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(Research Article)

Permeability and pore pressure prediction from well logs using machine learning: A study in the Niger delta

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Abstract

Machine learning provides a robust method for characterizing reservoirs in the Niger Delta. This study applied machine learning techniques to well log data to predict permeability and pore pressure. Feature selection identified depth, density, velocity, and porosity as critical variables, while resistivity and neutron porosity (NPHI) showed strong correlations with pore pressure (correlation coefficients: 0.5–1.0). Random forest and gradient boosting emerged as the most effective models, achieving R-squared scores above 0.99 for both permeability and pore pressure predictions. This corresponded to a root mean squared error (RMSE) under 20,000, indicating a precise fit between predicted and actual values. Although the Decision Tree model also performed well (R-squared > 0.99), further optimization could improve its RMSE and generalization. These results highlight the potential of machine learning to enhance reservoir characterization and inform decision-making in oil and gas exploration and production. Accurate predictions of reservoir properties can optimize operations and reduce uncertainties. Future work could expand these findings by integrating additional data, such as 3D seismic information, and applying the models to diverse geological settings. This would improve the robustness and transferability of predictions, enabling more comprehensive reservoir analysis.

Keywords: Permeability; Pore Pressure; Well Logs; Machine Learning; Random Forest Model; Gradient Boosting Model; Decision Tree Model; R-squared; Root Mean Squared Error

1. Introduction

The Niger Delta, a prolific oil and gas-producing region in Nigeria, has been the focus of extensive exploration activities for over 50 years [1]. However, the accurate prediction of crucial reservoir properties, such as permeability and pore pressure, remains a challenge in this basin [1, 2]. These parameters are essential for determining a reservoir's commercial viability and optimizing its development and management strategies [2, 3].

Traditionally, well logs, core analysis, and seismic data have been used to assess permeability and pore pressure in the Niger Delta. However, these conventional methods have limitations in terms of accuracy, cost, and time-consumption [4, 5]. The industry demands more cost-effective, real-time, and reliable prediction techniques to enhance reservoir characterization and management [8].

Machine learning (ML) techniques offer a promising alternative, as they can leverage data-driven models to make predictions on unseen data [6]. While supervised learning algorithms, such as support vector machines and decision trees, have shown success in predicting reservoir properties elsewhere [9], their applicability in the unique geological setting of the Niger Delta remains unexplored.

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1.1. Objectives and Scope

This study investigates the use of supervised learning for predicting permeability and pore pressure in the Niger Delta. Here are the specific objectives:

- Review traditional prediction methods and the use of ML for reservoir properties [6].
- Collect and preprocess well log data from selected Niger Delta wells for use in ML models.
- Train and evaluate supervised learning models (e.g., multiple linear regression, decision trees, and support vector machines) for permeability and pore pressure prediction using the collected data.
- Compare the performance of these models with traditional methods.
- Analyze the models to understand the relationships between predictor variables and permeability and pore pressure.
- Assess the applicability of supervised learning for prediction in the Niger Delta and identify areas for further research.

The scope is limited to predicting permeability and pore pressure in the Niger Delta using supervised learning with well log data from selected wells. The models will be based on regression and classification algorithms, and their performance will be compared to traditional methods.

Limitations

The study is limited by:

- Data availability: data on permeability and pore pressure might be limited to specific wells, potentially affecting generalizability.
- Model assumptions: The models' accuracy relies on assumptions that may not always hold true [10].
- Model generalizability: Models developed on a specific dataset might not perform well on others [10].
- Uncertainty: Prediction of these properties inherently involves uncertainties, which the models cannot entirely eliminate [10].
- Despite these limitations, the study will provide valuable insights into using supervised learning for permeability and pore pressure prediction in the Niger Delta.

2. Geologic Setting of the Niger Delta

The Niger Delta, a prolific hydrocarbon basin in southern Nigeria, boasts a unique geologic history that significantly influences its reservoir properties [11, 12]. This section delves into the basin's geological makeup, highlighting key features relevant to permeability and pore pressure prediction.

2.1. Prograding Delta System

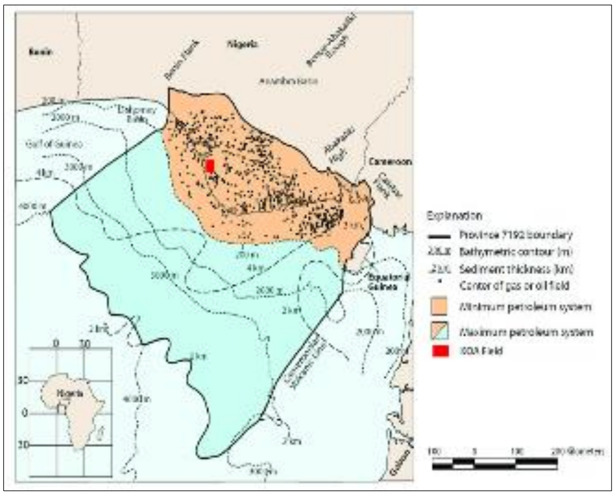

Figure 1 Map of the Niger Delta, including province boundaries and structural elements (after Petroconsultants, 1996)

The Niger Delta, situated within the Gulf of Guinea (Fig. 1) [11], is a tertiary delta system formed by the progradation (outward growth) of the delta over time [12].

This progradation resulted in depobelts, zones with thicker sediments, representing the delta's most active regions during various stages of its development [12]. Exploration has been concentrated in this basin since 1937 due to its proven hydrocarbon potential, estimated at 34.5 billion barrels of oil and 93.8 trillion cubic feet of gas [13].

2.2. Stratigraphy and Sedimentary Layers

The Niger Delta basin is characterized by a layered sequence of sedimentary formations deposited over time. As a prograding delta, the advancing delta front would cover existing sediments, with younger sediments overlying the submerged delta fringe [14]. However, the Niger Delta's history is marked by multiple transgressions (periods of sea level rise) that disrupted this typical sequence [14]. These transgressions resulted in discontinuities within the overall stratigraphic column.

Three main formations—the Akata, Agbada, and Benin—make up the thick sedimentary wedge of the Niger Delta (Fig. 2) [15].

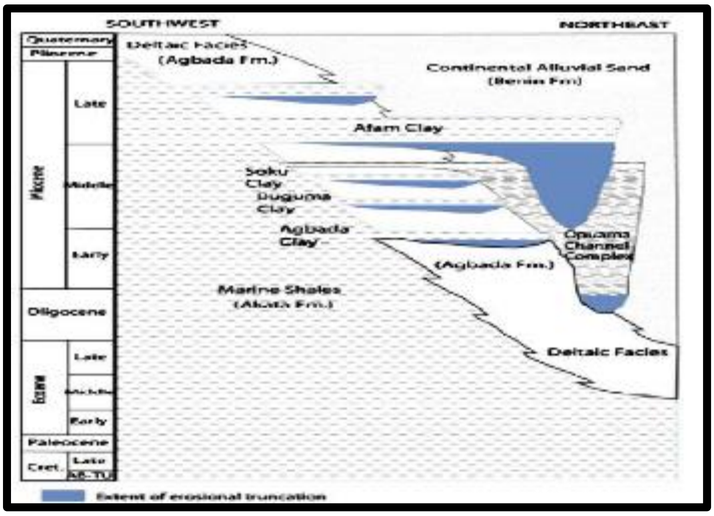

Figure 2 Stratigraphic column of the Niger Delta Basin (after Shanon and Naylon, 1989; as cited by Peter and Abdulquadri, 2018)

These formations are diachronous, meaning their ages vary laterally across the basin, and they cut across established stratigraphic boundaries with a characteristic S-shape [15].

Akata Formation (Base Layer): The Akata Formation, primarily composed of dark gray marine shale with occasional silty layers, forms the basin's basal unit, deposited during the Oligocene to Recent epoch [16]. These shales were laid down in prodeltaic environments with minimal sand content (usually less than 30%) [17]. The Akata Formation thickens towards the basin center and is known for being overpressured, a factor influencing hydrocarbon migration [18].

Agbada Formation (Hydrocarbon Reservoir): This formation, the primary source of the Niger Delta's proven hydrocarbon reserves, consists of alternating layers of sandstone, siltstone, and shale [19]. The sandstones range from very fine to very coarse-grained and are largely unconsolidated. Shales within the Agbada Formation are generally gray and become progressively shalier with depth [19]. The formation is believed to be up to 14,000 feet (4,200 meters) thick and represents sediments deposited in various deltaic settings, including the lower delta plain, coastal barrier, and fluvio-marine environments [19, 20].

Benin Formation (Top Layer): The uppermost layer of the deltaic sequence is the Benin Formation, characterized by a high sand content (70-100%) [21]. These sands were deposited in a continental setting, representing fluvial environments like braided and meandering river systems [21]. The Benin Formation is dominated by non-marine sands with some shale layers. The size of the sand grain varies from fine to coarse, and the formation thickness can reach up to 1,000 feet (300 meters) [21].

2.3. Macrostructures and Megastructures

The Niger Delta's structural framework is complex, characterized by a series of faults and fault blocks. Groups of these fault blocks can combine to form larger features and macrostructures, which often exhibit rollover deformation [22]. The updip (landward) boundary of a macrostructure is typically defined by a major bounding fault [22]. When multiple macrostructures align parallel to the Niger Delta's axis, they form even larger-scale features called megastructures [22]. Boundaries between megastructures often correspond to significant changes in the basin's regional dip.

2.4. Traps and Seals

While stratigraphic traps (reservoir formations sealed by impermeable rock layers) are uncommon in the Niger Delta, structural traps formed during the deposition of the Agbada Formation's paralic sequence (environments influenced by both marine and terrestrial processes) are the dominant type of hydrocarbon trap [23].

2.5. Hydrocarbon Generation and Migration

The Niger Delta's hydrocarbon deposits originate from the breakdown of organic matter buried within the sediments under suitable temperature, pressure, and chemical conditions. The peak oil window in the basin, where conditions are most favorable for oil generation, is estimated to be around 115°C (240 °F) [24]. Evamy (1978) identified this isotherm as the key indicator for oil occurrence in the Niger Delta [24]. However, the depth of this zone can vary depending on the ratio of sand to shale overburden [25].

2.6. Source Rocks and Debate

The origin of the organic matter that transformed into hydrocarbons in the Niger Delta has been a topic of debate. Some researchers propose that the shales within the Agbada Formation itself act as the primary source rock [26]. Others argue that the underlying Akata Formation, composed mainly of marine shales, is the dominant source [27, 28]. Short and Stauble (1967) were the first to suggest the Agbada Formation as a source rock, while Weber and Daukoru (1975) pointed towards the Akata Formation due to its greater depth and age [26, 27].

The current understanding leans towards a more nuanced view, acknowledging the potential contribution of both formations [29]. The Akata Formation likely plays a more significant role in the generation of gas, particularly in the basin's central area, where it's deeply buried. The Agbada Formation, on the other hand, is considered a source rock for oil in specific regions where it has reached sufficient thermal maturity [29].

2.7. Hydrocarbon Migration

Hydrocarbon migration, the movement of generated hydrocarbons from source rocks to reservoir rocks, typically occurs after the completion of sedimentation and major structural deformation events [30]. In the Niger Delta, migration likely involved both short-distance movement within the source formations themselves and longer-distance migration along faults or through permeable sandstone layers within the Agbada Formation [31]. Weber (1987) proposed the possibility of cross-fault migration, where overpressured shales on one side of a fault expel hydrocarbons towards less pressured formations on the other side [32].

The interplay between source rock distribution, thermal maturity, and the presence of migration pathways plays a crucial role in determining the location and abundance of hydrocarbon accumulations within the Niger Delta. Understanding these geological factors is essential for the successful exploration and development of the basin's hydrocarbon resources.

3. Material and methods

Permeability and pore pressure are crucial reservoir properties that influence fluid flow and hydrocarbon production. Accurate predictions of these properties can provide valuable insights into reservoir behavior and optimize development strategies. This study employs supervised machine learning algorithms to predict these properties in the Niger Delta reservoir. Well-log data will be collected from various sources, ensuring quality and consistency. Supervised learning techniques will be used to establish relationships between well-log measurements and target variables, such as permeability and pore pressure. Various machine learning models, including random forest, support vector machines, and neural networks, will be explored to identify the most effective model for this application. Each model's hyperparameters will be carefully tuned to optimize its performance.

Model evaluation will use metrics like mean squared error (MSE) and R-squared to select the best-performing model for permeability and pore pressure prediction in the Niger Delta reservoirs. This research is expected to contribute to a more comprehensive understanding of reservoir properties within the Niger Delta basin, enabling the development of machine learning models for reservoir characterization, production forecasting, well placement optimization, and more efficient hydrocarbon exploration and development efforts.

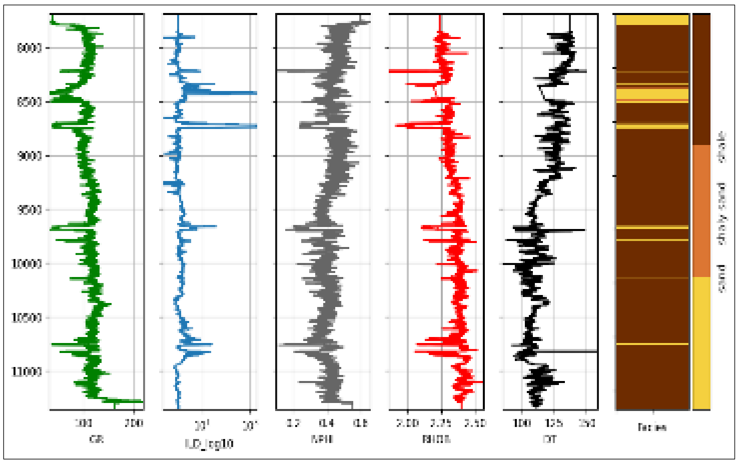

Figure 3 Well logs showing facies log and other parameters

The data visualization revealed a significant presence of shale, which significantly affects permeability and pore pressure. The petrophysics class's functions were used to calculate key reservoir properties, including velocity, gamma ray index, Vshale, effective porosity, and formation factor. Water saturation and permeability were determined using Equation 2.12 from Owolabi et al. (1994), enabling a comparative analysis between calculated, measured, and predicted values.

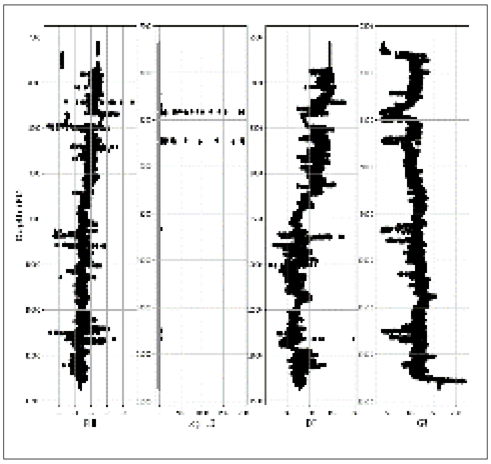

Figure 4 Scatter plot of well log parameters

A scatter plot was employed to visualize potential outliers in key parameters, aiming to trim the data and protect the model from errors. Outliers, such as Gamma Ray values exceeding 150, were identified. Since the Niger Delta typically has Gamma Ray values ranging from 0 to 150 (Alasi et al., 2023), such outliers can be misleading if used for model training. Therefore, outlier detection and removal were performed to enhance the model's accuracy and reliability.

3.1.1. OUTLIER DETECTION

The outlier function processes 1D numpy array data, using a threshold value (defaulting to 3) to identify potential outliers. It calculates the mean and standard deviation of the input data and then computes the z-score for each data point. If a data point's z-score exceeds the threshold, its index is added to a list of potential outliers.

The method assumes a normal distribution of input data but may not perform well with skewed or heavy-tailed data, suggesting alternative outlier detection methods should be considered in such cases.

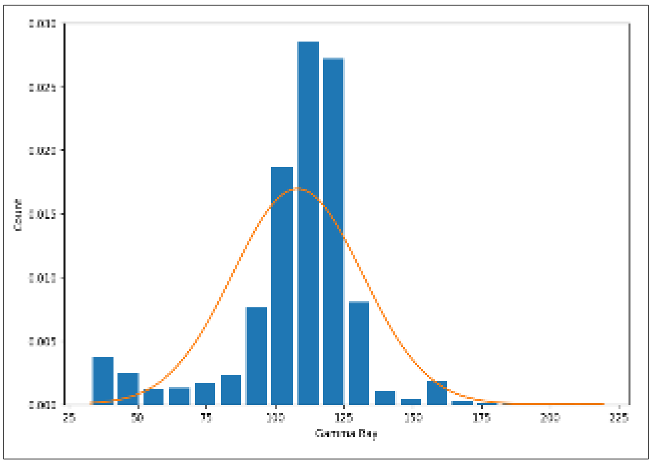

Figure 5 Normal distribution of the Gamma ray data present in the data set

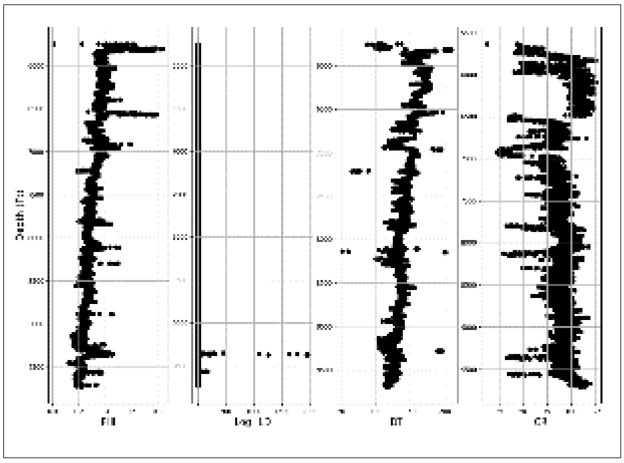

Figure 6 Scatter plot of well log parameters after outlier detection and removal

3.1.2. Feature selection and correlation analysis

Feature selection is crucial for predictive models' accuracy and efficiency. A correlation analysis was conducted to examine the relationship between feature variables and permeability, using the "corr()" function. Additional parameters were needed for pore pressure calculation, including velocity_'vs', Eaton_method, and Bowers_method. A plot was generated for visualization.

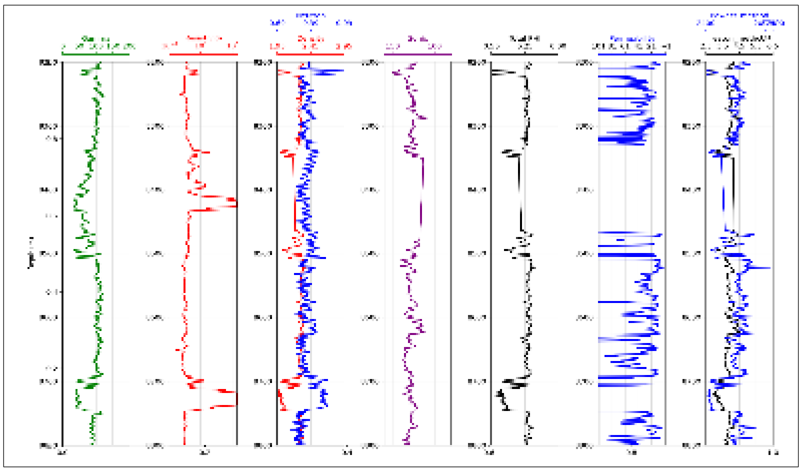

Figure 7 Well log plots with Bowen's and Eaton's pore pressure plots

While Eaton's Method and Bowers' Method both predict increasing pore pressure with depth, they may not always produce matching results due to differing approaches and data inputs. Plotting their predictions together allows for a comparative analysis to understand underlying assumptions, identify discrepancies, and select the method aligning best with expected pore pressure behavior. For this work, Eaton's method was chosen for pore pressure prediction.

The correlation coefficients between features and permeability were calculated and visualized. Porosity (PHI) showed the strongest positive correlation with permeability, suggesting that higher porosity facilitates easier fluid flow. Bulk density (RHOB) exhibited a weak negative correlation, indicating that denser materials have lower permeability. Sonic travel time (DT) and velocity displayed weak positive correlations, possibly related to pore structure. Other features showed a negligible correlation with permeability.

Permeability model: Depth, Log_ILD, NPHI, RHOB, vshale, PHIeff, swirr, Facies_code

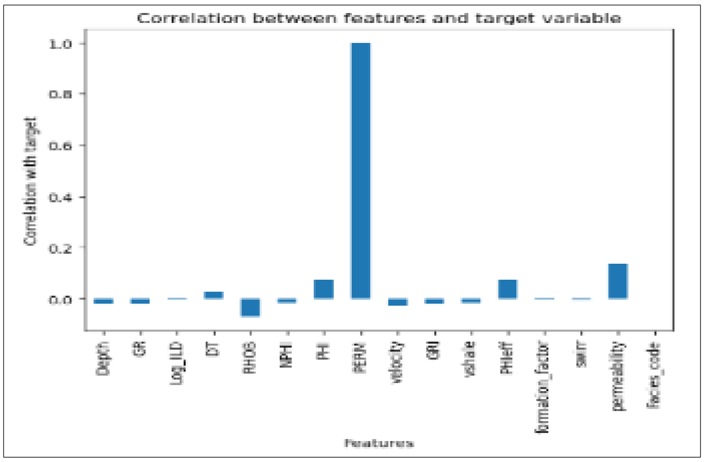

Figure 8 Correlation between features in the data and the target variable (Permeability)

For pore pressure, depth showed the strongest positive correlation with pore pressure, implying increasing pressure with depth. Negative correlations were observed with DT, PHI, and PHIeff, while positive correlations were noted with RHOB, Velocity, and Vs. Other factors not included in the analysis may also influence the pore pressure. These correlations provide insights into the factors influencing pore pressure behavior.

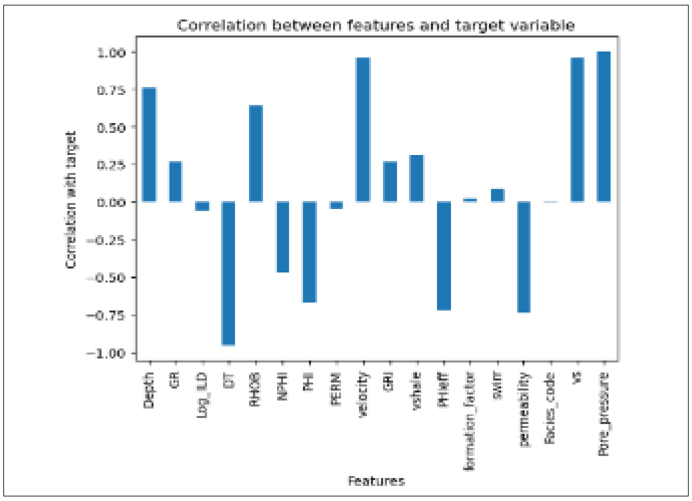

Figure 9 Correlation between features in the data and the target variable (Pore pressure)

Velocity and Vs exhibited strong positive correlations with pore pressure, suggesting a close relationship between high wave velocities and increased pore pressure values.

Pore pressure model: Log_ILD, RHOB, GR, Facies_code, Depth, vs, PHI

3.2. Model Selection and Training

The dataset was split into training (80%) and testing (20%) sets for model evaluation using scikit-learn's train_test_split.

3.3. Model Comparison and Hyperparameter Tuning

Several machine learning algorithms (SVM, Random Forest, Decision Tree, Neural Network, and Gradient Boosting) were compared using grid search with cross-validation to identify the best model for pore pressure prediction. R-squared was used for evaluation.

Table 1 Hyperparameter Exploration

Model	Hyperparameters
SVM	Kernel: linear, RBF, poly C: 0.1, 1, 10 Gamma: scale, auto
Random Forest	Kernel: linear, RBF, poly C: 0.1, 1, 10 Gamma: scale, auto
Decision Tree	max_depth: 5, 10, 15 min_samples_split: 2, 5, 10
Gradient Boosting	learning_rate: 0.05, 0.1, 0.2 n_estimators: 50, 100, 150 max_depth: 3, 5, 7
Neural Network	hidden_layer_sizes: (10,), (20,), (30,) activation: ReLU, Tanh, logistic

3.4. Evaluation and Selection

The best-performing models were evaluated on the test set using RMSE and R-squared. The winning models for each method were saved using joblib. dump.

4. Results

4.1. Permeability

This section analyzes permeability prediction using various machine learning models, assessed with RMSE and R-squared metrics. Random forest, decision tree, and gradient boosting models performed best, closely matching actual permeability values. In contrast, SVM and neural network models underperformed, with the neural network showing particularly poor results.

4.1.1. Model Evaluation

The performance of each model was evaluated using metrics such as RMSE and R-squared. The results are in Table 4.3.

Table 2 Model Evaluation Results

Model	Best Parameters	Best Score	RMSE	R-squared
SVM	{'svr__C': 10, 'svr__gamma': 'auto', 'svr__kernel': 'poly'}	0.24198	1493.45	0.081268
Random Forest	{'max_depth': 10, 'n_estimators': 50}	0.686534	585.374	0.858851
Decision Tree	{'max_depth': 15, 'min_samples_split': 2}	0.693036	204.671	0.982745
Neural Network	{'activation': 'tanh', 'hidden_layer_sizes': (20,)}	-0.00093	1558.89	-0.00102
Gradient Boosting	{'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 100}	0.711957	246.197	0.975032

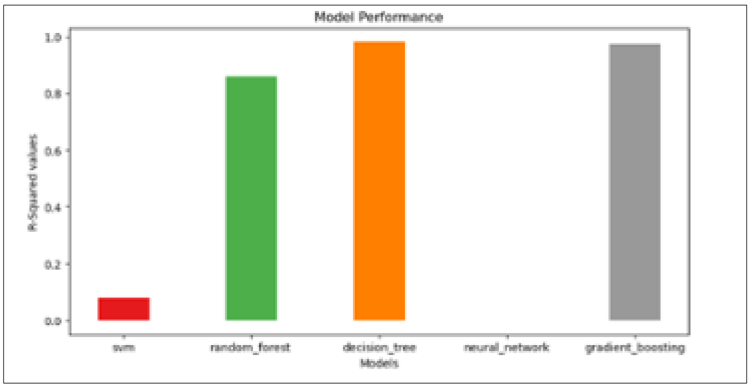

Figure 10 Comparing model performance (Permeability test)

4.1.2. Results Summary

Random Forest, Decision Tree, and Gradient Boosting models excelled with high R-squared scores and low RMSE, indicating accurate and reliable predictions. SVM and neural network models demonstrated poorer performance, with SVM having a low R-squared score and the neural network showing a negative score, indicating inaccurate predictions. Therefore, decision tree, random forest, and gradient boosting models are recommended for their superior accuracy in predicting permeability.

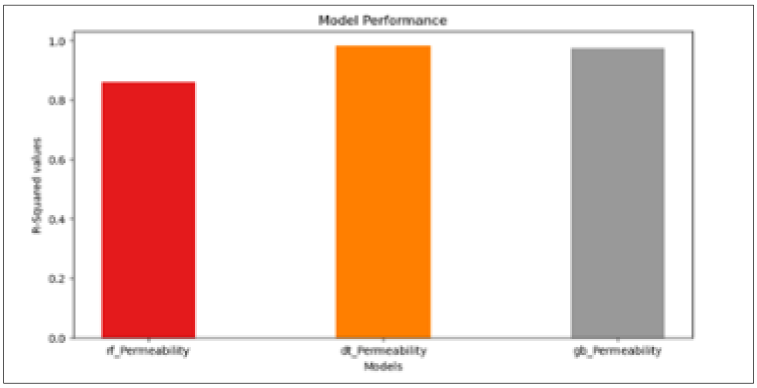

Figure 11 Comparing model performance (Permeability train)

4.2. Pore Pressure

In this chapter, different machine learning models were explored for predicting pore pressure. The analysis included evaluation metrics such as RMSE and R-squared. Random forest and gradient boosting models exhibited the best performance, closely matching actual pore pressure values. Support vector machines (SVM) showed the poorest performance, while decision tree and neural network models showed intermediate results.

4.2.1. Model Evaluation

Different machine learning models were explored for predicting pore pressure. Random forest and gradient boosting models exhibited the best performance, closely matching actual pore pressure values. SVM showed the poorest performance, while decision tree and neural network models produced intermediate results. The performance of each model was evaluated using metrics such as RMSE and R-squared. The results are summarized below:

Table 3 Model Evaluation Results

Model	**Best Parameters**	**Best Score**	**RMSE**	**R-squared**
SVM	{'svr__C': 10, 'svr__gamma': 'scale', 'svr__kernel': 'linear'}	0.423286	375672.5	0.504918
Random Forest	{'max_depth': 30, 'n_estimators': 150}	0.998659	15175.88	0.999192
Decision Tree	{'max_depth': 15, 'min_samples_split': 5}	0.996824	22144.38	0.99828
Neural Network	{'activation': 'relu', 'hidden_layer_sizes': (30,)}	0.840123	208368	0.847693
Gradient Boosting	{'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 150}	0.999087	15104	0.9992

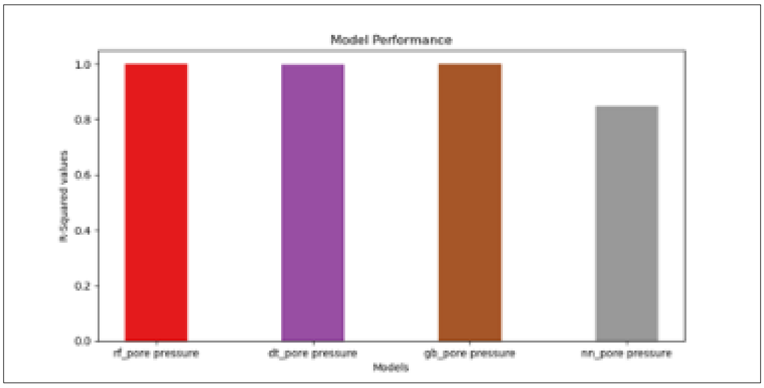

Figure 12 Comparing model performance (Pore pressure test)

4.2.2. Results Summary

Random Forest and Gradient Boosting models stood out with very high R-squared values and low RMSE, indicating precise predictions. SVM performed the worst, with a relatively high RMSE and a lower R-squared. Decision Tree and neural network models showed intermediate performance. Random Forest, Decision Tree, and Gradient Boosting models are recommended for accurate pore pressure prediction due to their high precision and strong correlation with actual values. The choice of model depends on specific requirements and trade-offs between accuracy and computational complexity.

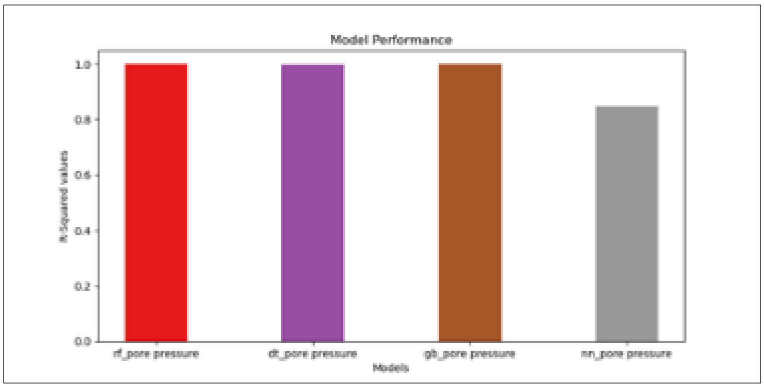

Figure 13 Comparing model performance (Pore pressure train)

5. Discussion

5.1. Permeability

5.1.1. Model comparison

The machine learning model's performance in predicting permeability is evaluated through plots comparing actual and predicted values. The analysis shows strong prediction ability, with an R-squared value of 0.858. Comparing predicted permeability tracks with actual tracks reveals close alignment for 90% of the log depth, with the models' predictions often shadowed by the actual track.

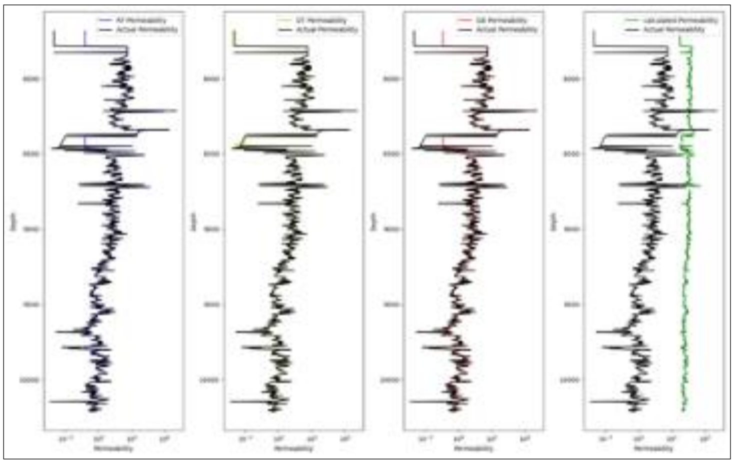

Figure 14 Actual vs predicted permeability (Training data)

Root Mean Squared Error (RMSE) values further support the models' superior performance, ranging from 204.671 to 585.374 for model predictions, significantly lower than the calculated permeability's RMSE of 1558.89.

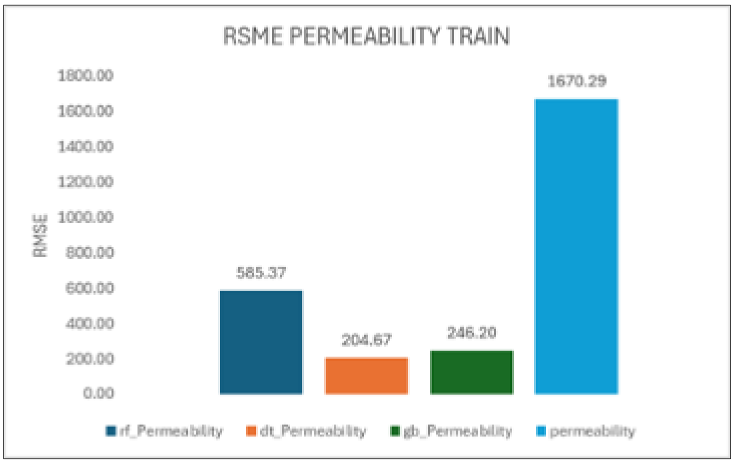

Figure 15 RMSE for all models and calculated permeability (Training data)

The decision tree method outperforms random forest and gradient boosting for permeability prediction, with an RMSE of 204.67, indicating higher accuracy.

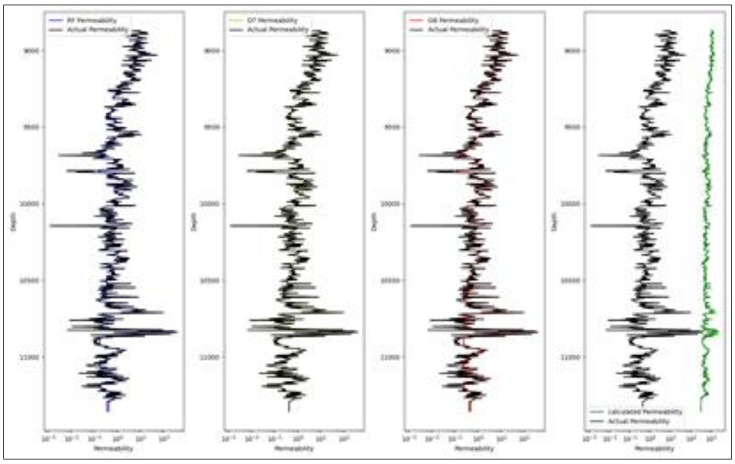

Figure 16 Actual vs predicted permeability (Test data)

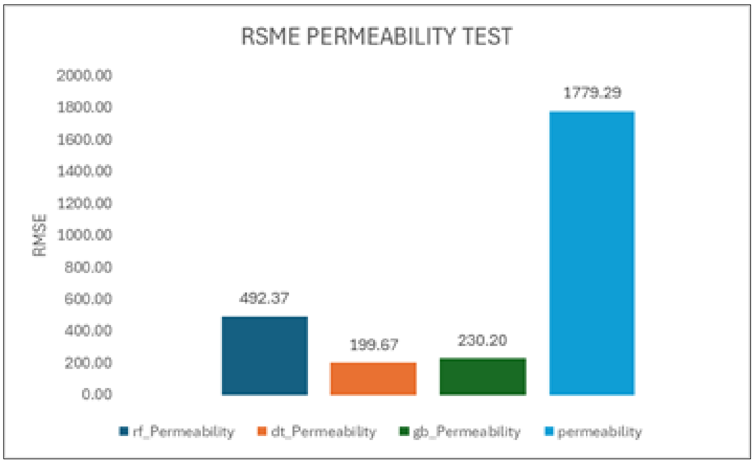

Figure 17 RMSE for all models and calculated permeability (Test data)

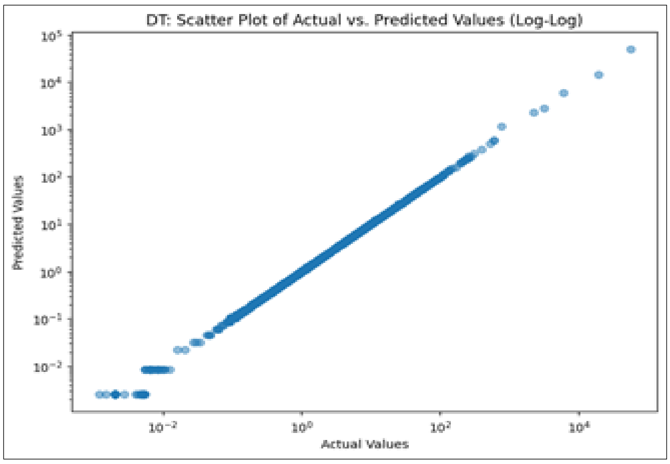

Figure 18 Decision Tree Scatter Plot of Actual vs. Predicted Permeability (Test Data)

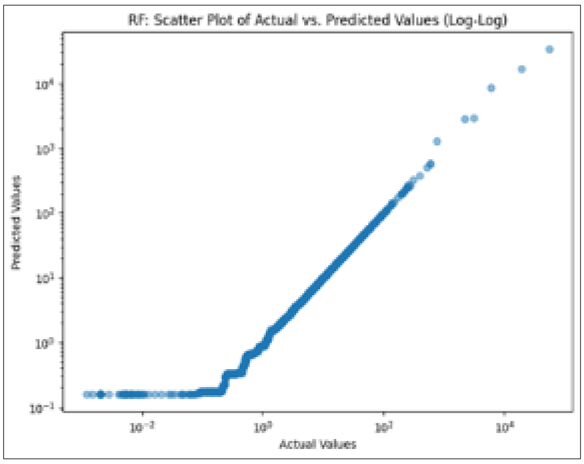

Figure 19 Random Forest Scatter Plot of Actual vs. Predicted Permeability (Test Data)

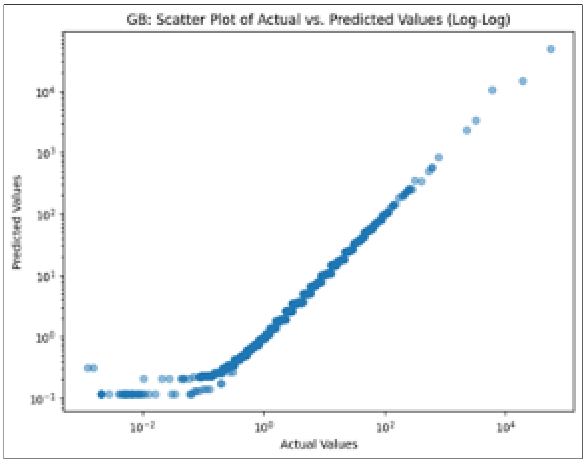

Figure 20 Gradient Booster Scatter Plot of Actual vs. Predicted Permeability (Test data)

These findings demonstrate the effectiveness of machine learning models in predicting permeability compared to traditional calculation methods, enhancing our understanding of subsurface properties. Visualizations such as scatter plots help evaluate model performance, with data points closer to the diagonal line indicating better predictions and outliers influencing performance assessment.

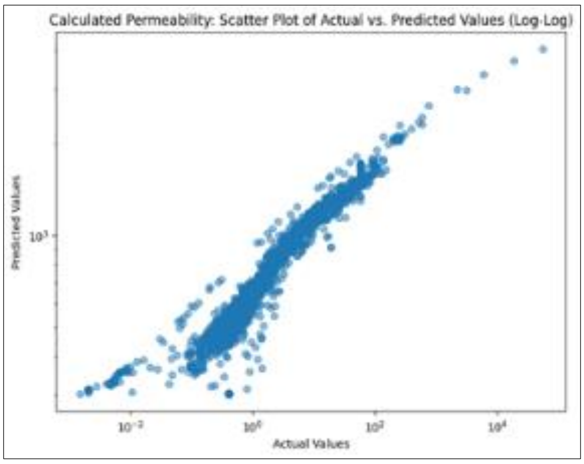

Figure 21 Calculated Permeability Scatter Plot of Actual vs. Predicted Permeability (Test Data)

5.1.2. Traditional view

Petrel is a powerful software platform used in the oil and gas industry for reservoir characterization and modeling. Its core functionality is estimating permeability from well-log data. The process involves importing the data in the correct format, ensuring data quality, identifying key logs like porosity, density, resistivity, and sonic logs, analyzing log curves to identify lithology, fluid contacts, and formation boundaries, and performing basic log calculations like Vshale and water saturation for additional information.

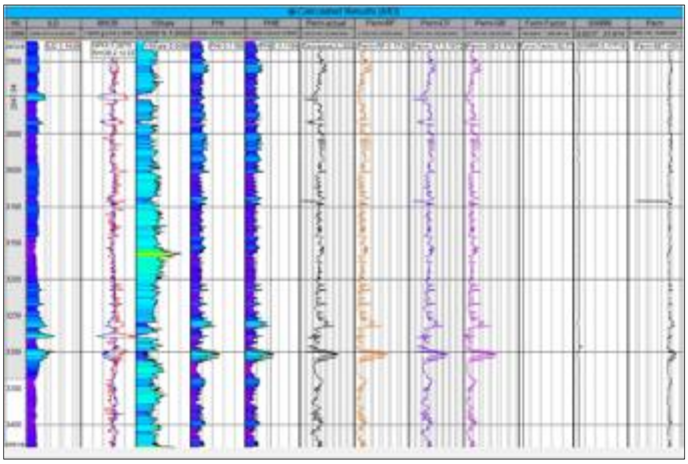

Figure 22 Freeman 1 Well Log Analysis from Petrel Software

Empirical correlations are used to estimate permeability based on log-derived parameters, such as porosity and grain size. Wells are clustered based on similar log responses to identify rock types. Representative permeability values are assigned to each rock type using core data or correlations. A 3D permeability model is created using geostatistical methods, incorporating well-log data, core data, and geological information to create a realistic permeability distribution.

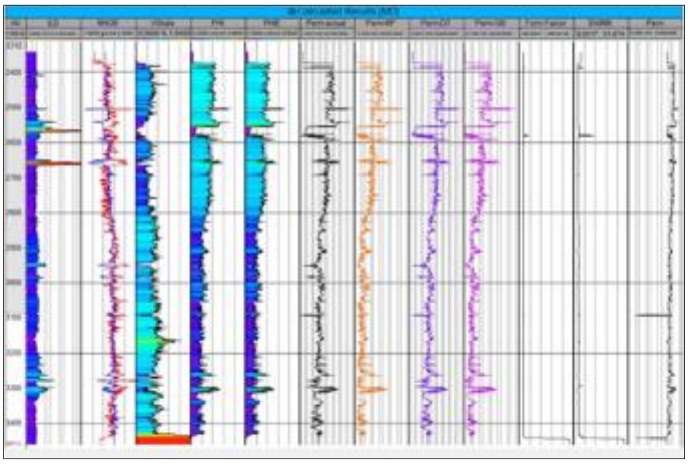

Figure 23 Freeman 7 Well Log Analysis from Petrel Software

Key well logs for permeability estimation usually include porosity logs, which provide information about pore space volume directly related to permeability; density logs, which help in lithology identification and can be used in combination with porosity to estimate mineral composition; resistivity logs, which can determine water saturation affecting permeability; and sonic logs, which provide information about rock matrix properties related to permeability.

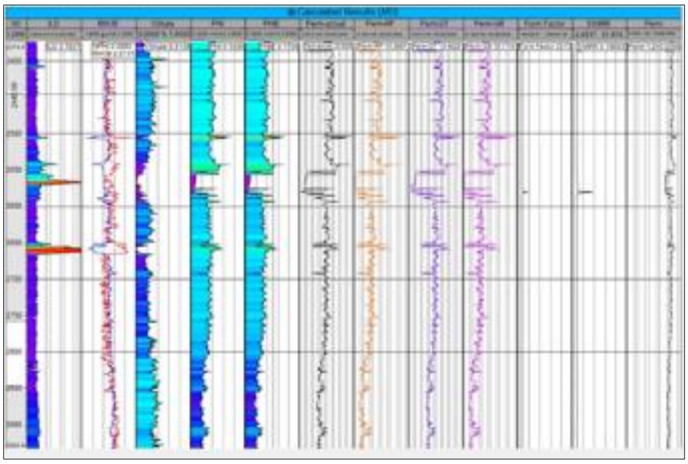

Figure 24 Freeman 5 Well Log Analysis from Petrel Software

Well-log-based permeability estimation has limitations due to its point-based nature, representing measurements at discrete points. This leads to uncertainty between wells and region-specific empirical correlations. It may not fully capture complex reservoir heterogeneity, like fractures and diagenesis. Core data integration can improve the estimated permeability distribution's accuracy. Understanding the reservoir's geology and petrophysics is crucial for reliable estimation. Sensitivity analysis can help assess uncertainty by evaluating input parameters and correlations.

5.2. Pore pressure

5.2.1. Model comparison

We employ visual plots to assess the performance of machine learning models in predicting pore pressure. Each plot compares actual pore pressure with that predicted by a specific model, along with depth, aiming for perfect alignment to indicate accurate predictions.

The analysis of training data shows promising results for pore pressure prediction, supported by a high R-squared value of 0.858, indicating a strong correlation between predicted and actual values. Visual comparisons reveal close alignment between predicted and actual trends, with predicted tracks often obscured by actual tracks due to their close match.

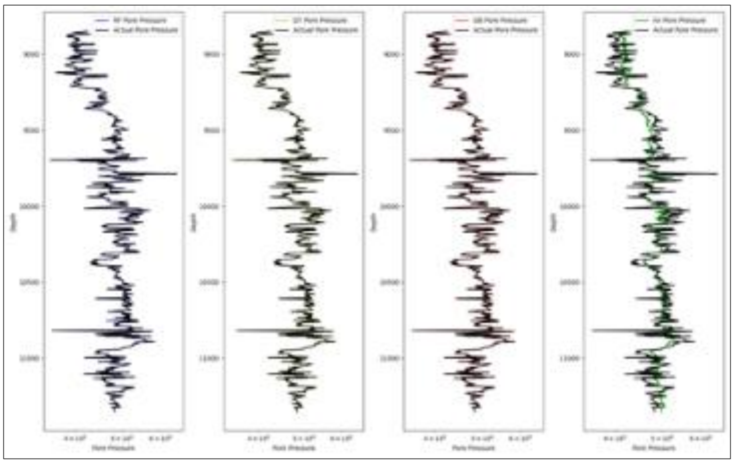

Figure 25 Actual vs predicted Pore Pressure (Test Data)

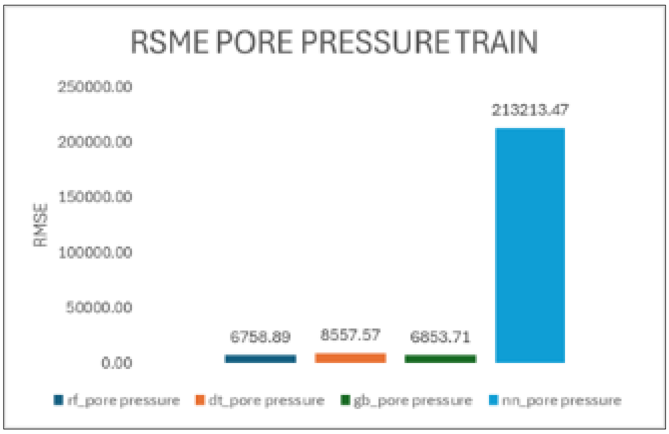

Figure 26 RSME for all Pore Pressure Models (Test Data)

The neural network model exhibits the most significant deviations from actual measurements, supported by its lower R-squared value of 0.84 compared to other top-performing models (excluding SVM). Among these models, Random Forest (RF) and Gradient Boosting (GB) perform well with lower RMSE values, indicating higher accuracy. Decision Tree (DT) also performs reasonably well, though slightly less accurate than RF and GB. In contrast, the Neural Network (NN) method shows significantly higher RMSE, suggesting lower accuracy for this dataset.

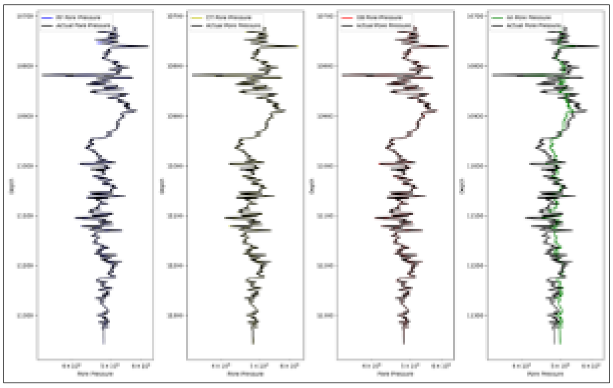

Figure 27 Actual vs predicted Pore Pressure (Training data)

If your model is overfitting, it means that it is performing well on the training set but not on the validation set. This can happen if the model is too complex and has too many parameters compared to the size of the training data.

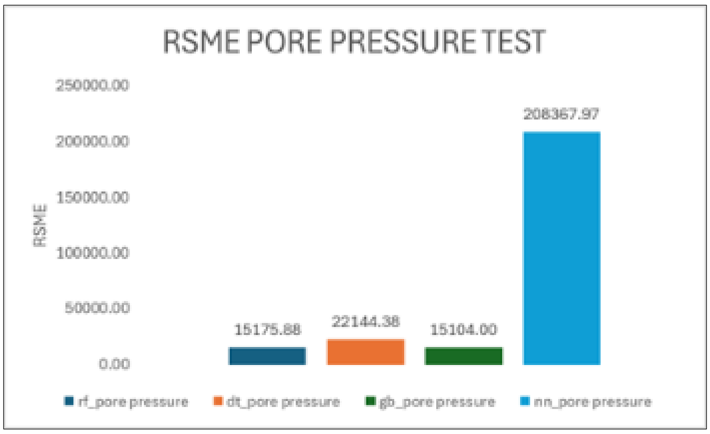

Figure 28 RSME for all Pore Pressure Models (Test Data)

Analysis of RMSE values indicates that gradient boosting achieved the best performance for pore pressure prediction, with the lowest RMSE of 15103.99. This indicates higher accuracy compared to RF and DT. However, the NN method exhibits a significantly higher RMSE of 208367.97, implying less accurate predictions compared to other models.

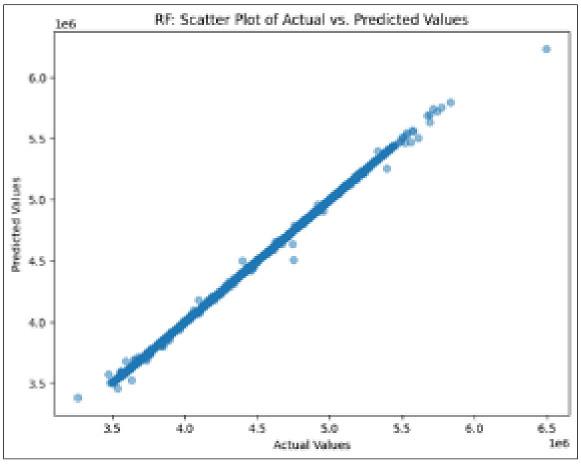

Figure 29 Random Forest Scatter Plot of Actual vs. Predicted Pore Pressure (Test Data)

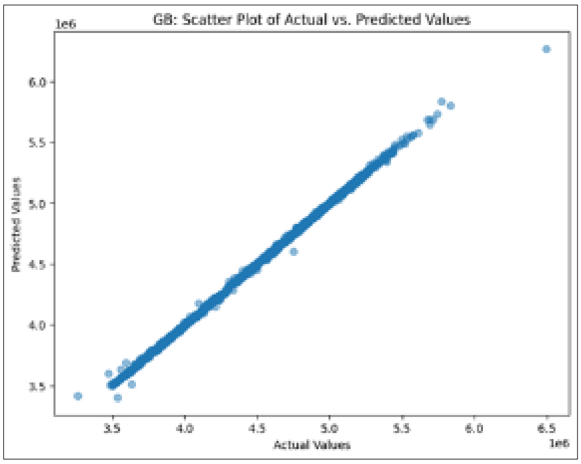

Figure 30 Gradient Booster Scatter Plot of Actual vs. Predicted Pore Pressure (Test Data)

During fine-grained analysis, the NN model shows a more scattered pattern compared to other models, suggesting larger discrepancies between predicted and actual values. The random forest, decision tree, and gradient boosting models are highly suitable for accurate pore pressure prediction, exhibiting strong correlations and low RMSE values.

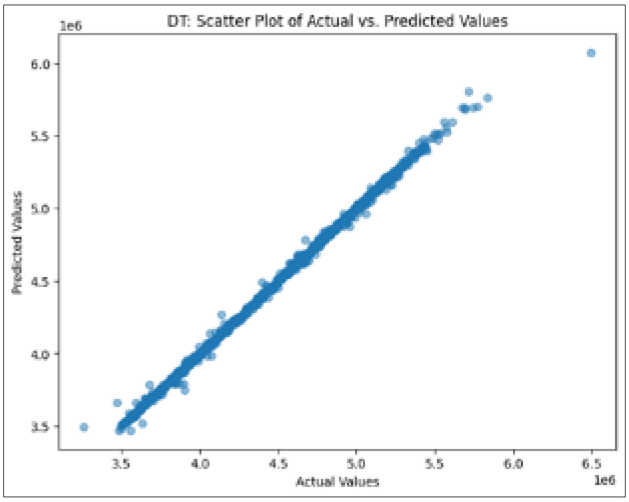

Figure 31 Decision Tree Scatter Plot of Actual vs. Predicted Pore Pressure (Test Data)

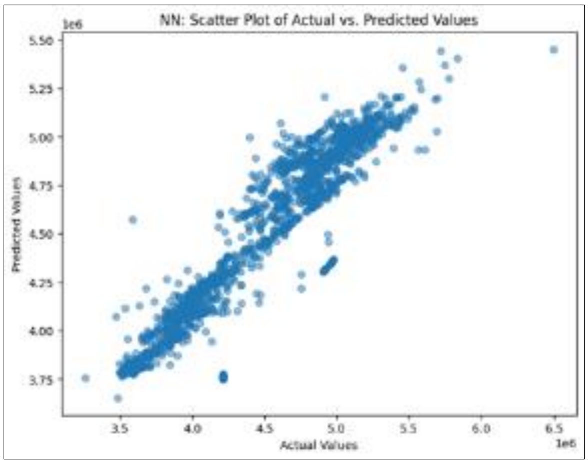

Figure 32 Neural Network Scatter Plot of Actual vs. Predicted Pore Pressure (Test Data)

While SVM and NN models demonstrate reasonable predictive capabilities, further investigation and optimization may be beneficial to improve performance and reduce prediction errors. These findings provide valuable insights into predicting pore pressure values, which are crucial for various geotechnical applications.

5.3. Traditional view

Analyzing the data using traditional methods involves plotting them in tracks with software like Petrel. These tracks typically include the ILD (Deep Induction Log), which measures electrical resistivity to identify hydrocarbon zones and water saturation. The RHOB (Bulk Density) and NPHI (Neutron Porosity) logs are crucial for determining porosity, with bulk density aiding in lithology identification and neutron porosity indicating the formation's porosity. The VShale log represents the volume of shale in the formation, which significantly impacts porosity and permeability. The Velocity (Sonic) log provides information about rock matrix properties, crucial for understanding formation pressures. Permeability estimates from various methods (Perm-actual, Perm-RF, Perm-DT, Perm-GB) complement porosity and pressure analysis. Additionally, the Pore Pressure track is critical for understanding fluid pressures within the reservoir, and the Facies track identifies different rock types and characteristics, aiding in comprehensive interpretation.

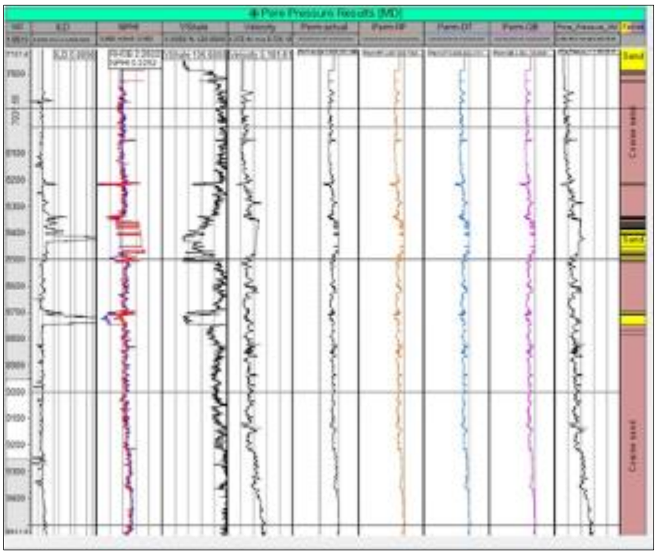

Figure 33 Freeman 7 Well Log Analysis from Petrel Software for Pore Pressure Estimation

Estimating the pore pressure from well logs involves several steps. First, well-log data is imported into Petrel in the correct format (LAS, DLIS, etc.), and data quality is ensured by checking for inconsistencies, gaps, and outliers. Key logs relevant to pore pressure estimation, such as resistivity, density, neutron, and sonic logs, are identified. Log curves are analyzed to identify lithology, fluid contacts, and formation boundaries, and basic log calculations (e.g., VShale, water saturation) provide additional information.

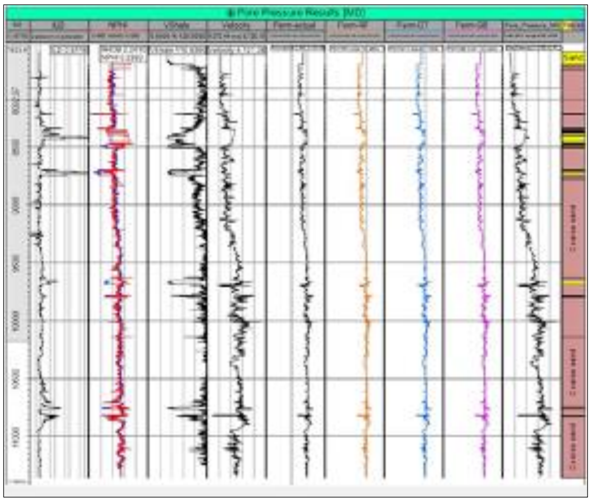

Figure 34 Freeman 5 Well Log Analysis from Petrel Software for Pore Pressure Estimation

Empirical correlations are then applied to estimate pore pressure based on log-derived parameters. These correlations relate various log measurements to pore pressure, often using region-specific data. Wells are clustered based on similar log responses to identify rock types, and representative pore pressure values are assigned to each rock type based on core data or empirical correlations. Finally, a 3D pore pressure model is created using geostatistical methods (e.g., kriging, sequential Gaussian simulation), incorporating well-log data, core data, and geological information to create a realistic pressure distribution.

Key well logs for pore pressure estimation include porosity logs, which provide indirect information about fluid pressures through the volume of pore space; density logs, which help in lithology identification and can indicate overpressure zones; resistivity logs, which determine water saturation affecting pressure; and sonic logs, which provide direct measurements of formation pressures and rock matrix properties.

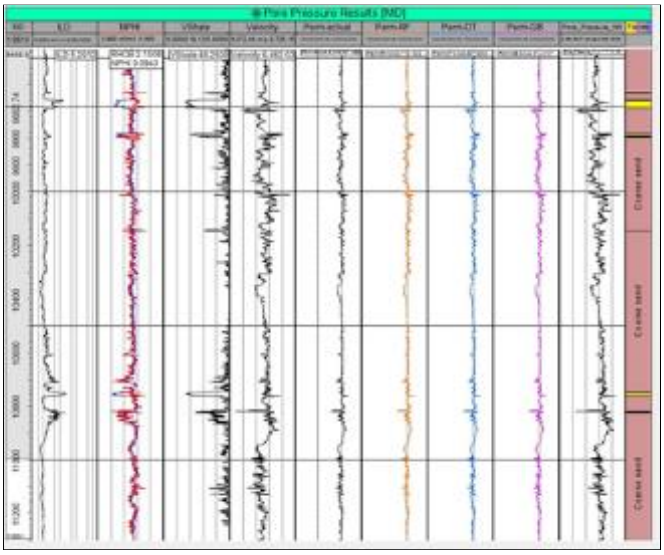

Figure 35 Freeman 1 Well Log Analysis from Petrel Software for Pore Pressure Estimation

Despite the benefits, well-log based pore pressure estimation has limitations. Well-log data represents measurements at discrete points, leading to uncertainty in between wells. Empirical correlations are often region-specific, with accuracy varying depending on the geological setting. Complex reservoir heterogeneity, such as fractures and diagenesis, may not be fully captured by well logs.

Additional considerations include core data integration, which can significantly improve the accuracy of the estimated pore pressure distribution. A detailed understanding of the reservoir's geology and petrophysics is essential for reliable pressure estimation. Sensitivity analysis, evaluating the impact of different input parameters and correlations on pressure estimates, can help assess uncertainty.

6. Conclusion

This study has demonstrated the significant potential of machine learning techniques for predicting permeability and pore pressure in the Niger Delta region. Our analysis revealed that factors such as depth, gamma rays, bulk density, and velocity significantly influence both permeability and pore pressure. The relationships uncovered between these variables provide valuable insights into the complex interplay of geophysical properties and reservoir behavior in the Niger Delta.

Among the machine learning algorithms tested, Random Forest and Gradient Boosting models consistently outperformed other methods, achieving remarkably high accuracy with R-squared scores exceeding 0.99 for both permeability and pore pressure predictions. The decision tree model also showed promising results, though further optimization may be necessary to refine its accuracy and generalization capabilities.

Importantly, our comparative analysis revealed that these machine learning models generally outperformed traditional empirical methods in terms of accuracy and reliability. This underscores the potential of data-driven approaches to enhance reservoir characterization in the Niger Delta, potentially reducing uncertainty in property estimation and optimizing exploration and development strategies.

While our results are promising, future research could benefit from incorporating additional data sources, such as 3D seismic data, to further enhance prediction capabilities. Additionally, exploring ways to integrate these machine learning approaches with existing geological and geophysical workflows could maximize their practical utility in the field.

In conclusion, this study represents a significant step forward in applying machine learning techniques to reservoir characterization in the Niger Delta. The high accuracy and reliability of our models demonstrate the potential of these approaches to revolutionize how we understand and manage subsurface resources in this critical oil-producing region.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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