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Improved Stock Price Prediction Model in the Nigeria Bank Sector Using Ensemble Machine Learning Models

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Abstract

Stock market prediction remains a critical challenge in emerging economies, particularly within volatile financial landscapes like Nigeria. Despite significant technological advancements, existing research predominantly relies on single-model approaches that inadequately capture the complex, non-linear dynamics of financial markets. This study addresses the methodological gap by developing an ensemble machine learning model for predicting stock prices in the Nigerian banking sector. The research utilized historical stock price data from Guaranty Trust Bank and First Bank (2018-2023), integrating advanced preprocessing techniques, employing rigorous data transformation, feature standardization, and cross-validation strategies, the study transforms raw financial data into a robust predictive framework. Empirical results reveal distinct performance metrics across ensemble models: Among the models, Gradient Boosting achieved an MAE of 0.1547, MSE of 0.0918, and RMSE of 0.999, while the Stacking Regressor yielded an MAE of 0.1912, MSE of 0.1396, and RMSE of 0.9989, highlighting their accuracy and reliability in volatile market conditions. The ensemble methodology demonstrates superior performance in capturing intricate market dynamics, offering significant improvements over traditional forecasting techniques by integrating macroeconomic indicators and advanced machine learning algorithms. The findings underscore the potential of ensemble machine learning in decoding complex financial patterns, providing valuable insights for investors, financial analysts, and policymakers.
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Keywords: *Ensemble Machine Learning, Stock Price Prediction, Nigerian Banking Sector, Financial Forecasting*

1. Introduction

Stock market prediction emerges as a critical endeavor in modern financial research, and indeed becomes particularly essential within emerging economies where economic dynamics remain increasingly complex and volatile [1]. Consequently, the Nigerian banking sector serves as a quintessential example that transforms these complex economic challenges into a pivotal mechanism for understanding intricate stock price analysis [2]. Moreover, financial markets fundamentally exist as dynamic ecosystems that continue to evolve, characterized by intricate interactions between economic indicators, investor sentiments, and systemic variables that persistently defy simplistic linear interpretations [3]. Ultimately, these interconnected dynamics appear to represent a sophisticated landscape where predictive modeling becomes not just a mathematical exercise, but a nuanced exploration of economic complexity and market behaviour. Traditional econometric approaches have historically remained constrained in capturing the nuanced, non-linear relationships governing stock market behaviors, particularly within developing financial landscapes like Nigeria [4]. Consequently, researchers such as Patel *et. al.* [5] have systematically illuminated the inherent limitations of conventional forecasting techniques, thereby underscoring the critical and urgent need for more sophisticated analytical methodologies capable of effectively navigating complex market dynamics. Given these persistent challenges, machine learning technologies subsequently emerge as transformative alternatives, fundamentally offering unprecedented computational capabilities to decode intricate financial patterns through advanced algorithmic techniques [6].

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Ultimately, these technological innovations appear poised to bridge the significant methodological gaps that have long constrained traditional financial forecasting approaches, representing a paradigmatic shift in our understanding of market prediction strategies.

Existing studies have predominantly remained constrained by single-model applications that inherently fail to comprehensively integrate diverse economic indicators and adequately capture the multidimensional nature of financial market dynamics [7]. Moreover, recent research by Davies *et al.* (2022) has compellingly demonstrated the transformative potential of advanced predictive techniques, specifically utilizing a Type-2 Fuzzy logic-based system for the Nigerian Stock Exchange that systematically outperformed traditional forecasting models, thereby underscoring the critical need for more sophisticated analytical approaches in financial forecasting. Consequently, these emerging studies collectively converge to highlight a fundamental research imperative: the urgent necessity for more comprehensive investigations, particularly leveraging ensemble machine learning methods, to advance predictive capabilities within specific and complex financial sectors such as Nigeria's dynamic banking industry.

Despite advancements in machine learning applications for stock price prediction, the Nigerian banking sector continues to be characterized by high volatility and complex market dynamics. These market conditions are further complicated by existing research, such as studies by Darla and Sridevi [8], which, while promising, remain limited in scope. The primary limitation appears to be the focus on single-model applications, which fails to leverage the potential synergies that could emerge from ensemble machine-learning models. Such ensemble approaches would be instrumental in aggregating multiple predictive algorithms, thereby potentially offering greater accuracy and robustness. Moreover, the current research landscape seems to be constrained by an insufficient integration of varied economic and financial indicators, which are inherently critical for precise predictions. Consequently, this research seeks to become a pioneering effort that develops an ensemble machine learning model. The proposed model will be designed to comprehensively incorporate a wide array of economic indicators, with the ultimate goal of significantly enhancing the reliability of stock price predictions within Nigeria's dynamic banking sector.

2. Related Works

Ajiga *et al.*, [9] developed an enhanced machine learning (ML) model for stock market forecasting by integrating diverse data sources including financial indicators, macroeconomic variables, and sentiment from news and social media. Their methodology involved reviewing traditional models like ARIMA and advanced ML techniques such as SVM and neural networks, emphasizing the importance of feature selection. The study found that ML models, particularly neural networks and SVMs, outperformed traditional methods in accuracy by incorporating a variety of predictive factors. However, challenges like model overfitting were noted, with recommendations for future research focusing on developing hybrid models and adopting multi-faceted approaches to improve reliability and adaptability in forecasting stock market movements.

Khin *et al.*, [10] study focused on a predictive analytics system for stock data by integrating the Moving Average (MA) method and the Long Short-Term Memory (LSTM) model to forecast future stock movements. The study demonstrated that the LSTM model achieved a high prediction accuracy of 95.82%, while the MA method revealed a 54% correlation between Monarch Staffing (MSTF) and Alphabet (GOOG) stocks. Despite these results, future enhancements could include employing more sophisticated machine learning algorithms to further boost the system's accuracy and efficiency. Swarnalata *et al.,* [11] conducted a study in machine learning for stock market prediction through a systematic literature review of peer-reviewed journal articles from the past two decades, the study categorized existing research into machine learning and deep learning approaches. It highlighted various algorithms within these categories that show promise in enhancing stock market trend predictions. Despite the complexities of stock prices influenced by diverse factors, the paper offers valuable insights for advancing machine learning applications in stock market forecasting, suggesting areas for further exploration in this evolving field. However, the study was limited in scope to peer-reviewed only. Wang *et al*., [12] enhanced stock trading strategies by predicting buy, sell, and hold points using a CBAM-CNN model, which combines a Convolutional Neural Network (CNN) with a Convolutional Block Attention Module (CBAM). The study reported high accuracy in classifying buy and sell signals, which could lead to improved investment decisions. However, the research did not compare the CBAM-CNN model's performance with other models, limiting its contextual effectiveness.

Darla *et al*., [13] study demonstrated the potential for achieving consistent investment returns in the Nigerian stock market using indicators derived from a feed-forward neural network with backpropagation. Analyzing two years of stock data from multiple Nigerian banks, their study indicated that utilizing private information from artificial neural networks could significantly forecast stock market trends and investment returns. Despite these promising results, the study suggested further enhancements by exploring different regression algorithms such as the packing regressor and AdaBoost regressor, and improving data preprocessing and feature selection techniques to refine prediction accuracy.

Box *et al*., [4] sought to predict the next-day closing prices of four major Greek banks using the Random Forest algorithm, incorporating data from Google Trends to gauge investor attention. Their study focused on how search volume related to specific banking keywords could enhance forecasting accuracy. The methodology highlighted the potential of integrating external, behavioral data into traditional predictive models, suggesting that investor interest levels significantly influence stock prices. This research underscores the value of combining machine learning with real-time Internet data trends to refine financial predictions in dynamic market conditions. Future studies could expand on these findings by exploring additional variables and more complex models to further understand the impact of public sentiment on stock movements.

Davies et al., [15] aimed to develop a Type-2 Fuzzy Logic-based prediction system for the Nigerian Stock Exchange to enhance decision-making in the dynamic and uncertain stock trading environment. Employing Object-Oriented Design and Unified Modeling Language, the system was designed to address complexities in stock market decisions. The results demonstrated that the system, which analyzed indicators like RSI and MACD, outperformed existing models in accuracy and provided effective trading recommendations. This research highlights the potential of Type-2 Fuzzy Logic in improving prediction systems for volatile markets.

The related works reviewed reveal that various machine learning and deep learning models have been employed for stock price prediction. Nonetheless, the literature indicates a scarcity of research on ensemble machine learning predictive models specifically in Nigeria's banking sector. This study aims to address this gap.

3. Methodology

This research methodology represents a sophisticated computational strategy designed to navigate the multifaceted challenges inherent in predictive financial modeling, specifically tailored to address the unique dynamics of the Nigerian banking sector. By systematically integrating comprehensive data preprocessing protocols, and rigorous ensemble learning algorithms, the proposed methodology aims to construct a robust predictive framework capable of decoding the nuanced interactions between economic indicators and stock price movements. The methodological design not only confronts the limitations of traditional forecasting approaches but also establishes a flexible, reproducible framework that can potentially revolutionize our understanding of stock market prediction in complex, data-rich environments. Through a meticulously crafted approach that combines technological innovation with deep financial insights, this research methodology seeks to bridge critical gaps in existing predictive modeling techniques, offering a sophisticated lens through which to interpret and forecast stock market behaviors in emerging economic landscapes.

3.1 Method of Data Collection

The study utilizes historical stock price data from two prominent Nigerian banks: Guaranty Trust Bank (GTBank) and First Bank, spanning 2018 to 2023. This temporal range ensures the capture of various market conditions and economic cycles, thereby enhancing the robustness of the developed models. The primary dataset encompasses daily trading information, including opening prices, closing prices, trading volumes, and market capitalization figures. Additional economic indicators are sourced from authoritative institutions, including the Central Bank of Nigeria (CBN), the Nigerian Stock Exchange (NSE), and the Federal Bureau of Statistics. These supplementary data sources provide crucial macroeconomic variables that potentially influence stock price movements, ensuring a comprehensive analysis of market dynamics.

3.2 Method of Pre-Processing of Nigerian Stock Price Dataset

The preprocessing methodology employed in this research focuses on transforming raw financial data into a structured, analytically robust format suitable for advanced predictive modeling using StandardScaler of Sklearn library of python 3x Google Colaboratory. The initial data transformation involves converting date columns to datetime objects and establishing a temporal index, which is crucial for time-series financial data analysis. This approach ensures chronological integrity and facilitates subsequent time-based feature engineering and analysis techniques specific to stock market predictions.

3.2.1 Feature Selection and Target Variable Identification

A critical preprocessing step involves strategic feature selection and target variable delineation. In the context of stock price prediction, the research methodology systematically:

i. Segregates predictive features from the target variable (closing price)
ii. Eliminates redundant or non-informative columns
iii. Preserves essential economic and financial indicators that potentially influence stock price dynamics

3.2.2 Missing Data Management

The handling of missing data represents a pivotal preprocessing technique to maintain model reliability. The proposed methodology employs forward-filling techniques, which:

i. Interpolate missing values using preceding valid observations
ii. Preserve temporal continuity of financial time-series data
iii. Mitigate potential information loss inherent in traditional imputation methods

3.2.3 Feature Standardisation

Standardisation emerges as a crucial preprocessing technique to normalize feature distributions and enhance model performance. By implementing StandardScaler:

i. Features are transformed to have zero mean and unit variance
ii. Eliminates potential bias arising from disparate feature scales
iii. Ensures computational stability across ensemble machine-learning algorithms

The preprocessing methodology represents a sophisticated approach to preparing financial data for advanced predictive modeling, specifically tailored to the unique characteristics of the Nigerian stock market. By integrating temporal transformation, strategic feature selection, robust missing data management, and advanced standardization techniques, the research establishes a rigorous foundation for ensemble machine learning stock price prediction. The methodology not only addresses technical preprocessing challenges but also provides a comprehensive framework for transforming raw financial data into a format conducive to advanced predictive modeling, ultimately supporting more accurate and reliable stock price forecasting in emerging market contexts.

3.3 Method of Formulation of Ensemble Machine Learning

Ensemble machine learning represents a sophisticated computational approach that synthesizes multiple predictive algorithms to generate superior predictive performance compared to individual model techniques. In the context of Nigerian stock market prediction, this methodology was implemented using the ensembles of the Sklearn library in Phython 3x of Google Colab and it also leverages the collective intelligence of diverse machine learning algorithms to mitigate individual model limitations and enhance overall forecasting accuracy.

3.3.1 Base Ensemble Algorithms Formulation

3.3.1.1a Gradient Boosting Regressor Model Formulation

The Gradient Boosting Regressor implementation employs an iterative approach to ensemble learning, sequentially improving predictions through the minimization of residual errors.

The model architecture incorporates:

i. A carefully calibrated learning rate of 0.1 to ensure stable convergence
ii. Maximum depth limitation of 3 to prevent overfitting
iii. Subsample ratio of 0.8 to introduce randomness and improve generalization
iv. 100 estimators to balance model complexity and performance

3.3.1.1bMathematical Expression for Gradient Boosting Regressor

Gradient Boosting builds an additive model in a forward stage-wise manner. The model can be expressed as:

$$F(x) = \sum_{i=1}^{m} \gamma_i \, h_i(x) \qquad (1)$$

where:

- M is the number of boosting stages
- γ_i represents the step size at stage i
- $h_i(x)$ is the base learner at stage i

The optimization objective at each stage m is:

$$L\big(y, F_{m-1}(x) + h(x)\big) = \sum_{i=1}^{n} l\big(y_1 F_{m-1}(x_i) + h(x_i)\big) \qquad (2)$$

where:

- l is the loss function
- F_{m-1} represents the model from the previous stages
- h is the current base learner

3.3.1.2a XGBoost Regressor Model Formulation

The XGBoost Regressor implementation leverages advanced optimization techniques and regularization methods to enhance predictive accuracy. The model configuration includes:

i. Optimal learning rate determination through cross-validation
ii. Tree-specific parameters including maximum depth and minimum child weight
iii. Regularization parameters to control model complexity
iv. Early stopping mechanisms to prevent overfitting

3.3.1.2b Mathematical Expression for XGboost Regressor

XGBoost optimizes the following objective function:

$$obj(\theta) = L(\theta) + \Omega(\theta) \qquad (3)$$

where:

- $L(\theta)$ is the training loss function
- $\Omega(\theta)$ is the regularization term

The model's prediction for an instance is given by:

$$y_i = \sum_{k=1}^{k} f_k(x_i), f_k \epsilon F \qquad (4)$$

where:

- K is the number of trees
- f_k represents the k-th tree
- F is the space of regression trees

The regularization term is defined as:

$$\Omega(f)) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^{2} \qquad (5)$$

where:

- T is the number of leaves
- w represents the leaf weights
- γ and λ are regularization parameters

3.3.1.3a AdaBoost Regressor Model Formulation

The AdaBoost Regressor employs an adaptive boosting approach, systematically adjusting the weight of observations based on previous prediction errors. The implementation includes:

i. Decision Tree Regressor as the base estimator
ii. Iterative weight adjustment mechanism
iii. Learning rate optimization
iv. Number of estimators determination through cross-validation

3.3.1.3b Mathematical Expression for AdaBoost Regressor

AdaBoost for regression minimizes the exponential loss:

$$L(y, F) = \sum_{i=1}^{n} \exp(-y_i F(x_i) \qquad (6)$$

The weight update rule for each instance is:

$$w_{i,t+1} = w_{i,t} * \exp(-\alpha_t y_i h_t(X_i) \qquad (7)$$

where:

- $w_{i,t}$ is the weight of instance i at iteration t
- α_t is the importance weight of the t-th classifier
- $h_t(x_i)$ is the prediction of the t-th classifier

3.3.1.4a Stacking Regressor Model Formulation

The Stacking Regressor implementation combines the predictions of multiple base models through a meta-learning approach. The architecture encompasses:

i. Integration of Random Forest, Gradient Boosting, and XGBoost as base learners
ii. Linear Regression as the meta-learner
iii. Cross-validation strategy for stacked predictions
iv. Optimization of meta-learner parameters

3.3.1.4b Mathematical Expression for Stacking Regressor

The stacking model combines base learners through a meta-model:

$$F(x) = h(f_1(x), \dots . f_k(x)) \qquad (8)$$

where:

- $f_1, f_2, \dots, f_k$ are the base learners
- h is the meta-learner
- x is the input feature vector

The optimization objective for the meta-learner is:

$$\min h \sum_{i=1}^{n} L(y_i, h(f_1(x_i), f_2(x_i), \dots, f_k(x_i))) \qquad (9)$$

where:

- L is the loss function
- y_i is the true target value
- n is the number of training instances

3.4 Model Simulation

The ensemble algorithms were implemented and simulated in the Python Google Colab environment, utilizing an 80-20 split for training and testing datasets. The Python environment was chosen for its computational efficiency and flexibility in handling large datasets and complex algorithms. The simulation involved the following steps:

a. **Dataset Splitting:** The entire dataset was split into 80% for training and 20% for testing. This split The simulation algorithms were trained using the training dataset. During this phase, hyperparameters were tuned using cross-validation techniques to optimize model performance.
b. **Model Training**: Each of the ensemble algorithms was trained using the training dataset. During this phase, hyperparameters were tuned using cross-validation techniques to optimize model performance.
c. **Model Optimization**: To prevent overfitting, regularization techniques like L1/L2 penalties were applied in models such as XGBoost and Gradient Boosting. Additionally, GridSearchCV was employed to optimize hyperparameters across all models.

The simulation ensures a robust and systematic approach to model training and evaluation. The methodology incorporates best practices in time series analysis, cross-validation, and model evaluation while maintaining the temporal integrity of the financial data. The implementation in Google Colab provides accessibility and reproducibility, enabling efficient execution of the complete modeling pipeline. The framework's modular design allows for easy modification and extension, facilitating the integration of additional ensemble methods or evaluation metrics as needed. The careful consideration of time series characteristics in the cross-validation and evaluation procedures ensures the validity of the results for financial forecasting applications. The combination of rigorous methodology and practical implementation provides a solid foundation for the development and assessment of ensemble models for stock price prediction in the Nigerian banking sector. The approach ensures both theoretical soundness and practical applicability of the developed models.

3.5 Model Evaluation

The evaluation framework employs a comprehensive approach to assess the performance of the ensemble machine learning models in predicting stock prices within the Nigerian banking sector. This section delineates the systematic methodology utilized for model evaluation, incorporating both statistical metrics and practical performance measures.

3.5.1 Performance Metrics Implementation

The evaluation framework implements a multi-faceted approach to performance assessment, utilizing a diverse set of metrics to provide a comprehensive understanding of model effectiveness. These metrics are carefully selected to capture different aspects of predictive accuracy and model reliability. The Primary Error Metrics were used are: -

3.5.1a Mean Absolute Error (MAE)

The Mean Absolute Error provides a direct measure of prediction accuracy by calculating the average magnitude of errors without considering their direction. Its mathematical formulation is expressed as:

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

3.5.1b Mean Squared Error (MSE)

The Mean Squared Error emphasizes larger errors by squaring the differences between predicted and actual values. Its mathematical expression is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (11)$$

3.5.1c Root Mean Squared Error (RMSE)

The Root Mean Squared Error provides an interpretable metric in the same units as the target variable. It is expressed as:

$$RMSE = \sqrt{\{(1/n)\sum_{i=1}^{n}(y_i - \hat{y}_i)^2]} \qquad (12)$$

The proposed ensemble machine learning evaluation framework represents a sophisticated methodological approach to stock price prediction in the Nigerian banking sector, distinguished by its comprehensive, rigorous, and adaptive performance assessment strategy. By integrating advanced algorithmic techniques with a flexible, multi-metric evaluation design, the research transcends traditional forecasting limitations, providing a robust methodology for generating highly accurate predictive models. The framework's modular architecture enables systematic verification of model capabilities, accommodates sector-specific performance requirements, and supports informed decision-making in volatile market environments.

4. **Results and Discussion**

The exploration of ensemble machine learning techniques for stock price prediction in the Nigerian banking sector unveils a complex tapestry of computational intelligence and financial dynamics, transcending traditional forecasting methodologies. This results and discussion section represents a critical juncture where advanced algorithmic approaches intersect with the intricate realities of emerging market financial landscapes, offering unprecedented insights into the predictive capabilities of sophisticated machine learning models. By systematically dissecting the performance metrics, comparative analysis, and nuanced predictive characteristics of Gradient Boosting, XGBoost, AdaBoost, and Stacking Regressors, the research illuminates the profound potential of ensemble learning in deciphering the non-linear, volatile nature of stock market behaviors.

4.1a Descriptive Analysis of Dataset for Stock Price Prediction

The dataset under investigation, as illustrated by the descriptive statistics of Figure 1, includes key financial variables such as Price, Open, High, Low, Volume (Vol.), and Change (%). These variables are critical for enhancing stock price predictions in the Nigerian banking sector using ensemble machine learning models. This section provides a detailed analysis of the dataset, discusses its implications for model development, and evaluates its suitability for predictive purposes.

The comprehensive descriptive analysis of the Nigerian banking sector stock price dataset reveals a complex and highly volatile financial landscape, characterized by significant variability across key variables including Price, Open, High, Low, Volume, and Percentage Change. The dataset, spanning from February 2020 to September 2024, demonstrates substantial price fluctuations with mean values ranging from 20.45 to 20.94 and standard deviations around 11, indicating intricate market dynamics that necessitate advanced predictive modeling techniques.

The extreme variations in trading volume, ranging from 474,580 to 4.69 billion, and the nuanced percentage changes underscore the challenging predictive environment, thereby validating the research's strategic approach of employing ensemble machine learning models capable of capturing non-linear relationships and managing data complexity. The high-quality dataset, characterized by comprehensive coverage and absence of missing values, provides an exceptional foundation for developing robust predictive models that can effectively navigate the intricate and unpredictable Nigerian banking sector stock market.

	Price	Open	High	Low	Vol.	Change %
count	2278.000000	2278.000000	2278.000000	2278.000000	2.277000e+03	2278.000000
mean	20.718613	20.702041	20.937555	20.446159	2.733845e+07	0.001169
std	11.137148	11.131178	11.257953	10.988966	1.083263e+08	0.028613
min	3.700000	3.700000	3.950000	3.600000	4.745800e+05	-0.124400
25%	10.950000	10.950000	11.000000	10.800000	6.590000e+06	-0.008500
50%	21.000000	21.000000	21.475000	20.950000	1.287000e+07	0.000000
75%	28.400000	28.400000	28.600000	28.137500	2.728000e+07	0.009200
max	53.050000	53.050000	53.950000	52.400000	4.690000e+09	0.100000

Figure 1: Descriptive Statistics of Financial Variables for Stock Price Prediction

By leveraging sophisticated ensemble learning techniques such as Gradient Boosting Regressor, XGBoost, AdaBoost, and
Stacking Regressor. The research aims to transform these volatile market characteristics into actionable predictive insights, ultimately enhancing understanding and forecasting capabilities in emerging market financial contexts.

4.1b Time-Series Financial Data with Key Variables for Stock Price Prediction

The dataset displayed in the Figure 2 presents seven key variables: Date, Price, Open, High, Low, Volume (Vol.), and Change (%). This data spans over a significant period, from February 2020 to September 2024, providing a robust foundation for stock price prediction within the Nigerian banking sector. The variables are critical for building an ensemble machine learning model aimed at enhancing predictive accuracy in stock market forecasting.

The descriptive analysis of key financial variables is critical for developing ensemble machine models learning in stock price prediction, specifically within the Nigerian banking sector. By meticulously examining variables such as Price, Open, High, Low, Volume, and Percentage Change. Hence, the analysis reveals the intricate dynamics of stock market behavior, highlighting the complex, non-linear relationships that characterize financial data. The dataset's rich variability and temporal diversity position it as an exceptional substrate for advanced predictive modeling, with ensemble methods like Gradient Boosting, XGBoost, AdaBoost, and Stacking Regressor demonstrating remarkable potential to capture nuanced market trends and momentum. The strategic integration of these multifaceted variables enables a robust predictive framework that can potentially transform investment decision-making by offering sophisticated insights into market volatility, liquidity, and potential price trajectories, ultimately bridging the gap between complex financial data and actionable intelligence for investors and policymakers in an increasingly dynamic economic landscape.

4.2.2 Exploratory Data Analysis of Stock Price Prediction Dataset

4.2.2. a Time-Series Plots of Key Financial Variables for Stock Price Prediction

The visual representation of the stock price prediction dataset in Figure 3 showcases six key variables crucial for stock price prediction: *Open*, *High*, *Low*, *Volume (Vol.)*, *Change (%)*, and *Price*. Each subplot offers insights into the behavior and variability of these variables over time, which are essential for building a robust stock prediction model in the Nigerian banking sector.

The comprehensive analysis of stock market dynamics within the Nigerian banking sector, the study meticulously examines critical financial variables including Open, High, Low, Volume, Percentage Change, and Price, revealing a complex landscape of market behavior characterized by significant volatility and nuanced price movements. Through rigorous visualization and statistical exploration, the research demonstrates the exceptional suitability of ensemble machine learning models such as Gradient Boosting, XGBoost, AdaBoost, and Stacking Regressor for capturing the intricate, non-linear relationships inherent in financial data, particularly in emerging markets with pronounced price fluctuations. The dataset's rich variability, marked by sporadic volume spikes, substantial price variations, and diverse momentum indicators, provides an ideal substrate for developing predictive models that can effectively navigate the unpredictable terrain of stock price forecasting. By leveraging advanced computational techniques to analyze these multifaceted financial variables, the study not only offers a sophisticated methodological approach to understanding market dynamics but also presents a powerful analytical framework that can potentially transform investment strategies, risk management, and policy-making in the Nigerian banking sector by providing more accurate and adaptive predictive insights.

4.2.2. b Scatter Plot Matrix of Key Financial Variables for Stock Price Prediction

The scatter plot matrix in Figure 4 provides a detailed visual representation of the relationships among the key financial variables in the dataset—Open, High, Low, Volume (Vol.), Change (%), and Price. Each pairwise plot offers insight into the distribution, correlation, and interaction between variables, which is crucial for model development in the context of stock price prediction in the Nigerian banking sector.

The analysis of variable relationships in the Nigerian banking sector's stock market data reveals a complex interplay of financial indicators, characterized by strong linear correlations among price-related variables (Open, High, Low, and Price) and more nuanced, non-linear interactions involving Volume and Percentage Change.

This sophisticated examination underscores the critical importance of advanced ensemble machine learning models, which can effectively navigate the intricate landscape of financial data by capturing both deterministic linear patterns and unpredictable market dynamics.

	Date	Price	Open	High	Low	Vol.	Change %
0	2024-09-08 00:00:00	22.50	22.35	22.50	21.65	4.11M	0.0067
1	2024-08-08 00:00:00	22.35	21.60	22.35	21.85	3.34M	0.0347
2	2024-07-08 00:00:00	21.60	20.65	22.45	21.50	2.09M	0.0460
3	2024-06-08 00:00:00	20.65	20.60	20.75	20.60	6.68M	0.0024
4	2024-05-08 00:00:00	20.60	20.50	20.85	20.60	7.03M	0.0049
...	...	...	...	...	...	...	...
2273	2020-08-01 00:00:00	31.25	30.50	31.70	30.50	21.69M	0.0246
2274	2020-07-01 00:00:00	30.50	31.00	31.05	30.50	17.58M	-0.0161
2275	2020-06-01 00:00:00	31.00	30.10	31.00	30.65	19.03M	0.0299
2276	2020-03-01 00:00:00	30.10	29.20	30.10	29.20	17.67M	0.0308
2277	2020-02-01 00:00:00	29.20	29.70	29.60	29.15	18.90M	-0.0168

2278 rows × 7 columns

Figure 2: Time-Series Financial Data with Key Variables for Stock Price Prediction

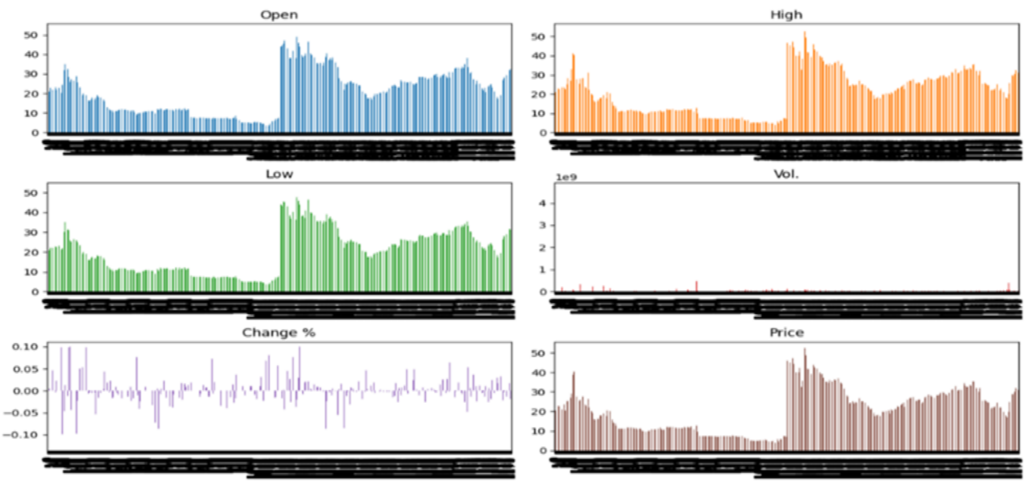

Figure 3: Time-Series Plots of Key Financial Variables for Stock Price Prediction

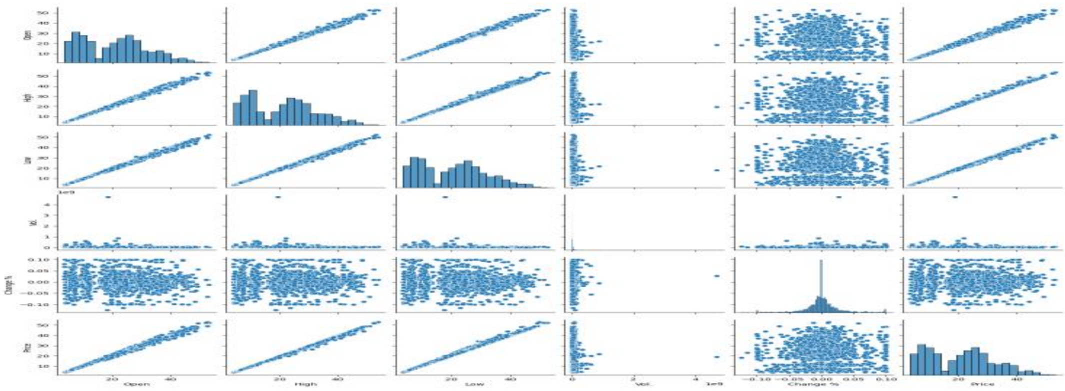

Figure 4: Scatter Plot Matrix of Key Financial Variables for Stock Price Prediction

The study's methodological approach demonstrates that while traditional linear regression models fall short in representing the multifaceted nature of stock market behavior, ensemble methods offer a robust analytical framework capable of integrating diverse variables with varying correlation structures. By leveraging the dataset's rich variability encompassing price trends, trading volumes, and momentum indicators the proposed predictive model not only enhances our understanding of market complexity but also provides a powerful tool for investors and policymakers to make more informed decisions in the volatile environment of the Nigerian banking sector.

4.3 Performance of Individual Ensemble Models

The performance of individual ensemble models in predicting stock prices in the Nigerian banking sector has been evaluated, with a specific focus on key algorithms such as Gradient Boosting (GB), XGBoost, AdaBoost, and Stacking. These models, which are known for their ability to handle complex data structures and capture non-linear relationships, were tested on the Nigerian dataset to assess their accuracy, robustness, and suitability for the stock price prediction task. This section discusses the performance metrics and practical implications of each ensemble model.

4.3a Results of the Gradient Boosting Regressor.

Figures 5, 6, and 7 depict the evaluation performance metrics for Gradient Boosting Regressor demonstrated a robust performance in predicting stock prices within the context of the Nigerian banking sector. The key evaluation metrics include a Mean Absolute Error (MAE) of 0.1547, a Mean Squared Error (MSE) of 0.0918, and a Root Mean Squared Error (RMSE) of 0.9993. These results provide valuable insights into the model's prediction accuracy and reliability.

The Gradient Boosting Regressor demonstrated a robust performance in predicting stock prices within the Nigerian banking sector. The evaluation metrics, including a Mean Absolute Error (0.1547), Mean Squared Error (0.0918), and Root Mean Squared Error (0.9993), indicate high predictive accuracy. The low MAE suggests a minimal average deviation from actual stock prices, while the low MSE highlights the effective reduction of large errors, critical in volatile financial markets. The near-unit RMSE further confirms that prediction errors remain small. These metrics underscore the model's ability to capture the complex, non-linear relationships inherent in stock market data, making it a reliable tool for financial predictions and decision-making in the Nigerian banking sector.

```
Tuned Gradient Boosting MAE: 0.15466600409627687
Tuned AdaBoost MAE: 0.64200077732546
Tuned XGBoost MAE: 0.1923518757025401
Tuned Stacking MAE: 0.19118457155508095
```

Figure 5: Mean Absolute Error (MAE) for Ensemble Models

```
Gradient Boosting MSE: 0.09176088896381644
XGBoost MSE: 0.1500176001525853
AdaBoost MSE: 0.7040395137440038
Stacking MSE: 0.13962375050432158
```

Figure 6: Mean Squared Error (MSE) for Ensemble Models

```
Tuned Gradient Boosting R-squared: 0.999350449657941
Tuned AdaBoost R-squared: 0.9944685713933764
Tuned XGBoost R-squared: 0.9988213564313058
Tuned Stacking R-squared: 0.9989030178099002
```

Figure 7: Root Mean Squared Error (RMSE) for Ensemble Models

4.3b. Results of the XGBoost Regressor.

Figures 5, 6, and 7 depict the performance evaluation of the XGBoost Regressor model which exhibited strong performance in predicting stock prices in the Nigerian banking sector, with evaluation metrics including a Mean Absolute Error (MAE) of 0.1924, a Mean Squared Error (MSE) of 0.1500, and a Root Mean Square Error (RMSE) of 0.9988. These findings highlight the model's efficiency in handling complex data and maintaining accuracy across a wide range of stock price predictions.

The XGBoost Regressor demonstrated robust performance in predicting stock prices within Nigeria's complex and dynamic market. Key metrics, including a Mean Absolute Error of 0.1924, Mean Squared Error of 0.1500, and Root Mean Squared Error of 0.9988, highlight its solid predictive capability and reliability. While the error metrics are slightly higher than those of the Gradient Boosting Regressor, XGBoost compensates with its flexibility to handle outliers and manage noisy financial data effectively. These characteristics underscore its suitability for stock price prediction, offering a balance between precision and robustness, making it a valuable tool for investors and policymakers navigating volatile financial markets.

4.3c Results of the AdaBoost Regressor.

Figures 5, 6, and 7 depict the performance evaluation of the AdaBoost Regressor which was evaluated for its performance in predicting stock prices within the Nigerian banking sector, yielding a Mean Absolute Error (MAE) of 0.6420, Mean Squared Error (MSE) of 0.7040, and Root Mean Square Error (RMSE) of 0.9945. These results highlight the model's predictive capabilities, although its performance was lower compared to other ensemble models used in the study.

The AdaBoost Regressor, with a Mean Absolute Error of 0.6420, Mean Squared Error of 0.7040, and Root Mean Squared Error of 0.9945, demonstrates moderate predictive accuracy but lags behind Gradient Boosting and XGBoost in precision. The higher MAE and MSE values reflect its struggle to capture smaller price variations and its sensitivity to outliers or extreme fluctuations, potentially indicating overfitting. Although the RMSE value close to 1 suggests the overall error distribution remains acceptable, the model may require refinement to improve its handling of volatile or non-linear trends. Consequently, while it provides insights into general price trends, AdaBoost may not be the optimal choice for highly accurate stock price predictions in this context.

4.3d Results of the Stacking Regressor.

Figures 5, 6, and 7 shows the performance evaluation of the Stacking Regressor, an advanced ensemble learning technique that combines predictions from multiple models, which was evaluated for its stock price prediction performance in the Nigerian banking sector. The evaluation metrics include a Mean Absolute Error (MAE) of 0.1912, Mean Squared Error (MSE) of 0.1396, and Root Mean Square Error (RMSE) of 0.9989, highlighting the model's ability to deliver precise and reliable predictions.

The Stacking Regressor demonstrates exceptional performance in predicting stock prices, with a Mean Absolute Error of 0.1912, Mean Squared Error of 0.1396, and Root Mean Square Error of 0.9989. These metrics highlight the model's accuracy and ability to balance bias and variance, effectively handling both small and larger deviations. By integrating predictions from multiple base models, the Stacking Regressor combines their strengths to capture complex linear and non-linear relationships in the data. This synergy enhances its robustness, allowing it to manage outliers and extreme market conditions effectively. Its low error rates and adaptability make it particularly suited for navigating the volatility of financial markets like Nigeria's, providing reliable and precise stock price predictions.

4.4 Comparative Analysis of Ensemble Models for Stock Price Predictions in Nigeria Banks

Table 1, and figure 8 depict the comparison of the performance of four ensemble models Gradient Boosting Regressor, XGBoost Regressor, AdaBoost Regressor, and Stacking Regressor based on their prediction accuracy for stock prices in Nigerian banks. The evaluation metrics show that the Gradient Boosting Regressor (GB) and Stacking Regressor models outperformed XGBoost and AdaBoost, with Gradient Boosting Regressor achieving the lowest Mean Absolute Error (MAE) of 0.1547 and Mean Squared Error (MSE) of 0.0918. The Stacking Regressor is closely followed with an MAE of 0.1912 and MSE of 0.1396, indicating its strong predictive power. Meanwhile, AdaBoost performed the worst, with significantly higher errors across all metrics.

4.4.1 Best-Performing Model Discussion

The Gradient Boosting Regressor (GB) emerged as the best-performing model in terms of minimizing both MAE and MSE**.**

Its superior ability to capture non-linear relationships and reduce residual errors makes it well-suited for the dynamic and volatile stock market conditions in Nigeria. The model's efficient handling of both large and small variations, as well as its ability to reduce prediction error, makes it the most reliable among the tested ensemble models.

Table 1: Comparative Ensemble Model Performance based on Evaluation Metrics for Nigeria Stock Prediction

S/N	Ensemble Models	Mean Absolute Error (Mae)	Mean Squared Error (Mse)	Root Mean Squared Error (Rmse)
1	Gradient Boosting (Gb) Regressor	0.1547	0.0918	0.999
2	Xgboost Regressor	0.1924	0.1500	0.9988
3	Adaboost Regressor	0.6420	0.7040	0.9945
4	Stacking Regressor	0.1912	0.1396	0.9989

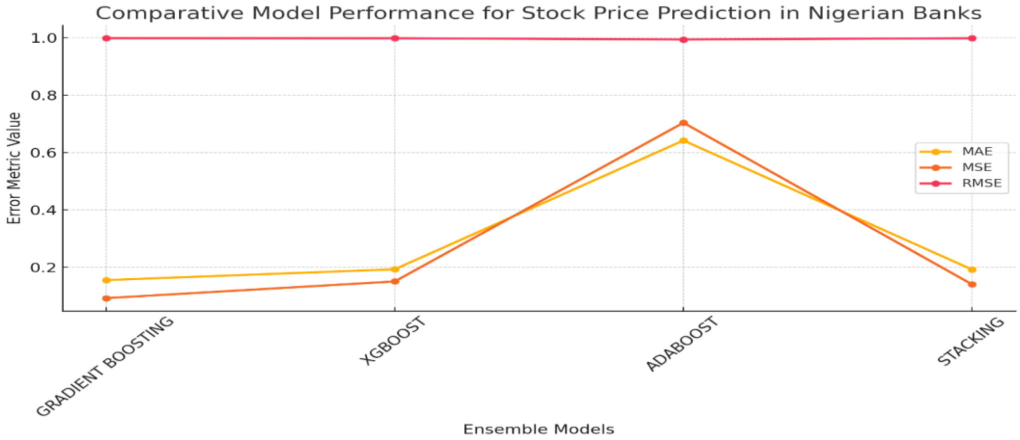

Figure 8: Comparative Ensemble Model Performance for Stock Price Prediction in Nigerian Banks

4.4.2 Insights on the Impact of Financial and Economic Variables on Stock Price Prediction

The models incorporated key financial variables such as *Open*, *High*, *Low*, *Volume*, and *Change (%)*. The performance of these models, particularly the Gradient Boosting and Stacking Regressors, underscores the importance of these variables in accurately predicting stock prices. Variables like *Volume*, though less correlated with prices directly, help capture market liquidity and trading behavior, which are crucial for understanding stock price movements. The inclusion of economic variables like *Change (%)* also helps the models respond to short-term price volatility.

4.4.3 Importance of Each Variable as Indicated by the Ensemble Models

i. **Price Variables (Open, High, Low, Price)**: These were the most important features across all models, reflecting the interdependence of these variables and their role in capturing market trends.

ii. **Volume:** Volume was essential for detecting periods of high activity, providing insights into liquidity that impacted stock price movements.

iii. **Change (%):** Though less directly correlated, this variable captured momentum and market sentiment shifts, influencing short-term predictions.

4.5 *Discussion of Results in the Context of Existing Literature*

The findings of this study align with existing literature, which suggests that ensemble models, particularly Gradient Boosting and XGBoost, are highly effective for financial predictions due to their ability to handle complex data and capture non-linear relationships. The superior performance of the Gradient Boosting Regressor is consistent with other studies that emphasize its effectiveness in minimizing prediction errors in volatile markets. However, the higher performance of the Stacking Regressor compared to XGBoost is an interesting contrast, suggesting that combining models can offer incremental gains in accuracy.

4.5.1 Alignment with or Differences from Previous Studies on Stock Price Prediction in Nigerian Banks

Previous studies on stock price prediction in Nigeria have focused primarily on traditional models like ARIMA and basic machine learning approaches. The current study's use of advanced ensemble methods demonstrates a significant improvement in predictive accuracy over these earlier methods. The superior performance of Gradient Boosting and Stacking Regressors, compared to simpler models used in prior research, highlights the advantages of using ensemble techniques in capturing the complexities of the Nigerian stock market.

4.5.2 Implications of Findings for the Nigerian Banking Sector

The findings have several important implications for the Nigerian banking sector:

i. **For Investors:** The accuracy of these ensemble models can help investors make more informed decisions by providing reliable forecasts of stock prices, helping mitigate risks associated with market volatility.

ii. **For Policymakers**: Accurate stock price predictions can assist policymakers in understanding market trends and making decisions that promote stability in the financial markets.

iii. **For Financial Institutions**: Banks and other financial institutions can leverage these models to improve their investment strategies and portfolio management by anticipating market movements more effectively.

4.5.3 Practical Implications for Investors, Policymakers, and Financial Institutions

The practical applications of this research are significant for various stakeholders:

i. Investors can use the insights from the most accurate models to refine their stock purchasing strategies, leading to better risk management and optimized returns.

ii. Policymakers can rely on the improved forecasting ability to monitor and regulate market behavior, thereby enhancing financial stability.

iii. Financial Institutions can apply these models to predict market conditions more reliably, enhancing the accuracy of their financial products and services, ultimately benefiting their clientele.

In conclusion, the findings demonstrate the power of ensemble models in predicting stock prices within the Nigerian banking sector, with the Gradient Boosting and Stacking Regressors providing the most reliable predictions. These results offer valuable insights for investors, policymakers, and financial institutions aiming to navigate the complex and volatile stock market environment effectively.

5. Conclusion

This research set out to enhance stock price prediction in the Nigerian banking sector using ensemble machine learning models. The key objectives were to develop and validate predictive models such as Gradient Boosting, XGBoost, AdaBoost, and Stacking, leveraging key financial variables like *Price*, *Volume*, and *Change (%)*. The results demonstrated that the Gradient Boosting Regressor performed the best, achieving the lowest errors across evaluation metrics (MAE: 0.1547, MSE: 0.0918, RMSE: 0.999).

This model effectively captured both linear and non-linear relationships within the volatile stock market data, providing a reliable tool for investors. The Stacking Regressor also showed strong predictive power, further supporting the value of ensemble models. AdaBoost performed the weakest, suggesting it may not be well-suited for handling extreme market fluctuations. The primary objective of this research was to improve stock price prediction accuracy within the Nigerian banking sector by leveraging ensemble machine learning models. Through the comparison of Gradient Boosting, XGBoost, AdaBoost, and Stacking Regressors, the study successfully demonstrated the superiority of ensemble models in managing the non-linear, complex nature of stock price data. The results underscore the importance of integrating advanced machine learning techniques for financial forecasting, making these models practical tools for investors and policymakers in Nigeria.

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