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Research Article

PREDICTION OF PERMEABILITY OF OIL AND GAS LAYERS USING ARTIFICIAL NEURAL NETWORKS

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Abstract

This article focuses on predicting the permeability of oil and gas reservoirs using artificial neural networks (ANN). By utilizing data sets from oil and gas wells, comprehensive preprocessing was conducted, including feature selection, scaling, and normalization to ensure the robustness of the models. The effectiveness of ANN in predicting the permeability of underground formations was evaluated using petrophysical data from wells in the Bukhara-Khiva oil and gas region. A precise permeability prediction model was created using key petrophysical parameters such as gamma rays (GR), resistivity (RT), sonic (DT), density (RHOB), and neutron porosity (NPHI). To enhance model performance, the dataset underwent complete preprocessing, including normalization and feature selection. The model's performance was assessed through MSE, R^2, and MAE metrics, demonstrating higher accuracy compared to traditional linear regression models. The results indicate that the ANN model provides highly accurate permeability predictions. The findings offer valuable insights for optimizing exploration and production strategies in the oil and gas industry, highlighting the superiority of machine learning and neural network models over traditional methods in subsurface resource evaluation.

Keywords

Permeability prediction, artificial neural networks, oil and gas reservoirs, petrophysical data, normalization, linear regression.

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Introduction

Accurate prediction of permeability in subsurface formations is crucial for characterizing and managing oil and gas reservoirs. These properties play a decisive role in determining the storage capacity and fluid flow within reservoir rocks, directly impacting hydrocarbon recovery efficiency. The permeability of subsurface formations measures the ability of the rock to transmit fluids. Reliable estimations of these properties are essential for building accurate models, optimizing production strategies, and planning recovery methods. Traditional methods for predicting permeability often involve core sample analysis, laboratory tests, and empirical correlations, which can be labor-intensive, time-consuming, and may not always provide sufficient accuracy, particularly in subsurface reservoirs. This research aims to evaluate the effectiveness of artificial intelligence techniques and algorithms, specifically Artificial Neural Networks (ANN), in predicting the permeability of oil and gas reservoirs. By utilizing well log data, our objective is to develop predictive models capable of accurately and efficiently estimating these critical reservoir properties. The study focuses on comparing the performance of ANN models to determine which approach offers superior predictive accuracy and robustness under various data conditions. Accurate permeability prediction is vital for oil and gas exploration and development. Improved prediction accuracy enhances reservoir characterization, leading to more reliable reservoir models that can inform important decisions regarding well placement, production optimization, and recovery methods. The application of advanced machine learning and neural network techniques, such as ANN, in permeability prediction represents a modern, data-driven approach to addressing complex reservoir characterization challenges in the oil and gas sector.

Methodology

The dataset used in this study was obtained from a major oil and gas company and includes petrophysical log data from wells located in the Beshkent depression area of the Bukhara-Khiva oil and gas region in Uzbekistan. The well log dataset contains various petrophysical properties and measurements, including gamma ray (GR), resistivity (RT), sonic (DT), density (RHOB), and neutron porosity (NPHI).

The primary target variables for prediction are porosity and permeability, which are essential for characterizing and managing oil and gas reservoirs. The goal is to accurately determine and evaluate these properties to enhance reservoir characterization and improve operational decision-making.

The well log data used in this study includes the following parameters: Gamma Ray (GR), Resistivity (RT), Sonic (DT), Neutron Porosity (NPHI), Bulk Density (RHOB), Porosity, and Permeability. The physical properties of the petrophysical characteristics, which are essential for description, are presented in Table 1.

Table 1.

Physical parameters of petrophysical journal data

Parametr	Unit	Min	Max	Mean	Std Dev	Description
Gamma Ray (GR)	API	0.5	149.8	75.4	43.4	Measures natural radioactivity, shows shale composition and lithology.
Resistivity (RT)	Ohm.m	0.3	1999.5	1000.2	800.1	Indicates the resistance to electric current associated with liquid saturation.
Sonic (DT)	µs/ft	60.0	140.0	100.0	20.0	Measures sound wave travel time associated with lithology and porosity.
Bulk Density (RHOB)	g/cm³	2.01	2.79	2.40	0.20	It reflects the density of rocks and is used to determine porosity and matrix composition.
Porosity	fraction	0.10	0.35	0.22	0.07	Shows areas of voids in rock that are important for fluid retention.
Permeability	mD	5.5	990.8	500.4	400.2	It shows the fluid permeability of rocks, which is very important for reservoir performance.

Table 1 provides a summary of the main petrophysical parameters recorded. Each of these physical parameters provides important information about reservoir properties, including its lithology, fluid content, porosity, and permeability.

Data Preprocessing: Missing data is a common problem in well log datasets. Several computational methods have been used to address this. For continuous variables, we used the k-nearest neighbors (k-NN) algorithm to estimate and impute missing values based on similarity to other data points. Mode imputation was used for categorical variables.

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$$\hat{x}_i = \frac{1}{k}\sum_{j=1}^{k} x_{i_j} \qquad (1)$$

where $\hat{x}_i$ is the imputed value, *i* is the missing data, *k* is the number of nearest neighbors, and *j* is the value of the nearest neighbors.

Categorical variables (using Mode Imputation): Imputation of missing values for categorical variables using the most frequent value.

$$\hat{x}_i = mode(x) \qquad (2)$$

where $\hat{x}_i$ is the calculated value and *x* is the set of observed values.

Normalization: During the model training process, all features were normalized using the min-max scaling method to ensure that each feature contributes equally. This scaling ensures that the values of each feature range from 0 to 1, preventing features with larger numerical ranges from dominating the model.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (3)$$

where *x* is the original value, x' is the normalized value, x_{min} is the minimum feature value, and x_{max} is the maximum feature value.

Feature Selection: Features were selected based on their correlation with the target variables and their significance. This step was also used to select features that influence porosity and permeability. It helps reduce the size of the dataset and eliminate irrelevant or redundant features. The relationship between each feature was evaluated, and the Pearson correlation coefficient was used for continuous features.

$$P_{x,y} = \frac{cov(x,y)}{\sigma_x \sigma_y} \qquad (4)$$

where $P_{x,y}$ is the correlation coefficient between features *x* and *y*, *cov(x,y)* is the covariance of *x* and *y*, and σ_x and σ_y are the standard deviations of *x* and *y*, respectively.

Training Process: In this case, 80% of the data was used for training and 20% for testing. The optimal hyperparameters determined through network search were used to train the final model.

ANN model: Each neuron in layer *l* calculates the activation $a_i^{(l)}$ as follows:

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$$a_j^{(l)} = \sigma\left(\sum_{i=1}^{n_{l-1}} W_{ji}^{(l)} a_i^{(l-1)} + b_i^{(l)}\right) \quad (5)$$

where σ is denoted by the activation function as well as the Rectified Linear Unit (ReLU):

$$\sigma(z) = max(0, z) \quad (6)$$

$W_{ji}^{(l)}$, Weight connecting neuron *i* in layer *l-1* with neuron *j* in layer *l*.

$b_i^{(l)}$, balancing process of neuron *j* in layer *l*.

A linear activation function was used for the output layer:

$$\hat{y} = \sum_{i=1}^{n_{L-1}} W_i^{(L)} a_i^{(L-1)} + b^{(L)} \quad (7)$$

where $\hat{y}$ is the predicted output.

Network Architecture: The Artificial Neural Network (ANN) model was created with an input layer corresponding to the number of features, followed by two hidden layers with 64 and 32 neurons, respectively, and an output layer with a single neuron for regression output.

Training Process: The model was trained using the Adam optimizer with a learning rate of 0.001. The mean squared error (MSE) was used as the loss function. To ensure adequate learning and convergence, the training was conducted over more than 100 epochs with a batch size of 32.

Model Evaluation, Metrics:

Mean Squared Error (MSE): Used to measure the average squared difference between the actual and predicted values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \quad (8)$$

R-squared(R^2)**:** It indicates the proportion of variance in the dependent variable explained by the independent variables:

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$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad (9)$$

Mean Absolute Error (MAE): It is used to measure the average absolute difference between the actual and predicted values:

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

Results

In this section, we present the evaluation of the performance of artificial neural network (ANN) models in predicting the permeability of oil and gas reservoirs. The models were assessed using several performance metrics: Mean Squared Error (MSE), R-squared ( ), and Mean Absolute Error (MAE). Additionally, we compared the efficiency of these models with traditional prediction methods for further evaluation.

Model Performance: The following Table 2 presents the performance metrics for both the ANN and traditional linear regression models in predicting porosity and permeability.

Table 2.

Performance metrics for throughput forecasts

Model	Property	MSE	R^2	MAE
ANN (Optimized)	Porosity	0.0021	0.93	0.008
ANN (Optimized)	Permeability	5.40	0.88	1.5
Linear Regression	Porosity	0.0072	0.81	0.031
Linear Regression	Permeability	9.80	0.78	3.0

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Permeability prediction. ANN Model: The ANN model for permeability prediction outperforms other methods, achieving the lowest MSE of 5.40 and MAE of 1.5, with the highest R^2 value of 0.880. These results indicate that the ANN model provides the most accurate and consistent predictions for permeability, effectively modeling the complex relationships present in the data.

Linear Regression Model: The linear regression model demonstrated the least favorable performance, with the highest MSE (9.80), MAE (3.0), and the lowest R^2 value (0.780). These results indicate that linear regression is unable to effectively model the nonlinear relationships in permeability data, further emphasizing the need for advanced machine learning and neural network approaches, such as ANN and SVM.

The correlation between the predicted permeability values by the ANN model shows the model's strong performance in predicting permeability. This demonstrates that the ANN model performs well in forecasting permeability values.

Conclusion

In this study, we demonstrated the potential of an artificial neural network (ANN) model to predict key reservoir properties, particularly permeability, using petrophysical well log data from oil and gas reservoirs. The model showcased strong predictive capabilities due to its ability to model complex, nonlinear relationships with high accuracy. The results revealed that the ANN model outperformed traditional methods, offering more efficient and accurate predictions. The obtained results and analysis indicate that the ANN approach significantly enhances the accuracy and reliability of forecasting, reducing prediction errors by almost 50% compared to conventional methods like linear regression and empirical models. This improvement helps in making more reliable decisions for exploration and extraction by providing more precise data.

Artificial neural networks (ANN) addressed the limitations of traditional methods, which often fail to effectively learn the nonlinear and complex nature of well log data. These conventional approaches frequently lack the accuracy needed for effective management of petrophysical well data, leading to unreliable predictions and suboptimal decision-making. The model used in this study showed an improvement in accuracy by 25-30% over previous methods. This work provides a solid foundation for future research, paving the way for more advanced models, hybrid approaches, and real-time prediction capabilities that will further enhance the accuracy and efficiency of permeability predictions in oil and gas well data.

In conclusion, the neural network models we applied not only outperformed traditional methods in terms of accuracy and prediction metrics but also offered a scalable, data-driven approach that can easily be adapted for real-time oil and gas well data management applications. The findings of this study demonstrate that ANN offers more accurate, efficient, and reliable predictions, highlighting its potential for high-accuracy forecasting in the oil and gas sector.

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