

Research Article

Experimental XGBoost Method for Predicting the Ghana Cedi Exchange Rate Against Major Developed Currencies

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Abstract

Exchange rate prediction is a crucial aspect of international finance, impacting decisions by governments, investors, and businesses. Accurate prediction supports the development of sound monetary policies, effective risk management, and strategic international trade planning. According to literature, traditional econometric models like ARIMAX and VAR often struggle to capture the complex, non-linear dynamics of foreign exchange markets. In contrast, machine learning methods, particularly Extreme Gradient Boosting (XGBoost), have shown superior performance due to their ability to handle large datasets, model non-linear relationships, and resist overfitting. This study evaluates the efficacy of the Extreme Gradient Boosting (XGBoost) model by predicting the GHc/USD, GHc/GBP and GHc/EUR exchange rates. Four different types of XGBoost models were employed on the financial data to determine the best performed model. The four different XGBoost models include, the XGBoost all feature, the XGBoost difference feature, the XGBoost ratio feature and the XGBoost lagged feature. The data sourced from Bank of Ghana and World Bank websites spans from January 2015 to March 2025. Findings from the study reveals that the XGBoost lagged feature and XGBoost all feature models outperformed the other two models, with an average R^2 of 99%, RMSE of 0.05, and MAE of 0.01. Gold price was the biggest contributor to the GHc/USD exchange rate with the feature important score of 80% followed by monthly interest rate 60%, Government debt 25%, M2 20%, price of oil 20%, BCI 15%, and CCI 10%. This result provides valuable insight for financial analyst and policymakers seeking to forecast/predict exchange rates and develop policies aimed at addressing exchange rate menace in Ghana.

Keywords

XGBoost, All Features, Difference Features, Ratio Features, Lagged Features, Exchange Rate, Hyperparameter Tuning, Regularization Parameter

1. Introduction

Exchange rate predictions is a critical component of international finance, directly influencing decisions made by policymakers, investors, and global businesses. Accurate predictions of currency movements are essential for formulating effective monetary and fiscal policies, managing financial risks, and devising strategic plans in international trade and

investment. Reliable exchange rate prediction enables stakeholders to project an anticipated market trend, optimize pricing strategies, and make informed decisions that enhance economic stability and profitability [1].

Despite the extensive literature on the subject, the unpredictable and non-linear behavior of foreign exchange markets

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remain difficult for traditional econometric models like AR-IMAX and VAR to accurately capture, especially when dealing with complex economic interactions. Recently, machine learning (ML) has emerged as a strong alternative, offering improved performance by effectively identifying intricate patterns, managing large datasets, and modeling non-linear relationships in time series data [2]. Among various machine learning algorithms, Extreme Gradient Boosting (XGBoost) has gained significant recognition for its high predictive accuracy, fast computation, and strong resistance to overfitting. Its effectiveness and interpretability make it especially suitable for financial applications where both performance and robustness are critical [3]. This study proposes the application of an XGBoost model to predict the exchange rate of the Ghanaian cedi (GHS) against three major global currencies, thus, the United States dollar (USD), British pound sterling (GBP), and euro (EUR), using a comprehensive set of macroeconomic and financial indicators.

Ghana, as a West African lower middle-income country, import dependent economy with a history of currency depreciation and inflationary pressures, provides a unique and policy-relevant context for such predictive modeling. The exchange rate of the GHc is influenced by both domestic macroeconomic fundamentals and global financial trends, making it a suitable case for testing the efficacy of advanced ML models [4]. The macroeconomic indicators incorporated into this study include inflation rate, interest rate, gross domestic product (GDP) growth, trade balance, consumer confidence index, business confidence index and external debt. Financial indicators such as international commodity prices (Gold and Oil), remittance inflows, and capital market indices are also integrated to enrich the feature space.

By combining these inputs, the study seeks to enhance the model's ability to discern subtle patterns and interactions that influence currency movements in Ghana over time. The contributions of this paper are in threefold: Firstly, it introduces a novel implementation of the XGBoost algorithm for exchange rate prediction in the context of the Ghanaian economy, where such applications remain relatively underexplored. Secondly, it offers a comparative analysis of GHc performance against multiple major currencies, thereby broadening the scope and relevance of the findings. Finally, it provides insights into the relative importance of different macroeconomic and financial features which influences exchange rate dynamics, thereby contributing to both academic literature and policy implementation.

2. Literature Review

2.1. Traditional Approaches to Exchange Rate Predictions and Limitations

Exchange rate prediction has long been a focal point in international finance, given its profound implications for

economic policy, investment decisions, and risk management. Traditional econometric models, such as Autoregressive Integrated Moving Average with eXogenous regressors (AR-IMAX) and Vector Autoregression (VAR), have been extensively employed to model and predict exchange rate movements. However, these models often assume linear relationships and may struggle to capture the complex, nonlinear, and dynamic nature of foreign exchange markets, especially in the presence of structural breaks and regime shifts. This limitation is particularly evident in emerging economies like Ghana, where exchange rates are influenced by a myriad of volatile macroeconomic and financial features [5].

2.2. Emergence of Machine Learning in Exchange Rate Prediction

In recent years, machine learning (ML) techniques have gained prominence as powerful tools for modeling and predicting exchange rates. These methods, including ensemble algorithms like Extreme Gradient Boosting (XGBoost), offer the ability to model complex, nonlinear relationships and interactions among a large number of features without stringent assumptions about data distribution. Extreme Gradient Boosting, in particular, has demonstrated superior predictive performance, computational efficiency, and robustness against overfitting, making it well-suited for financial applications where accuracy and interpretability are paramount [6]. Empirical studies have showcased the efficacy of XGBoost in exchange rate prediction. For instance, [7] applied XGBoost and Long Short-Term Memory (LSTM) models to predict the Chinese Yuan to US Dollar exchange rate, finding that both models outperformed traditional approaches, with LSTM slightly edging out XGBoost in predictive accuracy. Similarly, [8] employed XGBoost, among other ML algorithms, to forecast Nigeria's exchange rate against the US Dollar, demonstrating that XGBoost achieved commendable accuracy, second only to Random Forest models.

2.3. Macroeconomic and Financial Indicators in Exchange Rate Modeling

The selection of relevant macroeconomic and financial indicators is crucial for effective exchange rate prediction [9]. Key indicators commonly utilized include Gross Domestic Product (GDP), inflation rates, interest rates, trade balances, foreign exchange reserves, and employment data. These variables reflect the economic health of a country and influence investor perceptions and capital flows, thereby affecting currency values [10].

In the context of Ghana, studies have identified several macroeconomic factors that significantly impact the Ghanaian Cedi's (GHc) exchange rate. [11] found that GDP, inflation, and interest rates are significant determinants of the GHc exchange rate. Moreover, [12] emphasized the impact of both domestic economic conditions and global financial trends on GHc per-

formance against major currencies like the USD, GBP, and EUR.

2.4. Application of XGBoost in Ghana's Exchange Rate Forecasting

Despite the growing body of research applying ML techniques to exchange rate forecasting and prediction globally [13-15], there is a paucity of studies focusing specifically in Ghana [16]. The unique economic structure of Ghana, characterized by its reliance on commodity exports and imports, vulnerability to external shocks, and evolving monetary policy framework, presents a compelling case for the application of advanced ML models like XGBoost [17]. Such models can effectively capture the nonlinear interactions between macroeconomic indicators and exchange rate movements, providing more accurate and robust predictions.

Furthermore, integrating XGBoost with interpretability tools such as SHapley Additive exPlanations (SHAP) can enhance the robustness of the model's predictions, offering valuable insights for policymakers and investors [18]. This approach aligns with the findings of [3], who demonstrated that combining XGBoost with interpretability techniques yields models that are both accurate and explainable, facilitating better decision-making in financial environment.

3. Materials and Methods

3.1. Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting is an optimized, distributed gradient boosting method designed to be highly efficient, flexible, and portable [19]. It is widely used for supervised learning tasks such as classification and regression, offering high accuracy and performance, especially with structured/tabular data. XGBoost implements the gradient boosting algorithm using decision trees as base learners with enhancements in regularization, parallel processing, and missing value handling [20].

3.2. Model Formulation

Given a dataset in equation (1), where $x_i \in \mathbb{R}^m$ is the feature vector and $y_i \in \mathbb{R}$ or $y_i \in \{0, 1, \dots, K-1\}$ is the target label for regression or classification.

$$D = \{(x_i, y_i)\}_{i=1}^n \quad (1)$$

Let the goal be to predict the exchange rate of a local currency against a foreign currency (e.g., GHc/USD, GHc/GBP

and GHc/EUR). The model seeks to learn a functional relationship shown in Equation (2),

$$\hat{y}_i = f(x_i) \quad (2)$$

where, $\hat{y}_i$ is the predicted exchange rate at time i , $x_i \in \mathbb{R}^m$ is the vector of dimension m of macroeconomic and financial features observed at time i , and $f(\cdot)$ is the nonlinear mapping learned by the XGBoost algorithm.

3.2.1. Additive Model in XGBoost

XGBoost builds the model in an additive manner. At iteration t , the additive model for the XGBoost is given by equation (3), where f_k is the regression tree (decision tree) and F is the space of all regression trees.

$$\hat{y}_i^{(t)} = \sum_{k=1}^t f_k(x_i), f_k \in F \quad (3)$$

3.2.2. Objective Function of the XGBoost Model

The learning task is to find a model $f_k \in F$ that minimizes the regularized loss function in equation (4).

$$L^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^K \Omega(f_k) \quad (4)$$

where, $\hat{y}_i^{(t)} = \sum_{k=1}^K f_k(x_i)$ is the prediction function, l is the

loss function, $\Omega(f_k) = \tau T + \frac{1}{2} \lambda \|w\|^2$ is the regularization for tree f_k , K is the number of boosting iteration, T is the number of leaves in each tree, w is the leaf weights, and τ, λ is the regularization parameters.

3.2.3. Second-Order Taylor Expansion

To optimize $L^{(t)}$, XGBoost uses a second-order Taylor expansion of the loss function which is indicated by equation

(5), where $g_i = \frac{\partial l(y_i, \hat{y}_i)}{\partial \hat{y}_i}$ is the first-order gradient and

$h_i = \frac{\partial^2 l(y_i, \hat{y}_i)}{\partial \hat{y}_i^2}$ is the second-order gradient often referred to as Hessian.

$$L^{(t)} \approx \sum_{i=1}^n \left[l(y_i, \hat{y}_i^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \quad (5)$$

The constant term $l(y_i, \hat{y}_i^{(t-1)})$ is dropped in optimization.

3.2.4. Tree Structure and Leaf Weights

Each tree partitions the data into T leaves. Let I_j denote the instance set of leaf j , the optimal weight w_j for leaf j is given by equation (6).

$$w_j^* = - \frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \quad (6)$$

The optimal value of equation (4) after adding tree f_t becomes equation (7). This score is used to determine the best tree structure (i.e., how to split the nodes).

$$L^{(t)} = - \frac{1}{2} \sum_{j=1}^T \frac{\left(\sum_{i \in I_j} g_i \right)^2}{\sum_{i \in I_j} h_i + \lambda} + \tau T \quad (7)$$

3.2.5. Greedy Tree Construction

XGBoost builds the tree using a greedy algorithm by following the procedure below.

- 1) Enumerate all possible splits on all features.
- 2) For each split, calculate the information gain. This is calculated using equation (8).
- 3) Choose the split with the highest gain, where, G_L, H_L is the sum of gradients and Hessians for left split and G_R, H_R is the sum of gradients and Hessians for right split.

$$Gain = \frac{1}{2} \left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right] - \tau \quad (8)$$

3.2.6. Regularization and Overfitting Control

To control overfitting, XGBoost incorporates several regularization techniques such as:

- 1) Shrinkage (learning rate), which multiplies the contribution of each tree by a factor $\eta \in (0,1)$
- 2) Column subsampling. It uses random subsets of features at each tree or node.
- 3) Early stopping. Halts training when performance on a validation set degrades.

The structural algorithm of the XGBoost model is shown in Figure 1.

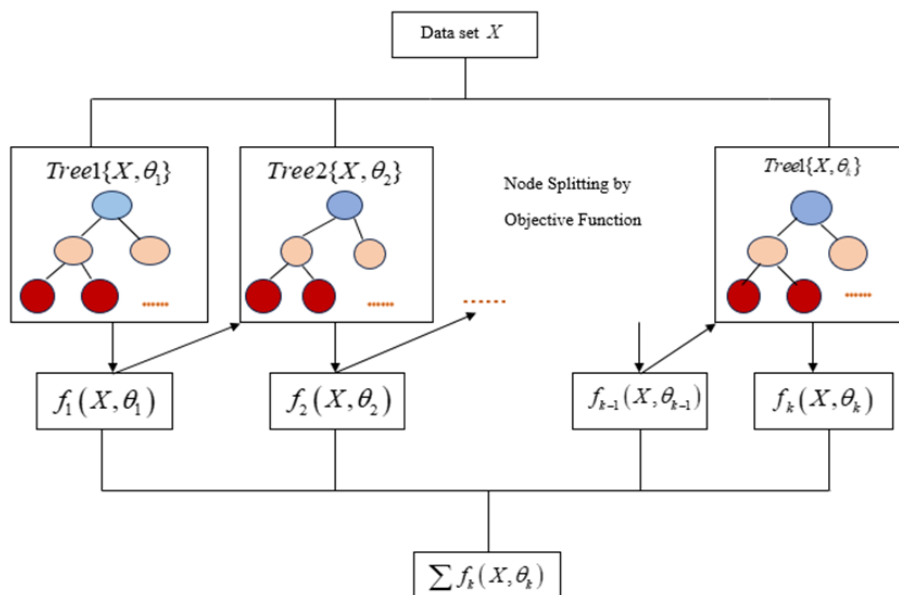


Figure 1. Structure of the XGBoost Algorithm.

3.3. XGBoost Performance Evaluation

While building a powerful model is essential, evaluating its performance accurately is even more important to ensure its effectiveness in real world application. Performance evaluation ensures that:

- 1) The model generalizes well to unseen data,
- 2) Overfitting and underfitting is detected, and
- 3) The model meets the specific needs of the application, whether it is accuracy, interpretability, or computational efficiency.

Regression Tasks

For regression problems, XGBoost performance is evaluated using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-Square (R^2) Score which are indicated in equation (9), (10), and (11).

$$RMSE = \sqrt{\frac{1}{2} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (10)$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (11)$$

4. Results

The models were developed using a time series analysis approach appropriate for the dataset, which comprises of 120 observations. Instead of employing a shading window approach, that data was divided into training set comprising of 80% of the data and a test set comprising the remaining 20%. This division ensured that the data remains in chronological order, preserving the temporal structure of the time series for accurate prediction. The training set, spanning from 2015 to 2023, was used to train the models. All the dataset from 2015 to 2025 formed the test set which ensured that the models were validated on both in-sample (2015 to 2023) and out-of-sample (2024 to 2025) data, maintaining the temporal integrity of the time series. At the end of the training phase, each model's performance was evaluated on the test set. This approach helped in capturing temporal dependencies and ensured that the models were robust across different time periods, providing reliable prediction for the monthly change in GHc/USD, GHc/GBP, and GHc/EUR exchange rate.

The performance of these models was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) and the predictive accuracy was assessed. The models were trained and validated on different subsets of the data to ensure robustness and generalizability. Despite the high volatility

and frequent market interventions affecting the GHc, these models provided valuable insight into exchange rate movements. One significant challenge encountered during the analysis was the high degree of market volatility, which introduces noise and reduces the predictability of exchange rate movements. In Ghana, the exchange rate is susceptible to both domestic and international political events, macroeconomic indicators, prices of commodities and market sentiments. These factors contribute to the high volatility observe in the GHc/USD, GHc/GBP and GHc/EUR exchange rate. Also, frequent interventions by the Bank of Ghana and other regulatory bodies further complicate the modeling process by introducing sudden and unpredictable shifts in the data.

Moreover, it was observed that the predictive performance varied significantly across different models. While the ratio-features model offered robust predictions for certain periods, it did not fully capture extreme volatility. Again, the all-features demonstrated better adaptability to certain fluctuating market conditions but still faced challenges in capturing the abrupt changes caused by regulatory interventions. In this study, the hyperparameter tuning is performed for all four different models, which are all-features XGBoost model, ratio-features XGBoost model, Difference-features XGBoost model, and lagged-features XGBoost model. Hyperparameter tuning is a crucial step in machine learning as it involves optimizing the parameters that directly influence the model's performance. The goal is to find the best set of hyperparameters that yields the lowest RMSE and MAE and highest score on the test dataset. For each model, a grid of hyperparameter is defined and randomized search CV is used to perform the search. The best parameter was selected based on a deep red color of the heatmap shown in Figure 2.

Figure 3 shows the interaction and trends of macroeconomic indicators (monthly interest rate, GDP, trade balance, inflation, etc.), commodity price (gold price, oil price) and market sentiment indicators (business confidence index and consumer confidence index) from 2015 to 2025, providing a comprehensive overview of the factors influencing the GHc/USD, GHc/GBP, and GHc/EUR exchange rate. Government debt and money supply (M2) are pivotal measures of market risk and uncertainty. Spikes in these indices typically signal heightened market stress, often leading to depreciation of the GHc against USD, GBP, and EUR. For instance, during periods of global economic turmoil, both Government debt and M2 spikes correlate with significant movements in the GHc/USD exchange rate, reflecting increased risk aversion among investors. Example of such instance is the Government debt restructuring program that happened in 2014 where risk-free asset becomes a risky asset due to the high impact of Government debt which came post covid-19. This heightened risk drives investors towards safer assets, such as the USD, thereby weakening the GHc.

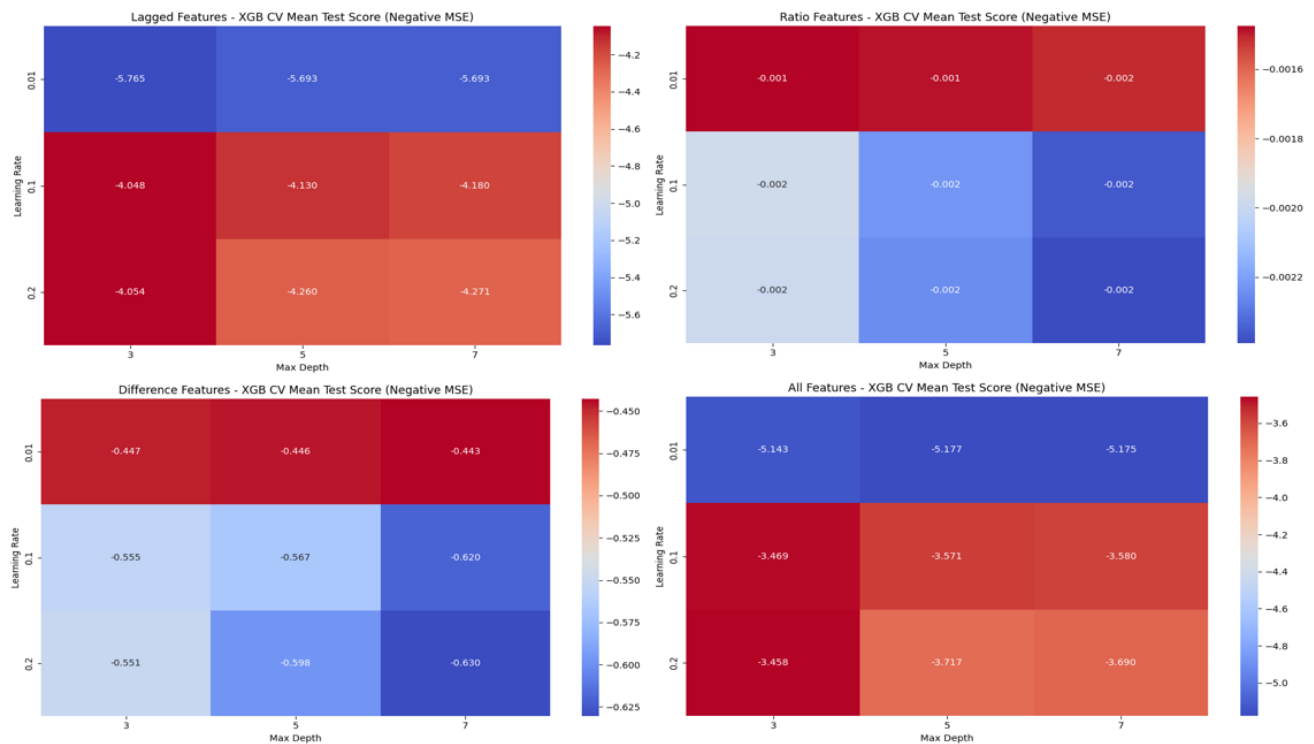


Figure 2. Hyperparameter Tuning of GHc/USD Exchange Rate across Experiment.

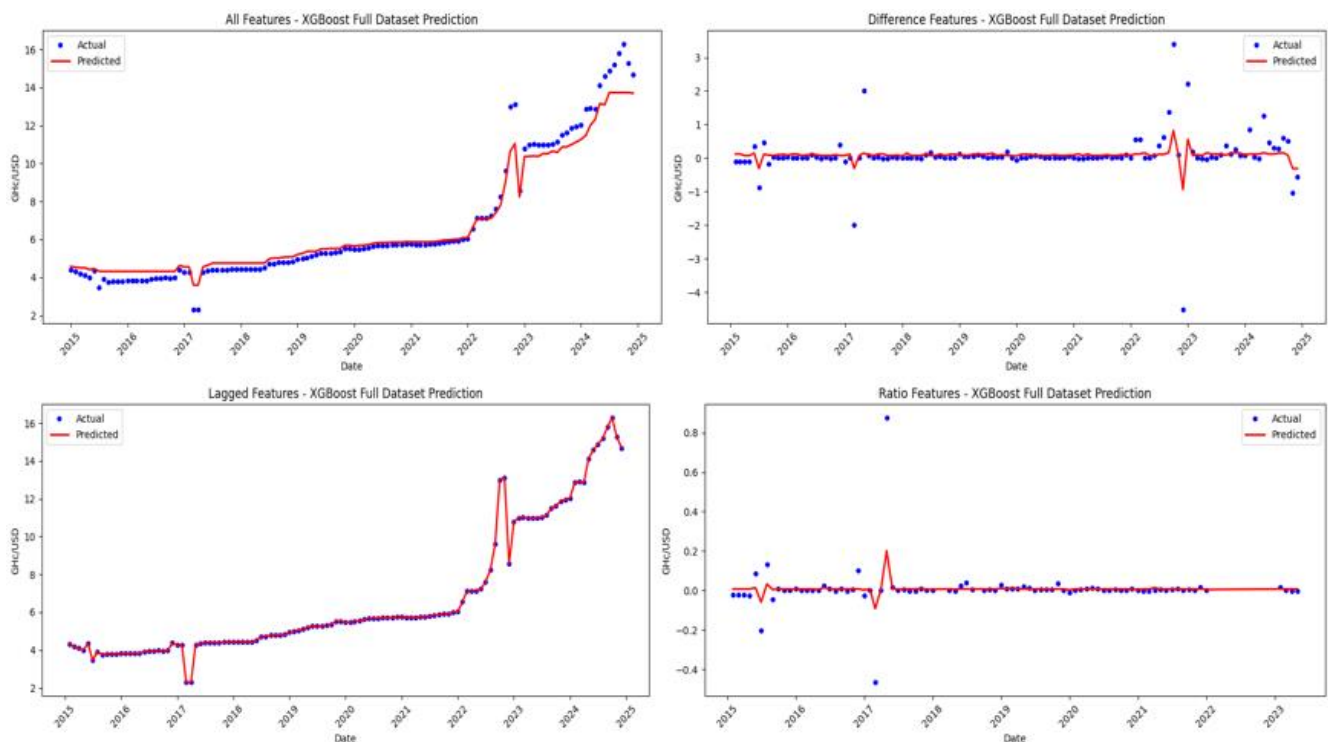


Figure 3. XGBoost Model Predictions vs Actual GHc/USD Exchange Rate Across Experiment.

Interest rate and inflation illustrate similar patterns, underscoring that the performance of these indicators is closely linked to the exchange rate trends in Ghana. Higher inflation reduces the purchasing power of the cedi, leading to increase

in demand for foreign currencies like the USD. This drives the GHc/USD exchange rate upwards indicating GHc depreciation. On the other hand, interest rate decline weakens the GHc as both local and foreign investor withdraw their funds. Gold

price and oil price provide insight into commodity markets' influence on the GHc/USD, GHc/GBP, and GHc/EUR exchange rate. Gold often acts as safe-haven asset, with its price increasing during periods of market uncertainty which directly affect GHc/USD parity. As investors flock to gold in times of uncertainty, the corresponding increase in gold price signifies broader market concerns, which often leads to stronger GHc against the USD, GBP, and EUR. Conversely, oil price fluctuations have a direct impact on Ghana's economy, given its status as an oil importer. Volatile oil price can lead to economic instability, influencing the GHc through

impacts on inflation, trade balance and GDP. Refer to feature importance in Figure 4.

The interplay of macroeconomic indicators, commodity price, monetary policies, and market sentiment collectively shape the dynamics of exchange rate. This comprehensive analysis offers valuable insights for financial analyst and policymakers, enabling them understand the multifaceted factors driving exchange rate fluctuations and to devise policies to mitigate them. The ability to decipher this relationship is crucial for making predictive assessments and managing the risk associated with currency volatility.

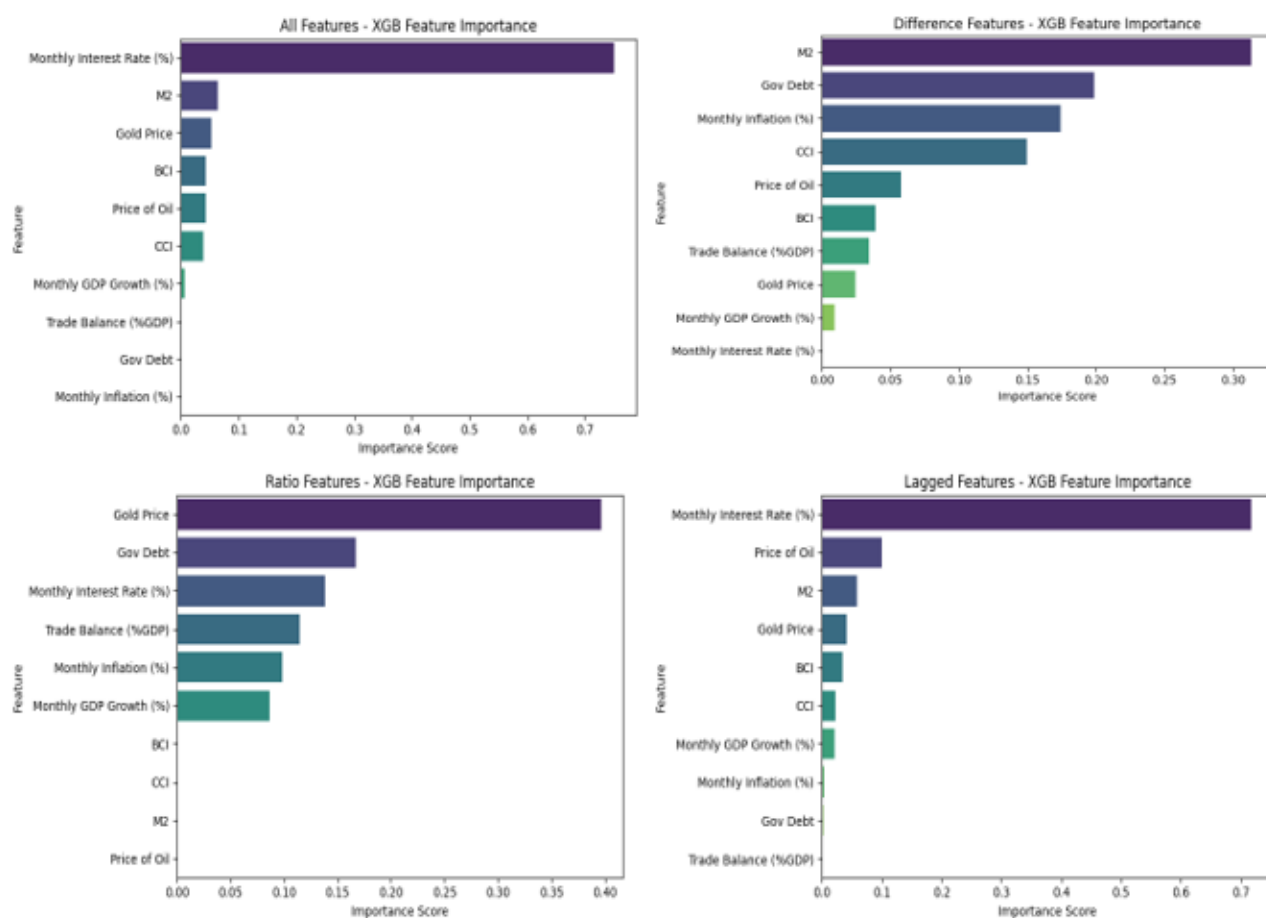


Figure 4. XGBoost Feature Importance of GHc/USD Across Experiments.

Table 1 shows the comparative analysis of the various predictive models for exchange rate, highlighting the efficacy of multivariate time series prediction method when dealing with noisy, non-stationary and chaotic financial time series data. This study evaluates four models, i.e., XGBoost all features, XGBoost difference features, XGBoost ratio features, and XGBoost lagged features, using three different exchange rates (GHc/USD, GHc/GBP, and GHc/EUR). For GHc/USD exchange rate, XGBoost difference features model yields RMSE of 5.4345, MAE of 2.3525 and R^2 value of 34.48%. This low R^2 value indicates the model poor performance, failing to capture the underlying dy-

namics of GHc/USD fluctuations. This is due to lower dimensionality of the features set. Also, the model's inability to effectively process high volatility features results in poor predictive performance. The XGBoost ratio features model did not perform any better than that of the difference features, although it was able to reduce the RMSE and MAE values significantly. The XGBoost all features model on the other hand, performs significantly better with an RMSE of 0.0065, MAE of 0.0045, and an R^2 value of 96.46%. This indicates very good predictive performance and a better handling of the feature sets compared to difference and ratio features. All features ability to use the features raw dimensionality, cou-

pled with better boosting and regularization techniques helps capture the relevant patterns in the data, leading to better prediction accuracy. However, if compared to XGBoost lagged features model, there is still room for improvement, as indicated by the RMSE and MAE values. The XGBoost lagged features model outperformed all the other models

with the lowest RMSE of 0.0005, MAE of 0.0001 and the highest R^2 of 99.99%. Lagged features architecture, which predict the GHc/USD using the previous feature sets was very effective and rightly so, because most macroeconomic, financial, and commodity price features predict better using their past features.

Table 1. Model Results Comparison.

Exchange Rate	Model	RMSE	MAE	R-Square
GHc/USD	XGBoost All Features	0.0065	0.0045	0.9646
	XGBoost Difference Features	5.4345	2.3525	0.3448
	XGBoost Ratio Features	0.8759	0.2510	0.3890
	XGBoost Lagged Features	0.0005	0.0001	0.9999
GHc/GBP	XGBoost All Features	0.0917	0.0687	0.9995
	XGBoost Difference Features	0.6592	0.3341	0.2980
	XGBoost Ratio Features	0.0321	0.0220	0.2973
	XGBoost Lagged Features	0.0010	0.0008	0.9999
GHc/EUR	XGBoost All Features	0.0067	0.0046	0.9651
	XGBoost Difference Features	5.0159	2.2638	0.4000
	XGBoost Ratio Features	0.3024	0.1888	0.3408
	XGBoost Lagged Features	0.0066	0.0047	0.9658

5. Discussion

Figure 3 present the actual and predicted GHc/USD exchange rate for the various experiments, that actual values (blue dot) and predicted values (red line) are plotted against time. The XGBoost lagged features model follows the actual values for most of the time series, capturing the trends and fluctuations effectively well, especially in the periods of significant volatility. The XGBoost all features model also perform very well, almost mirroring the actual values with slight deviations, indicating its effectiveness in modeling temporal dependencies. The XGBoost ratio features model did not perform well, although it was able to capture some volatility in the data but it showed pronounced deviation and higher level of noise compared to the lagged and all features, reflecting its low performance as indicated in Table 1. The least performing model was the XGBoost difference features with very appalling performance indicators Shown in Table 1. The discussion from this section was also done for the GHc/GBP and GHc/EUR exchange rate, and the results which shown in Appendix 1 and 2 also gave the same results as the GHc/USD exchange rate.

6. Conclusions

This study provides a comprehensive analysis of the predictive ability of the XGBoost model on GHc/USD, GHc/GBP, and GHc/EUR perform under four different experiments, utilizing a feature sets comprising of macroeconomic indicators, financial indicators, commodity price and market sentiment indicators. Its addresses the challenges posed by prediction of exchange rate in Ghana, by evaluating a more sophisticated model for exchange rate prediction i.e., XGBoost all features model, XGBoost difference features model, XGBoost ratio features model, and XGBoost lagged features model. A significant insight was gained into the performance and suitability for exchange rate prediction. The findings demonstrate that, XGBoost lagged features was the best performing model to predict GHc/USD, GHc/GBP, and GHc/EUR exchange rate with RMSE 0.0005, 0.0010, and 0.0047, MAE of 0.0001, 0.0008, and 0.0047, and R^2 value of 99.99%, 99.99%, and 96.58% respectively. This emphasizes XGBoost lagged features model's efficiency and effectiveness, in contrast, the XGBoost difference features model performs poorly, particularly with periods of extreme volatility.

In line with existing literature on the strength of XGBoost model, this study proves that the XGBoost model at different experiments performs differently and better. This provides a better insight to financial analyst and policymakers aiming to accurately predict exchange rate in Ghana. It also aids in policy formulation that intends to mitigated the spiral depreciation of the Ghana cedi against the major developed currency under study.

7. Recommendation

Futures work may explore the hybrid of traditional and XGBoost model to see it effectiveness in predicting exchange rate in Ghana.

Abbreviations

GDP Gross Domestic Product

XGBoost Extreme Gradient Boost
BCI Business Confidence Index
CCI Consumer Confidence Index

Author Contributions

Isaac Ampofi: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft

Lewis Brew: Supervision, Writing – review & editing

Eric Neebo Wiah: Supervision, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

Appendix

Appendix I: XGBoost Model Predictions vs Actual GHc/GBP Exchange Rate Across Experiment

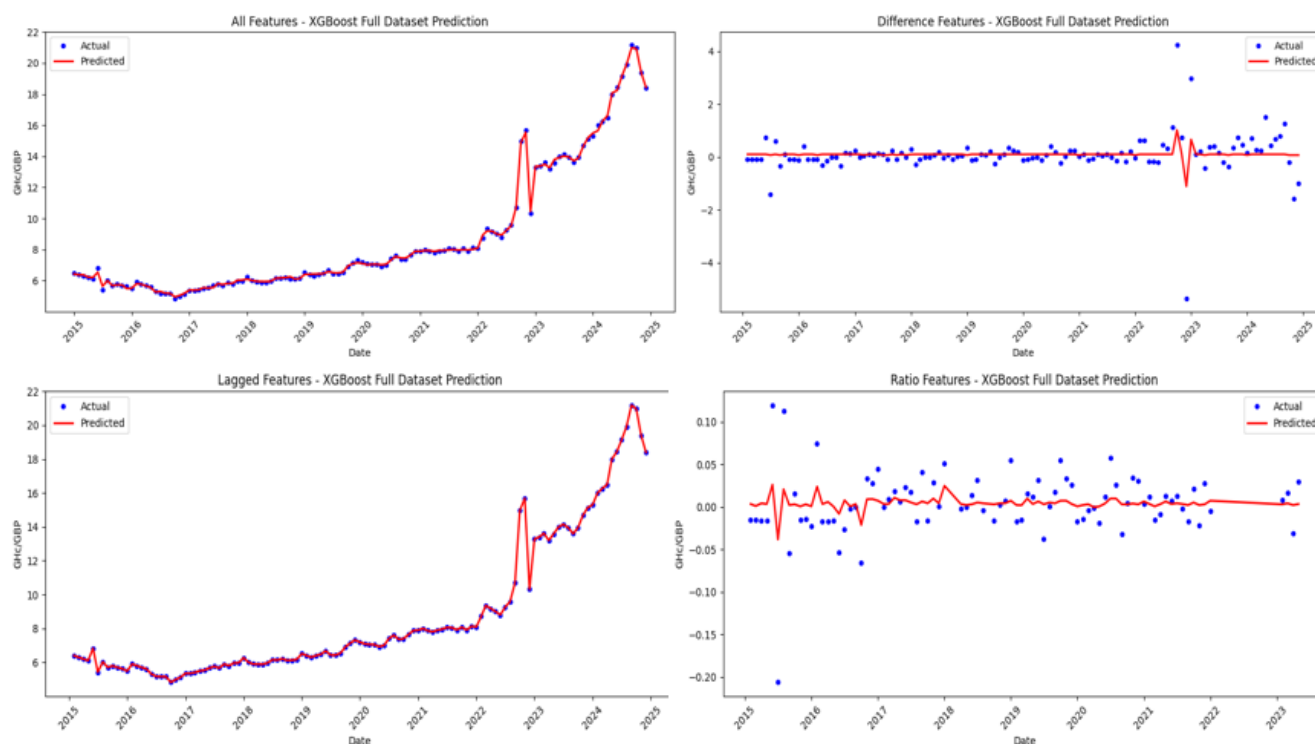


Figure 5. XGBoost Model Predictions vs Actual GHc/GBP Exchange Rate Across Experiment.

Appendix II: XGBoost Model Predictions vs Actual GHc/EUR Exchange Rate Across Experiment

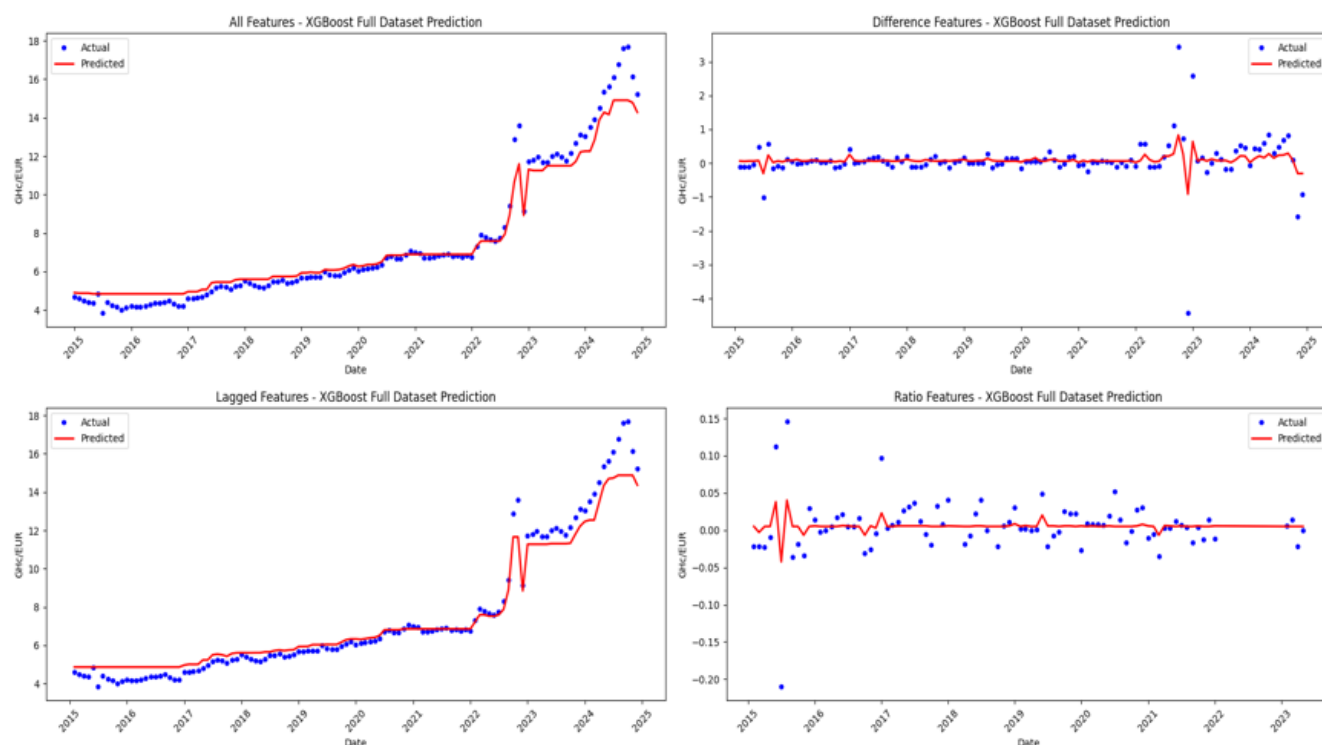


Figure 6. XGBoost Model Predictions vs Actual GHc/EUR Exchange Rate Across Experiment.

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