International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

(RESEARCH ARTICLE)

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Machine learning-based prediction of well logs in the Niger Delta for improved hydrocarbon exploration: Comparison of models for density log predictions

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International Journal of Science and Research Archive, 2024, 13(02), 2677–2689

Publication history: Received on 29 October 2024; revised on 07 December 2024; accepted on 09 December 2024

Article DOI: https://doi.org/10.30574/ijsra.2024.13.2.2379

Abstract

This study explores the usefulness of machine learning methods to predict well-log data in the Niger Delta, a geologically complex region that poses challenges for traditional prediction methods. The research specifically compares the effectiveness of various machine learning models, including Linear Regression (LR), k-Nearest Neighbors (KNN), Random Forest (RF), Gradient Boosting Regressor (GBR), and the traditional Gardner's equation. The models were evaluated based on their performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) scores. The results indicate that machine learning models, particularly the tree-based models (R^2 scores above 0.90, MAE and RMSE scores below 0.05), outperform Gardner's equation (R^2 scores below 0.30, MAE and RMSE scores above 0.1) in predicting density logs, signifying higher accuracy and robustness. The study also underlines the importance of data quality, the selection of appropriate models, and the need for hyperparameter optimization to improve model performance. The results indicate that the incorporation of sophisticated machine learning models into exploration workflows can significantly improve subsurface predictions, thereby boosting exploration effectiveness and success rates within the Niger Delta. This study gives valuable insights into the potential of machine learning in geophysical applications and offers practical recommendations for the adoption and implementation of these techniques in the oil and gas industry. The research emphasizes the need for ongoing efforts and partnerships to enhance the use of machine learning techniques in predicting well-log data, to optimize hydrocarbon exploration in various geological contexts.

Keywords: Machine Learning; Regression; Well logs; Gardner's Equation; Density

1. Introduction

Petroleum exploration and production in the Niger Delta are vital to Nigeria's economy, supported by tools like well logs, which measure properties such as electrical, nuclear, acoustic, and seismic characteristics essential for analysing subsurface geology [23, 21]. Density logs, in particular, play a critical role in estimating reservoir porosity and lithology, influencing hydrocarbon volume calculations.

While traditional methods like Gardner's equation [8] have been widely used due to simplicity, they often fail in geologically complex regions like the Niger Delta, highlighting the need for more advanced approaches. Machine learning, with its ability to model complex relationships and enhance predictive accuracy in large datasets, offers transformative potential in geosciences (14, 16, 20, 31, 32]. These techniques can improve well-log parameter predictions by uncovering patterns those traditional methods might miss.

This study aims to explore machine learning models—such as linear regression, random forest, gradient boosting, and KNN regressors—to improve the accuracy of density log predictions in the Niger Delta. By comparing these models with

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Gardner's equation, the research seeks to determine the most effective approach for well-log prediction, ultimately contributing to more precise and efficient hydrocarbon exploration.

1.1. Study Area

The Niger Delta is a major hydrocarbon province located on the Gulf of Guinea's continental margin, spanning latitudes 4° to 7°N and longitudes 3° to 9°E [17, 33].

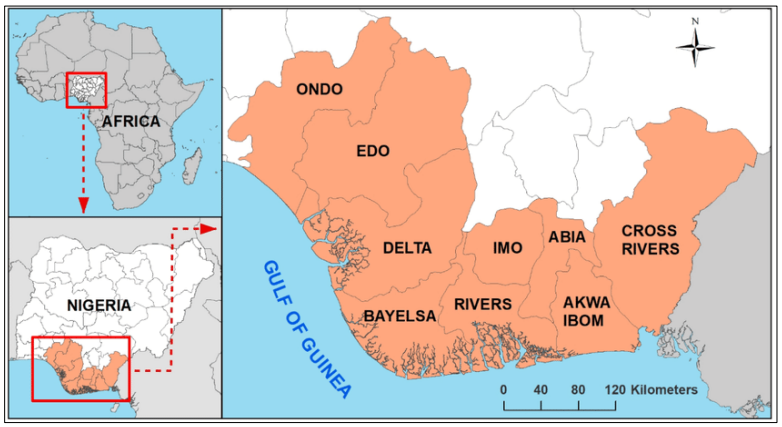

Figure 1 Map of the Niger Delta region in Southern Nigeria [6]

This delta, with its sedimentary fill from the Tertiary period, has been a key player in global energy supply for over 60 years [21]. It covers over 300,000 square kilometres and features a sediment volume of 500,000 cubic kilometres with a thickness exceeding 10 kilometres at its deepest point [12, 15].

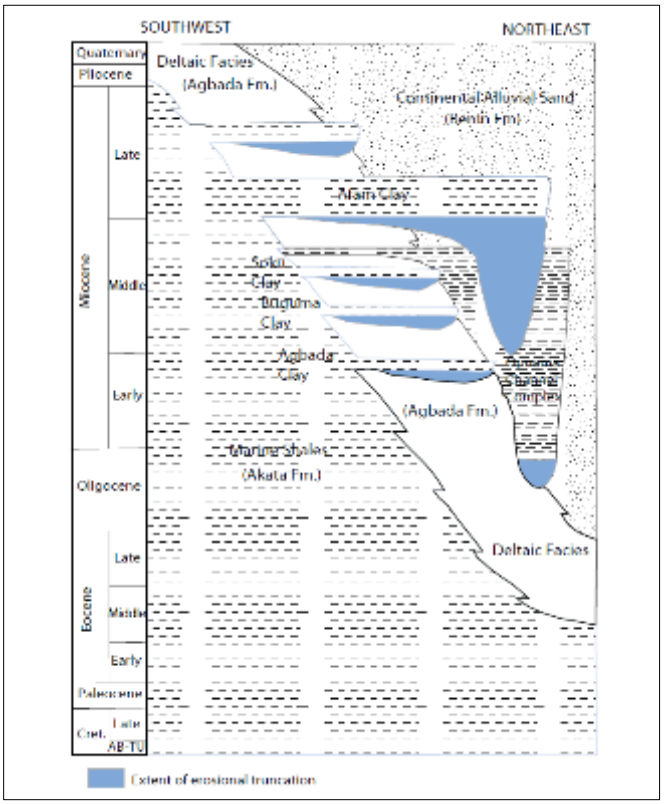

Figure 2 Stratigraphic column showing the three formations of the Niger Delta [25, 5]

The delta's Tertiary sequence comprises three primary formations: the Akata, Agbada, and Benin formations. The Akata Formation, the base unit, consists of marine shales and turbidite sands and is up to 7,000 meters thick [5]. The Agbada

Formation, which started forming in the Eocene, is the primary petroleum-bearing unit, consisting of deltaic siliciclastics and extending over 3,700 meters [1]. The Benin Formation, the topmost unit, is composed of alluvial and upper coastal plain sands up to 2,000 meters thick [1]. These formations reflect a history of complex sedimentation patterns, from tide-dominated to wave-dominated environments [24, 3].

1.2. Theoretical Background

Traditional methods like Gardner's equation [8] have been widely used in the oil and gas industry to predict well-log parameters. This empirical formula relates seismic velocity to rock bulk density and is particularly valuable for estimating density logs in regions where direct measurements are unavailable. Gardner's equation [8] is favoured for its simplicity and ease of use. However, in geologically complex areas like the Niger Delta, where rock properties can vary significantly, its accuracy may be compromised. Despite these limitations, Gardner's equation [8] remains useful for hydrocarbon exploration due to its simplicity and quick estimates.

Machine learning, a subset of artificial intelligence, enables systems to autonomously improve prediction accuracy by analysing historical data without explicit programming for specific tasks [27]. By building models from training data, machine learning algorithms can predict outcomes or make decisions, with some techniques, like neural networks, mimicking the brain's functioning [18]. Machine learning has been applied in various fields, including medicine, speech recognition, and computer vision, particularly where traditional algorithms fall short [13]. In geosciences, its use has grown rapidly over the past decade in areas like reflection seismology, petrophysics, and remote sensing. In the Niger Delta, accurate well-log predictions are crucial for improving hydrocarbon exploration, making the comparison of machine learning models vital for selecting the best approach to predict density logs.

2. Literature Review

Bougher [2] applied supervised and unsupervised machine learning models to geophysical data analysis, achieving a 67% success rate in predicting stratigraphic units from gamma-ray logs. The study also explored reframing pre-stack seismic data analysis as an unsupervised machine learning problem, improving reservoir segmentation. Xie et al. [34] compared machine learning algorithms for lithology classification using well-log data, finding Gradient Tree Boosting and Random Forest to be the most effective models. Dell'Aversana et al. [4] combined geophysical methods with machine learning for risk mitigation in exploration, focusing on two regions, including Nigeria's deep offshore. Syed & Neghabhan [28] reviewed the rising influence of AI and ML in geosciences, particularly in shale reservoir development, noting their efficiency in automating tasks. Syed et al. [29] highlighted AI's role in improving reservoir modelling accuracy through vast data analysis. LeCompte et al. [19] used AI to predict logs in real-time during drilling in the Gulf of Mexico, achieving a close match with conventional methods, and enhancing cost-effectiveness and operational safety. Finally, Tahiru et al. [30] demonstrated that gradient-boosting regressor outperforms traditional methods in predicting sonic logs, offering higher accuracy across various geological contexts.

3. Material and methods

3.1. Data Collection

The data for this study consist of well logs from four wells in the X-Field of the Niger Delta. Predictor variables were chosen based on their relationship with the target variable, formation density, to enhance model performance. These predictors include measured depth, gamma ray, resistivity (deep), sonic velocity, and neutron logs. The target variable for the study is the density of the formation layers. Data pre-processing steps included cleaning the data to remove null values (-999.25), concatenating well data to generate the train set, and converting the sonic log from interval transit time to velocity, which was then used to calculate the density using Gardner's equation.

3.1.1. Gardner's Equation

Gardner's equation [8] is an empirical relationship between seismic velocity (often derived from sonic logs) and bulk density. The equation is given by [8]:

$$\rho = K \times V_p^n \text{ ……(eq.1)}$$

Where ρ is the Bulk density (g/cm^3); V_p is the P-wave velocity (ft/s or m/s); K and n are constants. For velocity measured in metres per second (m/s): K≈0.31 and n≈0.25. For velocity measured in feet per second (ft/s): K≈0.23 and n≈0.25

The P-wave velocity is calculated from the interval transit time (Δt) provided by the sonic log as [8]:

$$V_p = \frac{1}{\Delta t} \times 10^6 \text{ .....(eq.2)}$$

Using the calculated P-wave velocity in Gardner's equation allows the estimation of bulk density, with adjustments for lithology by selecting or calibrating appropriate K and n values.

3.1.2. Machine Learning Algorithms

Linear regression models assume a linear relationship between the target variable y and a vector of predictors x [22]. It is a straightforward and computationally efficient method that fits a linear equation to the data, making it widely used in predictive modelling [9]. However, its reliance on linearity can restrict its ability to capture complex patterns.

Random Forest is an ensemble learning method that combines predictions from multiple decision trees. It uses a voting mechanism for classification and averaging for regression, enhancing prediction stability and accuracy. Key hyperparameters include the number of trees, minimum samples for splitting a node, and tree depth [10].

Gradient Boosting trains models iteratively, minimizing a specified loss function (e.g., mean squared error) at each step using gradient descent. Each successive model improves on the errors of the previous ones, creating a robust ensemble.

K-Nearest Neighbors predicts a target value or class by averaging or voting based on the K-nearest neighbors, identified using metrics like Euclidean or Manhattan distance. It is particularly versatile, with metrics such as Hamming Distance allowing for comparisons involving strings or Boolean data. This simplicity and adaptability make KNN effective across various problem types.

4. Results and discussion

4.1. Data Analysis

The data analysis phase begins with a detailed overview of the dataset. The distribution of facies in the dataset comprises 41,898 data points with a significant imbalance of over 25,000 data points for shale, compared to approximately 8,000 data points each for sandstone and sandy shale. This imbalance can introduce bias into model performance. To address this, the dataset was resampled: the shale facies were downsampled to 15,000 units, and the other facies were upsampled to 15,000 units each.

4.1.1. Correlation matrix

The correlation matrix (figure 3) reveals that measured depth and sonic logs have strong correlations with the density log, making them crucial for model performance. Gamma-ray and neutron logs show weaker correlations but still play a role due to the complex geology of the Niger Delta. Resistivity logs show no significant correlation with the density log and can be excluded from the model without affecting predictions.

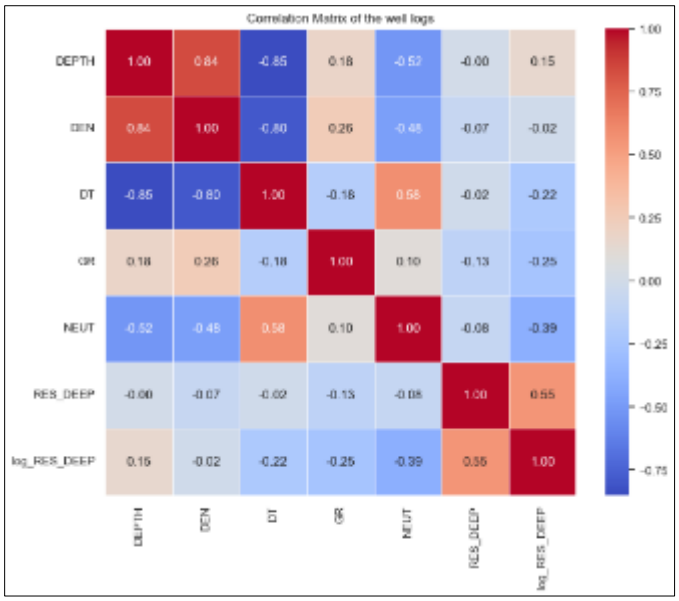

Figure 3 Correlation matrix of the dataset set features

4.2. Model Performance

The dataset was divided into train and test sets with a split an 80/20 split. The performance of each model is evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 values to identify the most accurate model for predicting density logs in the Niger Delta.

4.2.1. Linear Regression

Linear Regression serves as a baseline model in this study, offering a straightforward and interpretable method for predicting well-log data. It captures some linear relationships between input features and the target variable, as shown by moderate evaluation metrics. However, its performance is limited by its inability to model non-linear patterns, resulting in a lower R-squared value compared to more complex models. The coefficients indicate that depth and sonic logs are the most influential contributors to the model's performance.

Table 1 Model Performance Evaluation for Linear Regression

	R^2	**MAE**	**RMSE**
Train	0.74	0.06	0.08
Validation	0.75	0.06	0.08
Test	0.57	0.06	0.08

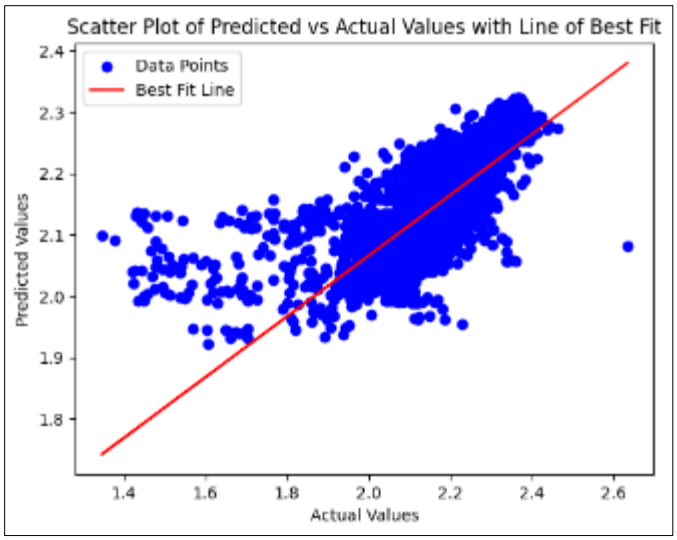

Figure 4 Scatter plot of actual density against predicted density for Linear Regression

4.2.2. Random Forest

The Random Forest model outperforms Linear Regression by effectively capturing non-linear relationships and interactions between features, resulting in lower error values and higher R-squared scores. Feature importance analysis shows that the model prioritizes resistivity, porosity, and depth logs as key predictors for the density log. The model exhibits consistent performance across cross-validation folds, highlighting its robustness and reliability.

Table 2 Model Performance Evaluation for Random Forest

	R^2	**MAE**	**RMSE**
Train	0.997	0.004	0.008
Validation	0.981	0.011	0.021
Test	0.965	0.011	0.023

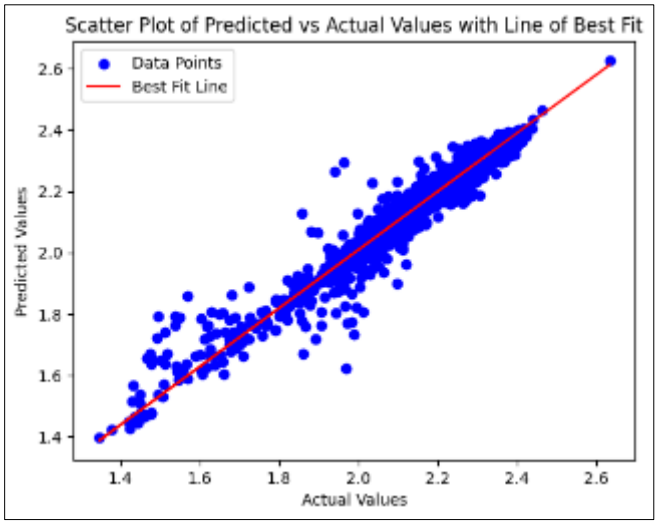

Figure 5 Scatter plot of actual density against predicted density for Random Forest

4.2.3. Gradient Boosting Regressor

The Gradient Boosting model excels in predictive accuracy, achieving the lowest error values and highest R-squared scores among all models. Its iterative approach, which refines predictions by addressing residual errors from previous models, effectively captures complex data patterns. The model demonstrates flexibility across various geological formations and maintains consistent performance across different cross-validation folds, underscoring its robustness and reliability.

Table 3 Model Performance Evaluation for Gradient Boosting Regressor

	R^2	MAE	RMSE
Train	0.93	0.03	0.04
Validation	0.92	0.03	0.04
Test	0.89	0.03	0.04

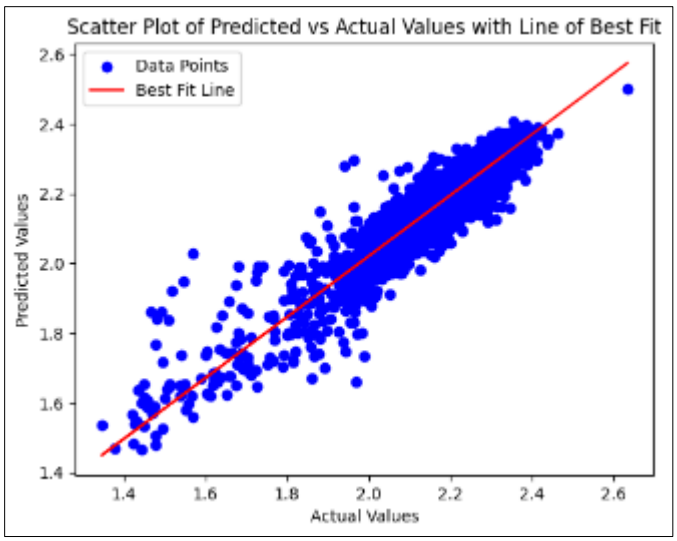

Figure 6 Scatter plot of actual density against predicted density for Gradient Boosting Regressor

4.2.4. KNN Regressor

The K-Nearest Neighbors (KNN) model, a non-parametric method, performs moderately in predicting well-log data. Its accuracy is highly dependent on hyperparameters like the number of neighbors and distance metric. KNN performs well with dense data but struggles in sparse regions. This sensitivity underscores the need for careful tuning and optimization to achieve optimal results.

Table 4 Model Performance Evaluation for KNN Regressor

	R^2	MAE	RMSE
Train	0.98	0.01	0.02
Validation	0.95	0.02	0.03
Test	0.90	0.02	0.04

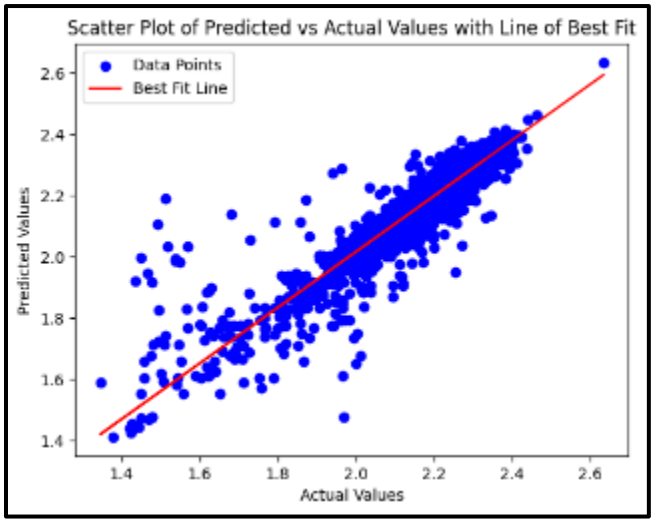

Figure 7 Scatter plot of actual density against predicted density for KNN Regressor

4.2.5. Gardner's equation

The analysis shows that while Gardner's equation provides a rough estimate of the target variable, its accuracy is significantly lower than the machine learning model outputs. The high error and low R-squared values indicate that it is not suitable for accurately predicting well-log data in complex geological settings. The comparison with machine learning models highlights the limitations of traditional empirical models and the potential of machine learning methods to provide more accurate and reliable predictions.

Table 5 Performance Evaluation for Gardner's Equation

	R^2	**MAE**	**RMSE**
Train	0.26	0.11	0.13
Validation	0.29	0.11	0.13
Test	0.06	0.09	0.12

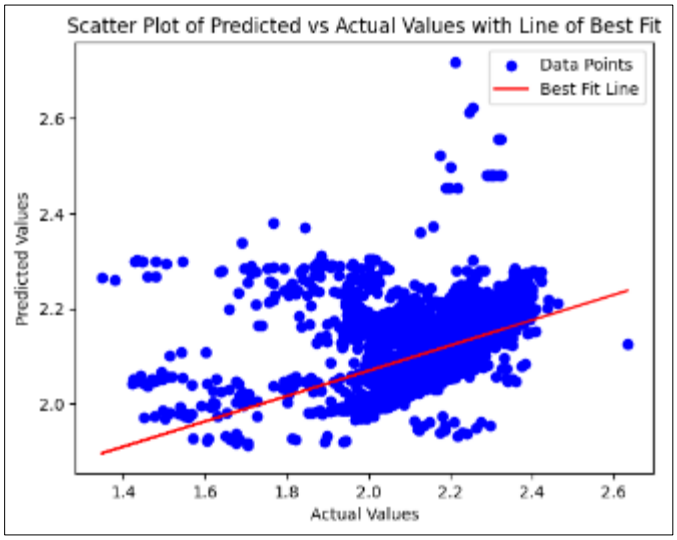

Figure 8 Scatter plot of actual density against predicted density for Gardner's Equation

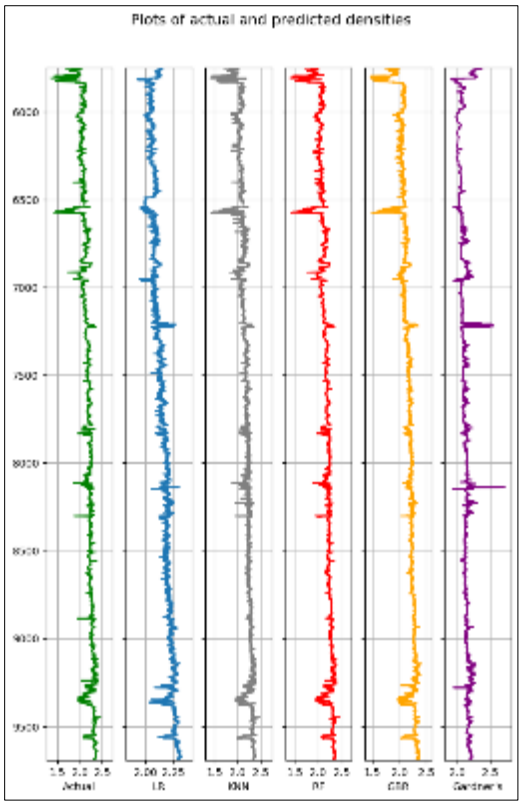

Figure 9 Plots of the actual density against the predicted densities

Figure 9 compares actual density logs with predictions from various models and Gardner's equation. Actual Density (Far Left Column) Provides the reference for comparison. Linear Regression (LR) Shows moderate agreement but notable deviations, especially in deeper sections. K-Nearest Neighbors (KNN) Captures the overall trend well with fewer deviations than LR, particularly in deeper sections. Random Forest (RF) Closely matches actual density logs with less variability and a smoother profile. Gradient Boosting Regressor (GBR) Strongly agrees with actual logs, smoothing out finer details while maintaining the overall trend. Gardner's Equation (Far Right Column) Displays significant discrepancies and a flat curve in lower sections, indicating limitations in capturing data variability.

Table 6 summarizes model performance, showing that ensemble learning methods, specifically Random Forest and Gradient Boosting, outperform others in accuracy and robustness. Gradient Boosting stands out with the lowest MAE and RMSE values and the highest R-squared (R^2) value, highlighting its superior performance in predicting well-log data. Its effectiveness in managing overfitting and robustness to outliers make it the most suitable model for well-log prediction.

Table 6 Comparison of Model Performance Metrics

Model	**MAE**	**RMSE**	**R^2**
Linear Regression	0.06	0.08	0.57
Random Forest	0.01	0.02	0.97
Gradient Boosting	0.03	0.04	0.89
K-NN	0.02	0.04	0.90
Gardner’s Equation	0.09	0.12	0.06

4.2.6. Mean Absolute Error

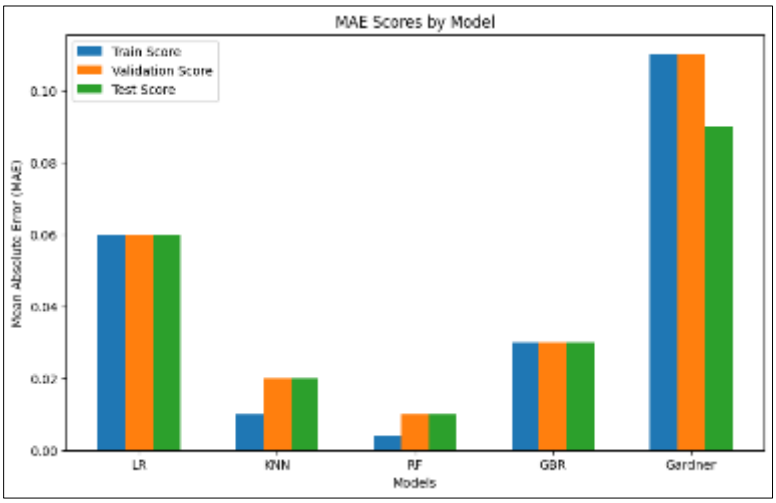

Figure 10 Comparison of Mean Absolute Error across the models

Figure 10 shows that KNN and Random Forest (RF) have the lowest Mean Absolute Error (MAE) scores, indicating the most accurate predictions across all datasets. Gradient Boosting Regressor (GBR) also performs well but with slightly higher MAE compared to KNN and RF. Gardner's equation has the highest MAE, suggesting it is the least accurate method among those evaluated, with Linear Regression (LR) falling in between.

4.2.7. Root Mean Squared Error

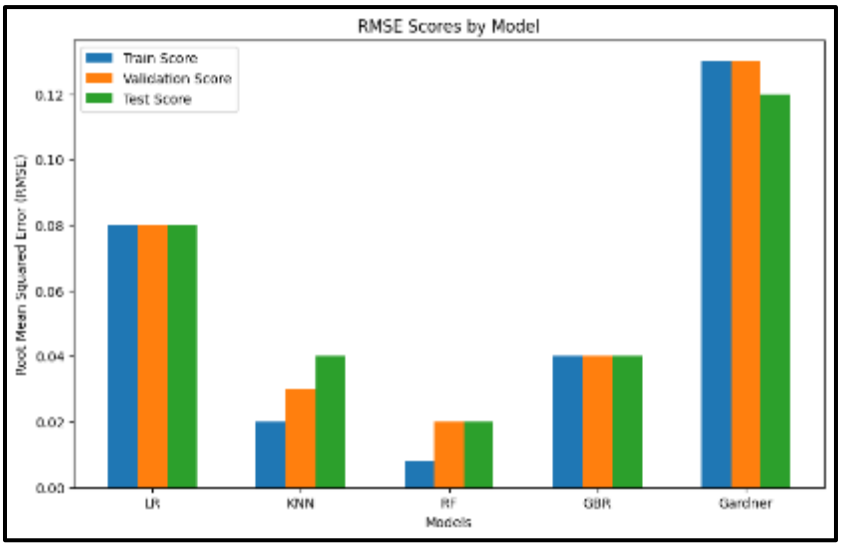

Figure 11 Comparison of Root Mean Squared Error across the models

Figure 11 shows that KNN and Random Forest (RF) have the lowest RMSE scores, indicating the highest predictive accuracy and smallest large errors across all datasets. Gradient Boosting Regressor (GBR) also performs well but with slightly higher RMSE compared to KNN and RF. Gardner's equation has the highest RMSE, making it the least accurate model, while Linear Regression (LR) shows intermediate performance.

4.2.8. Coefficient of Determination (R^2)

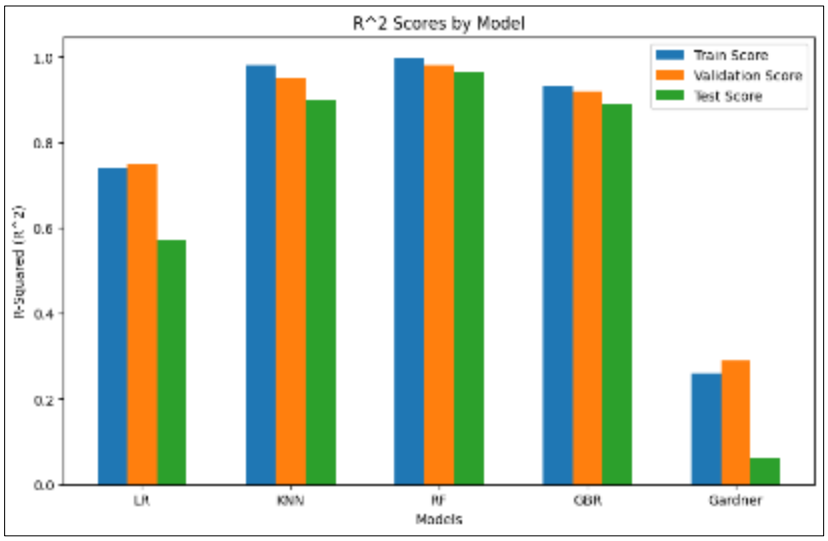

Figure 12 Comparison of R-squared across the models

Figure 12 illustrates that KNN and Random Forest (RF) achieve the highest Coefficient of Determination (R^2) scores, indicating they best capture the data's complexity. Gradient Boosting Regressor (GBR) also performs well but with slightly lower R^2 values compared to KNN and RF. Gardner's equation has the lowest R^2 scores, reflecting its lesser effectiveness in explaining data variance, while Linear Regression (LR) performs moderately better than Gardner's equation but falls short of KNN, RF, and GBR.

Overall, the charts show that machine learning models such as KNN, RF, and GBR outperform traditional methods like Gardner's equation in predictive accuracy. This is evidenced by their higher R^2 scores and lower MAE and RMSE values. These machine learning models more effectively capture underlying data patterns, resulting in more accurate predictions.

5. Discussion

The study reveals that machine learning models—K-Nearest Neighbors (KNN), Random Forest (RF), and Gradient Boosting Regressor (GBR)—significantly outperform the traditional Gardner's equation in predicting density logs. These models achieved lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) scores and higher R-squared (R^2) values, indicating better accuracy and fit to the actual data. RF and GBR were especially effective, with RF capturing complex patterns through its ensemble method and GBR achieving high accuracy with its iterative error-minimizing approach.

In contrast, Linear Regression (LR) showed limitations, with higher MAE and RMSE scores and a lower R^2 value, particularly struggling to capture the complex, non-linear relationships in the data. Gardner's equation, while useful for quick estimates, was less accurate, as evidenced by its higher MAE and RMSE scores and lower R^2 value. Its predictions, especially at greater depths, showed significant deviations from actual logs. Overall, machine learning models are recommended for more accurate and reliable well-log predictions in complex geological settings like the Niger Delta.

The findings from this study have significant implications for hydrocarbon exploration in the Niger Delta and similar regions. The superior predictability of the regression models over traditional methods suggests that these techniques can greatly enhance the accuracy of subsurface predictions, leading to more informed decision-making in exploration activities. Specifically, the use of RF and GBR models could improve the identification of hydrocarbon-bearing formations, optimize drilling operations, and reduce exploration risks.

6. Conclusion

The data analysis demonstrates the effectiveness of machine learning models, particularly Gradient Boosting, in predicting well-log data for the Niger Delta. These models outperform traditional methods like Gardner's equation by accurately capturing complex relationships between input features and target variables. The study highlights the

importance of feature selection and hyperparameter tuning in improving model performance, emphasizing that meticulous optimization can lead to significant gains in accuracy and robustness. Cross-validation is crucial for assessing the models' generalizability and reliability. Overall, the findings underscore the value of ensemble learning methods, such as Random Forest and Gradient Boosting, in enhancing well-log predictions and advancing hydrocarbon exploration in complex geological settings.

Compliance with ethical standards

Acknowledgments

I acknowledge the Editor-in-chief and the Reviewers for their selfless services in improving this research work.

Disclosure of conflict of interest

I declared that there is no conflict of interest.

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