Uncertainty-Aware Reservoir Permeability Prediction using Gaussian Processes Regression and NMR Measurements

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Abstract

This study investigates the challenges of permeability prediction in reservoir engineering, focusing on addressing uncertainties inherent in the data and modelling process, and leveraging Nuclear Magnetic Resonance (NMR) log data from the Northern Sea Volve field. The study uses a probabilistic machine learning method called Gaussian Process Regression (GPR) with different kernels, such as Matern52, Matern32, and Radial Basis Function (RBF). LSboost, K-nearest neighbour (KNN), and XGBoost are some of the existing models that are used for comparison. Performance metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), and coefficient of determination (R^2) are utilized for assessment. Additionally, the uncertainty associated with different GPR kernels is analyzed, and confidence intervals are generated to provide insights into model behaviour. The inclusion of confidence intervals enhances interpretability by quantifying the range within which the true permeability value is likely to fall with a specified level of confidence, offering valuable information for decision-making processes in reservoir engineering applications. Findings demonstrate the effectiveness of GPR with Matern52 and Matern32 kernels in permeability prediction, offering competitive performance and robust uncertainty quantification. This research contributes to advancing reservoir engineering by providing a comprehensive and uncertainty-aware approach to permeability prediction.

Keywords

Gaussian process regression, permeability prediction, uncertainty quantification, reservoir engineering, NMR logs

ACM Reference Format:
Ahmad Lawal, Yingjie Yang, Nathanael L Baisa, and Hongmei He. 2024. Uncertainty-Aware Reservoir Permeability Prediction using Gaussian Processes Regression and NMR Measurements. In *2024 The 8th International Conference on Advances in Artificial Intelligence (ICAAI 2024), October 17–19, 2024, London, United Kingdom.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3704137.3704145

ICAAI 2024, October 17–19, 2024, London, United Kingdom

ACM ISBN 979-8-4007-1801-4/24/10
https://doi.org/10.1145/3704137.3704145

1 Introduction

Permeability stands as a pivotal parameter in reservoir characterization, offering crucial insights into the transmission capacity of oil and gas from subsurface formations. Accurate prediction of reservoir permeability holds paramount significance in the field of reservoir characterization, directly impacting the efficient extraction of oil and gas resources [3]. The ability to precisely assess how fluid flows through subsurface formations is instrumental in optimizing reservoir management strategies, well placement, and overall production performance. It is a critical factor for making informed decisions in the oil and gas industry, influencing economic feasibility and environmental sustainability. However, obtaining a precise measurement of permeability poses a formidable challenge. The most accurate methodologies, such as core analysis and well testing, are both time-consuming and financially demanding. To overcome these limitations, well logs become indispensable, serving as a means to extrapolate relationships from core analysis data for predicting uncored intervals and wells. Subsequently, machine learning algorithms can be trained to forecast permeability based on these derived relationships [8, 15, 18, 24]

Nevertheless, the data sourced from well logs is inherently susceptible to various uncertainties originating from acquisition, processing, interpretation, and environmental factors[5, 30]. Furthermore, these datasets may exhibit incomplete coverage of the geographical domain, introducing potential biases. Consequently, a model trained on such data may excel in regions where information is abundant while performing poorly in others. Subsequently, this uncertain data is fed into a machine learning model for training. Beyond the data fed into the model, the efficacy of the model is intricately tied to its parameters and hyperparameters, representing additional layers of uncertainty. Machine learning algorithms introduce uncertainties stemming from the selection of these parameters and hyperparameters. Consequently, understanding the reliability of model outputs becomes paramount in the presence of these uncertainties.

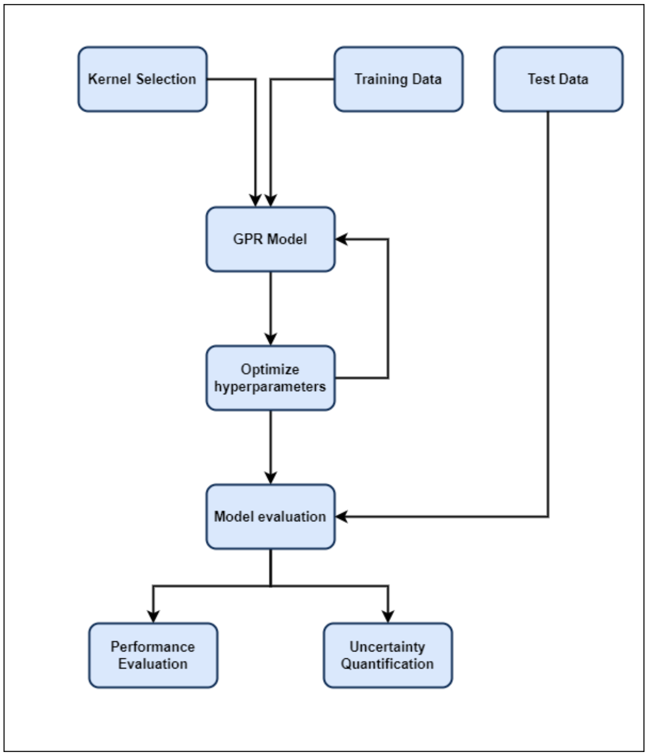

Figure 1: Proposed workflow for Uncertainty-aware permeability prediction

Regrettably, existing methodologies often overlook the intricacies of these uncertainties and fall short of providing a robust framework for quantifying and expressing confidence in model outputs [12]. Quantifying uncertainty plays a significant role in the oil and gas industry when it comes to making decisions [16, 17, 28]. Quantifying uncertainty plays a critical role in oil and gas exploration and development, especially when decisions like reserve estimation, enhanced oil recovery (EOR), and field development planning are at stake. Inaccurate predictions based on uncertain data can lead to costly consequences, such as underestimating recoverable resources, implementing ineffective EOR strategies, or building infrastructure for the wrong reservoir characteristics. By capturing and interpreting uncertainties, companies can make more informed risk assessments, prioritize exploration efforts, and design robust operational plans. Investing in robust tools and methods for uncertainty quantification is crucial for maximizing returns and optimizing decision-making in this high-risk industry. Uncertainties in data and models can lead to underestimating recoverable resources in a reservoir. This can result in inefficient investment decisions, early abandonment of fields and missed opportunities for enhanced oil recovery (EOR). Conversely, overestimating reserves can also have negative consequences such as inflated asset valuations, and excessive infrastructure investment. Furthermore, it can lead to model-related uncertainties such as poor well placement, ineffective EOR strategies and risky development plan.

Based on a probabilistic machine learning approach, this study aims to comprehensively understand and quantify uncertainties inherent in both the data and the model. It confronts the challenges associated with permeability prediction using machine learning, accounting for uncertainties throughout the entire process. To tackle this issue, Gaussian Process Regression (GPR) is employed. This technique is capable of capturing the inherent uncertainties in the data stemming from environmental factors, data collection, and processing. Moreover, our objective is to establish a robust framework that integrates these uncertainties into the machine learning model and provides a means to assess and articulate the confidence level in the model's predictions. This approach enhances the interpretability of prediction models, fostering greater trust and insight into the underlying dynamics of the predicted outcomes.

This paper presents several novel contributions to the field of uncertainty-aware permeability prediction using machine learning techniques as listed below:

(1) Comprehensive Uncertainty Quantification: This method emphasizes the significance of measuring uncertainties that arise from both the process of gathering data and the framework of modelling. By accurately capturing and including these uncertainties in the predictions, we can provide a more practical and dependable evaluation of the estimations of permeability.
(2) Interpretable Uncertainty Estimates: Unlike traditional point estimates, this methodology uses GPR to generate predictive distributions that quantify the associated uncertainties. These estimates are presented in an understandable way, allowing reservoir engineers to make informed decisions and assess the reliability of predictions.
(3) Uncertainty Visualization: Our study includes visualizations and examples that effectively communicate the uncertainty estimates provided by the GPR models. These visual representations enhance the interpretability of the results and aid in understanding the reliability of permeability predictions.
(4) Practical Implications and Future Directions: In our research, we have identified practical implications that could be useful for the oil and gas industry. These implications can have a significant impact on risk assessments, operational planning, and decision-making processes. Furthermore, we have outlined future research directions that may pave the way for more advancements in uncertainty-aware reservoir characterization.

The paper is organized as follows: In Section 2, we provide a review of related works in the field of predicting permeability. Section 3 discusses the methodology and the uncertainty quantification ability of GPR used in this study. Subsequently, the dataset and evaluation metrics are discussed in Sections 4 and 5 respectively. Then we discuss the results and comparative analysis in Section 6, subsequently the findings and recommendations for further study in 7.

2 Related Work

The process of Nuclear Magnetic Resonance (NMR) logging involves using electromagnetic waves to analyze the volume, composition, viscosity, and distribution of fluid-filled pores within reservoir rock that contain water, oil, and gas. This technique is highly effective in characterizing these substances and is considered to be a unique approach [6, 7]. This method used for assessing formations is highly sophisticated and efficient, and it provides accurate evaluations of petrophysical parameters like total porosity, effective porosity, pore size distribution, and permeability [2, 14, 26, 31]. The NMR log is a highly effective technique that allows for the continuous assessment of a formation's permeability.

The process of predicting permeability using NMR is based on the assumption that the distribution of NMR relaxation times T2 accurately represents the distribution of pore sizes under ideal conditions. The size of the pore and T2 relaxation time are positively correlated. This correlation makes it possible to relate the distribution of pore sizes to the distribution of pore throat sizes, which is an essential factor in managing the flow of fluids in a reservoir[4, 9, 21]. These aided in the development of widely used empirical models for estimating permeability. These models include Timur Model [25] and the Schlumberger Doll Research (SDR) model [10]. Both permeability models are limited in that they summarize relaxation spectra to a single variable, disregarding the possibility of a unique relationship between each spectra point and the pore throat. Furthermore, the SDR model only considers average pore size and porosity, while the Timur model only weighs the effect of T2 cut-offs and porosity on permeability[13, 23].

Researchers have developed various permeability models to predict permeability. One such model is proposed by Rios et al. [23], which uses NMR echo data and the T2 distribution along with a multivariate modelling technique, partial least squares (PLS) algorithm to predict permeability. This model showed greater accuracy compared to the SDR model. Trevizan et al. [27] introduced a Radial Basis Function (RBF) that uses a small number of principal components instead of the full spectrum. This method provided good results when predicting permeability in a complex carbonate formation.

Furthermore, Parchekhari et al. [20] proposed an NMR-based permeability prediction in carbonate reservoirs using the LSboost technique. The author used peak analysis as a feature extraction method on the NMR T2 distribution curve. After deriving five parameters, an LSboost technique was used to make a prediction from core measure permeability. The accuracy was better than the free-fluid and SDR models. Also, Osman et al. [19] applied a KNN regression algorithm to predict permeability and porosity using an NMR log.

Despite the advancements of these methods in predicting permeability, there is a need for approaches that account for uncertainties in the prediction process. These uncertainties emerge from various sources, such as measurement errors, environmental factors, and modelling assumptions. The existing models also often lack confidence intervals, which are crucial for assessing the reliability of predictions and making informed decisions in reservoir engineering practices. Employing uncertainty quantification techniques offered by GPR can provide a more comprehensive understanding of the reliability and robustness of permeability predictions. This study aims to contribute to the development of more accurate and interpretable permeability prediction models by addressing these challenges, thereby enhancing the effectiveness of reservoir engineering practices.

3 Proposed Methodology

3.1 Gaussian Process Regression

Gaussian Process Regression (GPR) is a non-parametric probabilistic model used to solve regression problems [29]. It is especially suited for data that is limited or expensive, as it allows building a model that incorporates both prior information and observational data while naturally providing estimates for uncertainty quantification. GPR offers a flexible and powerful framework for permeability prediction. Unlike traditional regression models that assume a fixed functional form, GPR models the relationship between variables as a distribution over functions. This adaptability is particularly advantageous in the context of permeability prediction, where complex and non-linear relationships often exist. The GPR is given as follows:

$$\mu(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

Where:

- $\mu(x)$ represents the latent function, indicating the underlying true relationship between input x and the output
- GP denotes the Gaussian Process, characterized by a mean function $m(x)$ and a covariance (or kernel) function
- $m(x)$ represents the expected value of $\mu(x)$ at any given x
- $k(x, x')$ represents the covariance matrix between the values

The covariance function captures the similarity between output values at different inputs and plays a crucial role in shaping the distribution of possible functions. This helps in understanding the underlying patterns in the data. The choice of the kernel function allows GPR to model the spatial correlations inherent in reservoir properties, making it well-suited for predicting permeability across different locations. The kernel function incorporates prior information about data structure to better capture variations in permeability. In this study, we explored three different kernel functions namely Matern52, Matern32, and Radial Basis Function (RBF).

The Matern family of kernels [22] is particularly well-suited for modelling functions that exhibit a certain degree of roughness or non-smoothness. The Matern52 and Matern32 kernels were selected because they can effectively capture the potential non-linearities and complexities in the relationship between NMR log data and permeability. In addition to the Matern kernels, we also included the RBF kernel [22], which is a widely used kernel in machine learning applications. The RBF kernel is particularly effective in capturing non-linear relationships and can model a wide range of functions. The kernels are then evaluated to determine the most accurate in portraying the underlying relationships and uncertainties, resulting in more accurate and dependable permeability estimates. Matern52, Matern32 and RBF kernels are denoted as follows:

RBF Kernel:

$$k_{RBF}(x, x') = exp(-\frac{(x - x')^2}{2l^2})$$

Matern32 Kernel:

$$k_M^{\frac{3}{2}}(x, x') = (1 + \frac{\sqrt{3}|x - x'|}{l})exp(-\frac{\sqrt{3}|x - x'|}{l})$$

Matern52 Kernel:

$$k_M^{\frac{5}{2}}(x,x') = (1 + \frac{\sqrt{5}|x-x'|}{l} + \frac{5(x-x')^2}{3l^2}))exp(-\frac{\sqrt{5}|x-x'|}{l})$$

Where l is a lengthscale parameter.

3.2 Uncertainty Quantification

The process of predicting permeability from NMR logs is inherently complicated by various sources of uncertainties, arising from both the data acquisition process and the modelling framework. NMR logging tools are subject to measurement errors, leading to uncertainties in the recorded data. Variations in tool calibration, environmental conditions, and logging procedures contribute to measurement uncertainties in NMR-derived properties, including porosity and fluid saturation. Also, models used for permeability prediction often rely on empirical relationships and assumptions about rock properties and fluid behaviour. Uncertainties in model parameters, such as correlation coefficients and petrophysical properties, propagate into permeability predictions, impacting their reliability.

GPR inherently provides probabilistic predictions by modelling the relationship between features and permeability as a distribution over functions. Instead of producing single point estimates, GPR generates predictive distributions that capture the uncertainty in permeability predictions.

GPR estimates confidence intervals around predictions, indicating the range within which the true permeability value is likely to fall with a specified level of confidence. These confidence intervals offer insights into the uncertainty associated with individual predictions which can aid in risk assessment and decision-making.

Reservoir engineers can reduce the risks associated with reservoir development and production strategies by using GPR to include uncertainties into permeability estimations and make well-informed decisions under uncertain conditions. The probabilistic nature of GPR predictions provides a comprehensive understanding of the uncertainty landscape, guiding resource allocation and operational planning in reservoir management.

4 Data Preparation

The dataset used in this study was sourced from the Volve field, a North Sea oil field. The Volve open dataset, accessible for research and development purposes [1], provides comprehensive data from this field. Situated in the central region of the North Sea, approximately 5 km north of the Sleipner East field, and with a water depth of 80 meters, the Volve field was discovered in 1993. The reservoir in the Volve field comprises Jurassic sandstones located between depths of 2750 and 3120 meters. For this study, we focused on two specific wells: 15_9_F1 and 15_9_F11_T2.

The data from these two wells were merged into a single CSV, with a well identifier column created to distinguish between wells. Subsequently, preprocessing was performed on the data. This included checking for missing values and duplicates. Furthermore, the input data was standardized using Scikit-learn StandardScaler to ensure consistency and comparability across features. This step transforms the input features to have a mean of 0 and a standard deviation of 1, mitigating the influence of feature scales on model training. The input data comprises 4407 rows and is detailed in table 1. While, the output is the reservoir permeability.

Table 1: Features in the Input Data

Feature	Description
DEPTH	Depth at which the measurement was taken
WELL	Well identifier
T2GM	Geometric mean of the T2 distribution
MPHS	Mean Porosity from Hydrogen Index
MPHE	Mean Porosity from Effective Porosity
MBVI	Bulk Volume Irreducible
MBVM	Bulk Volume Movable
MBW	Bound Water

5 Evaluation Measures

Three metrics were used to examine the accuracy performances of the proposed model and other machine learning models in predicting permeability: Mean Absolute Error (MAE), Mean Squared Error (MAE), and Coefficient of determination (R^2).

MSE is a widely used metric to quantify the average squared difference between predicted and actual values. The metric computes the mean squared differences of errors, penalizing larger discrepancies between predictions and ground truth. A smaller MSE indicates that the model's predictions are closer to the true values. MAE is another performance metric that quantifies the absolute average difference between the predicted and true values. In contrast to MSE, MAE employs a more intuitive measure of the average prediction error by not penalising larger errors. A smaller MAE indicates that the model's predictions are closer to the true values. Also, R-Squared (R^2) is a popular statistical measure of the variation in the dependent variable that is explained from the independent variables. It illustrates how well the data fit to the model with a value of 1 to indicate perfect fit and 0 to be the worse fit and are commonly represented by 100% and 0%. Mathematically, they are computed as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{SSR}{SST} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Where N presents the total number of data samples. y_i presents the actual observed value. $\bar{y}_i$ presents the mean of the observed values. $\hat{y}_i$ presents the predicted value.

To quantify the uncertainty of the models, the variance of the model's prediction is calculated. In the case of GPR, uncertainty is typically quantified by calculating the variance of predictions for a given input data point. This variance represents the spread or dispersion of predicted values around the mean prediction. Mathematically, the uncertainty associated with the prediction of the target variable y for a new input point x can be calculated as follows:

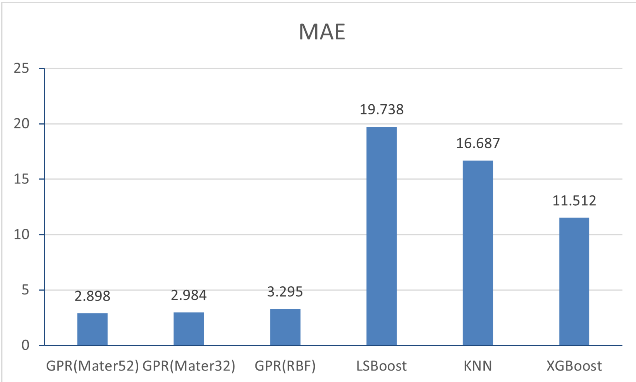

Figure 2: Comparison of the models' MAE on test data

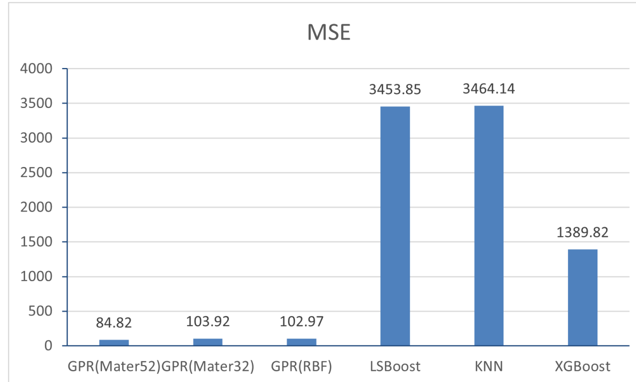

Figure 4: Comparison of the models' MSE on test data

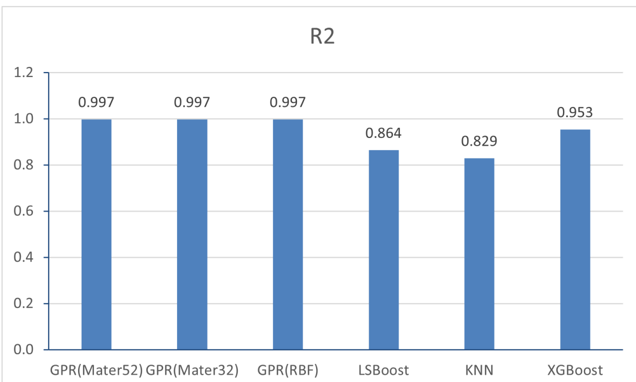

Figure 3: Comparison of the models' R^2 on test data

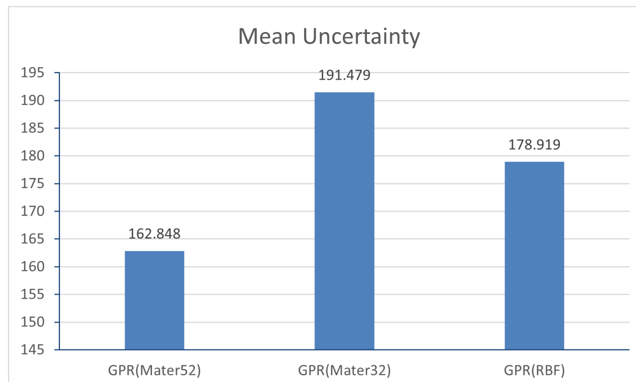

Figure 5: Comparison of the GPR kernel's mean uncertainty on test data

$$Uncertainty = Var(y\_pred)$$

Where $Var(y\_pred)$ denotes the variance of the predicted value of the target variable for a new input point (x^*) across different model runs or training data splits.

6 Results and Discussion

This section presents a comparative analysis of the proposed model's performance against several existing models from previous literature. The proposed models include GPR with Matern52, Matern32, and RBF. Model from previous literature encompasses LSboost, KNN, and XGBoost. Key performance metrics including MAE, MSE, and R^2 are utilized for comparison. The uncertainty associated with different GPR kernels is also examined to provide deeper insights into model behaviour.

The comparison of performance metrics across models serves as a crucial evaluation criterion. The MAE and MSE offer insights into the average magnitude of errors and their dispersion, respectively, while R^2 provides a measure of the proportion of variance in the target variable explained by the model. It is illustrated in Figures 2, 4 and 3

In order to visually compare the performance and uncertainty of different GPR kernels in permeability prediction, we present a bar plot illustrating the mean variance values across various test data points in Figure 5. This plot offers insights into the average spread or variance of predictions generated by each kernel, allowing for a comparative assessment of their uncertainty levels. Additionally, prediction interval plots are constructed to visualize the prediction intervals associated with each kernel's predictions in Figures 7, 6 and 8. These plots depict the range within which the true permeability values are likely to fall with a specified level of confidence, providing a comprehensive understanding of the reliability and robustness of predictions generated by each GPR kernel. Points where the confidence interval width is large indicate high uncertainty in predictions, suggesting less confidence in the model's estimates. In such cases, decision-making may be guided by the model's predictions while considering the potential for deviation from the true underlying value. Conversely, when the confidence interval width is narrow, indicating low uncertainty, greater confidence can be placed in the model's predictions, and decisions may be made more confidently based on these estimates. Ultimately, understanding and interpreting uncertainty in GPR predictions enables practitioners to make informed decisions and manage risks effectively in reservoir engineering applications.

The results demonstrate that the proposed GPR models utilizing Matern52 and Matern32 kernels deliver competitive performance

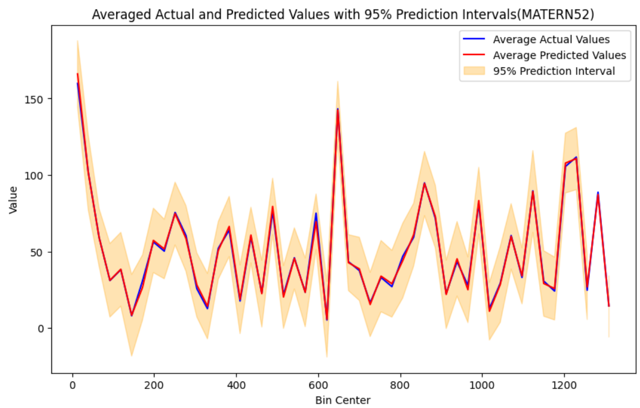

Figure 6: Uncertainty Quantification in Permeability Prediction: GPR with Matern52 Kernel and 95% Prediction Intervals

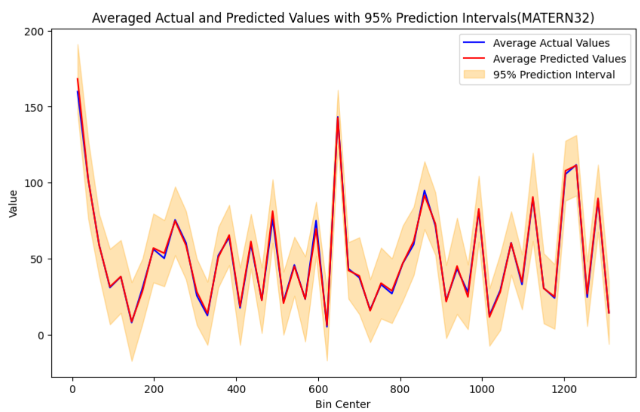

Figure 7: Uncertainty Quantification in Permeability Prediction: GPR with Matern32 Kernel and 95% Prediction Intervals

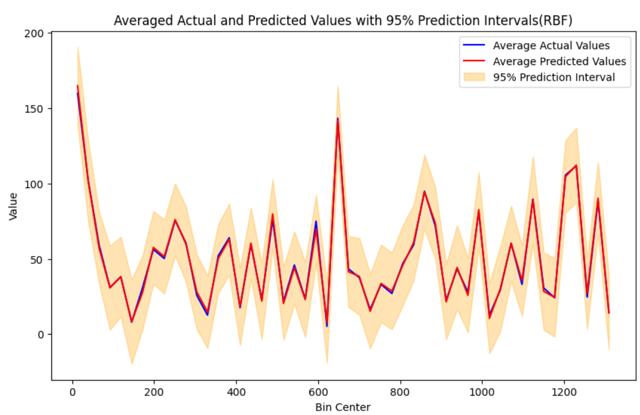

Figure 8: Uncertainty Quantification in Permeability Prediction: GPR with RBF Kernel and 95% Prediction Intervals

across key metrics such as MAE, MSE, and R^2, when compared to other models. These kernels offer varying degrees of smoothness in modelling the underlying data, providing adaptability to capture intricate relationships within the dataset. Notably, the RBF kernel, while exhibiting respectable performance, ranked third in terms of MAE, MSE, and R^2. However, it showcased lower mean uncertainty compared to the Matern32 kernel, as shown in Figure 5. Furthermore, it demonstrated superior performance even without the standardization process. This underscores the effectiveness of the RBF kernel in permeability prediction tasks, particularly in scenarios where variability in data distribution is pronounced. The superior performance of the GPR models can be attributed to their inherent capability to account for uncertainties during modelling.

Moreover, the examination of uncertainty associated with GPR kernels reveals valuable insights into the reliability and robustness of predictions. By comparing the uncertainty estimates provided by different kernels, practitioners gain a nuanced understanding of the model's confidence levels across various regions of the input space. This information is instrumental in making informed decisions, particularly in scenarios where uncertainty management is paramount. Figures 6, 7 and 8 illustrate simplified visualization using binning [11] for the average actual values against the average predictions and prediction intervals. The average uncertainty of the kernels is illustrated in Figure 5.

The comparative analysis highlights the effectiveness of GPR with Matern52 and Matern32 kernels in permeability prediction, underscoring their superior performance and robustness across evaluated metrics. Additionally, the examination of uncertainty provides valuable context for interpreting model predictions and enhances decision-making capabilities in reservoir engineering applications.

7 Conclusion

In this study, we investigated the application of GPR for permeability prediction, emphasizing the importance of addressing uncertainties in both data and modelling. The proposed method was compared with models from existing literature and state of the art models. Through this approach, we aimed to enhance the accuracy and robustness of permeability predictions, crucial for effective reservoir management.

Our results highlight the significant impact of addressing uncertainties in permeability prediction using GPR. By modelling the uncertainty inherent in the data and prediction process, GPR provides valuable insights for reservoir engineers, enabling informed decision-making and risk mitigation strategies. The probabilistic nature of GPR not only offers point estimates of permeability but also quantifies the associated uncertainties, providing a comprehensive view of the predicted permeability distribution. This capability is particularly crucial in complex subsurface environments where uncertainties abound and can have profound implications for reservoir development and production strategies.

Quantifying uncertainty is crucial in the oil and gas industry. Inaccurate predictions based on uncertain data can lead to costly consequences, such as underestimating recoverable resources or implementing ineffective EOR strategies. By accurately interpreting uncertainties, companies can make informed risk assessments and design robust operational plans. Uncertainties in data and models can result in inefficient investment decisions, missed opportunities, and negative consequences such as inflated asset valuations.

The application of GPR yielded promising results, with permeability predictions exhibiting high accuracy and uncertainty quantification. The Matern52 provided the highest accuracy and lowest mean uncertainty followed by Matern32 and RBF.

For future work, further efforts could focus on refining the GPR methodology, exploring other kernels and the combination of multiple kernels. Additionally, extending the application of GPR to other reservoir properties beyond permeability could provide a holistic understanding of subsurface dynamics and facilitate more comprehensive reservoir management strategies.

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