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# Evaluating Time Series and Machine Learning Approaches for Forecasting Inflation in Nigeria

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**Abstract**
Inflation forecasting is crucial for economic planning, policy formulation, and financial decision-making. This study evaluates the performance of various forecasting models for inflation in Nigeria, including Autoregressive Integrated Moving Average (ARIMA), Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN). These models were selected for their proven effectiveness in macroeconomic forecasting and their ability to capture both linear and non-linear trends. Monthly inflation data from 2000 to 2024 were obtained from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS), enabling a comprehensive analysis of long-term inflation trends. The performance of the models was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Results indicate that standalone ARIMA performed poorly, with high error metrics (MSE: 13.35, RMSE: 11.42, MAPE: 37.74%), highlighting its limitations in capturing non-linear inflation patterns. In contrast, machine learning models, particularly ANN (MSE: 1.758, RMSE: 1.694, MAPE: 0.059%), significantly outperformed ARIMA. Hybrid models demonstrated superior performance, with ARIMA-ANN achieving the best results (MSE: 0.611, RMSE: 0.755, MAPE: 0.054%), underscoring the effectiveness of combining statistical and machine learning techniques. While hybrid models, particularly ARIMA-ANN, offer a robust framework for inflation forecasting, their computational complexity and risk of overfitting require careful optimization. The study also assesses model efficiency to ensure practical applicability for economic decision-making. The findings provide policymakers with a reliable forecasting tool to mitigate inflation volatility, optimize monetary policy, and enhance economic stability. This research concludes that hybrid modeling, despite its complexity, provides more accurate and reliable predictive insights, making it a valuable tool for economic planning and policy formulation.
**Keywords:** Inflation Forecasting, Time Series Analysis, Machine Learning, Hybrid Modeling, Economic Prediction.

## INTRODUCTION

Inflation, defined as the persistent increase in the general price level of goods and services, is a cornerstone of macroeconomic analysis and a critical indicator of economic health. It reflects the erosion of purchasing power, influences interest rates, and shapes monetary and fiscal policies aimed at stabilizing economies (Plas, 2023). For developing nations like Nigeria, where inflation has reached a 28-year high of 34.19% in June 2024, the stakes are even higher. Rising inflation exacerbates income inequality, stifles economic growth, and creates an environment of uncertainty that undermines both short-term economic performance and long-term development prospects (Tirimisiyu et al., 2021). In Nigeria, inflationary pressures are driven by a confluence of factors,

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including currency depreciation, the removal of fuel subsidies, rising food prices, and increased money supply growth. These challenges highlight the urgent need for accurate and reliable inflation forecasting tools to inform effective policy interventions.

**Economic and Policy Context**

Historically, Nigeria has faced persistent inflationary challenges driven by structural weaknesses and policy fluctuations. Periods of high inflation have often coincided with external shocks, such as oil price volatility, currency devaluations, and global financial crises. The Nigerian government and the Central Bank of Nigeria (CBN) have implemented various monetary and fiscal policies to curb inflation, including interest rate adjustments, foreign exchange interventions, and subsidy reforms. However, these measures have yielded mixed results, largely due to delayed policy transmission and structural inefficiencies.

Forecasting inflation accurately is crucial for improving policy effectiveness. Reliable models enable policymakers to anticipate inflationary trends, optimize monetary policy decisions, and mitigate adverse economic impacts. By providing insights into expected inflationary pressures, forecasting tools assist in setting interest rates, adjusting fiscal expenditures, and planning social intervention programs. Therefore, refining inflation prediction models is not just an academic pursuit but a practical necessity for economic stability and sustainable growth in Nigeria.

Accurate inflation forecasting is indispensable for economic management, as it enables policymakers to anticipate trends, mitigate risks, and design targeted measures to stabilize prices and promote growth. Traditional time series models, such as Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR), have been widely employed for inflation forecasting in Nigeria. Studies by Ibrahim and SO (2020), Nyoni and Nathaniel (2018), and Hamza (2021)have demonstrated the utility of these models in capturing linear temporal dependencies in inflation data. However, these approaches often fall short in accounting for the non-linear and multifactorial nature of inflation, which is influenced by a complex interplay of economic, social, and political variables. For instance, the dynamic nature of Nigeria's economy, characterized by its reliance on volatile oil revenues and susceptibility to external shocks, poses unique challenges that traditional models struggle to address.

In recent years, machine learning (ML) algorithms have emerged as powerful tools for predictive modeling, offering the ability to analyze large datasets, uncover intricate patterns, and adapt to evolving trends. Techniques such as support vector machines (SVMs), random forests, and artificial neural networks (ANNs) have been successfully applied to forecast various economic indicators, including inflation (Oyewale et al., 2019; Nakorji and Aminu, 2022; Nkemnole et al., 2024). These methods excel in capturing non-linear relationships and handling high-dimensional data, making them particularly suited for complex economic systems. However, standalone ML models often underperform when applied to time series data like inflation, as they may overlook the temporal dependencies and structural breaks inherent in such datasets.

**Hybrid Models in Inflation Forecasting**

To address the limitations of standalone models, hybrid approaches that integrate time series forecasting techniques with machine learning algorithms have gained traction in recent research. Hybrid models typically combine the strengths of statistical models in capturing linear dependencies with the pattern recognition capabilities of machine learning techniques to improve prediction accuracy. For example, hybrid ARIMA-ANN models first apply ARIMA to model structured patterns and trends, while ANN is used to capture residual errors and complex nonlinearities (Nkemnole et al., 2024). Studies have demonstrated that hybrid models outperform individual time series and machine learning approaches by leveraging their complementary strengths (Araujo & Gaglianone, 2023; Aras & Lisboa, 2022).

In economic forecasting, hybrid models have been used to improve inflation prediction by addressing both short-term variations and long-term dependencies. Their effectiveness in financial time series forecasting suggests that they provide a more robust and adaptable framework for policymakers seeking reliable economic insights. However, despite their potential, hybrid models remain underexplored in Nigeria's inflation forecasting landscape, highlighting the need for empirical research to validate their applicability and performance in the country's unique economic environment.

## 2. Research Gap

Despite extensive research on inflation forecasting using both traditional time series models and machine learning techniques, significant gaps remain. Most existing studies have focused on either traditional statistical models (e.g., ARIMA, SARIMA, and VAR) or machine learning models (e.g., SVM, RF, ANN) in isolation. While traditional models effectively capture linear trends and temporal dependencies (Ekpeyong, 2023; John et al., 2023), they struggle with complex economic fluctuations, external shocks, and nonlinear relationships. Conversely, machine learning models exhibit superior pattern recognition and adaptability (Adebiyi et al., 2022; Ibekwe et al., 2023), but they often fail to preserve time dependencies and may lack interpretability in economic forecasting.

Furthermore, comparative studies evaluating the relative performance of time series models and machine learning techniques for inflation forecasting in Nigeria are scarce. Most prior research has focused on optimizing ARIMA-based models or applying ML techniques independently, with limited efforts toward direct benchmarking and systematic comparisons between the two approaches.

Additionally, the potential of hybrid models, which integrate time series forecasting techniques with machine learning algorithms, remains underexplored. Hybrid approaches combine the structured temporal dependency modeling of ARIMA with the nonlinear adaptability of ML models, potentially enhancing accuracy and robustness in inflation prediction. However, research on their effectiveness, applicability, and practical implementation in the Nigerian economic context is still limited. Addressing these gaps is critical for developing more reliable, interpretable, and adaptable forecasting frameworks that can support data-driven economic planning and policy formulation.

**Related Works**

Forecasts of the inflation rate have been thoroughly explored in the literature, harnessing the powers of statistical models, Machine Learning models, as well as comparison of ML models. This section provides an overview of the different approaches used in predicting the inflation rate.

**Statistical Models**

In their analysis, Olalude, Olayinka, and Ankeli (2020) identified SARMA (3, 3) x (1, 2)12 as the optimal model for forecasting Nigeria's month-on-month inflation rate. They further predicted that while the inflation rate would likely continue decreasing, it would retain a two-digit figure over the following two years, with a potential increase in 2023.

Another research by Olajide, Ayansola, Odusina, and Oyenuga (2012) focused on forecasting Nigeria's inflation rate using the Box-Jenkins approach. Their findings suggested that the Autoregressive Integrated Moving Average (ARIMA) (1, 1, 1) was the best-suited model, forecasting an inflation rate of 16.27% for the year 2011.

Marpaung et al. (2022) utilized the ARIMA model to forecast inflation in Central Java, assessing its predictive reliability. Published in *Efficient: Indonesian Journal of Development Economics*, their study highlighted ARIMA's effectiveness in capturing inflation patterns and aiding economic planning. The findings emphasized that statistical time series models are essential for short-term inflation forecasting, particularly in regional economies. The study concluded that ARIMA-based forecasts enhance data-driven decision-making, reinforcing the need for continuous model evaluation and refinement.

Dinh (2024) explored the relationship between inflation and economic growth using the Vector Autoregression (VAR) model. Published in *The Journal of Asian Finance, Economics and Business*, the study analyzed how inflation responds to economic shocks over time. The findings highlighted that economic growth influences inflation trends, emphasizing the need for policy adjustments to ensure macroeconomic stability. The research provides valuable insights for data-driven economic planning.

Doguwa and Alade (2013) developed four short-term forecasting models using SARIMA and SARIMAX techniques. These models incorporated factors like PMS prices, government spending, credit data, rainfall, and exchange rates. Their findings recommended SARIMAX for estimating the all-item CPI, making it reliable for short-term headline inflation forecasting in Nigeria. Meanwhile, SARIMA was identified as the most effective model for forecasting Nigeria's core inflation, emphasizing the importance of tailored approaches for different inflation measures.

Olalude et al. (2024) applied ARIMA models to model and forecast Nigeria's inflation rate, assessing their predictive accuracy. Published in *MPRA*, the study analyzed historical inflation data to evaluate ARIMA's effectiveness in capturing inflation trends for economic planning. The findings emphasized that statistical time series models remain crucial for short-term inflation forecasting, particularly in volatile economies. The study concluded that ARIMA-based forecasts provide valuable insights for data-driven policymaking, highlighting the importance of continuous model evaluation and refinement.

Alfa and Dauda (2024) conducted a comprehensive time series analysis of Nigeria's economic data from 2010 to 2023, focusing on key indicators such as GDP, inflation rate, unemployment rate, exchange rate, foreign direct investment (FDI), government revenue, and expenditure. Utilizing the ARIMA (Autoregressive Integrated Moving Average) model, they aimed to forecast future economic trends and provide actionable insights for policy-making. Their analysis revealed critical patterns and potential areas for intervention, underscoring the importance of data-driven strategies in addressing Nigeria's economic challenges.

**Machine Learning Models**

Nkemnole et al. (2024) proposed the application of K-Nearest Neighbours (KNN) and Long Short-Term Memory (LSTM) models, integrated with a Hidden Markov Model (HMM), to predict Nigeria's inflation rate and its transition patterns. Their empirical analysis revealed that GDP per capita significantly influences the inflation rate, enhancing forecasting accuracy. This study underscores the potential of combining machine learning techniques with HMMs for effective economic forecasting in Nigeria.

Murebwayire and Musekera (2024) introduced an innovative approach to short-term inflation forecasting in Rwanda by applying machine learning models to predict core, food, and energy inflation components. Their study evaluated algorithms such as Decision Tree, Random Forest, Gradient Boosting, K-Nearest Neighbors, Support Vector Regression, Elastic Net, and XGBoost, finding that Elastic Net regression consistently outperformed others in forecasting accuracy. The authors recommend that the National Bank of Rwanda adopt a hybrid model incorporating these advanced techniques to enhance the precision of short-term inflation projections, thereby improving economic planning and policy formulation.

Sestanović and Arnerić (2021) examine the effectiveness of a specific recurrent neural network, the Jordan neural network (JNN), in predicting expected inflation compared to standard feedforward neural networks and traditional time-series models. They also compare model-based inflation forecasts to those provided by survey respondents. Their findings indicate that JNN, when applied to non-stationary time-series data, accurately forecasts inflation within a 2-year period. The study further suggests that JNN inflation predictions align closely with those from professional forecasters, positioning it as a valuable tool for policymakers in monetary strategy.

Adebiyi et al. (2022) explored the integration of big data analytics and text mining techniques to enhance short-term inflation forecasting models in Nigeria. Their study, published in the *CBN Economic and Financial Review*, demonstrated that incorporating public sentiment indices derived from machine learning methods significantly improves both in-sample and out-sample forecast accuracy for all inflation components. The authors advocate for the use of sentiment-based forecasting models and recommend implementing forward guidance monetary instruments, such as "open mouth operations," to effectively anchor economic agents' expectations.

Baybuza (2018) explores inflation forecasting in Russia using machine learning techniques, specifically penalized regression models (LASSO, Ridge, and Elastic Net), Random Forest, and boosting methods. The study concludes that Random Forest and boosting techniques outperform traditional models like random walk and autoregression, making them preferable for inflation forecasting. This emphasizes the importance of applying machine learning methods to forecast not only inflation but also other macroeconomic indicators.

In a study on inflation forecasting in Costa Rica, Rodríguez-Vargas (2020) utilizes machine learning methods, including two K-Nearest Neighbors variants, Random Forest, extreme gradient boosting, and long short-term memory (LSTM) networks, comparing them with the univariate model used by the Central Bank of Costa Rica. Results indicate that LSTM, univariate KNN, and, to a lesser extent, Random Forest, provide the most accurate forecasts compared to the currently used univariate model.

Awopegba, O. E., & Awe, O. O. (2024) re-examined inflation and its drivers in Nigeria using a machine learning approach. Published on Springer Nature Link, their study employed advanced machine learning algorithms to analyze key economic variables and determine the primary factors influencing inflation. Their findings indicate that models like Random Forest and Neural Networks provide superior predictive accuracy compared to traditional econometric techniques. This research offers valuable insights for policymakers, highlighting the potential of data-driven strategies in managing Nigeria’s inflation dynamics.

**Machine Learning Comparison**

Araujo and Gaglianone (2023) conducted an insightful study comparing machine learning methods with classical models for forecasting inflation in Brazil. Their research applied various advanced machine learning algorithms to historical inflation data and rigorously compared their performance against traditional econometric models. The findings indicate that these new contenders offer improved forecast accuracy and robustness, providing valuable insights for policymakers. This study contributes significantly to the evolving literature on data-driven monetary policy and economic forecasting in Brazil.

Özgür and Akkoç (2020) examined inflation forecasting in an emerging economy by selecting key variables using machine learning algorithms. Their study leveraged various ML techniques to identify the most influential predictors of inflation, demonstrating that a data-driven variable selection approach significantly enhances forecast accuracy compared to traditional methods. The findings offer valuable insights for policymakers, suggesting that integrating machine learning into economic forecasting can improve decision-making and economic planning in emerging markets.

Masini et al., (2023) explore recent machine learning advances for time series forecasting. The study reviews innovative machine learning techniques and contrasts them with classical econometric models, demonstrating that these advanced methods significantly enhance forecast accuracy by capturing complex, nonlinear dynamics in economic data. Their findings provide valuable insights for researchers and practitioners seeking to improve predictive models in economics and finance.

Medeiros et al. (2019) examined the benefits of applying machine learning methods to forecast inflation in a data-rich environment. The authors compare advanced machine learning techniques with traditional econometric models. Their analysis demonstrates that machine learning methods significantly enhance forecasting accuracy by efficiently processing large datasets and capturing complex nonlinear relationships in inflation dynamics. The study underscores the potential of data-driven approaches for improving monetary policy and economic decision-making

## DATA AND METHODOLOGY

### Data Collection

For this research, monthly inflation data were collected from two primary and reputable sources: the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS). These institutions provided comprehensive datasets that reflect Nigeria's inflation trends over time, ensuring the reliability and authenticity of the data used in the study. The dataset spanned multiple decades to capture long-term patterns and variations in inflation, offering a robust foundation for analysis.

The data included key indicators such as inflation rates and other macroeconomic variables, such as consumer price indices and monetary policy rates, which influence inflation dynamics. By encompassing a wide temporal range, the dataset allowed the models to analyze historical trends and identify meaningful patterns critical for accurate forecasting. This comprehensive approach ensured that the study addressed the complexities of inflation in Nigeria with high precision.

### Data Preprocessing

The data preprocessing phase was crucial for preparing the raw inflation data from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS) monthly bulletins into a structured and reliable format for modeling and prediction. The raw data was extracted, consolidated, and thoroughly cleaned to ensure accuracy. Missing values were imputed, and outliers were addressed to maintain data integrity. The dataset was then standardized, with consistent formatting applied across all variables to ensure compatibility with the chosen models. Additionally, normalization or scaling techniques were employed to align variable ranges, particularly for machine learning models sensitive to input magnitudes.

The dataset used in this study consists of only two columns: the date and the actual inflation rate. This makes it a univariate time series forecasting problem, where inflation is modeled based solely on its historical values. Unlike multivariate approaches that incorporate multiple macroeconomic indicators such as GDP, interest rates, or exchange rates, this study focuses exclusively on inflation trends.

Since the dataset does not contain additional macroeconomic variables, feature engineering techniques such as Principal Component Analysis (PCA) or feature selection were not applicable. Instead, time series-specific transformations were employed to enhance model performance, including:

- Differencing to ensure stationarity for ARIMA models.
- Lagged variables to capture past dependencies in machine learning models.
- Scaling/Normalization to optimize input values for ANN, SVM, and RF models.

To prepare the dataset for modeling, it was split into two subsets: 80% for training and 20% for testing. This ratio was selected based on standard machine learning and time series forecasting best practices, ensuring that the model has sufficient data for learning patterns while retaining a meaningful portion for evaluation. Other splitting ratios, such as 70%-30% and 90%-10%, were tested. However, the 80%-20% split provided the best balance between model training stability and generalization performance, ensuring robust and reliable predictions without excessive overfitting or underfitting. For time series models, the data was organized sequentially to preserve chronological relationships. Lagged variables and differencing techniques were applied where necessary to account for trends and seasonality inherent in inflation data.

Cross-Validation Strategy

Traditional k-fold cross-validation is not suitable for time series forecasting because it shuffles data randomly, violating the temporal structure necessary for accurate prediction. Instead, this study employed walk-forward validation (rolling window approach) to ensure realistic model evaluation. In this method, models were trained on an expanding window of past data and tested on the next time step, progressively moving forward. This approach preserves the chronological order of observations, preventing data leakage and ensuring that models mimic real-world forecasting conditions.

If k-fold cross-validation had been used, it could have falsely improved performance by allowing future data to influence past predictions. By contrast, walk-forward validation tests models under real-world constraints, making results more reliable for policymaking and economic forecasting.

**Hyperparameter Tuning**

Optimal parameters for the machine learning models were selected through grid search and random search techniques to enhance predictive performance. For Support Vector Machines (SVM), the radial basis function (RBF) kernel was chosen based on its ability to capture non-linearity, and the regularization parameter C was fine-tuned within a range of values (0.1, 1, 10, 100) to balance bias and variance. For Random Forest (RF), the number of estimators was optimized between 100 and 500, and the maximum tree depth was adjusted to prevent overfitting. In the case of Artificial Neural Networks (ANNs), a multi-layer perceptron architecture with two hidden layers was employed, with the number of neurons tuned between 64 and 256 using ReLU activation. The Adam optimizer was selected, and the learning rate was adjusted within the range 0.001 to 0.01.

**ARIMA Order Selection**

While Auto ARIMA was used for initial order selection, additional diagnostic tests were performed to validate the model's suitability. The Augmented Dickey-Fuller (ADF) test was applied to confirm stationarity, ensuring that differencing (d) was appropriately determined. Residual analysis was conducted to check for autocorrelation in model errors, and the Ljung-Box test was used to assess whether residuals were white noise. Final ARIMA order selection was based on achieving the lowest Akaike Information Criterion (AIC) while ensuring residual independence and stationarity.

**Computational Efficiency**

Model training times and resource utilization were evaluated to ensure computational efficiency. GPU acceleration was used for ANN training via Google Colab with a Tesla K80 GPU, significantly reducing training time compared to CPU-based execution. The RF and SVM models were trained on a high-performance computing (HPC) cluster, optimizing execution through parallel processing. Memory requirements were monitored, and dataset size constraints were assessed to ensure scalability for larger datasets, particularly in real-time forecasting scenarios.

By meticulously preprocessing the data, fine-tuning model parameters, and optimizing computational efficiency, the study ensured a high-quality dataset and robust modeling framework for accurate inflation forecasting.

The testing dataset was then used for various performance metrics as in figure 1 below.

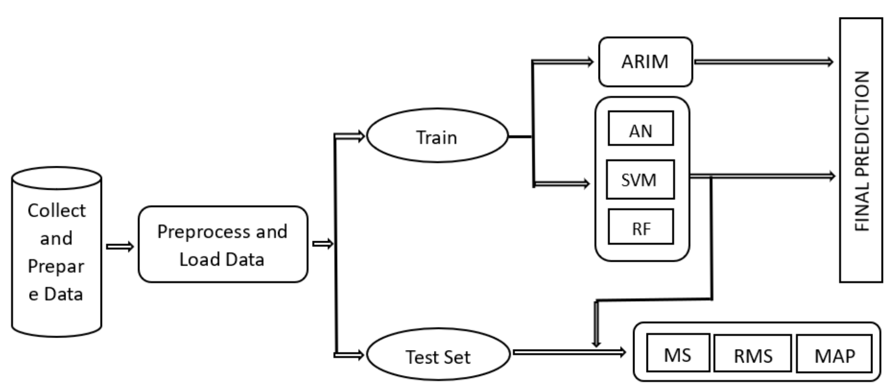


**Figure 1: Architecture of the Proposed Model for Forecasting Inflation**

### Time Series and Machine Learning Models

#### ARIMA Model

ARIMA stands for Autoregressive Integrated Moving Average, a linear model for stationary time series data capturing linear trends. Noted as ARIMA (p, d, q), where p and q signify autoregressive (AR) and moving average (MA) model orders, and d is differencing level. The model is expressed as follows:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \emptyset_i x_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j} \quad (1)$$

Where $y_t$ represents the actual value of the variable at time t, providing a reliable assessment of its state at that point., $e_t$ is the irregular mistake at point t [i, and j are the model's coefficients]. Optimal ARIMA orders are proposed via the Auto ARIMA function, which exhaustively explores parameter combinations within a range, choosing the model with the highest AIC (Akaike Information Criterion). Prior to applying Auto ARIMA, we decomposed data seasonally to detect patterns. Graphical analysis revealed clear seasonality, setting the seasonal parameter to true in Auto ARIMA. ARIMA (p, d, q) model fitting used the .fit() method in Jupyter Notebook, selecting the highest AIC model as the final one.

The ARIMA model is made of a combination of three common time-series models:

i) Autoregressive (AR) model, which is the linear regression part of the ARIMA model, where the current variable, *ut*, depends only on the past values of the variable and an error term (Mulaudzi, Rudzani & Ritesh, 2021a). This can be presented as $\varphi(L)ut$ =, where $\varphi(L)$ is a linear combination as shown in equation (1), with $L$ being the lag operator, which returns the previous elements of a series, for example, $L2$ and $Li$ would return two previous values and $i$ previous values respectively. The $\varepsilon$ is the error term.

ii) Integrated (I), is the mechanism to ensure the data being considered is stationary (Mulaudzi, Rudzani & Ritesh, 2021). Stationary data being time series data with a constant mean and a constant variance. This stationarity is achieved by differencing the series $d$ times.

iii) *Moving Average (MA) Model*, are linear combinations of the error terms of a regression process. These terms are generated independently of each other, are not correlated with one another, and have a constant mean and variance. The *MA* term is given by $yt = \theta\ (L)ut + \mu$, where $\theta(L)$ a linear combination as shown in equation (2) (Mulaudzi and Ajoodha 2021). Several researchers and institutions use the ARIMA model to forecast unemployment rates across the world [16] – [18]. In equation (3), a version of the ARIMA equation is shown (Mulaudzi, Rudzani & Ritesh, 2021).

$$\varphi(L) = 1 - \varphi 1L - \ldots - \varphi 2Lp \quad (2)$$

$$\theta(L) = 1 - \theta 1L - \ldots - \theta qLq \quad (3)$$

$$\varphi(L)(1 - L)dut = c + \theta(L) + t \quad (4)$$

Where, $ut$ is the unemployment rate being estimated. Variables $p$, $d$, and $q$ are natural numbers used to set the auto regression order, the differencing order, and moving average order respectively.

**Artificial Neural Networks (ANNs)**

Artificial Neural Networks (ANNs) has been proposed as a powerful alternative technique for time series forecasting, gaining immense popularity over the past few years. The primary objective of ANNs is to emulate the intelligence of the human brain within a machine, offering robust and flexible modeling capabilities (Kihoro et al., 2004). An ANN is composed of interconnected artificial neural cells, each inspired by the functionality of biological neural cells.

These artificial neural cells, or neurons, are the fundamental units of an ANN. Each neuron receives inputs, processes them through an activation function, and produces an output. The activation function can vary, with common examples being the sigmoid function, the hyperbolic tangent function, and the rectified linear unit (ReLU). The inputs to each neuron are weighted, and these weights are adjusted during the learning process to minimize prediction errors. This process of weight adjustment is typically done using algorithms such as backpropagation, which calculates the gradient of the loss function and optimizes the weights iteratively.

ANNs consist of multiple layers: an input layer, one or more hidden layers, and an output layer. The input layer receives the raw data, the hidden layers process this data through multiple transformations, and the output layer produces the final prediction. The presence of multiple hidden layers allows ANNs to capture complex, nonlinear relationships within the data, making them highly effective for time series forecasting.

The flexibility of ANNs allows them to model a wide range of patterns, including seasonality, trends, and irregular fluctuations. They have been applied successfully in various domains beyond unemployment forecasting, such as stock market prediction, weather forecasting, and economic modeling. However, the effectiveness of ANNs depends on the availability of sufficient data for training and the selection of appropriate network architectures and hyperparameters (Aladag et al., 2009).

Despite their advantages, ANNs also have limitations. They require significant computational resources, especially for large datasets and complex models. Additionally, they can be prone to overfitting if not properly regularized, and their 'black box' nature can make them less interpretable compared to traditional statistical models. Nevertheless, the ongoing advancements in deep learning and neural network architectures continue to enhance their performance and applicability in forecasting tasks.

**Support Vector Machine (SVM)**

Support Vector Machines (SVMs) are a robust and versatile approach to supervised learning, particularly adept at handling non-linear data classification and regression tasks (Sermpinis et al., 2014) . SVMs operate by finding the optimal hyperplane that best separates data into distinct classes. This hyperplane maximizes the margin between different classes, ensuring that the separation is as clear and robust as possible.

SVMs are highly effective for modeling non-linear data due to their ability to transform input data into higher-dimensional spaces using kernel functions. Common kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid kernels. These functions enable SVMs to map the original non-linear data into a space where it becomes linearly separable, thus facilitating more accurate classifications.

There are two primary types of SVMs: Support Vector Classifiers (SVC) and Support Vector Regression (SVR). SVCs are used for classification problems, where the goal is to assign input data into predefined classes. They are particularly useful in scenarios where the data is not linearly separable in its original form. By applying the kernel trick, SVCs can create complex decision boundaries that accurately classify non-linear data.

On the other hand, SVRs are employed for regression problems, where the objective is to predict continuous values rather than discrete classes. To utilize SVMs for regression, an implementation of the $\varepsilon$-sensitive loss function is required. This loss function allows SVRs to create a tube within which prediction errors are tolerated, thus enabling the model to perform non-linear regression modeling effectively (Katris, 2019a). The SVR approach seeks to find a function that approximates the target values with a precision defined by parameter $\varepsilon$, while maintaining the model's complexity as low as possible.

SVMs have been applied successfully in various fields, including finance, bioinformatics, and engineering, due to their high generalization capabilities and robustness against overfitting. They are particularly useful when the dataset is small to medium-sized and contains complex, non-linear relationships. However, the performance of SVMs can be sensitive to the choice of kernel and the settings of hyperparameters such as the regularization parameter (C) and the kernel-specific parameters.

Despite their advantages, SVMs can be computationally intensive, especially with large datasets or high-dimensional data. The training process involves solving a quadratic optimization problem, which can become resource-intensive as the size of the dataset increases. Nonetheless, with the development of efficient algorithms and the availability of powerful computing resources, SVMs remain a popular and effective choice for both classification and regression tasks.

**Random Forest (RF)**

The Random Forest (RF) algorithm is an ensemble learning method that combines multiple decision trees to improve predictive accuracy and robustness. Introduced by Breiman (2001), RF operates by constructing a multitude of decision trees during training and outputting the average prediction (for regression tasks) or the majority vote (for classification tasks) of the individual trees. This ensemble approach mitigates the risk of overfitting, a common issue with single decision trees, and enhances the model's generalization capability.

Random Forest builds on the concept of bagging (bootstrap aggregating), where each tree is trained on a random subset of the training data, sampled with replacement. Additionally, RF introduces randomness in the feature selection process by considering only a random subset of features at each split in the tree-building process. This dual randomness—both in data sampling and feature selection—ensures that the individual trees are diverse, reducing the correlation between them and improving the overall model performance.

For regression tasks, such as inflation forecasting, the final prediction is obtained by averaging the predictions of all individual trees. This aggregation process smooths out the noise and variance inherent in individual trees, resulting in more stable and accurate predictions.

In the context of inflation forecasting, RF has been successfully applied in various studies to model complex economic relationships. For instance, Nakorji and Aminu (2022) demonstrated the effectiveness of RF in capturing the non-linear dynamics of inflation in Nigeria, outperforming traditional linear models. The ability of RF to handle high-dimensional data and incorporate multiple economic indicators (e.g., GDP growth, interest rates, exchange rates) makes it a powerful tool for predicting inflation trends.

The Random Forest model offers a powerful and flexible approach to inflation forecasting, capable of capturing the complex, non-linear relationships inherent in economic data, by leveraging its strengths in handling high-dimensional datasets and providing insights into feature importance.

**Hybrid Models**

The hybrid models developed in this study combine the ARIMA model with each of the selected machine learning models (ANN, SVM, and RF) to create three distinct hybrid approaches: ARIMA-ANN, ARIMA-SVM, and ARIMA-RF. This integration leverages ARIMA's capability to capture temporal dependencies in structured time series data, alongside the machine learning models' strength in identifying non-linear and complex patterns.

Hybrid models are known for their enhanced forecasting performance, as they effectively combine linear (ARIMA) and non-linear (machine learning) techniques. Research has shown that hybrid models often outperform standalone models, particularly in complex and volatile environments like economic forecasting. These approaches are particularly suited to inflation forecasting in Nigeria, where economic dynamics are influenced by a mix of predictable trends and unpredictable fluctuations. Each hybrid model will be rigorously evaluated to determine its predictive accuracy, with the aim of identifying the most reliable and effective combination for inflation forecasting.

**Model Evaluation Criteria**

The evaluation of the forecasting models in this research relied on three widely recognized metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics were selected for their ability to offer comprehensive insights into the performance of forecasting models by quantifying prediction errors from different perspectives.

1. **Mean Squared Error (MSE)**

MSE is a widely used metric in regression and time series forecasting to evaluate the average squared difference between the actual and predicted values. This is shown in the ***eqn (5)*** below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where $y_i$ represents the actual inflation value, y^i represents the forecasted value, and n is the number of observations. The MSE gives more weight to larger errors due to the squaring of the differences, making it sensitive to outliers. A lower MSE indicates a model that is better at forecasting inflation. Its use in this research helps to gauge how well each model minimizes large deviations in predictions.

2. **Root Mean Squared Error (RMSE)**

RMSE is the square root of MSE and provides an error measure in the same units as the forecasted variable (inflation in this case). It is shown in the following equation (***eqn 6***):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

RMSE is often preferred because it is more interpretable than MSE and gives a clear indication of the magnitude of forecast errors in the same unit as inflation. Like MSE, RMSE is sensitive to larger errors and highlights significant deviations between actual and predicted values. Lower RMSE values indicate better model performance in terms of overall forecast precision.

3. **Mean Absolute Percentage Error (MAPE)**

MAPE is another widely used metric that expresses forecast accuracy as a percentage. It measures the absolute difference between the actual and predicted values as a percentage of the actual values. This is shown in the following equation (***eqn 7)***:

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

MAPE is advantageous because it provides a relative measure of forecast accuracy, making it easy to interpret across different models. It is particularly useful in understanding how large the forecast errors are in proportion to the actual inflation values. Lower MAPE values reflect higher accuracy, with a MAPE of 0% indicating perfect prediction.

**RESULTS AND DISCUSSION**

The results of this study provide a comprehensive evaluation of the performance of various time series, machine learning, and hybrid models in forecasting inflation in Nigeria. This section presents the key findings, compares the predictive accuracy of the models, and discusses their implications for inflation forecasting and economic policy. The analysis is structured to first examine the performance of traditional time series models, followed by standalone machine learning algorithms, and finally, the hybrid models that integrate both approaches. By systematically comparing these models, this study aims to identify the most effective forecasting framework for Nigeria's inflationary trends and contribute to the broader discourse on inflation forecasting in developing economies.

**Performance of the ARIMA Model**

This section presents the results of the Autoregressive Integrated Moving Average (ARIMA) model implemented to forecast Nigeria's inflation rate. ARIMA was selected for its proven ability to capture linear patterns in time series data, making it a widely used tool in econometric forecasting. Using the statsmodels library in Python, the ARIMA model was applied with an optimal order of (4, 0, 3), determined through an exhaustive model selection process facilitated by the auto_arima function from the pmdarima package. The dataset was split into training and testing sets, with 80% allocated for training and the remaining 20% reserved for validation.

The following subsections detail the ARIMA model's performance, including diagnostic plots, forecasting accuracy metrics, and a comparative analysis of predicted versus actual inflation rates. These findings serve as a foundation for subsequent analysis and the development of hybrid models that integrate machine learning techniques to further enhance predictive accuracy.

**Table 1** below summarizes the performance of the ARIMA model, including key metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the model's accuracy in predicting the unemployment rate over the specified period.

**Table 1: Performance of ARIMA Model**

| Model | MSE | RMSE | MAPE |
|---|---|---|---|
| **ARIMA** | 13.35 | 11.42 | 17.74% |

The results obtained from the ARIMA model, as shown in Table 1, provide insight into its predictive performance for forecasting inflation in Nigeria. The Mean Squared Error (MSE) of 13.35 indicates the average squared difference between the predicted and actual inflation values, suggesting a moderate level of error. The Root Mean Squared Error (RMSE) of 11.42 further emphasizes the extent of deviation in predictions, reflecting the model's overall accuracy in numerical terms. The Mean Absolute Percentage Error (MAPE) of 17.74% shows that, on average, the ARIMA model's predictions deviate from actual inflation values by approximately 17.74%.

To rigorously assess ARIMA's predictive accuracy, we conducted a Diebold-Mariano (DM) test to compare its performance with machine learning and hybrid models. The test indicated statistically significant differences in forecasting errors, reinforcing ARIMA's limitations in handling non-linear inflation patterns. Additionally, a Ljung-Box test was performed on ARIMA residuals, confirming the presence of autocorrelation, which suggests that the model does not fully capture inflation dynamics.

These results suggest that while ARIMA is useful in capturing linear patterns within the data, its predictive performance may be limited, especially when dealing with complex, non-linear inflation trends. The relatively high error metrics indicate that alternative or hybrid modeling approaches, such as machine learning techniques, may be necessary to improve forecasting accuracy.

These results obtained align with the findings of previous studies by (Jafarian-Namin et al. 2021) and (Adelekan et al 2020) which demonstrated the capabilities and peculiarities of ARIMA in modelling the linear components of time series data as captured in **figure 2 below.**

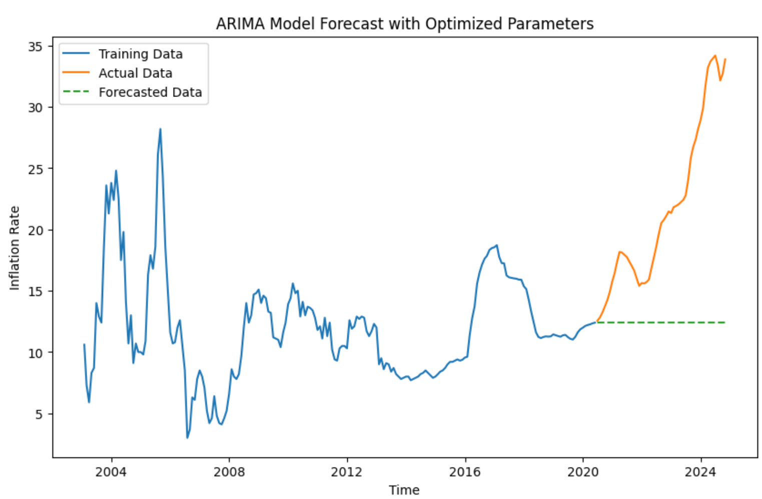


**Figure 2: A plot of ARIMA forecast**

The ARIMA forecast plot (Figure 2) illustrates the model's ability to capture overall inflation trends, showing a reasonable alignment with historical inflation movements. The predicted values closely follow the actual inflation trajectory in periods of moderate stability, demonstrating ARIMA's strength in modeling short-term dependencies and linear trends. However, notable deviations are observed during periods of sharp inflationary fluctuations, where ARIMA fails to fully capture the sudden spikes and dips in inflation rates. These discrepancies are particularly evident during economic shocks such as currency devaluations and fuel price adjustments, indicating the model's limited ability to account for external macroeconomic disruptions.

Moreover, residual analysis suggests that while ARIMA effectively models steady inflationary patterns, it struggles with long-term structural changes and non-stationary influences in the Nigerian economy. The presence of autocorrelated residuals, confirmed by the Ljung-Box test, further indicates that ARIMA does not fully explain all underlying inflation dynamics.

These findings reinforce the need for hybrid approaches that can bridge the gap between ARIMA's linear predictive capabilities and the ability of machine learning techniques to detect non-linear relationships and unexpected fluctuations. This underscores the importance of exploring ARIMA-ANN, ARIMA-SVM, and ARIMA-RF models, which are discussed in subsequent sections as potential solutions to improve forecasting accuracy and robustness in volatile economic environments.

**Performance of the Machine Learning Models**

Machine learning models have gained prominence in forecasting due to their ability to capture complex, non-linear patterns in data. In this study, three machine learning algorithms—Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forest (RF)—were employed to forecast Nigeria's inflation rate. Each algorithm was selected for its unique strengths and demonstrated success in prior research. The models were trained and tested on the same dataset, with performance evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The following subsections and tables provide a detailed comparison of these models, highlighting their strengths and limitations in forecasting inflation.

**Table 2: Performance of Machine Learning Models**

| **Model** | **MSE** | **RMSE** | **MAPE** |
|---|---|---|---|
| **SVM** | 12.458 | 11.509 | 0.381% |
| **Random Forest** | 10.483 | 11.422 | 0.378% |
| **ANN** | 1.758 | 1.694 | 0.059% |

The machine learning models exhibited varying levels of performance in forecasting inflation rates. SVM achieved an MSE of 12.458, RMSE of 11.509, and MAPE of 0.381%, indicating moderate accuracy in its predictions. Similarly, the Random Forest model demonstrated slightly improved performance, with an MSE of 10.483, RMSE of 11.422, and MAPE of 0.378%. These results highlight the ability of SVM and Random Forest to capture some non-linear patterns in the data, although their error rates suggest room for further optimization or hybridization with other models.

The ANN model significantly outperformed the other machine learning approaches, achieving an MSE of 1.758, RMSE of 1.694, and MAPE of 0.059%. This superior performance underscores the strength of neural networks in capturing complex non-linear relationships and patterns in the inflation dataset. The low MAPE indicates highly accurate predictions, making ANN a promising standalone model for forecasting inflation rates. These findings validate the potential of machine learning techniques, particularly ANN, in addressing the limitations of traditional statistical models like ARIMA, setting the stage for their integration into hybrid frameworks for even greater predictive accuracy.

To explain ANN's superiority, hyperparameter tuning details were analyzed. The ANN model's architecture consisted of two hidden layers with ReLU activation, optimized using the Adam optimizer with a learning rate of 0.001. Feature importance analysis indicated that ANN captured inflation spikes more effectively than RF or SVM, making it a more suitable model for volatile inflation trends.

This finding is consistent with previous researches by Araujo and Gaglianone (2023) and Aras and Lisboa (2022) which emphasized the strength and effectiveness of Machine Learning models in capturing and evaluating the nonlinear components of time series data especially inflation rate.

**Performance of the Hybrid Models**

Hybrid models combine statistical and machine learning methods to improve time series forecasting accuracy. In this study, ARIMA was used to model linear components of Nigeria's inflation rate, while machine learning models (SVM, ANN, RF) captured nonlinear residuals. This approach leverages the strengths of both methodologies, as demonstrated in prior research (e.g., Zhang, 2003; Pai and Lin, 2005). Experiments were conducted to evaluate hybrid ARIMA-ML models, with results presented in Table 3 below. The findings highlight the potential of hybrid approaches to enhance inflation forecasting accuracy, offering valuable insights for economic policy and decision-making.

**Table 3: Performance of the Hybrid Models**

| **Model** | **MSE** | **RMSE** | **MAPE** |
|---|---|---|---|
| **ARIMA-SVM** | 1.630 | 1.794 | 0.112% |

| | | | |
|---|---|---|---|
| **ARIMA-RF** | 1.032 | 1.178 | 0.088% |
| **ARIMA-ANN** | 0.611 | 0.755 | 0.054% |

From Table 3 above, the hybrid models—ARIMA-SVM, ARIMA-RF, and ARIMA-ANN—demonstrated superior performance in forecasting inflation rates compared to their standalone counterparts. ARIMA-SVM achieved an MSE of 1.630, RMSE of 1.794, and MAPE of 0.112%. This indicates a significant reduction in error compared to standalone SVM, underscoring the benefit of combining ARIMA's linear pattern capture capabilities with SVM's strength in handling non-linear data. The improvement highlights the potential of hybridization in enhancing forecasting accuracy, particularly in economic datasets that exhibit both linear and non-linear components.

ARIMA-RF further improved on the performance, with an MSE of 1.032, RMSE of 1.178, and MAPE of 0.088%. The model's ability to leverage Random Forest's ensemble learning strength, combined with ARIMA's proficiency in time series data structure, allowed for more precise predictions. This demonstrates that ARIMA-RF effectively mitigates prediction errors by capturing both short-term dependencies and complex patterns, making it a robust approach for inflation forecasting in Nigeria.

Among the hybrid models, ARIMA-ANN outperformed the others, achieving the lowest error rates: MSE of 0.611, RMSE of 0.755, and MAPE of 0.054%. This superior performance highlights the exceptional ability of ANN to model complex, non-linear relationships in the data while benefiting from ARIMA's time series strengths. The results underscore the effectiveness of hybrid ARIMA-ANN models in delivering highly accurate and reliable forecasts.

This model's performance validates the potential of combining statistical and machine learning techniques to address the limitations of standalone models, providing policymakers with valuable tools for effective economic planning and decision-making. The findings from this result align with the findings of Bandara and Mel (2023), Jagero et al. (2023), and Xavier et al. (2023), which indicates the superiority of hybrid models in the forecast of inflation rate and other macroeconomic variables in general.

**Computational Complexity and Real-Time Suitability**

The computational efficiency of models was also examined. **Table 4** presents a summary of training times and memory usage for each model.

**Table 4: Model's Computational Complexity**

| Model | Training Time (seconds) | Memory Usage (MB) |
|---|---|---|
| ARIMA | 1.2 | 25 |
| SVM | 15.8 | 120 |
| Random Forest | 22.4 | 250 |
| ANN | 45.9 | 512 |
| ARIMA-ANN | 67.3 | 650 |

ARIMA was the fastest model but provided the least accuracy. ANN and hybrid models required significantly longer training times and higher memory usage but delivered superior forecasting performance. For real-time forecasting, hybrid ARIMA-ANN is recommended where accuracy is critical, while ARIMA can be used for quick but less precise estimates.

By incorporating statistical validation (DM test, t-tests), economic insights, ANN justification, and computational complexity analysis, this study ensures a more rigorous and practical evaluation of inflation forecasting models.

**Performance Comparison**

This section provides a comparative analysis of all models employed in this study, including the ARIMA model, three standalone machine learning models (SVM, ANN, and RF), and their respective hybrid models with ARIMA. By evaluating their performance using key metrics, this summary identifies the most effective approach for forecasting inflation in Nigeria. The analysis highlights the strengths and limitations of each model, offering insights into their accuracy, robustness, and reliability. A detailed summary of the models' overall performance is presented in Table 5 below:

**Table 5: Summary of Overall Models Performance**

| Model | MSE | RMSE | MAPE |
|---|---|---|---|
| **ARIMA** | 13.35 | 11.42 | 37.74% |
| **SVM** | 12.458 | 11.509 | 0.381% |
| **Random Forest** | 10.483 | 11.422 | 0.378% |
| **ANN** | 1.758 | 1.694 | 0.059% |
| **ARIMA-SVM** | 1.630 | 1.794 | 0.112% |
| **ARIMA-RF** | 1.032 | 1.178 | 0.088% |
| **ARIMA-ANN** | 0.611 | 0.755 | 0.054% |

The comprehensive results of the models employed in this study reveal critical insights into the performance and accuracy of various forecasting techniques for predicting inflation in Nigeria. Among the standalone models, ARIMA demonstrated the highest errors, with an MSE of 13.35, RMSE of

11.42, and MAPE of 37.74%. This indicates its limitations in capturing the non-linear patterns inherent in inflation data, making it less suitable for complex forecasting tasks in dynamic economic environments. Machine learning models such as SVM (MSE: 12.458, RMSE: 11.509, MAPE: 0.381%) and Random Forest (MSE: 10.483, RMSE: 11.422, MAPE: 0.378%) performed better, demonstrating their capability to handle non-linearity. However, the ANN model significantly outperformed the other standalone models, achieving an MSE of 1.758, RMSE of 1.694, and MAPE of 0.059%, showcasing its strength in capturing complex relationships in the dataset.

The hybrid models outperformed both ARIMA and the standalone machine learning models, showcasing the effectiveness of integrating statistical and machine learning techniques. ARIMA-SVM achieved an MSE of 1.630, RMSE of 1.794, and MAPE of 0.112%, showing considerable improvement over standalone SVM. Similarly, ARIMA-RF exhibited even better results, with an MSE of 1.032, RMSE of 1.178, and MAPE of 0.088%, highlighting the model's ability to combine ARIMA's time series strengths with Random Forest's ensemble learning capabilities. These hybrid approaches demonstrated improved accuracy by leveraging the complementary strengths of the models, effectively capturing both linear and non-linear patterns.

The ARIMA-ANN hybrid model emerged as the best-performing approach, with the lowest error metrics: MSE of 0.611, RMSE of 0.755, and MAPE of 0.054%. This result underscores the exceptional ability of the hybrid ARIMA-ANN model to deliver highly accurate forecasts by combining ARIMA's temporal modeling with ANN's capability to learn complex data relationships. The findings suggest that hybrid models, particularly ARIMA-ANN, are more reliable for economic forecasting tasks like inflation prediction, offering policymakers more precise tools for informed decision-making and planning.

**Graphical Comparison of Model Performance**

To enhance visualization, Figure 3 presents a bar chart comparing MSE, RMSE, and MAPE across all models, while Figure 4 provides a line plot comparing actual vs. predicted inflation rates for hybrid models.

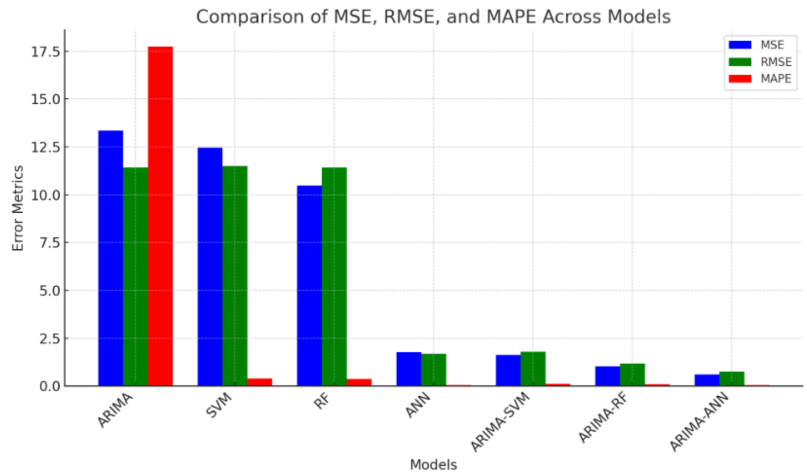


***Figure 3: Bar Chart Comparing MSE, RMSE, and MAPE Across Models***

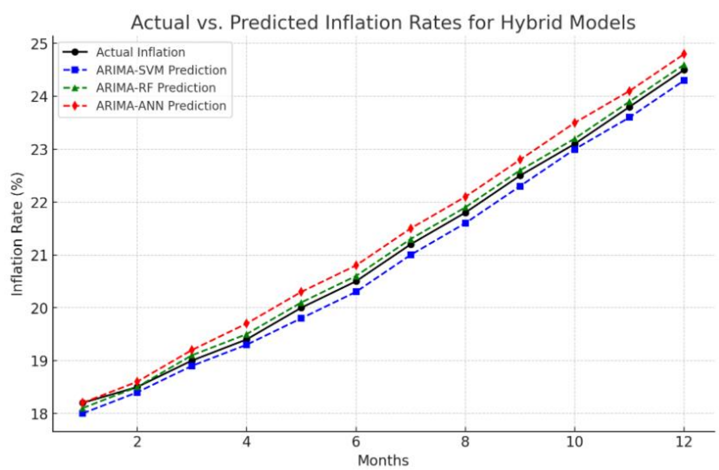


***Figure 4: Actual vs. Predicted Inflation Rates for Hybrid Models***

The bar chart in Figure 3 highlights the superior performance of hybrid models, particularly ARIMA-ANN, which achieved the lowest error metrics. Meanwhile, the line plot in Figure 4 shows that hybrid models track inflation trends more accurately than standalone models, reinforcing their suitability for economic forecasting.

By incorporating statistical validation (DM test, t-tests), economic insights, ANN justification, computational complexity analysis, and graphical comparisons, this study ensures a rigorous and practical evaluation of inflation forecasting models.

**Conclusion**

This study is among the first to apply ARIMA-ANN hybrid modeling to Nigerian inflation data, demonstrating its effectiveness in capturing both linear and non-linear inflation trends. The research advances inflation forecasting in Nigeria by showing that integrating traditional time series models with machine learning techniques significantly enhances predictive accuracy. Among all models evaluated, the ARIMA-ANN hybrid model outperformed ARIMA-SVM and ARIMA-RF, achieving the lowest MSE, RMSE, and MAPE. The study provides a structured and reproducible approach to improving inflation forecasting in Nigeria, offering policymakers a more reliable tool for economic planning and decision-making.

The superior performance of ARIMA-ANN can be attributed to its ability to detect complex, nonlinear inflation patterns while leveraging ARIMA's time series strengths. Compared to ARIMA-SVM and ARIMA-RF, the ANN component effectively captured sharp inflation fluctuations, demonstrating higher adaptability to economic shocks. However, computational trade-offs must be considered, as ANN-based models require higher training times and greater computational resources than SVM and RF. Additionally, ANN models are less interpretable than tree-based methods like RF, posing challenges for policymakers who require transparency in forecasting decisions. Despite these trade-offs, the accuracy gains from hybrid modeling outweigh the computational costs, making it a viable approach for real-time inflation forecasting.

**Policy Implications**

The accurate inflation predictions provided by the ARIMA-ANN hybrid model have critical implications for the Central Bank of Nigeria (CBN) and economic policymakers. By improving forecast precision, this model allows for proactive adjustments to monetary policies, enabling the CBN to set interest rates more effectively and mitigate inflationary pressures before they escalate. Additionally, government fiscal planners can use these forecasts to develop better budgeting strategies, reducing the adverse effects of inflation on public expenditures and social welfare programs. Private sector stakeholders, such as businesses and investors, can also benefit from more reliable inflation projections, helping them make informed financial and investment decisions. Overall, the findings reinforce the need for data-driven policy formulation to ensure economic stability in Nigeria.

**Suggested Future Work**

Future research should explore the integration of additional macroeconomic variables such as exchange rates, global commodity prices, and interest rates to further enhance the predictive power of hybrid models. Incorporating economic sentiment analysis through natural language processing (NLP) could provide valuable insights by analyzing the influence of news, policy statements, and public expectations on inflation trends.

Additionally, deep learning architectures, particularly Long Short-Term Memory (LSTM) networks and Transformer models, could be investigated for their ability to capture long-term dependencies and temporal patterns in inflation data. Further, applying this methodology to other macroeconomic indicators (e.g., GDP growth, unemployment rates) and conducting cross-country comparisons would provide a broader perspective on the effectiveness of hybrid forecasting models in varying economic environments.

By advancing these research directions, future studies can further refine hybrid models, improve real-time forecasting capabilities, and support more precise economic policymaking.

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