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COMPARATIVE ANALYSIS OF STOCHASTIC MODELS AND MACHINE LEARNING ALGORITHMS FOR INFLATION RATE PREDICTION IN NIGERIA

Edesiri Bridget Nkemnole and *Abiodun Simeon Oyelami

Department of Statistics, University of Lagos, Akoka, Lagos, Nigeria

*Corresponding Author Email Address:abbeytech4uall@gmail.com

ABSTRACT
Inflation forecasting is critical to economic planning, particularly in developing economies like Nigeria, where inflation volatility significantly impacts policymaking, investment decisions, and overall economic stability. This study evaluated the predictive performance of traditional stochastic processes such as Vasicek, Cox–Ingersoll–Ross (CIR), and Geometric Brownian Motion (GBM) against three machine learning algorithms: Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), in modeling Nigeria's inflation trends. The analysis was based on "All-items inflation rates" data from January 2003 to December 2024. The study uncovered that whereas stochastic models successfully captured the hypothetical inflationary change, their predictive accuracy was moderately restricted compared to machine learning methods. In particular, the Random Forest model outperforms stochastic approaches in terms of accuracy, robustness, and overall performance across key evaluation metrics. This research advocates for a paradigm shift in Nigeria`s economic modelling strategies by emphasizing the integration of advanced machine learning methods into inflation forecasting.

Keywords: Inflation Rate, Forecasting, Stochastic Models, Machine Learning, Random Forest,

INTRODUCTION
Inflation volatility significantly affects economic stability and policy-making in Nigeria. Accurate forecasting is essential for decision-makers, prompting interest in both traditional stochastic processes and modern machine learning (ML) methods. This study evaluated and compared these methods in forecasting Nigeria's inflation rate. The ability to accurately predict inflation trends is essential for government agencies, financial institutions, and businesses to formulate effective strategies for mitigating economic risks. Over the years, various approaches have been developed to model and forecast inflation rates, ranging from traditional stochastic processes to modern machine learning algorithms.
Stochastic models have long been employed in economic and financial forecasting due to their ability to capture the randomness inherent in macroeconomic variables. Among the most prominent stochastic models are the Geometric Brownian Motion (GBM) model (Mensah *et al*., 2023), the Vasicek model (Nadarajan and Nur-Firyal, 2024), and the Cox–Ingersoll–Ross (CIR) model (Bernaschi *et al.,* 2007).
In contrast, the advent of machine learning has introduced a paradigm shift in economic forecasting, providing more flexible and data-driven approaches for modeling inflation dynamics. Machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and k-Nearest Neighbors (KNN) have shown promising results in forecasting complex economic indicators (Ayyildiz and Iskenderoglu, 2024). Recent studies have extended this approach by integrating machine learning models with stochastic frameworks such as the Hidden Markov Model (HMM) to better capture the structural shifts and transition patterns in inflation. For instance, Nkemnole, Wulu, and Osubu (2024) applied KNN and Long Short-Term Memory (LSTM) models enhanced by HMM to forecast inflation rates and transition patterns in Nigeria, highlighting the critical role of GDP per capita as a significant predictor. Their findings underscore the growing relevance of hybrid machine learning-stochastic methods in improving the accuracy and interpretability of inflation forecasting models in developing economies.
Stochastic models have long been instrumental in modeling economic variables, including inflation rate. Techniques such as Autoregressive Integrated Moving Average (ARIMA) have been widely adopted due to their capacity to capture temporal dependencies in time series data (Box & Jenkins, 1976). A study examining Nigeria's inflation data from 1960 to 1999 utilized a time series approach, revealing that a quadratic trend effectively captured the inflation dynamics during that period (Iwueze and Akpanta, 2006). Furthermore, a recent study on Nigeria's inflation rate prediction using a Bayesian Seasonal Autoregressive Integrated Moving Average (Bayesian SARIMA) model emphasized the presence of a strong seasonal effect in the inflation rate (Oyelami & Ogundeji, 2025).
The integration of machine learning (ML) techniques has revolutionized inflation forecasting by enabling the detection of complex, nonlinear patterns in economic data. In Nigeria, studies have demonstrated the efficacy of ML algorithms in enhancing predictive accuracy. One notable research employed a stacked ensemble approach, combining base learners such as Random Forest (RF), Gradient Boosting Machines (GBM), and Generalized Linear Models (GLM) to disaggregate inflation components. This methodology not only improved prediction accuracy but also identified key drivers of inflation, suggesting that targeted policy interventions could more effectively manage inflationary pressures (Akande *et al.,* 2023).
Beyond Nigeria, other African countries have also explored ML applications in inflation forecasting. In South Africa, researchers investigated the use of statistical learning techniques and big data to enhance inflation forecast accuracy, finding that these advanced methods could provide more reliable predictions compared to traditional models (Mwamba and Nell, 2023). Similarly, a study focusing on Ghana examined how ML could enhance economic stability and growth strategies by providing accurate inflation forecasts, thereby aiding policymakers in making informed decisions (Baidoo and Obeng, 2024).

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Global Perspectives on Machine Learning in Inflation Forecasting

Globally, the International Monetary Fund (IMF) has recognized the potential of machine learning (ML) in economic forecasting. A recent study applied ML models to forecast near-term core inflation in Japan post-pandemic, demonstrating that incorporating a wider range of variables and allowing for nonlinear relationships can significantly improve forecasting performance (Liu, Pan, & Xu, 2024).

Comparative studies from various countries indicate that ML algorithms often outperform traditional stochastic models in forecasting accuracy. These models offer greater adaptability and robustness in capturing complex economic dynamics, especially in emerging and developing economies. Although specific research in this area is still expanding, the growing body of evidence supports the utility of ML in inflation prediction.

The development of hybrid models that combine the strengths of stochastic processes and ML techniques has also gained attention. Such models aim to enhance robustness and accuracy, particularly in economies like Nigeria that are prone to structural changes and external shocks.

While traditional stochastic models like ARIMA have long served as foundational tools in economic forecasting, the integration of ML—either as standalone models or within hybrid frameworks—has shown considerable promise. As data availability and computational capabilities continue to grow, these advanced methodologies are poised to play a pivotal role in supporting monetary policy and economic stability across diverse contexts.

However, challenges remain. The application of ML in inflation forecasting requires meticulous data preprocessing, effective feature selection, and improved model interpretability. These concerns are especially pressing in developing economies, where data quality and availability may be limited.

This study aims to contribute to the existing literature by conducting a comparative analysis of traditional stochastic models and ML algorithms in forecasting Nigeria's inflation rate. Using two decades' worth of economic data. The expected findings should offer valuable insights for policymakers, economists, and financial analysts, promoting more informed decision-making in economic planning and policy formulation.

MATERIALS AND METHODS

This study employed two categories of models to forecast Nigeria's inflation: traditional stochastic models and machine learning algorithms. The stochastic models—Vasicek, Cox–Ingersoll–Ross (CIR), and Geometric Brownian Motion (GBM)—are continuous-time processes commonly used in economic modeling to capture inflation dynamics such as trend, volatility, and mean reversion.

The machine learning models considered here are Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), which are capable of learning complex, non-linear relationships from historical data without strong distributional assumptions.

Vasicek Model

The Vasicek model, initially developed for interest rate modeling (Vasicek, 1977), has been adapted to model inflation rates due to its mean-reverting property. Inflation rates tend to revert to a long-term mean due to central bank interventions and macroeconomic policies. This feature makes the Vasicek model suitable for modeling inflation dynamics.

The Vasicek model follows a stochastic differential equation (SDE) given by:

$$dX_t = \kappa(\theta - X_t)\,dt + \sigma\,dW_t \qquad (1)$$

Where:

X_t represents the inflation rate at time t,

κ is the speed of mean reversion (κ>0),

θ is the long-term equilibrium level of inflation,

σ is the volatility parameter,

W_t is a standard Wiener process (Brownian motion).

This equation describes a process where the inflation rate X_t reverts toward θ at a rate of κ, with random fluctuations introduced by the Wiener process.

Analytical Solution of the Vasicek Model

By applying Ito's lemma and solving the stochastic differential equation, the explicit solution for X_t is:

$$X_t = X_0 e^{-\kappa t} + \theta(1 - e^{-\kappa t}) + \sigma \int_0^t e^{-\kappa(t-s)} dW_s \qquad (2)$$

Where X_0 is the initial inflation rate.

The mean and variance of X_t are given by:

$$E[X_t] = X_0 e^{-\kappa t} + \theta(1 - e^{-\kappa t}) \qquad (3)$$

$$\text{Var}(X_t) = \frac{\sigma^2}{2\kappa}(1 - e^{-2\kappa t}) \qquad (4)$$

At equilibrium (t⟶∞), the steady-state distribution of inflation follows a normal distribution:

$$X_\infty \sim \mathcal{N}\left(\theta, \frac{\sigma^2}{2\kappa}\right)$$

indicating that the inflation rate fluctuates around θ with a variance determined by σ^2 and κ.

Methodology for Empirical Estimation

To estimate the parameters κ, θ, and σ, econometric techniques are employed:

Maximum Likelihood Estimation (MLE)

Given discrete observations $X_0, X_1, \ldots X_T$, the transition probability density function of the Vasicek process follows:

$$X_t \mid X_s \sim \mathcal{N}\left(X_s e^{-\kappa(t-s)} + \theta\left(1 - e^{-\kappa(t-s)}\right), \frac{\sigma^2}{2\kappa}\left(1 - e^{-2\kappa(t-s)}\right)\right) \qquad (5)$$

The likelihood function is:

$$L(\kappa, \theta, \sigma) = \prod_{i=1}^{T} \frac{1}{\sqrt{2\pi \text{Var}(X_{t_i})}} \exp\left(-\frac{\left(X_{t_i} - E[X_{t_i}]\right)^2}{2\text{Var}(X_{t_i})}\right) \qquad (6)$$

Maximizing this function yields the estimates for κ, θ, and σ.

Generalized Method of Moments (GMM)

Moment conditions derived from the mean and variance equations can be used for GMM estimation. The system of equations:

$$E[X_t - X_{t-1} - \kappa(\theta - X_{t-1})] = 0 \qquad (7)$$

$$E\left[\left(X_t - X_{t-1} - \kappa(\theta - X_{t-1})\right)^2 - \sigma^2\right] = 0 \qquad (8)$$

Cox-Ingersoll-Ross (CIR) Model

The Cox–Ingersoll–Ross (CIR) model (Cox, Ingersoll, & Ross, 1985) extends the Vasicek model by addressing some of its shortcomings, particularly in the context of inflation modeling. While the Vasicek model is mean-reverting, it permits negative values,

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which may be unrealistic for inflation rates. The CIR model retains the mean-reversion property but incorporates a square root diffusion term that enforces a non-negativity constraint, making it more suitable for capturing the positive and persistent nature of real-world inflation dynamics.

Mathematical Formulation of the CIR Model

The CIR model is a mean-reverting stochastic process governed by the following stochastic differential equation (SDE):

$$dI_t = \kappa(\theta - I_t)dt + \sigma\sqrt{I_t}dW_t \quad (9)$$

where:

I_t is the inflation rate at time t,

K > 0 is the speed of mean reversion (higher κ implies faster adjustment to θ),

θ > 0 is the long-term equilibrium level of inflation,

$\sigma > 0$ is the volatility coefficient,

W_t is a Wiener process (Brownian motion) representing random fluctuations.

Compared to the Vasicek model, the CIR model differs in its volatility structure, which is proportional to the square root of inflation $\left(\sqrt{I_t}\right)$. This ensures that the process never goes negative, making it more realistic for inflation modelling.

Properties of the CIR Model

Mean Reversion

The CIR model ensures that inflation does not drift indefinitely but reverts toward θ. The expected value of I_t is:

$$E[I_t] = I_0 e^{-\kappa t} + \theta(1 - e^{-\kappa t}) \quad (10)$$

As t⟶∞, the expectation converges to:

$$\lim_{t\to\infty} \mathrm{E}\,(I_t) = \theta$$

This shows that inflation stabilizes around θ, the long-term mean level.

Variance and Stationarity

The variance of I_t is given by:

$$\mathrm{Var}(I_t) = \frac{\sigma^2}{2\kappa}(1 - e^{-2\kappa t})$$

At equilibrium (t⟶∞), the variance reaches a steady state:

$$\lim_{t\to\infty} \mathrm{Var}\,(I_t) = \frac{\sigma^2}{2\kappa}$$

Unlike the Vasicek model, where variance is independent of the state, in CIR, the variance depends on θ, ensuring inflation remains positive.

Non-Negativity Constraint

A key advantage of the CIR model is that it avoids negative inflation rates.

$$2\kappa\theta \geq \sigma^2$$

When this condition holds, the probability of inflation reaching zero is zero, making the CIR model more suitable for economies where deflation is rare.

Autocorrelation Structure

The autocorrelation function of the CIR model is:

$$\rho(\tau) = e^{-\kappa\tau}$$

indicating that inflation rates become less correlated over time, similar to the Vasicek model.

Solution to the Stochastic Differential Equation (SDE)

The explicit solution of the CIR model is obtained using **Ito's Lemma**:

$$I_t = I_0 e^{-\kappa t} + \theta(1 - e^{-\kappa t}) + \sigma\int_0^t e^{-\kappa(t-s)} I_s\, dW_s \quad (11)$$

Discretization for Estimation

To apply OLS, we discretize the CIR model:

$$I_{t+1} - I_t = \kappa(\theta - I_t)\Delta t + \sigma\sqrt{I_t}\sqrt{\Delta t}\epsilon_t \quad (12)$$

We rearrange this to a regression form:

$\Delta I_t = a + bI_t + \eta_t$, where $\eta_t \sim \mathcal{N}(0, \sigma^2 I_t)$

This is non-linear in variance, so while OLS can give us initial estimates, weighted least squares (WLS) or non-linear least squares (NLS) are typically used for better efficiency. However, for simplicity and comparison with Vasicek, the ordinary least square (OLS) method is used.

Estimating CIR Parameters Using OLS

Let:

$a = \kappa\theta$

$b = -\kappa$

Then from the regression:

$$\Delta I_t = a + bI_t + \epsilon_t \quad (13)$$

We estimate a and b using OLS, and then back-calculate the parameters:

$$\kappa = -b, \theta = \frac{a}{\kappa}$$

We estimate σ using the residuals and the structure of heteroskedasticity:

$$\hat{\sigma}^2 = \frac{1}{n}\sum_{t=1}^{n} \frac{\hat{\epsilon}_t^2}{I_t}$$

Geometric Brownian Motion (GBM) Model

The Geometric Brownian Motion (GBM) Model is widely used in financial and economic modelling to represent variables that evolve continuously over time with random fluctuations and exponential growth. Unlike mean-reverting models such as Vasicek and Cox-Ingersoll-Ross (CIR), GBM assumes that inflation follows a log-normal distribution and grows over time.

The **Geometric Brownian Motion (GBM)** model is defined by the following stochastic differential equation (SDE): Mensah, *et al* (2023)

$$dI_t = \mu I_t\, dt + \sigma I_t\, dW_t \quad (14)$$

where:

I_t is the inflation rate at time t,

μ is the **drift term**, representing the expected growth rate of inflation

σ is the **volatility term**, capturing the level of uncertainty or randomness in inflation changes

W_t is a **Wiener process (Brownian motion)**, introducing random shocks to inflation.

Unlike the Vasicek and CIR models, GBM assumes that inflation follows a **multiplicative stochastic process,** meaning that **percentage changes in inflation are normally distributed,** rather than absolute changes.

Properties of the GBM Model

Solution to the GBM Stochastic Differential Equation

Using **Ito's Lemma**, the explicit solution of the GBM model is:

$$I_t = I_0 e^{\left(\mu - \frac{1}{2}\sigma^2\right)t} + \sigma W_t \quad (15)$$

This solution shows that inflation evolves **exponentially over time** with a drift rate of $\mu - \frac{1}{2}\sigma^2$ and a stochastic term W_t.

Expected Value and Variance of Inflation
The **expected value** of inflation at time t is:
$E[I_t] = I_0 e^{\mu t}$
indicating that inflation grows exponentially at an average rate of μ.
The **variance** of inflation is given by:
$Var(I_t) = I_0^2 e^{2\mu t}(e^{\sigma^2 t} - 1)$
showing that variance increases exponentially over time, implying that **uncertainty in inflation grows as time progresses.**
Log-Normal Distribution of Inflation
Since GBM assumes a multiplicative process, the inflation rate follows a **log-normal distribution**:

$$ln(I_t) \sim \mathcal{N}\left(\ln(I_0) + \left(\mu - \frac{1}{2}\sigma^2\right)t, \sigma^2 t\right)$$

This means that, unlike Vasicek and CIR, GBM does **not** assume inflation reverts to a long-term mean. Instead, it assumes inflation follows a **random walk with drift.**

Autocorrelation Structure
For GBM, the autocorrelation function is **constant** over time, meaning that inflation changes at any given time are independent of past values. This contrasts with mean-reverting models where past values influence future movements.

Discretization for Estimation

Discretizing this over monthly time steps ($\Delta t = 1$) gives:

$$\ln\left(\frac{I_{t+1}}{I_t}\right) = \left(\mu - \frac{1}{2}\sigma^2\right) + \sigma\epsilon_t, \epsilon_t \sim \mathcal{N}(0,1)$$

Define:
$r_t = \ln(I_{t+1}) - \ln(I_t)$
This turns the model into a simple linear regression:
$r_t = \alpha + \epsilon_t$
Where:
$\alpha = \mu - \frac{1}{2}\sigma^2, \mathrm{Var}(r_t) = \sigma^2$
OLS Estimation of GBM Parameters
We can use OLS to estimate:
$\alpha = \mathbb{E}[r_t]$
$\sigma^2 = \mathrm{Var}(r_t)$
Then:

$$\mu = \alpha + \frac{1}{2}\hat{\sigma}^2$$

Machine Learning in Inflation Forecasting
The three models considered here are Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) and they belong to different categories of machine learning:

I. **Random Forest**: An ensemble learning method based on decision trees.
II. **Support Vector Machine (SVM)**: A supervised learning algorithm based on maximizing margin classification or regression.
III. **K-Nearest Neighbors (KNN)**: A non-parametric method based on instance-based learning.

Random Forest (RF) for Inflation Rate Prediction
Random Forest (Breiman, 2001) is an ensemble learning method that constructs multiple decision trees and aggregates their predictions to improve accuracy and reduce overfitting. For inflation prediction, **RF** can be used for both classification (inflation increase/decrease) and regression (continuous inflation rate prediction).
Given a dataset with n observations and p predictors $(X_1, X_2, ..., X_p)$, Random Forest constructs B decision trees, each trained on a random subset of the data using bootstrap sampling (bagging). The inflation prediction at time t is computed as:

$$\hat{Y}_t = \frac{1}{B}\sum_{b=1}^{B} f_b(X_t) \quad (14)$$

where:
$f_b(X_t)$ is the prediction from the b-th decision tree,
B is the number of trees in the forest,
X_t is the set of economic variables used to predict inflation.
Each decision tree uses a subset of predictors, preventing overfitting and improving generalization.

Support Vector Machine (SVM) for Inflation Rate Prediction
SVM is a powerful **supervised learning model** used for both **classification and regression (Support Vector Regression - SVR).** It works by **finding the optimal hyper plane** that maximizes the margin between classes or minimizes the error in regression. Cortes & Vapnik (1995)

Mathematical Formulation (SVR for Inflation Prediction)

Given a training dataset $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$), where X_i are the input features (macro indicators) and Y_i are the inflation rates, the objective is to find a function f(X) such that:

$$Y = w^T\phi(X) + b \quad (15)$$

where:
w is the weight vector,
$\phi(X)$ is a kernel function mapping features into a higher-dimensional space,
b is the bias term.
The optimization problem for SVR minimizes the error within a margin ϵ, using slack variables ξ_i to handle violations:

$$\min_{w,b,\xi} \frac{1}{2}\parallel w \parallel^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$

subject to:

$$Y_i - w^T\phi(X_i) - b \le \epsilon + \xi_i$$
$$w^T\phi(X_i) + b - Y_i \le \epsilon + \xi_i^*$$
$$\xi_i, \xi_i^* \ge 0$$

where C is the regularization parameter controlling the trade-off between margin width and prediction accuracy.
K-Nearest Neighbors (KNN) for Inflation Rate Prediction
KNN is a non-parametric, instance-based learning method where predictions are made based on the majority vote (classification) or average (regression) of the K nearest neighbors in the training data. Altman (1992).
Mathematical Formulation
For a given input X_t, the predicted inflation rate is:

$$\hat{Y}_t = \frac{1}{K}\sum_{i \in N_k} Y_i \quad (16)$$

where N_k represents the set of K nearest neighbors (determined by a distance metric such as Euclidean or Manhattan distance).

RESULTS AND DISCUSSION
The outcomes of the empirical analysis based on monthly inflation data obtained from the Central Bank of Nigeria's official website (https://www.cbn.gov.ng/rates/inflrates.html). The predictive performance of six models was evaluated using standard performance metrics. The comparative results, summarized in the tables below, provide insights into the strengths and limitations of each modeling approach in forecasting Nigeria's inflation rate.

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Table 1: Model Performance Metrics

	MSE	RMSE	MAE	R^2
Random Forest	2.6571	1.6301	1.02735	0.93040
SVM	6.9317	2.6328	1.31485	0.81844
KNN	5.2210	2.2846	1.22891	0.86325
Vasicek	90.0499	9.4894	7.37832	-1.35863
CIR	838.4134	28.9554	20.55378	-20.96011
GBM	8.0110E+58	8.9517E+28	5.90E+28	-2.10E+57

Table 1 presents the performance metrics—Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2)—used to evaluate the predictive accuracy of six different models for forecasting inflation rates in Nigeria. Random Forest outperformed all other models with the lowest MSE (2.6571), RMSE (1.6301) MAE (1.02735), and highest R^2 (0.93040). SVM and KNN also showed reasonable accuracy, while the stochastic models, especially CIR and GBM, performed poorly. This highlights the superior predictive capability of machine learning models.

Table 2: Detailed Metrics for each Model

	Target	Precision	Recall	F1 Score	Accuracy	Support
Random Forest	Down	0.929	0.963	0.945	0.942	27
Random Forest	Up	0.958	0.92	0.939	0.942	25
SVM	Down	0.963	0.963	0.963	0.962	27
SVM	Up	0.96	0.96	0.96	0.962	25
KNN	Down	0.862	0.926	0.893	0.885	27
KNN	Up	0.913	0.84	0.875	0.885	25
Vasicek	Down	0.538	0.519	0.528	0.519	27
Vasicek	Up	0.5	0.52	0.51	0.519	25
CIR	Down	0.35	0.259	0.298	0.365	27
CIR	Up	0.375	0.48	0.421	0.365	25
GBM	Down	0.519	0.519	0.519	0.5	27
GBM	Up	0.48	0.48	0.48	0.5	25

Table 2 shows how well each model predicted whether inflation would go up or down. Key metrics include precision (how often the model was right when it predicted a change), recall (how well it caught actual changes), and the F1 score, which balances the two. Accuracy shows the overall success rate, and support tells how many cases were in each category. Among the models, SVM performed best with high and consistent scores across all metrics (96% accuracy), followed closely by Random Forest. KNN did fairly well but wasn't as strong. The stochastic models—Vasicek, CIR, and GBM—struggled, showing much lower accuracy and weaker performance in predicting inflation direction.

Table 3: Hyperparameter Settings and Search Space for Machine Learning Models

Model	**Hyperparameter**	**Description**	**Search Space**
Random Forest	n_estimators	Number of trees	[100, 200, 500]
	max_depth	Maximum depth of trees	[10, 20, None]
	min_samples_split	Min samples for split	[2, 5, 10]
SVM	C	Regularization parameter	[0.1, 1, 10, 100]
	epsilon	Epsilon in loss function	[0.01, 0.1, 0.5]
	kernel	Kernel type	['linear', 'rbf']
KNN	n_neighbors	Number of neighbors	[3, 5, 7, 9]
	weights	Weight function	['uniform', 'distance']

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Table 3 outlines the key hyperparameters tuned for each machine learning model, along with their descriptions and search ranges. Hyperparameter tuning was conducted using grid search cross-validation with 5-fold splits to avoid overfitting and to ensure robust model generalization.
Stochastic models like CIR and GBM performed poorly, which isn't surprising given Nigeria's complex and often unpredictable inflation history. Their rigid assumptions— such as steady mean reversion or exponential growth—fail to capture the reality of policy shifts, structural breaks, and erratic volatility. This further supports the shift toward more adaptive machine learning approaches

Conclusion
The findings of this study highlight the superior performance of machine learning models—most notably the Random Forest algorithm—over traditional stochastic approaches in forecasting Nigeria's inflation rate. The results affirm the value of data-driven, nonlinear methods in navigating the complexities of macroeconomic prediction. Whereas stochastic models yield a robust theoretical framework, practical predictive power is constrained by stiff structural assumptions. The practical implication is clear: Nigerian policymakers and financial institutions must adopt machine learning approaches to enhance inflation management and economic stability. This shift toward data-driven forecasting can serve as a catalyst for more effective economic planning, fostering resilience and better respond to both domestic and global challenges.

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