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Prediction of permeability via nuclear magnetic resonance logging using convolutional neural networks

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ABSTRACT

Permeability is a critical parameter in subsurface fluid flow analysis, reservoir management, hydrocarbon recovery, and carbon dioxide sequestration. Traditional permeability measurement methods involve costly and time-consuming laboratory tests or well-related data. Machine learning (ML), specifically convolutional neural networks (CNN), is proposed as a cost-effective and rapid permeability prediction solution, harnessing interrelationships of input-output variables. In this study, empirical permeability correlation was developed using CNN. Forty nuclear magnetic resonance (NMR) T2 spectrums and 89 logarithmic mean NMR T2 distributions (T2lm) were preprocessed, screened and key spectra were identified using the principal component analysis (PCA). To develop the correlations, a custom-designed CNN architecture was employed to leverage the spatial patterns and intricate relationships embedded in the NMR data. The model was trained and validated rigorously using k-fold cross validation scheme to ensure robustness and generalization. Performance metrics like R-squared (R2), root mean squared error (RMSE), mean absolute error (MAE), standard deviation (SD), absolute deviation (AD), average absolute deviation (AAD), average absolute percentage relative error (AAPRE), and maximum error (Emax) were deployed to evaluate the model's accuracy and ability to predict permeability values accurately. Among the folds considered, the fold 1 emerged as the best-performing model with the highest R2 value of 0.9544. This CNN-based correlation outperformed conventional and other AI-based models in terms of R2, Emax, AD, AAD, AAPRE, among other metrics. Overall, the study demonstrates the effectiveness of CNN in predicting permeability, offering a superior alternative to costly and limited traditional methods, with fold 1 showing the most promising results.

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1. INTRODUCTION

Permeability prediction of porous media using numerical methods is a valuable adjunct. It is also more cost-effective and efficient, with its advantages over experimental measurements [1]. Analyzing a reservoir's transport and storage characteristics contributes to evaluating its reserves and formation. In particular, permeability distribution is crucial when constructing oil and gas field development strategies as well as controlling production. Apart from the oil and gas industry, accurately estimating permeability is crucial for subsurface fluid flow applications like CO2 storage, water management, and geothermal development [2], [3]. Petroleum engineering relies on permeability to assess a rock formation's ability to enable oil, gas, and water to pass. This attribute is crucial to hydrocarbon reservoir output and financial viability. High permeability suggests a porous, interconnected rock configuration that allows fluid mobility, whereas low permeability shows dense rock formations that prevent it.

Laboratory core measurements and well pressure transient testing (including Horner's 1951 pressure buildup, Jensen and Mayson's 1985 repeat formation testing, and Van Poollen's 1961 drill-stem testing) are typical reservoir permeability estimation methods [4]. Both approaches are time-consuming and costly in terms of resources producing permeability data for a limited number of drilled wells. Alternative geophysical well logging can determine porous media permeability.

Effectively evaluating permeability using conventional well logs is difficult. These logs, which measure porosity, require empirical or semi-empirical correlations to forecast permeability. Nuclear magnetic resonance (NMR) well logging has become popular in recent decades for more precise permeability estimations [4]. NMR measurements in logging correspond to volume, composition, viscosity, and fluid dispersion in porous media, unlike conventional logs, which are heavily influenced by mineral composition and react to both solid and fluid medium components. Thus, NMR logs measure rock hydraulic conductivity more accurately than other logs [5]. However, NMR logging instruments' higher accumulation cost, time-consuming analysis, and inapplicability un cased-hole wells prevent their widespread use. These constraints limit NMR data availability. To estimate reservoir properties like permeability using NMR logs, synthetic NMR logs (or NMR-derived outcomes) have been generated from more readily available conventional logs.

The remaining section of this work is organized as follows: section 2 discusses the CNN technique from deep learning (DL) technique, section 3 explains the methodology adopted in this study while section 4 presents the results and discussion. Section 5 concludes the study and also suggests future works.

2. LITERATURE REVIEW

In this section, we present a conceptual elucidation of artificial neural networks (ANNs) that incorporates machine learning (ML) and DL that has the CNN technique we proposed to establish an empirical correlation essential for the prediction of permeability. ML has gained popularity in petroleum engineering and geoscience applications. ML algorithms for estimating permeability in wells without core data have been extensively utilized in the oil and gas sector due to their efficacy in real-world circumstances [6]. The petroleum industry has successfully used ML for reservoir characterization, seismic pattern detection, property forecasting, lithofacies identification, well production trend estimation, and diverse reservoir portfolios [7]. Recently, many researchers have tried to link core permeability to well logs. Understanding permeability is crucial to reservoir characterization. Permeability of the geological formation affects well completions, stimulation methods, and reservoir management tactics [1]. Coring and well testing are time-consuming and expensive, thus they can't capture the reservoir's heterogeneity. This limits the number of viable well drilling operations. Absence of cores and partial core data during specified intervals cause difficulties.

Analyzing pressure transients in well testing gives an average permeability for the reservoir volume under study. The well test must be long enough to yield reliable data and reflect a considerable fraction of the reservoir volume [8]. Establishing coefficients in equations for each well is the second way. However, an equation for one geological formation may not work in other sectors. The majority of logging techniques do not directly assess permeability, requiring interpretation. Researchers have used nonlinear regression to indirectly correlate reservoir properties like depth and porosity with permeability. However, this method is superior for sandstone reservoirs and fails to forecast permeability in complex carbonate formations. Diagenetic processes increase variability in these formations, making this procedure difficult. Thus, a method to reliably forecast permeability across reservoir heterogeneity is needed [9]-[13]. Petroleum engineers are aiming to improve permeability estimates to reduce uncertainty in oil and gas exploration and production. They are pulling inspiration from nature and studying solutions that have evolved over time. Natural mechanisms can adapt to many situations, making them perfect models for inventive and reliable solutions [14].

The simulation of nature-inspired ANN, evolutionary computation (EC), swarm intelligence (SI), support vector machines (SVM), gaussian process regression methods (GPRM), and fuzzy systems (FS). Engineers can construct a robust and integrated system by integrating these methods [7], [15]. Recently, an empirical permeability correlation method was introduced by employing GPR and SVM. The research involved preprocessing and screening forty NMR T2 spectra and 89 logarithmic mean NMR T2 distributions (T2lm), with key spectra identified through principal component analysis (PCA). To develop the correlation, 80% of the data was randomly selected, and within this subset, 50% was allocated for both training and testing. Ten different kernel functions were explored. The results demonstrated that the squared exponential-based kernel GPR (with R-squared (R^2)=1.0 and root mean squared error (RMSE)=2.1512e-4) and the Cubic-based kernel SVM (with R-squared = 0.97 and RMSE=2.7393e-2) emerged as the most effective models. These findings were then compared to results obtained from ANN, SDR, and Timur-Coates models, highlighting the superior performance of the GPR model [5]. SEM-predicted permeability values to measured values were compared [16].

They discovered that surface roughness affecting pore throat shape underestimated permeability. An *et al.* [17] used a regular network model to study how pore throat ratio, coordination number, and orientation affect absolute permeability. Shah *et al.* [11] predicted pore network features such pore and throat counts, average pore throat radius, and coordination number. Lattice Boltzmann (LBM) and Pore network modeling (PNM) were used to simulate single-phase and dual-phase flow conditions. CNN are a type of DL, an extension of a neural network that is primarily used for image recognition and processing tasks [18]. They have proven to be highly effective in detecting patterns and features in images, and have been successfully applied to a wide range of applications, including object detection, facial recognition, and self-driving cars. Figure 1 depict the CNN architecture.

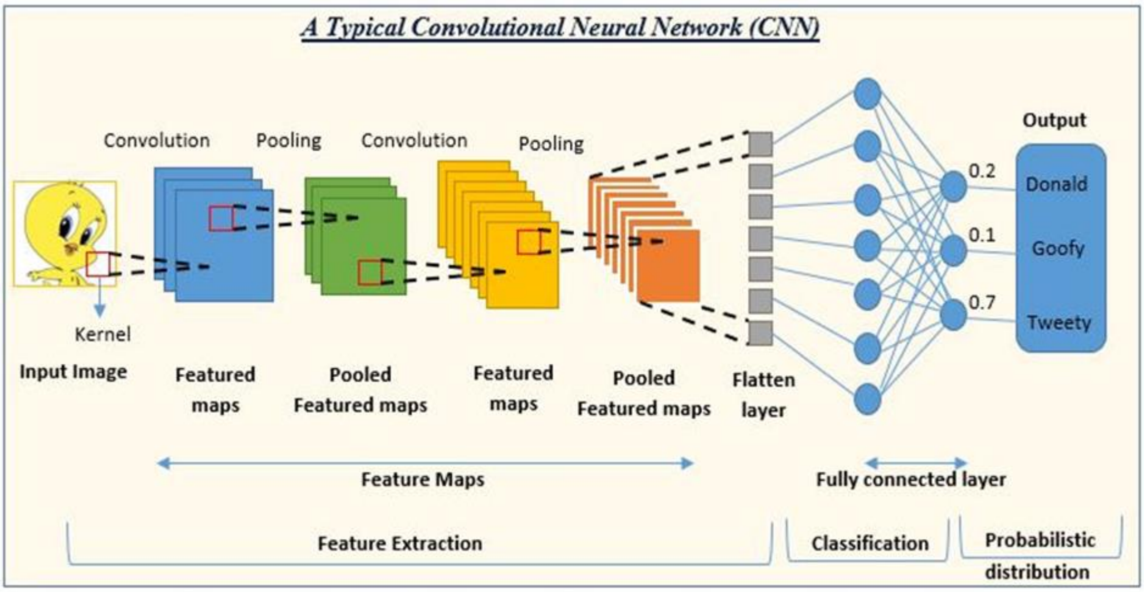

Figure 1. CNN architecture [19]

The CNNs' main feature is that they can learn and automatically find features in the data they get. This is done by convolutional layers, which apply filters to the input data and produce feature maps. After that, these feature maps go through several layers, like pooling and fully connected layers, to make the final result. CNNs have shown great promise in a variety of fields beyond image processing, including natural language processing (NLP), speech recognition, and even finance. They can also be used in geological and geophysical applications, such as predicting rock permeability from NMR logs. Overall, CNNs are powerful tool for learning from complex, high-dimensional data, and their versatility makes them an important area of research and development for ML and artificial intelligence (AI).

CNNs have emerged as a powerful ML technique for analyzing complex data, including NMR data. CNNs have been successfully used in various applications, such as image and speech recognition, NLP, and drug discovery. CNNs have also been applied to the prediction of petrophysical properties from well logs, including permeability. The measurement of permeability in reservoir rocks is crucial for evaluating the feasibility and productivity of hydrocarbon reservoirs. NMR logging is a commonly used method for measuring the petrophysical properties of rocks, including permeability. However, the interpretation of NMR logs can be challenging due to the complex signal response from the rocks. CNN has been proposed as a potential solution for the accurate prediction of permeability from NMR logs.

NMR logging measures the relaxation time of hydrogen protons in pore fluids and solid matrix in rocks, which can be used to estimate the pore size distribution and permeability of the rock. However, the interpretation of NMR logs requires a sophisticated understanding of the physical properties of the rock, and traditional analytical methods can be time-consuming and prone to errors. Therefore, there has been growing interest in the application of ML techniques, such as CNNs, for the automatic interpretation of NMR logs.

CNNs are a type of DL algorithm that has shown remarkable success in image recognition and processing tasks. Several studies have proposed the use of CNNs for the prediction of permeability from NMR logs. For example, in a study by Liu *et al.* [20], a CNN was used to predict permeability from NMR data with an accuracy of 84.4%, which outperformed traditional regression methods. The study also found that the CNN was able to capture the spatial distribution of pores in the rock, which is a critical factor in permeability estimation.

Zhang *et al.* [1] suggested a method that maps low-resolution porous media to high-resolution characteristics using an autoencoder (AE) module trained with unlabeled input. This helped the main CNN with prediction. The approach took into account both the high-resolution information from AE trained with a greater amount of unlabeled data and the low-resolution information from CNN trained with a smaller number of labeled data. By calculating mean-square errors (MSE) and R-squared (R2), the prediction performance of AE-CNN from low-resolution images was compared with the outcomes of conventional CNN and LBM techniques. When using the 5-fold cross-validation procedure, the average R2 value for the AE-CNN test dataset is 0.896, while for the conventional CNN without the AE it was 0.869. In the best-performance fold, the MSEs for AE-CNN are 0.022 and 0.064 for the training and test datasets, respectively. In contrast, the MSEs for CNN alone, without AE, were 0.034 and 0.083 for the training and test datasets, respectively. These results suggest that AE modules can significantly enhance the prediction performance from low-resolution images of porous media. According to the LBM approach’s simulation findings, there is a significant amount of numerical error at the blurred boundaries of low-resolution images, which causes its prediction reliability (average R2: 0.42; MSE: 0.37 and 0.36 in the best-performance fold) to be significantly worse than that of CNN-based ML methods.

Essentially, the study gap in the above literature and other related literature in [21]-[23] calls for further investigation and motivation for this study. The prediction of permeability from NMR logs with CNNs has demonstrated potential for enhancing prediction accuracy in the oil and gas sector, particularly in reservoir characterization. Nonetheless, numerous limits and obstacles are linked with employing CNNs for this task.

3. METHOD

3.1. STEP 1: data acquisition

The initial phase involves obtaining NMR log data from Field X situated in the Niger Delta Basin. This data was stored in the CSV format, a widely, commonly accepted standard format for storing data in tabular form and is supported by many different software programs. For the purpose of loading and parsing the CSV files, the Anaconda software was employed. Anaconda is a Python distribution that is commonly used for data science and ML which includes many webs based integrated development environments (IDE).

3.2. STEP 2: data preprocessing

After acquiring the NMR log data, the subsequent stage involves data preprocessing to enhance its quality and utility. This entails eliminating noise, addressing missing values, and carrying out feature engineering to derive meaningful insights from the data. Various Python libraries, including Keras, TensorFlow, and Scikit-learn, were installed for data preprocessing. The following steps were taken:

- Data cleaning: the initial focus was on detecting and handling missing values and outliers within the data. Missing values was addressed using mean imputation. Outliers, which can negatively impact the model’s performance, was removed and corrected.
- Data normalization: to ensure consistency in feature scales, the data was normalized using the standard scalar method. Normalization aids in enhancing the training process and accelerates the model’s convergence.

$$X^{new} = \frac{\log_{10}(X)-\log_{10}(X_{min})}{\log_{10}(X_{max})-\log_{10}(X_{min})} \quad (1)$$

Where:
X^{new} is the normalized input vector

X is the original input vector
X_{min} is the minimum value
X_{max} is the maximum value
- Feature engineering: the NMR log data was transformed using PCA, technique to yield meaningful features. This technique contributed to reducing the data's dimensionality while extracting pertinent features that are valuable for permeability prediction.

3.3. STEP 3: feature extraction

The preprocessed NMR log data was inputted into the CNN model to facilitate feature extraction. The architecture of the CNN model was designed to recognize spatial patterns and correlations within the data's features. The model architecture encompasses several layers:
- Convolutional layers: these layers undertake feature extraction by applying a set of filters to the input data. Each filter traverses the input data, computing dot products with overlapping values. The output of the convolutional layer is a collection of feature maps that encapsulate the spatial patterns present in the data.
- Pooling layers: pooling layers decreased the spatial dimensions of the feature maps through max-pooling which is a down-sampling techniques. This operation assisted in reducing the model's parameter count, subsequently enhanced its computational efficiency.
- Fully connected layers: the final classification or regression task was executed by the fully connected layers. These layers received the flattened output from the preceding layers, applied weights that generated the ultimate output.

This process of feature extraction enabled the CNN model to learn and identify the significant patterns and relationships within the preprocessed NMR log data, ultimately aiding in more accurate permeability prediction.

3.4. STEP 4: model development

The CNN model was created by utilizing Python libraries Keras and TensorFlow. These libraries provided a convenient interface for specifying the model's architecture, configuring hyperparameters, and training the model.
- Model architecture: the CNN model's architecture was established through the Keras API, which simplifies the construction of intricate neural networks. The model encompasses multiple convolutional layers, succeeded by pooling layers and fully connected layers.
- Hyperparameter tuning: hyperparameters such as learning rate, batch size, and epochs were fine-tuned to optimize the model's performance.

Figure 2 shows the model development description for the permeability prediction via NMR log using CNN in this study.

3.5. STEP 5: data preprocessing and model training

- Data splitting: the preprocessed data was splitted into 5 folds for training and validation subsets using the k-fold cross validation function provided by the Scikit-Learn library in Python.
- Model training: the CNN model was trained using the Keras API, with TensorFlow as the underlying framework.
- Model architecture tuning: the architecture of the CNN model was carefully tailored and optimized for the specific task. Hyperparameters such as the count of convolutional and pooling layers, filter sizes, number of neurons in fully connected layers, and the learning rate was also considered during this process.
- Optimizer and loss function: the CNN model was trained using the Adam optimizer and the mean squared error (MSE) loss function. MSE is suitable for regression tasks and was assisted in minimizing the discrepancy between predicted and actual permeability values.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \quad (2)$$

Where:
MSE = mean squared error
n = number of data points
Y_i = actual value
$\hat{Y}_i$ = predicted value

- Validation: at the end of each epoch during the training procedure, the model's performance was evaluated using the validation set. This helps monitor the model's progress and aids in preventing overfitting.
- Training termination: the training process was continued until the validation loss ceases to decrease and a pre-defined maximum number of epochs was reached, in which the model has already reached an optimal state to avoid overtraining.

3.6. Step 6: model evaluation and prediction

Following the completion of model training, the CNN model undergo comprehensive evaluation for the permeability prediction:

- Test set evaluation: the trained CNN model was assessed on a distinct test set that has been entirely separated from both the training and validation sets. This evaluation provides insight into the model's performance when presented with previously unseen data.
- Performance metrics: the model's performance was gauged using a range of metrics, including the coefficient of determination (R^2), RMSE, mean absolute error (MAE), standard deviation (SD), absolute deviation (AD), average absolute deviation (AAD), average absolute percentage relative error (AAPRE), and maximum error (Emax). These metrics offered a comprehensive view of the model's predictive accuracy and its ability to capture variations between predicted and actual permeability values [24], [25].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)}{\sum_{i=1}^{n}(Y_i - \mathrm{averag}(Y_i)} \tag{3}$$

Where:
R^2 = coefficient of determination
n = number of data points
Y_i = actual value
$\hat{Y}_i$ = predicted value

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{4}$$

Where:
RMSE = root mean square error
n = number of data points
Y_i = actual value
$\hat{Y}_i$ = predicted value

$$MAE = max\,|Y_i - \hat{Y}_i| \tag{5}$$

Where:
MAE = maximum absolute error
n = number of data points
Y_i = actual value
$\hat{Y}_i$ = predicted value

Figure 3 presents the Workflow for the CNN model in this investigation. After that, different ML algorithms are used to make models, and then different performance indicators are used to see how well the models work.

$$Emax = max\,|Ei\,| \tag{6}$$

Where: E_{max} = maximum error

$$\mathrm{Ei} = \frac{|Y_i - \hat{Y}_i|}{Y_i} \times 100$$
$$AAPRE = \sum\frac{|Ei|}{n} \tag{7}$$

Where: AAPRE = average absolute percentage relative error.

$$\mathrm{Ei} = \frac{|Y_i - \hat{Y}_i|}{Y_i} \times 100$$

– Real-world permeability prediction: the trained CNN model was then applied to predict permeability values from new NMR logs. These predicted values was juxtaposed against the genuine permeability values to assess the model's accuracy and reliability in a real-world scenario.

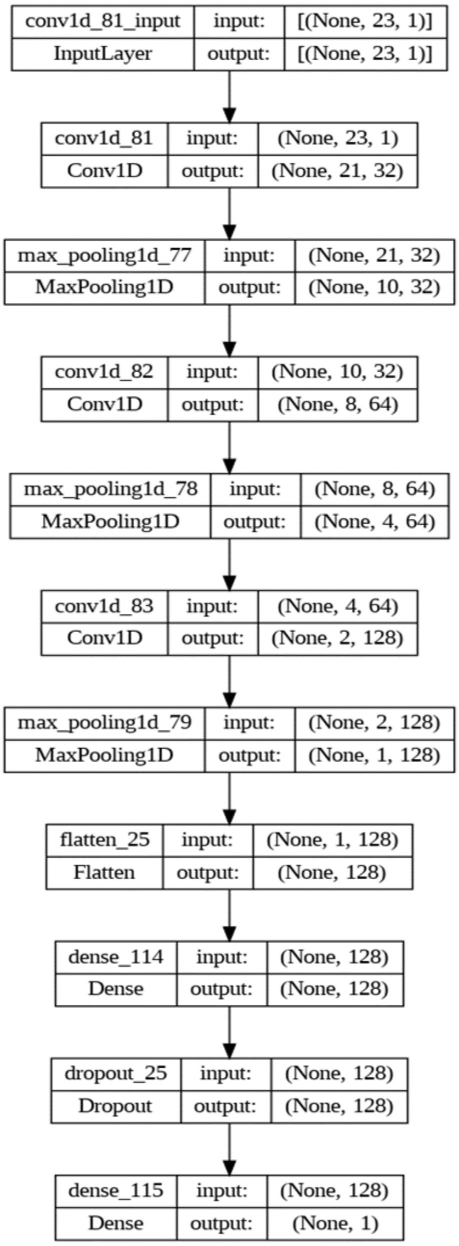

Figure 2. Model description of the CNN model

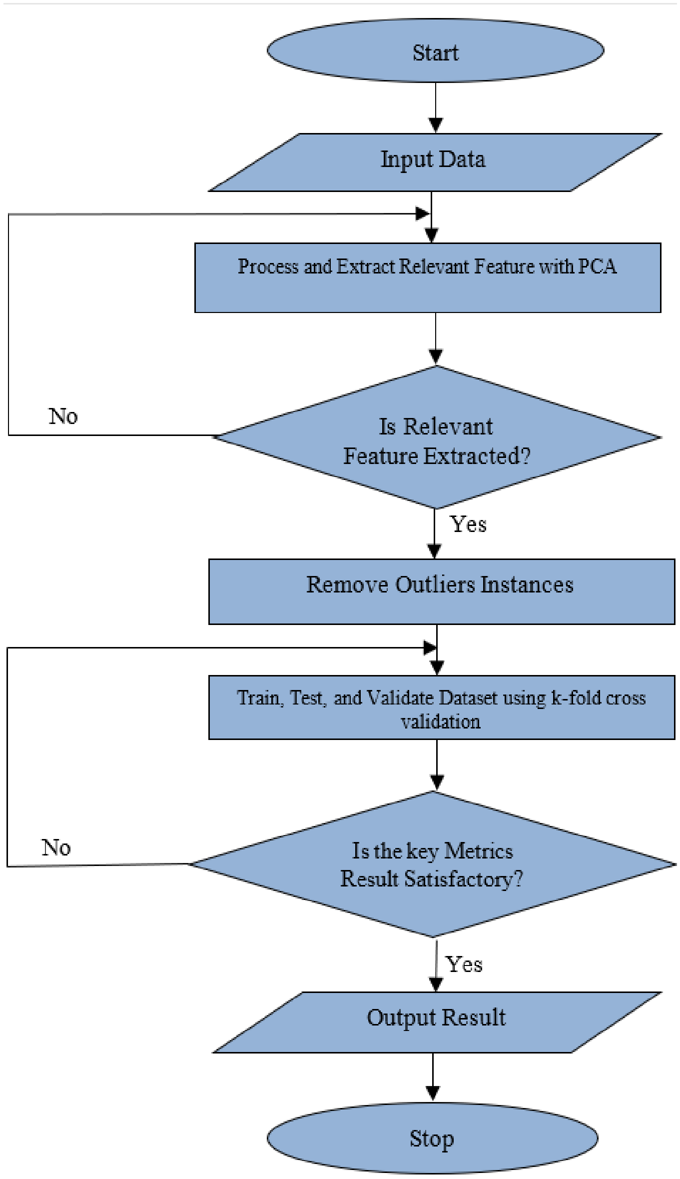

Figure 3. Workflow for the CNN model

3.7. Step 7: model interpretation and visualization

After the CNN model has been trained and evaluated, it is important to delve into the inner workings of the model to better understand its decision-making process and the features it has learned. This step involves model interpretation and visualization:

- Feature maps: the patterns and features that the CNN has detected within the input data were visualized, which provided a visual representation of the learned filters in the convolutional layers and offered insights into the spatial features that are most relevant for permeability prediction.
- Activation maximization: the input image to maximize the activation of specific neurons or feature maps within the CNN was optimized which generated the input images that strongly activate certain neurons.
- Gradient-weighted class activation mapping (Grad-CAM): grad-CAM technique was introduced to highlights the regions of the input image that contributed most significantly to the model's prediction. It generated heatmaps that indicate which parts of the input image are influential in the model's decision-making process.

Then, the permeability predicted results using CNN was compared with the predicted results from previous studies using ANN, SVM, and GPR to identify the best approach for permeability prediction from NMR logs. The model that works best is then moved on to the implementation stage. The implementation phase has the model of the best-performing model, and it gets inputs from the front end that are handled during the phase. The output of the yield is being delivered back to the front end. The frontend phase is linked to a database, which lets people sign up and log in.

4. RESULT AND DISCUSSION

4.1. Discussion of result

To verify the generalization ability and stability of the CNN model, a well-trained CNN model was used to predict the permeability values in one well in Field X of the Niger Delta Basin, from which the test data comprise 89 data points. The training and validation of the CNN model was divided into five folds which are measured by the state-of-the-arts performance metrics in neural network domain [26], [27]. According to the results, for fold one, the RMSE value is 2.390876 for the training process and 2.2772 for the testing process, then for fold two, the RMSE for the training is 2.7297054 and the testing process is 1.956999. The RMSE for fold three used for training process is 2.7777839 and for the testing process is 2.672934517. In fold four, RMSE for training is 2.307744885 and the testing process is 3.42918388 while the RMSE in fold five for the training and testing processes are 2.50440248 and 2.322125687 respectively.

4.2. CNN fold 1 to fold 5 performance evaluation results

Performance evaluation result gotten from CNN fold 1 to fold 5 are AD of (1.1873, 1.5081, 1.8855, 1.4615, 1.6928.), AAD of (0.15147, 0.4299, 0.97211, 0.85700, 0.4093.), RMSE of (2.2772, 1.9567, 2.6729, 3.4292, 2.3221), R2 of (0.9544, 0.9267, 0.8846, 0.904. 0.8879). The rest of the results are shown in Table 1, and the Table 2 shows the Statistical comparison with ANN, SVM, GPR, TC, and SDR models. Figure 4 shows the scatter plot of the predicted values obtained from the CNN model and the actual permeability values of the core for fold 1 in Figure 4(a) to fold 5 in Figure 4(e).

Table 1. Metrics for CNN folds results

Metrics	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
RMSE	2.2772	1.9567	2.6729	3.4292	2.3221
R^2	0.9544	0.9267	0.8846	0.904	0.8879
MAE	1.5369	1.5081	1.8855	2.1877	1.6928
Emax	110.8197	188.4445	2087.9464	948.6314	1026.4923
SD	1.0511	1.3293	1.7674	1.5181	1.7107
AD	1.1873	1.5081	1.8855	1.4615	1.6928
AAD	0.15147	0.4299	0.97211	0.85700	0.4093
AAPRE	2.7586	24.7136	149.4856	79.1761	74.9408

Table 2. Statistical comparison with ANN, SVM, GPR, TC, and SDR models

Measure	This study (CNN)	(SVM)	(GPR)	Olayiwola (2017) [15] (ANN)	Timur-Coates model	SDR model
AD	1.1873	0.3159	$-4.955e^{-12}$	0.020	-1.3169	-1.5724
AAD	0.15147	0.6816	0.1636	0.620	2.7953	3.0740
RMSE	2.2772	1.0573	0.1961	1.510	3.5021	3.8619
SD	1.0511	26.563	4.4842	6.100	66.991	209.05
E_{max}	110.8197	77.155	12.014	6.090	139.24	637.88
AAPRE	2.7586	14.467	3.1058	6.600	49.949	124.23

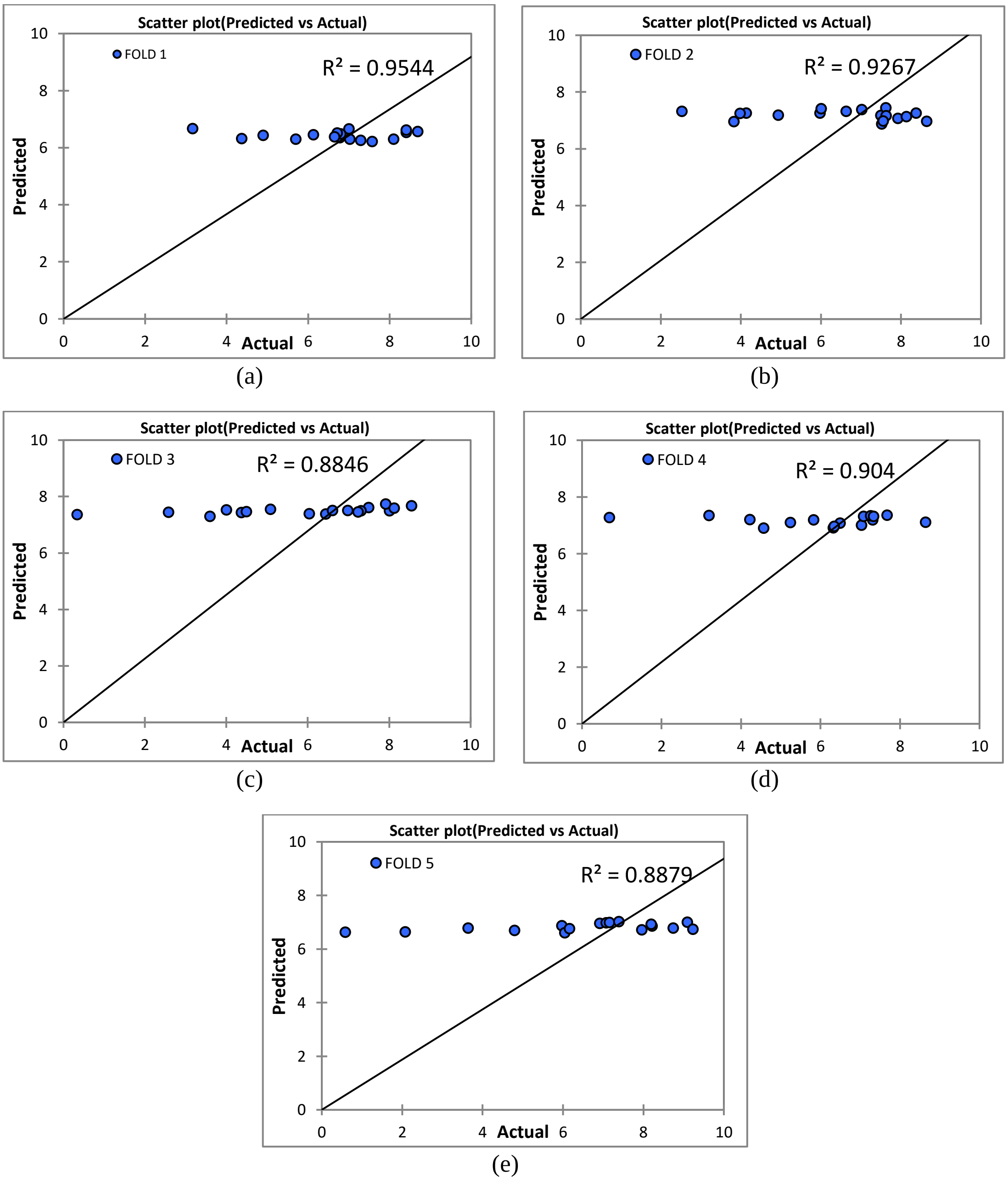

Figure 4. Prediction value versus test output for (a) fold 1, (b) fold 2, (c) fold 3, (d) fold 4, and (e) fold 5

5. CONCLUSION AND FUTURE WORKS

This study proposed a CNN technique for predicting permeability from NMR logs. CNNs have shown high efficacy in permeability prediction from NMR logs. Therefore, it is recommended for reservoir management and development. Nevertheless, it's important to note that CNN models are typically constructed based on extensive datasets from specific geographic regions, which significantly enhances their predictive performance. Consequently, it is advisable to employ substantial datasets when developing new CNN models. The developed correlation performed better than the conventional models and other AL-based models based on the R2, Emax, AD, AAD, and AAPRE. Further study is suggested using other DL/ML models to validate the study.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest concerning the publication of this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author Sunday Adeola Ajagbe upon reasonable request.

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