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Kuwaiti Carbonate Reservoir Oil Recovery Prediction Through Static Wettability Contact Angle Using Machine Learning Modeling

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Abstract

The objective of this study is to predict EOR efficiencies through static wettability contact angle measurement by Machine Learning (ML) modeling. Unlike conventional methods of measuring static wettability contact angle, the unconventional digital static wettability contact angle is captured and measured, then (ML) modeled in order to forecast the recovery based on wettability distribution phenomenon. Due to success in big data collection from reservoir imaging samples, this study applies data science lifecycle logic and utilizes Machine Learning (ML) models that can predict the recovery through wettability contact angles and thus identify the treatment of oil recovery for a candidate reservoir.

Using developed morphological driven pixel-data and transformed numerical wettability contact angle data are acquired from Scanning Electron Microscope Backscattered Electron (SEM-BSE) for 27 fresh core samples from top to bottom of the reservoir. These samples are properly sequenced and then images are selected. Big data from imaging technology have been processed in a manner to train, and test the model accuracy. Applied Data Science Lifecycle technique, such as data mining, is utilized. Data Exploration Analysis (DEA) is implemented to understand and review data distribution as well as relationships among input features. Different supervised ML models to predict recovery are utilized and an optimal model is identified with an acceptable accuracy. The selected prediction model is applied to model the optimal recovery practice.

Extreme Gradient Boosting (XGBoost) algorithm is utilized and found as a best-fit model for this Kuwaiti reservoir case practice. Moreover, decision tree and Artificial Neural Network (ANN) models could provide acceptable accuracy. Other supervised learning models were attempted and were not promising to provide feasible accuracy for this carbonate reservoir.

The novel of this unique solution of the data-driven ML model is to predict recovery based on static wettability contact angles (θ°). The static wettability contact angles (θ°) and pore morphological features introduce an insights method to support reservoir engineers in making value-added decisions on production mechanisms and hydrocarbon recovery for their reservoirs. Hence, it improves the field development strategy.

Introduction

A Classic Kuwait carbonate reservoir located in North Kuwait is recognized to be as a thick and fractured limestone formation, and it demonstrated a decent production, but primary production is getting difficult in this formation as the field become mature [1]. A limestone formation shows a low matrix permeability from 0.0001 to 10's millidarcies and high porosity – about 18% with around 430 feet of net-oil-pay thickness. These petrophysical characteristics of the reservoir highlight the need to maximize production from the limestone formation through characterizing the wettability distribution within formation for suggesting future improved oil recovery production programs.

Several factors have an influence on Improved Oil Recovery (IOR) methods such as reservoir properties, reservoir heterogeneity, and fluid properties which make the suggested plan not an easy task for field development. Thus, wettability is considered as one of important factors on recovery process.

According to this study, understanding wettability contact angle distribution in a reservoir will help to assist hydrocarbon production plan since it affects location, flow, and distribution of reservoir fluid in pore system.

Utilizing 2D digital imaging technology, the investigation of static wettability contact angle measurements through big data pore-scale modeling was conducted by selecting 27 core samples where these rock chips cover the whole thickness of the selected carbonate reservoir along with machine learning recovery prediction model.

Because the world's demand for oil is rising, and the price of oil is increasing as well, developing a production strategy of such limestone formation as soon as possible is a task of reservoir engineers who work in field development to accelerate future reservoir planning and development. This project presents a trial of reservoir characterization application for wettability contact angle determination for carbonate reservoir which effects on hydrocarbon recovery. Also, a machine learning recovery model is suggested.

Background

That wettability is a complex phenomenon is for many reasons. First of all, it is too difficult to yield accurate measurements, and to control quantitative repeatability. Also, the time of experimental data generation is shortened, and cost of analysis is high (2-10). Unlike the conventional way of measuring contact angle in this study a captured rock physics is deterministically reported by using big-data pore morphological features are measured and quantified as indicated in Figure 3. Via using the unit circle trigonometry, the wettability contact angle of pore/ grain is captured and measured precisely and accurately as presented in Figure 4 (11-14, 20). Hence, this knowledge will help in understanding the nature of the reservoir and how better to produce it.

In this study, 2-dimensional images are used to characterize the morphology of the grains and pores, using a two-step process (8, 14). In the first step, the image is captured. In the second step, the area and average pore contact angle of such features are scanned using image analysis software that has the ability to accurately measure several morphological parameters of pore and grain spaces as indicated in Figure 1. This study utilizes area measurement and contact angle as the criterion parameter for all analyses. Morphological features are calculated based on area and contact angle, which brings the level of information accuracy into two dimensions as shown in Figure 2. This information, which is considered "Big Data," is taken and analyzed to find answers that enable cost and time reductions. The images are captured using Backscattered Scattered Electron Microscopy (SEM) at different magnification scales.

Wettability, as defined by Donaldson and Alam from Texas Tech University in 2008, refers to the relative spreading or adhesion of two fluids to a solid surface in the presence of two immiscible fluids within porous media. It is a measure of the preferential tendency of one fluid to wet, or spread and adhere to, the interstitial surfaces of the pore walls in a porous medium when another fluid is present. The surfaces of pore walls in rocks consist of various exposed minerals that exhibit different affinities for water, hydrocarbons, and other constituents suspended or dissolved in the fluids [19].

In the context of a water/oil/rock system, wettability refers to the average and overall wetting preference of the interstitial surfaces of the rock. There are four generally recognized states of wettability: water-wet, fractional-wettability, mixed-wettability, and oil-wet. These states describe the varying degrees to which the rock surfaces preferentially interact with water or oil. A water-wet state indicates a preference for water to wet the rock surfaces, while an oil-wet state indicates a preference for oil. Fractional-wettability and mixed-wettability states represent intermediate conditions where both water and oil can wet the rock surfaces to some extent.

Understanding the wettability of a reservoir is crucial for effective oil recovery and production. It influences the flow behavior of fluids within the reservoir and can impact the efficiency of recovery techniques. By characterizing the wettability state of a reservoir, operators can tailor their production strategies to optimize oil recovery. This may involve adjusting injection fluids, modifying well placement, or implementing enhanced oil recovery techniques to overcome any challenges posed by the wettability characteristics of the reservoir.

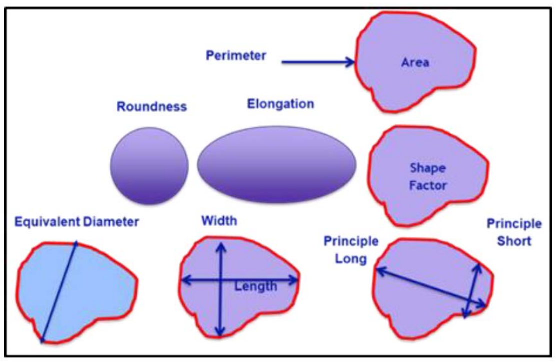

Figure 1—Pore/ grain boundary morphological reservoir wettability contact angle and model

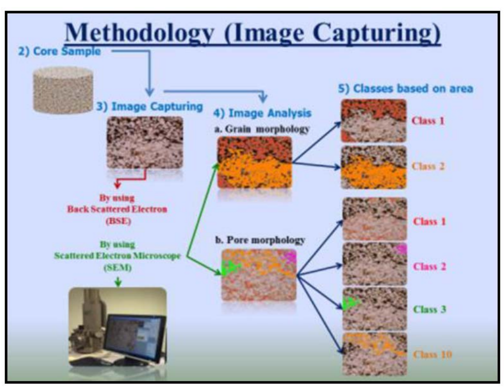

Figure 2—Image capturing procedure

Table 1—7 rock types of the studied reservoir

Reasons for Selection	Sample No. #	Rock Type Sequence	Depth (ft)
Dolomite, tight matrix	1	RT1	7684.2
maximum perm	2	RT1	7688.4
minimum perm	3	RT1	7700.4
maximum por	4	RT1	7708.6
Tight Matrix	5	RT2	7713.45
maximum perm	6	RT2	7718.45
maximum por	7	RT2	7720.2
KOC Selection	26**	RT2	7721.9
minimum perm	8	RT2	7735.3
minimum perm	9	RT3	7741.45
maximum perm	10	RT3	7755.2
maximum por	11	RT3	7759.85
KOC Selection	27**	RT3	7767.1
Dolomite	12	RT3	7773.8
maximum GD	13	RT4	7777.7
maximum por	14	RT4	7806
maximum perm	15	RT4	7820.75
minimum perm	16	RT4	7828.9
maximum perm	17	RT5	7838.95
Dolomite	18	RT5	7848
maximum por	19	RT5	7854.4
minimum perm	20	RT5	7878.2
maximum por	21	RT6	7887.8
maximum perm	22	RT6	7889.7
inimum perm, Tight matr	23	RT6	7918.3
inimum perm, Tight matr	24	RT7	7926.5
ximum perm, maximum	25	RT7	7933.8

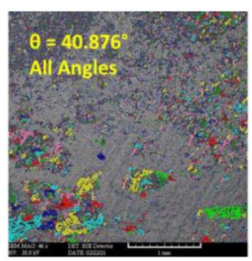

Figure 3—example of SEM machine which has successfully developed an image for all classes, and all are processed for wettability contact angle. This contact angles = 40.87° (21,22).

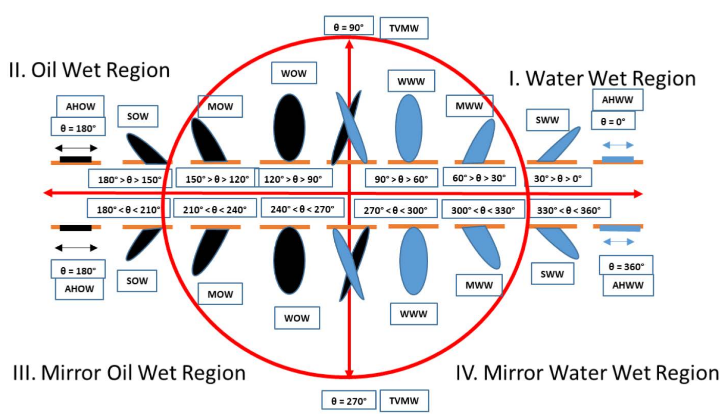

Figure 4—Al-Bazzaz Wettability contact angle(#°) Classification Chart. All Angles Follow the Central Angle Theorem in a Unit-Circle-Trigonometry (Red Circle). Blue Droplets Angles Define Water Wet Angles and Black Droplets Angles Define Oil Wet Angles. The Orange Surface Resembles the Grain Wall/ pore Boundary [20].

Table 2—The Complete 2D Digital Angle Measurements Classification Inside the Oolite Reservoir Sample

Wettability Symbol	Wettability Preference Strength	Al-Bazzaz's Wettability Classification system (2018-2019)	Contact Angle (θ°)	Type of Suggested Optimized Recovery
AHWW	Absolute Horizontal -Water-Wet	1	At 0°	Primary
SWW	Strong-Water-Wet	2	> 0° - 30°	Primary
MWW	Medium-Water-Wet	3	30° - 60°	Secondary Water flooding
WWW	Weak-Water-Wet	4	60° - < 90°	Low Salinity water flooding
TVMW	True Vertical Mixed Wet	5	At 90°	Low Salinity water flooding
WOW	Weak-Oil-Wet	6	> 90° - 120°	Chemical flooding with Low Heat
MOW	Medium-Oil-Wet	7	120° - 150°	Smart Water with 100< Heat < 300 °C
SOW	Strong-Oil-Wet	8	150° - < 180°	Unconventional Treatment at High Temp. >300 °C
AHOW	Absolute Horizontal -Oil-Wet	9	At 180°	Unconventional Treatment at High Temp. >300 °C
SOW	Strong-Oil-Wet	10	> 180° - 210°	Unconventional Treatment at High Temp. >300 °C
MOW	Medium-Oil-Wet	11	210° - 240°	Smart Water with 100< Heat < 300 °C
WOW	Weak-Oil-Wet	12	240° - < 270°	Chemical flooding with Low Heat
TVMW	True Vertical Mixed Wet	13	At 270°	Low Salinity water flooding
WWW	Weak-Water-Wet	14	> 270° - 300°	Low Salinity water flooding
MWW	Medium-Water-Wet	15	300° - 330°	Secondary Water flooding
SWW	Strong-Water-Wet	16	330° - < 360°	Primary
AHWW	Absolute Horizontal -Water-Wet	17	At 360°	Primary

According to Table 2 and Figure 4 in this study, 17 Wettability Preference was suggested to better describe the wettability contact angle distribution and recovery method suggested for good reservoir management and future production plan. The recommended recovery is proposed for each class which implies that the distribution of wettability contact angles within a porous media is important for production scheme. In Table 3, where the mirror angle effect is included, an example from sample 1 shows that all regimes of IOR are available but with different proportions in this formation. Overall, this sample is targeted for the primary recovery type (19, 20).

Table 3—Recovery Percentage for Each Wetting Class Pore Distribution Presented in Rock Sample 1 at 400X Magnification

Type of Recovery Method	Type of Wettability	Wettability Contact Angle (θ°)	Max. Recovery, %
Primary	SWW	0-30	25
Secondary Water flooding	MWW	30-60	12
Low Salinity water flooding	WWW	60-90	12
Chemical flooding with Low Heat	WOW	90-120	14
Smart Water with 100< Heat < 300 °C	MOW	120-150	19
Unconventional Treatment at High Temp. >300 °C	SOW	150-180	18

Machine learning (ML) which an artificial intelligent is used in several industry such as medicine, accounting, and other industries. Machine learning is divided to supervised, simi-supervised, and un supervised techniques. In petroleum engineering, machine learning can be applied for reservoir characterization to enhance the knowledge in reservoir engineering aspects [16].

Artificial Neural Network (ANN) considered as a deep learning methods where it uses a complex architecture of networks where it mimics human brain as shown in Figure 5. The neural network can be simple with one hidden layer or complex with several hidden layers. A schematic of artificial neural network is shown in Figure 6 [16, 23-24].

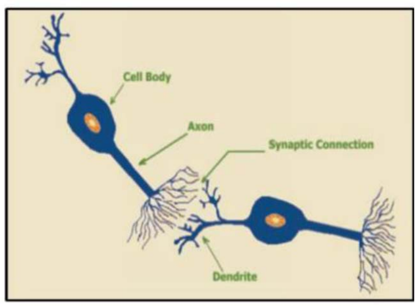

Figure 5—Human Neurons [16, 24]

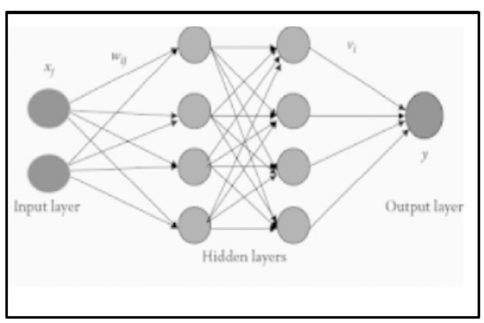

Figure 6—ANNs general architecture with hidden layers presenting input data, transfer function, and output value

Since wettability contact angle is vital factor in IOR applications, Zhang et. al. utilized advanced machine learning methods to predict the shale wettability contact angle based on laboratory parameters and the accuracy of the model was high [18].

Alhakeem, et. al. (2017 and 2017*), measured the Wettability using contact angle, the results was successfully captured using morphological analyses of the thin section (TS) imaging and artificial neural network was used for reservoir characterization where SEM-BSE was one of them. Better geological and petrophysical back-ground is involved with obtaining big data from 2D im-ages where accurate decisions made to describe wettability features (8, 15).

Al-Bazzaz utilized artificial neural network to predict permeability of a complex carbonate reservoir in Kuwait through several scales such as cores, logs, SEM-BSE, and thin section. It was conducted as supervised learning network with neural network called Multiple-Layer Feed-forward network with minimum error. [17].

Unsupervised machine learning method was explored on wettability contact angle preference by using K-Means clustering algorithm for 40X-SEM-BSE which represent thin section scale. The rock sample was Oolite from Kuwait reservoir [20].

In this study, the machine learning is a supervised regression where the target is the predicted recovery which is proposed for IOR techniques. It is based on the distribution of wettability contact angle in the reservoir which represents a pore scale level at 400X magnification where the input values are pore morphological features from the rock samples based on BSE-SEM technique.

Methodology

In the first part, the 27 core samples were selected, and these rock chips cover the whole vertical thickness of the selected carbonate reservoir as indicated in table 1. The image is captured using a Backscattered Electron detector- Scattered Electron Microscopy (BSE-SEM) imaging to characterize the morphology of the grains and pores boundaries in a 2D format. The morphology by angle of grain/ pore features is captured and then scanned using image analysis software to measure several pore morphological parameters as shown in Figure 2 [21], and it is considered as a big-data. The scope of work is shown in Figure 7.

In the second part, the ML model was build based on several steps which are: 1-Data loading and import necessary python (programming language) modules, 2- Read and visualize data, 3- Exploratory data analysis, 4- Data preprocessing, 5- Data cleaning, 6- Training a machine learning model, 7- Model deployment. The most time-consuming processes are exploratory data analysis, data preprocessing, and data cleaning.

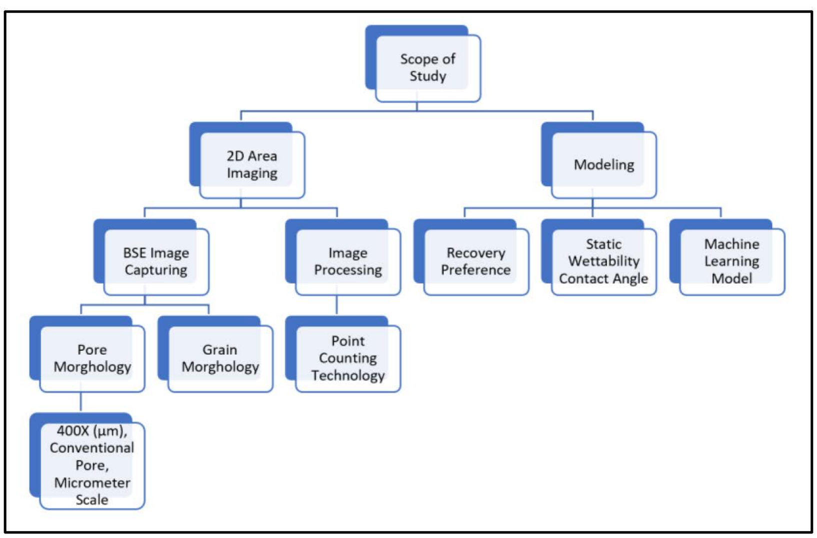

Figure 7—Scope of work

Data gathering and reprocessing

From the 27 core samples, the gathered data was with total number of 183737 rows and then based on wettability classes and distribution of wettability contact angles in all these sample it converted to 443 rows to be used for the model.

Statical analyses

After that, dataset is summarized in Table 4. It is used to understand the datasets and to know data distribution like average, median, percentile for different features. Also, a histogram is shown in Figure 8 for datasets to explore the distribution of data.

Table 4—Input parameters and statistics for 443 datasets in this study

					Percentiles		
Parameters	**Mean**	**Median**	**Minimum**	**Maximum**	**25th**	**50th**	**75th**
depth, ft	7792.96	7773.8	7684.2	7933.8	7720.2	7773.8	7854.4
Rock Type	3.6	3	1	7	2	3	5
Pore count	414.76	135	1	10600	68.5	135	235.5
Freq (pore count x Area sum)	6.06	0.859	1.04E-05	97.35	0.278	0.859	2
Area sum [um2]	2923.81	1669.5	4.29	128928	621.33	1669.5	2679.42
Area avg [um2]	30.12	10.5	0.621	2728	5.88	10.5	16.65
Perimeter [um]	13.88	11.8	0.299	201	7.32	11.8	17.1
hydraulic radius [um]	1.19	0.918	0.60194	15.93	0.843	0.918	1.11
Length [um]	5.11	4.97	0.835	24.7	3.495	4.97	6.46
Width [um]	3.11	3.04	0.724	14.3	2.375	3.04	3.78
Roundness	1.39	1.33	1	3.07	1.06	1.33	1.59
Aspect Ratio	1.67	1.67	1	2.41	1.56	1.67	1.79
Elongation	1.93	2.22	0.0747	3.41	1.82	2.22	2.5
Lgn.Prin.Long [um]	2.59	2.54	0.12	13.2	1.76	2.54	3.29
Lgn.Prin.Short [um]	1.24	1.28	0.0151	6.29	0.974	1.28	1.58
Equiv. diameter [um]	3.31	3.25	0.861	15.6	2.56	3.25	3.95
Angle [°]	173.48	180	0	360	90	180	270
Class	8.71	9	1	17	5	9	13

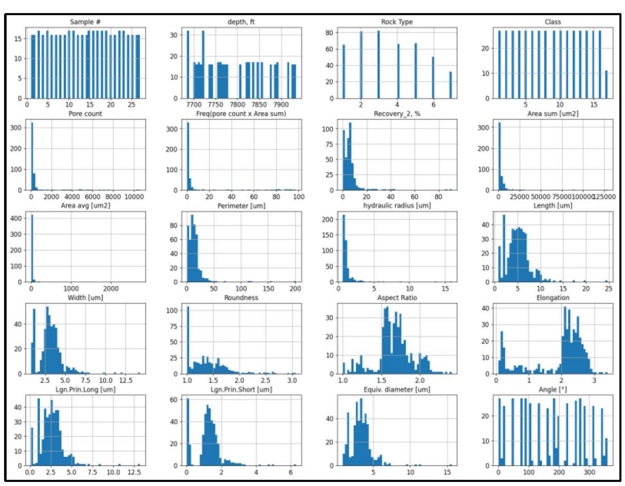

Figure 8—histogram of dataset

Data preprocessing

In this study, Standard Scaler is used as a data preprocessing technique. It is utilized in machine learning and data analysis to scale and standardize numerical features of a dataset. The aim of this function is to transform the data such that it has zero mean and unit variance. It is achieved by subtracting the mean from each data point and then dividing by the standard deviation, and the resulting transformed data will have a mean of 0 and a standard deviation of 1.

The formula for standardization using Standard Scaler can be described as follows in Equation 1 for a feature x:

$$z = \frac{(x - \text{mean})}{\text{standard deviation}} \tag{1}$$

Where z presents the standardized value of the feature, x presents the original value of the feature, mean presents the mean of the feature in the dataset, standard deviation presents the standard deviation of the feature in the dataset.

Correlation matrix and heat map are used to explore and visualize relationships between features and target as shown in Table 5 and Figure 9.

Table 5—Correlation matrix between features and target

Recovery, % (output)	1
hydraulic radius [um]	0.838
Area sum [um2]	0.829
Area avg [um2]	0.744
Freq(pore count x Area sum)	0.638
Perimeter [um]	0.625
Width [um]	0.424
Equiv. diameter [um]	0.406
Length [um]	0.383
Pore count	0.369
Lgn.Prin.Short [um]	0.358
Lgn.Prin.Long [um]	0.348
Roundness	0.294
Elongation	0.079
Sample #	0.003
Rock Type	-0.004
depth, ft	-0.005
Angle [°]	-0.146
Class	-0.147
Aspect Ratio	-0.169

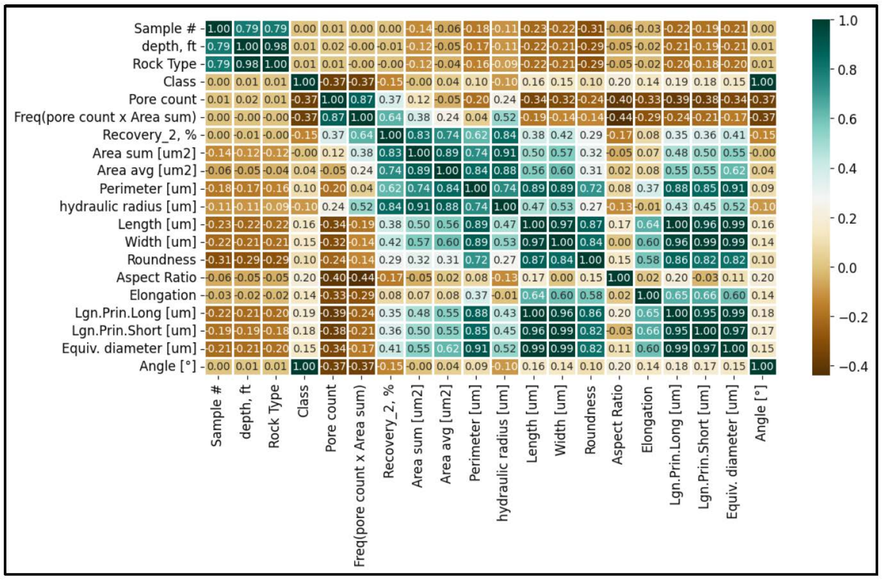

Figure 9—Heat map between features and target

Machine learning modeling

It is a supervised regression problem in order to predict recovery of each suggested IOR methods based on distribution of wettability contact angle distribution in the pore media while the input features are pore morphological features from the rock based on BSE-SEM technique.

Splitting the dataset is essential for an unbiased evaluation of prediction performance. It occurred by defining what is the proportion of data to be included in train and test of datasets. It was split the dataset such that the train set has 75% and the test set has 25% data.

Several models were conducted based on different algorithm such as Multi-Linear Regression (as base case), K-Neighbors, Support Vector Machine (SVM), decision tree, Random Forest, Xgboost (extreme Gradient Boosting), and Artificial Neural Network (ANN).

K-Nearest Neighbors (KNN) is a simple algorithm that predicts the target value based on the majority class of its K nearest neighbors. It is non-parametric and suitable for small to medium-sized datasets.

Support Vector Machine (SVM) finds the best hyperplane to separate data points of different classes while maximizing the margin. It is effective in high-dimensional spaces and can handle linear and nonlinear classification problems.

Decision Tree is a tree-like structure where each node represents a decision based on a feature. It is easy to interpret but prone to overfitting for deep trees.

Random Forest is an ensemble of decision trees that improves accuracy and reduces overfitting through majority voting.

Extreme Gradient Boosting (Xgboost) is an advanced gradient boosting framework that efficiently combines decision trees for high predictive accuracy and handling large datasets.

Artificial Neural Network (ANN) is a computational model inspired by the structure and functioning of the human brain's neural networks. It is a deep learning model that consists of interconnected nodes (neurons) organized into layers: an input layer, one or more hidden layers, and an output layer. ANNs can learn complex patterns and representations from data, making them highly effective. They are trained using optimization algorithms such as gradient descent to minimize the error between predicted and actual values.

These algorithms offer different strengths and are widely used in various applications based on their unique characteristics and performance.

A hyperparameter tunning for models was conducted for Random Forest, decision tree, Xgboost, and Artificial Neural Network. It was done via Randomized-Search-CV for both models where K-folds were used. The value of K-folds was 5 in this study. For ANN number of epochs was controlled.

K-fold cross-validation is a popular technique used in machine learning to evaluate and validate the performance of a model on a limited dataset. K-fold cross-validation is a valuable tool in machine learning for assessing model performance, selecting models, and tuning hyperparameters. It ensures that the model is evaluated thoroughly and fairly, leading to more reliable and generalized models that perform well on unseen data. Figure 10 shows a flowchart of machine learning process in this study.

ANN model structure is based on input layer which contains the similar number of inputs (number of neurons), two hidden layers with 64 neurons in each layer, and the output layer a single neuron. The activation function used is Rectified Linear Unit (ReLU) while the number of epochs is optimized. It uses the Adam optimizer to update the weights of the neural network during training. Also, it utilizes mean squared error (MSE) loss function to minimize the error between predicted and true values during training.

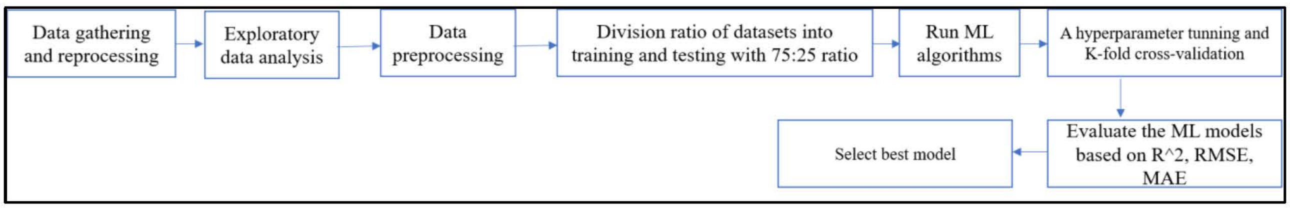

Figure 10—Flowchart of machine learning process for this study.

Evaluation of machine learning models

The evaluation error metrics for regression algorithms that had been utilized in this study are shown below in the equations. They are implemented to evaluate machine learning (ML) models and assess the accuracy of the ML models. They are indicated in Equation 2, 3, and 4.

The Mean Absolute Error (MAE) is the measure of errors between given pair of observations of the x and y axes, and lower values of MAE show a better fit in the training and testing model. Root Mean Squared Error (RMSE) is the average measure of squares of individual errors by taking its root. R^2 Score is known as coefficient of determination. A high R^2 value generally represents a good model i.e., equal to 1.0, and a low R^2 value means a model that does not fit well. Where n, Co_i, Co_i^*, and $\overline{CO}$ refers to overall data points, the measured recovery values, the predicted recovery, and the average recovery values, respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Co_i - Co_i^*)^2}{\sum_{i=1}^{n}(Co_i^* - \overline{Co})^2} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Co_i - Co_i^*)^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Co_i - Co_i^*}{Co_i}\right| \tag{4}$$

Results and Discussion

Table 6 and figure 11 is conducted to assess the predictive performance of machine learning models based on evaluation metrics which are mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2).

Table 6—Evaluation of ML models

		K-Neighbors	SVR	Linear Regression	Random Forest	Decision Tree	XGBoost	ANN (e=100)	ANN (e=10)
Train set	MAE	2.097	1.802	1.950	0.743	0.309	0.002	1.329	3.082
	RMSE	4.128	3.463	2.879	2.676	0.621	0.003	1.949	4.817
	R^2	0.782	0.847	0.894	0.909	0.995	1.000	0.835	0.515
Test set	MAE	1.886	1.426	1.983	1.024	1.083	0.790	1.079	2.651
	RMSE	2.638	2.153	3.074	1.650	1.528	1.216	1.565	3.805
	R^2	0.697	0.798	0.589	0.882	0.898	0.936	0.969	0.794

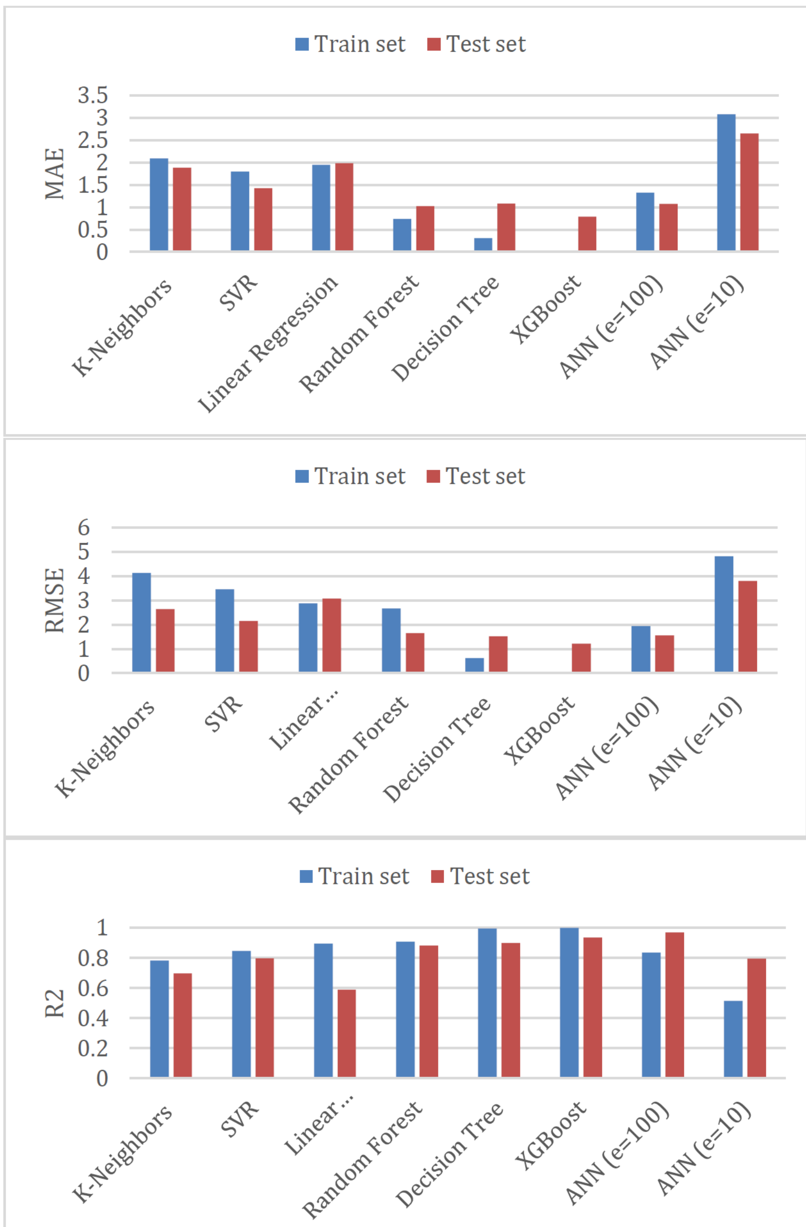

Figure 11—Evaluation of ML models based on bar plot

It is clear that from the investigation, Xgboost and decision tree models higher R^2 and lower values of RMSE and MAE and thus, they provide acceptable accuracy for both test and train set for machine learning model. The higher accuracy is for the Xgboost model, through which overfit and underfit issues are overcome. ANN model with 100 epochs could be used as a third option but the accuracy based on train set is slightly low, but it shows highest accuracy for test set. However, multi-linear regression and k-nearest neighbors demonstrate lower accuracy which may lead to underfit problems.

ANN model with acceptable epochs is shown in Figure 12 to minimize the chosen loss function. Furthermore, the cross plot is presented in Figure 13 between the predicted and experimental recovery (ground truth) for ANN model for test set.

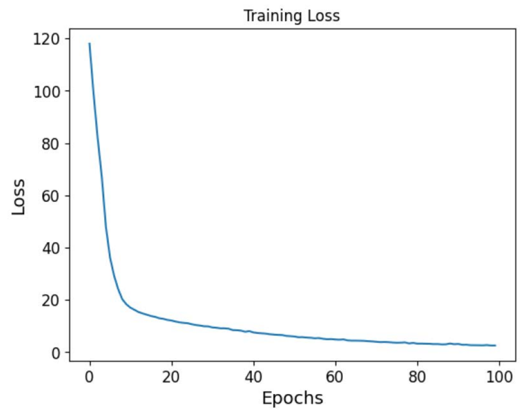

Figure 12—Optimized number of epochs to minimize the loss function

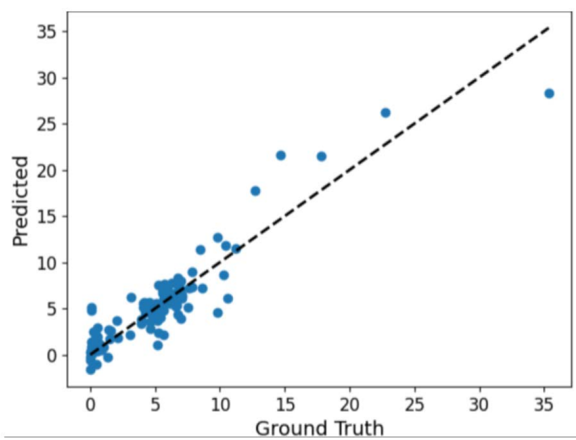

Figure 13—Cross plot between the predicted and experimental recovery for ANN model for test set

The cross plot is illustrated in Figure 14 and Figure 15 between the predicted and experimental recovery for Xgboost and decision tree models for test set. Figure 16 shows the matching outcomes between predicted and experimental recovery for Xgboost model, and it represents well matching. Therefore, it suggests optimum reliability, accuracy, and performance, so that the Xgboost model is recommended for modeling the recovery based on wettability contact angle distribution in the studied carbonated reservoir. The features impotence is explored in Figure 17 which is based on coefficients for the selected model Xgboost, and it depicts that perimeter and hydraulic radius have more impotence among other features.

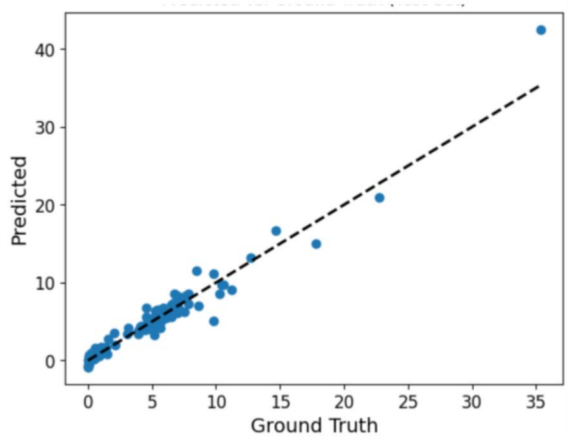

Figure 14—Cross plot between the predicted and experimental recovery for Xgboost model for test set

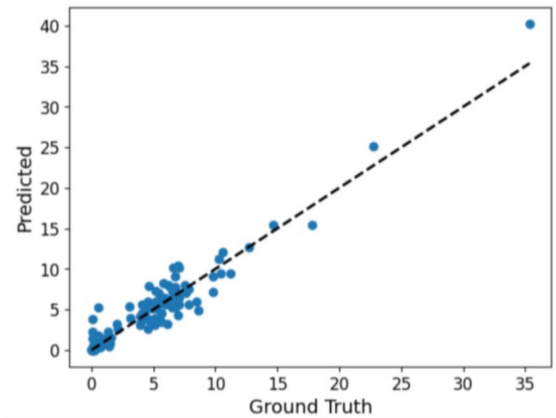

Figure 15—Cross plot between the predicted and experimental recovery for decision tree model for test set

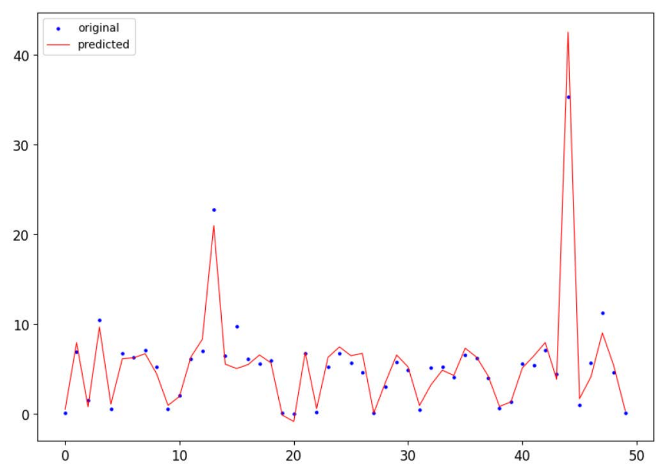

Figure 16—Matching results between predicted and experimental (original) recovery for Xgboost model on test set

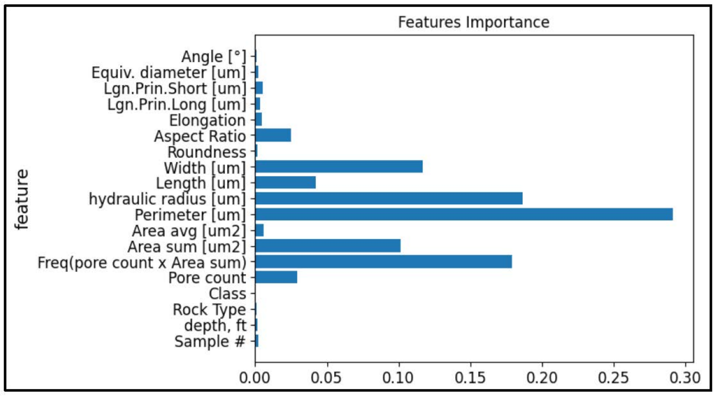

Figure 17—Features impotence based on coefficients for Xgboost model

Conclusions

A supervised regression is utilized as a machine learning to forecast the recovery of each offered IOR methods based on wettability contact angle distribution in the carbonate reservoir. The input values are pore morphological features from the rock based on Backscattered Electron Microscope Backscattered Electron BSE-SEM technique. It represents a pore scale level at 400X magnification.

All regimes of IOR are available but with different proportions of recovery so that understanding their distribution within the reservoir will help in reservoir characterization and management. Hence, a good development plan can be constructed.

Based on machine learning model evaluation, the optimum model is that with acceptable accuracy from higher value of and lower value of mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2). Therefore, Xgboost, decision tree, and ANN models provide the requirement of acceptable model accuracy. Xgboost offers the highest accuracy while the ANN model offers the acceptable accuracy as third option.

The Xgboost model is advised for estimating the recovery based on wettability contact angle distribution in the investigated reservoir since it suggests optimum reliability, accuracy, and performance.

The intelligent models utilized in this study are only suitable for datasets with similar features so the models had some limitations.

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