Comparative Analysis of Linear Regression and Artificial Neural Networks for Permeability Prediction

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Abstract

Permeability prediction from well log data is a critical aspect of reservoir characterization, providing essential insights for effective reservoir management and hydrocarbon recovery. This study investigates the efficacy of two distinct modeling approaches—linear regression and artificial neural networks (ANN)—in predicting permeability from well log data. The linear regression models explored include Standard Linear Regression, Interactions Linear Regression, Robust Linear Regression, while the ANN approach focuses on varying network structures to optimize performance. The Interactions Linear Regression model demonstrated strong predictive capabilities, with Root Mean Square Error (RMSE) values of 4.47 and an R-squared (R^2) value of 0.98, indicating a robust fit between the predicted and actual permeability values. However, the ANN model, particularly with a structure of 10 neurons in the hidden layer (n-10), outperformed the linear models, achieving an RMSE of 29.90 and a remarkably high R^2 value of 0.9996. This underscores the ANN's superior ability to capture complex, non-linear relationships within the data. The study provides a detailed analysis of model performance, highlighting the strengths and limitations of each approach. The ANN model's superior accuracy makes it particularly suited for complex reservoirs where non-linear interactions are prevalent, while the Interactions Linear Regression model offers a simpler, more interpretable alternative for less complex scenarios. Based on these findings, the study recommends the adoption of ANN models for intricate reservoir characterization tasks, while linear regression models can be utilized for quicker, more straightforward predictions. Furthermore, comparison of this model with other existing models were made and this study's model outperformed.

Introduction

The prediction of subsurface physical properties, such as permeability and porosity, is a fundamental challenge in reservoir characterization, influencing decisions related to exploration, drilling, and production in the oil and gas industry (Nelson 1994; Ezekwe 2010; Edlmann et al. 1996; Zhang 2013; Zhang et al. 1996; Johnson 1963; Ahmed 2006; Newman and Martin 1977; Dullien 1992; Byrnes 1994). Accurate permeability prediction from well log data can significantly enhance reservoir management by providing critical insights into fluid flow and reservoir performance. Traditional methods for predicting these properties often rely on linear regression models, which, while straightforward and interpretable, may not fully capture the complex, non-linear relationships present in subsurface geological formations (Leiphart and Hart 2001).

Recent advancements in machine learning have introduced more sophisticated approaches, such as Artificial Neural Networks (ANNs), which have shown promise in improving the accuracy of subsurface property predictions. The artificial neural network (ANN) technique is one of the latest techniques available to the petroleum industry for porosity and permeability prediction (Wills 2019; Jakhar and Kaur 2020; Azim 2020 and

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2021). ANNs are particularly effective in modeling non-linear relationships, making them a powerful tool for predicting properties like permeability in geologically complex reservoirs. The flexibility of ANNs allows them to learn intricate patterns in data that linear models might overlook, offering a more nuanced understanding of reservoir characteristics (Leiphart and Hart 2001).

The choice between linear regression models and ANNs is not merely a technical decision but one that can significantly impact the accuracy and reliability of permeability predictions. Leiphart and Hart (2001) compared the performance of linear regression models and a Probabilistic Neural Network (PNN) in predicting porosity from 3-D seismic attributes. They found that while the linear regression model provided a reasonable prediction with an R^2 of 0.74, the PNN offered a better correlation (R^2 of 0.82) and more geologically realistic porosity distribution, particularly in complex geological settings (Leiphart and Hart 2001). Smith et al. (1999) introduced a neural network algorithm designed to predict porosity, permeability, and grain density. Their approach utilized gamma ray, neutron porosity, and sonic travel time as input variables, and the predicted results were compared to actual core data, with errors assessed against specified tolerances. Similarly, Osborne (1992) employed a back propagation neural network to estimate permeability using porosity and reservoir flow units as inputs. However, the robustness of the model was questionable as it was developed using the same data for both training and testing, with only about 10% of the data used for these purposes. Despite this limitation, Osborne found that the neural network model's permeability predictions were superior to those obtained from a regression model. Jian et al. (1995) conducted a case study comparing genetic and non-genetic approaches for predicting porosity and permeability. Additionally, other research has employed various machine learning techniques to predict porosity and permeability at different depths (Huang et al. 1996; Huang and Williamson 1997; Helle et al. 2001; Rwechungura et al. 2011; Saputro et al. 2016; Ahmadi and Chen 2019). The growing interest in machine learning techniques, such as ANNs, reflects their potential to enhance reservoir characterization. These models can handle large datasets with multiple variables, identifying patterns and correlations that may not be apparent with traditional statistical methods. This capability is particularly useful in the oil and gas industry, where datasets are often extensive and complex, requiring advanced techniques for effective analysis and interpretation (leiphart 2001). Despite the advantages of ANNs, their application in reservoir characterization is not without challenges. The "black box" nature of these models can make them less interpretable compared to linear regression models, posing a challenge for geologists and engineers who need to understand the rationale behind predictions. However, when applied correctly and validated against geological data, ANNs can provide significant improvements in prediction accuracy, as demonstrated in various case studies and research (Leiphart and Hart 2001).

In this study, we aim to explore and compare the efficacy of linear regression and ANN models in predicting permeability from well log data. By evaluating these two approaches in a real-world scenario, we seek to identify the strengths and limitations of each method, providing insights that can guide the selection of appropriate modeling techniques for reservoir characterization. The results of this comparison will contribute to the ongoing discourse on the application of machine learning in the geosciences, offering practical recommendations for enhancing prediction accuracy in complex reservoir environments.

Materials and Method

Software Suites. For this study, two primary software suites were employed:

1. MATLAB (Version 2024): MATLAB was utilized for various tasks, including the development of Linear Regression Models and Artificial Neural Networks (ANNs). The neural network toolbox in MATLAB played a crucial role in training, validating, and testing the ANN for permeability prediction.
2. Microsoft Office Excel (Version 2013): Excel was used for data collation, computation of statistical performance indicators, and cross-plot generation for model validation. The Data Analysis ToolPak within Excel was specifically employed for plotting Pearson’s Correlation Matrix, aiding in feature selection.

Data Collection and Description. The dataset used in this study was obtained from open source (Kaggle). The dataset consists of log data and core data, with a total of 8,739 data points. The available log data includes gamma ray (GR), bulk density (RHOB), and deep induction resistivity (RILD). Corresponding core data for each log data point includes core permeability values. **Table 1** shows a summary of the data used in this study. **Table 2** shows the statistical analysis of the dataset used in this study.

Table 1—Summary of well log data used.

Factor	Type	Sub-Type	Minimum	Maximum	Mean	Std. Dev.
Gamma ray	Numeric	Continuous	0.0058	404.29	76.95	33.86
Bulk density	Numeric	Continuous	1.19	2.74	2.03	0.4157
Deep induction resistivity	Numeric	Continuous	0.2104	11510.6	34.51	251.24

Table 2—Statistical analysis of the dataset employed in this study.

S/N	Parameters	Units	Min	Max	Average	STD
1	Gamma Ray, γ	API units	0.006	404.288	76.949	33.859
2	Bulk Density, ρ_D	g/cm^3	1.191	2.742	2.034	0.416
3	Deep induction, I_D	Ohm-m	0.210	11510.642	34.512	251.238
4	Permeability, k	mD	0.001	782.431	27.628	25.561

Linear Regression Model. The first approach involved the development of linear regression models using MATLAB. The well log data, collected from literature, was used to train various forms of linear regression models, including linear, interactions linear, robust linear, and interactions linear models. Each model's performance was evaluated to identify the best-fitting model. The general form of the linear regression model used in this study is given by:

$$Y = \beta_o + \Sigma_{i=1}^{k} \beta_i X_i + \Sigma_{i=1}^{k} \beta_{ii} X_{ii}^2 + \Sigma_{i \neq j}^{k} \beta_{ij} X_{ij} + \epsilon, \quad (1)$$

where Y is the dependent variable; X_i are the independent variables; β_o is the intercept; β_i, β_{ii}, β_{ij} are the regression coefficients determined using least squares techniques.

MATLAB automatically determined these regression coefficients during model training. The best-performing model, based on data fit, was selected and exported from MATLAB for further analysis.

The selected linear regression model was then evaluated by applying it to the entire dataset. The model's accuracy was assessed by comparing predicted permeability values against measured values using statistical performance indicators such as mean absolute error (MAE), root mean square error (RMSE), and the correlation coefficient (R^2).

Artificial Neural Network (ANN) Model. Before developing the ANN, feature selection was performed to identify the most significant input parameters. The Pearson's Correlation Matrix was plotted using Excel's Data Analysis ToolPak to assess the correlation between input parameters (gamma ray, bulk density, and deep induction) and the output parameter (permeability). A threshold correlation coefficient of 0.01 was defined. Parameters with a correlation coefficient greater than 0.01 were considered significant. To ensure consistent scaling across all input and output parameters, normalization was performed using the following equation:

$$X_n(0{:}1) = \frac{X - Xmin}{Xmax - Xmin}, \quad (2)$$

where X_n (0:1) is the normalized value of the parameter; X is the actual value of the parameter; X_{min} and X_{max} are the minimum and maximum values of the parameter, respectively.

The dataset was then used to construct six different ANN structures, each with one hidden layer containing 5 to 10 neurons. The dataset was randomly divided into three sets: 70% for training, 15% for testing, and 15% for validation. Training continued until the following conditions were met:

1. The MSEs of the training dataset were lower than that of the validation and testing datasets.
2. The MSEs of the validation and testing datasets were approximately equal.
3. The R^2 increased in the order of testing, validation, and training datasets.

After training, each ANN structure was evaluated using the entire dataset, and the best-performing ANN was selected based on MAE, RMSE, and R^2. The selected ANN structure was then transformed into a set of equations using the activation functions and the extracted weights and biases from the ANN.

The developed ANN model was validated by applying the training, validation, testing, and entire datasets to predict permeability. Cross-plots of measured versus predicted permeability were generated to evaluate the model's accuracy. These plots included a unit slope line, +10% and -10% deviation lines, and the R^2 value. The model was considered accurate if

1. Most of the data points were on the unit slope line and within the +10% and -10% deviation lines.
2. The R^2 value increased in the order of testing, validation, and training datasets.

Results and Analysis

Linear Regression Model. Linear Regression is a fundamental statistical technique that models the relationship between a dependent variable and one or more independent variables. In this study, three different linear regression models were evaluated: standard linear regression, interactions linear regression, robust linear regression. **Table 3** presents a summary of the performance metrics for the three linear regression models. The performance of each model is assessed using various statistical indicators: root mean square error (RMSE), mean square error (MSE), coefficient of determination (R^2), and mean absolute error (MAE) for both the validation and testing datasets.

Table 3—Performance summary of different linear regression models.

Dataset type	Validation Dataset				Test Dataset			
Metrics	RMSE	MSE	R^2	MAE	RMSE	MSE	R^2	MAE
Linear Regression	3.193	10.193	0.981	1.789	4.657	21.689	0.982	1.828
Interactions Linear Regression	3.080	9.484	0.982	1.746	4.466	19.943	0.983	1.797

Standard linear regression model, while straightforward, yielded satisfactory results with an RMSE of 3.1926 and an R^2 value of 0.9805 on the validation dataset. However, when tested, the RMSE increased to 4.6572, indicating some level of overfitting or a potential lack of generalization to new data. Interactions linear regression model, by incorporating interaction terms between the input variables, improved the prediction accuracy, evidenced by a lower RMSE (3.0797) and a higher R^2 value (0.9819) on the validation set. The improvement was consistent in the test set, with an RMSE of 4.4658 and an R^2 of 0.9830, making it one of the best-performing linear models.

Overall, the interactions linear regression model emerged as the top performer among the linear models. The inclusion of interaction terms provided a more nuanced understanding of the relationships between the input variables, leading to improved predictions. This model's robustness was validated across both the validation and test datasets, indicating its suitability for permeability prediction in this context. Therefore, the interactions linear regression model was chosen for further analysis.

Permeability Response. **Figures 1** and **2** illustrate the permeability response for the training data, validation data, and test data, respectively. These plots compare the actual permeability values against the values predicted by the model. They are essential for evaluating how well the model predicts the actual permeability. The strong alignment of data points along the unit slope line in these plots indicates a high degree of accuracy in the model's predictions. Figure 1 shows that the model captured the underlying patterns in the training data very well, with most data points lying close to the line of equality. This strong correlation demonstrates that the model has successfully learned the relationships in the training data. Figure 2(a) reveals that the model generalizes well to unseen data. The proximity of the data points to the line of equality indicates that the model maintains its predictive power when applied to new data, reinforcing the model's robustness. Figure 2(b) further validates the model's accuracy with the testing data. Consistent performance of training, validation and testing datasets suggests that the model is not overfitting and has a strong ability to generalize.

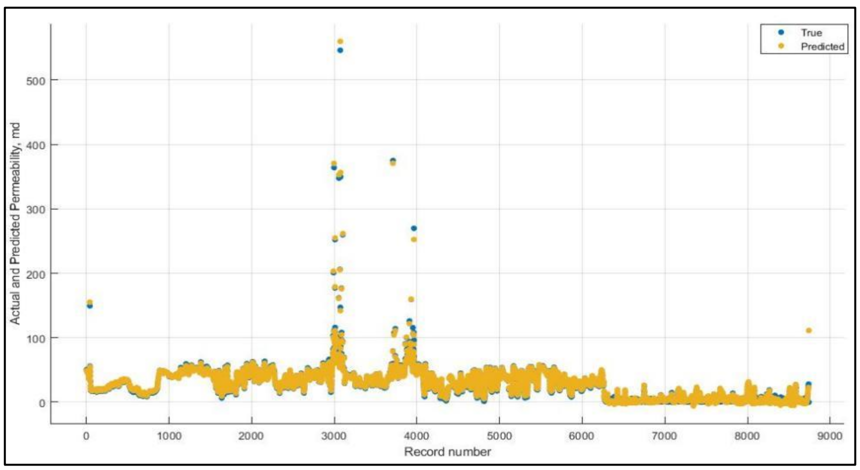
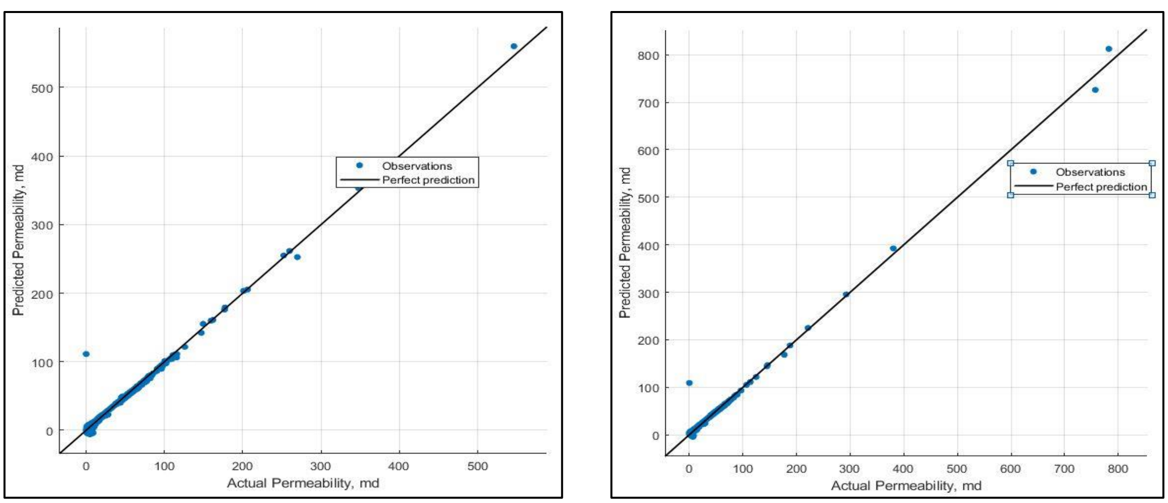


Figure 1—Permeability response plot.



(a)Training dataset (b) Testing dataset

Figure 2—Validation cross plots.

The high R^2 values and low RMSE, MSE, and MAE values across all datasets indicate that the trained model is accurate and generalizes well to unseen data. The linear regression model equation derived from the best-performing model (Interactions Linear Regression) provides a mathematical framework for permeability prediction. The coefficients of the linear regression model used for permeability prediction are detailed in **Table 4**, offering insight into the relative influence of each predictor variable and their interactions on permeability.

Table 4—Coefficients of linear model.

	Estimate	Squared error	t-sat*	p-value**
Intercept	109.0659	0.495134	220.2755761	0
X1	0.118014	0.006208	19.00926865	1.34E-78
X2	-40.8582	0.2262	-180.628774	0
X3	0.075784	0.001037	73.05783645	0
X1*X2	-0.06092	0.002848	-21.3910936	2.19E-98
X1*X3	0.000154	1.54E-05	9.998604339	2.22E-23
X2*X3	-0.01466	0.000853	-17.1769302	8.35E-65

*The t-stat is simply the estimate divided by the squared error.
**The p-value is associated with the t-stat and shows if a given response variable is significant in the model.

The linear regression model equation derived from these coefficients is expressed as,

$$Perm=109.0659+0.1180X_1-40.8582X_2+0.0758X_3-0.0609X_1X_2+0.000154X_1X_3-0.0147X_2X_3, \quad (3)$$

Eq. 3 can be applied in practical scenarios for quick and reliable permeability estimation, making it a valuable tool for reservoir engineers.

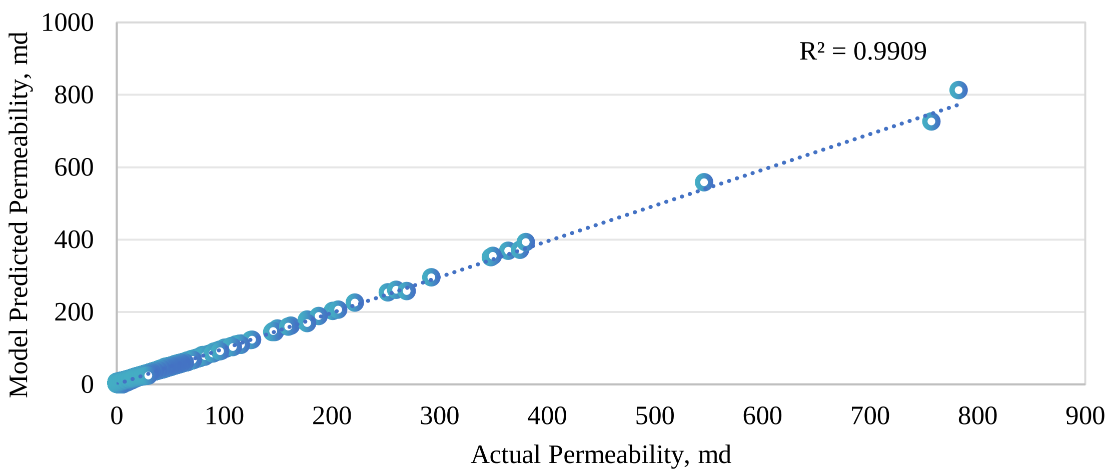


Figure 3—Cross plot of actual versus model predicted permeability.

Figure 3 shows that actual permeability versus model-predicted permeability reveals a strong correlation between the measured and predicted values, with most of the data points lying close to the unit slope line. It further confirms the model's accuracy and its potential for practical application in predicting permeability.

Artificial Neural Network (ANN) Model. Figure 4 presents the Pearson's correlation matrix for all parameters in the dataset, providing insight into the relationships between input parameters (gamma ray, bulk density, and deep induction) and the output parameter (permeability).

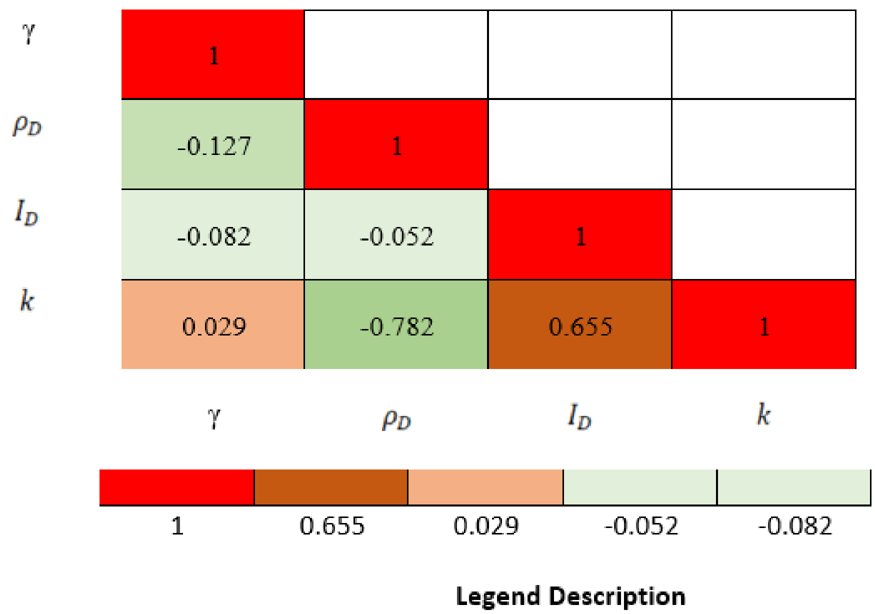


Figure 4—Pearson's correlation matrix for all parameter in the dataset.

Bulk density exhibited a strong negative correlation with permeability, indicating that as bulk density increases, permeability tends to decrease. This is consistent with geological principles, where higher density formations often have lower porosity and permeability. Deep induction showed a positive correlation with permeability, suggesting that higher values of deep induction are associated with higher permeability, likely due to the presence of more conductive, porous formations. Gamma rays had a weak correlation with permeability, implying that its influence on permeability is less significant compared to the other variables. These correlations are essential for understanding the influence of each parameter on the output and guiding the feature selection process.

ANN Structure and Performance. Six different ANN structures were constructed and evaluated based on 8,739 data points. The statistical performance of each structure is summarized in **Table 5**.

Table 5—Statistical performance of ANN structures.

ANN Structure	MAE	RMSE	R_2
n-5	1.0818	80.9924	0.9931
n-6	0.8362	75.7039	0.9963
n-7	0.6145	65.2532	0.9980
n-8	0.7439	76.8524	0.9962
n-9	0.5985	71.9866	0.9979
n-10	0.1445	29.9016	0.9996

Among the six ANN structures, the n-10 structure achieved the best performance. It achieved the lowest RMSE (29.9016) and the highest correlation coefficient (0.9996), indicating an exceptionally accurate model with minimal prediction error. This structure outperformed the linear models, highlighting the strength of ANNs in capturing complex, non-linear relationships in the data.

The architecture of the n-10 ANN, depicted in **Figure 5**, includes an optimized number of neurons and layers that enable the model to learn the intricate patterns in the well log data. The ability of the ANN to model non-linear relationships gives it an edge over linear regression models, particularly in complex reservoir environments.

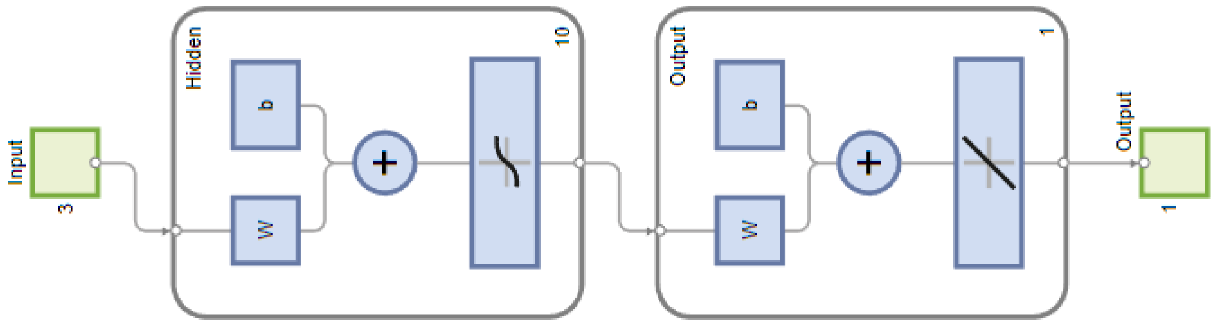


Figure 5—Structure of the best trained ANN.

ANN Model Equation. The ANN model developed in this study is represented by a series of equations (**Eq. 4** to **9**) that describe the transformation of input variables through the network's layers to produce the final permeability prediction.

$$k_p = \frac{1}{2}\left(\left(b2 + LW2 \cdot \tanh\left(b1 + IW1 \cdot X_{n(-1:+1)}\right)\right) + 1\right)(k_{max} - k_{min}) + k_{min}, \quad (4)$$

where,

$$X_{n(-1:+1)} = 2\left[\frac{X_{n(0:1)} - X_{min}}{X_{max} - X_{min}}\right] - 1, \quad (5)$$

$$X_{n(0:1)} = \frac{X - X_{min}}{X_{max} - X_{min}}, \quad (6)$$

$$X = [\gamma \;\; \rho_D \;\; I_D]^T, \quad (7)$$

$$X_{min} = [\gamma_{min} \;\; \rho_{Dmin} \;\; I_{Dmin}]^T, \quad (8)$$

$$X_{max} = [\gamma_{max} \;\; \rho_{Dmax} \;\; I_{Dmax}]^T, \quad (9)$$

The weights and biases extracted for the output layer (LW_2 and b_2) and the hidden layer (IW_1 and b_1) used in the model are shown in **Tables 6** and **7**, respectively.

Table 6—Key parameters for the output layer used in Eq. 4.

Extracted weight vector (LW_2)										**Bias (b_2)**
0.2514	-1.4538	-1.7993	1.2766	0.4177	2.6805	0.5586	1.3820	-1.4926	2.3865	-0.3288

Table 7—Key parameters for the hidden layer used in Eq. 4.

Extracted weight matrix (IW_1)			Bias vector (b_1)
0.7447	-0.9934	2.7596	-2.0319
0.2320	0.3227	0.7401	-0.8480
-0.1124	-0.2926	0.0548	0.4594
-0.5512	3.7046	-6.9747	-10.0962
-0.6787	2.3096	1.5510	-0.7071
0.6146	-3.1447	-0.3321	2.3459
-0.1447	-0.5907	1.1009	1.2524
0.5512	-3.9675	10.4580	13.5564
0.0538	0.2011	-0.7062	0.1829
-0.6129	3.5097	-2.2764	-5.0852

These equations encapsulate the weights, biases, and activation functions used in the model, providing a detailed mathematical framework for understanding the ANN's operation. The ANN model equation (Eq. 4) is more complex than the linear regression model equation (Eq. 1), reflecting the higher complexity and flexibility of ANNs. This complexity allows the ANN to achieve higher accuracy, especially in cases where the relationships between variables are not purely linear.

Model Validation and Performance Analysis. The performance of the ANN model is further validated through cross-plots of measured versus predicted permeability values for the training, validation, and testing datasets are presented in **Figures 6** through **8**. The alignment of data points along the unit slope line in Figure 6 indicates that the ANN has effectively learned the patterns in the training data, resulting in highly accurate predictions. The strong correlations between predicted and actual values in Figures 7 and 8 confirm that the model generalizes well to new data, maintaining high accuracy across different datasets, confirming the model's accuracy.

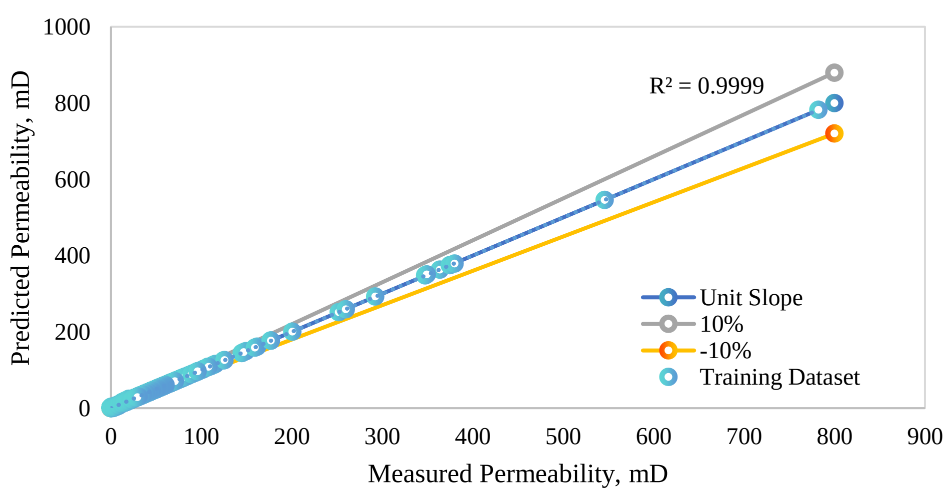


Figure 6—Measured and predicted permeability cross-plots based on the training dataset (6117 data points).

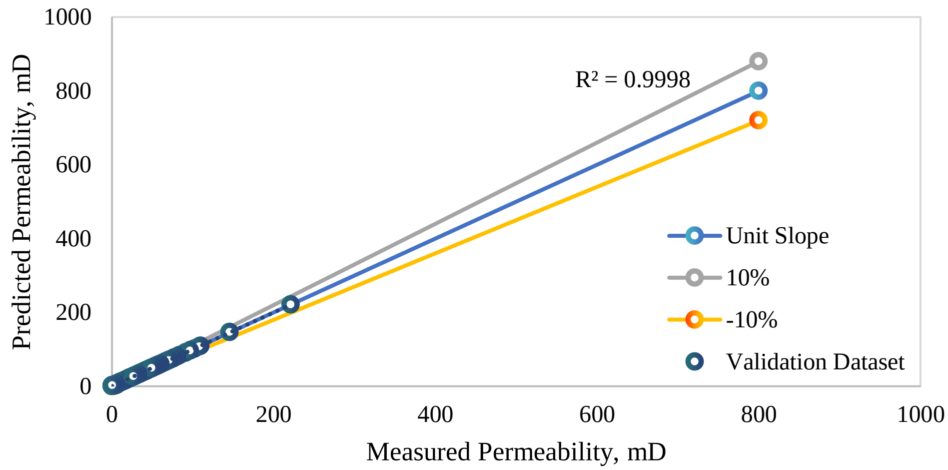


Figure 7—Measured and predicted permeability cross-plots based on the validation dataset (1311 data points).

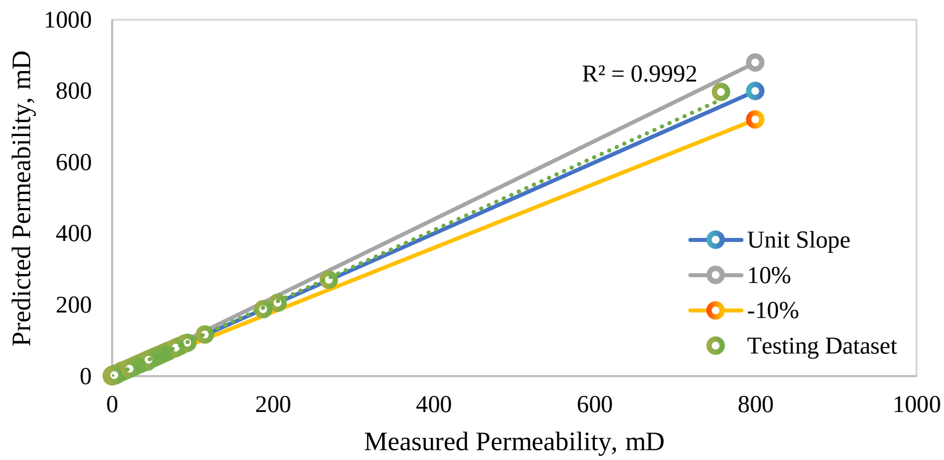


Figure 8—Measured and predicted permeability cross-plots based on the testing dataset (1311 data points).

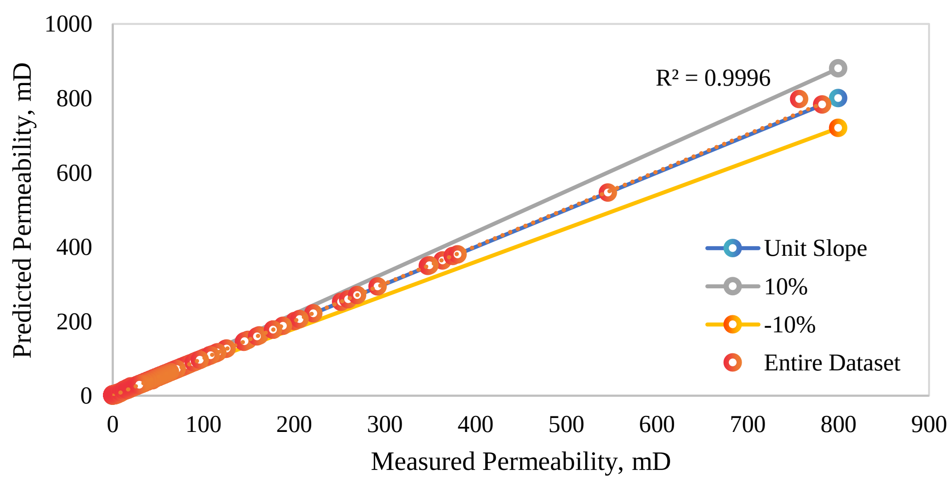


Figure 9—Measured and predicted permeability cross-plots based on the entire dataset (8739 data points).

The cross-plot based on the entire dataset (8,739 data points) in **Figure 9** further demonstrates the robustness of the ANN model in predicting permeability across diverse datasets. The high density of data points along the unit slope line across such a large dataset is a evidence of the model's reliability and effectiveness in real-world applications.

The comparison across the three studies highlights differences in modeling approaches, model types, and performance (**Table 8**). Leiphart and Hart (2001) utilized a combination of Linear Regression and Probabilistic Neural Network (PNN), with PNN achieving the best performance with an R^2 value of 0.82. This model demonstrated better geological realism in predicting porosity distribution, effectively capturing non-linear relationships between seismic attributes and porosity. In contrast, Azim and Aljehani (2022) employed an Artificial Neural Network (ANN) using the back-propagation learning algorithm implemented in FORTRAN. Their ANN model achieved an R^2 value of 0.94 and was particularly robust in predicting rock permeability with minimal wireline log data. In this study, a more diverse set of models was explored, including Standard Linear Regression, Interactions Linear Regression, and ANN with varying structures. The best-performing model was the ANN with 10 neurons in the hidden layer (n-10), achieving an exceptional R^2 value of 0.9996. This model provided superior accuracy in predicting permeability and was highly effective in capturing complex, non-linear relationships in well log data, surpassing the predictive capabilities of the models from the other two studies.

Table 8—Comparison of Modeling Approaches Across Studies.

Feature	Leiphart and Hart (2001)	Azim and Aljehani (2022)	This Study
Modeling Approaches	Linear Regression and Probabilistic Neural Network (PNN).	ANN model based on the back propagation learning algorithm using the FORTRAN language.	Linear Regression and Artificial Neural Network (ANN).
Model Types	Standard Linear Regression, Probabilistic Neural Network (PNN).	ANN model uses a weight visualization curve technique.	Standard Linear Regression, Interactions Linear Regression, and Artificial Neural Network (ANN) with varying structures.
Best Performing Model	Probabilistic Neural Network (PNN) with $R^2 = 0.82$.	ANN with $R^2 = 0.94$.	ANN with 10 neurons in the hidden layer (n-10) with $R^2 = 0.9996$.
Performance Metrics	Linear Regression: $R^2 = 0.74$. PNN: $R^2 = 0.82$.	$R^2 = 0.94$.	Interactions Linear Regression: $R^2 = 0.983$. ANN (n-10): $R^2 = 0.9996$
Strengths of Best Model	Better geological realism in predicted porosity distribution; higher accuracy in capturing non-linear relationships between seismic attributes and porosity.	ANN model is robust and has strong capability of predicting rock permeability using a minimum number of wireline log data.	Superior accuracy in predicting permeability; effective at capturing complex, non-linear relationships in well log data.

Conclusions

In conclusion, this study demonstrates the effectiveness of both linear regression and artificial neural network models in predicting permeability from well log data. The interactions linear regression model and the n-10 ANN structure were identified as the best-performing models in their respective approaches. While the ANN model demonstrated superior accuracy and robustness, the linear regression models, particularly the interactions model, offered valuable insights into the relationships between variables. The models developed in this study can be effectively applied in reservoir characterization, leading to improved decision-making in the oil and gas industry.

Recommendation

Based on the results and discussion of the modeling approaches for predicting permeability from well log data, the following recommendations are proposed:

1. Adoption of Artificial Neural Networks (ANN) for Complex Reservoirs: The ANN model, particularly the n-10 structure, demonstrated superior accuracy in predicting permeability, especially in complex reservoirs where non-linear relationships prevail. This model should be prioritized for reservoir characterization in such environments.
2. Use of Interactions Linear Regression for Simpler Reservoirs: The Interactions Linear Regression model performed well, with relatively high accuracy and strong generalization. This model is more interpretable and computationally less intensive than ANN models, making it suitable for reservoirs where relationships are expected to be more linear.
3. Integration of Both Modeling Approaches: Each modeling approach offers unique strengths--ANN for capturing complex, non-linear relationships, and linear regression for simplicity and interpretability. Integrating both approaches could provide a more comprehensive understanding of reservoir behavior. A hybrid approach can be employed where both models are run in parallel. The linear regression model can be used for initial, quick assessments, while the ANN model provides a more detailed analysis. This strategy would ensure that different aspects of reservoir characteristics are captured, enhancing overall decision-making.

Conflicting Interest

The author(s) declare that they have no conflicting interests.

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