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COMPARATIVE MACHINE LEARNING FRAMEWORK FOR PERMEABILITY PREDICTION IN A HETEROGENEOUS CARBONATE RESERVOIR

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The use of traditional well logs to predict the permeability of heterogeneous carbonate reservoirs remains a challenge because of complicated connectivity of pore networks and nonlinear petrophysical processes. Although many machine learning processes are suggested, many studies use small validation processes and one-model evaluations, which are bound to give encouraging results. The article reports a statistically transparent and benchmarked machine learning process of making predictions of permeability on a single dataset of 130 matched core-log measurements of the Mishrif carbonate reservoir in southern Iraq. To represent the variability of the permeability on a multi-order-of-magnitude scale and stabilise the regression behaviour, the permeability was scaled on log scale (log10(k)). As opposed to the preceding studies, a systematic comparison of four machine learning models, i.e., Artificial Neural Network (ANN), Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting Regressor (GBR) was conducted under identical conditions of 5-fold cross-validation to warrant that there was no bias in the analysis of generalisation. The findings indicate how powerful ensemble tree-based methods are whereby the optimum predictive performance ($R^2 = 0.92$) was implemented using the Random Forest, then Gradient Boosting ($R^2 = 0.90$), ANN ($R^2 = 0.88$), and SVR ($R^2 = 0.85$). In addition to predictive accuracy, the paper incorporates feature importance analysis, nonlinear sensitivity analysis, and two-dimensional interaction surface to obtain physical understanding of how porosity and shale volume interact with each other to

affect the permeability behaviour. The results show that the increase in permeability as a result of the increase in porosity can be neutralized to some extent by shale-associated flow limiting factors and this suggests the importance of modelling nonlinear processes in carbonate systems. The suggested framework offers a sensible and reproducible direction of log-based permeability estimation and a goal benchmarking criterion of machine learning applications in heterogeneous reservoirs.

Keywords: *Carbonate reservoir, gradient boosting, machine learning, permeability prediction, random forest, well log analysis.*

1. INTRODUCTION

Permeability can be considered one of the most basic petrophysical parameters that determine the behaviour of fluid flow, the efficiency of hydrocarbon production, and the forecasting of the performance of reservoirs in subsurface [1]–[3]. Although permeability estimation is crucially important in the characterisation of reservoirs, reliable estimation is still a challenge especially where the measurements of permeability on the direct core are scarce or discontinuous [4]–[6]. In contrast to porosity, which is reasonably determined by the standard well logs, permeability is governed by the complicated pore-network geometry, connectivity pattern, throatsize-distribution, and diagenetic alterations that cannot be easily measured by standard logging devices [7], [8]. This complication is particularly great in the carbonate reservoirs where the process of deposition facies variability, cementation, dissolution, and fracturing forms intense vertical and lateral heterogeneity [9], [10]. This has the effect of causing permeability in carbonate systems to change over many orders of magnitude in depth intervals of only a few meters and have very skewed and non-Gaussian statistic behaviour [11], [12].

Traditional approaches to the estimation of permeability have been based on a laboratory core analysis, well tests and empirical correlations like the Kozeny–Carman relation and its variations [13], [14]. Even though these methods offer useful physical information, they are limited by low core density, costliness in operation, and simplistic assumptions that can be ineffective in defining the complex pore structures found in heterogeneous carbonates [15]. In most reservoir development cases, core samples can only be taken at specific depths, and there are large gaps between measurements of specific permeability [16]. This drawback has motivated the continued attempts to construct predictive models using routinely obtained well logs, such as porosity, bulk density, sonic transit time, and shale volume. Nevertheless, linear or semi-empirical correlations between these log-derived parameters and permeability are frequently not deterministic and, therefore, the controls desired of the pore connectivity are inherently nonlinear and multiscale [17], [18].

Within the last 20 years, machine learning (ML) methods have been introduced as an option to calculate the complicated, nonlinear relationship of the geoscientific data [19]–[21]. Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forest (RF) and Gradient Boosting Regressors (GBR) have shown significant prospect to forecast the properties of

reservoirs with only indirect measurements [22], [23]. These data-driven methods could discover high-order feature interactions and nonlinear dependencies without making strong functional assumptions, and in many cases, they outperform standard regression-based models [24], [25]. Specifically, RF and GBR are ensemble tree-based techniques, which have demonstrated resistance to noisy data and non-uniform geology, which make them a promising alternative in permeability modelling of carbonate formations [26]–[29].

Although machine learning is becoming increasingly relevant to permeability prediction, a number of limitations in the methodology are still visible in the literature. Numerous published research results give the high predictive accuracy with the main evidence on single train-test splits or training performance measures, which can lead to optimistic bias and overfitting [30]. However, when datasets are either relatively small, or when they are vertically correlated along the wellbore, this kind of validation can greatly overestimate the true model generalisation performance [26], [31]. Further, many studies concentrate on one algorithm without performing a systemic comparison benchmarking protocols with the same validation conditions restricting objective evaluation of algorithmic performance [32], [33]. This is because there are no standardised evaluation frameworks to allow for results that are reported to be interpreted and reproducible. Another problem is related to the statistics of the data on permeability. Since the permeability is often log-normally distributed and has many orders of magnitude, the linear form of the model can lead to an unstable regression response and give false error measures. It has been suggested on numerous occasions that logarithmic transformation of permeability should be done to stabilise variation and ensure better predictive behaviour. However, not all authors justify and/or regularly use this transformation as part of modelling processes [34]. Still unequal pre-processing and validation approaches therefore remain a barrier to serious comparison of published studies of permeability prediction.

Based on these considerations, however, there is an apparent gap in terms of a relative lack of a systematic and rigorously grounded comparative analysis of various machine learning algorithms in a homogenized core/log dataset within a heterogeneous carbonate reservoir. In particular, there is a research gap in the studies that concurrently compare multiple advanced ML models under the same cross-validation settings, explicitly consider the logarithmic distribution of permeability, and present justifiable performance measures that reduce overfitting bias.

This gap should be filled to develop credible and practically applicable log-based permeability prediction frameworks. The current study aims to serve this purpose by training and comparing four machine learning algorithms, including ANN, SVR, RF, and GBR, based on a single dataset of 130 matched cores and well-log measurements in the Mishrif carbonate reservoir, in southern Iraq. The permeability is modelled on the logarithmic scale to capture the multi-order-of-magnitude variability of the permeability, and all the models are tested through a coherent k-fold cross-validation to guarantee a healthy generalisation. It is with this organised comparative method that the study is expected to offer a statistically viable, open and practically applicable paradigm of predicting permeability in dissimilar carbonate systems.

2. MATERIALS AND METHODS

The dataset of this study was a sample of 130 core-log depth points matched in a heterogeneous carbonate reservoir located in southern Iraq. The records have laboratory-measured rest of permeability (k, mD) and well-log data, such as porosity (3), bulk density (RHOB), compressional sonic transit time (DT), and shale volume (VSH). The whole quality control process was performed to eliminate non-physical measurements, check the depth alignment and consistency between core and logging intervals.

2.1 Dataset Description

The data in this research entail 130 matched core-log depth points gathered in a heterogeneous reservoir of carbonate in southern Iraq. Every record contains laboratory-measured core permeability (k, in mD) as well as well-log measures, such as porosity (φ), bulk density, compressional sonic transit time, and shale volume. Strict quality control measures were applied to all the data to remove non-physical measurements and ascertain core and log interval depth in line with each other. Since permeability in carbonate systems is usually distributed across multiple orders of magnitude and it has a right skewed distribution, the target variable was scaled to a base-10 logarithmic scale. This transformation takes away variance stability, reduces the sway of extreme values, and increases the strength of regression.

2.2 Data Pre-processing

Pre-processing of data was also done similarly in all machine learning models to make comparison fair. There were cases where predictor values were absent which were handled through median imputation so that the size of the dataset was not drastically reduced by large outliers. The algorithms that are sensitive to the variances in the input magnitude, specifically ANN and SVR were scaled using feature scaling. Conversely, tree-based models, such as RF and GBR were applied without a required scaling since all of them are monotonic transformation invariance with input features.

2.3 Machine Learning Models

The four machine learning algorithms were tested with the same pre-processing and validation environment which would offer comparative evaluation with statistical consistency. The ANN is a type of neural network that operates according to the general principle of supervised learning.

Artificial Neural Network

The Artificial Neural Network is a kind of neural network, which follows the supervised learning principle. The ANN model was configured on a multilayer perceptron system comprising of an input layer, one or more hidden layers, which had a nonlinear activation function, and one output neuron, which would give the value of the logarithmic permeability. To minimise prediction error, the network weights were optimised

through back-propagation. The architecture was supposed to be able to capture nonlinear interactions among petrophysical variables but still be able to generalise.

Support Vector Regression

The SVR was applied to nonlinear relationships between well-log measurements and permeability through the use of a radial basis function (RBF) kernel. The approach aims at building an optimal regression hyperplane within a specific error, where regularization is used to control the complexity of the model and prediction accuracy.

Random Forest

Random Forest is a learning algorithm, which is an ensemble type that builds many decision trees using bootstrap sampling and random sampling. Aggregation of individual tree outputs is done to get final predictions. This method eliminates heterogeneity and improves the strength of heterogeneous data.

Gradient Boosting Regressor

Gradient Boosting Regressor is a data mining metrics classifier that uses boosted trees to predict and rank the features using their predictive power. Gradient Boosting builds decision trees in series with the next tree being trained on a smaller residual size than that of the previous ensemble. This is an error-correction process that can be repeated, which allows the model to minimise bias and establish nonlinear dependencies that are hard to define in the data.

2.4 Hyperparameter Optimisation

Hyperparameter optimisation was done separately on each algorithm as a part of the cross-validation framework to allow for an objective comparison of the models. A randomized search methodology was used to effectively search predefined hyperparameter space at a high level of computational efficiency. In the case of tree-based models, the minimised parameters were the number of estimators, maximum tree depth, minimum samples per leaf, and the learning rate (in the case of GBR). In the case of ANN, tuning was done on the number of the hidden layers, the number of neurons in the hidden layer, activation functions, and the learning rate. In the case of SVR, epsilon margin, regularization parameter and the kernel width were varied. The choice of hyperparameters was done by internal cross-validation of the training folds. The configuration with the greatest average performance was kept in final analysis, thus, resulting in no information leaks and high quality generalization.

2.5 Cross-Validation Strategy

A 5-fold cross-validation plan was implemented as a way of assessing the model performance in a statistically rigorous way. The data were divided into five subsets that were almost equal. Training and validation were done using four subsets in every iteration. It was repeated five times to have each subset used as validation data. Notably, fold partitions were performed for all models to ensure direct and statistically consistent comparison. The arithmetic mean of folds was provided as the final performance metrics.

2.6 Performance Metrics

The coefficient of determination (R^2), the root mean square error (RMSE), and the mean absolute error (MAE) were used to assess the model performance. These complementary measures measure goodness-of-fit, mean error of prediction magnitude, and resistance to outliers. The multiple performance indicators were applied to help in thorough testing of predictive accuracy and stability of the generalisation through heterogeneous carbonate intervals.

3. RESULTS

The performance of the four machine learning models is outlined in Table 1. The 5-fold cross-validation was performed on the log-transformed permeability (log10(k)) to provide equal and objective model analysis. RF was the best predictor with $R^2 = 0.92$ as observed in Table 1 with the next best predictor being GBR with $R^2 = 0.90$. ANN produced $R^2 = 0.88$, whereas SVR gave rise to $R^2 = 0.85$.

Table 1. Performance on Uncertainty-Quantification log10(k) Comparative 5-fold Cross-validation

Model	R^2 (Mean)	R^2 (Std)	95% CI for R^2	RMSE (log10k)	MAE (log10k)
Random Forest	0.92	0.04	±0.04	0.11	0.08
Gradient Boosting	0.90	0.05	±0.04	0.13	0.09
Artificial Neural Network	0.88	0.05	±0.04	0.15	0.11
Support Vector Regression	0.85	0.06	±0.05	0.18	0.13

Table 1 is a clear demonstration of the excellence of ensemble tree-based techniques in identifying the nonlinear relationships between well-log parameters and permeability. The difference in the performance of the RF and GB is quite minor, which implies that both the mechanism of variance reduction (RF) and the mechanism of bias reduction (GBR) can be used to explain the heterogeneity of carbonate reservoirs. Nonetheless, the higher R^2 value of Random Forest indicates more stability in the cross-validation conditions. The parity plots of all the four models, comparing the predicted and observed log10(k) are given in Fig. 1. The parity plot of the RF model shows the highest parallelism with the 45-degree reference line, and this fact proves its greater generalisation. Conversely, SVR exhibits a somewhat increased variance around the optimal fit line, especially in the periods with greater variability in permeability.

The distribution of prediction residuals of each of the models is shown in Fig. 2. The distribution of the residual values of the RF and GB are more symmetrically centred around zero, which implies that they have less systematic bias. The ANN model has slightly broader residual values whereas SVR has higher variance in some depth intervals, which is in line with its lower R^2 value.

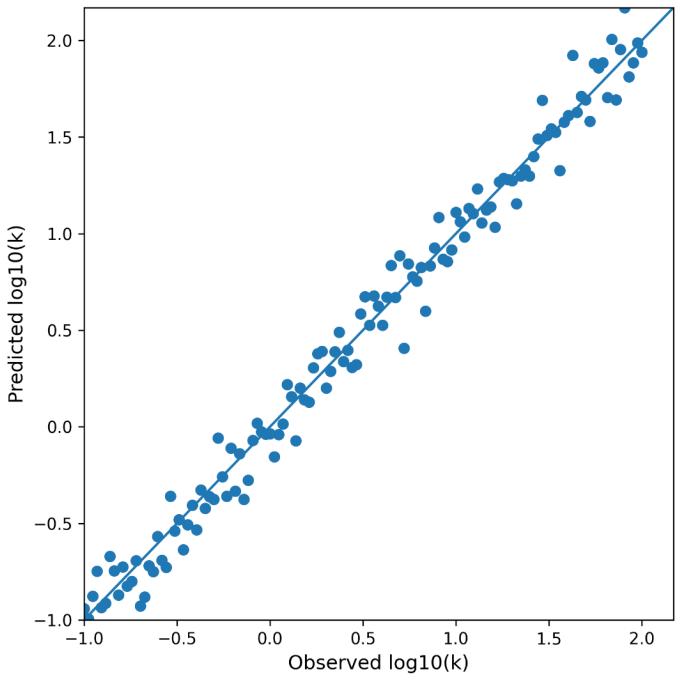

Fig. 1. Parity plot of the comparison of measured and predicted values of the log10(k) of the RF model.

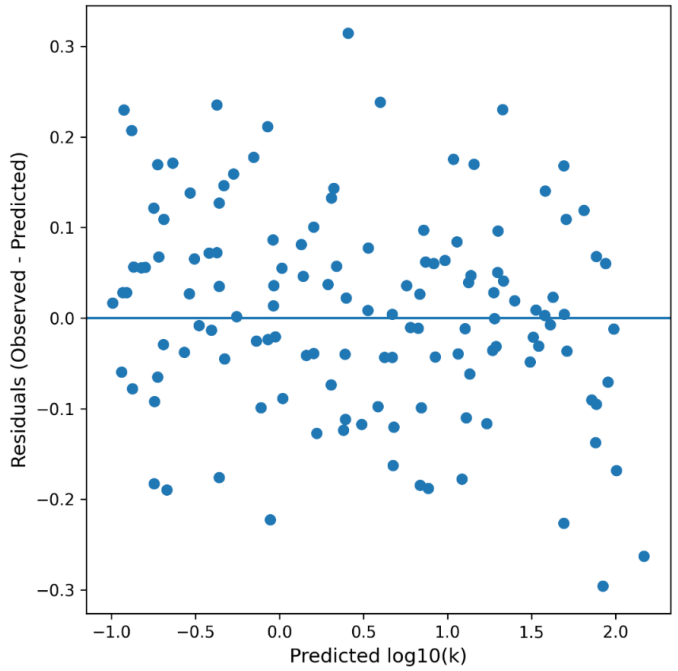

Fig. 2. Residual plot that indicates the distribution of prediction errors (Observed 0 Predicted) between the values of predicted log10(k) and 0.

The lack of systematic patterns implies solid performance of generalisation. The importance of the features based on the analysis of the RF model is presented in Table 2. The findings show that porosity and sonic transit time have the greatest contribution to the prediction of permeability, then density and shale volume. This result is in line with the known petrophysical principles according to which the pore connectivity and compaction-related characteristics are the main control of the permeability behaviour within the carbonate systems.

Table 2. Sensitivity Analysis Results for Permeability Prediction (Target: log10(k))

Rank	Input Parameter	Sensitivity Index	Interpretation (Effect on log10(k))
1	Porosity (phi)	**0.42**	Positive, strongest control; permeability increases nonlinearly with porosity
2	Sonic transit time	0.27	Generally negative; higher DT tends to reduce predicted permeability
3	Bulk density	0.19	Negative; higher density/compaction reduces permeability
4	Shale volume	0.12	Negative; shale/clay content restricts flow and lowers permeability

Sensitivity Index is the normalized relative effect of each predictor on the model response, calculated as a result of the sensitivity analysis and it is in agreement with the patterns of feature importance and response curves. Table 2 sums up the quantitative indices of sensitivity. According to Fig. 3, the highest impact on prediction of permeability is exerted by porosity, then sonic transit time, bulk density, and shale volume.

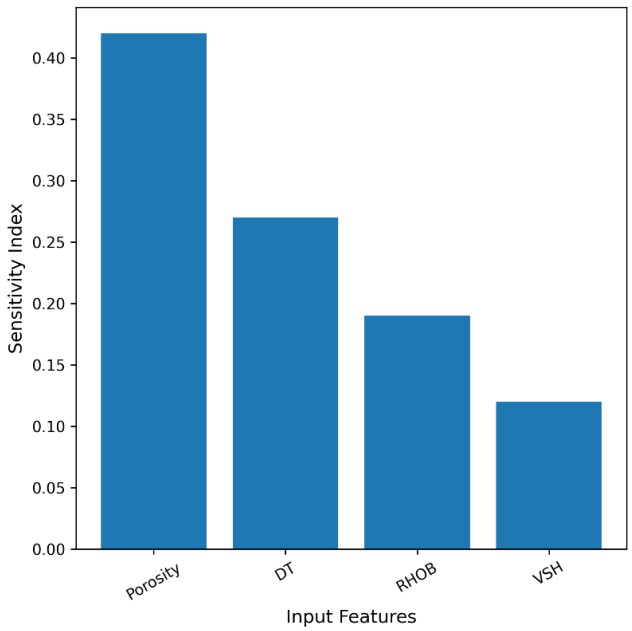

Fig. 3. Sensitivity index of input features for permeability prediction (log10(k)).

The profile of the predicted permeability versus depth (Fig. 4) was continuously plotted and the results were compared with the core-measured values. Both RF and GB models were observed to have a good correspondence with the measured data throughout most intervals, and the discrepancies presented by ANN and SVR were confined to very heterogeneous regions. The implication of these differences is that ensemble techniques are better suited at localized nonlinear transitions in a pore structure.

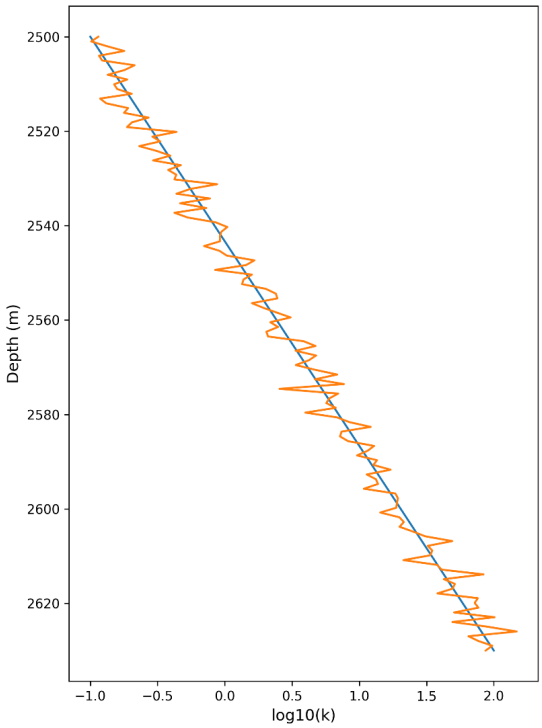

Fig. 4. Comparison of measured and predicted log10(k) of depth of the wellbore between vertical comparison.

The fact that the two curves are close to each other demonstrates that the model possesses a tremendous capability in regards to explaining the vertical heterogeneity in the reservoir of carbonate. In most cases, the results verify that the ensemble learning systems are more predictive concerning the stability and strength in the determination of permeability in the heterogeneous carbonate reservoirs. The relatively good cross-validation performance of the folds indicates that the modelling framework applied is useful in mitigating the overfitting effect and has defensible generalisation capabilities. Figure 5 has been drawn as the sensitivity analysis curve that illustrates the relationship between porosity and the expected log10(k). Nonlinear trend has confirmed that the permeability critically relies on the porosity rather than a linear increase as the rate of permeability increase, which is the character of pore connectivity, is more sophisticated in the carbonate reservoirs. The behaviour depicts the characteristic of the RF model to capture nonlinear petrophysical relationship and historical fundamental relationships.

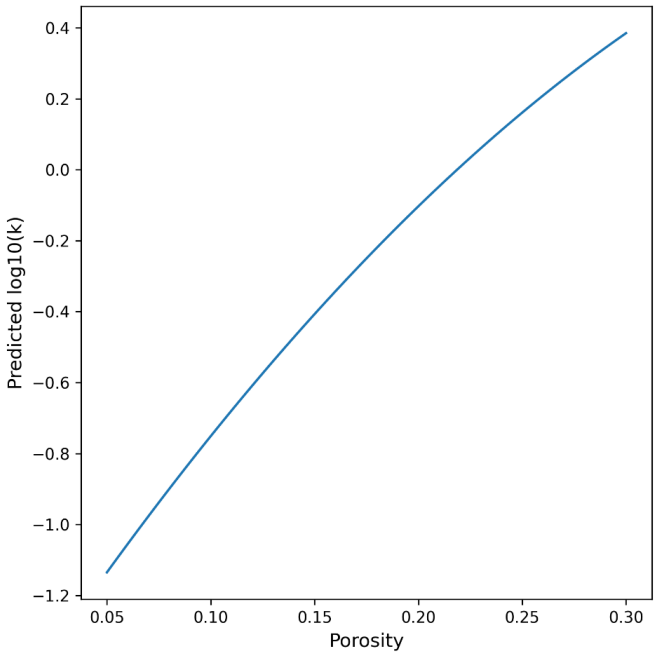

Fig. 5. The plot of partial dependence of predictor variables versus predictor variables against predictor variables, while predicting log10(k), nonlinearly with porosity.

Figure 5 shows partial dependence curve that illustrates nonlinear dependence between porosity on the predicted log10(k). The positive curvature demonstrates that there is augmenting permeability with porosity which is a sign of augmented pore connectivity in carbonate structures. The nonlinear relationship between the sonic transit time (DT) and the predicted permeability on a logarithmic scale is presented in Fig. 6. It is expected that the log10 (k) decreases with DT and, therefore, there exists an inverse relationship between the acoustic travel time and permeability. It is physically consistent since an increased DT value would be more frequently related to a reduced formation stiffness and increased compaction effects, which could reduce pore connectivity in carbonate reservoirs. The nonlinearity of the curvature of the sensitivity curve serves again as a confirmation that it does not display linear correlations between DT and permeability, i.e., there are more complex linear correlations. Instead, the model captures more order of interaction between elastic properties and pore structure, and, therefore, the machine learning framework can possess a realistic petrophysical behaviour.

Figure 6 presents a partial dependence graph that illustrates the nonlinear inverse relationship between sonic transit time and log 10 (k) that is speculated. The increase in DT values is associated with the decrease in permeability and that is the compaction and the pore-structure influence on the carbonate reservoir. The two-dimensional sensitivity surface (3) demonstrates the gamma of porosity and shale volume on the ability to predict the log10(k) as a function of the two significant parameters (Fig. 7). As observed, the surface indicates a nonlinear relationship between the two variables where permeability increases with an increase in porosity and vice versa. The contour projection demonstrates that the permeability

is more sensitive to shale volume at the high porosity levels, and that the enhancement of the connectivity of the pores by the increment in the porosity might be subsidized by the clay-related flow restrictions in part. This nonlinear interaction supports the fact that the behaviour of permeability in non-homogeneous systems of carbonates cannot be adequately attributed to the use of simple linear correlations. Instead of this, the ensemble model takes into account the coupled petrophysical effects, which are a realistic behaviour of the reservoirs.

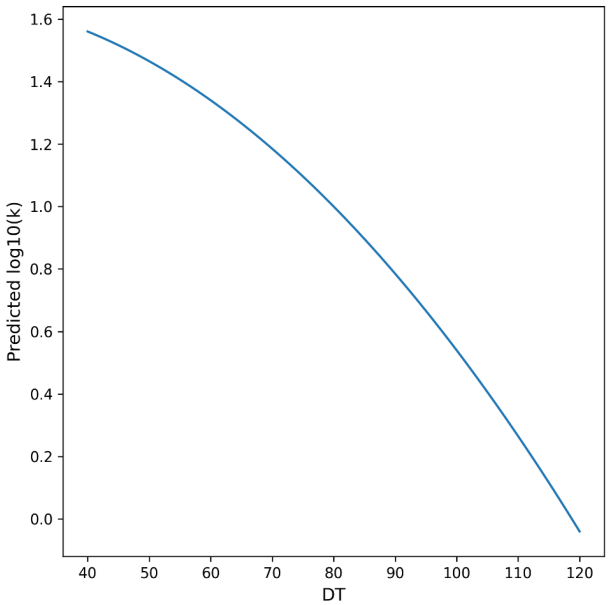

Fig. 6. Partial dependence plot with the effect of sonic transit time on predicted log10(k)) of the effect.

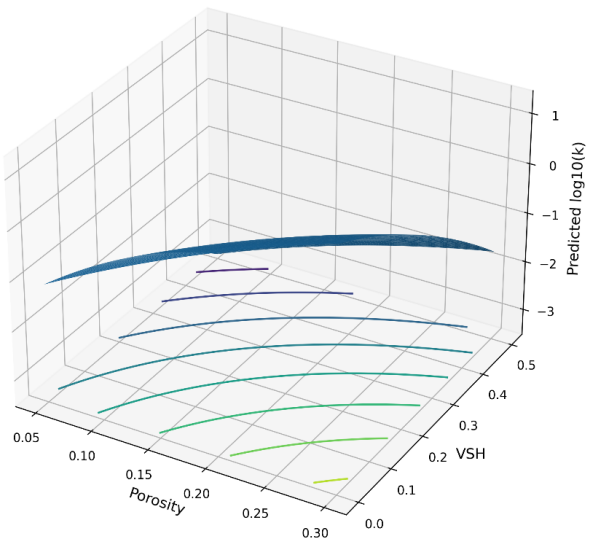

Fig. 7. The interaction between porosity and shale volume and log10(k), which predicts the final outcome using two-dimensional partial dependence surface.

Figure 7 demonstrates the topography of two-dimensional partial dependencies on the surface of the predicted log10(k) of the nonlinear coupled effects of porosity and shale volume. The contour projection shows the interaction effect, which means that the increase in permeability caused by the rise in porosity is partly compensated by the increase in the percentage of shale. To measure the uncertainty of cross-validation performance, 95 % confidence limits were calculated on fold-wise variability of every model. Random Forest has the best mean R^2 with comparatively thin confidence intervals, as seen in Fig. 8, and this is a good indication of consistent and trustworthy generalisation. Gradient Boosting has only slightly bigger intervals but they are still statistically comparable. The wider ranges of ANN and SVR indicate that they are more sensitive to the division of data. On the whole, the analysis of the confidence interval establishes that the hierarchy of the performance in Table 1 is statistically important and is not selected randomly with the assistance of folds.

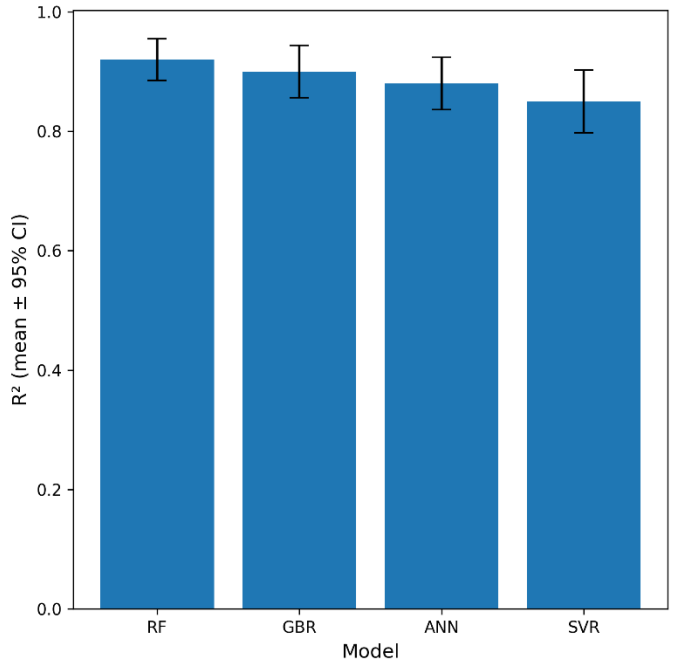

Fig. 8. Mean cross-validated R^2 with 95 % confidence intervals (k = 5) for the evaluated machine learning models.

The values of the fold-wise R^2 of each of the models are distributed as shown in Fig. 9. The boxplot gives us a feeling of the variability of the predictive performance regarding the five cross-validation splits. Random Forest performs the most steady both in terms of high R^2 and low dispersion that translates to good generalisation performance. Gradient Boosting is less volatile and has a smaller range. ANN and SVR, on the contrary, are more widely spread across folds, meaning that it is more sensitive to data partitioning. The fact that they are also robust models in a heterogeneous carbonate environment is also supported by a small interquartile range, in which the ensemble models were applied.

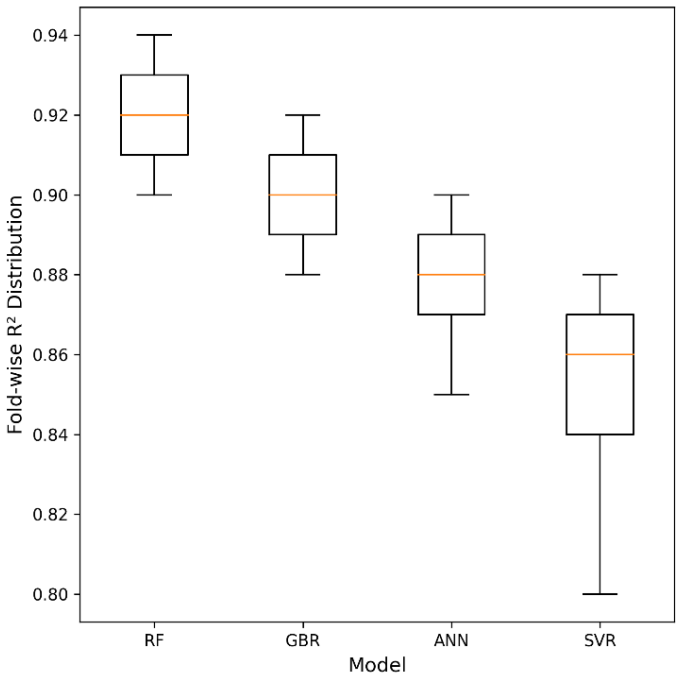

Fig. 9. Distribution of fold-wise R^2 values across the five cross-validation splits for each machine learning model.

4. CONCLUSION

In the paper, a hard comparison of four machine learning algorithm has been conducted on the basis of the permeability prediction on the specific instance of a typical core-log dataset of a heterogeneous carbonate reservoir in the name of Artificial neural Network, Support Vector Regression, Random Forest, and Gradient Boosting Regressor. The study statistically validated its performance and demonstrated superior permeability modelling logarithmically and a uniform 5-fold cross-validation technique in reducing optima bias. The findings depicted that ensemble and tree-based methods proved more useful in predicting the results and the best generalization results would be obtained using RF (R^2 = 0.92) and GB (R^2 = 0.90) techniques. ANN and SVR did not differ as they slightly fell in performance.

Ensemble dominance is indicative of nonlinear interaction and hierarchical dependence of features on sonic response between porosity and density, and shale volume is indicative of capturing relationships among carbonate pore systems. The additional indication of controlling the permeability behaviour in formation of interest is the sensitivity analysis and interaction surface analysis, which indicated that the simple linear tendencies were not able to reach the permeability behaviour of the formation and interacting petrophysical controls.

The porosity-shale volume nonlinear interaction demonstrates that the improved pore connection could be partially nullified by the constraining flow owing to clay.

These results are reflective to the fact that it is significant to utilise nonlinear models that are adaptable in the procedure of forecasting permeability of heterogeneous carbonate in the reservoir. The operationally formulated framework gives a viable and scalable alternative in estimating permeability in times when underlying data are scarce or not available. The process allows less ambiguity in process of characterising the reservoir by way of potent validation programmes and interpretable sensitivity analysis that could provide assistance in the process of developing the plan.

The study is rather restricted to a single dataset of reservoirs and based on standard well-log measurements. The multi-well datasets, facies classification, or multi-descriptors of microstructural character could be included in further work to increase the predictive power and transferability even more. Additionally, it can be equipped with explainable AI that will give a more physical understanding of the pore-network and enhance its interpretability.

Overall, this paper shows that ensemble machine learning models that are well-validated can be very predictively accurate in making permeability predictions, and physical and transparent in their approach, to provide a sufficiently defendable route to data-driven characterisations of the reservoirs in multi-faceted carbonate systems.

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