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PREDICTING FORMATION PERMEABILITY BASED ON A CONVOLUTIONAL NEURAL NETWORK

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Abstract. This study considers the problem of indirect prediction of formation permeability based on traditional geophysical logging data, which is important for hydrodynamic modeling, reserve estimation, and decision support in field development under conditions of limited availability of laboratory measurements and nuclear magnetic resonance logging. The objective of the study is to determine the effectiveness of using a modified multi-input convolutional neural network for predicting formation permeability based on traditional logging data, to characterize the impact of structural modifications on the model's accuracy and robustness, and to determine the influence of individual input parameters on prediction results using interpretation tools such as additive decomposition of feature effects. The object of the study is the relationship between reservoir permeability and a set of logging parameters presented in a mixed form of numerical curves and two-dimensional images. Based on an analysis of contemporary foreign and domestic works, a deep learning approach is proposed, within which a modified multi-input convolutional neural network with residual blocks has been developed, allowing for the simultaneous processing of one-dimensional numerical well logging series and artificially generated two-dimensional images of characteristics. Based on the proposed architecture, log vectors were transformed into feature matrices. Two data processing branches were also created for numerical and image representations, and their subsequent concatenation into a single feature space was implemented. On this basis, a regression model was implemented to estimate permeability based on calculations using nuclear magnetic resonance logging data. Particular attention was paid to optimizing the network structure by integrating residual connections and deeper narrow blocks. The model's hyperparameters were tuned using genetic optimization, the sample was divided into training, validation, and test subsets, and the quality of the forecast was quantitatively assessed using the correlation coefficient, root mean square error, absolute error, and percentage error. To improve the interpretability of the results, the study employed an additive decomposition approach for feature contributions, which allowed for a quantitative assessment of the influence of individual logging parameters and their series on the obtained permeability values. It became possible to identify the most informative curves and verify the consistency of the model's behavior with physical concepts of reservoir filtration properties. The implemented multi-input residual convolutional neural network is a perspective tool for accurate and cost-effective prediction of formation permeability based on traditional well logging data.

Keywords: formation permeability; logging data; convolutional neural network; multiple-input model; residual architecture; model interpretation.

Introduction

The permeability characteristics of reservoirs are one of the key parameters that determine the filtration properties of a formation and directly influence the results of hydrodynamic modeling, reserve estimation, and engineering decision-making in field development. Laboratory permeability measurements, as well as high-precision methods such as nuclear magnetic resonance logging, provide high-quality data but remain expensive, labor-intensive, and inaccessible for a significant portion of wells, particularly in cased wells. This creates a need for indirect approaches that establish a relationship between permeability and more commonly available types of logging data. Classical machine learning methods have demonstrated their suitability for building such relationships, but often prove limited when dealing with sparse, noisy, and heterogeneous datasets.

The development of deep learning has opened up the possibility of using convolutional neural networks to analyze both one-dimensional numerical logging curves and two-dimensional representations in the form of artificially generated images.

Combining these two types of data within a multiple-input CNN allows for the simultaneous consideration of local relationships between physical parameters and the spatial patterns of their variation with depth. The additional use of residual and «narrow» structures allows the network to be deepened without a significant increase in the number of trainable parameters, reducing optimization time and improving the accuracy of regression models. Under these conditions, approaches that combine the use of hybrid input data, modified CNN architecture, and interpretation tools for the quantitative assessment of the contribution of individual logging curves to permeability prediction become particularly relevant.

The objective of this study is to identify the effectiveness of a modified multiple-input CNN for estimating formation permeability based on conventional logging data, to characterize the impact of structural modifications to the network on the accuracy and consistency of the forecast, and to determine the contribution of individual input parameters to the simulation results using interpretive metrics.

The objective of this work is to demonstrate the effectiveness of using a modified multiple-input convolutional neural network for predicting formation permeability based on traditional logging data, characterize the effect of structural modifications (residual and “narrow” blocks) on the accuracy and stability of the model, and determine the contribution of individual input parameters to the prediction results using interpretation tools such as SHAP.

An analysis of current relevant research and publications

The problem of accurate prediction of formation permeability is complicated by the high cost and variability of laboratory experiments. It has been shown that convolutional neural networks are capable of reproducing complex filtration processes and estimating permeability changes under sand retention test conditions [1], making CNNs a promising tool for the regression-based permeability prediction tasks using geophysical data considered in this work.

Modern approaches demonstrate that CNNs can directly link the microstructure of a porous medium to permeability values by using images and hydrodynamic simulation results as training data [2]. This reinforces the feasibility of applying convolutional networks to permeability prediction tasks based on logging data. In another study, based on approaches where logging data are converted into geological images in the form of pseudo-images and processed by convolutional neural networks, the potential of CNNs for regression-based formation permeability prediction is noted, with individual elements of this approach being utilized in this work [3].

In scientific studies where permeability obtained from NMR logging is reproduced using traditional logging curves and nonlinear ML/DL models, the advantages of residual 2D-CNNs over classical algorithms and 1D-CNNs have been demonstrated, highlighting the promise of deep convolutional architectures for permeability estimation, upon which the proposed study is partly based [4].

Foreign studies indicate that specialized deep convolutional networks are capable of extracting structural features at various scales and handling small, dense objects in satellite images, which significantly improves the accuracy of identifying complex spatial structures [5]. In the proposed study, similar ideas of multiscale analysis and deep residual blocks are used to construct the architecture of a convolutional neural network aimed at more accurately reproducing the spatial variability of formation permeability based on geophysical data.

Results of work on creating deep residual neural networks show that adding shortcut connections between layers facilitates the training of very deep models and, at the same time, improves the precision of solving complex recognition tasks [6]. In the present study, these principles of residual learning were used to construct a deep convolutional architecture capable of consistently approximating the nonlinear relationship between logging data and formation permeability. Modern research asserts that for complex deep learning models, it is important not only to achieve high accuracy but also to possess explanatory capabilities and the ability to demonstrate how individual input features influence the final result. In our work, we use an additive decomposition approach to interpret the influence of logging curves on the formation permeability prediction by a convolutional neural network [7].

In oil and gas research, models that automatize the analysis of well logging data, reduce the subjectivity of expert assessments, and provide a quantitative evaluation of the similarity between intervals are becoming increasingly widespread [8]. The concepts of automated curve comparison and the identification of hidden relationships have been utilized in our work to construct a convolutional neural network designed for the regression-based prediction of formation permeability based on a suite of geophysical measurements.

The main part

Permeability plays a critical role in formation-related research, including fluid flow characterization, reservoir modeling and simulation, and reservoir management. However, operational constraints and high costs limit widespread access to direct measurements of reservoir permeability. For a long time, various machine learning methods have been used to predict reservoir permeability based on widely available datasets (such as logging data). However, experience from real-world case studies shows that there remains a need to improve the process of predicting formation permeability, particularly through deep learning using variations of convolutional neural networks (CNNs). The advantages of such network architectures include their ability to effectively utilize mixed data, providing flexibility compared to classical neural networks. CNNs can be applied to both 1D/numerical [1] and 2D/image-based datasets [2]. CNNs can predict reservoir permeability in two types of structures. The first form is suitable for use with 1D numerical datasets. In particular, a 1D-CNN was used to build a regression model for permeability estimation using drilling fluid logging data. The 2D-CNN architecture, which can be trained using 2D image datasets, is the second form of CNN used. 2D/image-based datasets can consist of artificially generated images using logging data. A 2D-CNN regression model was developed to predict permeability based on 2D images [3], and a modified version of the 2D-CNN was created that predicts permeability using artificial 2D maps generated from logging data [4].

Developing a deep neural network with multiple inputs – one that can simultaneously process datasets based on images and one-dimensional numerical data – reduces tuning issues and offers greater flexibility than a classic deep neural network with a single input. This makes the original deep learning models more accurate and faster. Accurate estimation of formation permeability significantly improves the effectiveness of decisions made at all stages of the reservoir life cycle. At the same time, predicting permeability in wells is a challenging task. Nuclear magnetic resonance (NMR) logging is an alternative approach for predicting permeability. Unlike conventional well logging methods, which are sensitive to fluids and solid particles in the formation, NMR logging measurements correlate with fluid volume, viscosity, composition, and distribution within the porous medium. Thus, NMR logging measurements correlate more accurately with rock permeability than any other type of well logging technique. However, NMR logging is expensive to acquire, difficult to analyze, and cannot be performed in cased wells, which limits the widespread availability of information obtained through NMR logging. To reduce the need for NMR logging, establishing relationships between measured permeability and widely available logging data can be considered an alternative strategy for predicting reservoir permeability in unselected wells (or wells without NMR logging). Machine learning methods are used to develop a cost-effective, rapid, and physically feasible relationship between measured permeability and logging data [3].

Deep learning (DL) approaches can be considered an alternative because they can handle sparse and limited datasets, generalize, and create nonlinear regression models. A DL-based approach for fast and accurate estimation of reservoir permeability is as follows. After the well logging dataset is collected and preprocessed, the model is trained and tested using selected traditional logging data as input and permeability calculated from NMR logging as the target. For this purpose, a multi-input convolutional neural network (CNN) is used. This model accepts two different types of data as input: a numerical well logging (NWL) dataset and graphical feature images (GFI), which are processed independently. Let us consider models with two-dimensional convolutional data. The image data can be viewed as a matrix of size $m \times n$:

$$A = \left(a_{ij}\right)_{m \times n}, \; i = 1,\ldots,m, \; j = 1,\ldots,n \; . \quad (1)$$

Each element of the matrix is a numerical value that can be interpreted as a color code within a specific spectrum. The characteristics of discrete well logging (i.e., a set of numerical data) are essentially one-dimensional vectors that can be written as follows:

$$v^k = \left(a_1^k, a_2^k, \ldots, a_N^k\right), \quad (2)$$

where k is the sample index, and N is the total number of samples in the dataset. Each element represents a position in the input object. The common dataset can be written as follows:

$$D = \begin{pmatrix} v^1 \\ v^2 \\ \vdots \\ v^N \end{pmatrix}. \quad (3)$$

To create a database suitable for training two-dimensional convolutional models, the one-dimensional vectors mentioned above must be properly converted into two-dimensional matrices. For training two-dimensional convolutional models, the number of rows and columns in the dataset samples must be greater than one. 1D vectors are converted into 2D matrices using the following steps:

1. Vector transposition:

$$v_T^k = \begin{pmatrix} a_1^k \\ a_2^k \\ \vdots \\ a_N^k \end{pmatrix}. \quad (4)$$

2. The grid sorting processes are performed on two vectors, resulting in the generation of the following two matrices:

$$A^k = \begin{pmatrix} a_{11}^k & a_{21}^k & \ldots & a_{n1}^k \\ a_{12}^k & a_{22}^k & \ldots & a_{n2}^k \\ \ldots & \ldots & \ldots & \ldots \\ a_{1m}^k & a_{2m}^k & \ldots & a_{nm}^k \end{pmatrix}, \quad (5)$$

$$A_T^k = \begin{pmatrix} a_{11}^k & a_{12}^k & \ldots & a_{1n}^k \\ a_{21}^k & a_{22}^k & \ldots & a_{2n}^k \\ \ldots & \ldots & \ldots & \ldots \\ a_{m1}^k & a_{m2}^k & \ldots & a_{mn}^k \end{pmatrix}.$$

3. The corresponding matrix elements are multiplied to create a sample matrix k, which can be used as input for two-dimensional convolutions:

$$A_F^k = \begin{pmatrix} a_{11}^k a_{11}^k & a_{21}^k a_{12}^k & \ldots & a_{n1}^k a_{1n}^k \\ a_{12}^k a_{21}^k & a_{22}^k a_{22}^k & \ldots & a_{n2}^k a_{2n}^k \\ \ldots & \ldots & \ldots & \ldots \\ a_{1m}^k a_{m1}^k & a_{2m}^k a_{m2}^k & \ldots & a_{nm}^k a_{mn}^k \end{pmatrix}. \quad (6)$$

The samples at the input layer of all neural networks have either no interaction or no connection. However, in the data transformation method under consideration, the values of each physical property are multiplied by themselves and by the values of other physical properties. Thus, the input layer of the CNN will, in a certain way, determine the influence of each input feature on the other features. The order of well logging is proportional to the order of pixel columns in the two-dimensional graphical log of characteristics. A two-dimensional graphical log of functions can represent variations in each physical property along with the corresponding depth interval through color resonance or attenuation, which can facilitate the visual interpretation of the log. A CNN is a neural network that uses convolution concepts to extract features from the input dataset. A special feature of a CNN is its ability to utilize the multidimensional nature/structure of the input data, meaning that higher-order features depend on the local neighborhood of each sample value (also known as the kernel size). This is why CNNs are used for a variety of deep learning problems. To improve the performance and precision of CNN models when solving complex classification or regression problems, their initial structure has been modified in terms of depth, depth, and width [5].

Regarding the tasks of predicting formation permeability, two modifications of the original CNN architecture are considered. The first modification involves the integration of residual and CNN architectures. By deepening the network using the residual architecture, the training process does not require any additional parameters or computational overhead [6].

Initially, the weights of each individual CNN layer do not depend on the weights of previous layers, which leads to a lengthy training process. Residual shortcut connections are incorporated into the new architecture to assist in training deep CNN models.

Figure 1 illustrates the construction of an identifier shortcut with a single residual block. The output of the previous layer (x) is fed as the input to the convolution block, where the function F transforms it into $F(x)$

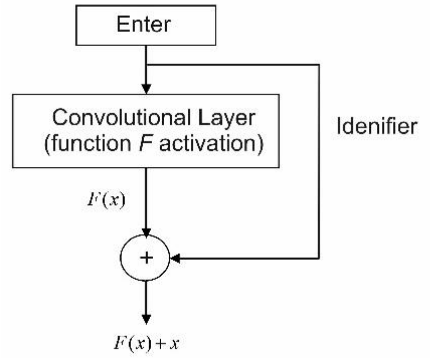

Figure 1 – Identifier label with a single residual block

The output is formed as the sum of $F(x)+x$, which is the result of the residual convolution block. Modifying the network structure to utilize linear and nonlinear dependencies during the feature extraction stage allows for the activation of functions to effectively optimize using the input data.

The second modification involves adding a deeper structure to the network. Instead of using a single convolutional layer, a stack of three layers is used (Figs. 2, 3). For a 2D-CNN, three 2D convolutional layers with kernel sizes and are added, where the layers with kernel size are responsible for downsampling and then upscaling (reconstruction), and thus the layer with kernel size acts as a bottleneck with smaller input/output dimensions. For a 1D-CNN, three one-dimensional convolutional layers with kernel sizes 1, 1, and 3 are used, where the layers with kernel size 1 are responsible for downsampling and then upscaling (reconvolution), and the layer with kernel size 3 acts as a bottleneck with smaller input/output dimensions. The narrow bottleneck structure deepens the network and reduces the number of trainable variables, which leads to a reduction in training time.

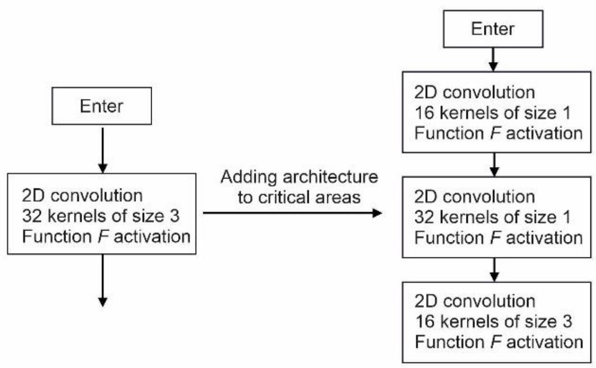

Figure 2 – Single-dimensional Slim Block (1D-SB)

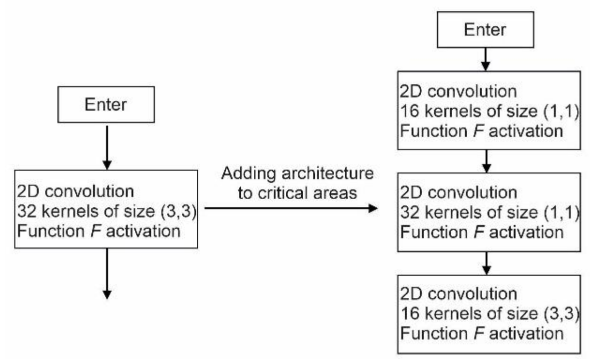

Figure 3 – Two-dimensional Slim Block (2D-SB)

Each convolutional layer has an activation function. The modifications to the CNN architecture described above are essentially based on the use of residual blocks, which consist of narrow blocks (1D and 2D residual blocks) within a deep CNN architecture. As shown in Fig. 4, CNNs (single and two-dimensional) are mostly constructed using residual blocks. Residual blocks A and C are based on a reduced identification connection, while residual block B is based on a convolutional reduced connection [6].

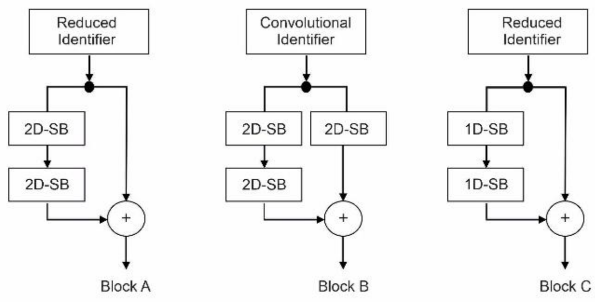

Figure 4 – Residual block configurations

The modified approach is based on the idea of multiple inputs and residual structures, which can effectively extract relevant and useful information from mixed data features.

The proposed architecture is shown in Fig. 5, which is characterized by two sets of input data. The left input is “Input-NWL,” where a numerical set of logging data is transferred to the network. The right input is «Input-GFI», where graphical representations of functions are transferred to the network. For the left branch, the NWL input passes through residual block C and generates an output activation or function map, which is then flattened into a one-dimensional array (A) for transmission to the next layer.

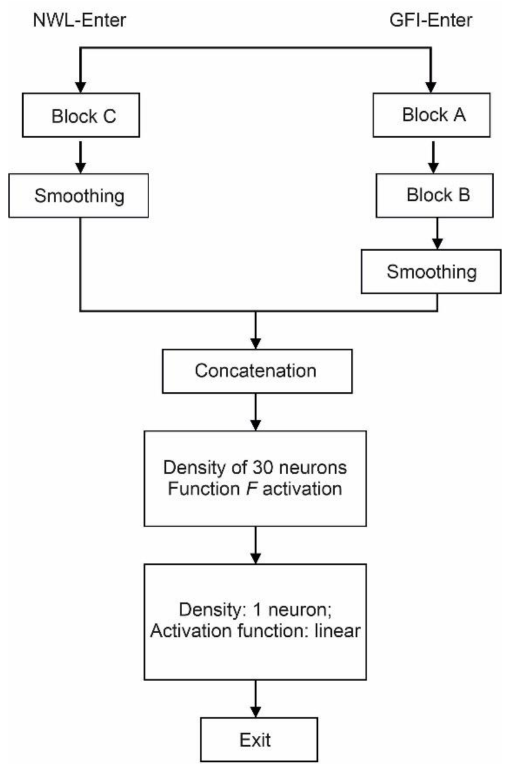

Figure 5 – The architecture of a modified deep residual CNN model

Similarly, the GFI input in the right branch passes through residual blocks A and B, which leads to the activation of the output or the function map, reduced to a one-dimensional array (B). Then, the deep GFI and deep NWL functions are combined via a concatenation layer as (L_c) як $F_1 = L_c(A,B)$. For the datasets, three groups of samples are randomly selected: training samples (70% of the training dataset), validation samples (15% of the training dataset), and test samples (15% of the training dataset). The models have their own specific set of hyperparameters. Correctly determining these hyperparameters can significantly affect the accuracy and performance of the network. We plan to use a genetic optimization algorithm to individually tune the network’s hyperparameters using appropriate NWL and/or GFI test samples. After the training and validation samples, the residual CNN models are trained separately, and their performance is then evaluated using a corresponding blind dataset. The correlation coefficient is widely used to evaluate network performance; however, this parameter is insufficient to fully characterize a complex regression task.

To evaluate the model’s accuracy and reliability, three additional performance metrics are used: mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

Therefore, it can be concluded that using image data as input features for the residual CNN model is justified, and the described image generation technique using CWL improves regression performance.

Measured properties of geophysical well logs may have some direct or indirect relationships with rock permeability. For example, logging reveals clay content, which typically affects rock permeability, or porosity obtained through logging often correlates with permeability. However, these input variables do not interact internally within the neural network, as the neurons in each hidden layer are not connected. If the input data is in the form of images, the influence of each physical feature on the others is incorporated into the process in a specific way. After computing the convolutional kernels, new feature maps are generated, including partial information about the density data. As a result, CNNs perform well in establishing a relationship between logging data and permeability.

The addition of residual and deeper narrow bottleneck structures helps improve the accuracy of permeability prediction. Furthermore, for example, the number of trainable parameters in the original 2D-CNN is reduced through the use of residual and bottleneck architectures, leading to a reduction in parameters while the number of hidden layers increases. As a result, residual and deeper bottleneck structures can further deepen the network without adding additional parameters or increasing training complexity. This reduces the number of parameters that need to be trained, leading to shorter training times.

The proposed CNN modification complements single-modality-based methods in well permeability prediction. However, it remains unclear how CWL input variables influence prediction results. To address this, the SHAP interpretation tool [7] is used, which can decode the extent of input variables' influence on predictions. Each feature has its own unique SHAP score. By comparing the model's predictions with and without a specific feature, one can calculate the SHAP score to determine the feature's significance. To ensure an adequate comparison of input features, all possible feature orders must be considered, as the order in which the model processes the features can influence its predictions.

Each of the CWL series has a different impact on the predicted results. SHAP values serve as a quantitative measure of the degree to which input variables contribute to the predicted results.

Modern approaches to well analysis demonstrate that deep learning methods can automate the comparison of logging curves and identify hidden similarities between intervals that are difficult to capture using traditional expert methods [8]. The use of architectures oriented toward sequential data makes it possible to account for the spatial sequence of measurements along the wellbore and to identify long-term dependencies between parameters. This creates a foundation for building models that not only classify intervals but also assess the similarity of reservoir conditions based on a set of geophysical indicators. In our study, these ideas were used to form a feature space and prepare input data for a convolutional neural network designed for quantitative prediction of formation permeability. Consequently, the results of studies on computerized grouping and comparison of wells serve as a conceptual basis for the further development of regression models for predicting the filtration properties of geological formations.

Conclusions

1. Modern approaches to the indirect estimation of formation permeability based on logging data were analyzed, and the limitations of classical machine learning methods when working with sparse and heterogeneous datasets were identified.

2. A modified multi-input convolutional neural network with residual and «narrow» blocks was created, capable of simultaneously processing numerical logging curves and two-dimensional feature images for regression-based permeability prediction.

3. Based on the proposed architecture, the conversion of one-dimensional logging vectors into two-dimensional feature matrices was implemented, residual structures with «narrow» blocks were constructed, and it was demonstrated that this representation improves the model's accuracy and performance compared to baseline CNN variants.

4. Particular attention was paid to the interpretation of simulation results: using an additive feature contribution decomposition of the SHAP type, the influence of individual logging parameters and measurement series on the predicted formation permeability values was quantitatively assessed.

5. A model development cycle was implemented – from feature space formation and hyperparameter optimization using genetic optimization to quality assessment based on an extended set of metrics (correlation coefficient, root mean square error, absolute error, and percentage error),

which confirmed the feasibility of using the proposed convolutional neural network for predicting formation permeability.

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Conflict of interest
None.

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ПРОГНОЗУВАННЯ ПРОНИКНОСТІ ФОРМАЦІЇ НА ОСНОВІ ЗГОРНУТОЇ НЕЙРОННОЇ МЕРЕЖІ

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Анотація. У цьому дослідженні розглядається проблема непрямого прогнозування проникності пласта на основі традиційних даних геофізичного каротажу, що є важливим для гідродинамічного моделювання, оцінки запасів та підтримки рішень при розробці родовищ в умовах обмеженої доступності лабораторних вимірювань та ядерного магнітного резонансного каротажу. Метою дослідження є визначення ефективності використання модифікованої багатовхідної згорткової нейронної мережі для прогнозування проникності пласта на основі традиційних даних каротажу, характеристика впливу структурних модифікацій на точність та робустність моделі, а також визначення впливу окремих вхідних параметрів на результати прогнозування за допомогою інструментів інтерпретації, таких як адитивне розкладання ефектів ознак. Об'єктом дослідження

є зв'язок між проникністю пласта та набором параметрів каротажу, представлених у змішаній формі числових кривих та двовимірних зображень. На основі аналізу сучасних зарубіжних та вітчизняних робіт запропоновано підхід глибокого навчання, в рамках якого розроблено модифіковану багатовхідну згорткову нейронну мережу із залишковими блоками, що дозволяє одночасно обробляти одновимірні числові серії каротажу та штучно згенеровані двовимірні зображення характеристик. На основі запропонованої архітектури каротажні вектори були перетворені на матриці ознак. Також було створено дві гілки обробки даних для числового та графічного представлень, а також реалізовано їх подальше об'єднання в єдиний простір ознак. На цій основі було реалізовано регресійну модель для оцінки проникності на основі розрахунків з використанням даних ядерного магнітного резонансу каротажу. Особливу увагу було приділено оптимізації структури мережі шляхом інтеграції залишкових зв'язків та глибших вузьких блоків. Гіперпараметри моделі були налаштовані за допомогою генетичної оптимізації, вибірка була розділена на навчальні, валідаційні та тестові підмножини, а якість прогнозу була кількісно оцінена за допомогою коефіцієнта кореляції, середньоквадратичної помилки, абсолютної помилки та відсоткової помилки. Для покращення інтерпретованості результатів у дослідженні було використано адитивний підхід декомпозиції для внесків ознак, що дозволило кількісно оцінити вплив окремих параметрів каротажу та їх серій на отримані значення проникності. Стало можливим виявити найбільш інформативні криві та перевірити узгодженість поведінки моделі з фізичними концепціями фільтраційних властивостей пласта. Реалізована багатовхідна залишкова згорткова нейронна мережа є перспективним інструментом для точного та економічно ефективного прогнозування проникності пласта на основі традиційних даних каротажу свердловин.

Ключові слова: проникність пласта; дані каротажу; згорткова нейронна мережа; багатовхідна модель; залишкова архітектура; інтерпретація моделі.