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Development of Empirical NMR Log-Derived Permeability Correlations Using Gaussian Process Regression and Robust Support Vector Machine Technique

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Abstract

Performing petrophysical analysis using the conventional well logs alone in poorly sorted sandstones identified with intercalated clay leads to poor prediction. Nuclear Magnetic Resonance (NMR) logging is an innovative technology for a better formation evaluation with wireline logging. However, the conventional Schlumberger Doll Research (SDR) and Timur–Coates models for predicting rock properties from NMR logs often overestimate or underestimate the permeability owing to the difficulties confronted while determining the exact model parameters. In this study, empirical permeability correlation is proposed using the Gaussian Process Regression (GPR) and Support Vector Machine (SVM). Forty NMR T_2 spectrums and 89 logarithmic mean NMR T_2 distributions (T_{2lm}) were pre-processed and screened and key spectra were identified using the Principal Component Analysis (PCA). To develop the correlations, 80% of the data were selected randomly, 50% of which were used for training and testing over a total of ten different kernel functions. The result revealed the squared exponential-based kernel GPR (R^2 = 1.0 and RMSE = 2.1512e^{-4}), and the Cubic based kernel SVM (R^2 = 0.97 and RMSE = 2.7393e^{-2}) as the best model. In comparison with the Artificial Neural Network, SDR, and Timur-Coates models, the GPR model exhibited superiority and therefore recommended.

Keywords: *Permeability; Nuclear Magnetic Resonance; Supervised Machine Learning.*

1. Introduction

Rock permeability is an important reservoir property that determines fluid movement and overall deliverability. Its distribution within the reservoir is an indication of heterogeneity which determines the ease with which fluids move in a porous media [1-2]. Permeability distribution within the reservoir is related to many factors including porosity, grain size, degree of sorting, cementation, and other geological events. In most formations, the average permeabilities are relatively high, but low permeabilities are found in shale strata which are usually responsible for the low sweep efficiencies. Traditionally, the permeability field can be measured through laboratory cores analysis under high confining pressure and from well test analysis [3]. Permeability obtained from cores can provide accurate values; the method is however limited technically by poor reservoir coverage [3-4].

Both the well test and core analyses methods are cost-ineffective and consume time compared to other methods [5]. Since almost all the oil and gas wells are logged from where parameter such as porosity are derived, the common practice involves the development of a statistical relationship between the well logs porosity and the laboratory-derived permeability [6-7].

Past studies have applied this technique to predict absolute permeability [8-11]. Despite many successes recorded from applying this technique in sandstone and carbonate reservoirs, the method fails to accurately predict the permeability using the conventional well log data in heterogeneous and anisotropic reservoirs.

The modern approach for improved permeability prediction from well logs, therefore, involved the use of continuous logs such as the Nuclear Magnetic Resonance (NMR) log which can predict petrophysical boundaries more accurately than the conventional well logs [12]. There are two ways by which permeability is predicted using the NMR log data. The first was focused on the average pore size determination known as the Schlumberger Doll Research (k_{SDR}) model (Eq. 1) and another which dependent on the irreducible water saturation, the Timur–Coates (k_{TC}) model (see Eq. 2) [13]. Both methods require T_2 distribution spectra.

$$k_{SDR} = a \times (\phi_{\mathrm{NMR}})^{m_1} \times \left(\mathrm{T}_{2_{\mathrm{lm}}}\right)^{n_1} \quad (1)$$

$$k_{TC} = \left(\frac{\phi_{\mathrm{NMR}}}{b}\right)^{m_2} \times \left(\frac{BVM}{BVI}\right)^{n_2} \quad (2)$$

where *a, b,* m_1, m_2, n_1, and n_2 are the empirical proportionality constants and can be determined statistically, ϕ_{NMR} is the NMR porosity (*pu*), $\mathrm{T}_{2_{\mathrm{lm}}}$ is the logarithm mean T_2, BVM, and BVI are the bulk volume movable and bulk volume irreducible respectively.

In the absence of core samples, *a, b,* m_1, m_2, n_1, and n_2 can be assigned 10, 10, 4, 2, 4, and 2, respectively [14]. In both cases, the T_2 distribution spectra are converted to a single variable, $\mathrm{T}_{2_{\mathrm{lm}}}$ or $\frac{BVM}{BVI}$ ratio the process which ignored the complexity and possible singular relationship of each spectrum with the pore throat that governs the resistance to fluid flow [15]. By this assumption, the existing correlations failed to accurately predict the permeability and there is a need for an alternative correlation for permeability prediction from NMR logs.

Several soft computing techniques including artificial neural networks and genetic algorithm adaptive network-based fuzzy inference systems have been proposed for identifying and forecasting parameters in petroleum engineering. Rostami *et al.* utilized six smart methods, the neuro-fuzzy inference system, radial basis function, genetic programming, multilayer perceptron, least-square support vector machine, and committed machine intelligent systems, to predict the permeability of fractured carbonate reservoir [16]. Gene expression programming and group method of data handling techniques were also proposed by Mahdaviara *et al.* [17] for permeability prediction from well logs [17-18]. In all these methods, accurate predictions were reported over the traditional correlations.

Much recently, the Gaussian Process Regression (GPR) has attracted significant interest in data modelling. The method was reported as an effective tool in developing empirical models for property estimation and predictions [19]. This method was preferred for addressing regression problems because it requires fewer data samples in comparison with the ANN [20]. It can describe inputs – output nonlinear relationships more accurately and can as well model uncertainties in the data. Consequently, it is commonly used in energy, meteorology, and reservoir modelling [21]. Also, the recent development in artificial intelligence has produced the Support Vector Machine (SVM). SVM is a machine learning theory originally developed for pattern recognition problems based on the structural risk reduction principle. The method is deeply rooted in Vapnik-Chervonenkis theory and as a result exhibits superiority over the other traditional learning methods [22]. The focus of this study is to examine the potential of GPR and SVM in predicting reservoir permeability using the NMR log data and compare the result with the ANN.

2. Machine learning techniques

The conceptual description of the proposed machine learning methods for the development of empirical correlation for permeability prediction is given in this section.

2.1. Gaussian process regression

Gaussian Process (GP) is classified as a non-parametric regression technique popularly deploys for classification problems. In this method, random variables are combined in linear form [23].

The name Gaussian process regression (GPR) comes from one of the applications of GPs through supervised machine learning. The kernel parameterization of this regression can be thought of as kernelized Bayesian linear regression, where the choice of covariance/kernel function, as well as the data used to make predictions, dictate the kernel parameterization [23-24]. To develop predictive models such as permeability using this technique, let us consider *n* number of the training set of NMR T_2 spectra with input $x \in R^n$ and output $y \in R$, in this case, the permeability. The Gaussian process can be represented using the mean and covariance functions as:

$$y^* \sim \mathcal{GP}\big(\mu(x), K(x,x')\big) \quad (3)$$

where $\mathcal{GP}$ denotes the Gaussian Process; $\mu(x)$ represents the mean function being the expected value of y^* at the point *x* as given in Eq. (4) and $K(x,x')$ is the kernel function which describes the confidence level of the $\mu(x)$ as expressed in Eq. (5).

$$\mu(x) = \boldsymbol{E}[f(x)] \quad (4)$$

$$K(x,x') = \boldsymbol{E}\big[\big(f(x) - \mu(x)\big)\big(f(x') - \mu(x')\big)\big] \quad (5)$$

If we assume normally distributed random variables, the mean function becomes zero and only the kernel function is considered. Many covariance functions had been reported in the literature [25-26]. Table 1 shows the selected covariance functions that this study evaluated in the proposed GPR for permeability prediction.

Table 1. Selected GPR Kernel Functions and their Mathematical Expressions [24]

Kernel type	Mathematical expression
1. Squared Exponential	$K(x,x') = \boldsymbol{\sigma}_f^2 exp\left[\frac{-r}{2}\right]$
2. Matern 5/2	$K(x,x') = \boldsymbol{\sigma}_f^2\left(1 + \sqrt{5r} + \frac{5r}{3}\right) exp\left[-\sqrt{5r}\right]$
3. Ornstein-Uhlenbeck (Exponential)	$K(x,x') = \boldsymbol{\sigma}_f^2 exp\left[-\sqrt{r}\right]$
4. Rational Quadratic	$K(x,x') = \boldsymbol{\sigma}_f^2\left(1 + \frac{1}{2\alpha l^2}(x - x')^T(x - x')\right)^{-\alpha}$

$$r = \frac{|x - x'|^2}{l^2} \quad (6)$$

where $\boldsymbol{\sigma}_f$ represents the noise and *l* denotes the length-scale of the process; α stands for the standard deviation of the noise fluctuations. Both parameters are called hyperparameters that control the activity of the GP.

The covariance will be decreasing exponentially with an increase in the distance between the input parameters. The expected permeability function value (y^*), denotes the prior gaussian joint distribution given the input (T_2^*) which is calculated using Eq. (7).

$$y^*|y \sim N\left(\bar{f}^*, cov\,(f^*)\right) \quad (7)$$

where $\bar{f}^*$ stands for the mean prediction value that gives the best estimate of f^*. The $cov\,(f^*)$ is a covariance that indicates uncertainty.

The parameter $\bar{f}^*$ in Eq. (7) is the mean prediction which relates to the target, *y*. The parameter, $cov\,(f^*)$ is the variance which is independent of the target but depends only on the inputs according to Eq. (8).

$$\begin{pmatrix} y \\ f^* \end{pmatrix} \sim N\left(\begin{pmatrix} \mu(x) \\ \mu(x_*) \end{pmatrix}, \begin{bmatrix} K(x,x) + \boldsymbol{\sigma}_n^2 \mathrm{I} & K(x,x_*) \\ K(x,x) & K(x_*,x_*) \end{bmatrix}\right) \quad (8)$$

where, $K(x,x)$ and $K(x_*,x_*)$ denote covariance matrix/kernel of the training and testing dataset, respectively. $K(x_*,x_*)\ is\ N \times N^*$ Covariance matrix obtained from training and testing data, $K(x^*,x)$. Eq. (9) is the marginal likelihood over function, f^*.

$$P(f^*|X,y,x_*) \sim N\left(\bar{f}^*, cov(f^*)\right) \quad (9)$$

2.2. Support vector machine (SVM)

Regressive SVM for prediction involves mapping onto a higher feature space F of a low-dimensional input space *x* using an estimation function expressed as follows:

$$f(x) = \boldsymbol{\omega}.\emptyset(x) + \boldsymbol{b} \quad (10)$$

where, $\emptyset$ represents the higher feature space F; $\boldsymbol{\omega}$ and b denotes weight and bias terms, respectively and can be estimated by minimizing the risk function:

$$R(C) = \frac{1}{2}\|\boldsymbol{\omega}\|^2 + C\frac{1}{l}\sum_{i=1}^{l} L_\varepsilon\big(y_i, f(x_i)\big) \quad (11)$$

$$L_\varepsilon\big(y_i, f(x_i)\big) = \begin{bmatrix} |y_i - f(x_i)| - \varepsilon & |y_i - f(x_i)| \geq \varepsilon \\ 0 & |y_i - f(x_i)| < \varepsilon \end{bmatrix} \quad (12)$$

where $L_\varepsilon\big(y_i, f(x_i)\big)$ denotes the ε-insensitive loss function; ε represents the radius of the tube situated around the regression function, and C the constant represents the trade-off between the training error and the performance.

The flatness of the function $L_\varepsilon\big(y_i, f(x_i)\big)$ is determined by the term $\frac{1}{2}\|\boldsymbol{\omega}\|^2$. By including slack variables, ξ and ξ* into Eq. (11), the optimization problem is stated as:

Minimize

$$\emptyset(\boldsymbol{\omega}, \xi, \xi^*) = \frac{1}{2}\|\boldsymbol{\omega}\|^2 + C\sum_{i=1}^{l}(\xi + \xi^*) \quad (13)$$

Subject to

$$\begin{cases} y_i - \boldsymbol{\omega}.\emptyset(x) - \boldsymbol{b} \leq \varepsilon + \xi_i & \xi_i \geq 0 \\ \boldsymbol{\omega}.\emptyset(x) + \boldsymbol{b} - y_i \leq \varepsilon + \xi^* & \xi_i^* \geq 0 \end{cases}$$

This is resolved using the Lagrangian of the form:

Maximize

$$\beta(\alpha, \alpha^*) = -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i - \alpha_i^*)\big(\alpha_j - \alpha_j^*\big)K\big(x_i, x_j\big) + \sum_i^l y_i(\alpha_i - \alpha_i^*) - \varepsilon\sum_i^l(\alpha_i + \alpha_i^*) \quad (14)$$

Subject to

$$\sum_{i}^{l}(\alpha_i - \alpha_i^*) = 0 \qquad 0 \leq \alpha_i, \quad \alpha_i^* \leq C$$

both $\alpha_i$and α_i^* are Lagrangian multipliers. The SVM function can therefore be stated as:

$$f(x) = \sum_i y_i(\alpha_i - \alpha_i^*)K(x_i, x) + \boldsymbol{b} \quad (15)$$

where, $K(x_i, x)$ is the kernel function that equals $\emptyset(x_i)\emptyset(x_i^*)$. The necessary calculations are made directly in the input space without the explicit map $\varphi(x_i)$ with the kernels. In this paper, six SVM kernel functions were examined as presented in Table 2.

Table 2. SVM Kernel functions [27]

SVM Type	Kernel Function	Narrative
1. Radial Basis Function (RBF)	$K(x_i, x) = \exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2}\right)$	σ denotes one class learning class kernel width. The widths $\frac{\sqrt{\sigma}}{4}$, $\sqrt{\sigma}$, and $4 \times \sqrt{\sigma}$ are used for fine, medium, and coarse kernels, respectively.
2. Linear Function	$K(x_i, x) = x_i^T x$	2- class learning.
3. Polynomial Function	$K(x_i, x) = \left(x_i^T x + 1\right)^\rho$	ρ, the order of the polynomial

3. Methodology

3.1 Data collection

A total of 21 core plugs were selected from one well in Field X of the Niger Delta Basin. The rationale for selecting these plugs was premised on the identified lithology, sedimentary structures, and range of petrophysical data such as porosity (22.3-23.7%) and permeability (23.7-5950 mD). Forty (40) H transversal relaxation NMR spectra (T_2) were acquired at both saturated (S_w=100%) and irreducible saturation (S_{wi}) states. Each of the T_2 spectra consisted of 89 data points that made up a total of 3560 datasets. The porosity, φ, and logarithmic mean of NMR T_2 spectra (T_{2lm}, ms) were obtained from NMR logs after the necessary hydrocarbon correction was done [14, 28]. The values of BVM and BVI were also calculated from NMR logs using appropriate $T_{2cutoff}$ according to Wei *et al.* [29] and Mao *et al.* [14]. The traditional permeabilities (k_{TC} and k_{SDR}) from NMR logs were then estimated using Eq. 1 and Eq. 2 (from the subsequent section) after appropriate calibration.

3.2. Data processing

Each of the T_2 spectra collected was preprocessed by adjusting the phases and the odd echoes (noise) were eliminated from the dataset using Matlab R2020a. The redundant input variables (columns) were expunged thereby leaving behind the active ones. These outliers could be from incorrect measurement and failure to remove them can impact negatively the prediction quality. The T_2 spectra with too much missing data were also removed. A similar operation was applied to the rows to remove the redundancy of 6 rows from the initial 89 rows.

3.3. Principal component analysis

A very large network size caused by a large number of independent variables increases the processing time and causes model overfitting [30]. To overcome this difficulty, Principal Component Analysis (PCA) available in the SPSS v26 software was performed for variables screening or size reduction. The correlation matrix option in the SPSS was activated and 22 T_2 spectra were screened using the Eigenvalues criteria.

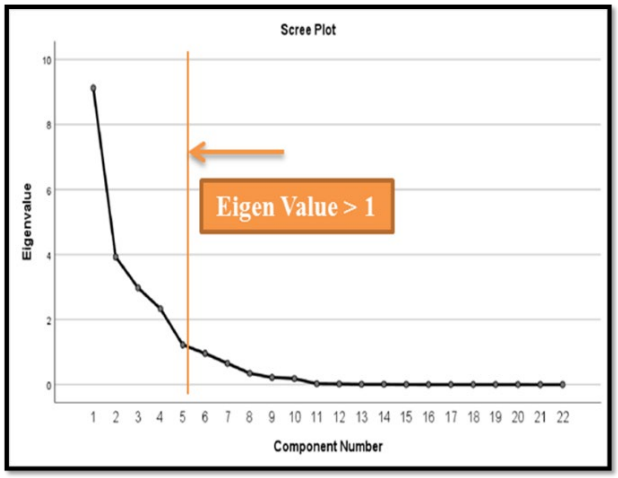

Figure 1 shows the selected component with Eigenvalues greater than 1. For the normalization process, the varimax rotation method was selected and applied due to its viability for large datasets. To construct the GPR and SVM models, the main steps involved are summarized as shown in Figure 2. Data preparation involved data partitioning, training, and validation. 80% of the data were selected randomly, 50% of which was used each for training (40%) and testing (40%). The remaining 20% was used for statistical analysis.

Figure 1. Selected T_2 Spectra with Eigen value greater than 1

3.4. Statistical analysis

The proposed NMR-based permeability correlation (GPR and SVM) and existing correlations including the SDR, Timur Coates, and Artificial Neural Network for Field X Niger Delta were comparatively evaluated to determine its competence and applicability. The statistical parameter used for this evaluation is presented in Table 3. The lower calculated errors and appreciable correlation coefficients are indicative of a strong relationship between the predictor and response variables.

Table 3. Statistical evaluation metrics [8,31]

Metrics	Mathematical expression
Absolute deviation (AD)	$\frac{1}{N}\sum_{i=1}^{N}\left(k_{Pred}-k_{Exp}\right)$
Average absolute deviation (AAD)	$\frac{1}{N}\sum_{i=1}^{N}\left\|k_{Pred}-k_{Exp}\right\|$
Root mean square error (RMSE)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(k_{Pred}-k_{Exp}\right)^2}$
Maximum error (E_{max})	$E_{max}=\mathrm{Max}\left\|E_i\right\|$
Standard deviation (SD)	$\frac{1}{N-1}\times\sum_{i=1}^{N}E_i^2$; * $E_i=\frac{k_{Pred}-k_{Exp}}{k_{Exp}}\times 100$

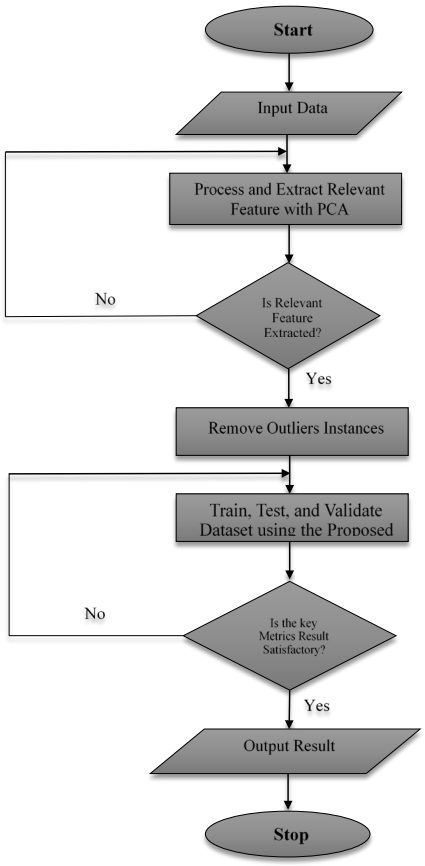

Figure 2. Workflow for the proposed GPR and SVM models

4. Result and discussion

4.1. Effect of kernel function on permeability prediction

Both SVM and GPR models' performance is determined by their kernel functions (see Table 1 and Table 2). The simulation results of each of the kernel functions are summarized in Table 4 and Table 5, respectively. From the SVM prediction results, the cubic kernel function of the SVM model outperformed all the other kernel functions. The R^2, RMSE, MSE, and MAE obtained for the Cubic kernel function of SVM are 0.97, 0.16551, 0.0274, and 0.1229. On the other hand, from the GPR prediction results, the squared exponential kernel function gave the best prediction performance with R^2, RMSE, MSE, and MAE of 1.00, $2.1512e^{-4}$, $4.6276e^{-8}$ and $1.4700e^{-4}$, respectively. In addition, the training time and prediction speed are a function of the workstation configuration as well as the kernel method. In order to have a visualized format of the simulation process from all the 10 kernel functions from the two machine learning techniques, the plot of the predicted permeability against the true permeability is presented in Figure 3 (SVM models) and Figure 4 (GPR models).

Table 4. SVM performance metrics

SVM kernel	RMSE	R^2	MSE	MAE	Prediction speed (Obs/sec)	Training time (sec)
Linear	0.91962	0.0700	0.8457	0.6891	~2200	5.2706
Quadratic	0.38824	0.8300	0.1507	0.2509	~1600	4.8778
Cubic	0.16551	0.9700	0.0274	0.1229	~1600	9.3677
Fine Gaussian	0.89765	0.1100	0.8058	0.6405	~1300	2.2071
Medium Gaussian	0.57367	0.6400	0.3291	0.3541	~1000	1.8800
Coarse Gaussian	0.87051	0.1700	0.7578	0.6407	~1600	1.4848

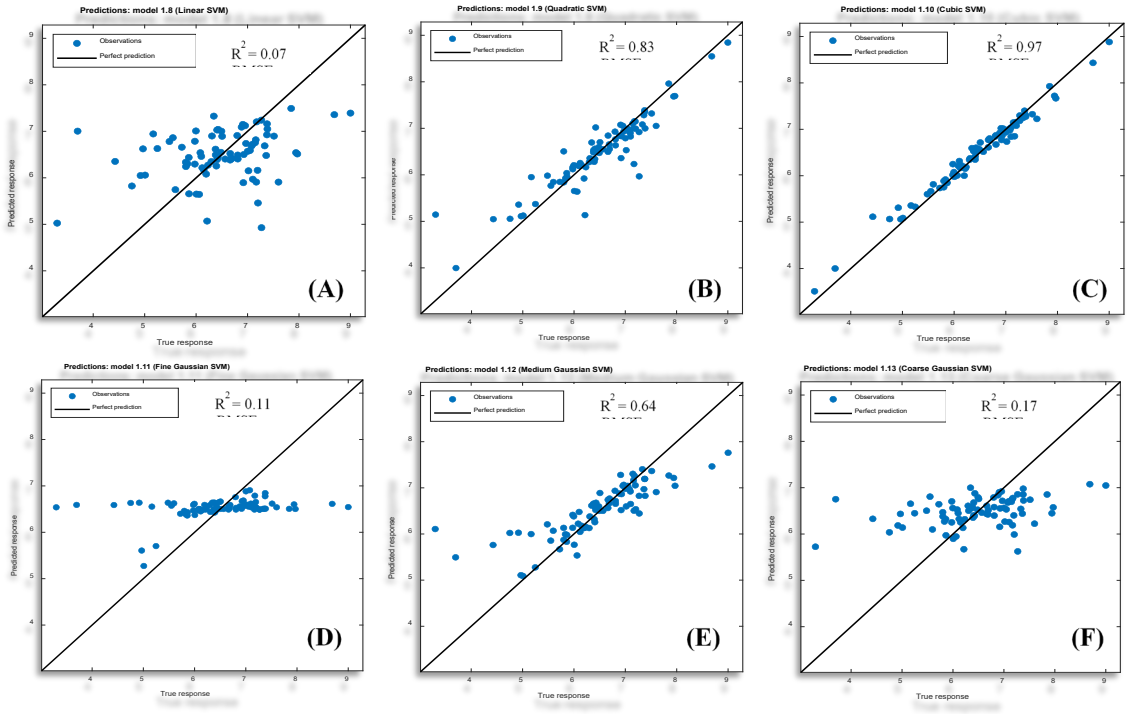

Figure 3. Prediction vs true Responses of the SVM models

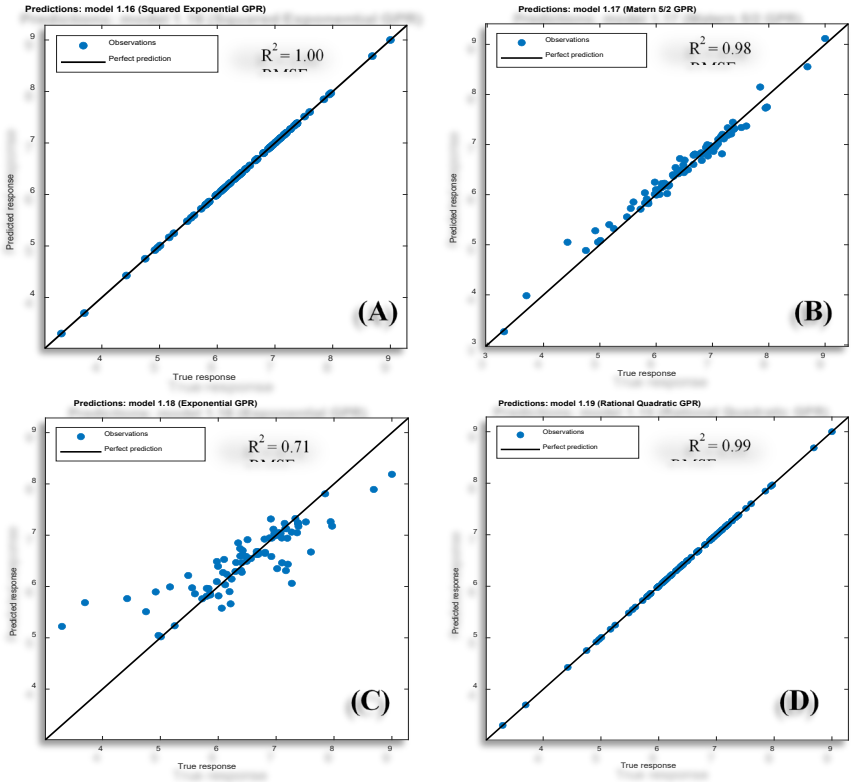

Figure 4. The GPR correlation prediction vs core permeability

Table 5. GPR Performance metrics

GPR Kernel	RMSE	R^2	MSE	MAE	Prediction speed (Obs/sec)	Training time(sec)
Squared Exponential	$2.1512e^{-4}$	1.0000	$4.6276e^{-8}$	$1.4700e^{-4}$	~3000	1.8365
Matern 5/2	$1.6770e^{-3}$	0.9800	$2.7812e^{-6}$	$1.1054e^{-3}$	~5000	2.5028
Exponential	0.5178	0.7100	0.2681	0.32912	~3000	1.3563
Rational Quadratic	$2.1518e^{-4}$	0.9999	$4.6302e^{-8}$	$1.4706e^{-4}$	~2900	2.4053

4.2. Model validation

Twenty-one (21) new T_2-distribution dataset that was not included in the previous training process was used for establishing the validity of the developed GPR, and SVM models. The prediction performance of these models was compared with the conventional SDR and Timur-Coates correlations.

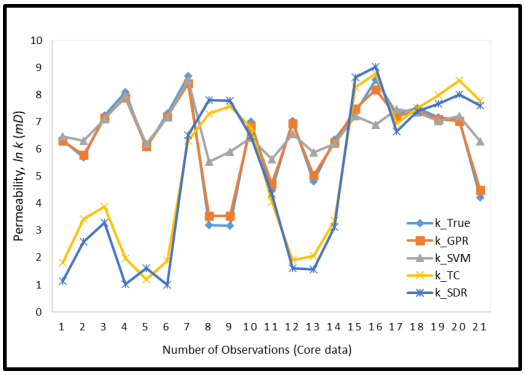

Figure 5. Permeability prediction comparison plot

Figure 5 shows the graph of the predicted permeability field on a logarithmic scale relative to the core data. The GPR model (R^2 = 0.999) exhibited the best performance as the predicted values are in close proximity with the actual core data. The SVM (R^2 = 0.98) prediction on the other hand shows some degree of deviation from the core data. It is obvious that the Timur-Coates and SDR correlations performed poorly on the permeability estimation in this study.

4.3. Performance evaluation

Table 6 presents the result obtained when the performance of the squared exponential-based kernel GPR and the cubic-based kernel SVM were evaluated using a new set of datasets (20% of acquired data) outside those used in developing them. The two correlations agreed more perfectly with the experimental data judging by the R^2 value, AD, AAD, AAPRE, SD, and Emax when compared with the predictions from the ANN, Timur-Coates, and SDR models. However, the GPR model exhibited the best performance and can be said to be the most reliable for predicting permeability. Both the feed-forward ANN model proposed by Olayiwola [31] for the same dataset and the cubic SVM investigated in this study also produced results that are far better for permeability prediction than the conventional Timur-Coates and SDR models. Similar to the observation made by Olayiwola the conventional methods always tend to underestimate or overestimate the reservoir permeability in most cases.

Table 6. Statistical comparison with ANN, TC, and SDR models

Measure	This study (SVM)	This study (GPR)	Olayiwola [??] (2017) (ANN)	Timur-Coates Model [??]	SDR model [??]
AD	0.3159	$-4.955e^{-12}$	0.020	-1.3169	-1.5724
AAD	0.6816	0.1636	0.620	2.7953	3.0740
RMSE	1.0573	0.1961	1.510	3.5021	3.8619
SD	26.563	4.4842	6.100	66.991	209.05
E_{max}	77.155	12.014	6.090	139.24	637.88
AAPRE	14.467	3.1058	6.600	49.949	124.23

4. Conclusion

NMR is the most advanced and efficient way for formation evaluation which provides an accurate calculation of Petrophysical properties. Estimation of permeability in oil reservoirs is the key to reservoir quantification. Through empirically supervised machine learning techniques such as Gaussian Process Regression (GPR), Support Vector Machine (SVM), and Artificial Neural Networks (ANN) amongst several others, the permeability of a reservoir can be predicted. From the results obtained in this study, it can be concluded that the prediction of permeability from NMR logs using empirical GPR correlation presents a good alternative to the conventional SDR and Timur-Coates models. The developed squared exponential kernel function-based GPR correlation performed better than the SVM model and show a very high accuracy when compared with the ANN method.

Declaration of competing interest

The authors declare that they have no known competing interests.

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