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FORECASTING INFLATION USING MACHINE LEARNING TECHNIQUES

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Abstract. Inflation forecasting is key in achieving the Central Bank mandate of price stability the world over. Different traditional methods were used to forecast inflation with little or no attention given to the area of forecasting the inflation rate in Nigeria using machine learning techniques. Data was sourced from CBN statistical bulletin (2021) on monthly basis. The study found that ridge regression and Artificial Neural Networks are the best in forecasting inflation in Nigeria when compared with the LASSO, elastic net, and PLS. The study further reveals that the major drivers of headline inflation in Nigeria were food inflation, core inflation, prime lending rate, maximum lending rate, and the inter-bank rate. The study recommends that ridge regression and Artificial Neural Network machine learning techniques be used in forecasting the inflation rate in Nigeria. Also, recommended is the need for the monetary authorities to focus more on ways to improve food production by improving security.

1. Introduction

Inflation as an important indicator of the welfare and wellbeing of the citizens of a nation is no doubt an integral part of economic development. It is a situation where too much money chases too few goods. It can also be referred to as a persistent rise in the general price level of a broad spectrum of goods and services. The core mandate of central banks across the globe is to achieve price and financial system stability. The Central Bank of Nigeria (CBN) is not different in this drive. The bank has the core mandate of ensuring monetary and price stability, issuance of legal tender currency, maintenance of external reserves and safeguarding the international value of the Naira, promoting a sound financial system, and acting as banker, economic and financial adviser to the federal government (CBN Act, 2007). In addition, the central bank performed some major developmental functions, which focussed on key sectors of the economy, such as the agriculture, industry, and financial sectors. These sectors have been supported by the banks through its numerous interventions programs, such as the Anchor Borrowers Programme (ABP) and Accelerated Agricultural Development Scheme (AADS loan) to support agricultural activities, the Creative Industry Financing Initiative (CIFI Loan), and Micro, Small and Medium Enterprises Development Fund (MSMEDF loan)to support the industrial sector to mention but few. These were conceived to boost economic activities in the sectors, increase the supply of goods and services, reduce prices and attain a sustainable level of economic growth.

The central bank of Nigeria to achieve this mandate used monetary policy instruments. These instruments include monetary policy rate (MPR), cash reserve ratio (CRR), open market operations (OMO), interbank rate, treasury bills, prime lending rate, maximum lending rate, broad money supply (M2 or M3), credits, and other interventions, as well regulatory policies. Most of the time the basic objective of the policy changes is to achieve price stability (control

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inflation) in the county. The role of maintaining price stability does not only vested in the central bank along, but the government at both federal, state, and local levels has a role to play, through fiscal policy. The government may decide to change taxation, expenditure borrowing, and budget to tackle inflation and achieve price stability.

The monetary and fiscal authorities over the years tried to stabilize the inflation rate and even bring it to a single digit by changing both the monetary and fiscal policy instruments, but these efforts seem not to yield the desired objective. Despite these efforts by the central bank and the government to stem the tide of inflation in the country, inflation keeps escalating. This calls for a critical and clinical look at the phenomenon of inflation, with the view to finding a solution to the ugly trend.

In addition to the aforementioned problems, insecurity in recent times has impacted negatively the productivity level in the country causing food scarcity and an increase in the prices of foodstuffs. This further exacerbates inflationary pressure in the country. Furthermore, some structural changes such as the economic recession witnessed in the country in 2016 and 2019 raise further the inflation rate in Nigeria. Hence the need to forecast inflation in the country.

Due to the unstable nature of inflation in Nigeria and the dimension researchers are looking at the phenomenon, inflation forecast has become a major concern for the monetary authorities in Nigeria and across the globe. The forecast means looking into the future value and behaviour of macroeconomic variables, and which accuracy of the forecast is an issue. The future is always and everywhere and involves uncertainty, there is the need to minimize the forecast error and maximize forecast accuracy. Most of the studies on inflation forecast in Nigeria focussed on the demand side of the determinant of inflation, living the supply side out. The supply side of the determinants of inflation has become a topical issue when it comes to forecasting inflation globally and Nigeria is not exceptional. In addition, most of the studies on inflation forecast in Nigeria employed the traditional univariate and vector autoregressive techniques in their analysis, with little or no attention given to the application of machine learning techniques to enhance forecast. Based on the foregoing arguments, the current study focussed on the combination of both the demand and supply side of the determinants to forecast inflation in Nigeria by applying the machine-learning technique. This, the study's belief ceteris-paribus, would improve inflation forecasting in Nigeria.

The main objective of the paper is to forecast inflation for Nigeria by incorporating the supply side and using machine-learning techniques.

The paper is structured into seven sections. Section 1 presents the introduction, motivations, and objective of the paper, section 2 comprises of literature review, section 3 is country experience, section 4 is the stylized facts, section 5 is the data and methodology, section 6 is the results and discussion of results, section 7 comprises of conclusion and recommendations.

2. Literature Review

2.1. **Theoretical literature.** Inflation is a highly controversial phenomenon and had undergone modification by different economists over the years (Jhingan, 2009). Neo-classical economists defined inflation as a galloping rise in prices resulting from an excessive rise in the quantity of money in circulation; assuming full employment level, therefore, inflation is a monetary phenomenon. To Keynes, Inflation is the persistent rise in the broad spectrum of goods and services because of a rise in aggregate demand. Inflation concisely is a sustained rise in the general price level of goods and services.

There are theories put forward to explain the concept of inflation. The monetarist's theory of inflation postulated that demand-pull inflation is principally caused by a rise in the money supply. Therefore, inflation to the monetarists is always and everywhere a monetary phenomenon. The monetarists adopted Fisher's quantity theory of money in explaining inflation. Fisher's equation of exchange is thus:

$$MV = PQ$$

Where M represents the money supply, V is the velocity of money in circulation, P represents the price level of goods and services and Q is the level of real output. The theory works on the assumption that V and Q are constant, and price level (P) varies proportionately with the supply of money (M). This implies that inflation, measured by price level is caused by a rise in money supply in an economy, therefore, inflation is a monetary phenomenon. Similarly, the modern quantity theory of money led by Friedman supports the view that inflation is caused by a rise in the money supply. To them, inflation is always and everywhere a monetary phenomenon, which arises from rapid expansion in the supply of money than in total output.

On the other hand, Keynesians viewed inflation as an increase in aggregate demand. To them, inflation is caused by demand-pull and not cost-push. An increase in aggregate demand will lead to an increase in the prices of goods and services. Bent Hasen's excess demand theory presented an explicit dynamic inflation model, which incorporates two separate price levels, the goods, and labour market prices (Day, 1952; Claes-Henric, 2020). The theory posited that when both excess demand for goods and the excess demand for factors are positive, prices and wage rates will increase. It then follows that a rise in excess demand for goods and factors of production will lead to inflation. All the theories reviewed above focus on the demand side of the determinants of inflation ignoring the supply side, which also played an important role in stabilizing prices, hence reducing inflation.

The supply-side economists opined that a reduction in tax rate provides greater incentives to work, save and invest. According to them, an increase in marginal tax rate will discourage saving and investment, as well as encourages consumption, which would increase the prices of goods and services (inflation). On the other hand, a reduction in marginal tax rates increases individuals' propensity to save. This would facilitate investment in new plants and equipment, and increase productivity and output, thereby reducing the prices of goods and services (Balami, 2006).

Some economists such as Lowe (2017) and Yellen (2017) opined that technological advancement has transformed the process of production such that affect the prices of commodities. Therefore structural changes in an economy such as technological progress should be factored into the inflation model to achieve an all-inclusive forecast accuracy. In the same vein Jongrim, Kose, and Ohnsorge (2019) observed that expectations are key to ensuring forecast accuracy and efficiency, though they find that expectations are more anchored in advanced countries than the emerging and developing countries, which Nigeria is inclusive.

In the case of Nigeria, the large index of inflation is coming from the food component of the Consumer Price Index basket which is largely attributed to the insecurity that is bedeviling the northeastern part of the country. These arguments further justify the need to incorporate insecurity and other macroeconomic variables from both the supply and the demand side to forecast inflation in the country.

The current paper combined the demand and the supply variables that influence inflation in Nigeria in its forecast.

2.2. **Empirical review.** Empirical studies related to inflation forecasting from within and outside Nigeria were reviewed to identify gaps for the current study. Olajide, Ayansola, Odusina, and Oyenuga (2012) conduct a study on forecasting the inflation rate in Nigeria using Box Jenkins Approach. They found that the best and most adequate model for forecasting the inflation rate in Nigeria was Autoregressive Integrated Moving Average (ARIMA) (1,1,1). The model was used to forecast the inflation rate for 2011 to be 16.27%. Again, Doguwa and Alade (2013) conclude that SARIMAX is the best headline inflation-forecasting model in Nigeria when compared with SARIMA. On the contrary, Ikechukwu and Adedoyin (2014) reveal that Vector Autoregressive (VAR) model is the best model to forecast inflation in Nigeria and not ARIMA. This is because VAR had a smaller mean square error than the ARIMA. Again, Raphael and Olanrewaju (2015) conclude that using the Kalman filter approach to forecast the headline inflation rate in Ni5geria is more efficient than the popular Box-Jenkins ARIMA(0,1,0).

In another development, John and Patrick (2016) wrote on short-term forecasting of the inflation rate in Nigeria using a seasonal ARIMA model. Their study revealed that Nigeria's Inflation rates are seasonal and the best model to forecast inflation in Nigeria is the seasonal ARIMA Model, (0, 1, 0) x (0, 1, 1)12. The model proved to be adequate because the forecast values obtained from it are close to the actual inflation values.

Again, Uduakobong (2017) reveals that the inflation rate at lag 1 had significant information about the current and future value of the inflation rate in Nigeria, but fiscal deficit, money supply, and output do not have. This implies that the previous year's inflation can be used to predict the current and future values of inflation in Nigeria. Ivan (2018) forecasts Inflation Using Machine Learning Methods of penalized regression (LASSO, Ridge, and Elastic Net) and Random forest, as well as Boosting techniques in Russia. Based on the prediction accuracies of the models, the paper concludes that the random forest and boosting model are the best inflation forecasting models when compared with traditional models like random walk and autoregression. Hence, the need for more attention to be given to the application of machine learning methods to forecast not only inflation but also all macroeconomic variables. Olalude, Olayinka, and Ankeli (2020) observe that SARMA (3, 3) x (1, 2)12 is the best model to forecast the month-on-month inflation rate in Nigeria. In addition, they conclude that the Inflation rate in Nigeria would continue to decrease but maintain a two digits value for the next two years, but is likely to rise again in 2023. Again, Adolfo (2020) conducts a study on inflation forecast in Costa Rica through machine learning methods. The study employs two variants of K-Nearest Neighbours, random forests, extreme gradient boosting, and long short-term memory (LSTM) network and compared with the univariate model currently in use. It was found that LSTM, univariate KNN, and to a lesser extent, random forest is the best-performing forecasts models when compared with the univariate model currently used in the Central Bank of Costa Rica.

From the foregoing empirical literature reviewed, there is no consensus as to which forecast model is the best for inflation. This is a gap that needed to be filled by applying machine learning techniques and compare with the current univariate method used in the Bank. This would help to identify the best inflation-forecasting model for the Central Bank of Nigeria, especially, in this digital era.

The study is structured into six sections. Following the introduction, section two is the literature review, section three is the stylized facts and trend analysis, section four is the methodology, section five is the results and discussion, and finally, section six is the conclusion and policy recommendations.

3. Trend analysis

Source: Excel output

Figure 3.1: Trend in INFL, FINFL, CINFL, and insecurity in Nigeria

Figure 3.1 shows the trend in the headline, food, core inflation, and insecurity in Nigeria between 2011M5 and 2021M7. A core movement was found between headline, food, and core inflation with food inflation at the higher level. This implies that the major driver of headline inflation in Nigeria is the food component of the Consumer Price Index (CPI), followed by the core inflation, and lastly insecurity. The figure revealed that, despite insecurity having an impact on inflation, its impact is not as significant as the impacts of food and core inflation.

In 2014M3 insecurity was observed to be at its peak at 3,462 deaths in the country, this can be attributed to the fact that "Boko Haram" insurgency activities were at the peak in 2014. This had affected productivity, especially in the agricultural sector of the North-Eastern region of the country, which is expected to increase the prices of goods and services. Surprisingly, headline, food, and core inflation were very low at single digit, precisely, 7.8, 9.3, and 6.8 per cent respectively. This implies that insecurity does not have an immediate effect on prices, but rather a lag effect. The figure further revealed that in 2016, which happen to be the recession period, both headline, food, and core inflations were on the rise but insecurity was decreasing.

This further justifies that insecurity may not have a significant influence on inflation and that recession may not cause insecurity in Nigeria.

4. Data and Methodology

The paper sourced data from the CBN statistical bulletin, (2019) National Bureau of Statistics (NBS) annual report (2020), and google trends. Data was sourced on the headline inflation (INFL), food inflation (FINFL), core inflation (CINFL), monetary policy rate (MPR), Cash Reserve Ratio (CRR), Prime Lending Rate (PLR), Maximum Lending Rate (MLR), Treasury Bills Rate (TBR), inter-bank rate (IBR), the exchange rate (EXR), money supply (MS), and insecurity (INS). The insecurity perception index was sourced from google trends. The paper employed machine-learning techniques, which include penalized regression technique (Ridge, LASSO & Elastic net regressions), partial least square (PLS) technique, and artificial neural network (ANN) technique. These machine-learning techniques are chosen because of their ability to handle a continuous dependent variable such as inflation rate and also techniques such as artificial neural network, which can handle both continuous and categorical dependent variables.

The R-packages and language used in estimating the parameters of the models of this study include the **neuralnet, pls, glmnet, caret, leaps, dynlm,** and **TSstudio**. The package **neuralnet** was used to estimate the ANN model, **pls** was used to estimate the PLS model, **glmnet** was used to estimate the ridge and LASSO models while **glmnet, caret, leaps, dynlm,** and **TSstudio** were used for the elastic net model (see R Core Team, 2020).

The Machine-learning technique was also, chosen because the current study wan to compare its effectiveness and performance in forecasting inflation and the traditional univariate and VAR methods currently used by the Central Bank.

4.1. **Models specification.** The study employed five (5) machine-learning techniques, therefore 5 models are specified one for each of the techniques.

4.2. **The Model I: Ridge Regression Model.** The ridge regression model is similar to the Ordinary Least Square regression model, only that the ridge regression model seeks to minimize the sum of residual sum of squares (RSS) and the sum of squares of penalized coefficients of the model. The regression model for this study is specified as follows:

$$Y = a_0 + \sum b_i X_i \tag{1}$$

Where Y is the dependent variable, in this case, inflation rate, b_i is the vector of coefficients, X_i is the matrix of the predictors (independent variables, this includes FINFL, CINFL, IBR, MPR, TBR, PLR, MLR, CRR, EXR, broad money supply (M3), and insecurity.

Ridge regression seeks to minimize:

$$RSS + \lambda \sum_{k=1}^{P} {b_k}^2 \tag{2}$$

Where λ is lambda and is the regularization or tuning parameter that controls the strength of the penalty. ${b_k}^2$ is the squares of the coefficients upon which the penalty was imposed.

4.3. **Model II : LASSO Regression Model.** The Least Absolute Shrinkage and Selection Operator (LASSO) is a penalized regression method that imposed a penalty on the sum of the absolute values of the coefficients of a model. Drawing from equation 1, LASSO seeks to minimize:

$$RSS + \lambda \sum_{k=1}^{P} |b_k| \tag{3}$$

Where λ as explained above, $|b_k|$ is the absolute values of the coefficients of a model.

4.4. **Model III: Elastic Net Regression Model.** Elastic net is also a type of penalizing regression that performs the feature extraction that ridge regression does not and groups the features that LASSO fails to do. Elastic net regression seeks to minimize the residual sum of squares, both sum of squares of the coefficients, as well as the absolute values of the coefficients of the model. Also, from equation 1, the elastic net seeks to minimize the following

$$RSS + \lambda_1 \sum_{k=1}^{P} |b_k| + \lambda_2 \sum_{k=1}^{P} {b_k}^2 \tag{4}$$

4.5. **Model IV: Partial Least Square (PLS) Regression Model.** PLS technique allows for the prediction of the dependent variable, based on very large sets of predictors. The model is specified as follows:

$$X = TP^T + E \tag{5}$$

$$Y = TP^T + F \tag{6}$$

$$Y = \alpha + \beta X + \varepsilon \tag{7}$$

Where X is the matrix of predictors, Y is the matrix of response, while E, F, and ε are the error terms. T and U are the score or factor matrix of X, while P and Q are orthogonal loading matrices respectively.

4.6. **Model V: Artificial Neural Network (ANN) Model.**

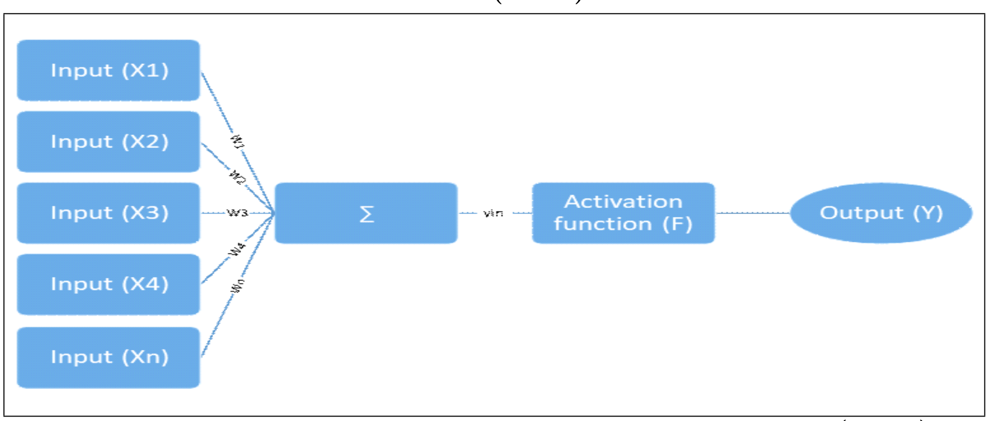

Figure 4.1: A general model of Artificial Neural Network (ANN)
Source: Designed by the Authors, 2021

From the general model of the artificial neural network, the net input is calculated as follows:

$$y_{in} = X_1.W_1 + X_2.W_2 + X_3.W_3 + X_4.W_4 - - - - - - - + X_n.W_n \tag{8}$$

where y_{in} is the net input, X_1 to X_n represents the monetary and fiscal policy variables, which are the independent variables, W_1, W_2, W_3, W_4, ..., W_n are the weight assigned to each input variable, F is the activation variable.

The output, which is the dependent variable is calculated by applying the activation function over the net input:

$$Y = F\left(y_{in}\right) \tag{9}$$

where Y is the output, which in this case is the inflation rate and is a continuous variable.

Variables	Definition	Measurement	Source
HINFL	Headline Inflation	Measured in %	CBN Reports and NBS Report
FINFL	Food Inflation	Measured in %	CBN Reports and NBS Report
CINFL		Measured in %	CBN Reports and NBS Report
IBR		Measured in %	CBN Reports and NBS Report
MPR		Measured in %	CBN Reports and NBS Report
TBR		Measured in %	CBN Reports and NBS Report
PLR		Measured in %	CBN Reports and NBS Report
MLR		Measured in %	CBN Reports and NBS Report
CRR		Measured in %	CBN Reports and NBS Report
EXR		Unit of Naira exchange for a unit of US Dolar	CBN Reports and NBS Report
MS		Proxy by M3	CBN Reports and NBS Report
INS		Number of people killed and kidnaped in Nigeria	https://docs.google.com/spreadsheets/d/1_QY-l4xhMu5nZVluprOgRs6rUzgkkBemapdsg5lFzKU/pub?output=xlsx
Source: Author's Compilation			
Note: HINFL is headline inflation, FINFL is food inflation, CINFL is core inflation, IBR is the interbank rates, MPR is the policy rate, TBR is the treasury bill rate, PLR is the prime lending rate, MLR is the maximum lending rate, CRR is the reserve ratio, EXR is the nominal exchange rate, Ms is the money supply, and INS is insecurity.			

5. Results and Discussion of findings

The results of the study from the penalized regression (ridge, LASSO, and elastic net), partial least square (PLS), and the artificial neural network are discussed in this section.

Table 5.1: Estimated results of five models				
CONS.	7.08	8.84	5.75	-
FINFL	0.55	0.51	0.49	1.98
CINFL	0.30	0.34	0.23	1.19
IBR	-0.01	-0.01	-0.003	0.03
MPR	0.15	0.08	0.07	0.06
TBR	0.08	0.11	0.05	0.12
PLR	-0.29	-0.37	-0.12	0.16
MLR	-0.10	-0.19	-0.07	-0.69
CRR	0.003	0.004	0.00001	0.11
EXR	0.01	0.01	0.01	0.91
MS	-0.0001	-0.000001	-0.0001	-0.04
INS	-0.0002	-0.0001	-0.0003	-0.03
MSE	0.4138	2.7588	0.6076	3.1804
RMSE	0.6433*	1.6610	0.7795	1.7834
Source: R-Studio output				
Note: MSE is the mean square error, and RMSE is the root mean square error used to determine the best forecast technique.				

Table 5.1 contained the results for the ridge, LASSO, elastic net, and Partial Least Square regression (PLS) machine learning technique. The best technique is chosen based on the Root

Mean Square Error (RMSE). The model having the lowest RMSE is the best in forecasting inflation in Nigeria. The RMSE of the ridge regression of 0.6433, LASSO of 1.6610, elastic net of 0.7795, and PLS of1.7834 show that the ridge regression technique is the best machine learning technique to be used to forecast inflation in Nigeria. Based on the RMSE the result of the ridge regression technique is interpreted.

The constant value of 7.08 implies that headline inflation on average is 7.08 when FINFL, CINFL, IBR, MPR, TBR, PLR, MLR, CRR, EXR, MS, and INS are zero. The coefficients of FINFL and CINFL of 0.55 and 0.30, implying that a one per cent increase in food and core inflation may likely lead to a 0.55 0.30 per cent increase in headline inflation in Nigeria, which is consistent with the theoretical expectation of the study.

The coefficients of IBR, PLR, and MLR of -0.01, -0.29, and -0.10 imply that a percentage point increase in inter-bank rate, prime lending rate, maximum lending rate, and insecurity will translate into a decrease in the headline inflation in Nigeria, which is expected. On the contrary, the coefficients of MPR, TBR, CRR, and EXR of 0.15, 0.08, 0.003, and 0.01 were found to be inconsistent with the theoretical expectation of the study, as an increase in them is expected to reduce inflation. This result is not surprising as MPR, TBR, CRR, and EXR may be ineffective within the context of the Nigerian economy, this is not unconnected to the low level of financial literacy and inclusion in Nigeria. The majority of Nigerians do not save their money in the bank, either due to religious beliefs or cultural inclinations. This would render monetary policy ineffective, especially in forecasting inflation in the country. Insecurity and money supply are expected to have a positive influence on the inflation rate, but the reverse is the case, as an increase in insecurity and money would lead to a decrease in the inflation rate by 0.0002 and 0.0001 respectively.

In summary, the result revealed that the major determinant of headline inflation in Nigeria is food inflation, followed by core inflation, then prime lending rate, maximum lending rate, and inter-bank rate.

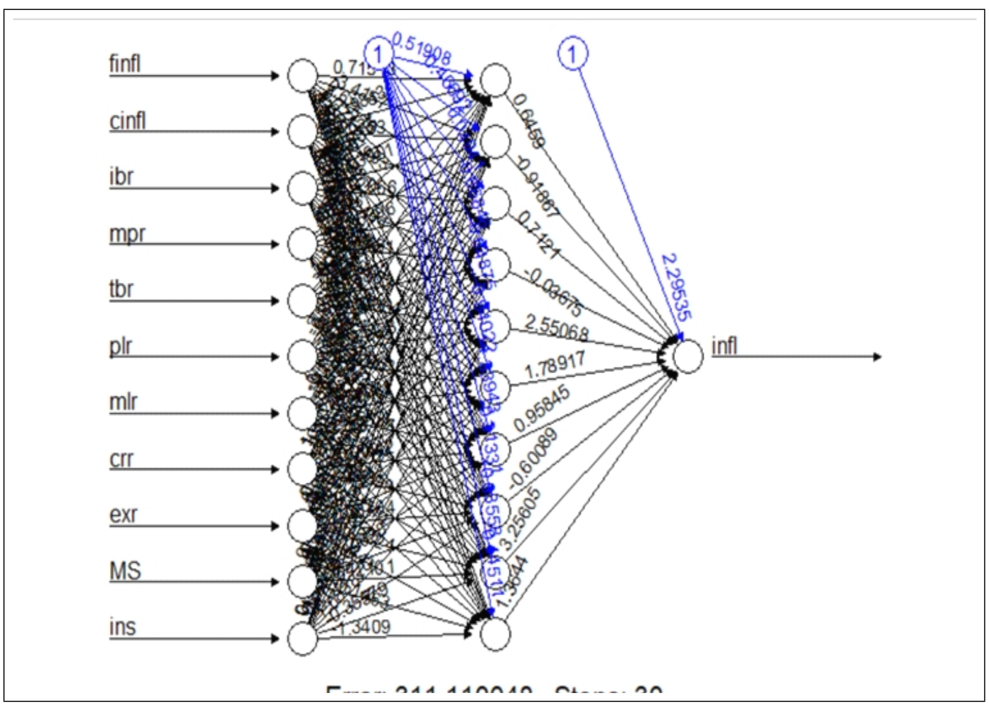

Figure 5.1: ???

Source: R-Studio output

Table 5.2 show the predicted values of the headline inflation in Nigeria using ridge, LASSO, elastic net, PLS, and ANN. Based on the ridge regression the predicted inflation rate for July

2021 is 18.22, for LASSO is 20.94, the elastic net is 17.08, PLS is 21.19, while ANN predicted that the inflation rate for August 2021 will be less than 17.38 with the predicted figure of zero.

Table 5.2: Forecasted values of inflation and the RMSE

Months	**Actual Inflation**	**Ridge**	**LASSO**	**Elastic Net**	**PLS**	**ANN**
2021M2	17.33	17.91	20.30	16.81	20.50	
2021M3	18.17	18.71	21.12	17.54	21.34	
2021M4	18.12	18.51	20.87	17.36	21.07	
2021M5	17.93	18.42	20.98	17.27	21.22	
2021M6	17.75	18.20	20.63	17.09	20.86	
2021M7	17.38	18.22	20.94	17.08	21.19	
MSE		0.4138	2.7588	0.6076	3.1804	2021M8
RMSE		0.6433	1.6610	0.7795	1.7834	Zero

Source: R-Studio output.

Note: ANN is the artificial neural network.

Table 5.3 is the summary of the ANN result contains in figure 5.1. Headline inflation was forecasted based on the assumption that zero (0) will represent the predicted value of inflation when inflation is less than 17.38 per cent found in 2021M7, if the inflation rate is greater than or equal to 17.38 per cent, then the categorical forecast of inflation will be one (1). The ANN result revealed that the forecasted headline inflation is zero (0), meaning that inflation is predicted to be less than 17.38 per cent in August 2021 in Nigeria. The august inflation rate according to the National Bureau of Statistics report (2021), headline inflation is 17.01 per cent, which conformed to the forecast. The figure and the table show that the overall constant is 2.30, implying that when FINFL, CINFL, IBR, MPR, TBR, PLR, MLR, CRR, EXR, MS, and INS are zero inflation will be on average 2.55098 in Nigeria.

Table 5.3: Summary of the Artificial Neural Network Results

Variables	Lay1	Lay2	Lay3	Lay4	Lay5	Lay6	Lay7	Lay8	Lay9	Lay10	Laysinfl
Const.	0.52	0.47	0.05	0.67	-0.7	0.94	-1.3	-0.3	-0.1	0.45	2.30
finfl	0.72	-3.4	0.68	1.07	0.30	1.04	-0.1	1.16	0.84	1.65	0.65(L1)
cinfl	0.20	0.63	0.18	-1.0	1.43	0.06	1.52	-0.1	0.25	0.07	-0.9(L2)
ibr	-1.0	-0.1	0.02	0.82	-1.6	0.39	-0.1	-0.3	-0.6	-0.1	0.71(L3)
mpr	0.57	0.7	-0.6	0.99	-0.5	-1.0	0.38	-0.1	-1.0	-0.2	-0.04(L4)
tbr	-1.4	-0.1	2.61	0.79	-1.6	-0.2	-1.4	-2.1	-0.1	-0.7	2.55(L5)
plr	-2.7	-0.9	-0.8	0.05	-0.2	1.42	0.18	1.48	-1.6	2.45	1.79(L6)
mlr	-1.5	-0.1	-0.9	1.40	-0.1	1.35	1.97	0.92	0.41	-1.4	0.96(L7)
crr	1.1	1.4	-0.6	0.49	-0.3	-0.4	0.18	0.85	-0.1	0.52	-0.60(L8)
exr	-0.6	-0.3	0.87	0.50	-0.8	-0.4	-0.2	0.26	0.46	0.04	3.26(L9)
ms	0.1	-0.1	-0.6	0.77	0.4	0.99	0.44	-0.9	0.42	-0.2	1.36(L10)
ins	0.6	0.2	-1.0	-1.3	0.87	-0.11	-0.1	1.08	-0.4	-1.3	

Source: R-Studio output.

Note: Lay (L) is the hidden layers, Const. is the intercept or constant, finfl is food inflation, cinfl is core inflation, ibr is the interbank rate, mpr is the monetary policy rate, tbr is the treasury bill rate, plr is the prime lending rate, mlr is the maximum lending rate, crr is the reserve ratio, exr is the nominal exchange rate, ms is the money supply, and ins is the insecurity index.

Table 5.3 reveals the impacts of FINFL, CINFL, IBR, MPR, TBR, PLR, MLR, CRR, EXR, MS, and INS on headline inflation from ten different hidden layers. Layer 1 (Lay1) shows that an increase in FINFL, CINFL, MPR, CRR, MS, and INS may likely raise headline inflation, while an increase in IBR, TBR, PLR, MLR, and EXR tends to reduce headline inflation. Lay2 reveals that CINFL, MPR, CRR, and INS exert a positive impact on headline inflation, but FINFL, IBR, TBR, PLR, MLR, EXR, and MS have a negative impact on headline inflation. Lay3 shows a positive relationship between FINFL, CINFL, IBR, TBR, EXR, and headline inflation, while a negative relationship was observed between MPR, PLR, MLR, CRR, MS, INS, and headline inflation. Lay4 shows that only CINFL and INS have a negative impact on headline inflation. Lay5 shows that only FINFL, CINFL, MS, and INS have a positive impact on headline inflation. Lay6 reveals that FINFL, CINFL, IBR, PLR, MLR, And MS have a positive impact on headline inflation except for MPR, TBR, CRR, EXR, and INS, which have a negative impact on headline inflation.

Similarly, Lay7 reveals that CINFL, MPR, PLR, MLR, CRR, and MS have a positive impact on headline inflation except for FINFL, IBR, TBR, EXR, and INS. Lay8 reveals that FINFL, PLR, MLR, CRR, EXR, and INS have a positive impact on headline inflation except for CINFL, IBR, MPR, and TBR. Lay9 shows a positive relationship between FINFL, CINFL, MLR, EXR, MS, and headline inflation in Nigeria, but a negative relationship was found between IBR, MPR, TBR, PLR, CRR, INS, and headline inflation. In the same vein, Lay10 shows that FINFL, CINFL, PLR, CRR, and EXR impact headline inflation a positive implying an increase in FINFL, CINFL, PLR, CRR, and EXR may likely raise headline inflation in Nigeria.

The summary of the ten hidden layers can be seen in the Layinfl column with an overall constant of 2.30. L1, L3, L5-LL7, and L9-L10 show that FINFL, CINFL, IBR, MPR, TBR, PLR, MLR, CRR, EXR, MS, and INS have a positive impact on headline inflation in Nigeria. L2, L4, and L8 show a contrary outcome. In summary, we could say that FINFL, CINFL, IBR, MPR, TBR, PLR, MLR, CRR, EXR, MS, and INS are the major drivers of headline inflation in Nigeria.

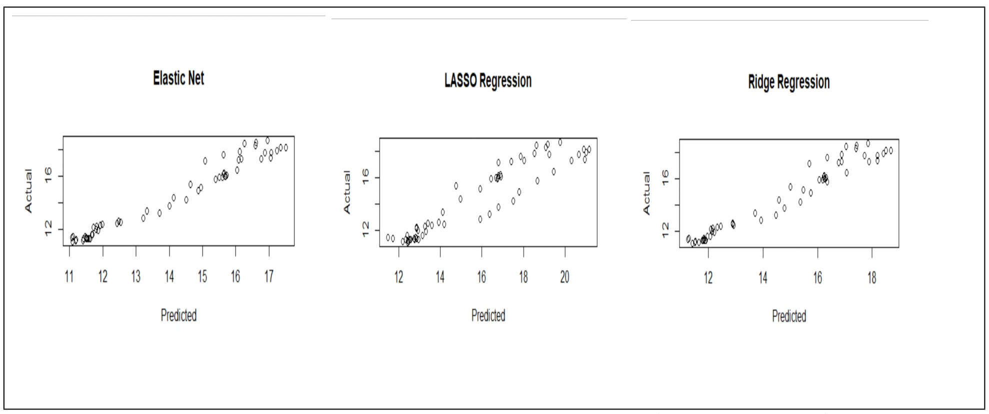

Figure 5.2: Actual and Predicted values of headline inflation
Source: R-Studio output

Figure 5.2 shows the actual and predicted headline inflation in Nigeria using elastic net, LASSO, and ridge regression techniques. It was revealed the ridge regression graph predicts headline inflation better than the elastic net and LASSO, as the predicted values were found to be close to the actual values as indicated by the plots. Therefore, ridge regression is the technique for forecasting inflation in Nigeria when compared with the elastic net and the LASSO regression technique.

6. Conclusion and policy recommendations

Forecasting inflation is an integral part of Central Banking in the world. Different traditional methods were used to forecast inflation with little or no attention given to the area of forecasting inflation using machine learning techniques, especially in Nigeria. This study came in handy to forecast inflation in Nigeria using machine learning techniques like the ridge, LASSO, elastic net, partial least square regression analysis, as well as the Artificial Neural Network. Based on the findings of the study, it was concluded that the ridge regression machine learning technique is the best in forecasting inflation in Nigeria when compared with the LASSO, elastic net, and PLS as it has the least RMSE value. It was also concluded that ANN can also perform well in forecasting inflation in Nigeria. The study further concluded that the major drivers of headline inflation in Nigeria were food inflation, core inflation, prime lending rate, maximum lending rate, as well as inter-bank rate.

The study recommends that ridge regression and Artificial Neural Network machine learning techniques be used in forecasting the inflation rate in Nigeria. Also, the study recommends the need for the monetary authorities to focus more attention on ways to improve food components of the CPI, through improving security in the farming communities and strengthening the unconventional monetary policies such as increasing intervention to the farmers and ensuring that the interventions get to the target farmers. This is because the major driver of inflation in Nigeria is the food component of the CPI, followed by core components, then prime lending rate, maximum lending rate, and inter-bank rate in forecasting inflation in Nigeria.

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