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A Novel Technique in Determining Mud Cake Permeability in SiO_2 Nanoparticles and KCl Salt Water Based Drilling Fluid using Deep Learning Algorithm

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ABSTRACT

The permeability of the mud cake formed at the formation-wellbore interface is an important factor in the designing of water-based drilling fluids. This study presents a novel approach to utilizing experimental thixotropic and rheological parameters of polymeric water-based drilling fluids having varying concentrations of SiO_2 nanoparticles and KCl salt. A fully connected feed-forward multi-layered neural network, more commonly known as a Multilayer Perceptron (MLP) was developed to predict the mud cake permeability using input parameters such as SiO_2 & KCl concentration, differential pressure, temperature, mud cake thickness, API LPLT and HPHT filter loss volume and spurt loss volume. The results suggested that the developed Multilayer Perceptron model effectively determined the mud cake permeability based on the input parameters of the WBDF mentioned above. The model converged on the global minima, minimizing the loss function using the Gradient descent algorithm. A higher Coefficient of Determination (R2) value i.e., 0.8781, and a lesser Root Mean Square Error (RMSE) value i.e., 0.04378 indicates the higher accuracy of the model. Pearson's Coefficient of Correlation obtained via the heatmap indicates that mud cake permeability is strongly influenced by the differential pressure followed by filter loss volume, spurt loss volume, mud cake thickness, and temperature. Previous similar studies have focused on using machine learning algorithms, this study utilized a robust deep learning algorithm i.e., Multilayer Perceptron (MLP) neural network to simultaneously model the combined effects of SiO_2 nanoparticles and KCl salt concentrations on mud cake permeability, offering an unprecedented level of accuracy in predicting key WBDF performance parameters.

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1. Introduction

Drilling fluids play a critical role during drilling operations [1, 2]. The main purpose of the drilling fluid is to clean the wellbore by removing the drill cuttings and allowing them to remain suspended in the wellbore, through which they can be transported to the surface [3-7]. Furthermore, drilling fluids also maintain the hydrostatic head in the wellbore which stabilizes the hole and prevents it from collapsing [3-6]. Drilling fluids also play a key role during logging as they provide a medium for the logging tool to send and receive signals [3-6]. Drilling fluids can be classified into oil-based fluids, water-based fluids, and synthetic-based fluids [8-11]. Water-based drilling fluids (WBDFs) are widely used during drilling operations, due to their environmentally friendly properties, reduced costs, and ease of handling [1, 2, 12, 13].

However, there are several problems associated with using water based drilling fluids, among which is the loss of fluid in the formations [14, 15]. This phenomenon occurs when the drilling fluid encounters a permeable formation, and the liquid phase (filtrate) enters the permeable region. Several different chemicals are added to the drilling fluid as an additive to minimize the fluid loss [16]. These additives allow the formation of a mud cake across the wall of the borehole interface that prevents further fluid loss [17, 18]. A mud cake must be homogeneous, thin, and poorly permeable if it is well-designed [14, 15]. The quality of the mud cake that forms at the interface between the wellbore and the geological formation determines the efficacy and efficiency of these drilling fluids in addition to their chemical makeup [19-21]. The purpose of this mud cake is to act as an impermeable, ideally thin barrier that stops drilling fluid from being lost further into the geological formation. Significant ramifications from such losses may include higher hydrostatic head and operating difficulties. Many problems encountered in drilling result from improper design of the drilling fluid, requiring special attention and good fluid design to minimize or correct the problems A thick filter cake causes problems such as a reduction in the effective diameter of the borehole, which then creates a possible risk of differential sticking of the pipe; in addition, a highly permeable filter cake increases both the filtering capacity and the fluid loss into the formation [22, 23]. Current practices indicate that it is impossible to reduce fluid loss with micro- or macro-type fluid supplements [24-26]. Several studies have recently experimentally investigated the measurement and minimization of static and dynamic filtration volume of drilling fluids [27-31]. With the advent of nanotechnology, it was discovered that nanoparticles have the potential to solve or mitigate the problem of fluid loss while maintaining optimal rheological properties. Aqueous drilling fluids contain many components, such as salt, which control the expansion of clay and shale [32]. KCl is the most commonly used salt in polymeric water-based drilling fluids [33]. Nanoparticles are significantly affected by the presence of salts in the liquid efficiency and properties such as surface charges that cause nanoparticle agglomeration [34, 35].

Many researchers have studied the effects of various nanoparticles, such as silica nanoparticles, on drilling fluid properties and filtration rate to date. Recent studies include Parizad *et al*., [32] which investigated the effects of SiO_2 nanoparticles and KCl salt on different aspects of polymer water-based drilling, including fluid filtration with nanoparticle concentrations of 0-7.5 gr/L, temperatures of 25-93 °C, and pressures of 0.69 and 2.76 MPa. They concluded that SiO_2 nanoparticles reduce the filtration volume by reducing the permeability of mud cakes at different temperatures. Salih *et al*., [36] investigated the effects of incredibly low concentrations of different metal oxide nanoparticles, such as silica nanoparticles, on a range of parameters, such as the filtration qualities of a high pH water-based mud and its flocculation qualities. The studies were conducted in accordance with API testing guidelines, with low-pressure and low-temperature settings. The results showed that the presence of silica nanoparticles at concentrations of 0.1% by weight or less resulted in a decrease in the filtering volume, an improvement in the mud cake’s structure, and the total avoidance of filtrate loss. It's crucial to remember that raising the concentrations of silica nanoparticles over this point did not result in any appreciable benefits [36]. A different study carried out by Salih *et al*., [37] sought to ascertain the ideal concentration of silica nanoparticles to improve water-based drilling fluids, with a particular emphasis on lowering filtering loss. Low temperatures and low pressure were used for these tests. The results showed that when the concentration of nanoparticles was less than 0.7% by weight, the filtration characteristics of the drilling fluid improved. It was discovered that the range of concentrations where silica nanoparticles worked best was between 0.1% and 0.3% by weight [37].

To solve non-linear regression problems, artificial intelligence techniques such as artificial neural networks and adaptive neuro-fuzzy systems have been used more recently. These tools are widely used in many other areas and industries, and the petroleum industry has seen an increasing usage of machine learning methods to solve complex field problems [38-42]. In this study, a widely used Feedforward Back Propagation deep learning algorithm, known as Multilayered Perceptron, has been utilized to predict the mud cake permeability using thixotropic and rheological properties as input parameters.

2. Methodology

2.1. Data Collection

The dataset used in this study was obtained from published literature [32], comprising of experimentally determined thixotropic and rheological parameters of 37 samples of polymeric water-base drilling fluid. These parameters included SiO_2 nanoparticle & KCl salt concentration, differential pressure, temperature, mud cake thickness, funnel viscosity, API LPLT and HPHT Filter Loss volume and Spurt Loss volume. Since these parameters were determined experimentally therefore the concentrations of other additives such as Xanthum Gum (XG), Partially Hydrolyzed Polyacrylamide (PHPA), Carboxy Methyl Cellulose – Low Viscosity (CMC-LV) were set as control i.e., their concentrations remained constant in all the 37 samples at 4 gr/L ,1 gr/L ,4.5gr/L respectively. In the original study [32] SiO_2 nanoparticles were dispersed using a UIP500hd ultrasonic device, and filtration tests (API LPLT and HPHT) were conducted using Whatman 50 filter paper [32]. API tests were performed at 100 psig and room temperature (25°C), while HPHT tests were done at 400 psig under various temperatures [32].

Table **1** shows the complete statistics of the dataset, while Fig. (**1**) shows the frequency and distribution of the dataset. The dataset was randomly divided into training and testing sets to train the Multi-layered Perceptron (MLP) Network. The optimum train-test split was found to be 80%-20%, hence 29 and 8 datapoints were used to train and test the accuracy of the Deep learning model respectively.

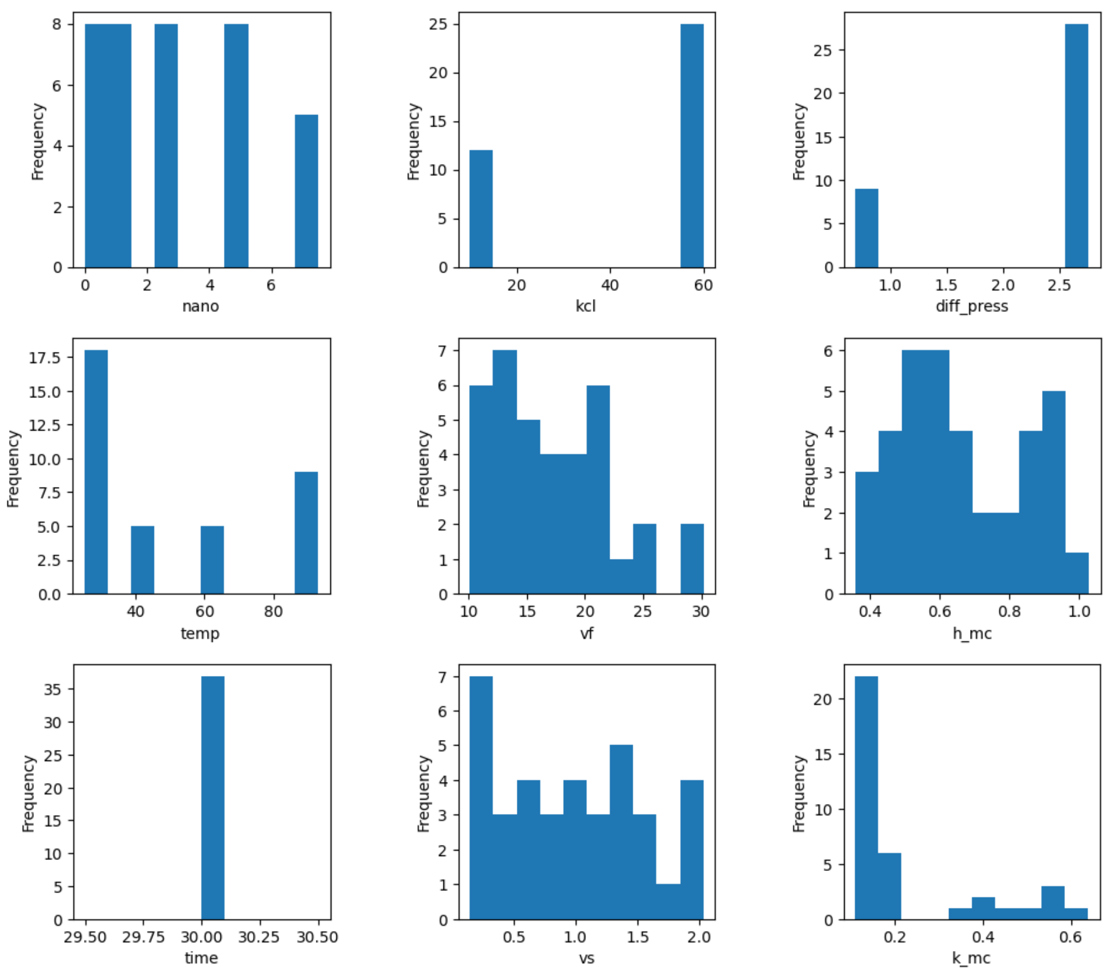

Figure 1: Distribution and frequency of the dataset.

Table 1: Statistics of the dataset.

Index	SiO_2 Conc. gr/L	KCl Conc. gr/L	Differential Pressure MPa	Temp. °C	Filter Loss Volume, cm^3	Mud Cake Thickness, mm	Time min	Spurt Vol. cm^3	Mud Cake Permeability, nm^2
Count	37.00	37.00	37.00	37.00	37.00	37.00	37.00	37.00	37.00
Mean	2.85	43.78	2.26	49.38	17.15	0.66	30.00	0.99	0.23
Standard Deviation	2.57	23.73	0.90	28.50	5.12	0.18	0.00	0.57	0.16
Minimum	0.00	10.00	0.69	25.00	10.1	0.36	30.00	0.15	0.11
25%	1.00	10.00	2.76	25.00	13.7	0.51	30.00	0.47	0.14
50%	2.50	60.00	2.76	43.00	16.4	0.6	30.00	0.95	0.16
75%	5.00	60.00	2.76	65.00	20.7	0.85	30.00	1.4	0.19
Maximum	7.50	60.00	2.76	93.00	30.2	1.03	30.00	2.03	0.64

2.2. Development of the Multilayered Perceptron Network

The history of Artificial Neural Networks (ANNs) can be traced back to 1943 when a fundamental neural network model was developed [43]. In 1949, Hebb introduced the concept of neural network learning rules; which allowed the use of ANNs to widely increase across various sectors [44]. ANNs are capable of recognizing and understanding both linear and non-linear correlations between input and output variables in a given dataset. The fundamental goal of a neural network is establishing a mapping between a group of input patterns and related output patterns [45, 46]. Artificial neural networks (ANNs) have the unique capacity to solve complicated issues that are impossible to formulate using traditional mathematical procedures [47]. Different kinds of neural networks can be built by adjusting the placement of neurons and the patterns of connections between them within layers. Multi-layer perceptron (MLP) and Radial Basis Function (RBF) networks are two examples of popular and adaptable neural network architectures that are often used in scenarios involving problem-solving [48-50].

A Multilayered Perceptron (MLP) Network is a combination of three individual layers which are known as the input layer, the hidden layer, and the output layer. These networks are essentially made up of neurons, each of which has a bias, is connected by links, and has a particular weight given to each link [51]. Training algorithms support the learning process, which is driven by input and target datasets. The following two equations can be used to officially describe a neuron, represented by the symbol **k**, in mathematics [51]:

$$y_k = f(u_k + b_k) \quad \text{Eq. 1}$$

$$u_k = \sum_{i=1}^{N} w_{ki} x_i \quad \text{Eq. 2}$$

Here the input signals are represented by $x_1, x_2, x_3 \ldots\ldots\ldots x_n$ the connection weights assigned to the neurons are represented by $w_{k1}, w_{k2}, w_{k3} \ldots\ldots\ldots w_{kn}$. Using a weighted summation of the input signals, the network initially calculates the linear output (u_k), in which the bias term (b_k) is also involved. After that, the activation function f is used to obtain the output signal y_k [51].

The backpropagation (BP) technique, which applies a learning process based on an error correction mechanism, is used to train MLP-NNs. To produce its output, this network processes input data. The algorithm determines the error by comparing the output of the network with the desired values. The training procedure is then repeated until the network achieves a predetermined acceptable level of error, during which repeatedly modifies the weights and biases to reduce this error [51].

Artificial Neural Networks (ANNs) and Multilayered Perceptron (MLPs) are widely used in the oil and gas industry due to their efficiency and accuracy in mapping complex relationships between multiple parameters. One of their application is reservoir characterization particularly the determination of saturation pressure [52], utilizing well-log data to predict parameters like porosity, permeability, lithology, and sand thickness [53], determining minimum miscibility pressure in CO_2 injection and, asphaltene adsorption and stability [54, 55]. Similarly, Fath *et al*. 2018, applied both Radial Basis Functions (RBF) and Multilayered Perceptron (MLP) to determine the solution gas-oil ratio of crude oil [51]. Another study by Vaferi *et al*., explored the use of MLPs on well-test data and developed a system to accurately classify the reservoir model based on the input parameters [56].

The proposed MLP network model in this study was developed using Python programming language. This developed model was used to determine the mud cake permeability using 8 inputs. A random division of the dataset was done, and two subsets were formed i.e., training and testing sets. The number of neurons in the hidden layer of a multilayered perceptron (MLP) model determines its size and prediction power. Choosing the right number of neurons for the best network architecture usually requires a trial and-error-based approach. A variety of unique network topologies with varying numbers of neurons were assessed to tackle this problem. In these analyses, the loss function was the mean squared error or MSE. The optimized network architecture was ultimately determined by minimizing the inaccuracy present in the test data. To lessen the possible impact of random correlations resulting from the first random weight initialization, this procedure was carried out several times. After several trials, it was observed that the model performed optimally with three hidden layers, having 1000, 100, and 10 neurons respectively. The ReLU activation function was used for the hidden layers of the MLP network and the regularization parameter (λ) was set to 0.001. The parameters of the MLP model are given in Table **2**.

Table 2: Different parameters of the MLP model.

Parameter	Value
Optimizer	Adam
Loss function	MSE
Number of hidden layers	3
Number of neurons in the hidden layer	1000,100,10

2.3. Model Evaluation

In this study, widely used measures for assessing accuracy in regression problems were used to evaluate the performance of theMultilayered Perceptron (MLP) model. The rootmean square error (RMSE), mean absolute error (MAE), mean squared error (MAE), and coefficient of determination (R^2) are some examples of these measurements. As an additional technique to assess the model validation, a cross-plot was used to compare the projected values against the actual data.

3. Results and Discussion

Cross-plots were constructed between actual mud cake permeability and MLP-predicted mud cake permeability for training and testing datasets (Fig. **2**-**3**). An analysis of the cross plots reveals that a good correlation exists between actual and MLP-predicted mud cake permeability, as the majority of the values lie in the line of best fit. Since the predicted values are closer to the laboratory-determined permeability values hence it can be inferred that the model performed efficiently and accurately.

The evaluation of the developed Multilayer Perceptron (MLP) model in this study involved the application of classical statistical techniques to assess its efficiency in estimating mud cake permeability within SiO_2 salt and KCl salt-added water-based drilling mud systems. The obtained results reveal the model's exceptional accuracy and reliability. The coefficient of determination (R^2) serves as a key metric in assessing how the model fits the actual data. Particularly, the R^2 value of 0.9982 for the training dataset and 0.8781 for the testing dataset indicates a

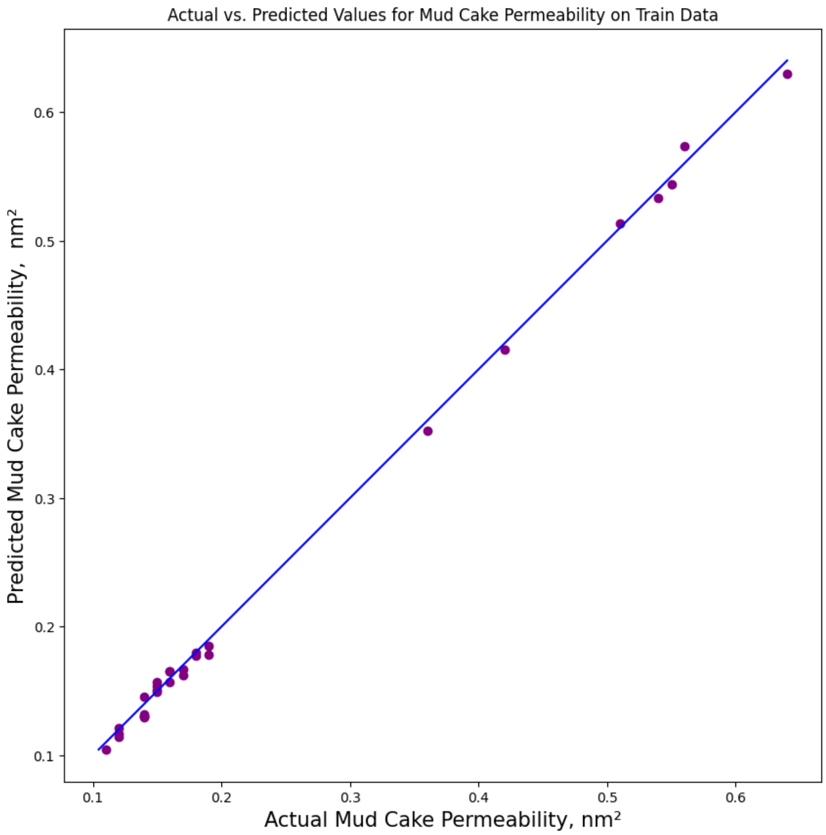

Figure 2: Actual vs predicted mud cake permeability for MLP on train data.

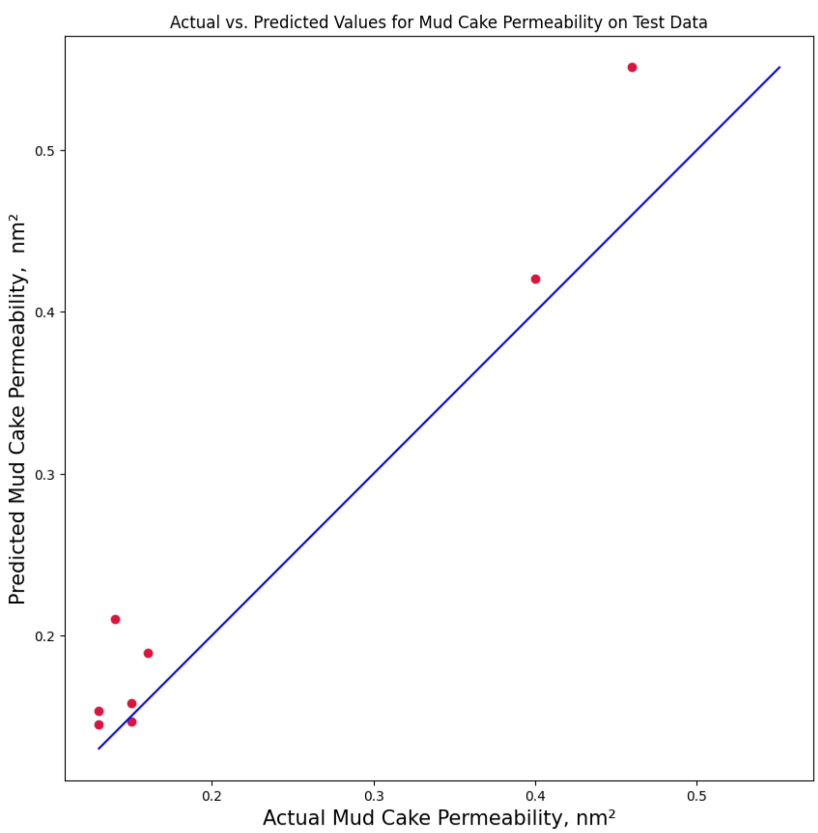

Figure 3: Actual vs predicted mud cake permeability for MLP on test data.

high-degree correlation between the predicted and observed values. The close alignment of the model's predictions with the actual data highlights its capability to capture the underlying patterns in the mud cake permeability. Furthermore, the model's performance is validated through the evaluation of Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). Lower values for these metrics suggest reduced errors in predicting the mud cake permeability, which is the target parameter in this case. The obtained values of 0.04378 for RMSE, 0.001917 for MSE, and 0.03256 for MAE demonstrate the model's accuracy in minimizing the discrepancies between predicted and actual permeability values. The high R^2 values and low error metrics collectively indicate the robustness of the MLP model in providing accurate estimations of mud cake permeability in SiO_2 salt and KCl salt-added water-based drilling mud systems. These findings not only validate the efficacy of the developed model but also underscore its potential for practical applications in predicting mud cake permeability in diverse drilling scenarios, contributing to enhanced efficiency and precision in wellbore operations.

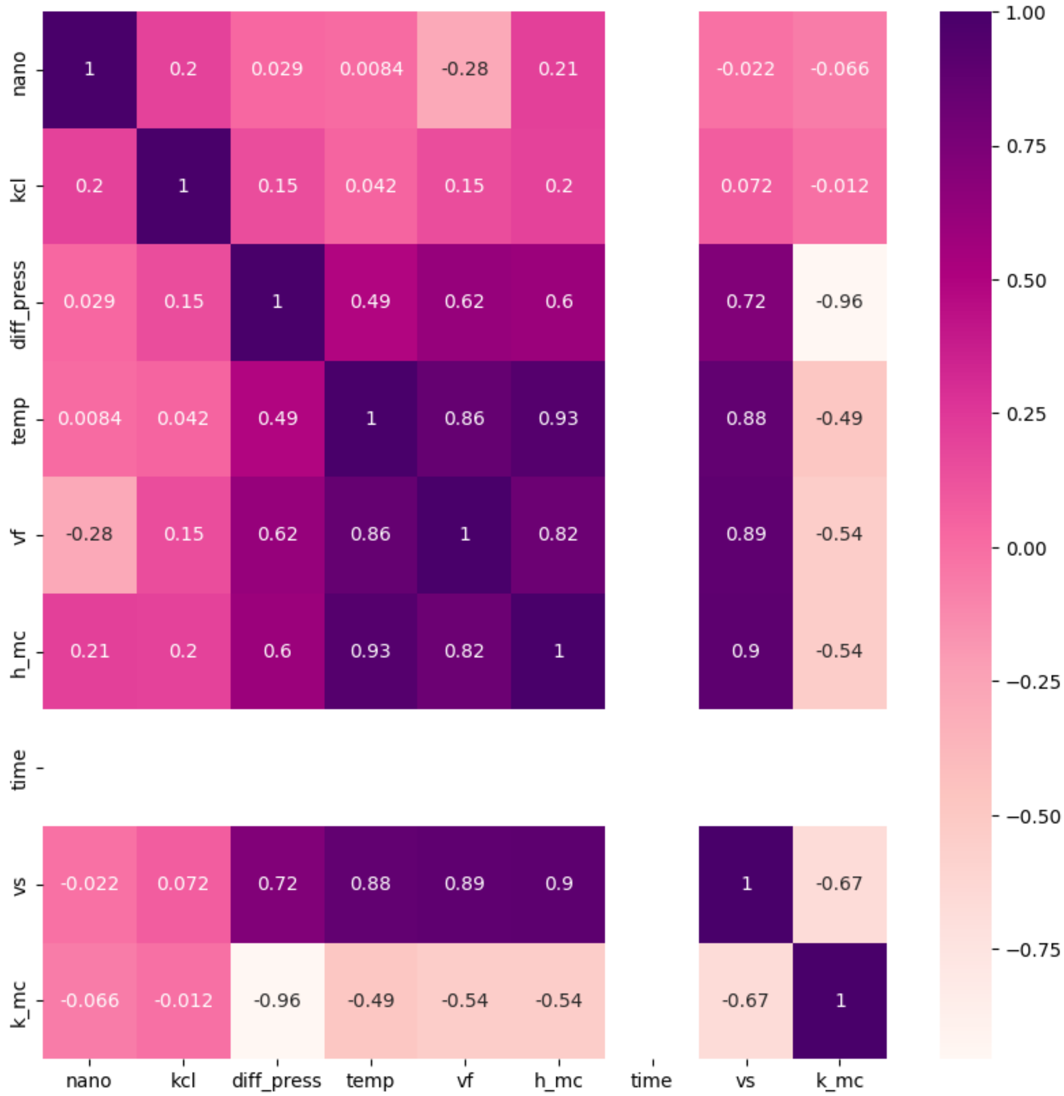

Figure 4: Correlation heatmap of feature pairs.

The correlation heatmap presented in Fig. (**4**) offers valuable insights into the relationship between mud cake permeability and various input features in wellbore conditions. The heatmap reveals distinct patterns of correlation coefficients, indicating the strength and direction of these relationships. Notably, there is a robust positive correlation (0.96) between mud cake permeability and differential pressure, suggesting that higher differential pressures are associated with increased mud cake permeability.

In an ideal scenario differential pressure does not directly influence the filtration volume, but real case scenarios it does affect the filtration volume, which indirectly influences the mud cake permeability . The impact of differential pressure on mud cake formation is influenced by the size and shape of the solid particles within the mud cake. Larger particle sizes and particle agglomeration result in increased filtration volumes under higher differential pressure conditions [14]. Similarly, the spurt volume exhibits a strong positive correlation (0.67), indicating a tendency for higher spurt volumes to coincide with elevated mud cake permeability. Spurt loss impacts mud cake permeability by influencing the initial volume of filtrate during fluid invasion before the filter cake forms [15]. A wider particle size distribution leads to lower permeability, as smaller particles fill voids between larger ones, creating a denser structure [15]. This denser packing reduces fluid flow through the mud cake. Additionally, a broader size distribution enhances the bridging mechanism, allowing for quicker mud cake formation and reduced spurt loss [15]. Consequently, lower spurt loss indicates a more effective filtration process, maintaining mud cake integrity and minimizing permeability [15].

Additionally, moderate positive correlations (0.54) are observed for funnel viscosity, mud cake thickness, and reservoir temperature. This suggests that these factors are moderately associated with mud cake permeability variations. High temperatures slightly increase the mud permeability since it leads to disruption of colloidal stability [32]. As temperature rises, the kinetic energy of particles in the drilling fluid increases, altering their interactions with the liquid phase [32]. This can lead to the breakdown of particle agglomerates and enhance the fluid's flow characteristics [32].

On the other hand, the concentration of KCl salt and nanoparticles demonstrates little impact on mud cake permeability, as reflected by lower or negligible correlation coefficients for these parameters.

4. Conclusion

This study highlights the novel application of a Multilayer Perceptron (MLP) neural network to predict mud cake permeability, a key factor in optimizing the performance of water-based drilling fluids (WBDFs) used in the oil and gas sector. Mud cake permeability is crucial for drilling efficiency, wellbore stability, and fluid control. It also offers insights into reservoir properties like porosity, aiding in reservoir evaluation and subsurface resource management in oil and gas operations. By incorporating thixotropic and rheological input parameters such as SiO_2 nanoparticles and KCl salt concentrations, the model provided a high level of accuracy, demonstrated by strong statistical metrics (R^2 = 0.8781, RMSE = 0.04378). The MLP model effectively captured the complex relationships between permeability and various drilling fluid properties, such as differential pressure, temperature, and filter loss volumes. The novel approach of integrating SiO_2 nanoparticles and KCl as key input parameters with a deep learning algorithm offers a more precise prediction tool, enhancing the ability to design efficient drilling fluids and improve wellbore stability. Future work could extend this model by utilizing a larger, more comprehensive dataset to develop a generalized model for broader applications in WBDF systems. This research offers significant potential for improving drilling efficiency and reservoir characterization, contributing to more efficient subsurface resource management.

Conflict of Interest

The corresponding author declared no conflicts of interest in this work on behalf of all the authors.

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Data Availability

All the data that is used to produce this study is here within the manuscript. Moreover, the code will be made available upon request.

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