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Machine Learning-Based Prediction of Formation, Facies, Porosity, and Permeability in a Carbonate Reservoir of the "GTR" Field

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ABSTRACT - Reservoir characterization is essential for understanding rock and fluid behavior in hydrocarbon field development. In the Baturaja Formation, Sunda Basin, this process is challenging due to heterogeneity resulting from depositional and diagenetic variations. Limited core data and the high cost of conventional analysis encourage the use of machine learning (ML). This study aims to predict formation, facies, porosity, and permeability using ML algorithms and to assess the impact of feature augmentation. The dataset includes well log and core data from 13 wells. The workflow consists of preprocessing, feature selection, feature engineering, and supervised learning using Decision Tree, Random Forest, XGBoost, and KNN. Performance is evaluated using the F1-score for classification and MAE/RMSE for regression, followed by blind testing on wells HARLEY and XSR. Random Forest achieves the best formation prediction (F1-score 0.9890; blind test 0.9975) because the well data fall within the range of the training data distribution, although accuracy decreases in XSR due to differences in data distribution. XGBoost is the most accurate for facies prediction, improving from an F1-score of 0.9648 to 0.9741 after feature augmentation. For porosity and permeability, Random Forest produces the lowest errors, although permeability remains challenging in heterogeneous carbonates. Overall, ML provides an efficient and accurate approach, with Random Forest and XGBoost performing best, and feature augmentation consistently enhancing model generalization.

Keywords: carbonate rock, machine learning, permeability, porosity, reservoir characterization

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INTRODUCTION

Reservoir characterization is a systematic process of collecting and analyzing various types of subsurface reservoir data. This process involves the integration of geological, geophysical, petrophysical, and engineering data to understand rock physical properties and fluid behavior within the reservoir (Seyyedattar et al., 2020).

Such understanding is crucial for predicting reservoir performance and optimizing field development. One of the basins contributing to hydrocarbon production in Indonesia is the Sunda Basin, particularly the Baturaja Formation, which represents a major carbonate unit in the region. The regional stratigraphy of the Sunda Basin, highlighting the position of the Baturaja Formation, is shown in Figure 1.

Reservoir characterization in carbonate rocks is generally more complex than in clastic rocks due to variations in depositional energy levels and sedimentation processes (Owusu et al., 2025; Wulandari & Rosid, 2023). The complexity of the Early Miocene depositional environment strongly influences facies distribution within the Baturaja Formation. These environmental variations result in complex textures and pore system development (Wight, 1986).

In addition, carbonate rocks commonly experience diagenetic processes such as dissolution, cementation, and dolomitization after deposition. The combined effects of depositional variability and diagenesis lead to high heterogeneity in petrophysical properties, particularly porosity and permeability (Alatrash & Velledits, 2024; Nikbin & Aminshahidy, 2025).

Determining petrophysical properties, particularly porosity and permeability, can be performed using methods such as core analysis and well testing. However, these methods have limitations, such as being expensive and time-consuming compared to wireline logging, resulting in many reservoirs having limited core data (Chowdhury et al., 2019).

Other conventional methods for permeability prediction, such as empirical correlations, also have limitations in terms of accuracy, reliability, and generalization because they rely on assumptions that may not be applicable to all reservoir types (Ahr, 2008; Lucia, 2007).

To address these limitations, Machine Learning (ML) approaches have begun to be applied in reservoir characterization (Ma, 2019; Shao et al., 2024). ML excels in identifying nonlinear and complex patterns between variables in well log data. Recent studies in Indonesia have also demonstrated the effectiveness of ML algorithms, such as the use of adaptive neuro-fuzzy inference systems (ANFIS) for permeability prediction in carbonate reservoirs (R. Wardhana et al., 2022) and computational algorithms for predicting rock properties such as TOC (S. G. Wardhana et al., 2021).

Furthermore, ML proxy models have shown high accuracy in solving complex nonlinear problems in oil and gas production (Septiano et al., 2022). Nugroho et al. (2024) utilized ML to overcome core data limitations by using well logging data and core data as the main inputs. Additionally, Al-Mudhafar et al. (2025) highlighted the challenge of predicting permeability in highly heterogeneous carbonate reservoirs and found that integrating facies classification into the model improved prediction performance, with XGBoost showing the most optimal results.

Based on previous studies, this research focuses on predicting formation, facies, porosity, and permeability using machine learning methods applied to available well log and core data from the "GTR" Field, Baturaja Formation, Sunda Basin. This study aims to expand upon previous work by assessing whether integrating formation and facies classification results (feature augmentation) can improve the performance of petrophysical parameter prediction models.

This integration is critical, as the strong relationships among formation, facies, and petrophysical properties in heterogeneous carbonate reservoirs are rarely fully incorporated into predictive modeling. Specifically, this research evaluates the influence of log data features, compares the performance of several machine learning algorithms (Decision Tree, Random Forest, XGBoost, and KNN), and tests model generalization using blind test wells with different data distribution characteristics.

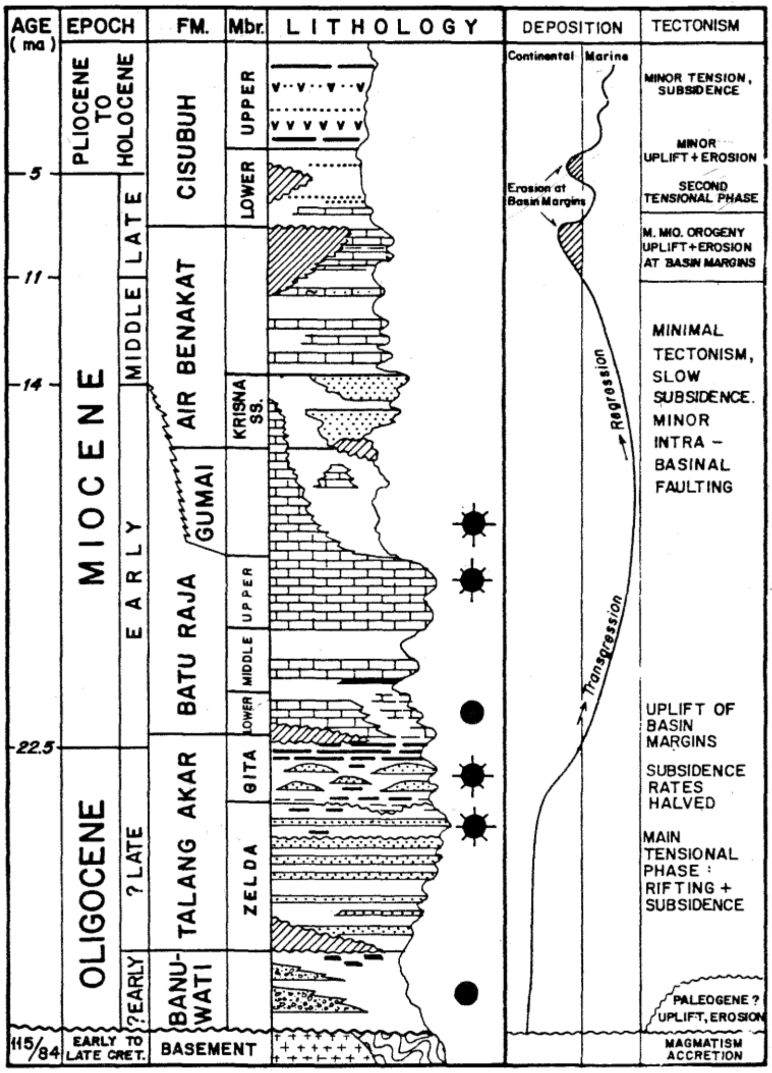


Figure 1. Stratigraphy of the Sunda Basin (Wight, 1986).

METHODOLOGY

Data availability and study area

This research utilizes a dataset from 13 wells located in the “GTR” Field, Sunda Basin, with a focus on the Baturaja Formation. The dataset comprises well log data (Gamma Ray, Resistivity, Neutron Porosity, Density, Sonic, and Spontaneous Potential) and core analysis data (porosity and permeability).

Geological interpretation markers and core data are used as ground truth for validating the machine learning models. The data are divided into training –testing sets (11 wells) and blind test sets (2 wells: HARLEY and XSR) to evaluate model generalization capability.

Research workflow

The research procedure includes data preprocessing, feature selection, feature engineering, modeling, and evaluation. The comprehensive workflow of this study is illustrated in Figure 2.

Data preprocessing

Exploratory Data Analysis (EDA) was conducted to identify patterns and outliers using histograms and boxplots, following the statistical principles described by Downey (2014) and Tukey (1977). Missing values were handled using iterative imputation, and data standardization (Z-score normalization) was applied to normalize feature scales. To address class imbalance in formation and facies data, the SMOTETomek

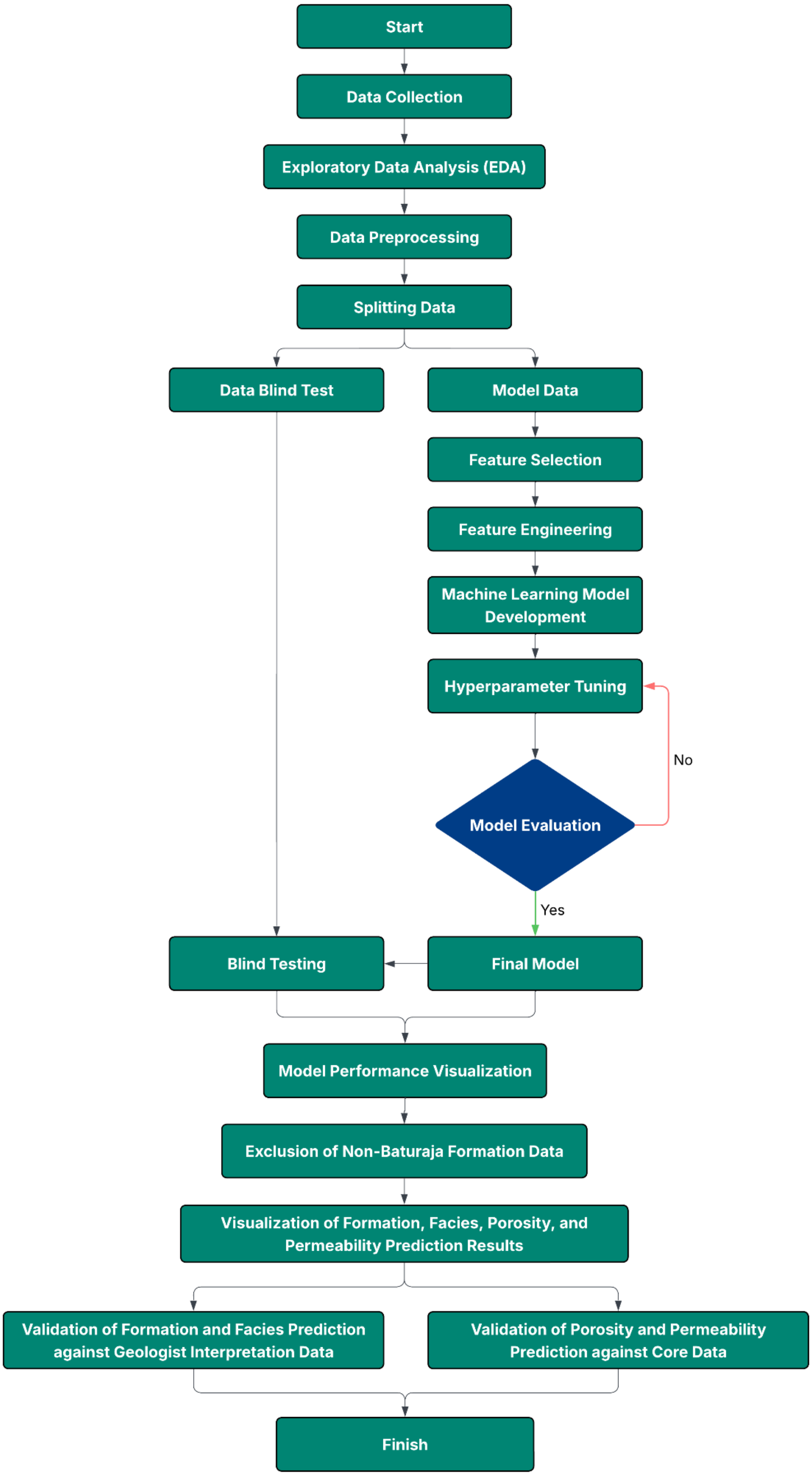


Figure 2. Research workflow diagram detailing data processing and modeling stages.

method was employed. This approach combines oversampling and undersampling techniques to balance the dataset distribution (Lv et al., 2025). Furthermore, the Yeo–Johnson transformation was applied to normalize numerical data distributions.

Feature selection

Feature selection was performed using Pearson and Spearman correlation methods. Pearson correlation measures linear relationships, while Spearman correlation identifies monotonic relationships and is more robust to outliers (Bruce et al., 2020).

This step is crucial for identifying key parameters affecting porosity and permeability in carbonate reservoirs, as also emphasized in recent studies using neuro-fuzzy systems (R. Wardhana et al., 2022). A key strategy in this study is “feature augmentation”, whereby predicted geological classification results (formation and facies) are incorporated as input features for petrophysical property prediction (porosity and permeability).

Machine learning modeling

This study employs a supervised learning approach using four algorithms: Decision Tree, Random Forest, Extreme Gradient Boosting (XGBoost), and K-Nearest Neighbors (KNN). The effectiveness of computational machine learning algorithms for predicting rock properties has been demonstrated in recent studies, including Total Organic Carbon prediction (S. G. Wardhana et al., 2021) and flow rate prediction models (Septiano et al., 2022). To optimize model performance, hyperparameter tuning was conducted using Bayesian Optimization (He et al., 2024).

Model evaluation

Model performance is evaluated using specific metrics. For classification tasks, the F1-score is used, with values greater than 0.8 considered acceptable (Sastra & Rohmana, 2024).

For regression tasks (porosity and permeability), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are applied, where lower error values indicate better predictive accuracy (Hafwandi et al., 2023).

Blind testing strategy

The final evaluation stage involves blind testing using data from two wells (HARLEY and XSR) that were entirely excluded from the training process. This step assesses the model’s ability to generalize to new, unseen data. The selection of these wells was based on statistical distribution analysis: HARLEY represents data with characteristics similar to the training set, whereas XSR represents data with a distinct distribution, providing a rigorous test of model robustness under data heterogeneity.

RESULT AND DISCUSSION

Data preparation and exploratory

Initial exploratory data analysis (EDA) revealed that most well logs (GR, NPHI, RHOB) exhibit non-normal distributions with varying degrees of skewness, while resistivity logs (RDEEP) show high positive skewness. To address this issue, logarithmic transformation was applied to stabilize variance.

A significant challenge identified was class imbalance in the target variables; for example, the formation data exhibited an imbalance ratio of 93.73%, while the facies data showed a 40.02% imbalance, dominated by Shale and Shelf Carbonate Mud facies. The application of the SMOTETomek method proved effective in balancing the class distribution and preventing model bias toward the majority class during training.

Formation and facies classification

Feature selection analysis using Pearson and Spearman correlations indicated that Measured Depth (MD), SP, RHOB, GR, DTC, and NPHI are the most influential features for formation classification. Visualizations of feature importance for the classification task are presented in Figure 3 and Figure 5 MD is particularly important as it represents the stratigraphic sequence, while SP and GR are effective for distinguishing lithological boundaries.

For formation prediction, the Random Forest (RF) algorithm outperformed Decision Tree, XGBoost, and KNN. After hyperparameter tuning,

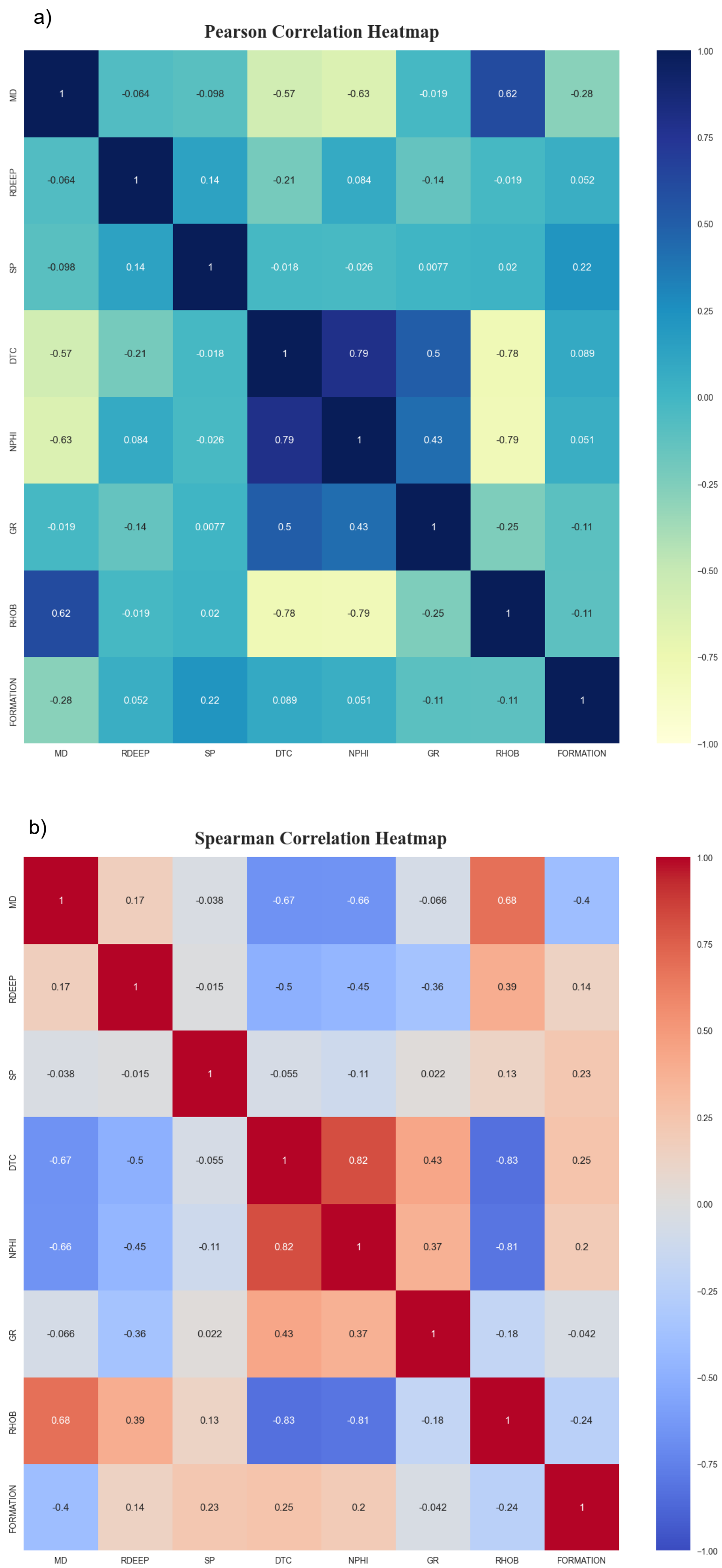


Figure 3. Pearson (a) and Spearman (b) correlation heatmaps for formation prediction illustrating the strength and direction of relationships among variables. Coefficients close to +1 and −1 indicate strong positive and negative correlations respectively, while values near zero reflect weak associations.

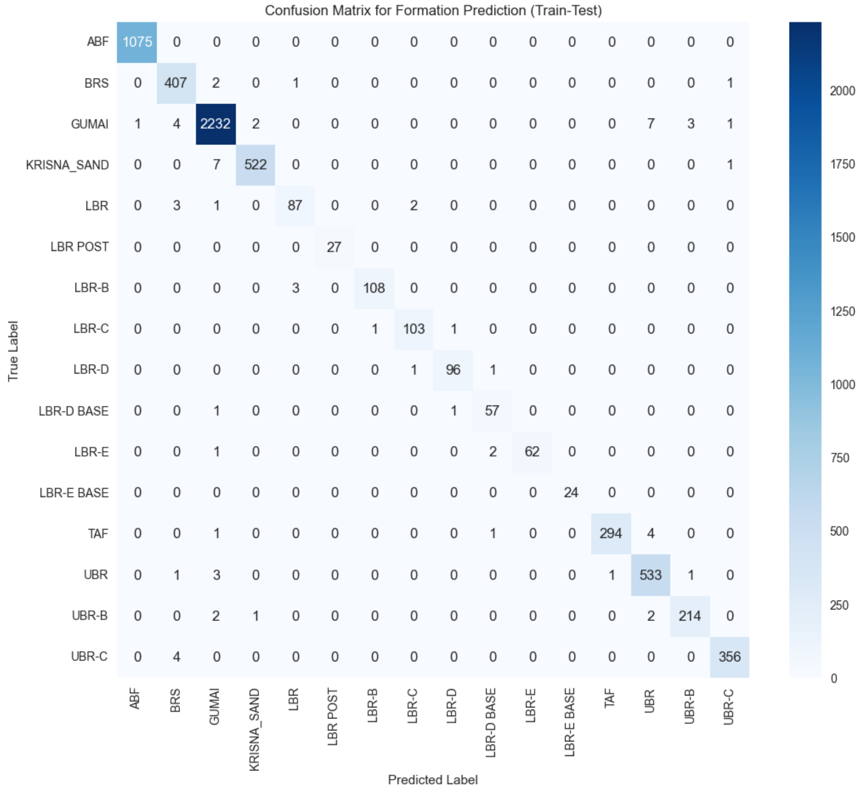
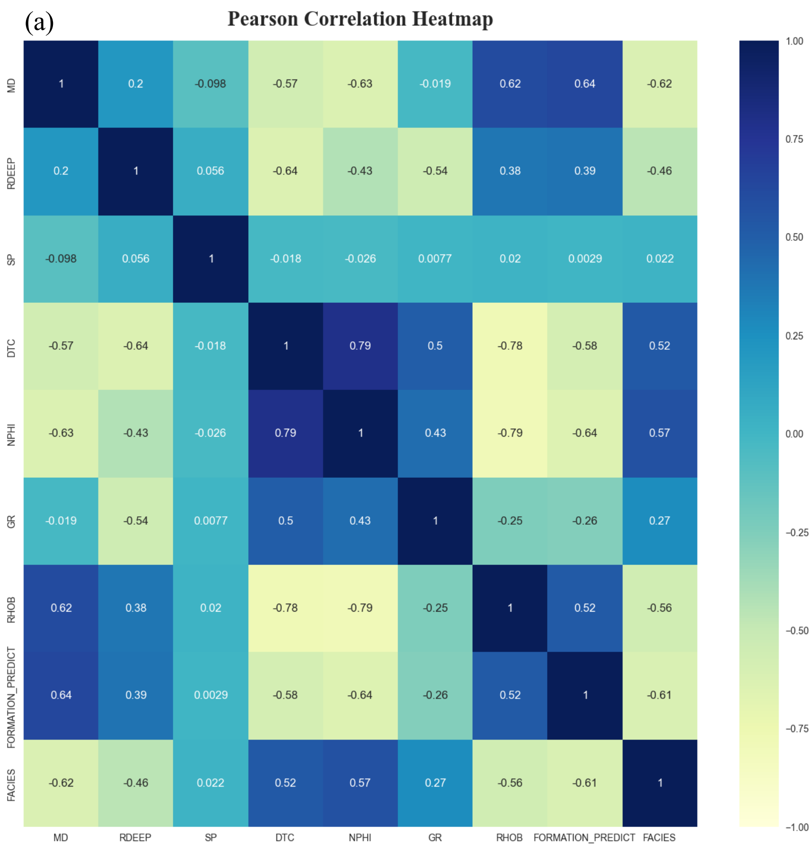


Figure 4. Confusion matrix for formation prediction across multiple formation units.
The strong concentration of values along the diagonal indicates high classification accuracy, with limited misclassification primarily occurring between stratigraphically adjacent formations.



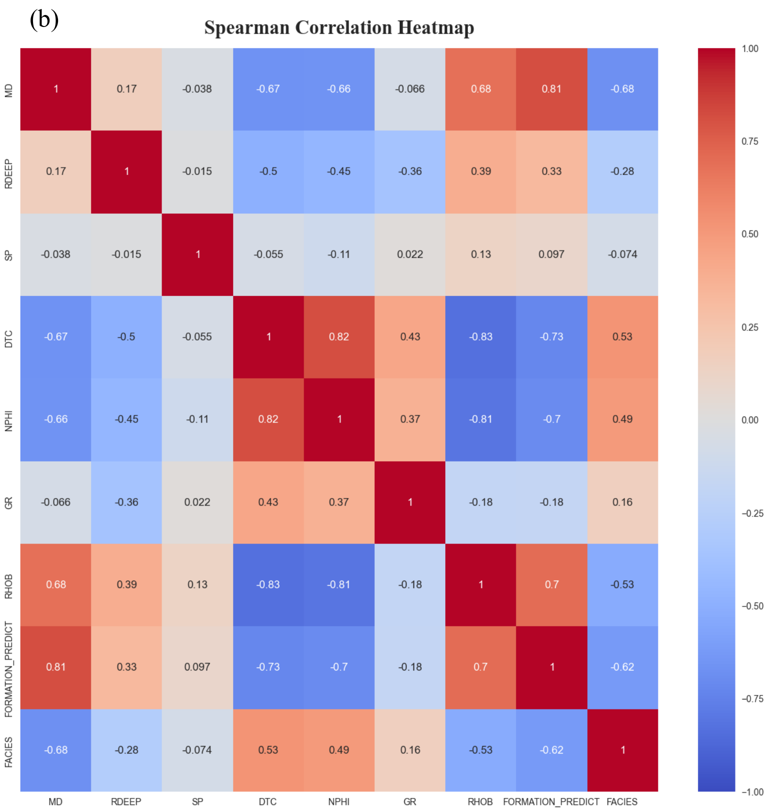


Figure 5. Pearson (a) and Spearman (b) correlation heatmaps for facies prediction. Coefficients close to +1 and −1 indicate strong positive and negative correlations respectively, while values near zero represent weak relationships among variables.

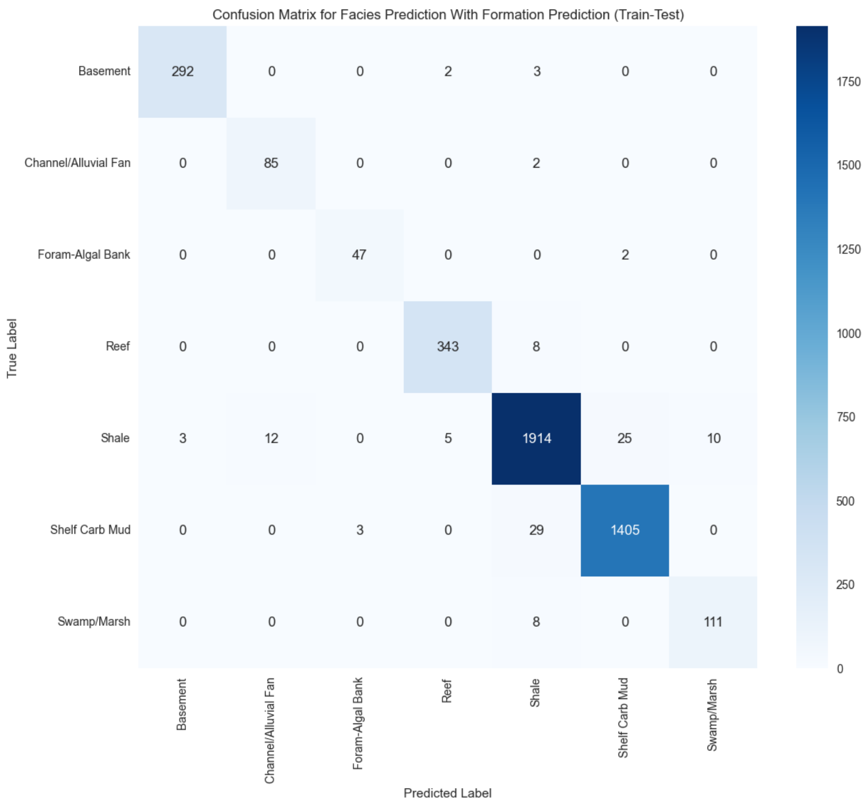


Figure 6. Confusion matrix for facies prediction, showing high classification accuracy with dominant diagonal values and minor misclassification among lithologically similar facies.

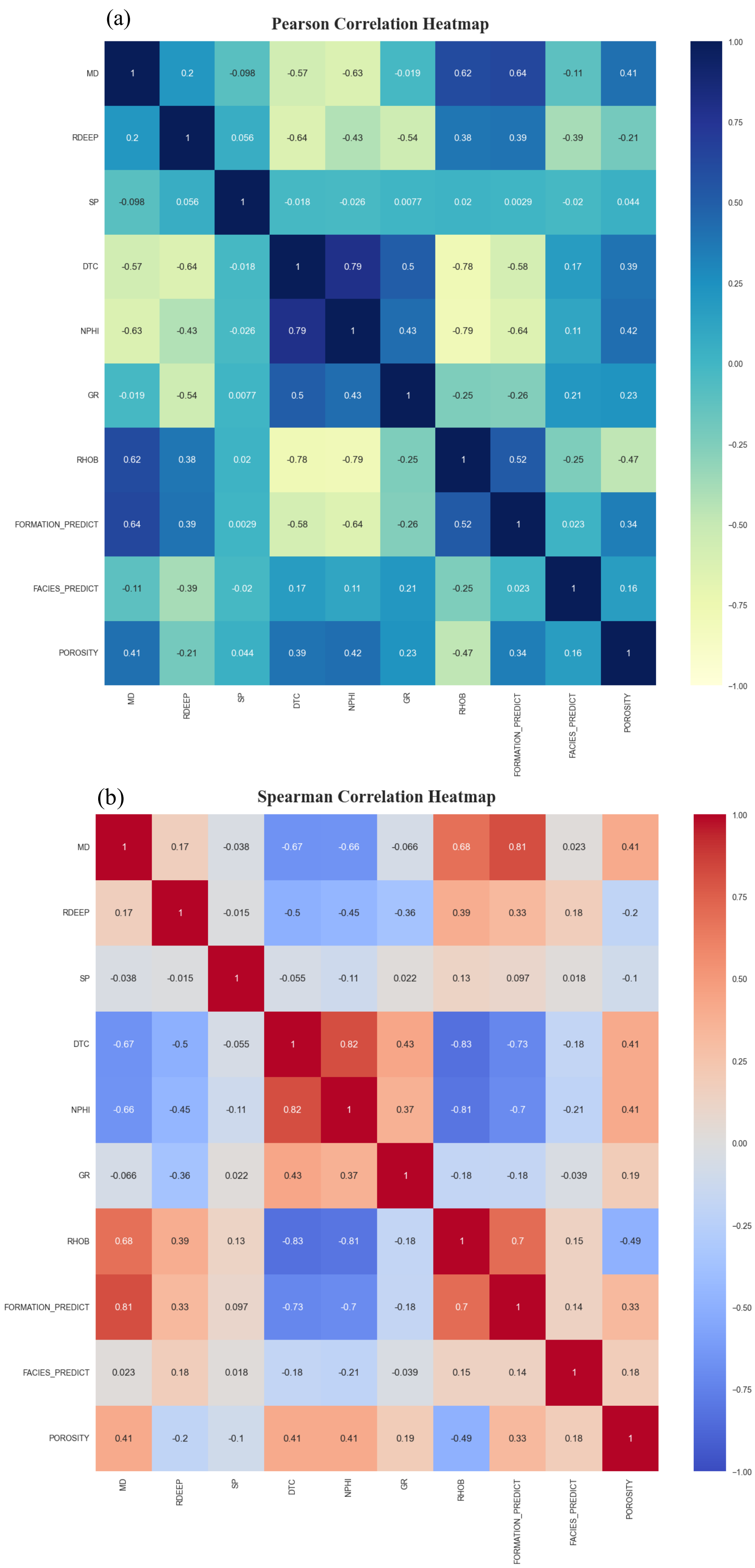


Figure 7. Pearson (a) and Spearman (b) correlation heatmaps for porosity prediction. Coefficients approaching +1 and −1 indicate strong positive and negative relationships respectively, while values near zero represent weak correlations with porosity.

RF achieved an F1-score of 0.9890 in cross-validation. The confusion matrix in Figure 4 illustrates the classification performance, showing accurate formation identification with minimal misclassification. During blind testing, the model demonstrated excellent generalization performance on the HARLEY well (F1-score of 0.9975). This high accuracy is attributed to the HARLEY well data falling within the range of the training data distribution, enabling the model to effectively apply learned patterns. However, performance declined on the XSR well (F1-score of 0.3769) due to significant distribution shifts, highlighting the model's sensitivity to data variance.

For facies prediction, two scenarios were evaluated: (1) prediction using only well logs, and (2) prediction with "feature augmentation" through the integration of predicted formation classes. XGBoost emerged as the best-performing algorithm. The inclusion of formation data (Scenario 2) improved the F1-score from 0.9648 to 0.9741 in cross-validation. This result confirms that incorporating geological context (formation) enhances the model's ability to distinguish facies with overlapping log responses, although challenges remain in transitional zones. Blind testing on the HARLEY well yielded consistently high accuracy (F1-score of 0.9941). The confusion matrix in Figure 6 illustrates the classification performance, showing accurate facies identification with minimal misclassification.

Porosity prediction

Feature selection analysis for porosity prediction, as presented in Figure 7, identifies Neutron Porosity (NPHI) and Bulk Density (RHOB) as the most dominant features. This finding is consistent with petrophysical principles, as these logs directly respond to fluid content and rock matrix density. Measured Depth (MD) also exhibits a strong correlation, reflecting porosity trends associated with compaction and depth-related diagenetic processes.

The Random Forest algorithm consistently outperformed the other models across both test scenarios. A key finding of this study is the impact of feature augmentation. In Scenario 2, where predicted formation and facies were incorporated as additional input features, model performance improved significantly. The crossplot in Figure 8 illustrates the agreement between predicted and core porosity values within the Baturaja Formation interval used for the train–test visualization, with data points aligning closely with the Perfect Prediction line.

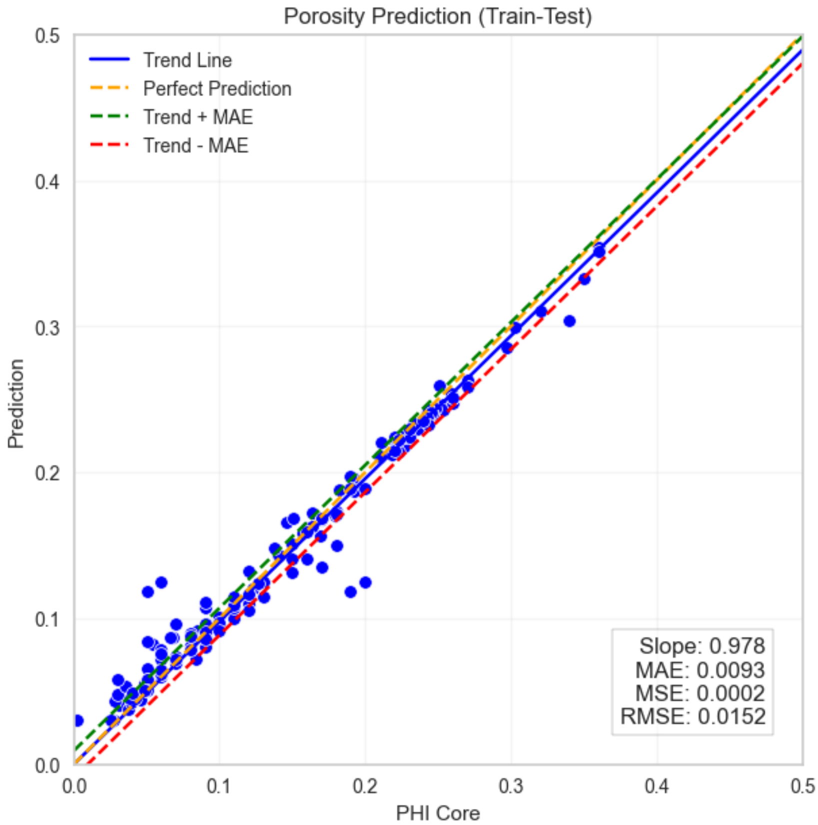
Quantitatively, model evaluation using the Random Forest algorithm across the full dataset shows that Scenario 2 reduced the Mean Absolute Error (MAE) from 0.0458 to 0.0411 and the Root Mean Squared Error (RMSE) from 0.0621 to 0.0538 during cross-validation. Blind testing on the HARLEY well confirmed the robustness of the model (MAE = 0.0177, RMSE = 0.0275), as the well data fall within the range of the training data distribution. In contrast, the XSR well exhibited higher prediction error (MAE = 0.0389) due to several data points lying outside the training data range.

Permeability prediction

Permeability prediction proved to be the most challenging task due to the complex pore structures within the Baturaja Formation. The feature importance analysis shown in Figure 9 indicates that Deep Resistivity (RDEEP) is the most influential log feature, reflecting changes in fluid saturation associated with permeable zones. Notably, the augmented features, specifically Predicted Porosity and Predicted Facies, also rank highly in importance. This result confirms that incorporating intermediate geological predictions enables the model to better capture the non-linear relationships between rock texture and fluid flow.

The application of feature augmentation (Scenario 2) substantially enhanced model accuracy. Figure 10 presents a comparison of permeability crossplots within the Baturaja Formation interval used for the train–test visualization, illustrating that the augmented model aligns more closely with the Perfect Prediction line than the baseline model. Quantitatively, model evaluation using the Random Forest algorithm across the full dataset shows that the MAE decreases to 0.6172 and the RMSE to 0.7280 during cross-validation. Blind testing on the HARLEY well confirms good agreement (MAE =

(a)



(b)

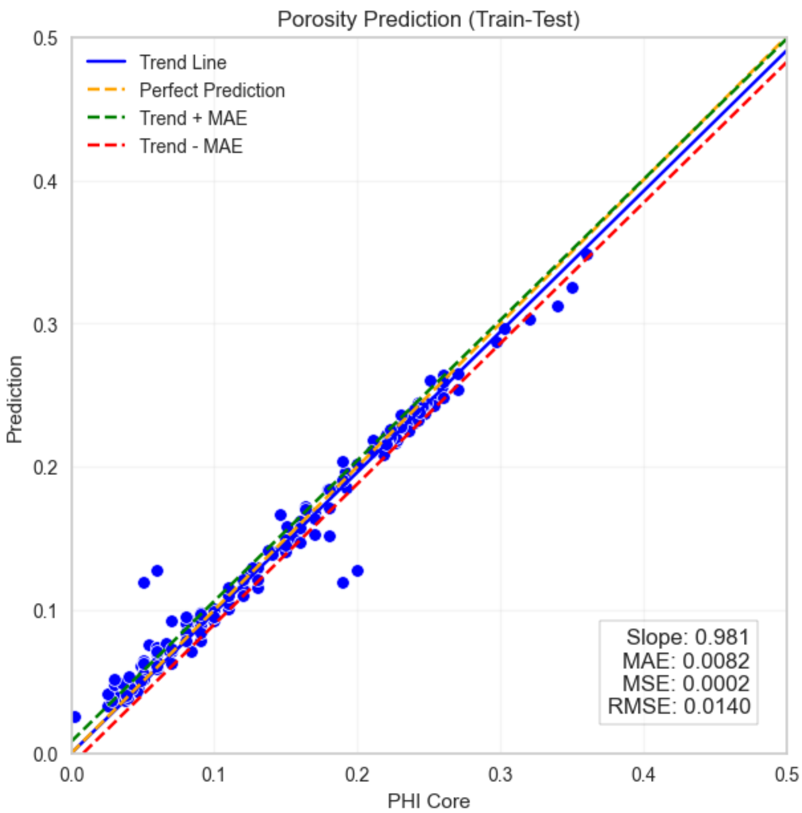


Figure 8. Crossplots of predicted versus core porosity for (a) Scenario 1 and (b) Scenario 2. Improved agreement with the Perfect Prediction line and lower MAE and RMSE are observed in Scenario 2.

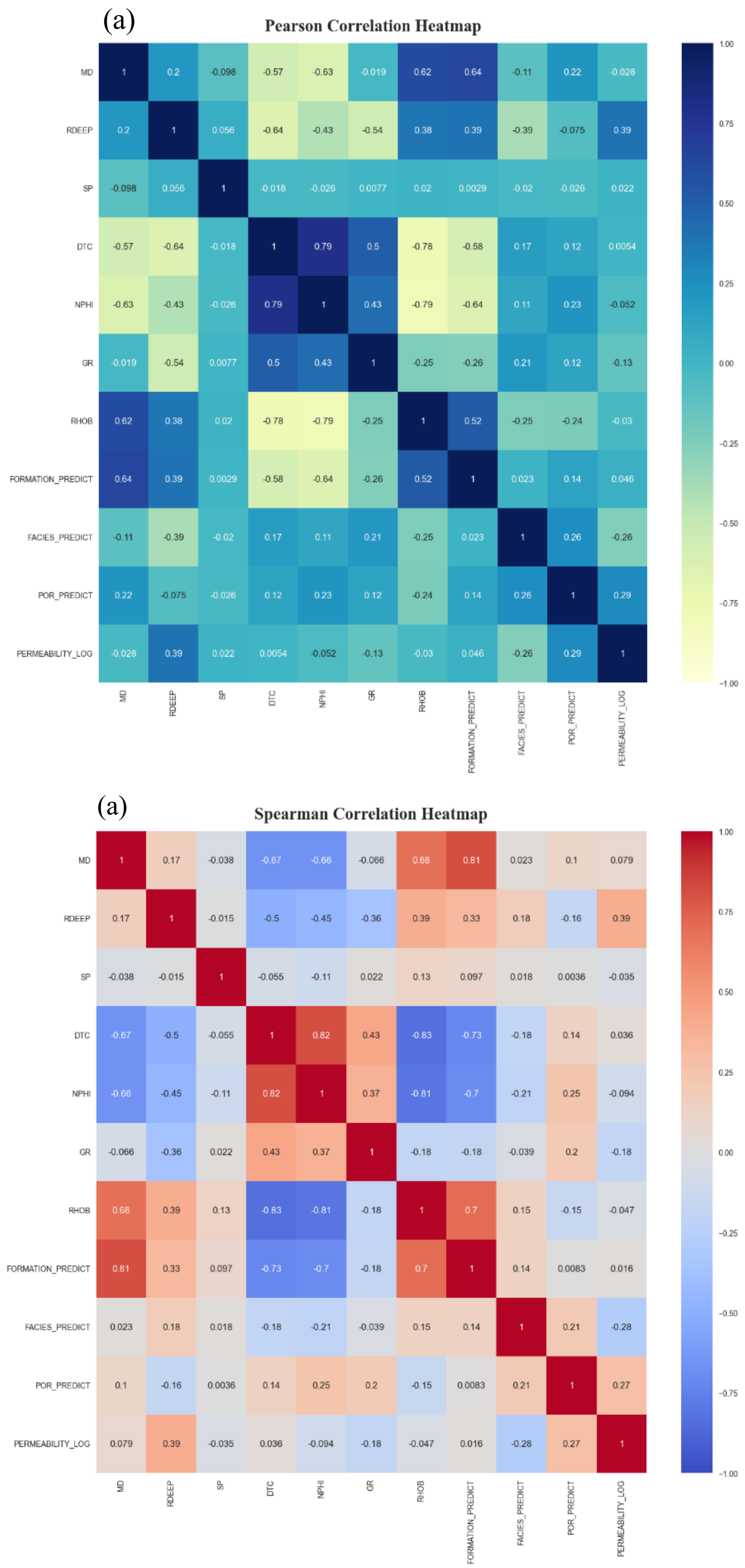


Figure 9. Pearson (a) and Spearman (b) correlation heatmaps for permeability prediction. Coefficients close to +1 and −1 indicate strong positive and negative correlations respectively, while values near zero represent weak relationships with permeability.

0.5500), as its petrophysical characteristics fall within the training data envelope. Conversely, the XSR well exhibits greater deviation, emphasizing the model's limitations when encountering data points beyond the range of the training dataset.

Validation and generalization

To visually validate model performance within a geological context, the predicted logs were plotted alongside the actual measured logs. Figure 11 presents a comprehensive well-log visualization for the HARLEY well, comparing actual and predicted curves for all parameters. The predicted porosity and permeability curves closely follow the trends of the core data, although minor deviations are observed in highly heterogeneous and fractured zones. The study concludes that while Random Forest with feature augmentation is highly effective for wells whose data properties fall within the training distribution range (e.g., HARLEY), generalization remains a challenge for wells with distinct data distributions (e.g., XSR). In such cases, log responses exceed the boundaries of the training data, suggesting the need for a broader training dataset to adequately cover these outliers.

CONCLUSION

This study demonstrates that machine learning provides an efficient and accurate approach for reservoir characterization in the heterogeneous carbonate rocks of the Baturaja Formation. Among the algorithms tested, Random Forest proved to be the most robust for predicting formation, porosity, and permeability, achieving high accuracy in both cross-validation and blind testing on the HARLEY well. Meanwhile, XGBoost emerged as the superior algorithm for facies classification. The feature selection analysis highlighted that Measured Depth (MD), Resistivity (RDEEP), Neutron Porosity (NPHI), and Density (RHOB) are the most critical well log parameters for defining these reservoir properties.

A significant contribution of this research is the validation of the "feature augmentation" strategy. The integration of predicted geological attributes (formation and facies) as input features for petrophysical modeling consistently improved model performance. This approach reduced prediction errors for porosity (MAE 0.0411, RMSE 0.0538) and permeability (MAE 0.6172, RMSE 0.7280) during cross-validation. These results confirm that incorporating geological context enables machine learning models to better capture the complex heterogeneity of carbonate reservoirs, which is often overlooked when using well log data alone.

However, the study also reveals challenges in model generalization. While the models performed exceptionally well on the HARLEY well, whose log data distribution falls within the range of the training dataset, performance declined on the XSR well, where some log data values lie outside the training data range. This finding underscores the importance of data representativeness in machine learning applications. Future work should focus on expanding the training dataset to encompass a wider range of geological variations and exploring deep learning methods to further enhance prediction stability across different wells.

ACKNOWLEDGEMENT

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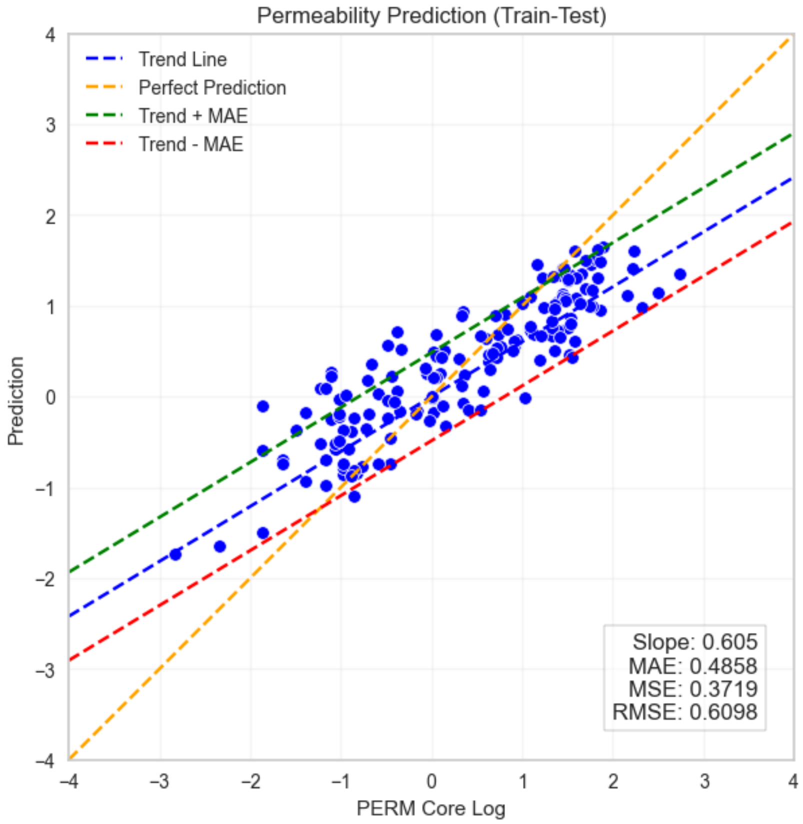
GLOSSARY OF TERMS AND SYMBOLS

Terms & Symbol	Definition	Unit
ANFIS	Adaptive Neuro-Fuzzy Inference Systems	-
DTC	Sonic Travel Time / Acoustic Log	μs/ft
EDA	Exploratory Data Analysis	-
GR	Gamma Ray Log	API
KNN	K-Nearest Neighbors	-
MAE	Mean Absolute Error	-
MD	Measured Depth	ft / m
ML	Machine Learning	-
NPHI	Neutron Porosity Log	v/v or fraction
RDEEP	Deep Resistivity Log	ohm.m
RF	Random Forest	-
RHOB	Bulk Density Log	g/cc
RMSE	Root Mean Squared Error	-
SP	Spontaneous Potential	mV
TOC	Total Organic Carbon	wt%
XGBoost	Extreme Gradient Boosting	-
ϕ	Porosity	fraction
k	Permeability	mD

a)



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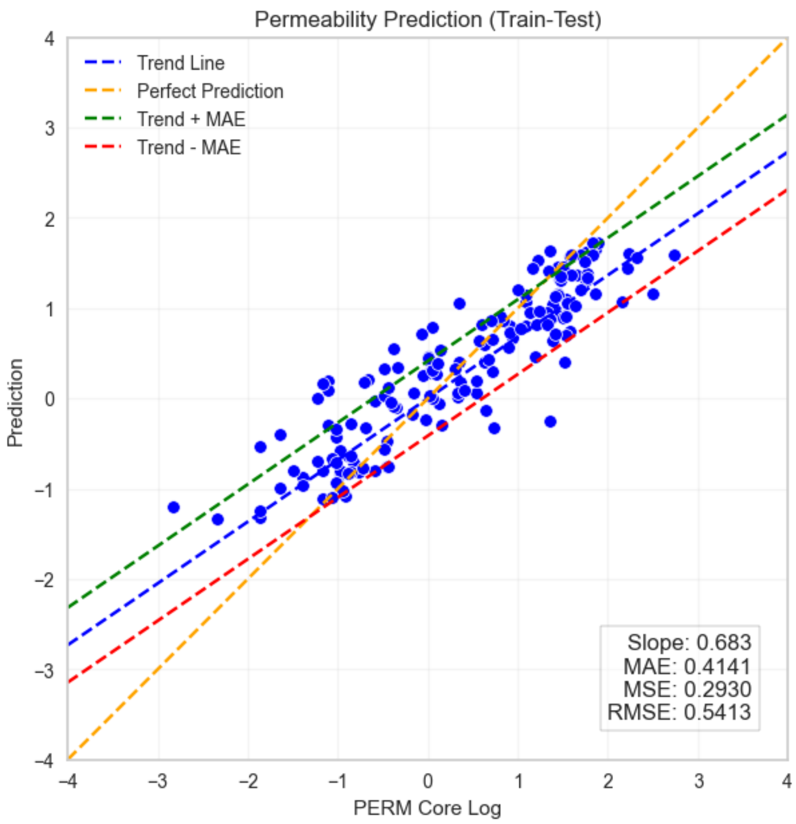

Figure 10. Crossplots of predicted versus core permeability for (a) Scenario 1 and (b) Scenario 2, including the Perfect Prediction line and corresponding MAE and RMSE values. Lower error metrics in Scenario 2 indicate improved predictive performance.

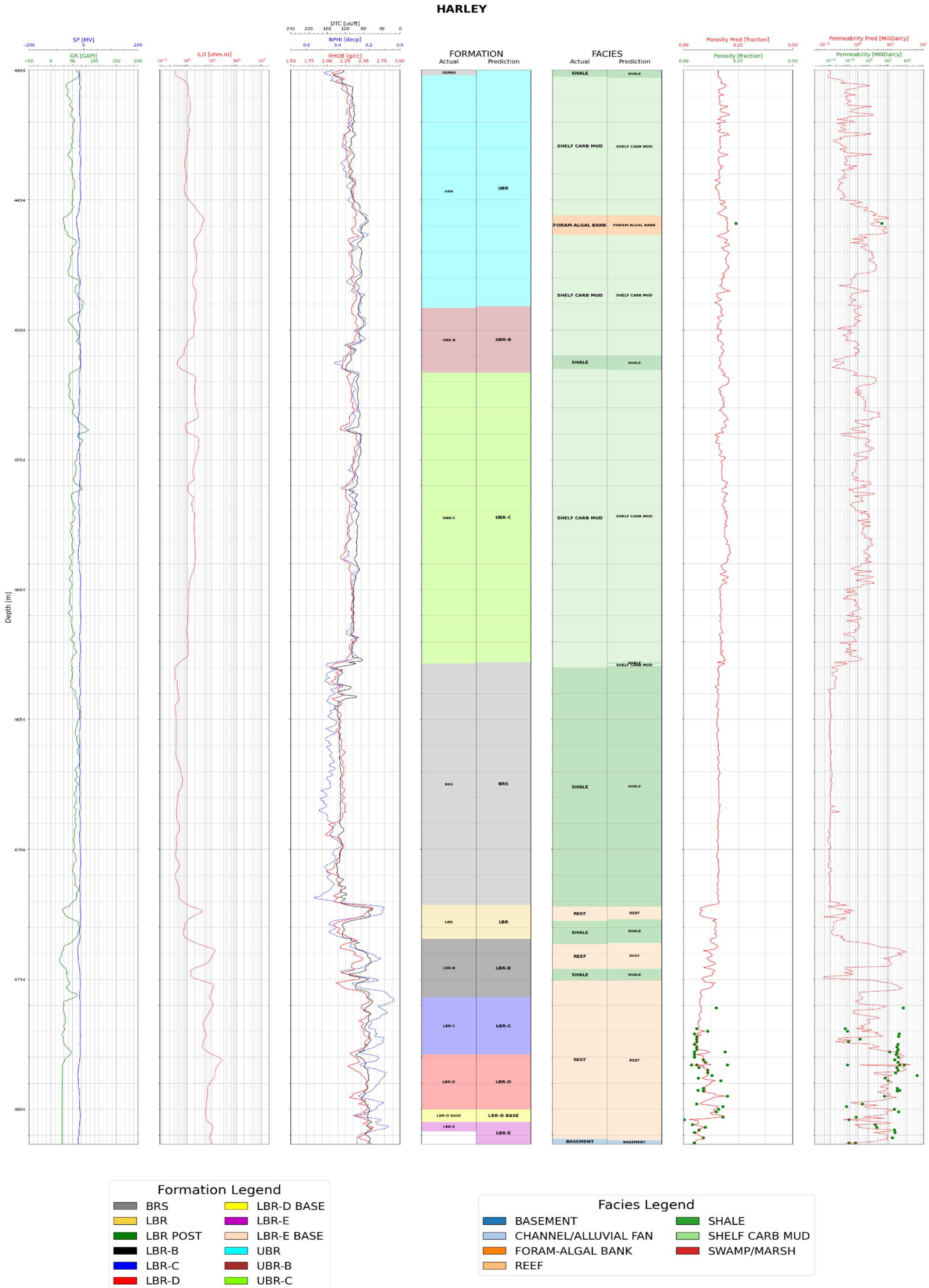

Figure 11. HARLEY blind-well visualization in the Baturaja Formation interval.

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