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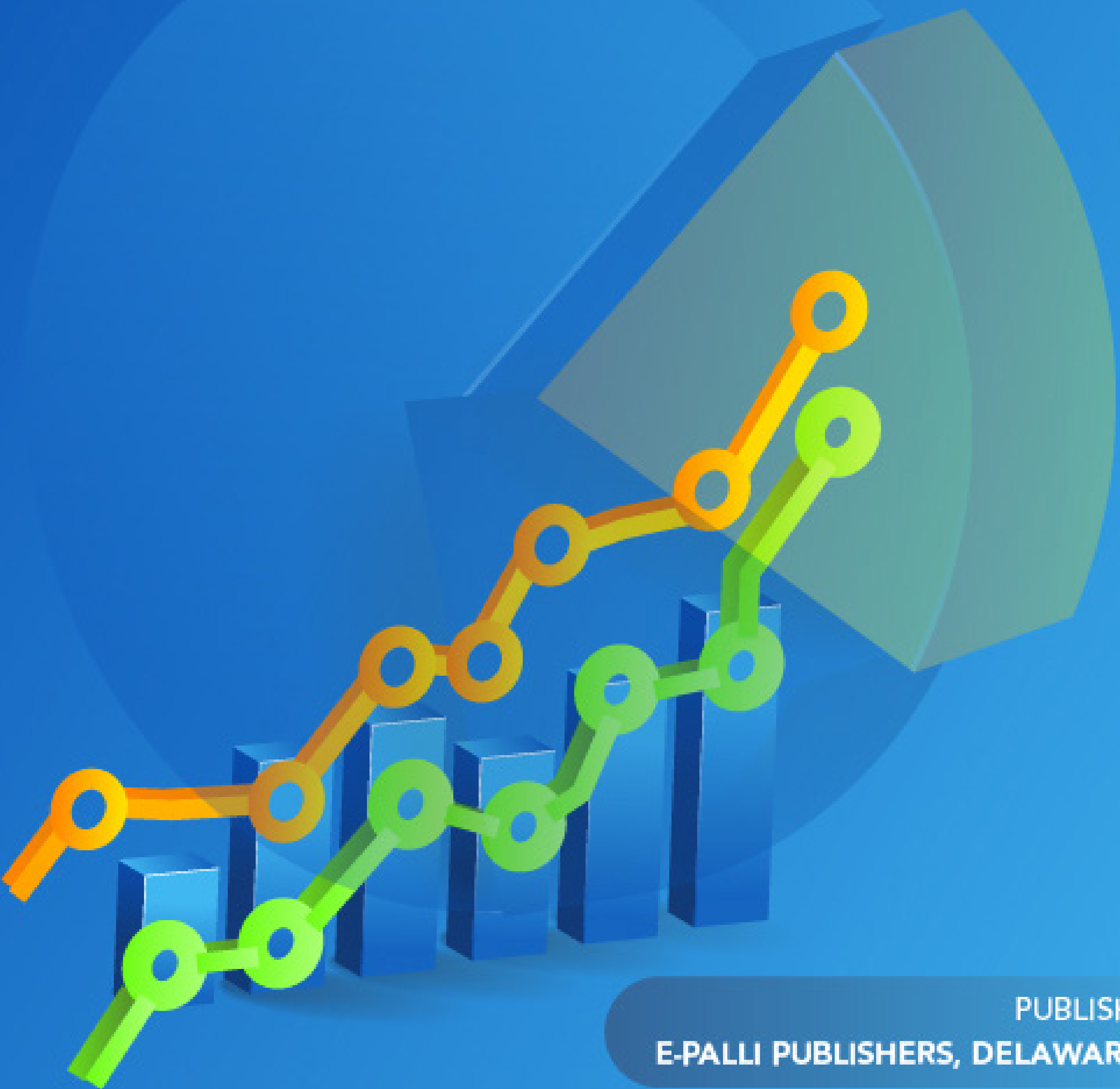

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AI-Enhanced Inflation Forecasting in Emerging Economies

Tobias Kwame Adukpo[1*], Jacob Obeng Bethel[2], Linda Fynn Prah[3]

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ABSTRACT

This study examines an AI-enhanced framework for forecasting inflation in Ghana and addresses the limitations of traditional models like ARIMA and VAR in capturing nonlinear and volatile pricing dynamics. The study uses monthly data from January 2010 to September 2025 and sourced data from the Ghana Statistical Service, Bank of Ghana, World Bank and IMF. The study compares traditional models like Vector Autoregression (VAR) and ARIMA against AI models such as Random Forest, XGBoost and AdaBoost and Long Short-Term Memory. Model accuracy was assessed using MAE, RMSE, MAPE and SMAPE. The results show that AI models, particularly XGBoost (MAE = 0.12, RMSE = 0.17) and Random Forest (MAE = 0.57, RMSE = 1.45), achieved the lowest forecasting errors and produced more stable and realistic inflation trajectories than traditional models such as VAR (MAE = 1.29, RMSE = 1.78) and ARIMA (MAE = 1.87, RMSE = 4.08). The findings indicated that incorporating global factors such as oil prices and food indices increased model accuracy. These findings highlight the importance of external shocks in Ghana's inflation behaviour, as well as the potential for artificial intelligence to improve forecast accuracy. The study suggests that incorporating AI-driven models into the Bank of Ghana's inflation-targeting framework could boost early warning systems and policy effectiveness.

INTRODUCTION

Inflation continues to be a significant macroeconomic concern in many rising economies. Inflationary fluctuations are frequently caused by exchange rate depreciation, global commodity price shocks and structural supply restrictions, which continue to impact monetary and fiscal policies. The Ghana Statistical Service (GSS) and the Bank of Ghana (BoG) produce the official inflation figures used for monitoring and policymaking. Notwithstanding these data sources, Ghana's inflation has been volatile, which makes reliable forecasting challenging (Korkpoe *et al.,* 2025).

Traditional econometric models, such as the Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR) models, have long been used to forecast inflation. Though these models work quite well in stable macroeconomic environments, they have limitations in capturing structural breaks, nonlinearity and complicated relationships between domestic and external factors (Akinsola & Odhiambo, 2017). The inflationary pressures in Ghana are driven not just by monetary dynamics but also by global commodity shocks, particularly crude oil and food prices and traditional models frequently give significantly inaccurate forecasts (Boateng *et al.,* 2024).

Recent breakthroughs in artificial intelligence (AI) and machine learning (ML) have provided interesting alternatives to traditional time-series forecasting methods. Random Forests, Extreme Gradient Boosting (XGBoost), Adaptive Boosting (AdaBoost) and Long Short-Term Memory (LSTM) neural networks have all demonstrated superior forecasting performance by capturing nonlinearities and efficiently processing high-dimensional data (Goulet *et al.,* 2022; Medeiros *et al.,* 2021; Narteh-Kofi *et al.*, 2025). Because of the ability of these models to manage sequential time-series dependencies, LSTM models are increasingly being used to forecast inflation and exchange rate volatility in emerging nations (Mirza *et al.,* 2024).

This article examines and assesses an AI-enhanced inflation forecasting system in emerging economies. The study combines monthly inflation data from the GSS with macroeconomic variables from the Bank of Ghana (BoG), such as exchange rate, broad money supply (M2+), interest rates and GDP growth, as well as global drivers including oil prices and food indices from the World Bank and IMF. The study addresses three issues by comparing AI/ML models to traditional benchmarks. The research questions were: (1) Can AI models outperform traditional methods for projecting Ghana's inflation? (2) What additional forecasting value is provided by including global drivers? (3) How might improved projections help Ghana's inflation-targeting mechanism perform more effectively?

This study also makes three distinct contributions. First, it is one of the first systematic comparisons of AI-based and traditional econometric models for forecasting inflation in Ghana. Second, it quantifies the impact of global factors on domestic inflation dynamics. Third, it provides practical insights into how central banks in

[1] Department of Accounting, University for Development Studies, Ghana
[2] Department of Economics, University of Ghana
[3] Department of Economics, Western Michigan University, Michigan, USA
[*] Corresponding author's e-mail: adukpotobias@gmail.com

emerging economies, particularly the BoG, can include AI-enhanced models into policy frameworks, however, addressing interpretability and data quality issues.

LITERATURE REVIEW

The Concept of Inflation in Emerging Economies

Inflation is usually defined as a long-term increase in the general price level of goods and services that reduces the purchasing power. Although moderate inflation boosts output and investment, excessive or erratic inflation reduces real incomes, diminishes savings and generates uncertainty in financial markets and the whole economy (Turdialiyev & Khujamurotov, 2025). In growing economies like Ghana, inflation is frequently driven by a combination of demand-pull, cost-push and structural forces. Demand-pull inflation occurs when aggregate demand exceeds supply, whereas cost-push inflation is caused by increased production costs, such as gasoline and imported commodities. Ghana's structural inflation is connected to poor domestic supply chains, reliance on imported goods and periodic currency rate depreciation (Awuku-Aboagye, 2024; Sani & Aryee, 2025).

The variables studied in this study include exchange rate, broad money supply, interest rates, GDP growth, oil prices and food prices, which are both domestic and global causes of inflation. For example, excessive expansion in the money supply tends to boost liquidity and aggregate demand, which puts upward pressure on prices (Adukpo & Bethel, 2025). Similarly, variations in interest rates have a direct impact on borrowing costs and aggregate demand. GDP growth represents supply-side capacity; when growth is slow, demand shocks accelerate inflation. Meanwhile, oil and food prices, which Ghana mainly imports, act as external cost-push shocks that directly affect the local CPI. This multi-layered interplay highlights the complexities of inflation in emerging economies, as well as the significance of advanced models capable of integrating these varied causes (Cabral *et al.,* 2020).

Figure 1 depicts the trend of monthly inflation rates in Ghana from January 2010 to September 2025. The data show numerous distinct phases in Ghana's inflation patterns. From 2010 to 2013, inflation was reasonably constant, ranging between 8 and 10%, which indicates a period of moderate price increase and relative macroeconomic stability. Between 2014 and 2016, inflation began to grow significantly and reached levels exceeding 17 percent, owing mostly to currency devaluation, energy price changes and fiscal imbalances that characterised this time.

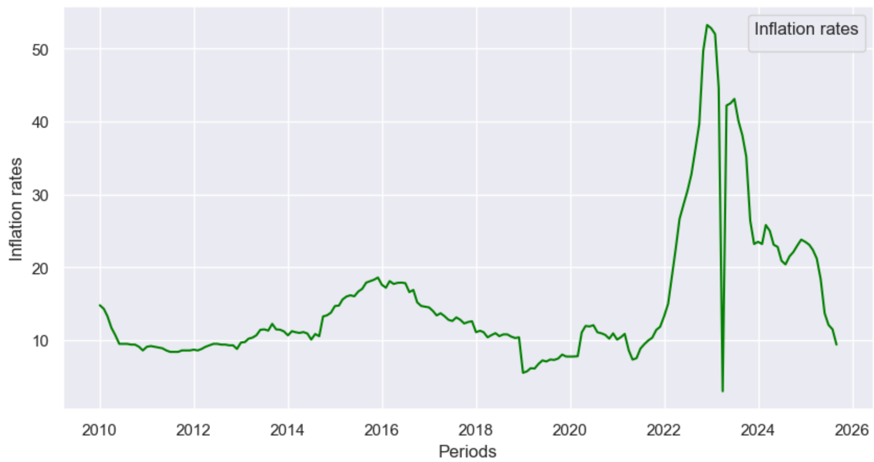

Figure 1: Time series plot of Inflation in Ghana from 2010 to 2024

Between 2017 and 2019, inflation stabilised in the single digits as the Bank of Ghana tightened monetary policy and improved budgetary discipline. The emergence of the COVID-19 pandemic in 2020 initially reduced demand pressures; nevertheless, supply chain disruptions and global price shocks in the following years resulted in a dramatic increase in inflation. This growing tendency culminated in an astonishing jump between late 2021 and 2022, when inflation surpassed 50%, which was the greatest rate in more than two decades. This surge was principally caused by global oil and food price shocks, currency depreciation and post-pandemic fiscal pressures. Following the 2022 peak, inflation fell gradually in 2023 and 2024, which shows a recovery aided by increased foreign exchange inflows, monetary policy tightening and stabilisation measures implemented under Ghana's IMF-supported program. Nonetheless, inflation rates remained above pre-pandemic levels, which highlights the underlying structural weaknesses and the ongoing impact of global commodity prices on domestic inflation outcomes. Overall, the graph shows the cyclical and externally sensitive nature of Ghana's inflation, which emphasises the need to include both internal and global variables in AI-enhanced forecasting models.

Traditional Approaches to Inflation Forecasting

Historically, inflation forecasting has been based on econometric and time-series models like ARIMA, VAR and GARCH. ARIMA models capture autocorrelations in price movements, whereas VAR models combine numerous macroeconomic variables, which makes them appropriate for studying the interconnections between inflation, interest rates and money supply (Coker, 2025). GARCH models are commonly used to predict volatility in inflation and exchange rates (Almısshal & Emir, 2021). Though these models have provided useful insights, their predictive power in emerging markets has frequently been restricted (Hezam *et al.,* 2025). First, they are based on linear connections, which render them unsuitable for instances where inflation is caused by nonlinear dynamics, such as rapid exchange rate depreciation or commodity price shocks (Habibi, 2024). Second, they presume stable structural links, while in Ghana, frequent policy changes, budgetary imbalances and external shocks result in recurring structural breaks (Bortey, 2015). For example, when global oil prices rise, the impact on domestic inflation is nonlinear, dependent on exchange rate fluctuations, fuel subsidies and supply constraints. Consequently, econometric projections frequently underestimate inflation during periods of instability (El-Shagi, 2011).

Furthermore, traditional models assume macroeconomic indicators like as the money supply and interest rates as exogenous, even though they are frequently influenced by feedback from inflation (endogeneity). This leads to specification errors, which further reduce forecast accuracy (Clark & McCracken, 2009).

Machine Learning and Artificial Intelligence in Forecasting

Recent advances in machine learning (ML) and artificial intelligence (AI) have led to new forecasting methods that are capable of capturing complex nonlinearities and relationships. Random Forests and XGBoost are especially effective at handling high-dimensional data and preventing overfitting, while Support Vector Regression (SVR) is well-suited for small-sample scenarios often found in emerging economies (Medeiros *et al.,* 2021). Deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, have demonstrated promise for sequential data like CPI time series because they can capture long-term dependencies and nonlinear lag structures (Mirza *et al.,* 2024; Narteh-Kofi *et al.*, 2025).

These models have proven successful in other emerging economies. Abdulraheem *et al.* (2021) found that machine learning methods considerably increased inflation forecast accuracy in emerging economies. Nkemnole and Oyelami (2021) reported comparable results in Nigeria, where ML approaches beat VAR models in predicting inflation and interest rates. Importantly, hybrid approaches that integrate classic time-series methodologies and machine learning have gained popularity. For example, Le *et al.* (2024) found that combining ARIMA with machine learning improved prediction performance by combining linear and nonlinear dynamics.

Unlike econometric models, AI/ML techniques can incorporate a wide range of predictors, including global commodities indices, money supply fluctuations and policy interest rate changes. This makes them ideal for scenarios such as Ghana, where inflation is influenced by both domestic monetary conditions and external shocks (Abbate *et al.,* 2023; Aryee *et al.*, 2025).

Empirical Studies

Empirical research on inflation forecasting in emerging economies has primarily relied on traditional econometric methods. Abdulai (2021) emphasised that money supply and currency rate depreciation continue to be the primary drivers of inflation in Ghana, which supports monetarist viewpoints. Similarly, Tsiboe *et al.* (2022) identified structural issues such as food prices, energy costs and transportation bottlenecks as key drivers of price volatility. However, these studies used VAR and ARDL frameworks, which presume stable long-run correlations that may not necessarily be true in practice.

More recent research has investigated the role of exogenous shocks. Adom *et al.* (2015) discovered that imported oil and food costs considerably increase Ghana's inflation, especially during periods of exchange rate depreciation. Notwithstanding these findings, no systematic study has compared AI/ML forecasting tools to traditional econometric models in Ghana.

Filling this gap is significant because inflation patterns in emerging economies reflect both domestic and global factors that interact nonlinearly. For example, money supply growth interacts with exchange rate depreciation to increase imported inflation, whereas global oil price spikes have asymmetric impacts depending on domestic subsidy programs. Traditional models may underestimate the permanence and volatility of inflation if these interactions are not considered. This paper tackles this gap by applying AI/ML algorithms to Ghana's inflation forecasts and rigorously comparing their results to established standards.

MATERIALS AND METHODS

Research Design

The study uses a quantitative and experimental strategy by combining classic econometric models with sophisticated artificial intelligence (AI) techniques to assess and enhance the accuracy of inflation predictions in emerging economies. The technique combines comparative model evaluation and policy relevance testing to see if AI-driven models can outperform traditional forecasting methods and improve Ghana's inflation-targeting framework (Gokah *et al.*, 2025). The research strategy focuses on both domestic macroeconomic indicators and global inflation drivers, which acknowledges that both internal dynamics and external shocks influence inflation in Ghana (Adom *et al.,* 2015; Narteh-Kofi *et al.*, 2025).

The analysis was structured around three key objectives:

1. To compare the in-sample forecasting performance of AI-based and traditional models for Ghana's inflation.
2. To evaluate the incremental predictive value of

incorporating global macroeconomic drivers.

3. To assess how enhanced forecast accuracy can improve the effectiveness of the Bank of Ghana's inflation-targeting framework.

Data Sources

This study used monthly inflation rate data from the Ghana Statistical Service (GSS) and the Bank of Ghana's (BoG) statistical bulletins. The analysis included key domestic macroeconomic indicators such as the currency rate (GHS/USD), interbank lending rate, broad money supply (M2+) and real GDP growth, which are primary drivers of inflation in Ghana. To account for external pricing influences, the analysis used international crude oil prices and the global food price index from the World Bank's Pink Sheet, as well as global macroeconomic estimates from the International Monetary Fund's (IMF) World Economic Outlook. This dataset spans the period from January 2010 to September 2025 and provides a detailed picture of Ghana's inflation dynamics across fifteen years marked by exchange rate changes, monetary policy moves and global commodity price shocks. This broad temporal horizon ensures that both domestic and international factors impacting inflation are properly recorded for rigorous empirical study.

Data Preprocessing

Before the analysis, the dataset was pre-processed to verify correctness, consistency and applicability for forecasting applications. The inflation data, which was gathered from the Ghana Statistical Service and the Bank of Ghana statistical bulletins, spanned the years January 2010 through September 2025. The dataset contained complete monthly observations with no missing values; hence, no imputation processes were required. The broad money supply (M2+) series was log-transformed to reduce skewness and improve model interpretability. Inflation and other economic indicators, such as the exchange rate and global oil prices, were kept in their original forms. Lag structures were also developed to account for the delayed effects of money supply, exchange rate adjustments and global commodity price fluctuations on inflation outcomes. Finally, the dataset was divided into training (2010–2022) and testing (2023–2025) subsets to facilitate out-of-sample evaluation. This structure enabled a realistic assessment of forecasting accuracy, simulating conditions under which Ghana's inflation-targeting framework operates in practice.

Model Specification

This study used a two-stage modelling framework to evaluate the prediction performance of AI-enhanced techniques in comparison to traditional econometric approaches. The first step concentrated on baseline econometric models typically employed for inflation forecasting. The second stage included machine learning algorithms capable of capturing nonlinearities and multidimensional relationships.

Econometric Baseline Models

(a) Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model provides a benchmark univariate time-series framework that captures autoregressive (AR), differencing (I) and moving average (MA) components. The general ARIMA (p, d, q) specification is:

$$\pi_t = \sum_{i=1}^{p} \phi_i \pi_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

where π_t is the inflation rate at time t, ϕ_i and θ_j are autoregressive and moving average parameters, and ϵt is a white-noise error term.

(b) Vector Autoregression (VAR)

To incorporate macroeconomic interactions, a multivariate VAR framework was specified as:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \epsilon_t$$

Machine Learning Models

Given the nonlinear and interactive nature of inflation dynamics in emerging economies, machine learning (ML) models were employed to complement the econometric baselines.

(a) Random Forest (RF)

Random Forest is an ensemble tree-based model that reduces overfitting by averaging predictions across multiple decision trees. Its prediction function is:

$$\hat{\pi} = \frac{1}{B} \sum_{b=1}^{B} T_b(X_t)$$

where Tb represents the b-th regression tree trained on bootstrapped samples of predictor variables X_t and B is the total number of trees.

(b) Extreme Gradient Boosting (XGBoost)

XGBoost improves predictive accuracy by sequentially building trees where each new tree corrects the residuals of the previous one. Its prediction function is:

$$\hat{\pi}_t = \sum_{k=1}^{K} f_k(X_t), \qquad f_k \in \mathcal{F}$$

where fk are regression trees in functional space F and K is the number of boosting iterations.

(c) AdaBoost (Adaptive Boosting)

AdaBoost is another ensemble model that combines numerous weak learners (usually shallow decision trees) into a powerful classifier or regressor. It works by iteratively reweighting data points, which puts more emphasis on those that were incorrectly predicted in previous rounds. The AdaBoost model prediction is provided by:

$$\hat{Y}_t = sign\left(\sum_{m=1}^{M} \alpha_m h_m(X_t) \right)$$

where $h_m(X_t)$ represents the m^{th} weak learner, α_m denotes its weight, and M is the total number of estimators. This adaptive weighting process enhances the model's accuracy, particularly in datasets with varying levels of nonlinearity.

(d) Long Short-Term Memory (LSTM) Neural Network
Given the sequential and time-dependent nature of inflation, an LSTM model was implemented. LSTM is designed to capture long-term dependencies in sequential data. Its key equations include:

Forget gate: $f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f$

Input gate: $i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i)$, $\tilde{C}_t = tanh(W_c \cdot [h_{t-1}, X_t] + b_c$

Cell state update: $C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$

Output gate: $o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o$, $h_t = o_t \odot \tanh(C_t)$

where h_t is the hidden state, C_t) is the memory cell, and σ denotes the sigmoid activation function.

Model Evaluation

To objectively assess the predicted performance of traditional econometric models versus AI-enhanced techniques, the study used statistical and econometric evaluation indicators. The goal was to guarantee that the chosen model not only reduced forecast errors but also produced consistent and policy-relevant projections.

(a) Mean Absolute Error (MAE)

MAE is the average absolute difference between observed values y_t and forecasts $\hat{y}_t$. It measures average forecast error in the same units as the target variable. It is calculated as:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\pi_t - \hat{\pi}_t|$$

(b) Root Mean Squared Error (RMSE)

RMSE is the square root of the average squared forecast errors. Because errors are squared before averaging, RMSE penalizes large errors more heavily than MAE. It is computed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\pi_t - \hat{\pi}_t)^2}$$

(c) Mean Absolute Percentage Error (MAPE)

MAPE expresses the forecast error as a percentage of the actual values. It is unit-free and easily interpretable as an average percent error. It is calculated as:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{\pi_t - \hat{\pi}_t}{\pi_t}\right|$$

(d) Symmetric Mean Absolute Percentage Error (SMAPE)

SMAPE is a measure of accuracy based on relative percentage errors. It is calculated by as:

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\frac{|\pi_t - \hat{\pi}_t|}{(|\pi_t| + |\hat{\pi}_t|)/2}$$

Incremental and Policy Effectiveness Analysis

To address Objective 2, models were estimated under two conditions: using only domestic indicators and then using both domestic and global indicators. The difference in accuracy metrics between these scenarios assessed the incremental forecasting utility of global macroeconomic integration.
For Objective 3, the study simulated policy effectiveness by evaluating forecast benefits from improved models and linking them to the possibility of earlier and more precise monetary policy changes. The observed accuracy increases were viewed as evidence of increased forecasting reliability, which directly supports the Bank of Ghana's proactive inflation-targeting policies.

Software and Implementation

All analyses were carried out in Python 3.12, with libraries including statsmodels for econometric models, scikit-learn and xgboost for machine learning methods and PyTorch for deep learning implementation. The model codes were run on the author's local computer environment (Windows 10, 64-bit, 16 GB RAM).

Data Analysis and Results

Table 1 presents the descriptive statistics of Ghana's monthly inflation rate from January 2010 to September 2025. The findings show that inflation in Ghana has been highly volatile, with minimum and maximum rates of 3.0% and 53.24% respectively and an average inflation rate of 15.16% over the last 15 years. The relatively high standard deviation of 9.50 highlights significant variations around the mean, which indicates periods of both price instability and severe inflationary pressure.

Table 1: Descriptive statistics of monthly inflation in Ghana from January 2010 to September 2025

Statistics	Min	Mean	std	25	Median	75	Max
Value (%)	3.0	15.16	9.48	9.47	11.43	17.60	53.24

Source: Authors' calculations

The interquartile range (IQR), which ranges from 9.47% (25th percentile) to 17.60% (75th percentile), suggests that inflation remained moderate to high for most of the period, which exceeded the Bank of Ghana's long-term target band of 6-10%. The median score of 11.43% indicates that inflation remained persistently above target, reflecting structural and policy-driven problems in sustaining price stability.

Trends and Seasonality analysis

The decomposition of the monthly inflation series in Ghana reveals distinct patterns in its observed, trend, seasonal and residual components. The observed series displays noticeable fluctuations over time, with inflation remaining relatively stable between 2010 and 2020, followed by a sharp upward surge from 2021 to 2023.

Figure 2: Seasonal decomposition of monthly inflation into trends, seasonality and residuals

This sharp increase corresponds to the post-COVID-19 global price shocks and domestic fiscal pressures that intensified inflationary dynamics in Ghana during this period. The trend component highlights a gradual increase in inflation between 2015 and 2016, which saw a brief decline around 2019–2020 and a pronounced upward movement peaking in 2023. This long-term pattern suggests that structural and macroeconomic factors, such as exchange rate depreciation, rising import costs and monetary expansion, contributed significantly to inflation growth. The seasonal component also shows a consistent cyclical pattern with regular peaks and troughs, which implies that inflation in Ghana exhibits strong seasonal behaviour, possibly influenced by agricultural harvest cycles, festive consumption patterns and periodic government expenditure adjustments. Finally, the residual component captures short-term irregularities or shocks not explained by trend or seasonality. The pronounced residual fluctuations between late 2022 and early 2023 indicate unexpected macroeconomic disturbances, likely driven by external supply constraints and exchange rate volatility.

Comparative Performance of AI and Traditional Models in Inflation Forecasting

The performance comparison of traditional econometric models (VAR and ARIMA) vs AI-based models (Random Forest, XGBoost, AdaBoost and LSTM) demonstrates that machine learning methods provide better forecast accuracy for Ghana's inflation dynamics. As demonstrated in Table 2, traditional models had substantially larger forecast errors, with ARIMA having an RMSE of 4.10 and a symmetric mean absolute percentage error (SMAPE) of 12.15, whilst the VAR model had a lower RMSE of 1.78 but still fell short of AI models' performance. Conversely, XGBoost produced the fewest errors across all metrics (MAE = 0.12, RMSE = 0.17, and SMAPE = 1.07), followed by Random Forest (MAE = 0.57, RMSE = 1.45). These findings show that ensemble-based AI models are better at capturing the nonlinear and erratic behaviour of Ghana's inflation than standard time series techniques.

Figure 3 illustrates the accuracy advantage of AI models compared to traditional models by plotting in-sample predictions against actual inflation values from 2010 to 2025. The Random Forest, XGBoost and AdaBoost models all closely tracked the observed inflation trend, particularly during periods of high volatility, such as the 2022-2023 inflation surge caused by exchange rate depreciation and global commodities shocks. In contrast, VAR and ARIMA models deviated significantly from actual values during sharp price changes, which highlights their shortcomings in dealing with sudden structural breaks and nonlinear interactions. Although the LSTM model is theoretically capable of capturing sequential dependencies, it fared poorly in our dataset (RMSE = 4.09), most likely due to overfitting or data sparsity in high inflation regimes.

Table 2: In-Sample Evaluation Metrics for machine learning and traditional models

Models	MAE	RMSE	MAE	SMAPE
VAR	1.29	1.78	11.24	10.50
ARIMA	1.87	4.10	17.80	12.15
Random Forest	0.57	1.45	5.62	3.61
XGBoost	0.12	0.17	1.07	1.07
AdaBoost	1.61	1.98	13.33	12.52
LSTM	2.35	4.09	23.35	16.27

Source: Authors' calculations

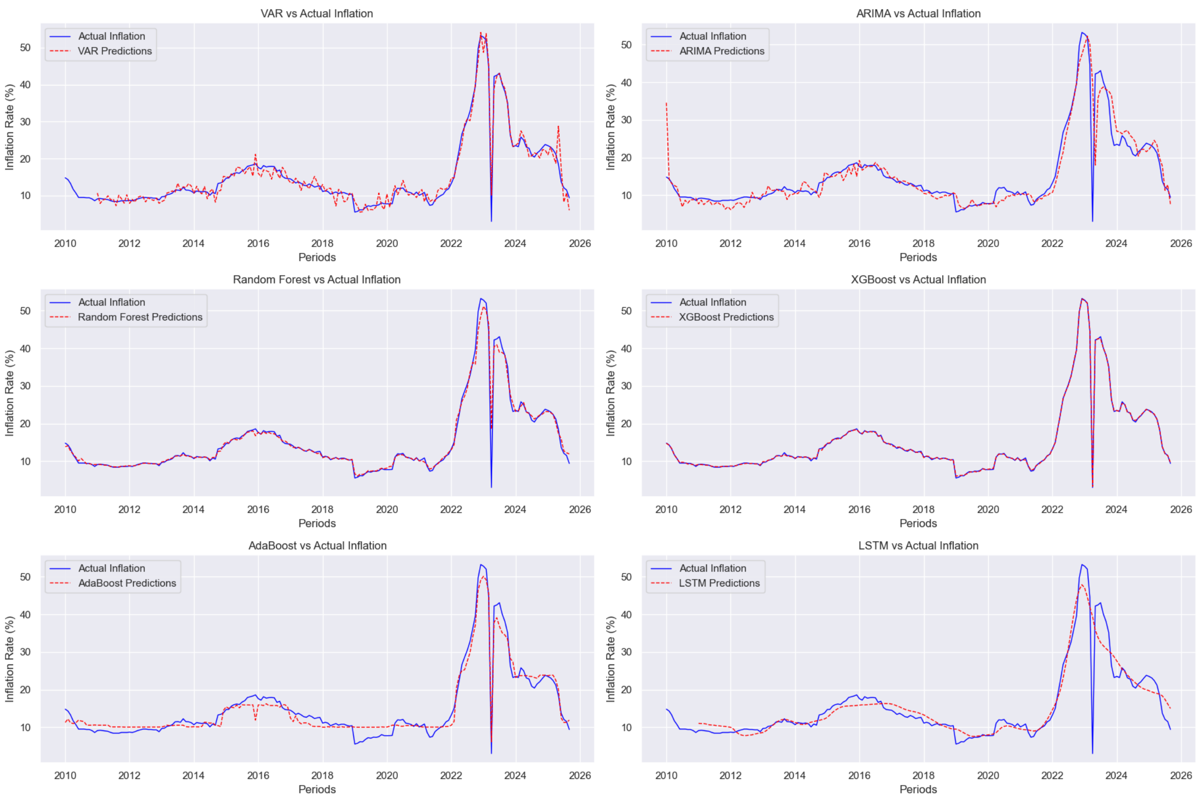

Figure 3: Monthly forecast inflation rates of both machine learning and traditional models

Table 3: In-sample inflation predictions using machine learning and traditional models

Periods	Actual	VAR	ARIMA	RF	XGBoost	AdaBoost	LSTM
2024-10-01	22.10	20.14	22.11	22.26	22.28	23.82	20.91
2024-11-01	23.00	22.41	22.20	22.53	23.01	23.82	20.66
2024-12-01	23.80	22.34	21.54	23.19	23.77	23.82	20.47
2025-01-01	23.50	21.02	22.14	23.19	23.44	23.72	20.26
2025-02-01	23.10	23.07	23.19	22.92	22.86	23.82	20.97
2025-03-01	22.40	20.92	24.58	22.43	22.53	23.82	19.73
2025-04-01	21.20	18.73	23.34	20.18	21.10	22.49	19.65
2025-05-01	18.40	28.76	19.86	17.34	18.32	20.02	19.61
2025-06-01	13.70	17.47	17.73	15.93	13.86	12.45	19.28
2025-07-01	12.10	8.23	11.26	12.72	11.97	11.27	18.46
2025-08-01	11.50	10.72	12.75	12.24	11.52	11.26	17.25
2025-09-01	9.40	6.04	7.57	11.91	9.62	11.90	16.03

Source: Authors' calculations

Further evidence, as presented in Table 3, confirms that AI models regularly delivered more stable estimates during Ghana's 2025 disinflation phase, when inflation fell from 23.8% in January to 9.4% in September. XGBoost and Random Forest detected these movements more correctly than VAR and ARIMA, which tended to exaggerate or lag behind the trend. The ability of AI models to adapt to new information and capture nonlinear linkages between macroeconomic and global factors (such as exchange rate changes and global commodities prices) explains their higher performance.

Incremental Forecasting Value of Incorporating Global Indicators

To evaluate the incremental impact of global factors in enhancing inflation projections, the models were initially estimated using just domestic indicators such as the exchange rate (GHS/USD), broad money (M2+), GDP growth rate and interest rate, as shown in Table 4. Global factors such as world oil prices and international food indices were then added to create an extended model specification, with the findings summarised in Table 5. The comparison of the two specifications shows that integrating global variables improves the predicted accuracy of both traditional and AI-based models, while the extent of increase differs by model.

When limited to domestic indicators, the XGBoost and Random Forest models showed strong performance, with RMSE values of 0.38 and 1.46, respectively, compared to 2.33 for VAR and 3.93 for ARIMA. However, in Table 5, including global indicators reduced forecast errors in most models. The RMSE of the XGBoost model decreased from 0.38 to 0.35, whereas the RMSE of the VAR model reduced significantly from 2.33 to 1.78, which reflects a 23.61% improvement.

Table 4: Evaluation Metrics for machine learning and traditional models with domestic indicators only

Models	MAE	RMSE	MAPE (%)	SMAPE (%)
VAR	1.50	2.33	12.78	12.11
ARIMA	1.78	3.93	17.12	11.58
Random Forest	0.54	1.46	5.44	3.39
XGBoost	0.24	0.38	2.03	1.98
AdaBoost	1.62	1.99	13.49	12.70
LSTM	4.61	6.51	41.78	28.75

Source: Authors' calculations

Table 5: Evaluation Metrics for Machine Learning and Traditional Models with Domestic and Global Indicators

Models	MAE	RMSE	MAPE (%)	SMAPE (%)
VAR	1.29	1.78	11.24	10.50
ARIMA	1.87	4.10	17.77	12.14
Random Forest	0.57	1.45	5.62	3.60
XGBoost	0.26	0.35	2.15	2.11
AdaBoost	1.56	1.92	13.14	12.37
LSTM	3.84	5.86	26.95	23.81

Source: Authors' calculations

Table 6: Incremental Improvement from Adding Global Indicators (%)

Models	MAE	RMSE
VAR	14.00	23.61
ARIMA	-5.06	-4.33
Random Forest	-5.56	0.68
XGBoost	-8.33	7.89
AdaBoost	3.70	3.52
LSTM	16.70	9.98

Source: Authors' calculations

The incremental improvements summarised in Table 6 show that VAR (MAE=14.00%; RMSE=23.61%) benefited the most from adding global indicators, followed by LSTM (MAE=16.17%; RMSE=9.98%) and XGBoost (MAE=-8.33%; RMSE=7.89%), whereas ARIMA and Random Forest showed marginal or negative changes in MAE, which was possibly due to overfitting or model saturation. These findings confirm that imported inflation, caused by exchange rate pass-through, global supply chain disruptions and energy price volatility, has traditionally been the primary driver of price instability in Ghana.

Enhancing Ghana's Inflation-Targeting Framework through Improved Forecasts

In order to assess how AI-enhanced inflation forecasts can strengthen the Bank of Ghana's inflation-targeting framework, which aims to maintain annual inflation within the medium-term target band of 8 ± 2 percent. The analysis focused on whether AI models produce forecasts that are not only statistically accurate but also consistent with the policy objective of price stability. The comparative evaluation metrics are presented in Table 7, while detailed out-of-sample forecasts are shown in Table 8. The overall forecast trajectories are visualized in Figure 3, which highlights the differences between traditional and machine-learning predictions.

Table 7 shows that AI-based models, particularly XGBoost and Random Forest, performed much better than traditional econometric techniques like VAR and ARIMA. The XGBoost model has the lowest MAE (0.12) and RMSE (0.17), with a 93.58 percent accuracy improvement over the ARIMA baseline. The Random Forest model also performed well, with a 69.52 percent improvement, which demonstrates its capacity to capture nonlinear dynamics and structural discontinuities in Ghana's inflation path. In contrast, LSTM underperformed due to a lack of training data and overfitting, whilst VAR and ARIMA had higher residual errors, which indicates an incapacity to adjust to unexpected inflationary shocks and regime shifts.

Table 7: Model Performance Metrics for Inflation Forecasting and Target Alignment (8 ± 2%)

Model	MAE	RMSE	Avg Dev from Target	% Within Target	Accuracy Gain (%)
VAR	1.29	1.78	7.37	23.81	31.02
ARIMA	1.87	4.10	7.31	35.98	0.00
RF	0.57	1.45	7.26	27.51	69.52
XGBoost	0.12	0.17	7.36	28.57	93.58
AdaBoost	1.61	1.98	7.01	3.70	13.90
LSTM	2.24	3.86	7.32	22.75	-19.79

Source: Authors' calculations

Table 8: Out-sample inflation predictions using machine learning and traditional models

Periods	VAR	ARIMA	RF	XgBoost	AdaBoost	LSTM
2025-10-01	17.69	8.41	13.15	14.98	16.10	16.61
2025-11-01	35.60	5.52	13.41	10.14	11.98	16.05
2025-12-01	34.02	3.62	14.31	10.86	11.98	15.61
2026-01-01	34.41	2.54	12.73	13.02	11.56	15.27
2026-02-01	22.00	2.62	13.08	10.73	11.90	15.10
2026-03-01	23.56	3.28	12.40	10.05	11.98	15.08
2026-04-01	33.17	3.88	14.12	15.07	16.10	15.20
2026-05-01	33.09	3.88	13.92	15.03	16.10	15.40
2026-06-01	49.42	3.90	12.21	11.57	16.10	15.63
2026-07-01	39.09	3.29	13.43	10.73	11.98	15.88
2026-08-01	37.14	1.68	14.13	10.76	11.98	16.08
2026-09-01	43.39	1.51	14.23	10.86	11.98	16.29

Source: Authors' calculations

The forecast visualisation in Figure 4 and Table 8 clearly illustrates that XGBoost and Random Forest offer stable and policy-consistent inflation pathways, with rates ranging from 10% to 16% during the 2025-2026 period. Notably, these forecasts gradually converge on the Bank of Ghana's target range of 6 to 10 percent by mid-2026, which reflects a realistic disinflationary path consistent with present stabilisation efforts. In contrast, VAR exhibits excessive volatility, with inflation peaking above 40%, whilst ARIMA consistently underestimates inflation, projecting levels as low as 2 to 5 percent, which fall unrealistically below the lower policy threshold. The AdaBoost and LSTM models, while smoother, keep forecasts over the upper goal band, which indicates a delayed convergence to price stability.

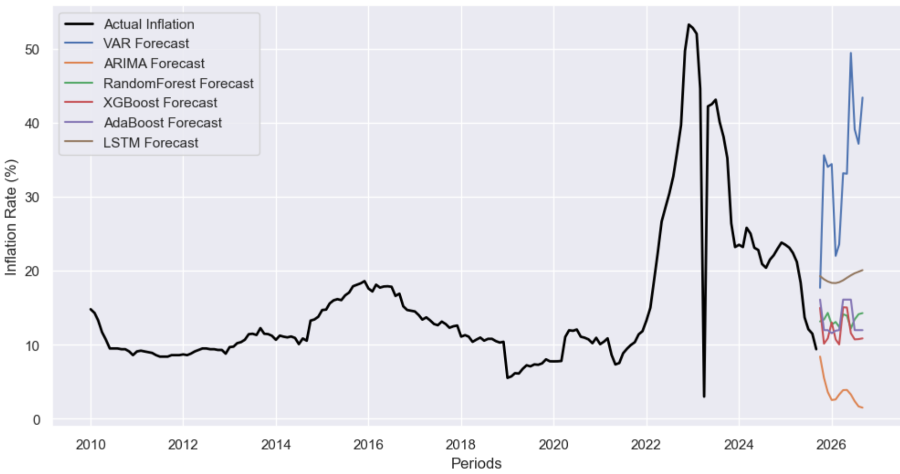

Figure 4: Monthly forecast inflation rates of both machine learning and traditional models.

CONCLUSION

This study examined an AI-enhanced framework for forecasting inflation in Ghana, with three main objectives in mind: determining whether AI models outperform traditional econometric models, assessing the incremental value of incorporating global indicators and examining how improved forecasts can strengthen the country's inflation-targeting framework. The results showed that AI-based models, particularly XGBoost and Random Forest, consistently outperformed traditional methods like VAR and ARIMA in both in-sample and out-of-sample forecasting. Their greater success is due to their capacity to model nonlinear relationships and identify complicated patterns in macroeconomic data. The incorporation of global factors such as commodity prices and international interest rates increased forecast accuracy, particularly for models that are sensitive to cross-border economic dynamics. This demonstrates Ghana's high susceptibility to external shocks, which emphasises the importance of policy frameworks

Policy Recommendations

To strengthen Ghana's inflation-targeting framework, the study recommends that policymakers and various stakeholder groups should integrate advanced AI models like XGBoost and Random Forest into the Bank of Ghana's Forecasting and Policy Analysis System (FPAS) for more accurate and responsive predictions. A hybrid approach combining traditional econometric models (VAR, ARIMA) with AI algorithms is advisable to balance interpretability and predictive power. We believe that enhancing data infrastructure through collaboration among key institutions would support real-time forecasting. The study also highlights the need for capacity building in AI-based economic modelling through partnerships with academic and international bodies (Hope *et al.* 2025). Furthermore, improved AI-driven forecasts should be used to enhance policy communication and public trust.

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