Application of the Backpropagation Neural Network Image Segmentation Method with Genetic Algorithm Optimization in Micropores of Intersalt Shale Reservoirs

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ABSTRACT: The pore types of intersalt shale reservoirs are diverse, and the pore structures are relatively complex. The size of the pores ranges from a few nanometers to a few microns, showing obvious heterogeneity and multiscale. Image segmentation is an important link in the study of micropore structures of intersalt shale using digital core technology. It can identify characteristics such as pore category, shape, size, spatial distribution, and connectivity characteristics. Therefore, how to improve the accuracy of image segmentation becomes very important. In this study, the research object is the 10 rhythmic layers of the Qian 34 oil group in the Wangping 1 well area of oil field A. First, focused ion beam scanning electron microscopy was used to obtain core imaging data. Then, in order to realize efficient processing of two-dimensional image information and compensate for the shortcomings of conventional segmentation methods such as long iteration period, slow convergence speed, and low accuracy, the backpropagation (BP) neural network segmentation method with a genetic algorithm (GA) was adopted. Also, the segmentation results before and after the improvement were compared. The results show the following: (1) Among the selected intersalt shale core samples, 90% of the pore radius is less than 150 nm and more than 90% of the throats are less than 100 nm. (2) Compared with the conventional BP neural network, the number of convergence steps is reduced to 10, the speed is 10 times faster, and the porosity prediction accuracy is increased by 4.03% on average, which is closer to the gas-measured porosity value. It shows that the BP neural network image segmentation method with a GA has the advantages of small calibration error, fast convergence speed, high efficiency, and high precision.

1. INTRODUCTION

As a typical tight reservoir, shale oil reservoirs have diverse pore types and complex pore structures. The size of the pores ranges from a few nanometers to a few microns, showing obvious heterogeneity and multiscale structures. To better understand the reservoir and migration mechanism of shale accumulation, many scientific researchers have gradually carried out evaluations of the pore structure characteristics of shale. Among them, the microscopic pore structure is the core point of the study of reservoir characteristics, and it is also an important research topic at present.

Currently, science and technology are developing rapidly. With continuous deepening research on special reservoirs, conventional experimental methods can no longer meet the needs of scientific research. Generally, the research methods for the microscopic pore structure of reservoirs are mainly divided into two categories: physical experimental method and numerical reconstruction method. Because shales have extremely small pores, physical methods often use scanning electron microscopy (SEM), focused ion beam SEM (FIB-SEM), atomic force microscopy, nanocomputed tomography (CT), transmission electron microscopy, and other scanning methods.1−8 Combined with energy spectral density or backscattered electron imaging, a three-dimensional (3D) distribution image of different mineral components can be obtained. FIB-SEM and the nano-CT method can directly provide the 3D real digital core. FIB-SEM has been widely used in shale microscopic pore imaging owing to its high accuracy. The CT imaging technology, with its lossless and convenient features, has also been used by many researchers. Watson (1994) used CT SEM to study the reservoir characteristics of shale and found microfractures in it. Other microscopes can only obtain 2D core images, and numerical

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reconstruction methods are required to reconstruct digital cores. Numerical reconstruction methods are widely used in Gaussian simulation, simulated annealing, process simulation, multiple-point statistics, and Markov random reconstruction. Yeong (1998) applied the simulated annealing method to digital cores and obtained more rock information. Verification results showed that the method has a certain modeling effect. To get closer to the real porous media, based on the original Gaussian simulation method, the 2D system was upgraded to a 3D space system. Adler (1990) considered periodic boundary conditions and added the Fourier transform method. The method was improved, but it could not accurately reflect the structural characteristics of the pore space. Okabe and Blunt (2004) applied the multiple-point statistics method to the construction of carbonate digital cores. Researchers in the Digital Core Laboratory of Australian National University (2004) used micro-CT equipment to reconstruct 3D digital cores from 2D images to examine the core pore structure. They used thin slice analysis CT image simulation and related mathematical algorithms to extract a network model that was similar to the real core. Wu (2006) extended the reconstruction of a 2D Markov chain Monte Carlo method to 3D, introduced the idea of neighborhood, and applied it in digital core technology. This method has the advantages of fast modeling speed and good pore connectivity. Nelson (2009) comprehensively compared the pore throat characteristics of conventional oil and gas reservoirs, tight gas reservoirs, and shale gas reservoirs; it was found that the pore throat distribution of shale was mainly within 0.1–0.05 μm. Zou (2011) used nano-CT imaging to study pores that are larger than 50 nm in tight sand and shale and then established a 3D reconstruction image of the pores. Chahners and Bustin (2012) found that using conventional methods to characterize the pore structure of shale reservoirs is not very effective, so high-resolution imaging techniques are gradually applied to describe most of the fine pores in shale.

After acquiring image data through SEM, the image segmentation technology is used to extract the pores and fractures to analyze the image and obtain the pore structure characteristics. Image segmentation is the most important and challenging step in image processing. Its purpose is to distinguish the regions with specific significance relative to other regions in the image and identify pore spaces, rock skeletons, interstitial material, organic material, and other components. At the same time, it provides a basis for studying the pore structure characteristics of cores. Conventional image segmentation methods include threshold segmentation, edge segmentation, region segmentation, and specific theoretical segmentation.

(1) Threshold segmentation is commonly used as the standard of image segmentation to extract the pore structure in the background image. This method is divided into full threshold and partial threshold. The essence is to set different gray scale values to create the grayscale histogram of an image. Pixels with gray scale values in the same gray range are considered to belong to the same category and have certain similarities.

(2) Edge-based image segmentation is proposed based on the discontinuity of the pixel gray scale value of the edge part between adjacent regions. The principle is to assume that the gray scale value difference between an image cable point and the adjacent image cable point in the image is relatively large. If it is large, it is considered that the pixel may be located at the boundary. If the pixels at these boundaries can be detected and connected, an edge contour can be formed, thereby dividing the image into different regions. In practical applications, since the edge flow is easily oversegmented, Wu (2010) proposed an image segmentation method that combines the edge flow and normalized cut. The method can obtain a better segmentation effect but is more complicated and has a low operating efficiency. The phenomenon of undersegmentation or oversegmentation is prone to occur when the gray value mutations between particles and between particles and the background are not obvious in the image. Chen (2013) proposed an algorithm for color image segmentation to obtain granule size distribution, which can automatically correct the segmentation results; however, there is no good segmentation for partially glued and overlapping gravels.

(3) The theory of region-based image segmentation is based on the spatial information of the image. The pixels are classified by their similarity characteristics to form regions. There are many methods for segmentation based on the regional concept. The more commonly used methods are region growing and splitting. The most classic and representative of this type of method is the maximum between-class variance method proposed by Otsu (1979), which uses a gray threshold T to divide the image into two parts, namely, the background area and target area. This method is simple and direct and has the advantage of speed. Gao (2009) divided the shale into several different mineral component regions according to the gray scale value and comprehensively used the Otsu threshold segmentation algorithm and the field emission environmental scanning electron microscope to propose a new segmentation method. Zhao (2009) proposed a new method of image segmentation that incorporates both the principle contribution porosity and the good adjustment made by the discriminant method according to the actual features of the CT image; it can generate more reasonable results in segmenting gray images.

(4) With the vigorous development of various disciplines and the continuous deepening of interdisciplinary research, many new theories and methods have been introduced, collectively referred to as image segmentation techniques, based on specific theories and methods. There are seven categories of segmentation methods based on specific theories, namely, mathematical morphology theory, fuzzy theory segmentation, neural network theory segmentation, support vector machine segmentation, graph theory segmentation, immune algorithms, and granular computing theory. For complex core images, because threshold segmentation and edge segmentation are respectively restricted by experience factors and accuracy, it is difficult to obtain satisfactory results; thus, it is particularly important to segment such images using specific theories. Holland (1973) proposed a genetic algorithm (GA) and introduced it to complex segmentation tasks under multiple parameters, simulating the natural survival of the fittest to obtain the optimal solution and realize optimal segmentation. Wu (2008) merged the watershed algorithm with the ISODATA algorithm, overcoming the characteristics of excessive segmentation. Tang (2013) applied the ant colony clustering algorithm to a rock scan image and obtained good segmentation results. The image segmentation method of the backpropagation (BP) neural network has strong adaptability and robustness, but it also has some shortcomings, such as slow convergence. Zhou (2014) improved the BP neural network by combining the fuzzy set theory.
In this study, the research object is the 10 rhythmic layers of the Qian 34 oil group in the Wangping 1 well area of oil field A. The lithology of the target layer belongs to high-quality source rock. The organic matter types are mainly type III and I. The lithology of the rock layer is rock salt, and the development of glauberite is more common. First, the imaging data of the shale sample were obtained using FIB-SEM. These data provided a basis for core reconstruction and were used as network training data. The results of the image segmentation of shale internal pores were used as the label data. Second, the initial weight and threshold of the individual representative network as well as the prediction error of the BP neural network initialized by the individual value were used as the fitness values of the individual. Subsequently, the optimal individual was searched by adding a GA for the selection, crossover, and mutation operations. The convergence was close to the optimal solution to a certain extent, and a trained neural network model was obtained. Finally, based on the reconstructed 3D digital core and the extracted pore network model, the shale nanopores were analyzed.

2. MATERIALS AND METHODS

2.1. Materials. Experiments were performed on core samples A and B (Figure 1). The intersalt shale oil reservoir in the study area is a set of strata sandwiched between two sets of salt rock layers. The intersalt layer mainly comprises glauberite–dolomite–argillaceous dolomite–dolomitic mudstone–argillaceous dolomite–dolomite–glauberite from the bottom to the top. The lithology is mostly brown laminar argillaceous dolomite and massive argillaceous dolomite. The main mineral components include not only mechanically deposited terrigenous clastic quartz, feldspar, and clay minerals but also chemically deposited dolomite, calcite, glauberite, and anhydrite. The content of glauberite on the plane varies significantly by up to 20.9%. The organic carbon content is 1.15–2.44%, with an average of 1.97%; the free hydrocarbon \(S_1\) is 4.24–9.85 mg/g, with an average of 7.29 mg/g. The porosity distribution range and permeability distribution range are 0.03–0.16% and 0.13–80.5 mD, respectively. The focused ion beam scanning electron microscope FEI Helios NanoLab 660 (Figure 15) is applied in this work to examine the dried core samples. The Helios NanoLab 660 focused ion beam scanning electron microscope utilizes 2D/3D scanning imaging of various lithology cores with different resolutions up to nanoscale, and thus, some basic core properties were analyzed by its imaging software.

2.2. Methods. In general, image segmentation often uses threshold segmentation, edge segmentation, region segmentation, and segmentation methods based on specific theories. For the core image, the above conventional segmentation method is more difficult to segment multitarget graphics. For example, the traditional threshold segmentation method is mainly based on manual experience and cannot achieve stable accuracy. On this basis, in order to achieve the purpose of stable and efficient segmentation, this study adopts a specific theory and introduces BP neural network image segmentation based on the GA.

2.2.1. BP Neural Network Model. In 1986, the BP neural network algorithm was proposed by Rumelhart et al. of Stanford University. This algorithm solves the problem of the connection weight of the hidden layer in a multilayer network model and effectively improves the self-learning and organization capabilities of a neural network. Hence, it is currently widely used in the engineering field. The BP neural network is a kind of a multilayer feed forward neural network. The BP neural network is a kind of a multilayer feed forward neural network. It is composed of an input layer, a hidden layer, and an output layer (Figure 2). Since each layer has a quantifiable number of nodes, it can be ensured that the number of input layer nodes is equal to the dimension of the input layer vector during the segmentation process. The output result is determined by the factors such as the characteristics of the training sample and the network structure.

(1) The expression formula for the input layer vector \(X\) is
In the above formula, the input vector $X$ is composed of three 3D feature values, $f_R(i,j)$, $f_G(i,j)$, and $f_B(i,j)$, and the corresponding pixel points are the red, green, and blue component values, respectively.

(2) The expression formula for the hidden layer is as follows:

$$ J = 2m + 1 $$

In the above formula, $m$ is the number of nodes in the input layer.

(3) The values of the output layer are $-1$, $0$, and $1$. They are used to represent pores, interstitials, and rock skeletons.

2.2.2. Neural Network Model Optimized by GA. The GA is good for global search, whereas the BP neural network is more effective for local search. To exploit their advantages and overcome the shortcomings of slow convergence and ease of falling into the local minima of the BP neural network, this study combines the GA and BP algorithms.

The procedure is to optimize the initial weight value and threshold value of the BP neural network, locate a better search space, and then use the BP algorithm to search for the optimal value in a small space. The GA uses repeated crossover, mutation, and selection to finally obtain the optimal solution, which has the characteristics of rapid calculation and high accuracy. The main steps of the BP neural network optimization process with the GA are as follows (Figure 3):

2.2.2.1. Determination of the network topology: determine the number of the input layer, hidden layer, and output layer.

2.2.2.2. Code: an initial population is randomly generated. The population contains two matrices: one is used for storing the fitness value of all individuals, and the other is for storing chromosome information. The weights and thresholds between the input layer, hidden layer, and output layer are converted into codes, and the chromosomes use these codes instead of assigning initial values to each gene. The process adopts real number coding. Each real number is considered to have 1 locus, and the length of individual locus coding is determined by the number of neurons in each layer.

2.2.2.3. Training the BP neural network: each individual is used as the initial weight and threshold of the BP neural network. The training data are used to train the BP neural network to obtain the predicted value.

2.2.2.4. Fitness function: after encoding, each gene has an initial value of a random number. The fitness function is used to generate a fitness value for each individual, and the initial value is a random number. The calculation results from the input training sample to the different chromosomes have different errors, and the predicted value is as close as possible to the expected value. Subsequently, the best fitness value is calculated through the initialization information of the population. Based on the sum of squared errors between the predicted output value and the actual value, the reciprocal is used as the fitness function.

$$ f_{\text{fitn}} V = \text{ranking(obj)} $$

$$ F = \frac{1}{\sum_{n=1}^{N} (t_i' - t_i)^2} $$

In the above formula, $n$ represents the number of test samples and the difference between $t_i'$ and $t_i$ represents the difference between the predicted and actual output values of each point.

2.2.2.5. Operator: when the random initialization of the fitness value of the individual is completed, the fitness value is converted into a probability and the sum of the probability of all individuals being selected is equal to 1. Ten individuals are put in a roulette wheel. The probability corresponds to the size of the sector, and then, a random number from 0 to 1 is generated. An individual will be selected from the sector where
the random number is located. The number of chromosomes in each generation remains unchanged; the greater the fitness of a selected individual, the higher the probability of inheritance to the next generation. The population iteratively selects the best individual. Based on the crossover, mutation, and selection of the GA, new individuals are obtained iteratively and continuous selection is performed until the population can obtain the best individual. The crossover probability is determined by the maximum fitness between two individuals. When the crossover operation is performed, a chromosome of the same length is randomly selected between different individuals for exchange. The mutation probability is the same as the crossover probability and is determined by the maximum fitness between two individuals. When performing mutation operations, a single individual randomly changes 1 locus.

\[
p_c = \begin{cases} k_1 e^{-\frac{(\max(f_1, f_2) - E_s)^2}{2(c_1^2)}} & , \text{max}(f_1, f_2) \geq E_s \\ k_2, \text{max}(f_1, f_2) < E_s \end{cases}
\]

\[
E_s = f^*, \quad E_n = \frac{f_{\text{max}} - E_s}{c_1}, \quad H_c = \frac{E_n}{c_2}
\]

In the formula, \(k_1\) and \(k_2\) are constants with values between 0 and 1; \(f^*, f_{\text{max}}\) represent the average fitness, fitness of a single individual, and maximum fitness, respectively; \(E_s\) represents the expectation; \(H_c\) represents a normal random number with a standard deviation.

2.2.2.6. Decoding: after the population has evolved for \(n\) generations, it reaches the maximum number of iterations and each gene has the best assignment. The chromosome with the smallest fitness value is determined and used as the optimal solution of the neural network after decoding.

2.2.2.7. Training the BP neural network: the network constructed at this time includes weights, thresholds, input layers, hidden layers, and output layers with clear values. Each individual is used as the initial weight and threshold of the BP neural network. The training data are used to train the BP neural network to obtain the predicted value.

Generation of training data: The training data are the input data. The reconstructed imaging data of the shale obtained by FIB-SEM are used as the training data, and the label data are the images of the internal pore structure of the shale.

Under the constraints of multienergy X-ray scan data, it is assumed that the total volume of a voxel is the sum of the subvolumes of its constituent materials. Moreover, when the X-ray beam passes through a voxel, the total attenuation is the sum of the attenuations of its constituent components. The label data can be obtained by training as described below: based on the reconstructed multienergy X-ray scan data of the shale, a cube grid is defined and a voxel is located at each grid point. This voxel’s objective function was constructed, and the smallest difference between the linear and measured absorption coefficient was calculated.

\[
T_i(v_i) = \sum_{l=1}^{L}(\delta k_i^2)^2 + \xi \Omega_n
\]

\[
\Omega_n = \sum_{m=0}^{M} v_n^m S_m + \sum_{k=0}^{K} \sum_{j=0}^{N^k} \sum_{m_1=0}^{M_1} \sum_{m_2=0}^{M_2} v_n^{m_1} v_{n+r+j}^{m_2} I_k^{(m_1+m_2)}
\]

In the above formula, \(\xi\) represents the regularization parameter, \(\Omega_n\) represents the experimental constraint of the solution, \(S_m\) represents the self-energy of the material component, and \(I_k^{(m_1+m_2)}\) represents the free energy between \(m_1\) and \(m_2\).

\[
\delta H^l = \sum_{m=0}^{M} H_{n+m} - \hat{H}_n^l
\]

In the above formula, \(\mu_n^m\) denotes the volume parameter of the \(m\)th component, \(\bar{\mu}_n^{m(l)}\) denotes the total absorption coefficient of the first dataset, and \(\hat{\mu}_n^{m(l)}\) denotes the absorption coefficient of the \(m\)th component under the X-ray beam corresponding to the first dataset.

Creating and Training the Neural Network: The training process of the neural network involves adjusting the weight between the neurons and the threshold of each functional neuron according to the training data to achieve the purpose of learning. It also involves modifying the connection weight coefficients between the neurons in each layer: the input mode is that the input layer nodes are directly transmitted to the hidden layer nodes. The input layer is the data buffer memory, and its function is to load the data source onto the network. The number of nodes can be determined by the dimension of the image feature vector. The number of nodes in the output layer is determined by the number of categories. In the hidden layer, after the characteristics of each unit are converted into sigmoid-type functions, they are used as input information for the next layer. The information is transferred to the next hidden layer through conversion until the response signal is outputted from the output layer.

Assuming that the neural network has \(N\) layers, the first layer is the input layer, 1 to \(N-1\) are the hidden layers, and the \(N\)th layer is the output layer. A certain layer in the hidden layer is layer \(r\) with \(nr\) nodes; then, the connection weight coefficient between the neuron of the \(r\) layer and the \(i\)th neuron of the \(r+1\) layer is \(\sigma_{ij}\). The input signal \(x_i^r\) and the output signal of node \(y_i^r\) are expressed as follows:

\[
x_i^r = \sum_{j=1}^{n} \sigma_{ij} y_j^{r-1}
\]

\[
y_i^r = f(x_i^r) = \frac{1}{1 + e^{-\eta x_i^r}}
\]

Assuming a training sample \((x_i, y_i)\), the weight and threshold can be obtained after training. The weight is iterated and updated continuously; \(\eta\) represents the learning efficiency, and \(E\) is the system response error.

\[
\omega_i \leftarrow \omega_i + \Delta \omega_i
\]

\[
\Delta \omega_i = \eta(y_i - f(x_i)) x_i
\]

\[
\omega_\eta(t + 1) = \omega_\eta(t) + \eta \frac{\partial E}{\partial \omega_\eta}
\]
path and is continuously updated between each layer. When all the connection weight coefficients are updated, the cycle is completed and so is the learning.

3. RESULTS AND DISCUSSION

3.1. Original Core Image. The focused ion beam scanning electron microscope FEI Helios NanoLab 660 was applied in this work to obtain high-resolution 2D images by scanning the continuous denudation of the rock. Figure 4 shows the scan images of sample A (Figure 4a) and sample B (Figure 4b) in nanoscale.

3.2. Image Processing. The FIB-SEM experimental instrument obtained a series of high-resolution 2D images by generating ion beams to continuously denude and scan the rock at a submicroscopic scale. One of the 2D images was selected as an example to denoise, sharpen, and segment the image respectively, and the other images were processed in the same way. Finally, some 2D images were reconstructed numerically.

3.2.1. Image Denoising. The types of noise in images usually include random noise, quantum noise, and electronic noise. The presence of noise makes the image appear with spots, fine grains, nets, snowflakes, or abnormal structures, so it is necessary to denoise the image. Image denoising is mainly used for reducing the noise in the image and minimizing the loss of features such as edges, corners, and other sharp structures. For image denoising, a median filter, mean filter, and Gaussian filter are commonly used.27

Using different filter masks to perform spatial neighborhood operations on an image can effectively reduce drastic changes in the image gray value. It can also reduce or even eliminate the influence of isolated noise points in the image, thereby eliminating the noise. In this study, the 2D median filter function medfilt2 was used to filter the image with noise interference. From the image comparison results in Figure 5, it can be observed that the number of isolated noise points decreases.

3.2.2. Image Sharpening. Owing to the discontinuity of the edge of an image, the target area cannot be accurately identified. After the image is sharpened, it is mainly improved in two aspects: the sharpness of the image is enhanced by recognizing the image edge, and the target area is distinguished. The boundary position of the object is determined, and then, image segmentation is performed. Image sharpening can be divided into two types: linear sharpening filter and nonlinear sharpening filter.28,29 The commonly used linear sharpening filter is the linear high-pass filter. The commonly used nonlinear differential sharpening operators include Roberts, Prewitt, Sobel, and Laplacian sharpening operators. The working principle of these differential sharpening operators is to process the gray value of the image to sharpen it. The resulting blurred edges are smoothed. To show the effect of image sharpening more intuitively, in this study, we used a second-order Butterworth filter to calculate the frequency distance and the value of the transfer function and the filtered image was obtained through the Fourier transform.

Figure 4. SEM image of sample A (a) and sample B (b) with a resolution in nanoscale.

Figure 5. (a,b) Grayscale image of sample A before and after denoising. (c) Slice of sample A before denoising and (d) after denoising. (e,f) Grayscale histogram of sample A before and after denoising. (g,h) Grayscale image of sample B before and after denoising. (i) Slice of sample B before denoising and (j) after denoising. (k,l) Grayscale histogram of sample B before and after denoising.
After filtering, the edges of the image became blurred but the isolated points in the image were removed. Linear sharpening was performed on the filtered image, and histogram grayscale transformation was finally conducted on the linear sharpened image to improve its brightness (Figure 6). A comparison of edge detection using the Prewitt, Sobel, and Robert operators is presented in Figure 7.

3.2.3. Image Segmentation. According to the size of the data set, the ability to fit the function increased. In this paper, the intelligent image segmentation approach adopted is a feed-forward multilayer neural network as a supervised classification method. The Matlab neural network function Newff was used to create the BP neural network and join the GA to segment the 2D rock sample image. The initial population number set in this study was 100. To expand the global shrinkage range of the GA, the initial crossover probability was set to 0.8. The latter fitness value was higher, the crossover probability was set to 0.3, and the mutation probability was 0.1. The GA parameters were as follows: number of chromosomes = 14, output range = [0, 1], evolutionary algebra = 50, and minimum fitness value = 0.00001. The neural network parameters are given below.

Figure 8 shows that the BP neural network structure was set to 2-5-1. The input, hidden, and output layers had 2 nodes, 5 nodes, and 1 node, respectively. There were $2 \times 5 + 5 \times 1 = 15$ weights and $5 + 1 = 6$ thresholds, so the code length of the individual GA was $15 + 6 = 21$.

The training samples were selected from 15 pore pixels, interstitial pixels, and rock skeletons. From the nonlinear function, 2000 sets of input and output data were randomly selected.

Figure 6. Slice of sample A after sharpening (a) and histogram equalization (b). Slice of sample B after sharpening (c) and histogram equalization (d).

Figure 7. Slice of sample A after Prewitt (a), Roberts (b), and Sobel (c) edge detection. Slice of sample B after Prewitt (d), Roberts (e), and Sobel (f) edge detection.

Figure 8. Neural network structure diagram.
obtained, 1900 sets were randomly selected as training data for network training, and 100 sets were used as the test data. The maximum number of training times was set to 500, the minimum error was 0.00001, the input range was [0, 255], and the output range was [0, 1]. The sum of the absolute values of the prediction errors of the training data was used as the individual fitness value. The smaller the individual fitness value, the better the individual.

The conventional BP training may not converge to the target value, or the number of convergence steps is extremely long. For the genetic BP training, it took a while for the GA to find the optimal weights and thresholds but the BP training was very fast. Figure 9 shows a schematic diagram of the sample mean square error decreasing tendency with the iteration proceeding. It can be seen that the error of BP neural network optimization by the GA decreases rapidly, and the iterative errors of the verification set, test set, and training set decrease synchronously. Finally, the 10th step converges to the target value, and the mean squared error is $5 \times 10^{-5}$, while that of the unoptimized network is $1.8876 \times 10^{-4}$. Moreover, the mean square error of prediction has been greatly improved.

The optimal initial weight and threshold were assigned to the neural network, and the training data were used 100 times to predict the output and compare the error of the nonlinear function (Figure 10).

The fitting values of the training set, validation set, and test set were compared with the label data (Figure 11). It can be seen from the figure that most of the sample data can fit the label data well and only a few samples have some errors which is due to the fact that the amount of sample data is not large enough and the model is relatively simple.

The pores in the original core were segmented (Figure 12). The yellow pores represent the pore segmentation results obtained by the conventional BP neural network method (Figure 12a,d). The red pore map shows the pore segmentation result obtained by the BP neural network method optimized by the GA (Figure 12b,e). Based on the test data of the shale core basic physical parameters (porosity,
density, permeability, specific surface, etc.), FIB-SEM was used to test the pore structure characteristics and connectivity data and complete the construction of the shale digital core (Figure 12c,f).

4. VERIFICATION

Porosity is a key parameter for shale gas reservoir evaluation and reserve calculation. In this study, the porosity was measured using the gas injection porosimetry (GIP) method and the image segmentation method of the BP neural network before and after optimization. Table 1 shows the porosity calculation results under different methods. It can be seen that after optimization, the calculated porosities of sample A and sample B are 8.92 and 2.32% and the porosity value obtained after optimization is closer to the porosity value obtained using the GIP method. In terms of the calculation accuracy of porosity, the calculation accuracy of sample A increased by 2.34% and of sample B improved by 5.73%, using the optimized BP neural network segmentation method, and the average improved by 4.03%.

The “maxima ball” method was used to extract and model the pore network structure. The structured pore and throat model was extracted from the binary 3D core image. It was found that the pore structure model maintained the pore distribution and connectivity characteristics of the original 3D core image (Figure 13).

According to the extracted 3D pore network model, the pore throat radius, coordination number, shape factor, and connectivity characteristics were analyzed. Figure 14 shows the result of pore throat distribution. In the distribution of the pore throat (Figure 14a,b), the pore-throat radii of sample A and sample B were measured and calculated.
and B are, respectively, within 9−242 and 14.3−359 nm, and the average radii are 75.5 and 132 nm, respectively. Among the selected intersalt shale core samples, 90% of the pore radius is less than 150 nm, and more than 90% of the throats is less than 100 nm. In the distribution of shape factor (Figure 14c,d), it can be seen that the pore and throat shapes of sample A and B are irregular. The shape factor is mainly within 0.04−0.06, and the average shape factors are 0.0478 and 0.051, respectively. According to the definition of the shape factor, when the shape factor is (0.0481, 0.07105), the cross-sectional shape is a square, and when the shape factor is (0, 0.0481), the cross-sectional shape is a triangle. Therefore, the pore and throat shapes are mainly triangular and square sections. In the distribution of the coordination number (Figure 14e), the mean coordination numbers of sample A and B were 3.09 and 2.79, respectively.

5. CONCLUSIONS

(1) To carry out microscopic pore structure research on intersalt shale reservoirs, a combination of the BP neural network and GA was used in core image segmentation. Based on the test data of the shale core basic physical parameters, FIB-SEM was used to test the pore structure characteristics and connectivity data and then to complete the construction of the shale digital core and to extract the pore network model, thus quantitatively describing the size, distribution, and connectivity of the pores. The results show the following: digital core technology has clear strengths in directly and quantitatively describing the micropore structure of intersalt shale reservoirs.

(2) The BP neural network is useful for local search, whereas the GA is good for global search. Combining the GA with the BP neural network can effectively overcome the shortcomings of slow convergence and the ease of falling into local minima. In this study, we used the GA-optimized BP neural network and conventional BP neural network to segment the core image. The comparison results show that the optimized BP neural network can realize autonomous learning and segmentation of core images; the accuracy of pore segmentation increased by 4.03% on average, and the step length of convergence is 10 steps; that is, the speed is ten times higher than that before optimization.

6. EXPERIMENT

6.1. Nanoscale Scanning Electron Microscope. The focused ion beam scanning electron microscope FEI Helios NanoLab 660 (Figure 15) is applied in this work to examine the dried core samples. The Helios NanoLab 660 focused ion beam scanning electron microscope utilizes 2D/3D scanning imaging of various lithology cores with different resolutions up to nanoscale, and thus, some basic core properties were analyzed by its imaging software.

6.2. Poroperm Conjunction Instrument. The principle of GIP is to determine the skeleton volume of rock by recording the pressure before and after the expansion of gas into the pores of the sample (eqs 15 and 16) and then to calculate the porosity of the rock sample (eq 17). Figure 16 shows the porosity−permeability conjoint measuring instrument. The maximum test pressure is 60 MPa, the range of test porosity is 0.1−40%, and the test accuracy is 0.5%.

\[
P_{V_1} = \frac{P_1(V_1 + V_2 - V_5)}{Z_1} \quad (15)
\]

\[
V_6 = V_4 - V_3 \left( \frac{P_{Z_2}}{P_{Z_1}} - 1 \right) \quad (16)
\]

In the above formula, \(P_1\) represents the pressure of the reference chamber before expansion, MPa. \(P_2\) represents the
equilibrium pressure of the system after expansion, MPa. \( V_t \) represents the volume of the reference chamber, cm\(^3\). \( V_s \) represents the volume of the sample frame, cm\(^3\). \( V_g \) represents the volume of the sample chamber, cm\(^3\). \( Z_1 \) and \( Z_2 \) represents the gas compressibility factor.

\[
\phi_{GIP} = \frac{\int_0^1 A dT_2}{V_t} + b \times 100\%
\]  

In the above formula, \( \phi_{GIP} \) represents the porosity of the sample determined by gas measurement; \( V_t \) represents the total volume of the sample, cm\(^3\).

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**Notes**

The authors declare no competing financial interest.

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