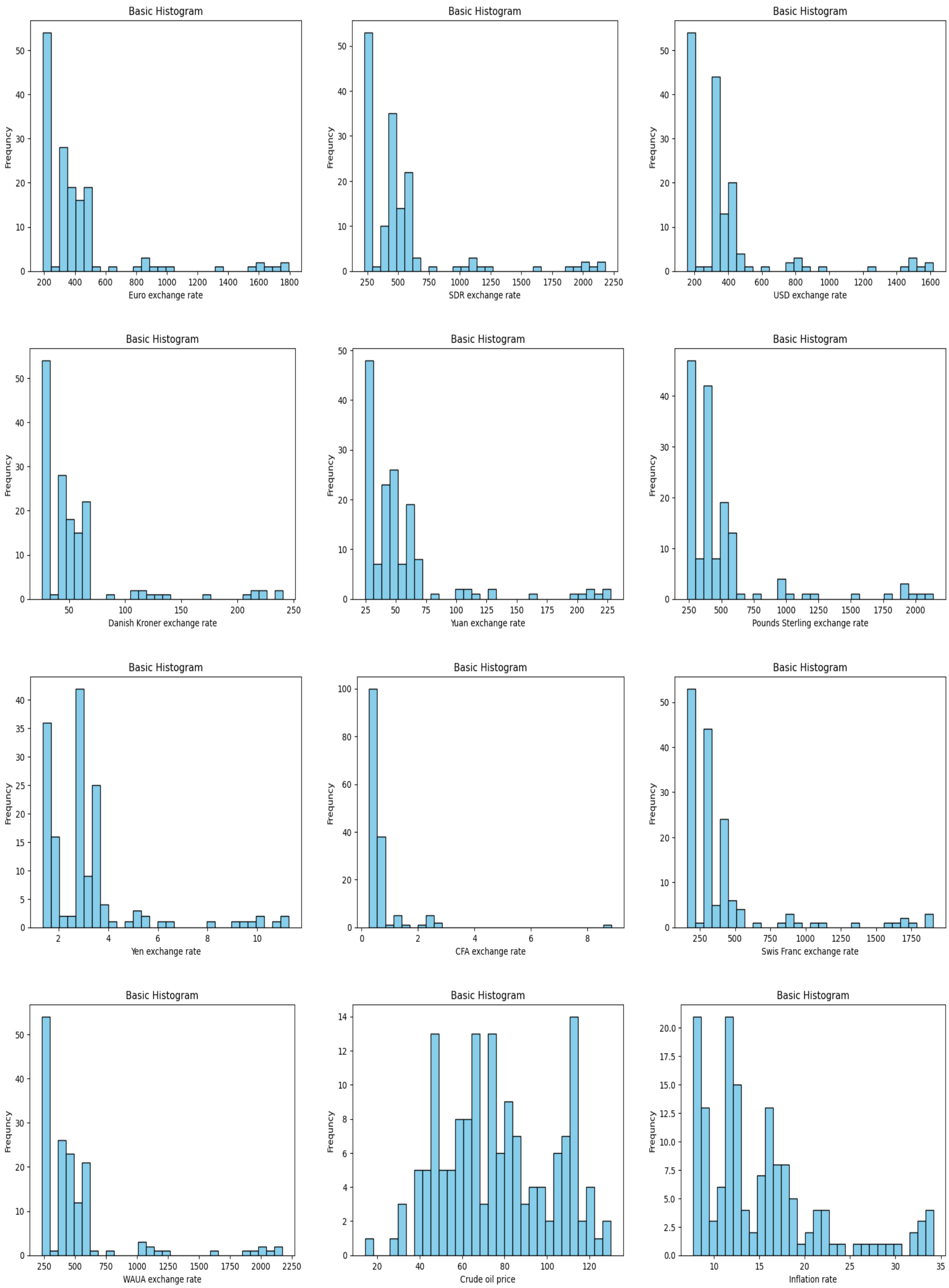

Figure 6. Histogram plots for the variables

Table 3. Multicollinearity diagnostic using Variance Inflation Factor (VIF) for the features

Feature	**VIF**
Euros	1423.106
CFA	3.136
SDR	221.754
USD	221.754
Danish Kroner	921.202
Yuan	806.601
Pounds Sterling	916.131
Yen	76.006
Swiss Franc	88.782
WAUA	856.890
Crude oil price	2.077
Months since subsidy removal	685.134
Months since floating of the Naira	568.947
Months since Russia-Ukraine war	151.009

Table 4. Comparative analysis of the performance of the Machine Learning algorithms with or without using Robust Scaler

ML Algorithms	**With Robust Scaler**					**Without Robust Scaler (Standard Scaler)**				
	RMSE	MAE	Huber Loss	R-Squared	Adj. R-Squared	RMSE	MAE	Huber Loss	R-Squared	Adj. R-Squared
Decision Tree Regression	1.8778	1.2364	0.9827	0.9312	0.9236	2.1334	1.1284	0.7939	0.9112	0.8976
Random Forest Regression	1.3271	0.9242	0.5791	0.9656	0.9618	1.4482	0.9668	0.6267	0.9591	0.9528
AdaBoost Regression	1.6291	1.3910	0.9634	0.9482	0.9425	1.5232	1.2254	0.8362	0.9547	0.9478
Bagging Regression	1.3352	0.9469	0.6028	0.9597	0.9535	1.4372	0.9389	0.6147	0.9597	0.9535
Gradient Boosting	1.2990	0.8132	0.5036	0.9671	0.9634	1.6513	1.0931	0.7364	0.9085	0.8938

profound positive impact in inflation therefore making them the major drivers of inflation in Nigeria. The impact of foreign currencies such as CFA, Pound Sterling, Swiss Franc, SDR, USD among others were found were also exert influence on the inflation rate but not as severe compared to that of the removal of oil subsidy and the floating of the Naira policy. This implies that what our domestic policy are much more importance in driving inflation as these policies have kept Nigeria's inflation high for months with an unprecedented high inflation rate. The SHAP plot in Figure 9 confirmed that the first PCA captured the strongest pattern in the data and has the strongest influence on inflation in Nigeria. This also corroborated that earlier finding that the combined effect of domestic policy and key exchange rates are the main drivers of inflation with removal of fuel subsidy and floating of the Naira as the most influential factors (Figure 9). These findings is also supported by the Partial Dependence plot as shown in Figure 6.

3. Discussion of the findings

This study has examined foreign currency exchange rates to Nigeria's Naira and inflation rates in Nigeria. This was done to examine the major factors that drive inflation in Nigeria. The study leverages the five Machine-learning algorithms. Preliminary findings showed that the exchange rates of these foreign currencies all have a positive relationship with the inflation rate in Nigeria which implies that as the exchange rates of these currencies increase, there is an increase in the inflation rate in Nigeria. This finding could as a result of the fact that Nigeria imports most of its products from other countries of the world. The study established that domestic policy such as the removal of fuel subsidy and the floating of the Naira exerted more significant positive impact on the inflation rate in Nigeria compared with other factors examined. This finding emphasizing the significant role played by the removal of fuel subsidy as a major driver of inflation is consistent with cost-push inflation theory which underscored the impact of

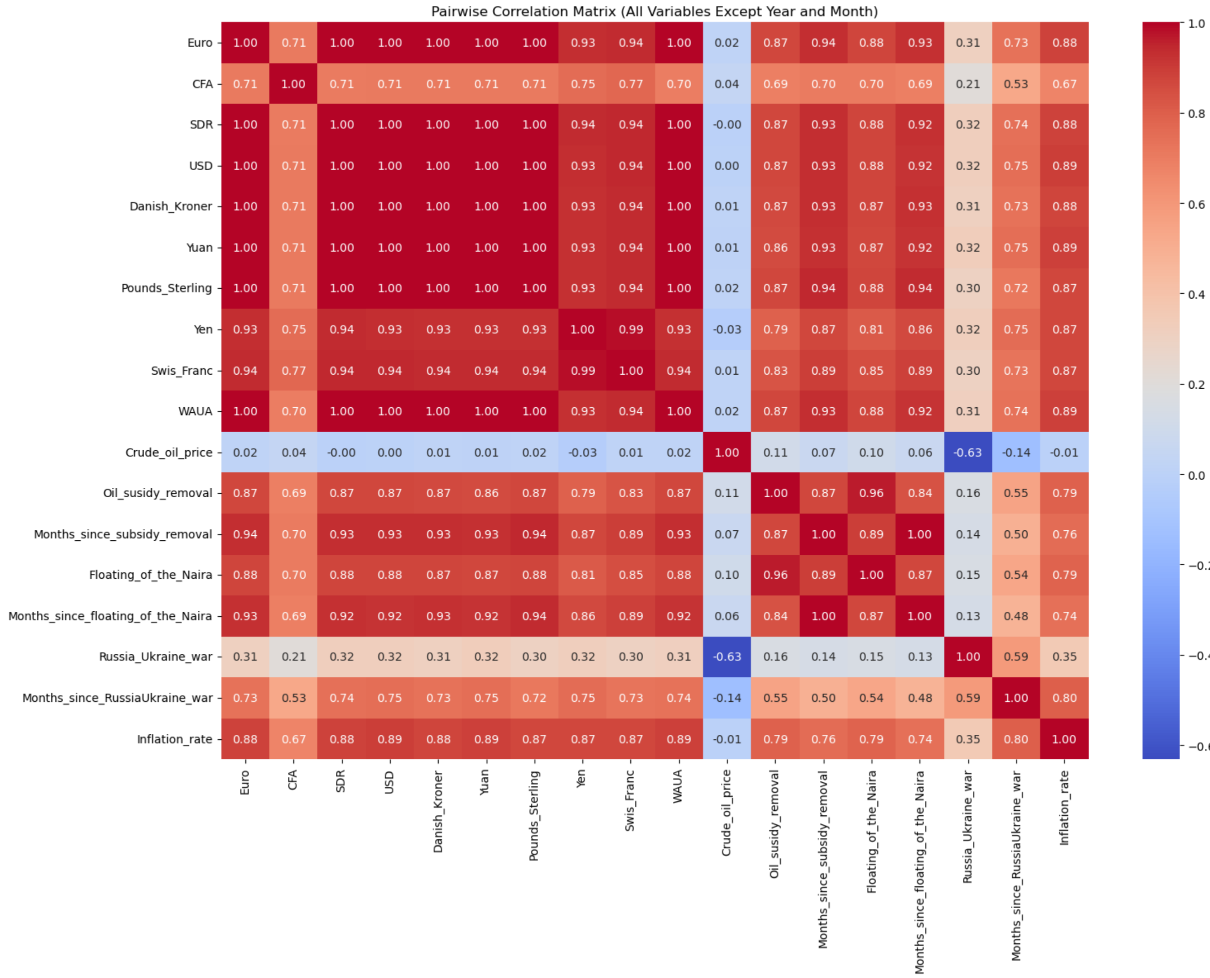

Figure 7. Heap map showing the relationship between inflation rate and the features .

rising cost of production as a result of fuel prices can drive the overall price level and in this case inflation. Also, the prominence of the impact of the floating of the Naira is an agreement with the Exchange Rate Pass-Through (ERPT) which emphasized that fluctuations in Naira value could have a direct impact on inflation through import prices. Therefore, the findings from the Machine Learning derived features are consistent with these theories. The impact of currencies such as USD is not unexpected even market women, traders, and merchants will tell you that the US dollar is the reason why product prices are high. This is due to the fact that the dollar was the preferred payment currency for the majority of internet transactions in Nigeria, including money transfers, online shopping, and the payment of bills for things like tuition and medical expenses. The USD could affect inflation rate in Nigeria through currency exchange rates as a result of the floating of the Naira, Nigeria high foreign debts, oil price dominated in USD and inflation on imports. The flotation of the Naira policy of the current Admiration of President Bola Hamed Tinubu, Nigeria large foreign debts, oil price dominated in USD and inflation on imports also could also be responsible for this finding. When the dollar appreciates, it becomes more expensive to import goods, which drives up domestic prices and contributes to Nigerian inflation. The fluctuations in oil prices, which are expressed in US dollars, have an impact on Nigeria's import costs and earnings, which in turn leads to inflationary pressures. Furthermore, a higher dollar makes it more expensive to service Nigeria's foreign debt in dollars, which puts pressure on the country's finances. The stability of the naira is impacted by changes in the USD, which also affect investment and liquidity. This finding is also consistent with that of Olayungbo & Ajuwon [19] which established

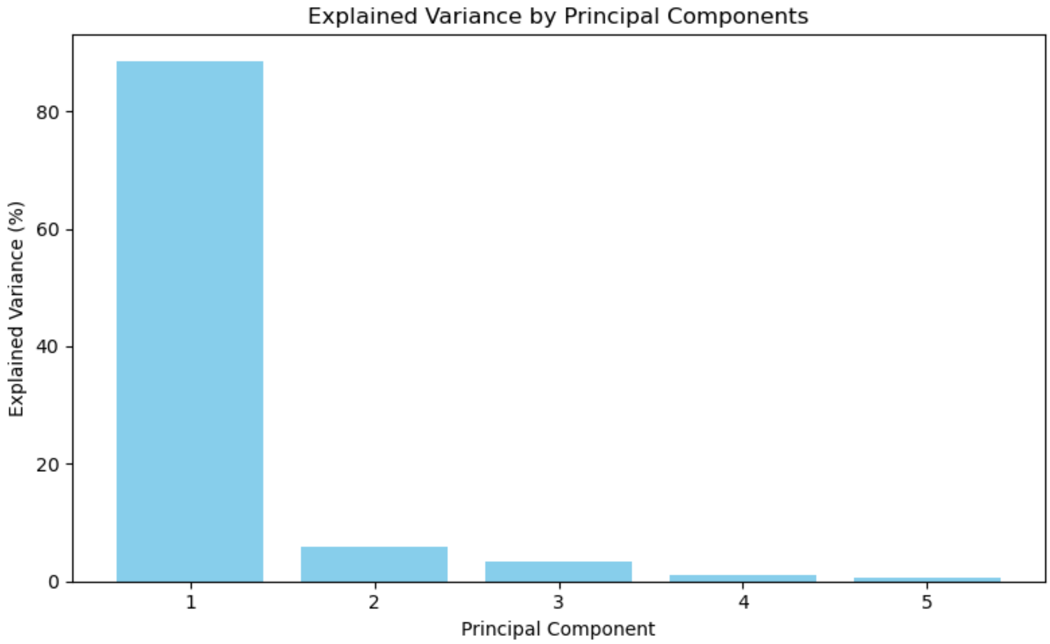

Figure 8. Plot of the explained variance by the principal components.

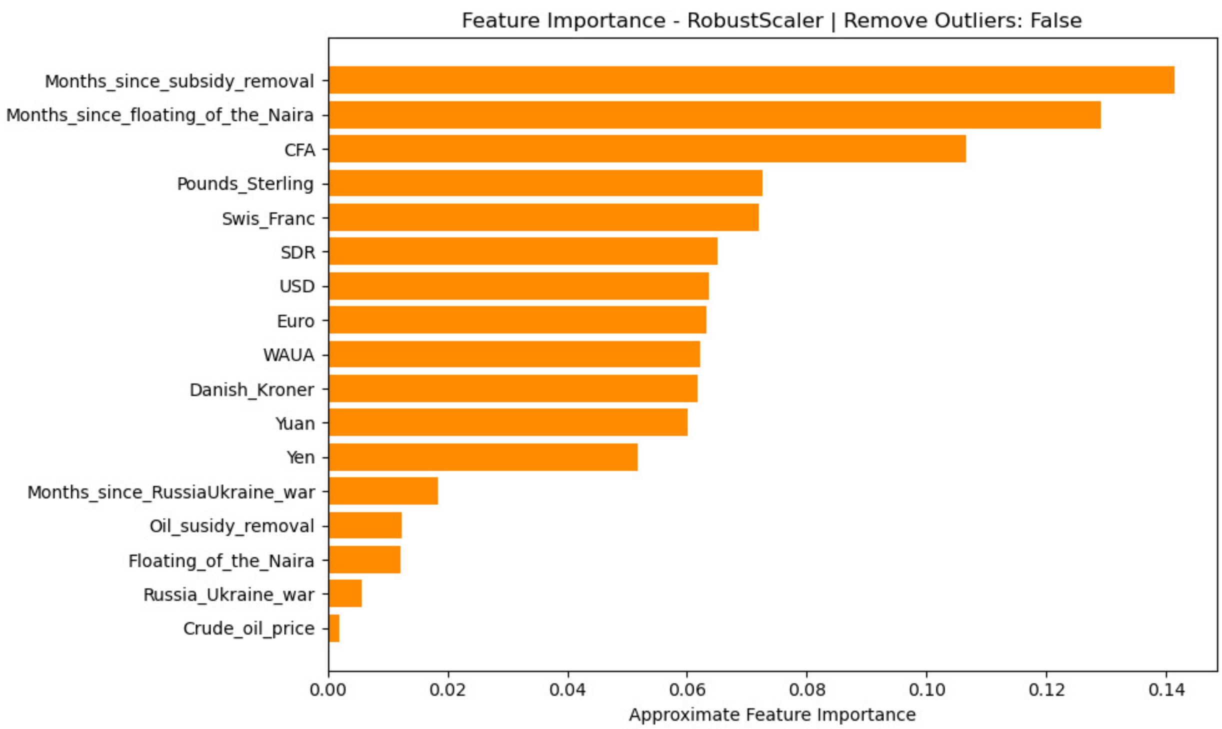

Figure 9. Feature importance plot for drivers of inflation in Nigeria based on Gradient Boosting.

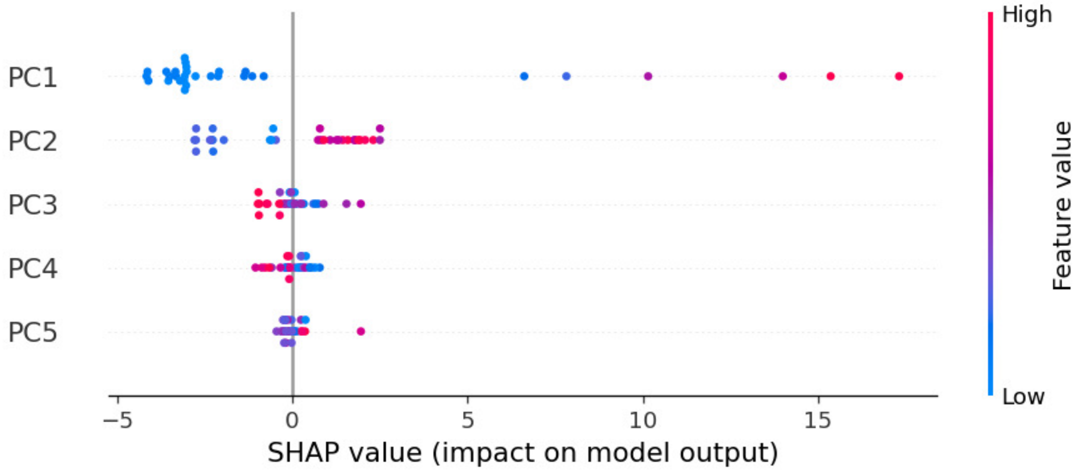

Figure 10. SHapley Additive explanations (SHAP) value plot for drivers of inflation in Nigeria.

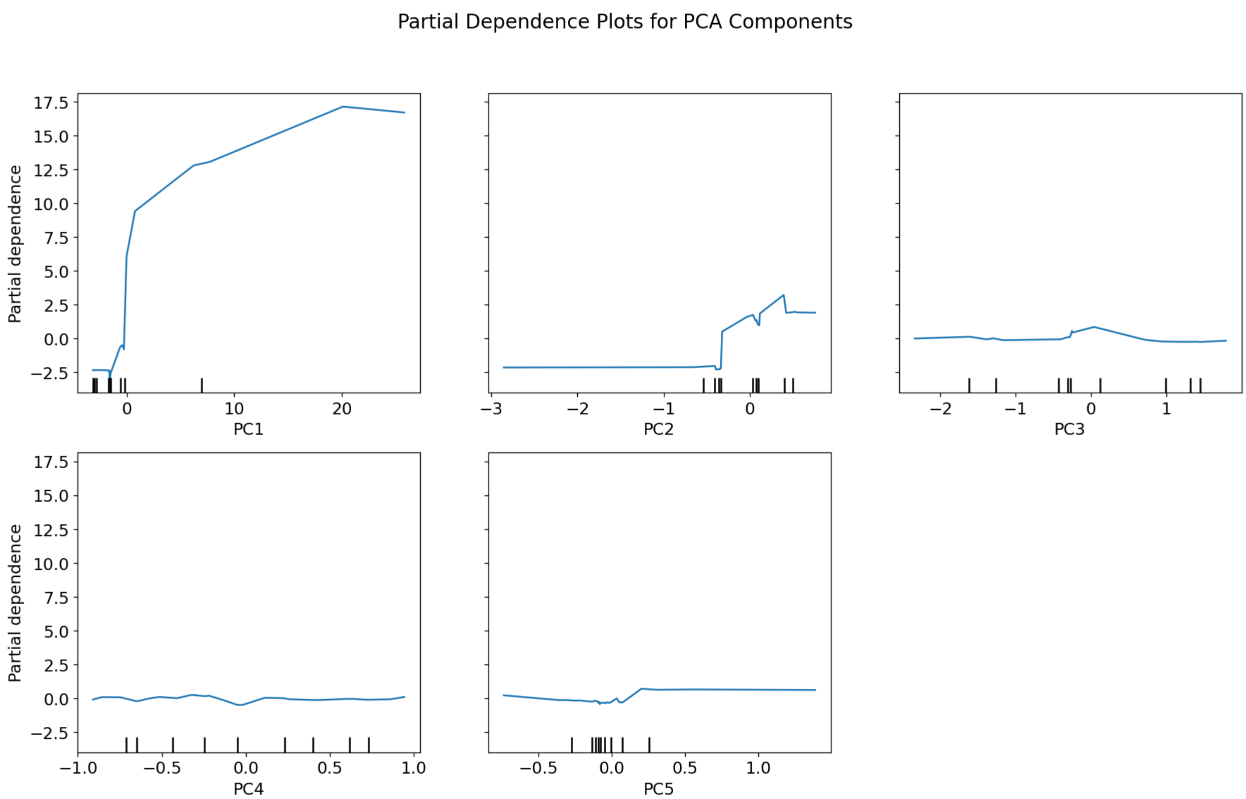

Figure 11. Partial Dependence plots for drivers of inflation in Nigeria.

a unidirectional relationship between the use of USD and inflation in Nigeria. This finding is also in line with that of the finding by Perpetua [20] which also established positive effect of exchange rate volatility on inflation rate. These findings are also supported by that obtained in other similar studies (Chinedu [21], Akbari et al. [13]). The finding established that the Russian-Ukrainian war has a minimal impact on the inflation rate in Nigeria and this may be due to the complex nature of the variable which the proxies used in this study may not have adequately captured. Also, the effects of subsidy removal and floating of the Naira may have also limited the ability of the model to properly isolate the effect of Russian-Ukrainian war on inflation in Nigeria.

4. Conclusions and Recommendations

This study investigated the drivers of inflation in Nigeria leveraging of the use of ensemble learning algorithms: Decision Tree, Random Forest regression, AdaBoost regression, bagging regression, and Gradient Boosting regression. The study established that the Random Forest regression better captures the nexus between inflation rate in Nigeria and the possible drivers examined (foreign currencies, oil prices, domestic policies and supply chain disruption). The findings shows that the domestic polices such as the removal of fuel subsidy and floating of the Naira alongside foreign exchange rates are the drivers of inflation in Nigeria with these domestic policies exerting more significant influence on inflation. the most important drivers of inflation in Nigeria. Other features, such as crude oil prices and exchange rate of these currencies were found to have a moderate influence on inflation rate. Although this study also provided a comprehensive analyses of the drivers of inflation in Nigeria, it relies primary on the data from the Central Bank of Nigeria (CBN) which may be subject to potential biases in the form of underreporting of these variables and lack of accuracy in exchange rates. To this end, there is need to carry out further research that leverage on alternative data sources or cross validating with independent market data. Reliance on historical data and exclusion of other variables such as government quality among others also poss a limitation to this study. Nevertheless, this study has been able to provide an empirical evidence of drivers of inflation in Nigeria based on some of the major variables. There is an urgent need for policy makers to focus on the key drivers while also enhancing a much holistic and broader economic context in addressing the problem of inflation of Nigeria. Specifically, the following actionable recommendations were made to hurt further increase in inflation rates in Nigeria for sustainable economic development.
1. These findings underscore an urgent need to reinvest savings from the subsidy removal into developmental projects such as building of refineries while also providing incentives and financial support to cushion the effect of subsidy removal.
2. The need to establish currency swap agreements with key trade partners particularly China will help stabilize the Naira and its exposure to USD volatility. These strategies could help in improving external balances, support industrial growth, and promote long –term resilience of Nigerian economy.
3. Enhancing foreign reserves and effectively manage currency supply, in addition to boosting exports, focus on policies that attract foreign investment can indeed stabilize the Naira against foreign currencies.
4. Providing adequate incentives and operational support to the Dangote refinery and ensuring functionality of the existing refineries in Nigeria could reduce over dependency on imported fuel that consequently reduce inflation rate in Nigeria.
5. Building stronger trade relationship with countries with stronger currencies than the Naira could help control import costs, mitigate inflationary pressures that often arise as a result of high reliance on import.
6. Redirecting extra funds as a result of fuel subsidy removal to infrastructure projects could stimulate domestic production, reducing the need for imported goods and creating a more resilient economy.
7. The provision of CNG-powered buses as a subsidy alternative can ease transportation costs, benefiting food pricing and household expenses, especially post-fuel subsidy removal.
8. Strengthening regional trade within ECOWAS can mitigate reliance on foreign currencies, fostering economic stability within the region and reducing the effects of external currency fluctuations on local economies.

Conflicts of Interest:

The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:
GBM - Gradient boosting machines
MAE -Mean absolute error
MAPE - Mean absolute percentage error
MSE - Mean square error
RF- Random forest
RMSE- Root mean square error
CBN -Central Bank of Nigeria
GDP - Gross Domestic Product
ADRL - Autoregressive Distributed Lag
VAR - Vector Autocorrelation

REFERENCES

1. D. B. Ewubare and U. A. Ushie, *Exchange rate fluctuations and economic growth in Nigeria (1981–2020)*, International Journal of Development and Economic Sustainability, vol. 10, no. 1, pp. 41–55, 2022. https://doi.org/10.37745/ijdes.13
2. A. S. Bada, A. I. Olufemi, I. A. Tata, I. Peters, S. Bawa, A. J. Onwubiko, and U. C. Onyowo, *Exchange rate pass-through to inflation in Nigeria*, CBN Journal of Applied Statistics, vol. 7, no. 1, p. 3, 2016. https://dc.cbn.gov.ng/jas/vol7/iss1/3
3. C. I. Eke, S. Magaji, A. O. Obalemo, and G. C. Ezeigwe, *An Economic Assessment Model of Employment Dynamics, Capacity Development and Household Telecommunication Expenditure in Nigeria*, Journal of Economics and Sustainable Development, vol. 11, no. 4, pp. 109–115, 2020. https://iiste.org/Journals/index.php/JEDS/article/view/51684/53405
4. C. Odoh, O. V. Ugwoke, and E. O. Onyeanu, *Exchange rate fluctuations and economic development in Nigeria*, International Journal of Mechanical Engineering and Technology (IJMET), vol. 14, no. 3, pp. 46–61, 2023. https://doi.org/10.17605/OSF.IO/C35GK
5. C. O. Odoh and E. O. Edith, *Exchange Rate Fluctuations and Inflation on Economic Development in Nigeria: The Economic, HEART of a Nation*, Seybold Report Journal, vol. 8, no. 10, pp. 47–64, 2023. https://doi.org/10.5110/77.1082
6. U. A. Umar and A. Umar, *Effects of Exchange Rate on Food Inflation in Nigeria: A Non-Linear ARDL Approach*, Gusau International Journal of Management and Social Sciences, vol. 5, no. 1, pp. 195–209, 2022. https://www.ajol.info/index.php/gijmss/article/view/258712/244330
7. T. Muhammad, A. T. Temidayo, and B. K. Bashir, *Analysis of Inflation and Standard of Living in Nigeria*, Journal of Oil Gas Res Rev, vol. 3, no. 1, pp. 52–58, 2023. https://www.opastpublishers.com/open-access-articles/analysis-of-inflation-and-standard-of-living-in-nigeria.pdf
8. C. N. O. Mordi, *Exchange rate and inflation: is there a relationship in Nigeria*, CBN Economic and Financial Review, vol. 52, no. 4, pp. 105–123, 2014. https://dc.cbn.gov.ng/cgi/viewcontent.cgi?article=1581&context=efr
9. C. John, P. I. Okoroafor, and C. T. Amobi, *Application of Factor Analysis in the Modelling of Inflation Rate in Nigeria*, Communication in Physical Sciences, vol. 10, no. 2, pp. 034–046, 2023. https://www.researchgate.net/publication/376646546_Application_of_Factor_Analysis_in_the_Modelling_of_Inflation_Rate_in_Nigeria/link/658229263c472d2e8e70badb/download
10. A. A. Alexander, A. H. Andow, and M. G. Danpome, *Analysis of the main determinants of inflation in Nigeria*, Research Journal of Finance and Accounting, vol. 6, no. 2, pp. 144–155, 2015. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=de02aa4b339f99a255db1747dc5dd88b85824db1
11. O. N. Mbagwu, *Inflationary Trends and Its Determinants in Nigeria*, Acman: Accounting and Management Journal, vol. 3, no. 1, pp. 1–14, 2023.
12. T. I. Nnoli, S. O. Enilolobo, C. O. Hassan, and A. B. Bello, *Inflation, Exchange Rate and Agricultural Export in Nigeria*, Greener Journal of Agricultural Sciences, vol. 13, no. 2, pp. 91–98, 2023. https://doi.org/10.5281/zenodo.8114742
13. A. Akbari, L. Ng, and B. Solnik, *Drivers of economic and financial integration: A machine learning approach*, Journal of Empirical Finance, vol. 61, 2021. https://doi.org/10.1016/j.jempfin.2020.12.005
14. A. Rani, N. Kumar, J. Kumar, and N. K. Sinha, *Machine learning for soil moisture assessment*, in Cognitive Data Science in Sustainable Computing, pp. 143–168, 2022. https://doi.org/10.1016/B978-0-323-85214-2.00001-X
15. Y. Liu, Y. Wang, and J. Zhang, *New Machine Learning Algorithm: Random Forest*, in Information Computing and Applications, 2012. https://doi.org/10.1007/978-3-642-34062-8_32
16. Y. Shin, T. Kim, S. Hong, S. Lee, E. Lee, S. Hong, C. Lee, M. Park, J. Park, and T.-Y. Heo, *Prediction of Chlorophyll-a Concentrations in the Nakdong River Using Machine Learning Methods*, Water, vol. 12, 2020. https://doi.org/10.3390/w12061822
17. T. Zhang, W. Lin, A. Vogelmann, M. Zhang, S. Xie, Y. Qin, and J.-C. Golaz, *Improving Convection Trigger Functions in Deep Convective Parameterization Schemes Using Machine Learning*, Journal of Advances in Modeling Earth Systems, vol. 13, 2021. https://doi.org/10.1029/2020MS002365
18. T. Zhang, W. Lin, A. Vogelmann, M. Zhang, S. Xie, Y. Qin, and J.-C. Golaz, *Improving Convection Trigger Functions in Deep Convective Parameterization Schemes Using Machine Learning*, Journal of Advances in Modeling Earth Systems, vol. 13, 2021. https://doi.org/10.1029/2020MS002365

19. D. O. Olayungbo and K. T. Ajuwon, *Dollarization, Inflation and Interest Rate in Nigeria*, CBN Journal of Applied Statistics, vol. 6, no. 1, Article 12, 2015. https://dc.cbn.gov.ng/jas/vol6/iss1/12
20. O. I. Perpetua, *Impact of Exchange Rate Variation and Inflation on the Economic Growth of Nigeria: An Empirical Approach*, Research Journal of Finance and Accounting, vol. 5, no. 22, pp. 166–176, 2014. https://core.ac.uk/download/pdf/234630293.pdf
21. E. U. C. Chinekwu, *Determinants of inflation in Nigeria*, Journal of Economy, Tourism And Service, vol. 2, no. 9, pp. 31–42, 2023. https://jets.innovascience.uz/index.php/jets/article/view/91/91