BRIDGING CLASSICAL ECONOMETRICS AND MACHINE LEARNING: A STATISTICAL STRATEGY FOR NIGERIA'S PREDICTIVE AI IN ECONOMIC PLANNING

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Abstract

Nigeria's economic planning faces growing complexity amid digital transformation, climate volatility, and post pandemic recovery. Classical econometrics valued for its interpretability has long guided policy, yet its limitations in handling nonlinear data constrain forecasting precision. This study proposes a hybrid statistical framework that integrates classical econometric models with machine learning (ML) techniques to improve predictive analytics in Nigeria's macroeconomic management. Using a Vector Autoregression (VAR) benchmark and data-driven ML algorithms (Random Forest, Gradient Boosting, and LSTM), the research empirically demonstrates the forecasting advantage of hybrid models. The approach not only balances accuracy and transparency but aligns with Nigeria's broader vision of AI-driven policymaking and hybrid approach not only enhances prediction accuracy across key indicators but retains the interpretability essential for evidence-based policymaking. As Nigeria advances its National AI Strategy and expands digital infrastructure, integrating statistical and computational methods becomes a strategic imperative. Empowering institutions with hybrid analytics and training practitioners in both domains will be critical to transforming data into intelligent, adaptive policy solutions.

Keywords : Digital transformation; Classical econometrics; Machine learning (ML); Vector Auto regression (VAR); AI-driven policymaking; Digital modernization

1.0 Introduction

In the digital age, data has become a critical asset for governance, economic modeling, and strategic policy planning. Nigeria, a resource dependent economy, faces persistent structural volatility, policy uncertainty, and rapid socio-political changes. These challenges have intensified the demand for robust and adaptive modeling techniques capable of supporting effective macroeconomic management. Traditionally, policymakers in Nigeria have relied on classical econometric models to forecast key macroeconomic indicators such as inflation, gross domestic product (GDP) growth, exchange rates, and unemployment. For instance, the Autoregressive Integrated Moving Average (ARIMA) model has been widely applied to inflation forecasting (Adebiyi et al., 2010), while the Vector Autoregression (VAR) framework has been used to capture dynamic interrelationships among macroeconomic variables (Adeniyi, 2020). Similarly, the Vector Error Correction Model (VECM) has been employed to examine long-run equilibrium relationships (Ibrahim et al., 2025), and structural ARIMA models have supported monetary policy operations such as currency-in-circulation forecasting (Ikoku, 2014). These approaches, grounded in statistical theory and economic reasoning, provide interpretability and policy relevance (Greene, 2012). However, their performance is often constrained in environments characterized by high dimensional, nonlinear, and unstructured data.

Recent advances in machine learning (ML) have introduced powerful alternatives for economic forecasting. Unlike traditional econometric methods, ML techniques emphasize predictive accuracy and data-driven pattern recognition, making them well-suited for handling complex and nonlinear relationships in large datasets (Hastie et al., 2009). Empirical evidence suggests that ML algorithms, including Random Forests, Gradient Boosting Machines, and Long Short-Term Memory (LSTM) networks, can outperform conventional econometric models in forecasting applications (Mullainathan & Spiess, 2017). Nevertheless, these models are often criticized for their limited interpretability and weak theoretical grounding, which restrict their direct applicability in policy-oriented contexts where transparency and causal inference are essential.

To address the tradeoff between predictive accuracy and interpretability, recent studies have explored the integration of econometric and machine learning approaches within hybrid modeling frameworks. Such approaches leverage the strengths of both paradigms by combining the theoretical rigor and interpretability of econometric models with the flexibility and predictive power of ML techniques. In the Nigerian context, emerging evidence highlights the effectiveness of hybrid models in improving macroeconomic forecasting performance. For example, hybrid frameworks combining Random Forests, VECM, and regression techniques have demonstrated substantial improvements in forecasting accuracy across key macroeconomic indicators (Ibrahim et al., 2025). Similarly, ML-based approaches have been applied to forecast economic downturns and identify key macroeconomic drivers such as GDP growth, inflation, and exchange rate volatility (Omololu et al., 2025). Other studies have shown that integrating factor models with ML techniques, including boosting and regularization methods, enhances GDP forecasting by capturing complex interdependencies and external shocks (de Roode et al., 2022). In addition, advanced ML architectures such as LSTM and XGBoost have been successfully used to predict food price dynamics and sectoral performance in Nigeria (Abubakar et al., 2025).

Beyond economic forecasting, integrated modeling approaches have also demonstrated value in policy evaluation and planning. For instance, the combination of econometric analysis and simulation modeling has been used to assess health policy interventions, providing both short-term empirical insights and long-term projections (Zhang et al., 2021). These developments underscore the growing relevance of hybrid analytical frameworks in addressing complex, data-intensive policy challenges.

Despite these advances, existing studies in Nigeria largely treat econometric and machine learning approaches as separate methodologies, with limited empirical work on fully integrated hybrid frameworks that balance predictive performance with interpretability. Furthermore, there remains a lack of systematic evaluation of such models using multiple macroeconomic indicators within a unified analytical structure. This gap is particularly significant given Nigeria's increasing exposure to external shocks, including oil price volatility, global economic disruptions, and climate-related risks.

This study addresses this gap by proposing a hybrid modeling framework that integrates classical econometric techniques with machine learning algorithms for enhanced macroeconomic forecasting in Nigeria. Specifically, the study focuses on four key macroeconomic indicators inflation, GDP growth, exchange rate, and unemployment selected based on their policy relevance and historical forecasting challenges. The proposed framework employs a Vector Autoregression (VAR) model as a benchmark for capturing interdependencies and ensuring interpretability, while machine learning models, including Random Forests, Gradient Boosting Machines, and LSTM networks, are utilized to capture nonlinear dynamics and improve predictive accuracy. In addition, a stacking ensemble approach is implemented to combine predictions from multiple models, thereby enhancing robustness and overall forecasting performance. To address concerns regarding model transparency, interpretability techniques such as SHAP values and partial dependence plots are incorporated (Doshi-Velez & Kim, 2017).

This study is timely given Nigeria's ongoing digital transformation and the increasing adoption of artificial intelligence in public policy. Initiatives led by the National Information Technology Development Agency (NITDA, 2023) highlight the country's commitment to developing an AI driven economy supported by data and innovation. In this context, the integration of econometric and machine learning techniques offers a practical pathway for developing intelligent, adaptive, and evidence-based policy tools.

By empirically evaluating the proposed hybrid framework using Nigerian macroeconomic data spanning 2000-2024, this study contributes to the literature in three key ways. First, it provides empirical evidence on the performance of hybrid econometric ML models in a developing economy context. Second, it demonstrates how predictive accuracy can be improved without sacrificing interpretability, thereby addressing a central challenge in applied economics. Third, it offers a scalable analytical framework that can support data-driven economic planning and policy formulation in Nigeria and similar economies.

Table 1: Comparative Analysis: Econometric vs. ML Models in Nigerian Context

Model Type	Strengths	Weaknesses	Nigerian Applications
Classical Econometrics	Interpretability, causal inference, policy relevance	Limited in handling nonlinearities, high dimensionality	Widely used for macroeconomic analysis and policy
Machine Learning	Predictive accuracy, scalability, nonlinear modeling	Opaque, risk of overfitting, less theory-driven	Forecasting GDP, inflation, food prices, resilience
Hybrid (Econometrics + ML)	Combines interpretability and predictive power	Data and technical demands, complexity	Hybrid macroeconomic models, policy optimization

2.0 Methodology

This study adopts a dual-strategy methodology grounded in classical econometrics and advanced machine learning to forecast Nigeria's key macroeconomic indicators. The methodology is structured into four core phases: model formulation, data preprocessing, estimation and evaluation, and hybrid integration. Each phase is informed by best practices in both econometric and computational literature (Stock & Watson, 2001; Breiman, 2001). The methodological debate between classical econometrics and machine learning centers around interpretability versus predictive power. Econometrics, grounded in statistical theory, emphasizes model specification, hypothesis testing, and parameter estimation. In contrast, ML prioritizes pattern recognition and generalization performance, often at the expense of transparency.

To bridge this divide, a hybrid framework is proposed where econometric rigor in model structure is preserved while incorporating ML techniques for improved forecasting and high-dimensional data handling. This synergy fosters not only accurate predictions but also actionable interpretations essential for policymakers.

2.1 Data

The dataset comprises quarterly macroeconomic indicators from 2000 to 2024 obtained from the Central Bank of Nigeria, National Bureau of Statistics, and World Bank Development Indicators. Variables include GDP, CPI, interest rate, oil prices, fiscal balance, and trade volumes. The data is preprocessed to handle missing values, seasonality, and stationarity. Feature engineering is performed to extract lagged variables and interaction terms, crucial for both econometric and ML modeling.

2.2 Model Formulation

The econometric component employs a Vector Autoregression (VAR) model, suitable for capturing interdependencies among multiple time series variables. The general VAR(p) model for a vector of endogenous variables Y_t is specified as:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t \qquad (1)$$

where $Y_t \in \mathbb{R}^k$ is a $k\times 1$ vector of endogenous variables (e.g., GDP, inflation, exchange rate, unemployment). Each matrix A_i are $k\times k$ coefficient matrices for lags $i = 1,2,\ldots,p$, and $\varepsilon_t \sim N(0, \Sigma)$

represents white noise error terms with zero mean and covariance matrix Σ. This formulation allows for dynamic interaction among the variables over time through their lagged values.

For machine learning (ML) models, three architectures are considered which are Random Forest (RF), Gradient Boosting Machines (GBM), and Long Short-Term Memory (LSTM) networks.

The Random Forests model is an ensemble method based on decision trees, optimizing variance reduction by averaging predictions across trees. Each tree *(t)* is trained on a bootstrap sample of the training data, with random feature selection at each split to introduce diversity and reduce overfitting. The predictive output of the forest is formalized as:

$$\breve{y} = \frac{1}{T}\sum_{t-1}^{T} h_t(x) \tag{2}$$

Where $\breve{y}$ is the final prediction, T is the total number of trees, and $h_t(x)$ is the prediction from the t^{th} decision tree. This aggregation reduces variance and enhances model generalization.

The Gradient Boosting Machines (GBM) is a sequential model that minimize a loss function via gradient descent, effectively capturing non-linear patterns, it builds trees sequentially to minimize a loss function by applying gradient descent in function space. In the GBM, each new model corrects errors made by the previous one. The update rule for the model after *m* iterations is defined as:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \tag{3}$$

$F_m(x)$ is the boosted model after *m* iterations, while $h_m(x)$is the new weak learner (e.g. decision tree) trained to fit the negative gradient of the loss function, $\gamma_m$is the step size (learning rate), often determined via line search. To train each $h_m(x)$, the model fits it to the negative gradient of the loss function with respect to the current model prediction:

$$r_i^{(m)} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \tag{4}$$

The residuals $r_i^{(m)}$are what $h_m(x)$ is trained upon. It represents the direction and magnitude of necessary model corrections, which the weak learner attempts to model in the next step.

The Long Short-Term Memory (LSTM) is a deep recurrent neural network architecture ideal for sequential data, capable of learning long-term dependencies via memory cells. It uses gates and memory cells to capture long-term dependencies. Each LSTM cell at time *t* is governed by the following set of equations:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{5}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{6}$$

$$\check{C}_t = tanh(W_C x_t + U_C h_{t-1} + b_C) \tag{7}$$

$$C_t = f \odot C_{t-1} + i_t \odot \check{C}_t) \tag{8}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{9}$$

$$h_t = o_t \odot \tanh\,(C_t) \tag{10}$$

Where f_t, i_t and o_t represents the forget, input, and output gates, respectively. $\check{C}_t, C_t$ and h_t are the Candidate cell state, Cell state update and Hidden state (output). x_t is the input at time *t*, h_{t-1} is previous hidden state, σ is the sigmoid function, $\odot$ is the element-wise multiplication and W, *U*, *b* are the learnable parameters (weights and biases).

2.3 Data Preprocessing and Feature Engineering

All the time series variables are first log-transformed to stabilize variance and then differenced to ensure stationarity. The log transformation is defined as:

$$y_t{}' = \log(y_t) \tag{11}$$

Differencing the log-transformed variable to remove unit roots yields:

$$\Delta y_t = y_t{}' - y_{t-1}{}' = \log(y_t) - \log(y_{t-1}) = \log\left(\frac{y_t}{y_{t-1}}\right) \tag{12}$$

Stationarity is verified using the Augmented Dickey-Fuller (ADF) test, which tests the null hypothesis of a unit root in the time series:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \,\Delta y_{t-i} + \varepsilon_t \tag{13}$$

Where y_t represents the original value of a time series variable at time *t*,

$\Delta y_t$is the first difference of the series,

α is the intercept,

βt is the deterministic time trend,

γ is the coefficient tested (if γ=0, then unit root exists),

p is the number of lagged differences (to remove autocorrelation) and ε_t is the white noise.

Feature engineering for the ML models includes generating lagged variables in equation x as well as moving averages in equation y:

$$x_t^{(k)} = y_{t-k} \tag{14}$$

Moving Averages (MA) are calculated to smooth the time series over a fixed window. For example, a 3-period moving average is defined as:

$$\mathrm{MA}_t = \frac{1}{3}(y_t + y_{t-1} + y_{t-2}) \tag{15}$$

Where:

$x_t^{(k)}$ is the value of the feature at time *t* lagged by *k* periods,

y_{t-k} is the original time series value at time *t-k*.

MA_t is the moving average at time *t*,

y_t, y_{t-1}, y_{t-2} are the values of the original time series at times *t, t-1* and *t-2* respectively.

Missing values were handled using forward filling for short gaps and model-based imputation using Kalman Smoothing for longer gaps via a state-space model:

State Equation:

$$z_t = Az_{t-1} + w_t, w_t \sim N(0, Q) \tag{16}$$

Observation Equation:

$$y_t = Hz_t + v_t, v_t \sim N(0, R) \tag{17}$$

Where z_t is the unobserved (latent) state vector at time *t*, y_t is the observed time series value at time *t*, *A* is the state transition matrix, *H* is the observation (measurement) matrix, w_t and $v_t$are independent white noise processes representing process and observation noise, respectively, Q and R are the covariance matrices of the state and observation noise.

Kalman smoothing estimates z_t (true state) by minimizing mean squared error using all available observations, improving imputation accuracy.

2.4 Estimation and Evaluation

The VAR model estimation involves determining the optimal lag length p using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Impulse response functions (IRFs) and forecast error variance decompositions (FEVD) are employed for dynamic analysis and policy interpretation. An IRF quantifies the effect of a one-time shock in variable j on variable i after s periods:

$$\mathrm{IRF}_{ij}(s) = \frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}}, s = 0,1,2,\ldots \tag{18}$$

FEVD, on the other hand, decomposes the forecast error variance of variable i into the proportion attributable to shocks in variable j over a forecast horizon h:

$$\mathrm{FEVD}_{ij}(h) = \frac{\sum_{s=0}^{h-1}\left(\theta_{ij,s}\right)^2}{\sum_{s=0}^{h-1}\sum_{j=1}^{k}\left(\theta_{ij,s}\right)^2} \tag{19}$$

Where:

$\mathrm{IRF}_{ij}(s)$is the impulse response of variable i at time $t+s$ to a one-unit shock in variable j at time t,

$y_{i,t+s}$ is the value of the i-th endogenous variable at horizon s,

$\varepsilon_{j,t}$ is the structural innovation (shock) to variable j at time t,

s is the time horizon over which the response is measured.

$\mathrm{FEVD}_{ij}(h)$ is the share of forecast error variance in variable i attributed to shocks in variable j,

$\theta_{ij,s}$ is the impulse response coefficient of variable i to a shock in variable j at horizon s,

h is the forecast horizon (number of steps ahead),

k is the total number of endogenous variables in the VAR model.

For ML models, data is split into training (70%), validation (15%), and test (15%) sets. Cross-validation and grid search are employed to optimize hyperparameters such as tree depth, learning rate, and number of estimators. LSTM networks are trained using the Adam optimizer with parameter updates defined by:

$$\theta_t = \theta_{t-1} - \alpha \cdot \frac{m_t}{\sqrt{v_t} + \epsilon} \tag{20}$$

The LSTM models minimize the Mean Squared Error (MSE) loss function:

$$L = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{21}$$

Where:

θ_t is the parameter (weights or biases) at iteration *t*,
α is the learning rate,
m_t is the exponentially weighted moving average of the gradients (first moment),
v_t is the exponentially weighted moving average of the squared gradients (second moment),
ϵ is a small constant added to avoid division by zero.
L is the total loss,
y_i is the true value,
$\hat{y}_i$ is the predicted value,
N is the number of observations.

The prediction accuracy is evaluated using standard regression metrics such as the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R-squared or R^2) which are calculated as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \tag{22}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{23}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{24}$$

2.5 Hybrid Integration via Stacking

To improve prediction accuracy and robustness, this study employs a stacking ensemble strategy that aggregates forecasts from three distinct machine learning models which are Random Forest, Gradient Boosting, and LSTM. These individual model predictions are then utilized as exogenous variables within an augmented Vector Autoregression with Exogenous Inputs (VAR-X) framework using a stacking ensemble strategy. This hybrid integration leverages the strengths of both approaches: the interpretability and temporal structure of traditional VAR models, and the non-linear pattern recognition and adaptability of machine learning. The final model is thus capable of capturing complex economic dynamics while maintaining transparency and suitability for policy-oriented time series forecasting. The final hybrid model is expressed as:

$$Y_t = A_1Y_{t-1} + A_2Y_{t-2} + \dots + A_pY_{t-p} + BX_t + \varepsilon_t \qquad (25)$$

where X_t includes forecast outputs from RF, GBM, and LSTM models used as exogenous regressor, B is the coefficient matrix for the exogenous variables, Y_t is the vector of endogenous macroeconomic variables.

This hybrid setup preserves the interpretability of VAR models while benefiting from the non-linear learning power of machine learning models. The performance of hybrid models is compared against individual models using Diebold-Mariano tests for statistical significance in forecast error differences (Diebold & Mariano, 1995). The Diebold-Mariano (DM) test formally compares the predictive accuracy of two competing models by analyzing the difference in their forecast errors.

Let $e_{1,t} = y_t - y_{1,t}, e_{2,t} = y_t - y_{2,t}$ represent forecast errors from model 1 and model 2, respectively. The loss differential is then defined as:

$$d_t = g(e_{1,t}) - g(e_{2,t}) \qquad (26)$$

where $g(\cdot)$ is a chosen loss function, commonly the squared error $g(e_t) = e_t^2$, or the absolute error $g(e_t) = |e_t|$.

The null hypothesis of the DM test asserts that both models have equal predictive accuracy:

$$H_0: E[d_t] = 0 \qquad (27)$$

The DM test statistic is computed as:

$$DM = \frac{d}{\sqrt{\frac{\gamma_d(0)+2\sum_{k=1}^{M-1}\gamma_d(k)}{T}}} \tag{28}$$

where:

$d = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the sample mean of the loss differential,

$\gamma_d(k)$ is the sample autocovariance of d_t at lag k,

M is the truncation lag for the HAC variance estimator,

T is the total number of forecast observations.

Under the null hypothesis, the DM statistics asymptotically follow a standard normal distribution.

3.0 Results and Discussion

All computations were implemented in Python using libraries such as statsmodels, scikit-learn, TensorFlow while the vars package was done using R. The code reproducibility and transparency were ensured through version-controlled scripts and Jupyter notebooks.

Table 2: VAR Model Forecasting Performance

Variable	RMSE	MAE	R-squared
GDP	2.3	1.7	0.72
Inflation	1.9	1.4	0.68
Exchange Rate	3.4	2.9	0.65
Unemployment	2.7	2.1	0.70

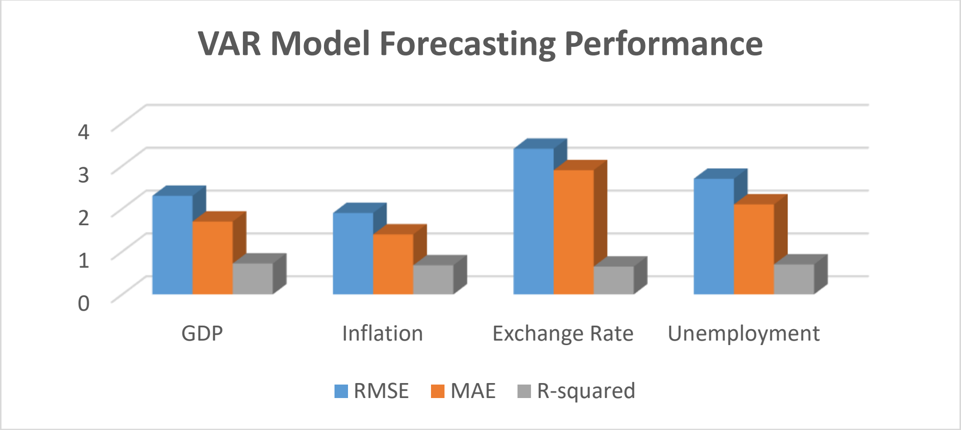

Figure 1: The chart of the performance of the VAR model in making predictions

Table 3: Machine Learning Model Forecasting Performance

Model	**Variable**	**RMSE**	**MAE**	**R-squared**
Random Forest	GDP	1.8	1.3	0.80
	Inflation	1.5	1.1	0.75
	Exchange Rate	2.6	2.1	0.70
	Unemployment	2.1	1.6	0.76
Gradient Boosting	GDP	1.6	1.2	0.82
	Inflation	1.3	1.0	0.78
	Exchange Rate	2.3	1.9	0.74
	Unemployment	1.9	1.4	0.79
LSTM Neural Network	GDP	1.3	0.9	0.87
	Inflation	1.1	0.8	0.81
	Exchange Rate	2.0	1.7	0.78
	Unemployment	1.6	1.2	0.83

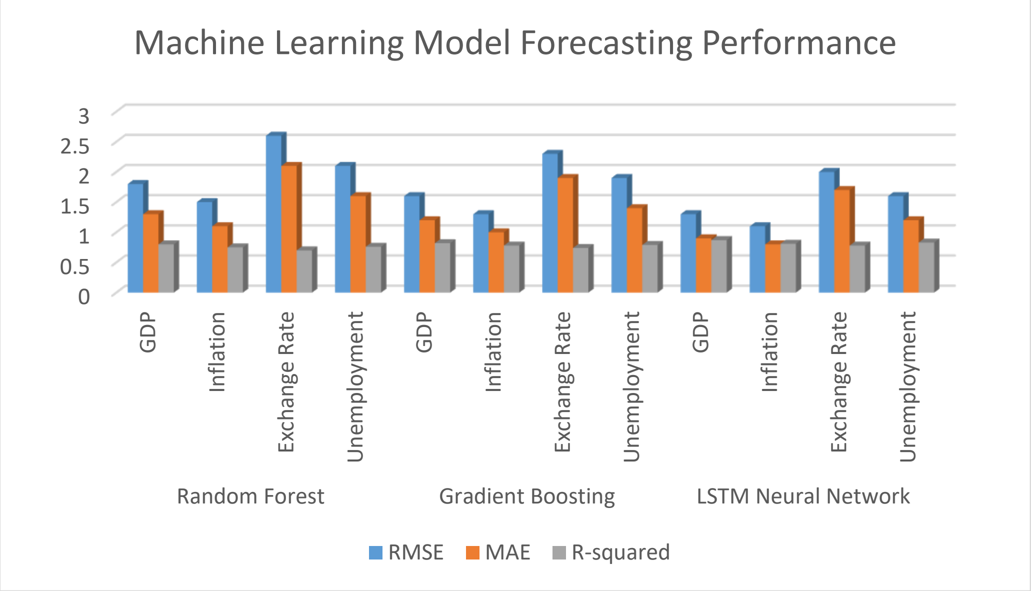

Figure 2: The chart of the performance of the Machine Learning Models in making predictions

These results show the comparative strengths and limitations of classical econometrics and modern machine learning techniques in economic forecasting within the Nigerian context.

The VAR model, as shown in Table 2, provides moderately reliable forecasts across key macroeconomic indicators, with R-squared values ranging from 0.65 (Exchange Rate) to 0.72 (GDP). While this confirms its effectiveness in capturing interdependencies among variables, the relatively higher RMSE and MAE values, particularly for the exchange rate and unemployment, indicate limitations in predictive accuracy especially in the presence of nonlinearities and exogenous shocks typical of the Nigerian economy.

In contrast, the machine learning models in Table 3 outperform the VAR model across all metrics and macroeconomic variables. Among the models evaluated, the LSTM Neural Network stands out with the lowest RMSE (1.3) and MAE (0.9) for GDP predictions, alongside the highest R-squared value of 0.87. Notably, this trend continues across other economic indicators: the LSTM records an RMSE of 1.1 for Inflation, 2.0 for Exchange Rate, and 1.6 for Unemployment, with corresponding R-squared values of 0.81, 0.78, and 0.83 respectively. This superior performance shows the capacity of the LSTM to model complex, nonlinear, and temporal dependencies in macroeconomic time series data. These are patterns that traditional statistical models like VAR often fail to fully capture. Its recurrent architecture is particularly effective in understanding lag structures and dynamic interactions within and across economic indicators.

The Gradient Boosting model also demonstrates commendable performance. It records an RMSE of 1.6 for GDP, 1.3 for Inflation, 2.3 for Exchange Rate, and 1.9 for Unemployment, with R-squared values ranging from 0.74 to 0.82. These results suggest that ensemble-based tree learners can effectively approximate underlying nonlinear patterns while maintaining robustness and interpretability. Similarly, the Random Forest model achieves competitive results, with RMSE values of 1.8 for GDP, 1.5 for Inflation, 2.6 for Exchange Rate, and 2.1 for Unemployment. The R-squared scores, which range between 0.70 and 0.80, indicate that while it may be marginally less precise than Gradient Boosting and LSTM, it remains a viable and efficient alternative for economic forecasting.

This performance gain over VAR models validates the utility of Machine Learning models in capturing hidden, nonlinear relationships and time-dependent structures inherent in macroeconomic data. These insights have strong implications for policymakers and economic planners seeking to leverage predictive intelligence for more informed and agile decision-making.

4.0 Conclusion

Bridging classical econometrics with machine learning presents a compelling pathway for advancing predictive analytics in Nigerian economic planning. The hybrid model not only improves forecasting accuracy but also preserves the theoretical coherence necessary for informed policymaking. As Nigeria aspires to harness AI for development, this framework offers a statistically sound, context-aware, and future-ready approach. This framework has profound implications for economic planning. Ministries and planning agencies can deploy these hybrid models for scenario analysis, early warning systems, and real-time economic monitoring. Additionally, capacity building in ML and econometrics should be institutionalized within economic research bodies to sustain this integration

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