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PREDICTION ACCURACY OF NIGERIAN MILITARY EXPENDITURE: MLR, ARIMAX, AND ANN MODELS IN STATISTICAL AND MACHINE LEARNING FRAMEWORKS

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ABSTRACT

Accurately predicting military expenditure is crucial for budgetary planning and national security. However, traditional forecasting methods often struggle to capture the complex dynamics of military spending. This study investigates the potential of statistical methods and machine learning to improve the accuracy of Nigerian military expenditure prediction. We compare the performance of three widely used models: multiple linear regression (MLR), autoregressive integrated moving average with exogenous variables (ARIMAX), and artificial neural networks (ANN). Using historical data on Nigerian military expenditure, GDP, and relevant economic indicators, we train and evaluate each model's prediction accuracy. We also employ statistical tests to assess the normality of residuals in the two distinct models of MLR and ARIMAX. Our findings indicate that the machine learning model, particularly ANN, significantly outperforms MLR in terms of prediction accuracy. ARIMAX shows promising results but lags behind ANN. We attribute the superior performance of the ANN to its ability to capture non-linear relationships and complex patterns in the data. This study adds to the body of knowledge by highlighting how machine learning methods can be used to increase the accuracy of military expenditure forecasts. Furthermore, the specific focus on Nigeria provides valuable insights into the unique dynamics of military spending in a developing country.

Keywords: Machine Learning, Military Expenditure Prediction, MLR, ARIMAX, ANN

INTRODUCTION

Military expenditure constitutes a substantial portion of a nation's budget, playing a pivotal role in national security and strategic planning. Accurate forecasting of military spending is crucial for effective resource allocation and policy formulation. Within Nigeria, the need for robust military expenditure forecasting is particularly acute. The country faces persistent security challenges, including insurgencies and terrorism, necessitating significant investments in its armed forces (Lenshie et al., 2022). Additionally, Nigeria's ambitions to modernize its military equipment and technology further emphasize the importance of accurately predicting future expenditure requirements. Despite the acknowledged importance of military expenditure forecasting, the application of machine learning (ML) models within this context remains relatively unexplored in Nigeria. Existing research has largely focused on traditional statistical methods, which often fail to capture complex non-linear relationships and dynamic trends within the data. This study aims to bridge this gap by investigating the effectiveness of three widely employed ML models: MLR, ARIMAX, and ANN. Previous research has highlighted the potential of ML models for predicting military expenditure in other contexts. For instance, Kollias et al (2018) utilized quantile regression analysis and panel data of twelve Latin American nations to estimate the demand of military spending from 1965 to 2015. According to the results shown, both internal and external variables have influenced this spending. A research by Olowononi and Aiyedogbon (2008) examined Nigeria's defence budget trends from 1986 to 2006. The study, which used ordinary least square, discovers that the primary factors influencing Nigeria's defence spending where inflation, rate of exchange, openness, and income per person. Anfofum (2013) study on Nigeria's defence expenditure (1970-2011) used a vector auto regression mode (VAR). Results showed that military budget innovations were fuelled by oil and gas revenue as well as real sector earnings, while foreign exchange and real gross domestic product also contributed positively. Oladotun et al (2019) utilized econometric methods to identify the primary factors influencing the rise in military expenditure in BRICS countries from 1970 to 2017, revealing that these factors include income, population, exchange rate, internal threats, inflation, and political regime. Refenes et al. (1995) used ANN to examine the factors related to external security that influence Greece's military spending in relation to the Greek-Turkish conflict. Kuo et al.(2011) article used ARIMA and ANN models to predict China's military spending. The single-variable ARIMA model showed better stability and accuracy, while multiple-variable models like military spending, GDP, and inflation rate provided accurate predictions. ANN Model II was the most accurate, providing valuable insights into China's military spending forecasting. As the article by Odehnal et al., (2020) shows that military budgets are closely tied to a country's economic health, understanding the predictive capacities of different models becomes essential for effective fiscal planning in the defence sector. As a foundational aspect of defence economics, military expenditure forecasting requires robust models that can capture the intricate relationships between economic indicators and defence budgets. Previous research has emphasized the importance of accurate forecasting in optimizing resource allocation and aiding policymakers in strategic decision-making (Kuo et al,, 2013; Sharma & Phulli, 2020). However, the choice of forecasting models remains a critical aspect of this process, as different models may exhibit varying degrees of accuracy and applicability in different contexts. This study builds upon existing literature by directly comparing the predictive performance of MLR, ARIMAX, and ANN in the specific context of Nigeria's military expenditure. Notable contributions in the field of defence economics underscore the need for advanced modelling techniques that consider both economic and geopolitical factors (Nukpezah et al., 2023; Stevens & Galloway 2022). By evaluating the strengths and weaknesses of these models, this research seeks to provide measure of insights that can inform policymakers and analysts involved in defence budgeting. By employing machine learning techniques to predict Nigerian military expenditure. Ultimately, this paper aims to advance the knowledge and understanding of military expenditure prediction using machine learning techniques. By developing accurate and reliable predictions, this research holds the potential to benefit a range of stakeholders and contribute to improved decision-making regarding national security and resource allocation.

MATERIALS AND METHODS

The methodology of the study aims to leverage the strengths of all the models, providing a comprehensive understanding of the temporal and non-linear dynamics influencing military expenditure in the Nigerian context. Three distinct forecasting models were selected for comparative analysis: MLR, ARIMAX, and ANN. MLR was chosen for its simplicity and interpretability, ARIMAX for its ability to capture time series dynamics with exogenous factors, and ANN for its capacity to handle complex, non-linear relationships. A careful selection of variables was crucial to model efficacy. Military expenditure served as the dependent variable, while economic indicators such as population size, GDP, and export trade were considered as potential independent variables. The selection process involved assessing the variables for multi-collinearity and ensuring their relevance to defence budget dynamics.

Multiple Linear Regression (MLR) Model

MLR builds a linear model that represents the functional dependence of a dependent variable on two or more independent variables (Montgomery et al., 2021). In the context of this study, MLR allows the exploration of how various economic indicators, termed independent variables, collectively influence the military budget. The MLR model can be expressed as follows:

$$D_i = C_0 + C_1 Z_{1i} + C_2 Z_{2i} + \ldots + C_n Z_{ni} + R_t \quad (1)$$

where:

D_i represents the dependent variable, which, in this case, is military spending.

C_0 is the intercept term.

C_1 , C_2,…, C_n are the coefficients corresponding to the independent variables $Z_{1i}, Z_{2i}, \ldots, Z_{ni}$. R_t is the error term, accounting for unobserved factors affecting the dependent variable.

In this equation, $Z_{1i}, Z_{2i}, \ldots, Z_{ni}$are the various independent variables, such as Gross Domestic Product (GDP), population size, and export trade data, chosen based on their potential impact on military expenditure. The model aims to estimate the coefficients C_0 C_1, C_2,…,C_n that minimize the difference between the predicted military expenditure (D_i) and the actual values in the dataset.

The MLR model assumes a linear relationship between the dependent variable and the independent variables. Through the estimation of coefficients, MLR provides insights into the magnitude and direction of the impact that each independent variable has on the military budget, offering a valuable tool for forecasting and understanding the complex dynamics of defence budgeting.

ARIMAX Model

The ARIMAX model is a time series forecasting method that combines ARIMA components with the inclusion of external or exogenous variables. It is particularly suitable for predicting a dependent variable, such as military expenditure, by incorporating the impact of both its past values and external factors. In the context of this study on the predictive accuracy of military expenditure in Nigeria, the ARIMAX model is expressed as follows:

$$D_t = \omega_1 D_{t-1} + \omega_2 D_{t-2} + \ldots + \omega_p D_{t-p} + \gamma_1 R_{t-1} + \gamma_p R_{t-p} + C_1 E_1 +, \ldots . + C_p E_{t-p} + R_t \quad (2)$$

where:

D_t represents the dependent variable at time t (military expenditure).

$\omega_1,\ldots,\omega_p$ are autoregressive parameters,

$\gamma_1,\ldots,\gamma_p$ are moving average parameters,

E_t denote exogenous variables at time t, such as GDP, population size, and export trade data,

C is the coefficient for the exogenous variable,

R_t is the white noise error term.

In this equation, the autoregressive component ($\omega_1 D_{t-1} + \omega_2 D_{t-2} + \ldots\ldots + \omega_p D_{t-p}$) captures the relationship between the current military expenditure and its past values, accounting for temporal patterns. Meanwhile, the exogenous variables ($C_1 E_1 +, \ldots . + C_p E_{t-p}$) allow the model to consider the influence of external factors on military spending.

The ARIMAX model combines the strengths of autoregressive and moving average models with the flexibility to incorporate additional explanatory variables, providing a comprehensive framework for time series forecasting in the context of military expenditure.

ANN Model

ANN is a computational model motivated by the framework and how the human brain functions. Comprising interconnected nodes (neurons) organized into layers, ANN processes information through a series of weighted connections to learn and make predictions. Within the framework of forecasting military expenditure in Nigeria, ANN offers a powerful tool for capturing non-linear relationships and intricate patterns within the data. ANN is a data-driven method as opposed to model-driven method, Kondylis et al.'s (2018). ANNs offer several advantages, including their non-linear nature, which allows for better data fitting for correlated or non-linear variables, and their automatic weighting of input. They do not require prioritizing relationships between variables, assigning high synaptic weights to important variables and lower weights to insignificant ones. Additionally, ANNs do not require data distribution assumptions, making them an efficient and effective method for data analysis (Katsaitis et al, 2019). The mathematical representation of a basic feed-forward neural network, a common type of ANN, can be described as:

$$D_k = f\left(\sum_{i=1}^{n} g_{ki} \cdot z_i + \tau_k\right) \quad (3)$$

where:

D_k is the output of neuron k in the output layer.

z_i represents the input from neuron i in the previous layer.

g_{ki} denotes the weight associated with the connection between neuron i and neuron k.

τ_k is the bias term for neuron k.

f is the activation function applied to the weighted sum.

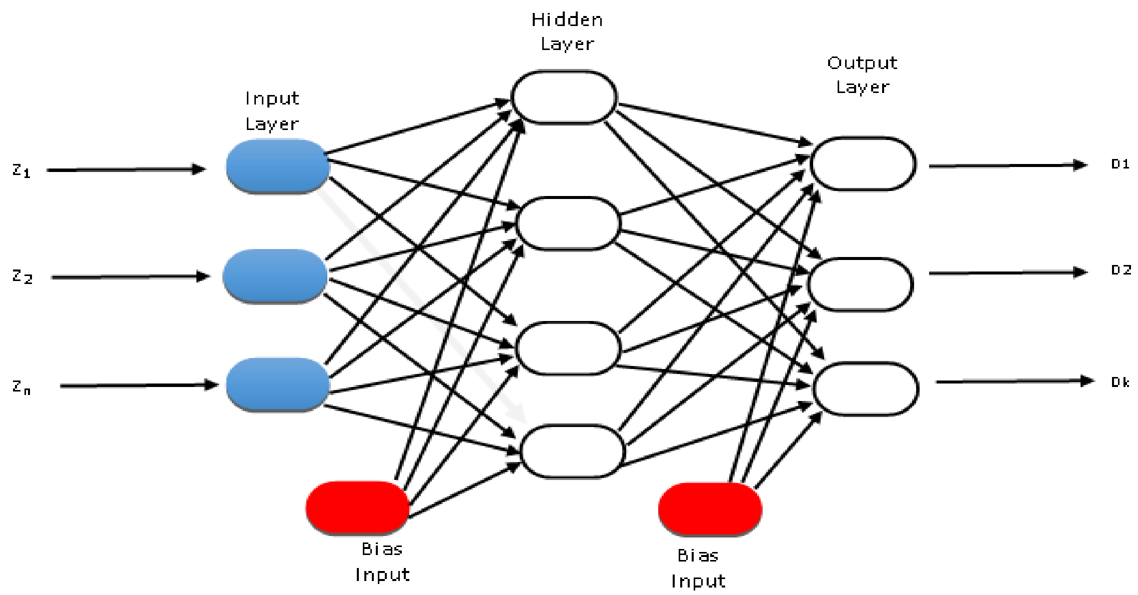

Figure 1: Architecture of ANN Model

In a multi-layer perceptron (MLP), a specific type of feed-forward ANN, this process is repeated across several levels, comprising an output layer, an input layer, and one or more hidden layers. The biases and weights are adjusted during a training process using techniques such as back-propagation, enabling the network to learn complex relationships within the data. The flexibility of ANN allows it to record complex patterns and dependencies that may be challenging for traditional linear models like MLR and ARIMAX. The ability of ANN to adapt to non-linearity and high-dimensional data enhances its utility in forecasting military expenditure.
Performance metrics such as Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) were employed to quantify prediction accuracy. The metrics are outline below:

$$\text{MSE}=\frac{1}{sz}\sum_{i=1}^{sz}(t_i-\hat{t}_i)^2 \quad (4)$$

$$\text{RMSE}=\sqrt{\frac{1}{sz}\sum_{i=1}^{sz}(t_i-\hat{t}_i)^2} \quad (5)$$

where:
t is the observed time series
sz is sample size

The Akaike Criteria Information (AIC) and Bayesian Information Criteria (BIC) were used to determined the best fitted model. Model fit and complexity are balanced by the AIC and BIC model selection criteria, penalizing models with more parameters, allowing for comparison and selecting the best fit. Lower AIC or BIC values indicate better fit in models like linear regression, time series, and machine learning, while penalizing complexity.
AIC is expressed as:
AIC= *-2.ln(Lh)+2(r)* (6)
where:
Lh is the model's likelihood
r is the number of parameters
ln denotes natural logarithm

BIC is expressed as:
BIC= *-2.ln(Lh)+ r. ln(sz)* (7)
where:
Lh denotes the model's likelihood
r is the number of parameters in the model
sz is the sample size

RESULTS AND DISCUSSION

The study employed a comprehensive dataset spanning historical military expenditure and relevant exogenous indicators in Nigeria. The source for military expenditure data and economic indicators such as population size, GDP, and export trade data were sourced from the World Bank Development Indicators. Military expenditure served as the dependent variable, while economic indicators such as population size, GDP, and export trade were considered as potential independent variables. The selection procedure included evaluating variables for potential correlations and confirming their significance in relation to the dynamics of defence budget. The dataset was split into training and testing sets. The models under study were then trained using the training set. Data splitting guarantees adaptability, prevents over-fitting, and allows for model performance evaluation (James et al., 2013; Chatzis et al., 2018 and Suleiman et al., 2023)

Descriptive Statistics

The first step in the data analysis involved computing descriptive statistics for the variables of interest, including military expenditure and relevant economic indicators. This provided an overview of the data's distribution, dispersion, and measures of location.

Table 1: Summary Statistics of the variables

	Military Expenditure	**Population size**	**GDP**	**Export**
Mean	136,529,862,903.23	107,223,177.61	141,374,555,267.55	4,122,048,834,733.42
Standard Error	37,245,161,102.10	6,318,653.47	21,329,424,761.49	844,506,764,182.48
Median	2,322,000,000.00	96,449,808.50	54,530,942,680.50	123,913,500,000.00
Standard Deviation	293,268,691,786.79	49,753,127.21	167,948,058,520.13	6,649,652,910,829.06
Sample Variance	8.60E+22	2.47E+15	2.82E+22	4.42E+25
Kurtosis	16.54	-0.85	-0.04	1.04
Skewness	3.63	0.58	1.21	1.53
Range	1,783,103,300,000.00	168,472,981.00	569,987,733,334.00	22,824,123,006,500.00
Minimum	16,700,000.00	44,928,342.00	4,196,092,258.00	276,993,500.00
Maximum	1,783,120,000,000.00	213,401,323.00	574,183,825,592.00	22,824,400,000,000.00

Source**:** Excel computations

The summary statistics of Table 1 provides a comprehensive overview of four variables: Military Expenditure, Population size, GDP, and Export. Below are the key observations and insights derived from the table: The summary statistics spanning 1960 to 2021 reveal significant variations in military expenditure, population size, GDP, and export values of Nigeria. With an average annual military spending of =N=136.53 billion, the country demonstrates a substantial commitment to national security. Population dynamics, averaging 107.22 million, show a right-skewed distribution, reflecting periods of larger population sizes. The GDP averages =N=141.37 trillion, exhibiting considerable variation influenced by factors like oil prices. Nigeria's average export value of =N=4.12 trillion, with high variability, signifies active participation in global trade. The positive skewness of 3.63 and high kurtosis of 16.54 indicate a distribution with a longer right tail, suggesting that there are certain years with significantly higher military expenditures, contributing to the overall positive skew. The report emphasizes the need for a historical context to interpret trends and outliers, guiding policymakers and researchers in formulating effective strategies for Nigeria's development.

Correlation Analysis

To assess the relationships between variables, correlation analysis was conducted. This step helped to gauge the direction and strength of linear associations.

Table 2: Correlation Analysis

	Military Expenditure	**Population size**	**GDP**	**Export**
Military Expenditure	1			
Population Size	0.757714	1		
GDP	0.746407	0.895715	1	
Export	0.778486	0.867488	0.935307	1

Source: Excel computations

The correlation analysis for variables outlined in Table 2, underscores substantial relationships among military expenditure, population size, GDP, and export values. The correlation coefficients, on a scale of -1 to 1, indicate the direction and strength of these associations. Military Expenditure exhibits a strong positive correlation with Population Size (0.757714), GDP (0.746407), and Export (0.778486). This implies that as military spending increases, there is a notable tendency for population size, GDP, and export values to rise as well. Population Size displays strong positive correlations with GDP (0.895715) and Export (0.867488). These coefficients suggest that as the population size expands, there is a significant inclination for both GDP and export values to increase. The study reveals a strong positive correlation between GDP and export, with a coefficient of 0.935307. This indicates a synchronized relationship between economic output and export earnings, suggesting that changes in GDP and export values tend to move together. The findings suggest that it's conceivable that changes in one variable will affect changes in other variables, emphasizing the importance of considering these relationships in strategic decision-making for economic and military planning in Nigeria.

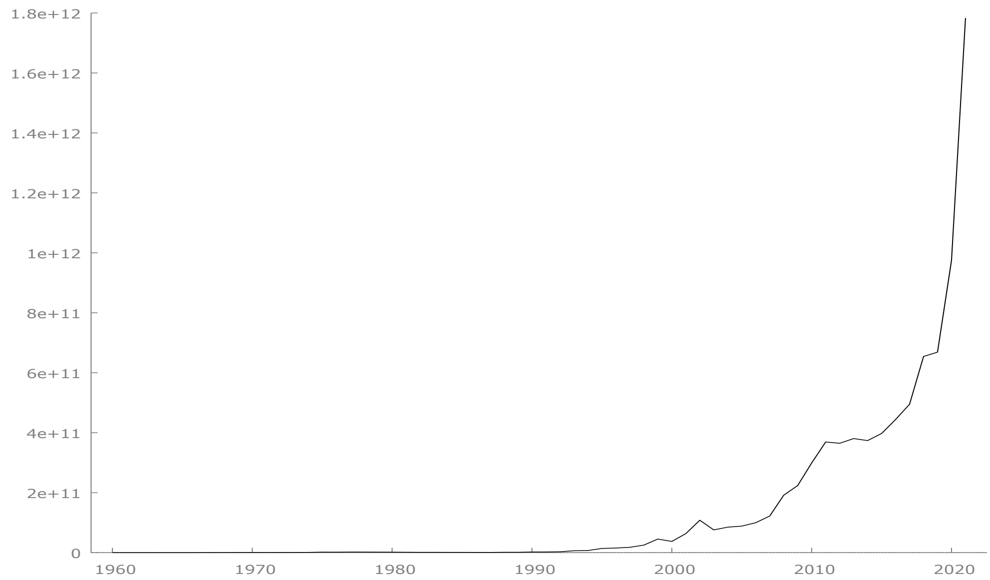

Figure 2: Plot of Military Expenditure Time Series

The time series plot in Figure 2 on Nigeria's military expenditure from 1960 to 2021 reveals a historical context, with a notable increase during the Nigerian Civil War (1967-1970). Long-term trends indicate consistent growth in defence spending since the 1980s. The data highlights a significant outlier in 1995, and recent years from the 2010s onward show accelerated military expenditure probably caused by the menace of the dreaded Boko Haram insurgent and banditry in northern Nigeria, reaching a substantial peak in 2021. This information provides valuable insights into the country's defence budget dynamics, emphasizing the need for careful consideration of geopolitical factors and national priorities in resource allocation.

Model Training and Evaluation

The MLR, ARIMAX), and ANN models were trained and evaluated using historical data. To make the train data steady for the statistical techniques of MLR and ARIMAX, the logarithm transformation was used to stabilize the data, and then differencing was employed in order to make it stationary. For the ANN analysis, the input and output data series are normalized within the interval of 0 and 1. The R Studio environment was used to develop each model in this study. Performance metrics such as MSE, and RMSE were computed for each model. The performance metrics for each model are presented in Table 3.

Table 3: Model Performance Metrics

	Metrics			
Model	**MSE**	**RMSE**	**AIC**	**BIC**
MLR	0.1811	0.4257	56.32	64.89
ARIMAX	0.1811	0.4257	54.32	61.18
ANN	0.0007245	0.0268	-261	-284

Table 3 presents the performance metrics of three different models: The metrics include MSE, RMSE, AIC, and BIC. Both MLR and ARIMAX models show similar performance in terms of MSE and RMSE, with values of 0.1811 and 0.4257, indicating equal accuracy in terms of the average squared difference between predicted and actual values. The ARIMAX model outperforms MLR in terms of AIC and BIC metrics, indicating better model fit while accounting for the number of parameters. The AIC values for MLR and ARIMAX are 56.32 and 54.32, and the BIC values are 64.89 and 61.18. Lower values suggest better model fit, so in this aspect, the ARIMAX model is preferred. The ANN model stands out with significantly lower MSE (0.0007245) and RMSE (0.0268) compared to both MLR and ARIMAX. This indicates that the ANN model provides the most accurate predictions among the three models. Additionally, the AIC and BIC values for the ANN model are -261 and -284, respectively, which are considerably lower than those of MLR and ARIMAX. This suggests that the ANN model not only achieves higher accuracy but also exhibits better overall fit based on information criteria. The ANN model demonstrates superior accuracy-related performance and model fit, as indicated by the lower MSE, RMSE, AIC, and BIC values. These results are consistent with earlier research indicating that neural networks possess greater forecasting capabilities for time-series data (Katsaitis et al., 2019; Hill et al., 1996; Adya and Collopy, 1998).

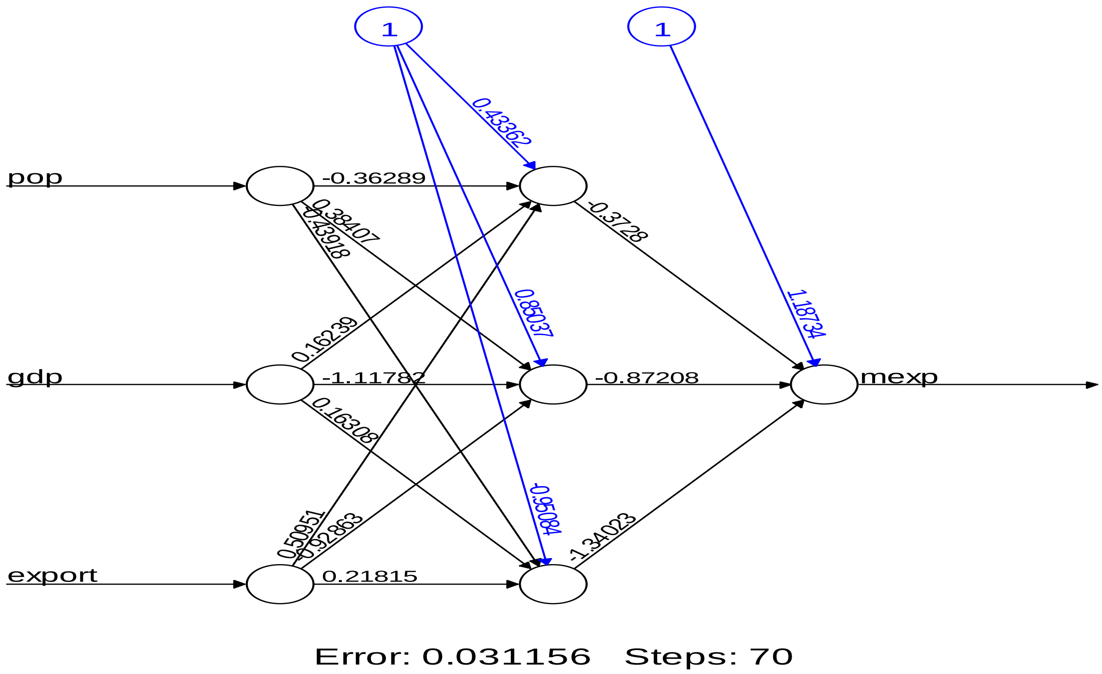

Figure 3: Plot of the Artificial Neural Network

The results of the ANN model with inputs of population (pop) size, GDP, and export values for Nigeria, and a dependent variable of military expenditure, reveal insights into the relationships among these variables. The three hidden layers in the model contribute to capturing complex patterns within the data. Notably, the model indicates that factors such as population size, GDP, and export values play roles in predicting military expenditure. Positive weights on GDP and export values suggest a positive association with higher military spending, aligning with expectations of economic capacity influencing defence expenditures. The model's complexity, introduced by the three hidden layers, allows for a nuanced understanding of these relationships. The ANN model for Nigeria, incorporating population size, GDP, and export values, reveals complex relationships among these variables.

Table 4: Residuals Normality Test

	Breusch-Godfrey (BG) Test			
Model	**LM**	**p-value**	**Null Hypothesis**	**Decision**
MLR	14.028	0.08104	Normality	Accepted
	Ljung-Box (LB) test			
	Test Statistic	p-value	Null Hypothesis	Decision
ARIMAX	13.454	0.09717	Normality	Accepted

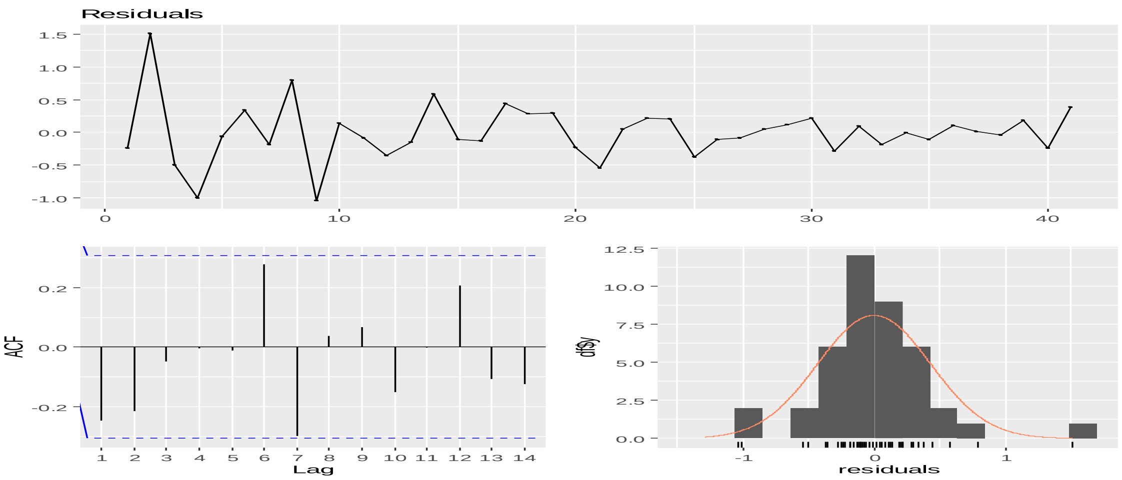

Figure 4: ACF and Histogram Plots of the MLR Residuals

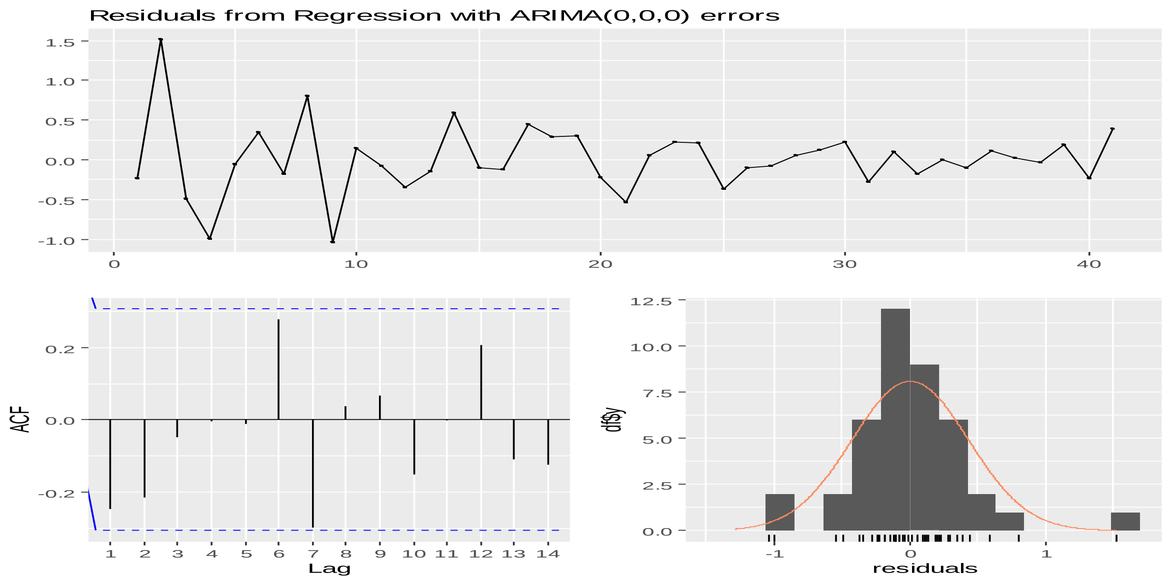

Figure 5: ACF and Histogram Plots of the ARIMAX Residuals

The analysis analyzed residuals in two models: MLR and ARIMAX, The results, outlined in Table 4 revealed that both models exhibit normal distribution residuals. The BG and LB Tests for the MLR and ARIMAX models confirmed the null hypothesis of normality, with p-values of 0.08104 and 0.09717 respectively, indicating no significant deviation from normality in the residuals. The normality of residuals is crucial for robust statistical analyses and predictions, but a comprehensive assessment of model reliability should include additional diagnostic checks and exploratory data analysis, as highlighted in figures 4 and 5.

CONCLUSION

The ANN model surpassed MLR and ARIMAX across all performance metrics, showcasing superior alignment with historical data and enhanced predictive accuracy. This superiority stems from its capacity to capture complex non-linear interactions and complex patterns within the data. Although MLR and ARIMAX exhibited reasonable predictive capabilities, their limitations in capturing non-linearity might have impacted their accuracy, especially in dynamic scenarios such as military expenditure. Incorporating advanced modelling techniques like ANN holds promise for improving prediction accuracy and supporting strategic decision-making by policymakers. In summary, this research illustrates that, when forecasting military expenditure in Nigeria, the ANN model outperforms traditional MLR and ARIMAX models. These results underscore the importance of integrating advanced modelling approaches in defence budget forecasting, offering valuable insights for policymakers and analysts involved in resource allocation and strategic planning.

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