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Estimation of Petrophysical Properties in Oil Reservoirs using Supervised Machine Learning Models.

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Abstract

The accurate determination of petrophysical properties in oil and gas reservoirs plays a fundamental role in the industry, directly influencing reserve evaluation and production planning. This study proposes an innovative approach to estimate porosity and permeability in Namorado Formation reservoirs (siliciclastic reservoirs) in the Campos Basin, RJ, using supervised machine learning models.

Initially, real well data was utilized, integrating basic geophysical logs (Transit Time - DT, Bulk Density - RHOB, Gamma Ray - GR, Neutron Porosity - NPHI, and Resistivity - RES) with laboratory data (porosity, permeability, and grain density). These data were carefully selected from 17 wells with core samples, where 15 were used in the main dataset and 2 were reserved as a "blind data set" for independent validation.

Rigorous data preprocessing was performed, followed by Exploratory Data Analysis (EDA) to identify and select the most relevant features (independent variables) capable of optimizing the prediction of porosity and permeability (dependent variables). This step was crucial to ensure the robustness and representativeness of the training data.

The data was then used to train various machine learning regression models, including K-Nearest Neighbors (KNN), Random Forest, Decision Tree, and Multiple Linear Regression. Cross-validation was employed to optimize each model's hyperparameters, ensuring their generalization and performance. The models' performance was statistically evaluated, utilizing metrics such as the coefficient of determination (R^2), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), focusing on their ability to make accurate predictions on unseen data, demonstrating the validity of the proposed methodology.

The obtained results suggest that the proposed methodology offers a robust and efficient tool for reservoir characterization, with significant potential to optimize reserve evaluation, assist in drilling and production planning, and reduce uncertainties in oil fields. The practical application of these machine learning-based models can lead to more informed decisions and more effective strategies in the exploration and development of siliciclastic reservoirs.