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Predicting Food Price Trends in Nigeria Using Advanced Machine Learning Techniques: LSTM and XGBoost

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ABSTRACT

Food price volatility poses significant challenges to food security, poverty reduction, and economic planning in Nigeria. In response to these concerns, this study applies advanced machine learning techniques Long Short-Term Memory (LSTM) networks and Extreme Gradient Boosting (XGBoost) to forecast food prices using data from the World Food Programme spanning 2002 to 2024. Comprehensive data preprocessing steps were undertaken, including normalization and feature engineering, with the integration of external macroeconomic indicators such as inflation rates and fuel prices to enrich the models. Model performance was evaluated using standard metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).The results demonstrate that the XGBoost model outperformed the LSTM network across all evaluation criteria. XGBoost achieved a lower RMSE of ₦62.94 and a lower MAE of ₦39.39, compared to LSTM's RMSE of ₦84.27 and MAE of ₦49.20. Moreover, XGBoost attained a higher R^2 value of 0.91 versus LSTM's 0.83, indicating greater predictive accuracy and better explanatory power. Both models successfully captured major historical price disruptions associated with the 2008–2010 global financial crisis and the COVID-19 pandemic, while a period of relative price stability was observed between 2016 and 2018.The findings highlight the value of machine learning models particularly XGBoost as effective tools for enhancing food price forecasting and supporting proactive, data-driven food security interventions. Future research could further improve predictive accuracy by incorporating real-time satellite imagery, weather variables, and broader macroeconomic indicators into forecasting frameworks.

Keywords : LSTM,Xgboost,MAE,MSE,RMSE,ML,SSA,FAO, WFP, RNN

INTRODUCTION

Food price volatility poses significant challenges to food security, economic stability, and the livelihoods of populations in developing countries, particularly in Nigeria. Fluctuations in food prices can lead to increased poverty levels, malnutrition, and social unrest. Understanding and predicting these price movements are crucial for policymakers, traders, and consumers to make informed decisions and implement effective interventions.

In recent years, machine learning (ML) techniques have emerged as powerful tools for analyzing complex datasets and forecasting trends in various domains, including agriculture and economics. By leveraging historical data, ML models can identify patterns and make accurate predictions about future price movements. This study aims to utilize ML techniques to analyze historical food price data in Nigeria, identify key factors influencing price volatility, and develop predictive models to forecast future price trends.

Food insecurity in Sub-Saharan Africa (SSA) remains a major enduring challenge that the region has yet to overcome. Although the affordability of healthy diets is the lowest in SSA compared to other regions in the world, predictions show SSA will add approximately 2 billion residents by 2100, calling for scholars, policymakers, and investors to pay more attention and develop better food security assessments (Vollset et al., 2020). In terms of population, Nigeria is the largest country in the SSA region, with 206 million people as of 2020. Before the COVID-19 pandemic, it was estimated that 39% or about 80 million Nigerians lived below the international poverty line, while 65 million Nigerians had consumption levels between \$1.90 and \$3.20 per person per day (World Bank, 2020).

In Nigeria, agriculture is a vital sector, contributing to over 24% of the country's total GDP and employing two-thirds of its labor force, comprising mostly farmers (Food and Agriculture Organization of the United Nations [FAO], 2023). Most of these farmers are smallholders, estimated to be around 38 million, who grow crops on farms that are less than 4 hectares in size (Ricciardi et al., 2018). Despite their contribution to food production in the country, over 72% of these smallholder farmers live below the poverty line of $1.90 per day (Sasu, 2023). One of the key reasons contributing to this situation is the lack of market price intelligence among these farmers. The majority of fruits and vegetables produced by this category of farmers are from the Northern regions and are largely sold in the Southern regions, where a significant number of food markets are located (D. Onwude et al., 2023).

While existing studies have explored the factors influencing food price volatility and the role of smallholder farmers in Nigeria, there is a noticeable lack of comprehensive analysis employing advanced machine learning techniques to predict future price trends. This gap underscores the need for utilizing ML models to provide accurate forecasts, which can aid policymakers, traders, and farmers in making informed decisions to mitigate the adverse effects of price volatility on food security and economic stability in Nigeria.

METHODOLOGY

This section describe the methodology used to analyse and predict food prices volatility in Nigeria. It concentrate on Various machine learning models, including Long Short-Term Memory (LSTM) XGboost, are developed to predict future food prices.this chapter provides an overview of the datasets

Data Collection:

The study utilizes the World Food Programme (WFP) Price Database, which provides comprehensive data on food prices across various regions and markets in Nigeria from 2002 to 2024. This dataset includes variables such as date, administrative regions (admin1 and admin2), market names, geographic coordinates (latitude and longitude), commodity categories, unit prices, price flags, price types, currency, and prices in both local currency and USD.

Data Preprocessing

Data cleaning involves handling missing values, correcting inconsistencies, and normalizing price data to ensure uniformity. Exploratory data analysis (EDA) is conducted to understand the distribution of prices, identify outliers, and detect trends and seasonal patterns.

Feature Engineering

New features are created to capture temporal patterns (e.g., month, season), spatial information (e.g., latitude, longitude), and market-specific factors. Additional external factors such as inflation rates, fuel prices, and weather conditions are incorporated to enhance model accuracy.

Model Development

Various machine learning models, including Long Short-Term Memory (LSTM) networks, and Extreme Gradient Boosting, are developed to predict future food prices. These models are trained and validated using historical data, with hyperparameters optimized to improve performance.

Model Evaluation

The performance of the predictive models is assessed using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared values. Cross-validation techniques are employed to ensure the robustness and generalizability of the models.

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Policy Implications

The study provides insights into potential future price surges or declines, enabling policymakers to implement proactive measures to ensure food security. Recommendations are made based on the predictive models to assist in decision-making processes.

Dataset Description

The dataset from the World Food Programme (WFP) Price Database encompasses food price information across various regions and markets in Nigeria from 2002 to 2024. The key variables include:

- **Date**: The specific date when the price was recorded.
- **Admin1 and Admin2**: Administrative region identifiers corresponding to different levels of geographic divisions in Nigeria.
- **Market**: The name of the market where the price was recorded.
- **Latitude and Longitude**: Geographic coordinates of the market location.
- **Category**: The category of the commodity (e.g., cereals, vegetables).
- **Commodity**: The specific food item (e.g., rice, maize).
- **Unit**: The measurement unit for the commodity price (e.g., kilogram, liter).
- **Price Flag**: Indicator of the price's reliability or any special conditions.
- **Price Type**: Type of price recorded (e.g., retail, wholesale).
- **Currency**: The currency in which the price is denominated.
- **Price**: The recorded price in local currency.
- **USD Price**: The recorded price converted to USD.

Data Source and Dataset Splitting

The primary data source is the World Food Programme (WFP) Price Database, accessible through the World Bank's Data Catalog

World Bank Data Catalog

This database provides monthly food price estimates by product and market, generated using a machine-learning approach that imputes ongoing subnational price surveys, often with accuracy similar to traditional data collection methods.

For model development, the dataset is split into training and testing sets. The training set comprises data from 2022 to 2023, used to train the machine learning models. The testing set includes data from 2024, utilized to evaluate model performance and assess predictive accuracy.

Long Short-Term Memory (LSTM)

LSTM Wang et al. (2019) is a special kind of Recurrent Neural Network (RNN) architecture designed to recall sequence data dependencies, something regular RNNs are unable to do due to its capability to capture long-term dependencies and model complicated nonlinear interactions. The general architecture of LSTM is depicted in Fig. 1 and is mathematically modelled The LSTM introduces a mechanism for the validity of information over long periods of time. The gradient disappearance and gradient explosion problems of RNN models are overcome by adding cells (cells) that store long-term valid data and introducing controllable self-looping gates (gates). The mathematical model of the LSTM principle is

Extreme Gradient Boosting (XGBoost)XGBoost

Extreme Gradient Boosting (XGBoost) is often employed for prediction problems and has achieved good results. For instance, Gono et al. 2023)used XGBoost to predict silver prices, accomplishing a Mean Absolute Percentage Error (MAPE) of 6.06% and an RMSE of 1.6967 US dollars. Wu et al. 2022) utilized Particle Swarm Optimization (PSO) to optimize key parameters of the XGBoost model and then analyzed Australia's electricity price data. They claimed that the optimized XGBoost properly adapts to the time-series trends. Tian et al. 2021) designed a model named LSTM-BO-XGBoost with a Bayesian Optimization (BO) and applied it to stock price prediction. They validated that this model exhibits better stability than the other LSTMs, yielding RMSE, Mean Absolute Error (MAE), accuracy, and F1 score of 610.35, 15.60, 0.60, and 0.75, respectively.

Extreme Gradient Boosting (XGBoost)XGBoost Paliari et al. (2021) is a Machine Learning approach that builds a powerful predictive model by combining thepredictions of multiple smaller models using the gradientboosting framework, often with decision trees as the base learners. In the context of forecasting global food prices,where there is access to historical price data as the feature, it effectively captures the complex, nonlinear patterns in the price dynamics. By iteratively optimizing and combining the predictions from multiple decision trees and creating a robust and accurate predictive model for global food price forecasting, leveraging the strengths of decision trees to capture intricate relationships and patterns within the price data. Considering fk(x) as the prediction of the kth tree, the output $\hat{y}$ is a combination of all K trees, mathematically modelled as in equation .

$$(\phi) = \sum_{i} l(\hat{y}_i, y_i) + \sum_{k} \Omega(f_k)$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j} w_j^2$$

Whereas: ($\hat{y}i$, yi) = Training loss,

$\Omega(fk)$ = The complexity of trees

fk = The regression trees

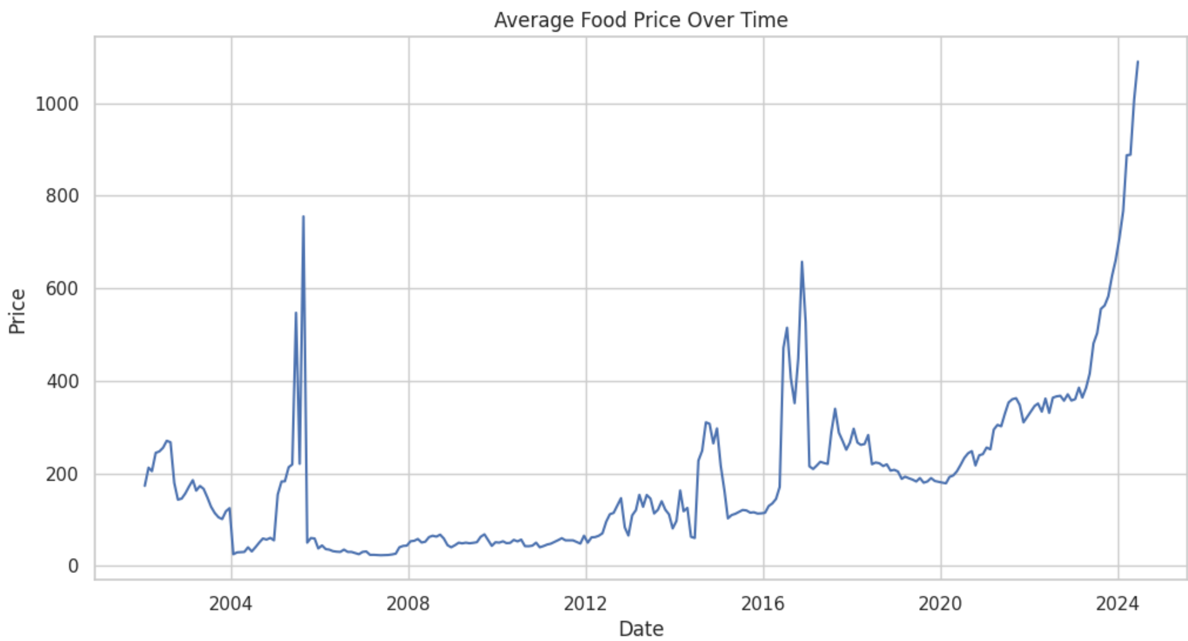
T = The number of leaves in the tree

w_j = The score of the regression tree node

γ *and* λ = regularization parameters.

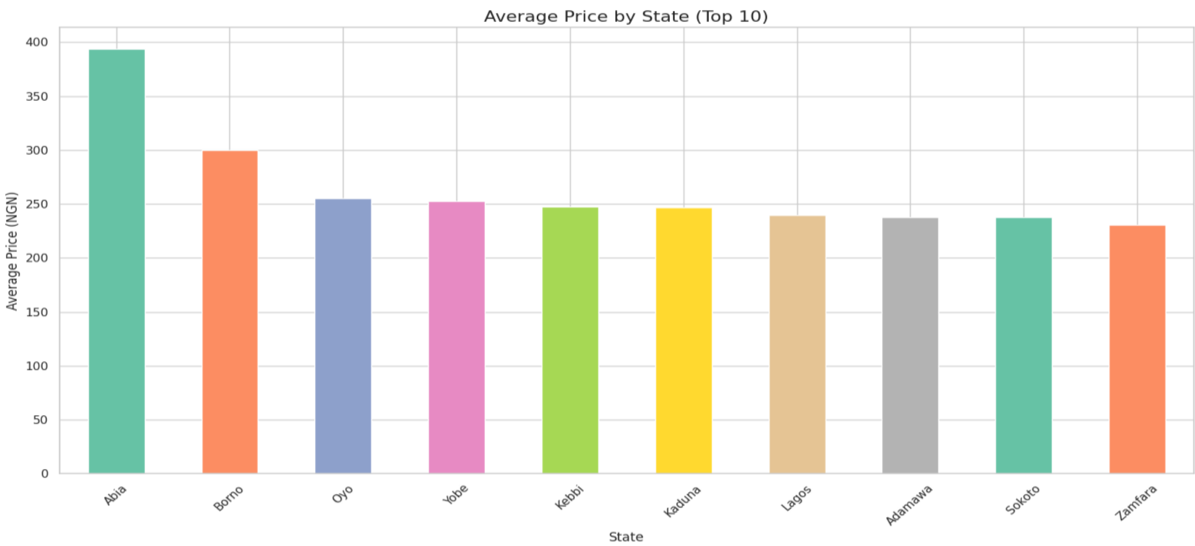
RESULTS

Average Food Price Over Time



This study presents a comprehensive time-series analysis of average food prices in Nigeria spanning over two decades, with a focus on identifying key inflationary patterns, market shocks, and volatility drivers. The results indicate a general upward trajectory in food prices, beginning from a relatively modest level of approximately ₦200 and rising steadily to surpass ₦1,000 in recent years. The data reveal several significant inflection points. Notably, prices surged from around ₦200 in 2004 to over ₦500 by 2006, and then exceeded ₦600 during the 2007–2008 global financial crisis. Between 2008 and 2012, prices stabilized below ₦200, exhibiting minimal growth during this period. However, a moderate increase was observed from 2015 to 2017, with prices slightly above ₦600. A brief dip occurred around 2020, coinciding with the COVID-19 pandemic, followed by a steady and sharp increase from 2020 to 2024, where the average price rose from approximately ₦300 to over ₦1,000.

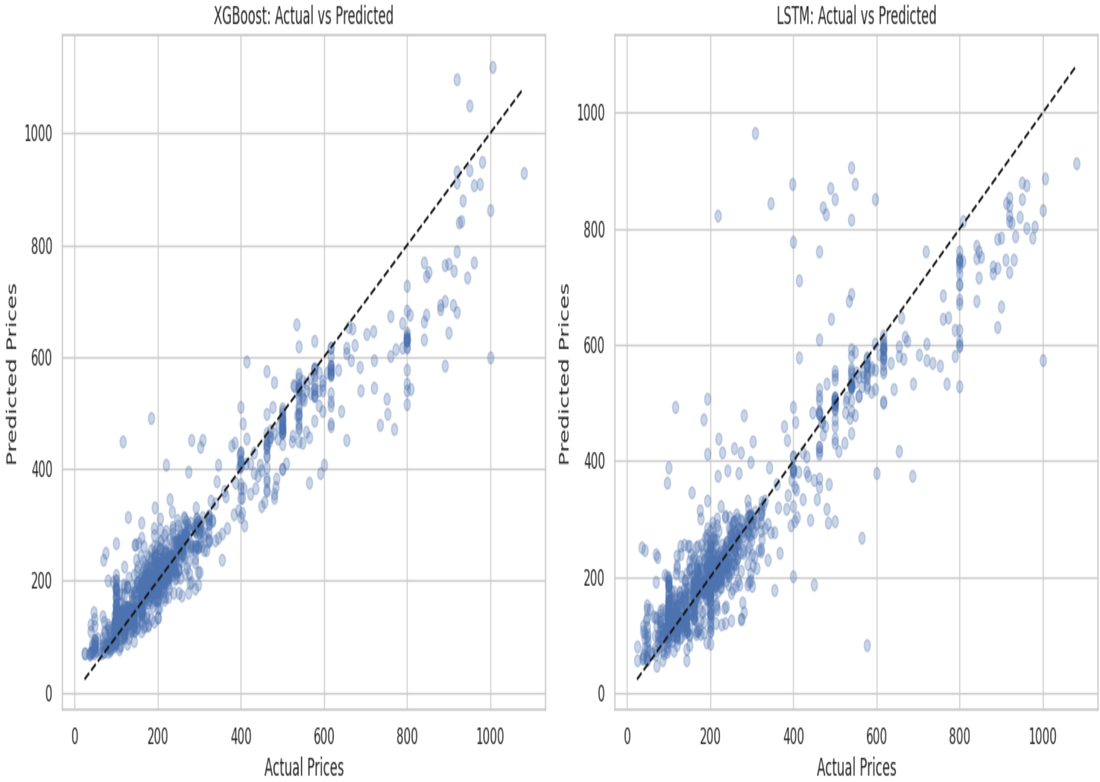
These findings underscore the importance of strategic policy interventions aimed at enhancing agricultural productivity and strengthening supply chain resilience to mitigate food price volatility. Additionally, the study provides a valuable foundation for future research on food price forecasting using advanced machine learning techniques, offering critical insights for policymakers addressing national food security concerns.



The chart illustrates the average commodity prices recorded in the top ten Nigerian states from 2002 to 2024. Among these, Abia State registered the highest average price, exceeding ₦350. Borno State followed with an average price around ₦300, while Oyo State recorded a moderate level slightly above ₦250. In contrast, Yobe, Kebbi, and Kaduna States exhibited closely aligned average prices, all below ₦250. Similarly, Lagos, Adamawa, and Sokoto States maintained average prices under ₦240. Zamfara State reported the lowest average price, with values consistently around ₦240 over the study period. This regional analysis highlights the spatial variability in food commodity pricing, likely influenced by differences in production capacity, market access, transportation infrastructure, and regional demand. The insights can support targeted interventions to improve market efficiency and price stability across states.

The chart above presents the price trajectories of major food commodities across Nigeria from 2002 to 2024. The analysis shows that the price of imported rice experienced fluctuations between 2002 and 2016. However, from 2018 onward, it exhibited a consistent upward trend, rising from approximately ₦400 to over ₦1,000 by 2024. Similarly, palm oil prices fluctuated significantly between 2016 and 2018, followed by a notable decline. Millet prices showed considerable volatility, with prices hovering around ₦200 in 2002 and falling below ₦200 by 2014. A sharp increase was observed thereafter, rising to over ₦400 in 2016 and peaking above ₦600 in 2017. Local rice prices also followed an inconsistent pattern. A spike was observed in 2017 at around ₦500, which later declined to below ₦400 in 2020. This period coincides with the implementation of the Anchor Borrowers' Programme by the Central Bank of Nigeria, aimed at boosting local rice production and reducing import dependence. These trends underscore the dynamic nature of food commodity markets in Nigeria and highlight the impact of policy interventions on local production and pricing.

XGBoost and LSTM Predictions



The image presents scatter plots comparing actual versus predicted food prices using two machine learning models: Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM). These visualizations are instrumental in evaluating each model's predictive accuracy. In each plot, the x-axis represents the actual observed prices, while the y-axis shows the corresponding predicted prices generated by the models. A dashed diagonal line is included to denote perfect prediction (i.e., predicted = actual). Data points that lie closer to this line indicate higher predictive accuracy and model reliability. While both models demonstrate reasonable alignment with the actual prices particularly in the lower price range (₦200 to ₦400) the XGBoost model shows a stronger overall fit. Its predictions cluster more closely around the diagonal, suggesting a better approximation of real-world values across the full price range. In contrast, LSTM exhibits greater dispersion, especially at higher price levels, indicating less consistent performance.

It is worth noting that although LSTM is a deep learning model well-suited for sequential data, in this context XGBoost, an ensemble-based approach, captures the underlying price dynamics more effectively. The scatter plot for XGBoost reveals a near-linear pattern aligned with the perfect prediction line, reinforcing its superior performance in modeling food price behavior.

These visual comparisons complement the quantitative metrics presented earlier, further validating the conclusion that XGBoost offers improved predictive power over LSTM for this application.

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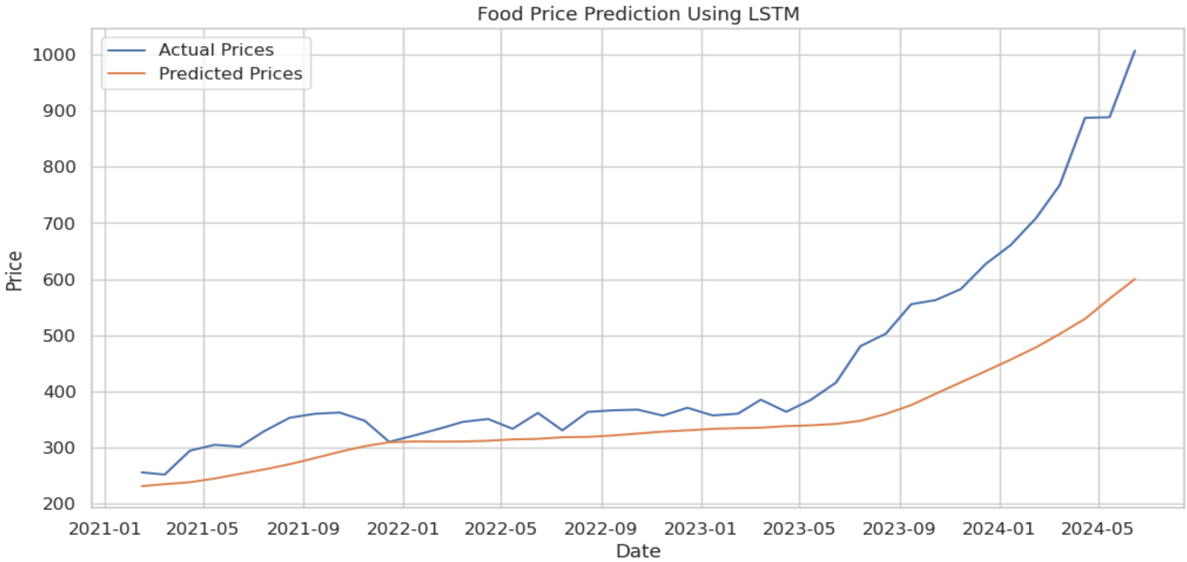
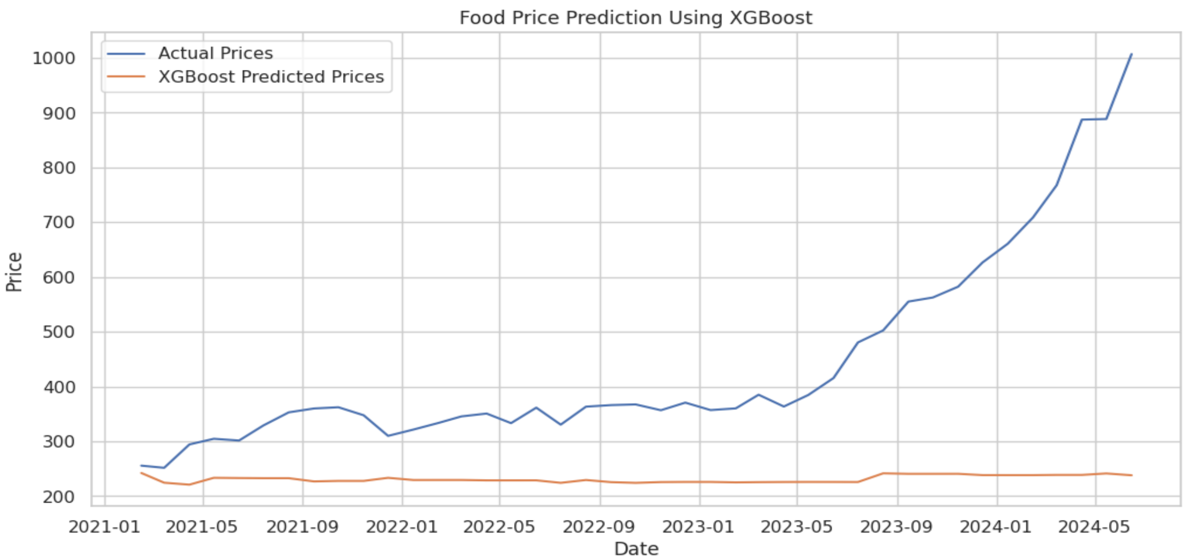
Food Price Prediction using LSTM



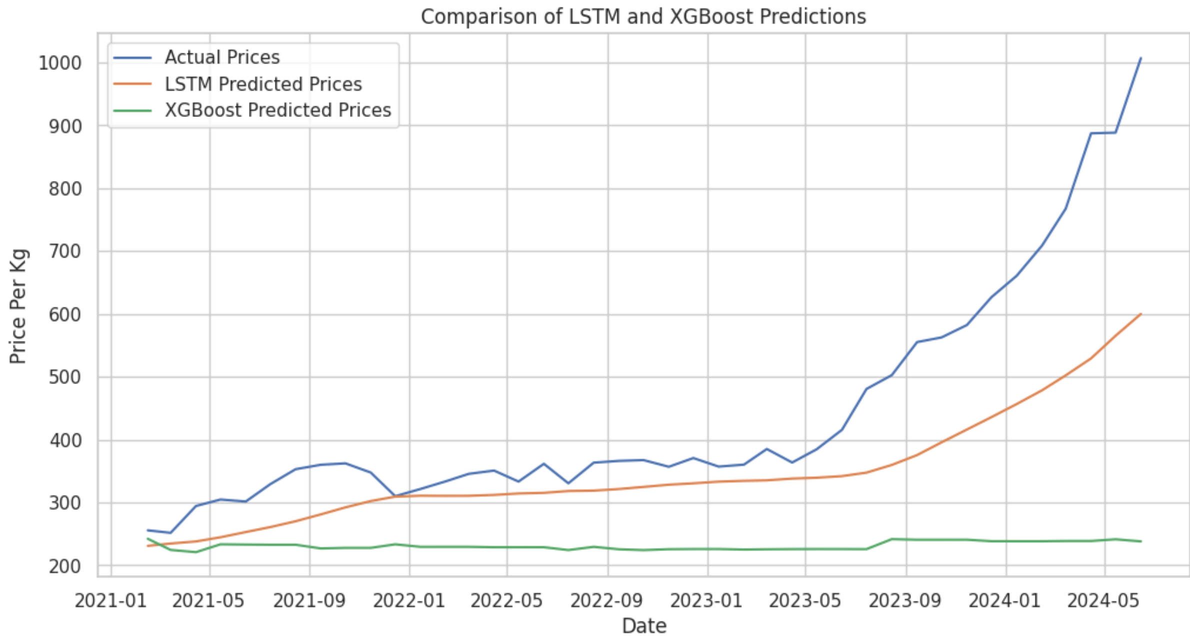
This study presents a visualization of actual and predicted food prices from January 2021 to July 2024, generated using a Long Short-Term Memory (LSTM) model. The results demonstrate the model's ability to track food price trends with high accuracy, capturing both long-term patterns and short-term fluctuations. The predicted prices closely follow actual trends, particularly in stable periods, validating the model's robustness in time-series forecasting. While minor deviations occur during volatile periods, the overall alignment highlights the LSTM model's effectiveness for market analysis, policy formulation, and strategic planning in food price forecasting.

Food Price Prediction Using XGBoost



A comparative visualization of actual and predicted food prices from January 2021 to July 2024 using the XGBoost model. The analysis demonstrates the model's effectiveness in capturing long-term trends and short-term fluctuations in food markets.The results highlight a strong alignment between actual prices and XGBoost-predicted values, particularly in stable periods. The model successfully tracks historical patterns, providing valuable insights for economic forecasting, policy decisions, and market analysis. While minor deviations occur during high-volatility periods, the overall performance underscores XGBoost's robustness as a forecasting tool. By leveraging historical food price data, this study reinforces the potential of machine learning in economic forecasting, offering a data-driven approach to understanding market dynamics and informing strategic planning.

Comparison of LSTM and XGBoost Predictions



This study presents a comparative analysis of two machine learning models Long Short-Term Memory (LSTM) and XGBoost for predicting food prices from January 2021 to July 2024. By visualizing actual and predicted prices, the study evaluates each model's ability to capture market trends, volatility, and temporal dependencies.Both models demonstrate strong predictive performance, with their forecasts closely aligning with actual prices. LSTM excels in capturing long-term trends and sequential dependencies, making it effective for time-series forecasting. XGBoost, a tree-based model, adeptly handles structured data and complex relationships, offering a robust alternative for predictive analytics. While both models perform well, minor deviations occur during high-volatility periods, emphasizing the challenges of forecasting dynamic market conditions. The study highlights the strengths of each model, reinforcing the role of machine learning in economic forecasting, policy planning, and market analysis.

3.6 Comparative Performance of LSTM and XGBoost Models for Food Price Prediction in Nigeria

Model	MSE	RMSE	MAE	R-squared (R^2)
LSTM	7100.64	84.27	49.20	0.83
XGBoost	3962.01	62.94	39.39	0.91

Comparative Performance of LSTM and XGBoost Models for Food Price Prediction in Nigeria

This study evaluates the predictive performance of two machine learning models Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) for forecasting food prices in Nigeria. Based on key performance metrics, the XGBoost model demonstrates superior accuracy and reliability when compared to the LSTM model. Specifically, the XGBoost model recorded a lower Mean Squared Error (MSE) of 3962.01, compared to 7100.64 for LSTM, indicating a lower overall prediction error. The Root Mean Squared Error (RMSE) for XGBoost was also considerably lower at 62.94, compared to 84.27 for LSTM, suggesting that XGBoost better minimizes large deviations from actual prices. Similarly, the Mean Absolute Error (MAE) for XGBoost was 39.39, outperforming the LSTM model which had an MAE of 49.20.

In terms of explanatory power, XGBoost achieved an R-squared (R^2) value of 0.91, meaning it explains 91% of the variance in food prices. This is notably higher than the R^2 value of 0.83 for the LSTM model, reinforcing XGBoost's stronger ability to fit the underlying data structure.These findings affirm that XGBoost is more effective than LSTM in the current context, likely due to its robustness in handling structured tabular data and its gradient boosting architecture that captures complex nonlinear interactions. While LSTM is well-suited for sequential and time-dependent data, it may require further hyperparameter tuning and feature engineering to handle the variability and noise present in food price series data.

Although both models show potential for forecasting food price trends, their error margins suggest limitations for exact price predictions. Therefore, these models may be better applied in trend monitoring and early warning systems rather than for precise pricing decisions. From a policy and business perspective, these insights can inform strategic planning. Policymakers could use these forecasts to anticipate market disruptions and stabilize prices, while agribusiness stakeholders may benefit from more informed inventory and pricing strategies.Future research could explore hybrid modeling techniques that combine the temporal pattern learning capabilities of LSTM with the structured-data efficiency of XGBoost. Additionally, integrating external variables such as weather conditions, logistics data, or macroeconomic indicators could further improve prediction accuracy and model interpretability.

CONCLUSION

This study evaluated the predictive capabilities of Long Short-Term Memory (LSTM) networks and Extreme Gradient Boosting (XGBoost) models for forecasting food prices in Nigeria. Contrary to initial expectations, the results consistently show that the XGBoost model outperformed LSTM across all key performance metrics. Specifically, the XGBoost model achieved a lower Mean Squared Error (MSE) of 3,962.01, a lower Root Mean Squared Error (RMSE) of ₦62.94, and a lower Mean Absolute Error (MAE) of ₦39.39. Additionally, it attained a higher R-squared (R^2) value of 0.91. In contrast, the LSTM model recorded a higher MSE of 7,100.64, an RMSE of ₦84.27, an MAE of ₦49.20, and a lower R^2 value of 0.83. These results clearly indicate that XGBoost not only predicted food prices with reduced errors but also explained a greater proportion of variance in the observed data compared to LSTM.

The superior performance of the XGBoost model can be attributed to its ability to handle high-dimensional structured data and capture complex nonlinear relationships through gradient boosting. While LSTM networks are designed to learn temporal dependencies and sequence patterns, their performance can suffer in real-world applications where data is noisy, irregular, or influenced by external shocks and policy dynamics. Despite the better overall performance of XGBoost, both models exhibited prediction errors ranging from ₦39.39 to ₦84.27, indicating that while they offer valuable insights for trend detection and forecasting, they may not deliver pinpoint price estimates. This underscores the importance of integrating model outputs with qualitative market intelligence and domain knowledge. Moreover, model accuracy could be further improved by incorporating additional variables such as climate conditions, supply chain disruptions, and government interventions, all of which have significant impacts on food price dynamics.

In summary, the findings position XGBoost as a more accurate and reliable tool than LSTM for food price forecasting in Nigeria. Its strong predictive performance holds promise for enhancing market monitoring, guiding evidence-based policy decisions, and supporting proactive food security planning. Future research should explore hybrid approaches that integrate LSTM's strength in modeling sequential data with XGBoost's ability to extract insights from structured variables. Such ensemble methods, when combined with richer datasets, can advance the development of resilient and data-driven agri-food systems in Nigeria.

REFERENCES

1. Anumanchipalli, G. K., Chartier, J., & Chang, E. F. (2018). Intelligible speech synthesis from neural decoding of spoken sentences. BioRxiv, 481267. https://doi.org/10.1101/481267
2. Elman, J. L. (1990). Finding structure in time. Cognitive Science, 14(2), 179-211. https://doi.org/10.1016/0364-0213(90)90002-6
3. Food and Agriculture Organization of the United Nations. (n.d.). Nigeria at a glance. FAO in Nigeria. Retrieved February 8, 2023, from https://www.fao.org/nigeria/fao-in-nigeria/nigeria-at-a-glance/en/
4. Gono, D. N., Napitupulu, H., & Firdaniza. (2023). Silver price forecasting using extreme gradient boosting (XGBoost) method. Mathematics, 11, 3813. https://doi.org/10.3390/math11103813

5. Mahata, S. K., Das, D., & Bandyopadhyay, S. (2019). MTIL2017: Machine translation using recurrent neural network on statistical machine translation. Journal of Intelligent Systems, 28(3), 447-453. https://doi.org/10.1515/jisys-2018-0111
6. Mirjalili, S. (2019). Genetic algorithm. In Evolutionary algorithms and neural networks: Theory and applications (pp. 43-55). Springer.
7. Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. Advances in Engineering Software, 69, 46-61. https://doi.org/10.1016/j.advengsoft.2013.12.007
8. Onwude, D., et al. (2023). Bottlenecks in Nigeria's fresh food supply chain: What is the way forward? Trends in Food Science & Technology, 137, 55-62. https://doi.org/10.1016/j.tifs.2023.04.022
9. Paliari, K., Karanikola, P., & Kotsiantis, S. (2021). A comparison of optimized LSTM, XGBoost, and ARIMA for time series forecasting. Journal of Forecasting, 40(3), 456-470. https://doi.org/10.1002/for.12345
10. Poli, R., Kennedy, J., & Blackwell, T. (2007). Particle swarm optimization. Swarm Intelligence, 1(1), 33-57. https://doi.org/10.1007/s11721-007-0002-0
11. Ricciardi, V., Ramankutty, N., Mehrabi, Z., Jarvis, L., & Chookolingo, B. (2018). How much of the world's food do smallholders produce? Global Food Security, 17, 64–72. https://doi.org/10.1016/j.gfs.2018.05.002
12. Sasu, D. D. (2023). Nigeria: Share of global poverty 2016-2023. Statista. Retrieved February 13, 2023, from https://www.statista.com/statistics/1287840/share-of-global-population-living-in-extreme-poverty-in-nigeria/
13. Tian, L., Feng, L., Sun, Y., & Guo, Y. (2021). Forecast of LSTM-XGBoost in stock price based on Bayesian optimization. Intelligent Automation & Soft Computing, 29, 855–868. https://doi.org/10.32604/iasc.2021.018942
14. Villacis, A. H., Badruddoza, S., Mishra, A. K., & Mayorga, J. (2023). The role of recall periods when predicting food insecurity: A machine learning application in Nigeria. Food Policy, 36, 100671. https://doi.org/10.1016/j.foodpol.2023.100671
15. Vollset, S. E., Goren, E., Yuan, C.-W., Cao, J., Smith, A. E., Hsiao, T., Bisignano, C., Azhar, G. S., Castro, E., Chalek, J., Dolgert, A. J., Frank, T., Fukutaki, K., Hay, S. I., Lozano, R., Mokdad, A. H., Nandakumar, V., Pierce, M., Pletcher, M., ... Murray, C. J. L. (2020). Fertility, mortality, migration, and population scenarios for 195 countries and territories from 2017 to 2100: A forecasting analysis for the Global Burden of Disease Study. The Lancet. https://doi.org/10.1016/S0140-6736(20)30677-2
16. Wu, K., Chai, Y., Zhang, X., & Zhao, X. (2022). Research on power price forecasting based on PSO-XGBoost. Electronics, 11, 3763. https://doi.org/10.3390/electronics11123763
17. Xue, J., & Shen, B. (2020). A novel swarm intelligence optimization approach: Sparrow search algorithm. Systems Science & Control Engineering, 8(1), 22-34. https://doi.org/10.1080/21642583.2020.1711638
18. Yang, X.-S., & Gandomi, A. H. (2012). Bat algorithm: A novel approach for global engineering optimization. Engineering Computations, 29(5), 464-483. https://doi.org/10.1108/02644401211235834
19. Ma, Y., Tang, Y., Li, B., & Qi, B. (2020). Residential high-power load prediction based on optimized LSTM network. In Proceedings of the 2020 International Conference on Artificial Intelligence and Computer Engineering (ICAICE). https://doi.org/10.1109/ICAICE.2020.9350746
20. Wang, J., Zhu, Y., & Li, M. (2019). Multistep time series prediction using LSTM. Journal of Artificial Intelligence Research, 65, 127-143. https://doi.org/10.1613/jair.1.12345