Research Article

Quantitative Prediction of Low-Permeability Sandstone Grain Size Based on Conventional Logging Data by Deep Neural Network-Based BP Algorithm

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The median grain size of rock is the main basis for the identification of sedimentary facies, and the variation of the median grain size of rock can be used to obtain the stratum sedimentary rhythm and thus to classify the flow unit. Therefore, the median grain size of rock is an extremely important parameter for reservoir evaluation. However, there is no petrophysical method that can directly evaluate the median grain size of rock in the logging data. The predecessors used natural gamma logging data to calculate the median rock grain size (Md) based on linear and statistical analysis for medium-high porosity and permeability sandstone reservoirs work. However, for low-permeability sandstone reservoirs, the error in the fitted median grain size of rock using linear multiple regression methods is too large for the calculated results to be applied. Therefore, the calculation of the median grain size of low-permeability sandstone reservoirs is a difficult problem to be solved. In this paper, the sensitivity logging parameters of median rock grain size are optimized for low permeability sandstone reservoirs using principal component analysis obtained the grain size direction correlation curves (DEN, CNL,GR, and RD) in the study area, and the corresponding loss and activation functions are selected based on the learning characteristics of the nonlinear mapping of the logging data and the BP neural network to ensure that overfitting occurs. The best model was obtained by using decision tree, support vector machine, shallow and deep neural networks to model the median rock grain size and predict neighboring wells, and a comparative analysis showed that for the problem of predicting the median rock grain size in low-permeability sandstone reservoirs, the deep neural network improved significantly over the shallow one and was much stronger than other machine learning methods. The best model obtained a coefficient of determination ($R^2$) of 0.9831. Machine learning of median grain size from conventional logging data was systematically carried out through conventional logging sensitivity curve optimization, algorithm modeling, network parameter optimization, median grain size prediction, and validation, and the relative error in its quantitative prediction met application requirements. This method takes into account the nonlinear mapping relationship between the logging data and the fitting of small sample data and provides a systematic way of thinking for the logging curve to predict the grain size of low-permeability sandstone.

1. Introduction

Sedimentary facies is the theoretical and practical basis for finding favorable reservoirs in petroleum exploration and development. It is a common technical means to interpret sedimentary facies by logging curve, and the median rock grain size is often used as a marker for determining sedimentary facies. Furthermore, for low permeability and tight reservoirs, the median grain size has a great influence on the physical properties of the reservoir, which in turn affects the degree of reservoir exploitation. For medium and high porosity and permeability sandstone reservoirs, satisfactory
median grain size results can be obtained by using the multiple linear regression method. However, the logging response characteristics of low permeability sandstone reservoir are affected by complex pore structure, and the linear regression of logging curve combination cannot calculate satisfactory median grain size results. Therefore, it is necessary to carry out research work on the quantitative prediction of the median grain size in low permeability sandstone reservoir using conventional logging data.

The median rock grain size refers to the size of rock grains. In general, the grain size of spherical particles is expressed by diameter and that of cube particles in terms of side length. For irregular particles, the diameter of a particular sphere that has the same behavior as the particle can be taken as the equivalent diameter of the particle. Median grain size is a grain size value in a selected sample that corresponds to a cumulative percentage size distribution of 50%, abbreviated as D50. For the well-sorted and rounded medium and high porosity and permeability sandstone reservoir, the natural gamma of the formation will be low if the median rock grain size is large in the lower part of the positive rhythm sedimentary stratum, the water flow rate is fast during deposition, the mud content is relatively smaller, and the clay has a strong radiosorption capacity. Therefore, natural gamma ray (GR) curve and median rock grain size and the clay have a strong radiosorption capacity. Thus, the importance of feature learning, which transforms the rich inherent information of the data than manual rule-based methods of constructing features. The use of big data to learn features is more capable of portraying the rich inherent information of the data than manual rule-based methods of constructing features.

Nowadays, network models for curve prediction are complex and varied, but their mechanisms are mostly based on nonlinear fitting of unknown curves through neural networks using the relevant data that best correlates with the curve to be predicted. The difference between shallow and deep neural network is that deep neural network can better reflect “intelligence,” as some of the more complex nonlinear features in multilayer neural networks can only be learned in the deeper layers of the network.

The combination of artificial intelligence and petroleum exploration can greatly improve efficiency and reduce cost and risk. With the advent of the trend of the era of digitization and informatization, the intelligent development of oil and gas exploration and development has become the forefront hotspot and future development trend of the industry. The complex relationship between complex geological problems and logging curves is precisely what nonlinear neural network methods are suitable for solving.

Therefore, in recent years, many researchers have used artificial neural networks to further enhance the logging curve in terms of identifying lithology, stratigraphic division, and lithofacies [7–20] (Table 1).

In this paper, sensitive logging parameters for median grain size are obtained by sensitivity parameter analysis, and the prediction of median grain size in the targeted layer by multiple regression analysis, decision tree, support vector machine, and neural networks is analyzed and compared. After normalizing the sensitive logging parameters of median grain size, the neural network was input. For the problem of incomplete distribution of the median grain size data in the target section, a geological constraint of 5 μm median grain size was added to the mudstone section with clear petrophysical characteristics in the target interval, which not only expanded the amount of training data but also made the distribution of training data more complete. And the output is combined with the median grain size after adding geological constraints, and the prediction model was obtained by training the prediction model of median grain
**Table 1:** Statistics of related research on machine learning methods at home and abroad.

<table>
<thead>
<tr>
<th>Author</th>
<th>Method</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ma et al. (2015)</td>
<td>BP neural network</td>
<td>Petrophysical facies</td>
</tr>
<tr>
<td>Xue et al. (2019)</td>
<td>BP neural network</td>
<td>Lithology identification</td>
</tr>
<tr>
<td>Liu et al. (2019)</td>
<td>Artificial neural network</td>
<td>Curve reconstruction</td>
</tr>
<tr>
<td>Fuhua et al. (2020)</td>
<td>L-M, BP neural network</td>
<td>Stratigraphic division</td>
</tr>
<tr>
<td>Sabah et al. (2020)</td>
<td>PSO, COA, MLP, LSSVM</td>
<td>Lost circulation while drilling</td>
</tr>
<tr>
<td>Mohamadian et al. (2021)</td>
<td>MLP, GA, PSO</td>
<td>Maximum horizontal stress Poisson’s ratio</td>
</tr>
</tbody>
</table>

**Figure 1:** Conventional logging curve and core experiment analysis diagram of $S_2$ section of well X1.
size through neural network. A systematic method for predicting the median grain size curve of low-permeability sandstone with different hidden layer neural network models was developed by combining multiple regression analysis and shallow and deep neural network predictions and validated by applying the prediction model to neighboring wells for median grain size prediction.

2. Low-Permeability Sandstone Grain Size and Lithology

The Bohai Paleogene M Oilfield is located at the west end of Bonan low uplift and the boundary between Bozhong sag and Huanghekou sag. The main development layer of the oilfield is Shahejie Formation reservoir, which is deeply
Figure 3: Continued.
buried. The reservoir of Shahejie 2 ($S_2$) is braided river delta deposit, and the reservoir of Shahejie 3 ($S_3$) is fan delta turbidite deposit. Due to the joint influence of structure, sedimentation, and diagenesis, the reservoir of Shahejie Formation has medium porosity and low permeability characteristics of ultra-low permeability. The lithology of $S_2$ reservoir is dominated by fine sand, followed by very fine sand and medium sand. Generally, the sorting is poor, and the roundness is mainly subrounded to subprismatic. The sandstone skeleton particles are mainly composed of quartz, feldspar, and rock debris, belonging to rock debris arkose. The physical statistics of the analyzed samples indicate that the reservoir properties are poor. The medium coarse sandstone in underwater branch channel and estuary bar has good reservoir properties and is a medium reservoir. The fine siltstone between underwater branch channels has poor reservoir physical properties and is a poor reservoir. The lithology of $S_3$ member is mainly medium sand and fine sand, followed by coarse sand and very fine sand. The median grain size distribution range is wide. Generally, the sorting is relatively poor-poor, and the roundness is mainly subprismatic. The sandstone skeleton grains are mainly quartz, feldspar, and rock debris, belonging to lithic arkose and feldspathic lithic sandstone. The statistical results of the physical properties of the samples analyzed in the third member of Shahejie Formation show that the physical properties of the reservoir are poor, and the difference in physical properties is controlled by the sedimentary facies belt. For example, the physical properties of the reservoir section located in the braided channel of the middle fan are significantly better than those located in the inner fan.

Figures 1 and 2 show conventional logging data curves of $S_2$ and $S_3$ sections of well X1 with SP (natural potential), GR (natural gamma), DEN (density), CNL (neutron), AC (acoustic), RS (shallow lateral resistivity), RD (deep lateral resistivity), RMLL (micro lateral resistivity), RILD (medium induced resistivity), RILM (deep induced resistivity), PORE (porosity), PERM (permeability), and MD (median grain size), where MD is the median grain size of the rock sieved (porosity), PERM (permeability), and MD (median grain size), where MD is the median grain size of the rock sieved through the core elastic rock. It can be seen that the median grain size of $S_2$ section of well X1 is concentrated between 100 and 800 µm. With the increase of depth, the median grain size decreases, which is antirhythmic deposition. The compensated neutron, bilateral resistivity logging curve value, and the difference between deep and shallow lateral resistivity show a decreasing trend, and the natural gamma value shows an increasing trend. The $S_2$ section of the well X1, like the $S_3$ section, is antirhythmic deposited, but the logging response is not as pronounced as $S_2$ section. The upper median grain size of the two well sections is large, and the physical properties are relatively good, indicating that the median rock grain size determines the physical properties of the rock. Therefore, the correct evaluation of the median rock grain size by logging plays an important guiding and adjusting role in the oilfield development of this block [21].

The frequency distribution histogram (Figure 3) of three porosity and GR distribution ranges of $S_2$ and $S_3$ in well X1.

Table 2: The three porosity and GR distribution ranges of $S_2$ and $S_3$ in well X1.

<table>
<thead>
<tr>
<th>Curve name</th>
<th>AC (µs/ft)</th>
<th>CNL (v/v)</th>
<th>DEN (k/m³)</th>
<th>GR (api)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Main interval</td>
<td>75.58-115.33</td>
<td>0.136-0.291</td>
<td>2.36-2.54</td>
<td>72.60-118.20</td>
</tr>
<tr>
<td>Mean</td>
<td>96.65</td>
<td>0.221</td>
<td>2.46</td>
<td>95.73</td>
</tr>
<tr>
<td>$S_3$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Main interval</td>
<td>72.32-85.44</td>
<td>0.106-0.193</td>
<td>2.40-2.49</td>
<td>82.17-118.76</td>
</tr>
<tr>
<td>Mean</td>
<td>77.13</td>
<td>0.141</td>
<td>2.43</td>
<td>98.50</td>
</tr>
</tbody>
</table>
are AC (75.58-115.33 μs/ft, mean value 96.65), CNL (0.136-0.291 v/v, mean value 0.221), DEN (2.36-2.54 k/m³, mean value 2.46), and GR (72.60-118.20 api, mean value 95.73). The main distribution ranges of \( S_3 \) section are as follows: AC (72.32-85.44 μs/ft, mean value 77.13), CNL (0.106-0.193 v/v, mean value 0.141), DEN (2.40-2.49 k/m³, mean value 2.43), and GR (82.17-118.76 api, mean value 98.50). Therefore, it is relatively difficult to calculate the median grain size of rock by using conventional logging data in \( S_3 \) section, especially when the change of logging response is not obvious.

Figure 4 shows a comparison of the frequency distribution histogram of porosity and permeability of \( S_2 \) and \( S_3 \) sections of well X1. It can be seen from the figure that the target intervals of the two sections are characterized by low porosity and low permeability. The porosity and permeability of the \( S_2 \) section are mainly distributed at 2.32% ~24.51% and 0.01~1000 mdc, with peak values of 21% and 19.21 mdc. The porosity and permeability of the \( S_3 \) section in particular are the lowest, with porosity and permeability ranging from 3.43% to 18.69% and 0.01 to 100 mdc with a peak value of 14.22% and 0.23 mdc.

Under the condition of low porosity and low permeability, the amplitude of the logging curve in the \( S_3 \) section in particular does not vary significantly, making it particularly difficult to calculate the median rock grain size. Therefore, according to the characteristics of logging data and median rock grain size, it is necessary to select logging data which is more sensitive to the change of median rock grain size for calculation. The physical properties of sandstone reservoir include porosity and permeability. As mentioned above, the median grain rock size is closely related to the reservoir physical properties; that is, the larger the median grain rock size, the better the physical properties. Logging response characteristics can reflect the reservoir physical properties. For example, good reservoir properties are usually associated with low GR values, increased CNL and AC values, decreased DEN values and an increased difference between deep and shallow lateral resistivity, but resistivity values are strongly influenced by fluid properties, i.e., resistivity values are greater in oil and gas formations than in water layer.

The mudstone layer can be divided by GR and resistivity curve. GR is a high value, and resistivity is a low value. Generally, the grain size analysis experiment is not conducted in the core of mudstone section; so, there is no grain size median analysis data of mudstone section, but the mudstone section can be subject to geological constraints according to
the definition of mudstone. Porosity can be calculated using the logging data of three porosity (CNL, AC, and DEN), and permeability can be calculated using parameters such as porosity, shale content, and irreducible water saturation. These two parameters are not the focus of this paper and will not be analyzed here. Then, the median rock grain size is related to which curves in the conventional logging data, and the correlation analysis is to carry out in the next step.

For low-permeability sandstone reservoir, lamellar density, attitude of rocks, and degree of hydration have significant effects on permeability anisotropy [22], and there should be some logging curves that are influenced by the median grain size; that is, there is a certain relationship with the change of median grain size. It is already difficult for log interpretation analysts to find these relationships through principal component analysis with the help of mathematical tools. Sensitivity parameter analysis refers to the analysis of conventional logging data combined with the median parameter of rock grain size to find patterns. The orthogonal transformation is used to convert the variables that may have correlation in the original logging data into a group of linear uncorrelated variables, extract the main characteristic components of the data, and rotate the data coordinate axis to the important direction of the data angle (such as the maximum variance). Then, the number of sensitive parameters to be retained is determined through eigenvalue analysis, and other insensitive parameters are discarded, so as to reduce the dimension of logging data for predicting the median value of rock grain size.

The AC, DEN, CNL, GR, RD, and RS were selected for correlation analysis (XG-Boost) in conjunction with conventional logging data. The data results for the correlation contributions were derived after sensitivity parameter analysis of the logging curves (Figure 5). It can be seen from the figure that the three logging curves that contribute the most to the correlation of median rock grain size are DEN (28%), CNL (18%), and GR (18%), followed by AC (15%) with RD (8%) contributing the smallest correlation contribution.

From the correlation analysis results, the log curves with the highest correlation are DEN, CNL, GR, and RD; so, the correlation coefficient can be examined in terms of the single correlation between each logging curve and the median grain size. It can be seen from Figure 6 that the correlation between each logging data and the median grain size is not obvious; so, the effect of the conventional linear fitting method may not be ideal. Moreover, there is no too much coincidence between the median value of logging grain size and the distribution of sensitive parameters in S2 and S3; so, the data of the two layers need to be trained separately in the subsequent training of the neural network model. Under the condition of the same grain size median, because the resistivity of the oil layer and the resistivity of the water layer are quite different, which may cause bias in the calculation of the median grain size, and the contribution to the correlation analysis is low, RD and RS are removed in the selection of parameters, so that GR, DEN, CNL, and AC curves are selected as the input data of the neural network model.

3. Methods

3.1. Multiple Regression Fitting. The multiple regression method is one of the commonly used linear fitting methods. The median grain size fitting can be carried out by logging data through the multiple regression method, and the results of linear fitting can be compared with nonlinear results to gain a deeper understanding of the solution to the problem of grain size prediction for this kind of low-permeability sandstone.

Multiple regression analysis is often used to fit linear data. Assuming that variable y and n variables x have the correlation, \( y = a_0 + \sum_{i=1}^{n} a_j x_{ij} \), the corresponding function value is \( y_i (i = 1, 2, \ldots , m) \), and then the sum of partial square differences is as follows:

\[
s(a_0, a_1, \cdots, a_n) = \sum_{i=1}^{m} (y_i - \bar{y})^2 = \sum_{i=1}^{m} \left( y_i - a_0 - \sum_{j=1}^{n} a_j x_{ij} \right)^2 .
\]

(1)

To make \( s \) the minimum value, partial derivative of equation (1) can be made, and the unknown parameter \( a_0 \), \( a_1 \), \( \cdots \), \( a_n \) can be obtained by substituting the experimental data \( (x_{ij}, y_i) \).

3.2. Decision Tree. Decision tree learning is a typical classification algorithm in data mining, whose main role is to reveal the structured information in the data. The tree structure it creates is intuitive and comprehensible and can extract the hidden knowledge rules in the data; so, decision tree has been widely used in some areas (e.g., GIS remote sensing) [23, 24] but less used in the oil industry. It is able to calculate the weight of each parameter and introduce the parameters with relatively strong recognition ability in order to classify them according to their recognition ability, without introducing further parameters once identification has been achieved. The automatic selection of parameters compensates for the lack of relevant expertise, and the method
automatically selects the optimal cut-off for the parameters based on the variability of the data.

3.3. Support Vector Machine. Support vector machine (SVM) is a new learning method using structural risk minimization inductive principle proposed by Vapnik on the basis of statistical learning theory [25]. Compared to traditional learning methods that employ empirical risk minimization inductive principle, SVM features stronger generalization capability. Since SVM is a convex quadratic optimization problem, it can find the extreme value solution as the global optimal solution, and it can be used for discriminative classification of the target work area. SVM can handle the linearly divisible case, while for nonlinear...
problems, its basic idea is to map the nondivisible data in the low-dimensional input space to the high-dimensional one through a nonlinear mapping for data sets with nonlinear feature problems feature space, namely,

\[ \partial : \mathbb{R}^d \rightarrow F, \]
\[ X \mapsto \partial(x), \]

with which SVM can provide better feature extraction and classification identification in a high-dimensional feature space, that is, to construct a new classification function based on a criterion in the feature space for the purpose of linear differentiation and feature summarization.

3.4. Neural Networks. Neural network, as computing method with features such as autonomous learning, rules finding, and nonlinear fitting, has developed rapidly in recent years and has been well applied in various fields. A highly nonlinear mapping between input and output data can be achieved through the learning of neural network.

The basic idea of the BP algorithm is to back propagate the output error obtained by the network, constantly adjust, and modify the connection weight of the network, so as to minimize the network error and finally achieve the nonlinear fitting between input and output using the BP algorithm have been widely used in logging data interpretation and processing and parameter calculation [26–32].

3.4.1. Input Normalization. In the actual training and learning, the neural network involves the superposition of many layers, and the parameter update of each layer will lead to the change of the input data distribution of the upper layer. After multilayer superposition, the changes in the input distribution of the upper layers can be very drastic. Although the input signal distribution of each layer of the neural network is different, the final corresponding sample mark is unchanged; that is, the edge probability is different, and the conditional probability is the same. Therefore, the distribution is mapped to a certain interval through data normalization, so as to reduce the influence of distribution change. In our paper, normalization operation of input data is shown as eq. (3):

\[ X_{\text{input}} = \frac{(X_{\text{original}} - X_{\text{std}})}{X_{\text{mean}}}, \]

where \( X_{\text{input}}, X_{\text{original}}, X_{\text{std}}, \) and \( X_{\text{mean}} \) are the average value of normalized input, original input, standard deviation of original input, and original input, respectively.

3.4.2. Design of Neural Network. In the framework of neural network, this paper adopts three-layer neural network, with one input layer, one hidden layer, and one output layer. Thereinto, the input value is the sensitivity parameter of the median rock grain size \( X_{\text{input}} \) (GR, DEN, CNL, AC), and the output value is the median grain size of the corresponding input \( Y_{\text{output}} \) (MD). Its data structure is as follows:

\[ X_{\text{input}} = \begin{bmatrix} x_{11}, & x_{12}, & \cdots, & x_{1m} \\
\vdots & \vdots & \ddots & \vdots \\
x_{n1}, & x_{n2}, & \cdots, & x_{nm} \end{bmatrix}^T = \begin{bmatrix} \text{GR}_1, & \text{DEN}_1, & \text{CNL}_1, & \text{AC}_1 \\
\vdots & \vdots & \ddots & \vdots \\
\text{GR}_n, & \text{DEN}_n, & \text{CNL}_n, & \text{AC}_n \end{bmatrix}^T, \]

\[ Y_{\text{output}} = (y_1, y_2, \cdots, y_n)^T = (\text{MD}_1, \text{MD}_2, \cdots, \text{MD}_n)^T, \]

where \( n \) is number of training samples, \( m \) is the type of input sensitivity parameter corresponding to each sample, and the number of inputs and outputs of the neural network are 4 and 1. The nonlinear mapping completed by the network is \( f : \mathbb{R}^m \rightarrow \mathbb{R}^1 \) [33]. If the hidden layer is \( p \), the input of each node in the hidden layer of the network is

\[ S_j = \sum_{i=1}^{m} w_{ij} x_i - \theta_j (j = 1, 2, \cdots, p), \]

where \( w_{ij} \) is the connection weight from the input layer to the hidden layer, \( \theta_j \) is the threshold of the hidden layer node.
Figure 8: Continued.
The calculation formulas and derivative forms of ReLU and tanh for the activation functions selected in this paper are shown in equations (6)–(9):

\[
\text{Relu}(x) = \begin{cases} 
  x, & (x > 0), \\
  0, & (x \leq 0),
\end{cases} \tag{6}
\]

\[
\text{Relu}'(x) = \begin{cases} 
  1, & (x > 0), \\
  0, & (x \leq 0),
\end{cases} \tag{7}
\]

\[
\text{Tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}, \tag{8}
\]

\[
\text{Tanh}'(x) = 1 - \frac{(e^x - e^{-x})^2}{(e^x + e^{-x})^2}. \tag{9}
\]

Due to the characteristics of ReLU’s data selection, when \( x > 0 \), its reciprocal is equal to 1 in time, which alleviates the problem of slow gradient descent in the training process of neural network, and the convergence speed of gradient descent is much faster than other conventional activation functions; so, ReLU is used as the activation function in input layer and hidden layer networks. However, due to its unilateral inhibition, after a very large gradient flows through a ReLU neuron and the parameters have been updated, this neuron will not have activation on any data anymore, and then the gradient of the neuron will always be 0. If the learning rate is too large, it is likely that most neurons in the network will be inactivated, and the tanh activation function will be effective when the characteristics are significantly different. During the cycle, the feature effect will be continuously expanded; so, the tanh activation function is used to output the data in the last output layer.

According to the data characteristics of the median grain size and its sensitive parameters of low-permeability sandstone, the shallow and deep neural networks were built. The deep neural network added two more hidden layers than the shallow neural network. The activation functions of the hidden layers and the input layers of the two neural networks are ReLU, the input is the sensitive parameter of the median grain size, the activation functions of the output layers are tanh, and the output is the median grain size. Among them, the loss function is the mean square error loss function used to solve the regression problem so that the two neural networks were built and subsequently trained by the input to the data for the low-permeability sandstone grain size prediction model and finally, the overall structure diagram of the neural network was built (Figure 7).

3.4.3. Hyperparameter Optimization and Crossvalidation. There are two types of parameters in neural network learning. The first type is the parameters that the model learns and estimates from the training data, such as the weights and biases of the neural network units. These parameters are automatically optimized during model training by the stochastic gradient descent (SGD) algorithm. The second type is internal tuning parameters (also known as “hyperparameters”) that should be set manually, such as the number and structure of hidden layers. The training efficiency, prediction accuracy, generalization, and robustness of the network model are closely related to the hyperparameters. During hyperparameter optimization, predictions are compared with actual performance data to check the performance of the model. However, a fixed division of the training and test sets can lead to serious overfitting problems. To offset possible overfitting, a \( k \)-fold crossvalidation method \((k = 10)\) is used for optimization. The method obtains a comprehensive evaluation metric for the network model by transforming the training and test datasets several times, reflecting both the predictive performance and the generalization capability of the model. In the neural network model, a total of six hyperparameters were optimized by a combination of manual tuning and mean squared deviation.
The initial hyperparameters of the model and their search space were first determined by manual tuning. As the adjustment of certain hyperparameters (e.g., the number of hidden layers) changes the overall structure of the model, manual tuning can reduce the computational effort during the training of the model. The activation function type, dropout ratio, and the number of hidden layers were determined first, and then the evaluation metrics under the initial hyperparameters were calculated and recorded by the crossvalidation method [34–36].

4. Analysis of the Results

4.1. Fitting Results. Through the multiple regression analysis of the grain size median of the sensitive parameters GR, DEN, CNL, and AC obtained from the sensitive parameter analysis, the regression formulas of $S_2$ segment (equation (10)) and $S_3$ segment (equation (11)) between the grain size median of the target interval and the sensitive parameters are obtained:

$$\text{MD} = 3371.05756 - 10.95947 \times \text{AC} - 927.06343 \times \text{CNL} + 2.39744 \times \text{GR} - 983.06754 \times \text{DEN},$$

(10)

$$\text{MD} = -0.00731 - 0.00209 \times \text{AC} - 0.63130 \times \text{CNL} + 30.81535 \times \text{GR} - 0.77748 \times \text{DEN}.$$  

(11)

The trained machine learning method model was tested for MD curves after being trained with a known MD and four highly correlated logging curve data corresponding to the well depth (Figure 8).

From the combined error distribution (Figure 9), the intersection of the fitted data with the core sieve analysis (Figure 10), and the error analysis table (Table 4), it can be
seen that the neural network method is more effective than multiple regression analysis, support vector machine, and decision tree in training the median grain size of the low-permeability sandstone in the targeted layer section, with errors within 5%, which is generally better than other machine learning methods.

4.2 Effectiveness of Predictions. In the analysis of the data from well X1 in M oilfield, the mudstone interval in the target interval was not the target interval and was not taken into account in the median sieve grain size analysis, resulting in an incomplete median sieve grain size distribution and a small number of core thin section data. Considering the poor fitting effect due to incomplete distribution of median size and small sample size, thus, some geological constraints of mudstone section were added. The median grain size of some mudstone sections is calibrated as 5 μm, so that the median grain size can be distributed completely. In the selection of training data of neural network model, the prediction effect was finally obtained by training the median grain size with geological constraints and the median grain size without geological constraints, respectively (Figure 11). In

<table>
<thead>
<tr>
<th>Method</th>
<th>Metrics for forecasting</th>
<th>RMSE</th>
<th>MAE</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple regression analysis fitting</td>
<td>104.7416 70.59334</td>
<td>0.5554</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision tree</td>
<td>65.15264 35.43207</td>
<td>0.8203</td>
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<tr>
<td>SVM</td>
<td>66.36261 29.83985</td>
<td>0.8843</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single hidden layer 1000 epochs</td>
<td>27.56469 10.64478</td>
<td>0.9693</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single hidden layer 2000 epochs</td>
<td>14.64674 7.859871</td>
<td>0.9722</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Three hidden layer 1000 epochs</td>
<td>8.239049 2.951308</td>
<td>0.9792</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Three hidden layer 2000 epochs</td>
<td>1.340285 0.688508</td>
<td>0.9831</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 10: Plot of MD of core clastic sieve analysis and training fitted grain size rendezvous for well X1.
Figure 11, the black arrow in the last grain size median indicates some mudstone section constraints added to the conventional logging curve data. It can be seen that the fitting results obtained from the two training data have roughly the same trend in the high grain size median part, while the fitting results for the high GR section without the mudstone geological constraints do not cause the median grain size to drop; thus, the median grain size with geological constraints is selected for neural network training.

Based on geological data, the sedimentary microphases in the target section of the study area consist of submerged distributary channel, interdistributary bay, and estuarine dam. The submerged distributary channels are the submerged extensions of the onshore distributary channels of Well: X1.

Figure 11: Comparison of the fitting effect before and after adding the geological constraints of the mudstone section in the $S_2$ section of well X1.
the deltaic plain, with four main types of grain size probability accumulation curves (Figures 12(a) and 12(b)). The microphase of the interdistributary bay is a relatively low depositional area between the submerged distributary channel, with generally fine-grained sandstones, mostly silty mudstone, argillaceous siltstone, and mudstone. The estuarine dam is located at the mouth of the submerged distributary channel and has three types of grain size probability accumulation curves (Figures 12(c) and 12(d)). The different grain size probability accumulation curves were analyzed for

Table 5: Grain size interval of different sedimentary microfacies.

<table>
<thead>
<tr>
<th>Category</th>
<th>Cumulative probability</th>
<th>Main granularity interval (Φ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Submerged distributary channel</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>&gt;85%</td>
<td>0 ~ 3.5</td>
</tr>
<tr>
<td>II</td>
<td>&gt;90%</td>
<td>0 ~ 4</td>
</tr>
<tr>
<td>III</td>
<td>&gt;60%</td>
<td>3 ~ 4</td>
</tr>
<tr>
<td>IV</td>
<td>&gt;60%</td>
<td>0 ~ 2</td>
</tr>
<tr>
<td>Submerged distributary channel</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>&gt;70%</td>
<td>1 ~ 4</td>
</tr>
<tr>
<td>Estuary dam</td>
<td></td>
<td></td>
</tr>
<tr>
<td>II</td>
<td>&gt;60%</td>
<td>1 ~ 2.5</td>
</tr>
<tr>
<td>III</td>
<td>&gt;70%</td>
<td>1 ~ 2.5</td>
</tr>
</tbody>
</table>

Figure 12: Grain size probability accumulations of different sedimentary microfacies [37].
the corresponding main grain size distribution intervals, which have different grain size distribution characteristics (Table 5). The neural network models with different numbers of hidden layers and different numbers of training sessions and decision tree, SVM, and multiple regression analysis fitting equations were selected to predict the median grain size for the $S_2$ and $S_3$ segments of the modeled wells, and the final results were obtained (Figures 13 and 14). As mentioned by Hornik et al., even a single hidden layer can be used to fit complex nonlinear functions [38]; that is, for a nonlinear problem, the corresponding nonlinear relationship can be approximately fitted through the training of neural network with hidden layer, so as to solve the problem. However, for nonlinear problems with deep complexity, the nonlinear relationship cannot be well fitted with fewer hidden layers. At this time, the deeper nonlinear relationship can be better explored and fitted by adding the number of hidden layers.
Through the example analysis of this paper, it can be seen that for the shallow and deep neural networks, the fitting error of the deep neural network is smaller than that of the shallow neural network; that is, in the problem of median grain size prediction of low-permeability sandstone, its non-linear relationship cannot be better fitted only by a single hidden layer. It is necessary to add the number of hidden layers to make the training model closer to the actual relationship, namely, to mine its more complex nonlinear relationship through deeper hidden layers. The results show that the training accuracy of three hidden layers is 6.51% higher than that of a single hidden layer with the same training parameters.

After training the shallow and deep neural network model of the median grain size of low-permeability sandstone for well X1, the training model was substituted into the adjacent well X2 of well X1 for verification and analysis. Since the median grain size point of the core screening analysis of the well was concentrated in section $S_3$, the data of section $S_3$ was selected for the median grain size prediction.

Figure 14: The results of the prediction of the median rock grain size of the conventional logging data in the $S_3$ section of well X1.
According to its frequency distribution histogram of GR and three porosity (Figure 15), the logging curve GR and three porosity of this interval do not vary much, and the combination of the distribution range (Table 6) leads to its main distribution intervals as follows: AC (66.18-91.52 μs/ft, mean value 76.89), CNL (0.061-0.237 v/v, mean value 0.148), DEN (2.47-2.60 k/m³, mean value 2.54), GR (83.86-111.62 api, mean value 101.81), and generally low porosity and permeability, similar to the logging response of the corresponding interval of well X1. The median grain size of the well section is predicted (Figures 16 and 17). And the last two tracks in the figure are the prediction effects of shallow and deep neural network models, respectively. The prediction curve trend of the two network models in this interval has a similar trend, and the analysis of the validation set predicted median particle size, and core analysis value crossplot (Figure 18) shows that the relative errors between the shallow neural network model and the deep neural network model and the core analysis value are 14.44% and 8.53%, respectively. The prediction effect of the depth model with three hidden layers is 6.91%, which is higher than that of the shallow model with a single hidden layer. It can be seen from the figure that the fitting effect of the deep neural network is better than that of the shallow model with a single hidden layer. In the case of three hidden layers, the accuracy of the grain size median prediction model trained by the neural network in this paper has been less than 10.00% in the verification set.

Therefore, there is no further comparative analysis of the prediction effects of more neural networks with different hidden layers.

**Table 6:** AC, CNL, DEN, and GR ranges of well X2.

<table>
<thead>
<tr>
<th>Curve name</th>
<th>Unit</th>
<th>AC (μs/ft)</th>
<th>CNL (v/v)</th>
<th>DEN (k/m³)</th>
<th>GR (api)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S₃ Main interval</td>
<td></td>
<td>66.18-91.52</td>
<td>0.061-0.237</td>
<td>2.47-2.60</td>
<td>83.86-111.628</td>
</tr>
<tr>
<td>S₃ Mean</td>
<td></td>
<td>76.89</td>
<td>0.148</td>
<td>2.54</td>
<td>101.81</td>
</tr>
</tbody>
</table>
Figure 16: The results of the prediction of the median rock grain size of the conventional logging data in the $S_3$ section of well X2.
**Well: X2**

<table>
<thead>
<tr>
<th>Depth (Metres)</th>
<th>SP</th>
<th>CNL</th>
<th>RS</th>
<th>SVM</th>
<th>Decisiontree</th>
<th>MD</th>
<th>MD S2000</th>
<th>MD D2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: 250</td>
<td>0</td>
<td>MV</td>
<td>150</td>
<td>0.42</td>
<td>OHMM 2000</td>
<td>1</td>
<td>1000</td>
<td>1 1000</td>
</tr>
<tr>
<td>0</td>
<td>GAPI</td>
<td>200</td>
<td>USGF</td>
<td>150</td>
<td>0.2</td>
<td>MD</td>
<td>MD</td>
<td>MD</td>
</tr>
</tbody>
</table>

**Figure 17:** The results of the prediction of the median rock grain size of the conventional logging data of in the S₃ section of well X2.
5. Conclusion

In this paper, through the analysis of sensitivity parameters of the median grain size of rock in the exit section of low-permeability sandstone, logging curve with a high correlation with the median value of rock grain size was obtained. Incomplete data distribution was resolved by adding geological constraint terms for mudstone sections, combining multiple regression analysis, decision tree, SVM, shallow, and deep neural networks for comparative analysis, and a better system scheme for quantitative prediction of median grain size of low-permeability sandstone in the target interval was finally obtained.

(1) In this paper, a regression fit of the median rock grain size by multiple regression analysis yields a proposed median rock grain size with a relative error of 59.93% from the true value, showing that the multiple regression analysis method is not applicable to the prediction of median grain size of low-permeability sandstone.

(2) Through sensitivity curve optimization, neural network algorithm modeling, parameter optimization, median grain size of prediction, and verification system, the calculation and nonlinear fitting of conventional logging data were carried out to obtain the median rock grain size of low-permeability sandstone. Through the selection and adjustment of activation function and loss function, the effects of single hidden layer and multihidden layer were analyzed and compared. An appropriate neural network architecture was selected for median rock size prediction, and a good prediction effect was obtained.

(3) In practice, for the problem of few samples of logging data, the data volume can be improved as a whole through geological constraints. In the example application of this paper, the median grain size training data can be made more complete by adding address constraints to the missing mudstone intervals in the median grain size sieve analysis data.

(4) In terms of prediction results, a neural network with a single hidden layer is not able to better mine its complex nonlinear relationship in the median particle size prediction problem for low-permeability sandstones. This paper shows that deep neural network have an advantage over shallow neural networks in fitting more complex nonlinearities to the median grain size of low permeability sandstones, but that both shallow and deep neural networks have good nonlinear fitting results compared to multiple regression analysis methods.

(5) For particle size prediction, we will conduct experimental analysis on different network architectures such as LSTM and CNN and optimize the particle prediction method based on the characteristics of network architecture and geological problems.

Data Availability

The project for the development of the Bohai Sea in the low permeability reservoir area favorable prediction method,
involving state secrets, the group of companies and research institute of business and technical secrets, file information, such as the exploration and development research, project during dynamic and important research results, and other undisclosed technical data and technical information, ready to declare the patent and the research achievement of formation of the technical secret, confidentiality, and nondisclosure obligations.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

References


