Short Research Article

ENERGY CONSUMPTION & ECONOMIC GROWTH IN NIGERIA (1971 - 2021): A Multifaceted Analysis using Descriptive Statistics, Charts, Logistic Regression, and Neural Networks.

Abstract:

This study examines the intricate interplay between electricity consumption and economic growth, specifically Gross Domestic Product (GDP), in Nigeria. Despite the acknowledged influence of electricity consumption on GDP, the research takes a comprehensive approach by scrutinizing various economic factors that may contribute to Nigeria's remarkable GDP performance within the African context. Utilizing a meticulous methodology, the investigation explores the relationships between GDP and variables such as unemployment, population, lending interest rates, importation costs, and inflation rates across a 50-case observational dataset. The findings highlight the substantial impact of electric power consumption, population, and lending interest rates on Nigeria's GDP, while revealing the relatively minor effects of other predictors.

Keywords: Nigeria’s GDP, Electric power consumption, electricity consumption, economic growth

Introduction:

This research aims to elucidate the complex relationship between energy consumption and economic growth, specifically focusing on Nigeria [1,2]. As the largest economy in Africa since 2013, Nigeria's GDP consistently surpasses that of its continental counterparts [3-5]. Despite the acknowledged influence of electricity consumption on GDP, the paradoxical scenario of inadequate electricity supply challenges conventional assumptions [6-8]. This study seeks to unravel the economic factors contributing to Nigeria's GDP growth, examining the roles and significance of these factors in the context of suboptimal electricity consumption.

Purpose of the Study:

Given the paradox of low electricity consumption and Nigeria's high GDP ranking in Africa, this research aims to discern the multifaceted economic factors contributing to this phenomenon. The study endeavors to delineate the roles and significance of these factors in shaping Nigeria's augmented GDP, scrutinizing whether electricity consumption remains the predominant determinant.

Research Questions:

Aligned with the research objectives, the study addresses pivotal questions:

1. What is the impact of electricity consumption on Nigeria's GDP during the periods under examination?
2. To what extent does electricity consumption significantly influence Nigeria's GDP?
3. In the absence of a substantial impact from electricity consumption, what alternative factors exert influence on Nigeria's GDP, and what are their respective roles and significance?

Statement of Hypothesis:

Considering the research queries, the study formulates hypotheses to assess the significance of electricity consumption on GDP: A. H0; Null hypothesis: B1 = 0 (Electricity consumption has no significant effect on Nigeria's GDP) B. H1; Alternative hypothesis: B1 ≠ 0 (Electricity consumption has a significant effect on Nigeria's GDP)

Data Source & Scope:

The statistical models employed in this study were implemented using Solver Excel XLMinertool, providing a robust analytical framework for investigating the relationships between energy consumption and various economic variables impacting Nigeria's GDP. The primary dataset for this analysis is derived from the World Bank Development Indicators (WDI) database, encompassing the years 1971 to 2021. The choice of this temporal span allows for a comprehensive exploration of energy consumption trends and their correlations with key variables influencing Nigeria's economic dynamics. The reliability and relevance of the data are ensured through its careful curation from https://databank.worldbank.org/source/world-development-indicators.

MODEL SPECIFICATION

The modeling process involves a meticulous examination of the selected variables, including electric power consumption, population, lending interest rates, unemployment, importation costs, and inflation rates. Leveraging the Solver Excel XLiner, the study aims to optimize the coefficients and parameters within the selected models to best fit the observed data. The XLMiner tool iterative optimization capabilities enable the identification of the most fitting relationships and their respective magnitudes, contributing to a nuanced understanding of the intricate economic dynamics at play.The regression equation that captures the effect of energy consumption, vis-a-vis other macroeconomic variables, on GDP is captured by the equation as stated below:

$$\mathbf{Y = \beta0 + \beta1X1 + \beta2X2 + \beta3X3 + \beta4X4 + \beta5X5 + \beta6X6 + \epsilon}$$

$$\mathbf{GDP = \beta0 + \beta1ElectricityConsumption + \beta2TInflationRate + \beta3TotalPopulation + \beta4ImportationCost + \beta5BankLendingInterestRate + \beta6UnemploymentRate + \epsilon}$$

Where; Y is the dependent variable that captures GDP

X1 is one of the independent variables that captures electricity consumption

X2 captures inflation rate

X3 captures total population

X4 captures importation cost

X5 captures bank lending interest rate

X6 captures Unemployment rate

Є is the error term

Table 1.DESCRIPTIVE STATISTICS

GDP (current US$)		Electric P.C (kWh per capita)		Inflation		Population		Imports		Lending IR..		Unemployment	
Mean	1.71892E+11	Mean	95.78869	Mean	18.30378	Mean	1.2E+08	Mean	2.425E+10	Mean	15.56737	Mean	4.534018
Standard Error	23832729935	Standard Error	4.673296	Standard I	2.208795	Standard I	6323714	Standard I	3589937982	Standard I	0.841492	Standard E	0.223803
Median	73615090340	Median	90.47039	Median	12.77549	Median	1.12E+08	Median	1.0829E+10	Median	16.82042	Median	3.9535
Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	7	Mode	#N/A
Standard Deviation	1.68523E+11	Standard Deviati	33.04519	Standard I	15.61854	Standard I	44715413	Standard I	2.5385E+10	Standard I	5.950245	Standard D	1.582525
Sample Variance	2.84E+22	Sample Variance	1091.985	Sample Va	243.9388	Sample Va	2E+15	Sample Va	6.4438E+20	Sample Va	35.40541	Sample Va	2.504385
Kurtosis	-0.774588375	Kurtosis	-0.8851	Kurtosis	3.396652	Kurtosis	-0.93366	Kurtosis	-0.11722403	Kurtosis	-0.29695	Kurtosis	5.053148
Skewness	0.916593677	Skewness	-0.07108	Skewness	1.996456	Skewness	0.460345	Skewness	1.07639954	Skewness	0.113007	Skewness	2.529328
Range	5.34402E+11	Range	124.0694	Range	69.37785	Range	1.53E+08	Range	8.7293E+10	Range	25.65	Range	6.088
Minimum	12274416018	Minimum	32.72775	Minimum	3.45765	Minimum	58665813	Minimum	1447830923	Minimum	6	Minimum	3.7
Maximum	5.46676E+11	Maximum	156.7972	Maximum	72.8355	Maximum	2.11E+08	Maximum	8.8741E+10	Maximum	31.65	Maximum	9.788
Sum	8.59462E+12	Sum	4789.434	Sum	915.1888	Sum	6E+09	Sum	1.2125E+12	Sum	778.3687	Sum	226.7009
Count	50	Count	50	Count	50	Count	50	Count	50	Count	50	Count	50

Table 2. CORRELATION

	GDP (current U	tric power c (kWh per cap	Inflation---	Population	Imports	Lending IR..	Unemployment
GDP (current US$)	1						
Electric power consu	0.827166	1					
Inflation, consumer p	-0.31591	-0.087994963	1				
Population, total	0.886983	0.885343236	-0.196945341	1			
Imports of goods and	0.938179	0.811001679	-0.31355436	0.85721268	1		
Lending interest rate	0.080489	0.460680449	0.317217485	0.390184579	0.118099	1	
Unemployment, tota	0.522103	0.377872203	-0.073582303	0.644571049	0.464807	-0.002106582	1

Analysis: Each cell in the above table shows the correlation between two specific variables. The increase in GDP is strongly related to the Electric power consumption, Imports and Population at 0.83, 0.94 and 0.88. The correlation between "Inflation" and the "GDP (current)" is -0.316, which indicates that they are weakly negatively correlated. That is, the increase in GDP is associated with inflation.

Table 3. **PIVOT TABLE**

GDP (current US$	Series Name	Average of Electric power consumption (kWh per capita)
5.46676E+11	2014 [YR2014]	144.5254385
5.08693E+11	2013 [YR2013]	142.729212
4.86803E+11	2015 [YR2015]	122.5882514
4.55502E+11	2012 [YR2012]	156.7971517
4.4812E+11	2019 [YR2019]	132.6985635
4.40777E+11	2021 [YR2021]	133.5680311
4.32294E+11	2020 [YR2020]	133.3029686
4.04994E+11	2011 [YR2011]	150.1980159
4.0465E+11	2016 [YR2016]	125.7947602
3.9719E+11	2018 [YR2018]	130.7752289
3.75746E+11	2017 [YR2017]	129.1430924
3.61457E+11	2010 [YR2010]	136.4262652
3.39476E+11	2008 [YR2008]	127.2446137
2.95009E+11	2009 [YR2009]	120.6350712
2.75626E+11	2007 [YR2007]	138.9094166
2.36104E+11	2006 [YR2006]	111.7524163
1.76134E+11	2005 [YR2005]	129.3270312
1.64475E+11	1981 [YR1981]	50.90103784
1.42769E+11	1982 [YR1982]	81.89592594
1.36386E+11	2004 [YR2004]	123.6324865
1.04912E+11	2003 [YR2003]	101.9252114
97094911792	1983 [YR1983]	81.73535221
95385819321	2002 [YR2002]	104.6610449
74030364472	2001 [YR2001]	75.56977626
73745821158	1985 [YR1985]	80.4544837
73484359521	1984 [YR1984]	62.06356225
69448756933	2000 [YR2000]	74.49061979
64201788123	1980 [YR1980]	68.0570943
59372613486	1999 [YR1999]	75.76719632
54805852581	1986 [YR1986]	90.88641197
54604050168	1998 [YR1998]	76.96886384
54457835193	1997 [YR1997]	82.00415836
54035795388	1990 [YR1990]	87.07894453
52676041931	1987 [YR1987]	89.30353228
51075815093	1996 [YR1996]	85.90498293
49648470440	1988 [YR1988]	87.13950744
49118433048	1991 [YR1991]	89.59979699
47794925815	1992 [YR1992]	90.05437487
47259911894	1979 [YR1979]	59.82247397
44062465800	1995 [YR1995]	91.48820715
44003061108	1989 [YR1989]	97.07070111
36527862209	1978 [YR1978]	60.68837566
36308883249	1976 [YR1976]	51.5781796

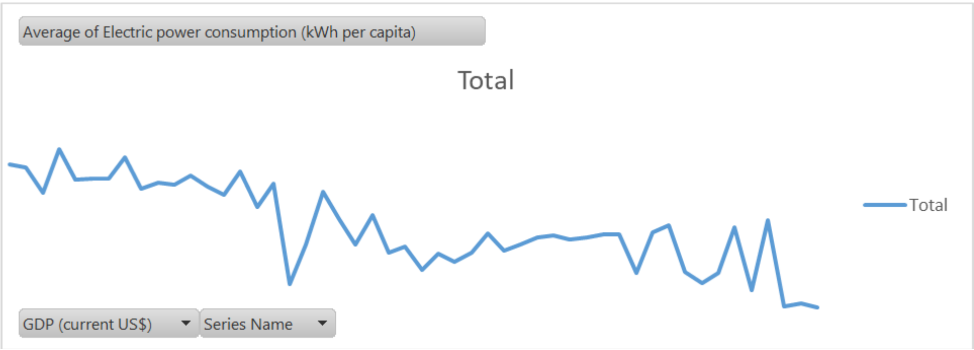

Fig 1.

From the Above Pivot table, the GDP (Y Variable) and the Average Electric Consumption is the explanatory variable. Broadly speaking, Average Electric power consumption (KWh per capita) decreases as the GDP decreases and also Increases as GDP increase. In Year 2012, the GDP had the highest Electric power consumption at 157. We see a positive correlation between these two variables in the Economic growth of Nigeria

HISTOGRAM

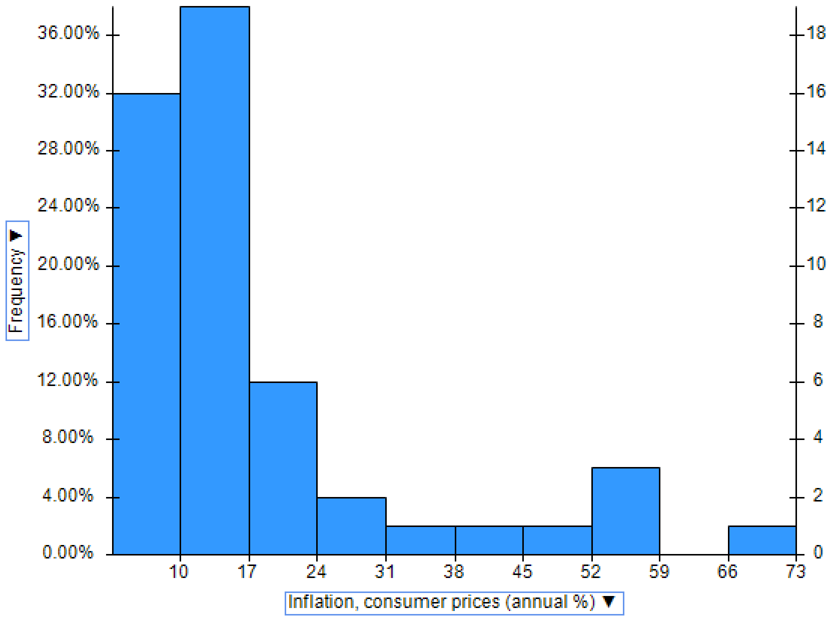

Fig 2. HISTOGRAM

Analysis of Histogram: The GDP shows a slightly skewed distribution with a minor long tail to the right with an outlier at 71. There is an increase in inflation at the 10 to 17 range.

SCATTERPLOT MATRIX

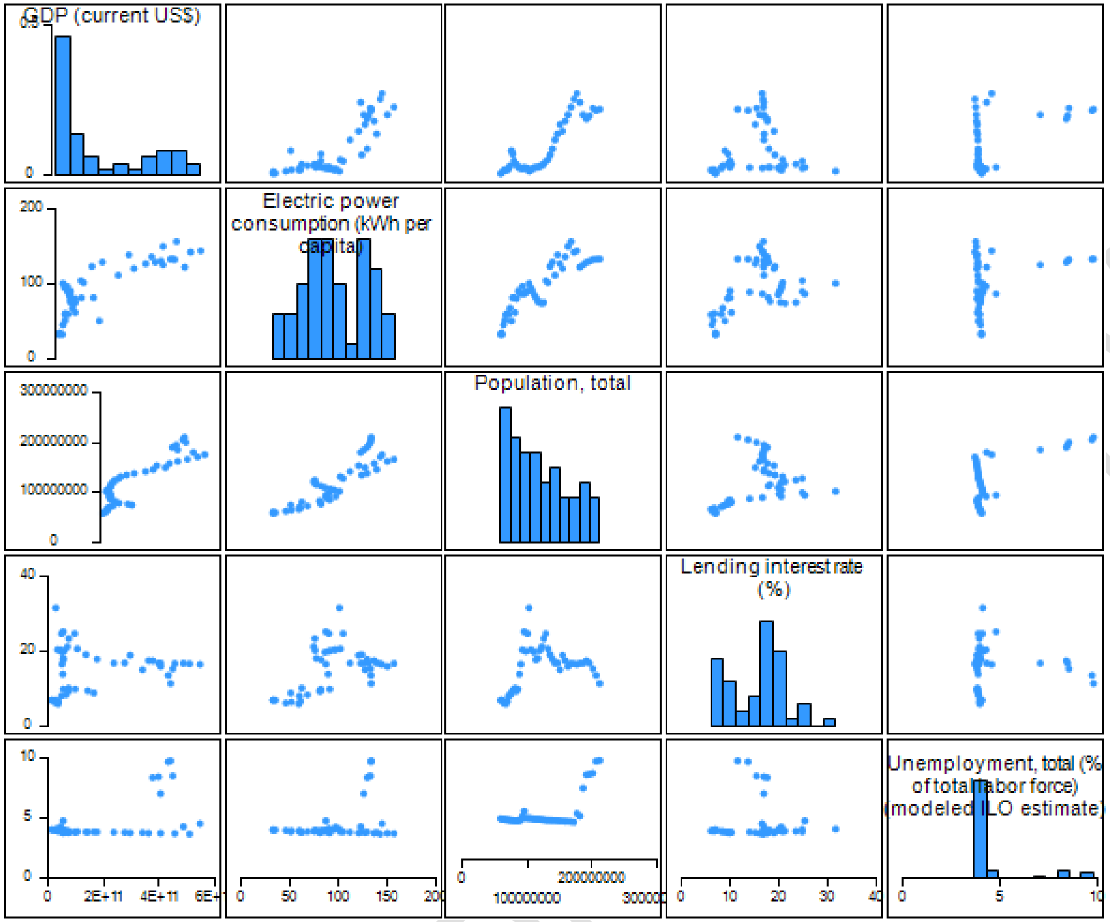

Fig 3. SCATTERPLOT MATRIX

From the Scatterplot matrix above, we can make the following statement:

1. There is a positive relationship between the GDP and Electric power consumption. That is, an increase in GDP also leads to a corresponding increase in Electric power consumption
2. Also we can see a positive relationship between the GDP and Population. That is, an increase in population yields a corresponding increase in GDP

3. There is a horizontal line in the relationship between GDP and Unemployment. That is, there is no relationship between GDP and Unemployment.

Because the line of best fit slants from left to right, the above scatter plot shows a positive relationship between GDP and Populations. That means in General, the higher the GDP, the higher the population. (Note: Birth rate increases population)

EXHAUSTIVE SEARCH ANALYSIS

Table 4.

Regression Summary

Metric	Value
Residual DF	43
R2	0.93751171
Adjusted R2	0.92879241
Std. Error Estimat	4.497E+10
RSS	8.6959E+22

Feature Selection

Best Subsets							
Subset ID	Intercept	Electric power cons	Inflation, consumer	Population, total	Imports of goods and se	Lending interest ra	Unemploym
Subset 1	1	0	0	0	0	0	0
Subset 2	1	0	0	0	1	0	0
Subset 3	1	0	0	1	1	0	0
Subset 4	1	0	0	1	1	1	0
Subset 5	1	1	0	1	1	1	0
Subset 6	1	1	0	1	1	1	1
Subset 7	1	1	1	1	1	1	1

Best Subsets Details						
Subset ID	#Coefficients	RSS	Mallows's Cp	R2	Adjusted R2	Probability
Subset 1	1	1.3916E+24	640.1288733	-8.88178E-16	-8.88178E-16	3.00897E-24
Subset 2	2	1.66741E+23	36.45168576	0.880179878	0.877683625	2.42093E-05
Subset 3	3	1.30795E+23	20.67678759	0.906010647	0.9020111	0.001266495
Subset 4	4	1.00696E+23	7.793017901	0.927639982	0.92292085	0.094568962
Subset 5	5	9.04448E+22	4.723913267	0.935006486	0.929229285	0.429502967
Subset 6	6	8.71289E+22	5.084240256	0.937389286	0.930274432	0.773026474
Subset 7	7	8.69586E+22	7	0.937511705	0.928792408	N/A

The variable "Imports of goods and services" entered the model first. Imports accounts for 94.0% of the variability in the GDP. We then move on to select the best two models. We make this selection from the best two models with the highest Adjusted R-Square.
The best two models in this Featured selection are Subset 6 and Subset 5 with 5 and 4 regressors respectively. They have the highest Adjusted R-square at 0.9303 and 0.9292 respectively.

We then selected the best model model for our analysis
See analysis below:
Table 5. ONE OF THE BEST MODEL WITH FIVE (5) REGRESSORS

Feature Selection

Best Subsets

Subset ID	Intercept	Electric power consumption	Population, total	Imports of goods and services (c	Lending interest rate (%)	Unemployment, total (% of total labor force)
Subset 1	1	0	0	0	0	0
Subset 2	1	0	0	1	0	0
Subset 3	1	0	1	1	0	0
Subset 4	1	0	1	1	1	0
Subset 5	1	1	1	1	1	0
Subset 6	1	1	1	1	1	1

Best Subsets Details

Subset ID	#Coefficients	RSS	Mallows's Cp	R2	Adjusted R2	Probability
Subset 1	1	1.3916E+24	654.7551198	-2.22045E-16	-2.22045E-16	2.58212E-25
Subset 2	2	1.66741E+23	38.20420441	0.880179878	0.877683625	7.23552E-06
Subset 3	3	1.30795E+23	22.05149904	0.906010647	0.9020111	0.00042564
Subset 4	4	1.00696E+23	8.851373371	0.927639982	0.92292085	0.041428554
Subset 5	5	9.04448E+22	5.674524421	0.935006486	0.929229285	0.202404856
Subset 6	6	8.71289E+22	6	0.937389286	0.930274432	N/A

Coefficients

Predictor	Estimate	Confidence Interval: Lower	Confidence Interval: Upper	Standard Error	T-Statistic	P-Value
Intercept	-6.8108E+10	-1.29741E+11	-6474646782	30581505448	-2.2270853	0.0311059
Electric pow	814346178	-206729392.7	1835421750	506644834.5	1.607331454	0.1151351
Population, t	2095.53435	964.8297997	3226.238901	561.0413529	3.735080025	0.0005366
Imports of g	2.66476204	1.389408582	3.940115505	0.63281432	4.210969883	0.0001237
Lending inte	-7295940536	-10467894333	-4123986739	1573883512	-4.63562931	3.179E-05
Unemploym	-8918179447	-22807619278	4971260385	6891765059	-1.29403417	0.2024049

ANOVA

Source	DF	SS	MS	F-Statistic	P-Value
Regression	5	1.30447E+24	2.60894E+23	131.751024	2.58212E-25
Error	44	8.71289E+22	1.9802E+21	N/A	N/A
Total	49	1.3916E+24	2.84E+22	N/A	N/A

Training: Prediction Summary

Metric	Value
SSE	8.71289E+22
MSE	1.74258E+21
RMSE	41744201762
MAD	32828810350
R2	0.937389286

Table 6.

i. From the above Model with 4 Regressors), the estimated regression equation is: Y^=-0.0000 +814346178 ELECTRIC CONS. +2095.53 POPULATION + 2.664 IMPORT – 72959 LENDING RATE – 89181 UNEMPLOYMENT

At 20 % Significant level:

ii. Reject Ho: $\beta 2 = 0$ since p-value of 0.0005 is less that 20%

iii. Reject Ho: $\beta 3 = 0$ since p-value of 0.00001 is less that 20%

iv. Reject Ho: $\beta 4 = 0$ since p-value of 0.00000 is less that 20%

That is, the regression coefficient (β2,β3 & β4 all have p-value less that 20%, thus, the coefficients are significant at 20%. That is, they all reject the H0: $\beta 1 = 0$ at 20% significance level, and that the regression coefficients is statistically different from 0.

At 20% Significant level, the following explanatory variables are **not** statistically significant:

- Electric Consumption &
- Unemployment

The above variables have p-value > 20%

Removing the insignificant variables at the 20% level and re-run the regression gives the following printout:

Table 7. Data statistic result

Coefficients

Predictor	Estimate	Confidence Interval: Lower	Confidence Interval: Upper	Standard Error	T-Statistic	P-Value
Intercept	-8.6696E+10	-1.41479E+11	-31914004603	27199336110	-3.18744102	0.0026109
Electric pow	1065103873	115217324.5	2014990421	471617571.1	2.258405831	0.0288157
Population,	1550.54924	798.4012247	2302.697264	373.4406207	4.152063698	0.0001449
Imports of g	2.94177534	1.733407513	4.150143162	0.599953225	4.903341148	1.268E-05
Lending inte	-6474055939	-9396101702	-3552010176	1450792337	-4.46242772	5.375E-05

ANOVA

Source	DF	SS	MS	F-Statistic	P-Value
Regression	4	1.30115E+24	3.25288E+23	161.8441963	4.2928E-26
Error	45	9.04448E+22	2.00988E+21	N/A	N/A
Total	49	1.3916E+24	2.84E+22	N/A	N/A

Y^=-0.0000 +106510 ELECTRIC CONS. + 1550.5492 POPULATION + 2.9418 IMPORT – 647406 LENDING INTEREST

Regression Summary

Metric	Value
Residual DF	45
R2	0.93500649
Adjusted R2	0.92922929
Std. Error Est	4.4832E+10
RSS	9.0445E+22

Training: Prediction Summary

Metric	Value
SSE	9.04448E+22
MSE	1.8089E+21
RMSE	42531121976
MAD	31436674669
R2	0.935006486

At Population, The Sum of squared estimate is 904448E+22. Also, there is a minor decrease in SSE from 1.30115E+24 to 9.04448E+22 . Therefore, this deviation speaks to the better fit of the line to the data.
The MSE =18089
The RMSE= 42531
The MAD= 31436
Comparing these two models, the model with 4 regressors which gives the highest Adjusted R-square seems to be the best. This model also gives us the lowest RMS error and total sum of squared errors in the training data.

Owing to the above analysis and significance level, it is important to state that electricity consumption is not a major contributor to the current GDP buoyancy that Nigeria as a country currently enjoys. It is also worthy to note that the Unemployment rate in the country has been high from time immemorial. One would have concluded that a country with low electricity consumption and high unemployment rate would rank among countries with the lowest GDPs however, that is not the case for Nigeria.
This therefore means that since other variables like population, bank lending interest rates, importation cost and inflation rate contribute significantly to the GDP, the government should implement policies geared towards;
1. Increased birth rate through provisions of outstanding health care centers for pregnant women.
2. Reduced cost of borrowing loans of businesses from commercial banks, reducing the interest rates to a one digit percent to a figure less than 5%
3. Reduced importation costs by reducing tariffs and import duties
4. Implement effective price legislation aimed at reducing the general price levels of goods and services.

COMPARING LOGISTIC REGRESSION AND NEURAL NETWORK MODEL IN SELECTING THE BEST MODEL THAT PERFORMS BETTER

LOGISTIC REGRESSION MODEL SPECIFICATION

The logistic regression equation that captures the effect of energy consumption, vis-a-vis other macroeconomic variables, on GDP is captured by the function as stated below:

First;

$$\hat{P} = \frac{1}{1 + e^{-(a+bX)}}$$

Explicitly;

P = 1 / 1 + e^ -(β0 + β1ElectricityConsumption + β2InflationRate + β3TotalPopulation + β4ImportationCost + β5BankLendingInterestRate + β6UnemploymentRate + ϵ)

Where; P is the probability value of dependent variable that captures GDP

X1 is one of the independent variables that captures electricity consumption

X2 captures inflation rate

X3 captures total population

X4 captures importation cost

X5 captures bank lending interest rate

X6 captures Unemployment rate

Є is the error term

For report 1, the linear regression model was adopted and Y, the dependent variable was numerical. However, for project 2, the logistic regression is adopted and instead of Y to be numerical, Y would be 1 or 0 hence, the basis for the logistic regression model.

Logistic regression is similar to the linear regression adopted in project 1 but it is different such that logistic regression is used when a categorical response is involved.

The same data set used in previous analysis would be further used in the logistic regression model but Y would be grouped into two classes (1 & 0) by using some meaningful criteria.

For this study, the mean of the GDP will be used and for GDP value above the mean, it would be tagged "1" and below the mean, it will be tagged "0" hence, high GDP/low GDP.

The mean of the GDP is 171,892,422,082.72 hence, if (GDP > 171,892,082.72), GDP is 1 otherwise, zero.

The new GDP column was created to account for the new GDP value (1,0) for logistic regression purpose.

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Table 8.

Regression Summary

Metric	Value
# Iterations Used	7
Residual DF	46
Residual Deviance	6.5022606
Multiple R2	0.89856629

Coefficients

Predictor	Estimate	Confidence Interval: Lower	Confidence Interval: Upper	Odds	Standard Error	Chi2-Statistic	P-Value
Intercept	3.47900552	-2373.209646	2380.167657	32.42745756	1212.618533	8.23117E-06	0.9977109
Electric power	-0.34859146	-39.24684646	38.54966354	0.705681371	19.84641315	0.00030851	0.9859863
Inflation, cons	0.14888575	-106.9390203	107.2367918	1.160540384	54.63769075	7.42543E-06	0.9978258
Population, to	9.2744E-07	-7.03935E-05	7.22484E-05	1.000000927	3.63889E-05	0.000649579	0.9796666
Imports of goo	1.5956E-10	-3.86599E-08	3.8979E-08	1	1.98062E-08	6.49032E-05	0.9935721
Lending intere	-3.16257576	-117.2854124	110.9602609	0.042316603	58.22700701	0.002950074	0.9566845
Unemployme	-10.3785383	-585.1604265	564.40335	3.10927E-05	293.2614542	0.001252456	0.9717687

All the variables were insignificant at 10% or 20% or 30% or 40% at the first logistic regression output hence, we decided to drop a couple of the variables and rerun the logistic regression.

Table 9. **Removing some variables and re-running the regression gives the following printout**

Coefficients

Predictor	Estimate	Confidence Interval: Lower	Confidence Interval: Upper	Odds	Standard Error	Chi2-Statistic	P-Value
Intercept	-22.7561983	-62.44530653	16.93290983	1.31E-10	20.24991709	1.262853355	0.2611117
Electric pow	0.23779383	-0.02736459	0.502952255	1.268448	0.135287395	3.089487916	0.0787996
Lending inte	-0.48161399	-1.574837056	0.611609076	0.617785	0.55777712	0.74555004	0.3878888
Unemploym	1.03777522	-8.712239312	10.78778975	2.82293	4.97458862	0.043520337	0.8347486

At the second logistic regression output, electric power consumption and lending rate are significant at 40% because their probability values (0.078 and 0.387) are lesser than 40% significance level. To achieve this, we dropped inflation rate variable, population variable and imports of goods variable.

The estimated logistic regression function is given as;

$$\hat{P} = \frac{1}{1+e^{-(a+bX)}}$$

and for the purpose of this project , the logistic regression function is written as:

P̂ = 1 / 1 + e^ -(β0 + β1X1 - β2X2 + β3X3)

Where; β0 = -22.756, β1 = 0.237, β2 = -0.481, β3 = 1.037

From the above Model with 3 Regressors, the estimated regression equation is:

$\hat{P}$ = 1/ 1 + e^- (-22.756 + 0.237 ELECTRIC CONS – 0.481 LENDING RATE – 1.037 UNEMPLOYMENT RATE)

At 40 % Significant level:

v. Reject H0: $\beta 1 = 0$ since p-value of 0.078 is less than 40%

vi. Reject H0: $\beta 2 = 0$ since p-value of 0.387 is less than 40%

vii. Do not reject H0: $\beta 3 = 0$ since p-value of 0.834 is greater than 40%

That is, the regression coefficient β1,β2 except β3 all have p-value less that 40%, thus, the β1 and β2 coefficients are significant at 40%. That is, we all reject the H0: β1 = 0, β2=0 at 40% significance level, and that the regression coefficients (β1,β2) are statistically different from 0.

Therefore in a case, say year 2021, where Nigeria's electric power consumption (Kwh per capita) was 133.56, lending interest rate (converted from percentage) was 0.114 and unemployment rate (converted from percentage) was 0.0978, the logistic equation would be estimated as;

$\hat{P}$ = 1 / 1 + e^ -(-22.75 + 0.237*133.56 - [-0.481*0.114]+ 1.037*0.0978) = 14.395

Hence, the estimated probability $\hat{P}$ = 1 / 1 + e^ -14.395 = 0.99

We estimated that the probability of a higher GDP in Nigeria is 0.99 given that Nigeria as a country consumes 133.56 (Kwh per capita), fixes interest rate at 11.4% where unemployment rate stands at 9.78 in 2021

1.0 TRAINING & VALIDATION DATA

For the purpose of this project, the data set adopted is divided randomly into training(70%) and validation (30%) data

Table 10. **Partition Summary**

Partition	# Records
Training	35
Validation	15

Detailed Report Output

Training: Classification Details

This table reflects the calculation of GDP for each of the selected years in the data using the logistic regression to predict the chance of high GDP (that is, calculating the probability that the GDP for a particular year is in group 1)

In the table below, there are 50 observations. Xlminer employs the logistic regression form to plug in the x values and find the probabilities to be in class one for each of the observation.

It should be noted that the default cut-off is 0.5, so a probability value exceeding 0.5 assigns "1" to the group and "0" if probability value is less than 0.5.

For instance, record 1 to 32 have probability values less than 0.5 as such these records have low chance to be in group 1 hence, they are classified into group 2 as “Low GDP”. Hence, comparing the columns of zeros and ones in the table show how good the model classifies.

Overall, the table explains how many GDP observations are zeros (low GDP) and are classified correctly. It also explains the number of GDP observations that are ones (high GDP) and are classified correctly and by extension shows observations that are misclassified as indicated by the “red” print in the table.

Table 11.**Training: Classification Details**

Record ID	Y = NEW GDP FOR LOGISTIC REGRESSION)	Prediction: Y = NEW GDP FOR LOGISTIC REGRESSION)	PostProb: 1	PostProb: 0
Record 1	0	0	7.25E-07	0.999999
Record 2	0	0	1.31E-06	0.999999
Record 3	0	0	7.19E-07	0.999999
Record 4	0	0	2.17E-05	0.999978
Record 5	0	0	7.5E-05	0.999925
Record 6	0	0	0.000569	0.999431
Record 7	0	0	0.000558	0.999442
Record 8	0	0	0.000227	0.999773
Record 9	0	0	0.001377	0.998623
Record 10	0	0	1.81E-05	0.999982
Recor	0	0	0.0205	0.97948

d 11			15	5
Record 12	0	0	0.015771	0.984229
Record 13	0	0	0.000129	0.999871
Record 14	0	0	0.014664	0.985336
Record 15	0	0	0.119153	0.880847
Record 16	0	0	0.014413	0.985587
Record 17	0	0	0.002558	0.997442
Record 18	0	0	0.006212	0.993788
Record 19	0	0	9.48E-05	0.999905
Record 20	0	0	0.001086	0.998914
Record 21	0	0	0.000121	0.999879
Record 22	0	0	5.82E-05	0.999942
Record 23	0	0	0.003477	0.996523
Record 24	0	0	0.001455	0.998545
Record 25	0	0	0.000451	0.999549
Record 26	0	0	0.000471	0.999529
Record 27	0	0	0.000116	0.999884

Record 28	0	0	3.13E-05	0.999969
Record 29	0	0	1.39E-05	0.999986
Record 30	0	0	6.2E-06	0.999994
Record 31	0	0	0.003111	0.996889
Record 32	0	0	0.011556	0.988444
Record 33	0	1	0.806512	0.193488
Record 34	1	1	0.966755	0.033245
Record 35	1	0	0.421513	0.578487
Record 36	1	1	0.997761	0.002239
Record 37	1	1	0.984864	0.015136
Record 38	1	1	0.673316	0.326684
Record 39	1	1	0.994157	0.005843
Record 40	1	1	0.999895	0.000105
Record 41	1	1	0.999967	3.28E-05
Record 42	1	1	0.999061	0.000939
Record 43	1	1	0.999769	0.000231
Recor	1	1	0.9400	0.05994

Record 44			57	3
Record 45	1	1	0.998273	0.001727
Record 46	1	1	0.999727	0.000273
Record 47	1	1	0.999874	0.000126
Record 48	1	1	0.999964	3.55E-05
Record 49	1	1	0.999996	3.91E-06
Record 50	1	1	0.999999	1.2E-06

Table 12.**TWO WAY TABLE**

		Predicted	
Actual		0	1
	0	True negative **32**	False Positive **1**
	1	False negative **1**	True Positive **16**

Table 13.

Training: Classification Summary

Confusion Matrix		
Actual\Predicted	0	1
0	32	1
1	1	16

The Classification summary report is based on the detailed report of the model classification as reported by Xlminer. It gives us insightof how good or bad the model performed.

ERROR REPORT

The error report table records that just two observations out of 50 cases are misclassified.

In our data, there are 33 cases that are “zeros” (Low GDP), 17 cases are ones (High Gdp) and out of the 33 cases, one is misclassified (1/33 = 3.03 % -> False Postitve Percentage of the model). Similarly, there are 17 cases that are “ones” (high GDP) and 1 case is misclassified (1/17 = 5.88% -> False Negative Percentage of the model)

This translates to the fact that our classification rule correctly classified 96% of the observations and about just 4% error in the entire model.

So, the overall misclassification error is 4% (2/50).

Table 14. Error report

Error Report			
Class	# Cases	# Errors	% Error
0	33	1	3.03030303
1	17	1	5.882352941
Overall	50	2	4

False Positive Error - This is a scenario where our model captures “1” when it is actually supposd to be “0” and that accounts for 3.03%. This is just one case out of 33 according to the table above.

False Negative Error - On the other hand, the false negative error is a scenario where it is actually “1” but the model predicts “0”. That is one case out of 17 whichis 5.8%

METRICS

Table 15. Metrics results

Metrics	
Metric	Value
Accuracy (#correct)	48
Accuracy (%correct)	96
Specificity	0.96969697

Sensitivity (Recall)	0.941176471
Precision	0.941176471
F1 score	0.941176471
Success Class	1
Success Probability	0.5

Accuracy: Explains the correctness of the classification of the model and in this case, it is (33 & 17) as such, we correctly classified 48 cases out of 50 cases. The model records 96% accuracy which is not a bad one.
Sensitivity: This is also known as "Recall of the Model". The table records True Positive percentage of about 94% (33 out of 34 -positive cases were correctly classified). This is a good score for the model.
Specificity: Explains the True Negative percentage which is 96% (17 out 18 negative cases that were correctly classified). Overall, the model is okay.

LIFT CHART

The lift chart measures the model performance as such, the higher the lift chart, the better the model.
Here, the lift chart is high and by implication, the model is good

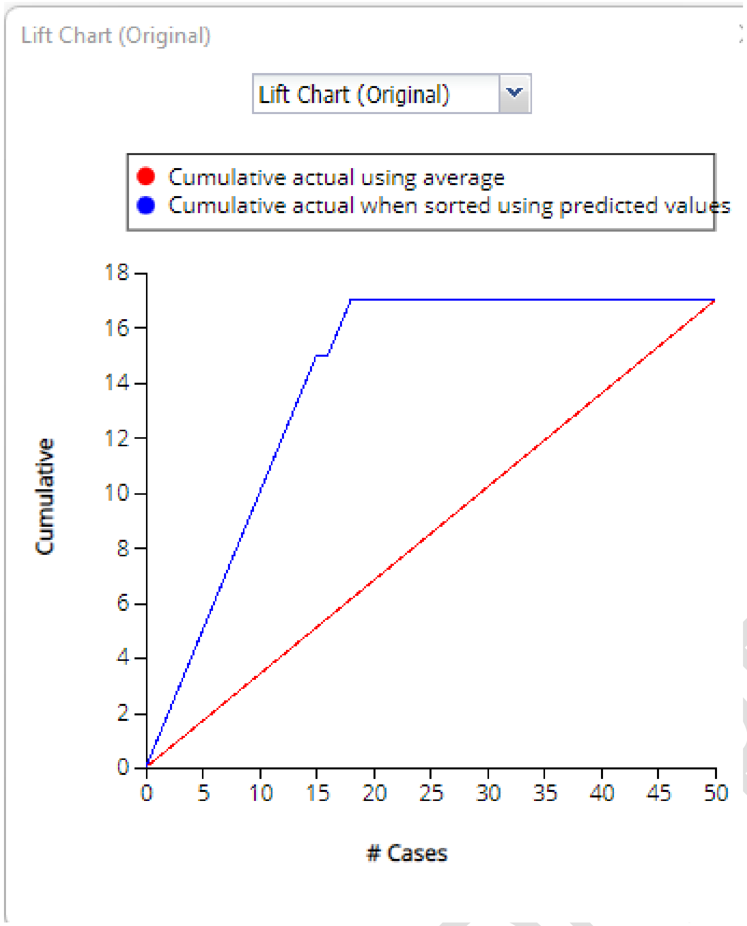


Chart1. **Lift chart**

For the ROC curve, we look at the area under the curve and in this case, that is 99% which is also very good.

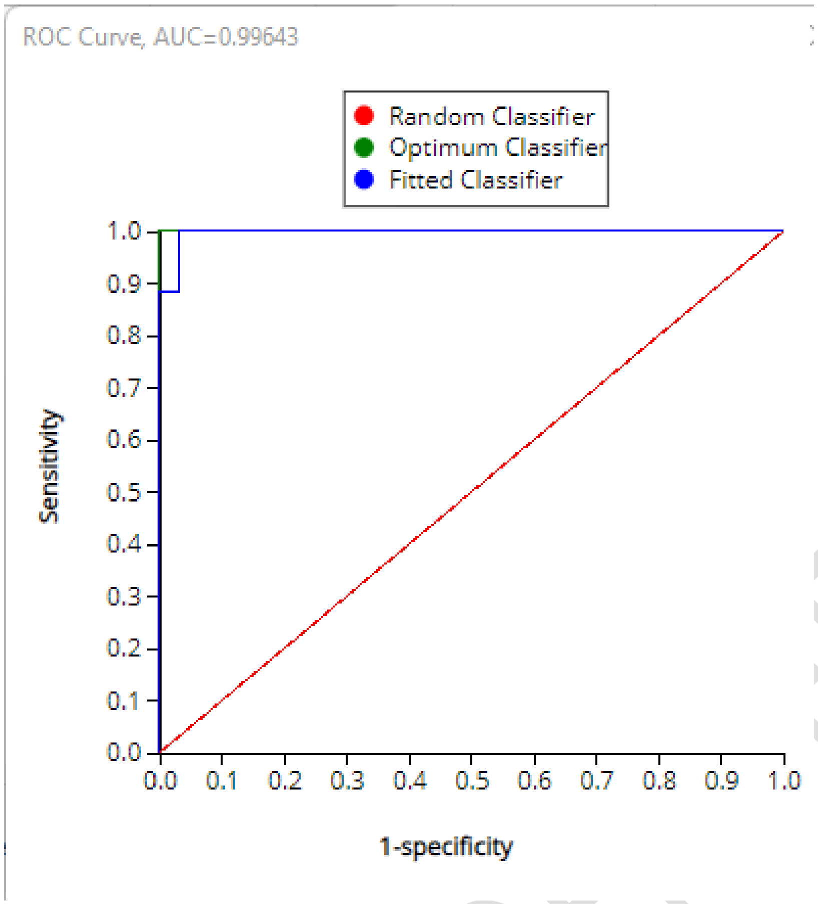


Chart 2. **ROC CURVE**

Overall, from the outputs, it can be concluded that there is some sort of high level of consistency which also spans through the validation data.

LOGISTICS REGRESSION:
Overall, an increased energy consumption with low interest rate and low unemployment rate leads to a high GDP in Nigeria.

Therefore, central bank policies aimed at reducing bank lending rate should be implemented to serve as incentive for firms to borrow more and increase output/production

Policies geared towards increased power/electricity generation and supply should be implemented, thus making power available to firms at reduced costs. This would increase the overall GDP in the country.

Owing to the above, as firms produce more, they would also need to hire more people to meet the increased supply of goods and services

NEURAL NETWORK MODEL

BUILDING THE BEST MODEL

After a series of trials and errors, in the final model; the Neurons were reduced to just 4 and one significant change we made was "Changing the variables". The explanatory variables used in the logistics regression where: Electric Power Consumption, Lending Interest rate and Unemployment but in this final trial, the variables adopted are: Electric power consumption, Lending Interest Rate and Population

Table 16.

Training: Classification Summary

Confusion Matrix		
Actual\Predicted	0	1
0	23	1
1	0	11

Error Report			
Class	# Cases	# Errors	% Error
0	24	1	4.166666667
1	11	0	0
Overall	35	1	2.857142857

Metrics	
Metric	Value
Accuracy (#correct)	34
Accuracy (%correct)	97.14285714
Specificity	0.958333333
Sensitivity (Recall)	1
Precision	0.916666667
F1 score	0.956521739
Success Class	1
Success Probability	0.398752

Table 17.

Validation: Classification Summary

Confusion Matrix		
Actual\Predicted	0	1
0	9	0
1	0	6

Error Report			
Class	# Cases	# Errors	% Error
0	9	0	0
1	6	0	0
Overall	15	0	0

Metrics	
Metric	Value
Accuracy (#correct)	15
Accuracy (%correct)	100
Specificity	1
Sensitivity (Recall)	1
Precision	1
F1 score	1
Success Class	1
Success Probability	0.398752

TRAINING DATASET:

- Partitioned: 70-30
- Probability Cut-off: 0.398792 (Re-adjusted based on the Average of previous result)
- 3 Explanatory Variables (Electric, Population, Unemployment)- A different variable from the Logistics regression model
- Neurons: 4
- Hidden Layer: 1
- Rescale Data: Yes
- True positive (Sensitivity)- 100%
- True Negative (Specificity)- 96%
- Correctly classified 97%
- False Positive and False Negative is 4.2% and 0% respectively

VALIDATION DATASET:

- Partitioned: 70-30
- Probability Cut-off: 0.398792 (Re-adjusted based on the Average of previous result)
- 3 Explanatory Variables (Electric, Population, Unemployment)- A different variable from the Logistics regression model
- Neurons: 4
- Hidden Layer: 1
- Rescale Data: Yes
- True positive (Sensitivity)- 100%
- True Negative (Specificity)- 100%
- Correctly classified 100%
- False Positive and False Negative is 0% and 0% respectively

Taking into account the three (3) explanatory variables from our data, and setting the probability cutoff at the default which is 0.398752, we can see:
In the training data, the Overall Misclassification Error is 1 out of 35 observations = 2.8% while in the Validation data, the Overall Misclassification Error is 0 out of 15 = 0%
On classification: our classification rule correctly classified 97% in the training and 100% in the validation data

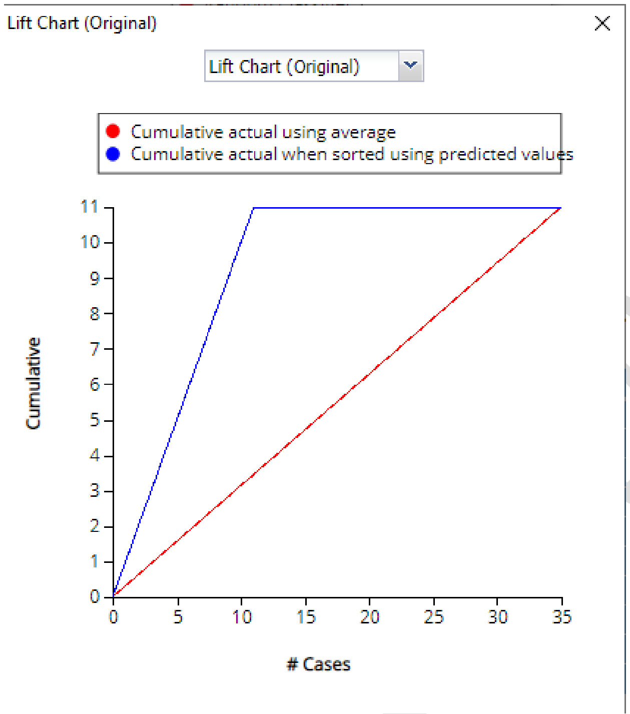
LIFT CHART

The lift chart measures the model performance as such, the higher the lift chart, the better the model.
Here, the lift chart in the training and validation data is high and by implication, the model is good

ROC CURVE

For the ROC curve, we look at the area under the curve and in this case, that is 100% and 100% for both the training and validation data which is a very good model performance. See charts for both Training and Validation Dataset:

Chart 3. TRAINING DATA LIFT CHART AND AUC



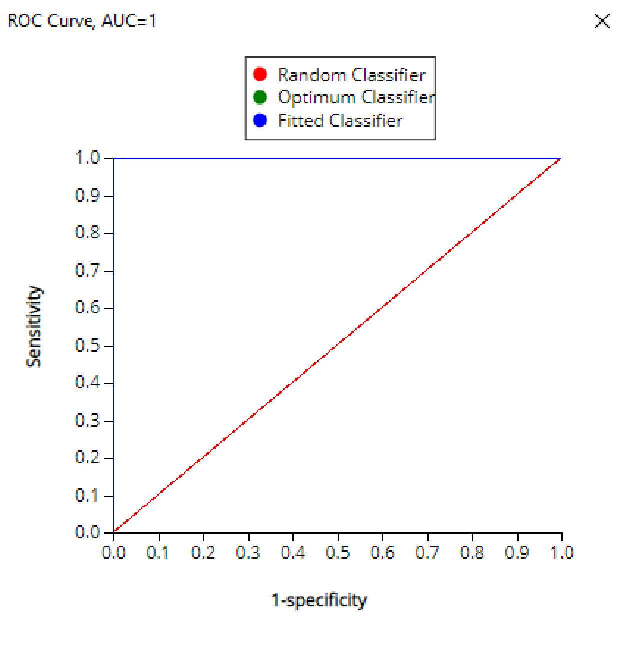
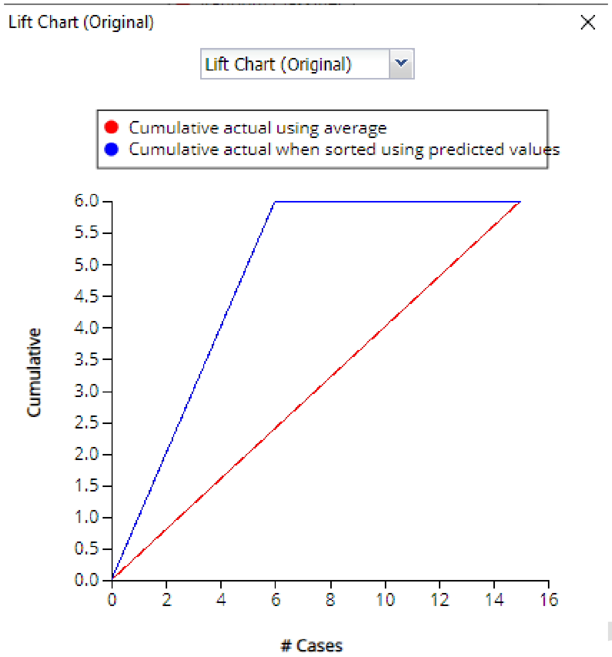
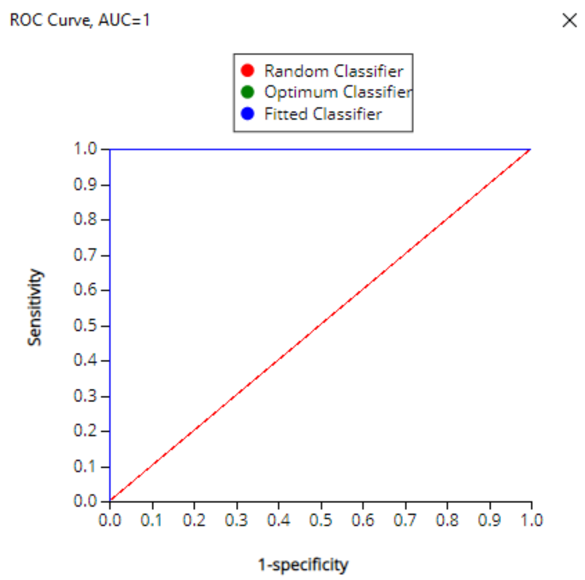

ROC Curve, AUC=1
Random Classifier
Optimum Classifier
Fitted Classifier
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Sensitivity
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
1-specificity

Chart 4. VALIDATION LIFT CHART AND AUC





COMPARISON

In the Logistic Regression model, after series of tests, Electric power consumption and lending rate are significant at 40% because their probability values (0.078 and 0.387) are lesser than 40% significance level. To achieve this, we dropped inflation rate variable, population variable and imports of goods variable. See coefficient below:

Table 18. Correlation coefficient result

Coefficients

Predictor	Estimate	Confidence Interval: Lower	Confidence Interval: Upper	Odds	Standard Error	Chi2-Statistic	P-Value
Intercept	-18.4229734	-36.30049004	-0.545456741	9.98E-09	9.121349572	4.079446569	0.0434079
Electric pow	0.23234233	-0.023443657	0.488128314	1.261552	0.130505452	3.169562844	0.0750225
Lending inte	-0.46715088	-1.515746415	0.581444651	0.626786	0.535007552	0.762420423	0.3825721

On the other hand, results from the Neural Network classification model revealed the coefficientsas presented in the table below:

Table 19. Neuron weight result

Neuron Weights

Neuron Weights: Input Layer - Hidden Layer 1				
Neurons	Electric power consumption (kWh per capita)	Lending interest rate (%)	Unemployment, total (% of total labor force) (modeled ILO estimate)	Bias
Neuron 1	-0.095485075	0.362711386	-1.325130979	-0.0347214
Neuron 2	0.521630007	0.542443597	0.491132982	-0.0125665
Neuron 3	-0.144760377	0.605782742	-0.093453618	-0.0435881
Neuron 4	0.833419481	-0.49237841	-0.37513595	-0.010458

Neuron Weights: Hidden Layer 1 - Output Layer					
Neurons	Neuron 1	Neuron 2	Neuron 3	Neuron 4	Bias
0	0.286756588	0.315081249	-0.868064399	0.49326575	0.397142
1	0.024789237	0.331743867	-0.604229897	0.39580746	-0.53512

Logistics Regression

TRAINING: CLASSIFICATION SUMMARY

The Logistic Regression model had an overall % Error of 5.71%, Accuracy of 94.29%, and Sensitivity of 91%. This shows the model is good. There
were four (4) cases of False Positives and nine (9) cases of False Negatives.
However, the Specificity stood at 95%.

Table 20.

Training: Classification Summary

Confusion Matrix		
Actual\Predicted	0	1
0	23	1
1	1	10

Error Report			
Class	# Cases	# Errors	% Error
0	24	1	4.166666667
1	11	1	9.090909091
Overall	35	2	5.714285714

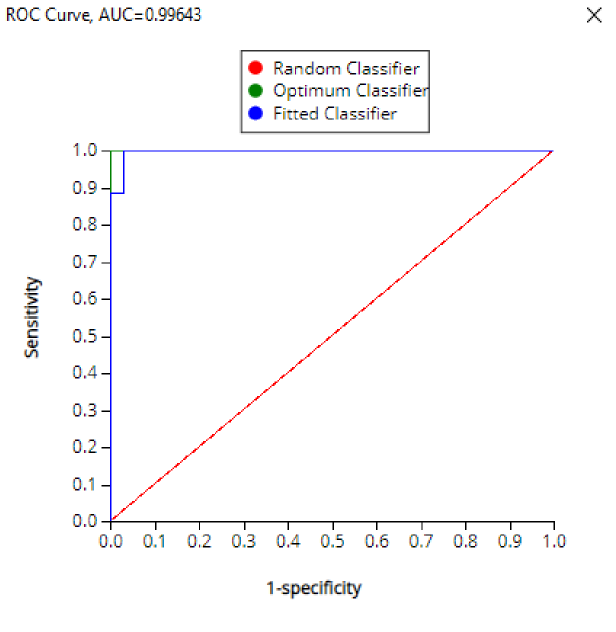
Metrics	
Metric	Value
Accuracy (#correct)	33
Accuracy (%correct)	94.28571429
Specificity	0.958333333
Sensitivity (Recall)	0.909090909
Precision	0.909090909
F1 score	0.909090909
Success Class	1
Success Probability	0.5

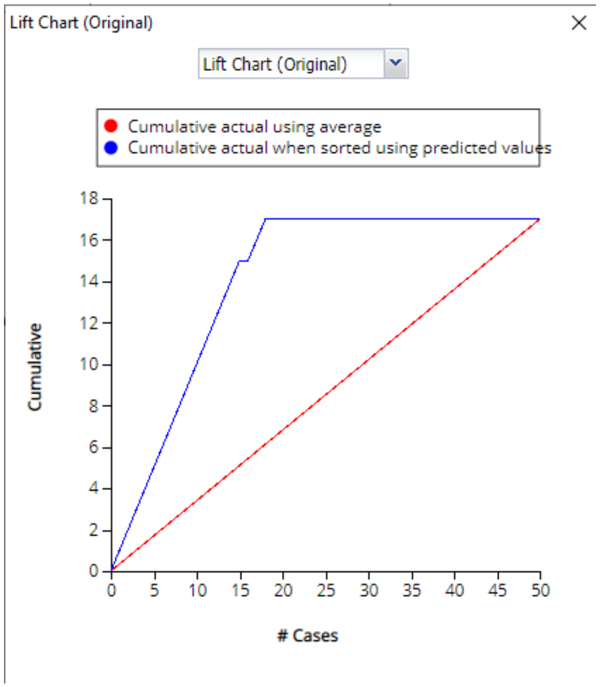
On the Training data set, the Neural network seems to have a better Sensitivity figure (100%) when compared to the Logistic Regression model (91%) , and overall, the % mis-classification error for the Neural Network model is also lower (2.71%) compared to the overall mis-classification %error (5.71%) in the logistics regression model. This is impressive owing to the complexity of Neural Network models.

Therefore, the Neural Network model performs better for our dataset owing to the overall misclassification % and accuracy metrics.

Chart.5. ROC and Lift Chart

Recall, the ROC curve speaks to the better performance of the model and this aims closer to 1. The AUC in the Neural Network is at exactly 100% while the AUC in the Logistics regression model is 99.6% (See below) in both the training and Validation dataset. Judging from this, the NN model performs better for our dataset.





CONCLUSION

The results of the Neural Network model performed better than the Logistics Regression model in this study. There is need for the improvement of the Logistic Regression model for a
better GDP classification.

RECOMMENDATION

Electric power consumption and Lending interest rate are the best regressors to study Nigeria's Gross Domestic Product (GDP) in the span of 50 years

Using the Neural Network model, Electric power consumption, Population and Lending interest Rate when compared to the performance of the Logistic Regression model, the Neural Network model seems to be a better model to be used in this classification project. The Neural Network model performed better across the metrics including Confusion Matrix, Accuracy, Specificity, AUC curve, Lift Chart, and the Sensitivity report.

Out of the many predictor variables we tried, only the Electric power consumption, Population and Lending interest Rate are used to determine the high or low GDP rate in our 50 case observation and it is very interesting to find that all other predictors like Unemployment, Importation cost and Inflation rate do not have much effect.

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