Production prediction and main controlling factors in a highly heterogeneous sandstone reservoir: Analysis on the basis of machine learning

Zhao Wang¹ | Hongming Tang¹ | Hui Cai² | Yawei Hou² | Hongfu Shi² | Jingling Li² | Tao Yang¹ | Yutian Feng¹

¹School of Geoscience and Technology, Southwest Petroleum University, Chengdu, China
²Tianjin Branch of China National Offshore Oil Co., Ltd., Tianjin, China

Abstract

Owing to a lengthy oil-bearing interval, strong anisotropism, and significant difference in the fluid properties of the sandstone oil reservoir in P Oilfield, it is quite challenging to accurately the productivity of the oil well at the initial stage. In this study, a deep neural network model is established, based on a gradient boosting algorithm, XGBoost, to forecast the initial productivity of oil wells, followed by an evaluation of the main controlling factors of productivity. One hundred oil wells in the study area were divided into training and verification groups. With a specific productivity index of an oil well with a stable period of approximately 6 months at the initial production stage as the target data, and geological, engineering, and oil reservoir parameters as input data, hyper-parameters for adjustment and optimization were selected, and a deep-learning-based unconsolidated sandstone productivity forecast model was established to forecast the initial productivity of oil wells in the target area. The mean square root error of the forecast result was <0.15, which is highly consistent with actual productivity. Finally, by adopting the XGBoost algorithm, the weight ranking of the controlling factors of productivity was clarified as follows: microscopic pore structure parameter > crude oil viscosity > median grain size > lithology index > well completion method > flow zone indicator. Machine learning has the advantages of effective forecasting of oil well productivity and the main controlling factors using multiple dimensions and big data.

KEYWORDS

deep learning, microscopic pore structure, productivity prediction, unconsolidated sandstone
1 | INTRODUCTION

The P oilfield is a continental multilayer sandstone reservoir. It is a large offshore oilfield with oil reserves greater than $6 \times 10^8$ t. The oil-bearing intervals of this oilfield are located in the lower member of the Neogene Minghuazhen and the Guantao Formations, and the multilayer commingled production development method of one set of directional wells is adopted. However, the oil-bearing layers in this oilfield are long (100–650 m) and divided into 13 oil groups and 47 sublayers vertically. Reservoirs are highly heterogeneous, with significantly varying fluid properties. The aggregate crude oil is medium-quality heavy crude oil, with properties that are quite different vertically and horizontally, thereby making the prediction of the initial production of oil wells very difficult. The initial production capacity of an oil well directly affects the subsequent production of oil wells very difficult. The initial productivity is a comprehensive reflection of the geological, reservoir, and engineering parameters. The factors affecting oil well production involve a wide range of aspects. It is difficult to manage production needs by relying only on simple linear models. DNNs contain more hidden layers and have the advantage of being good at processing large amounts of multiple sourced and dimensioned data. Therefore, using a DNN for production prediction has advantages over using traditional methods.

The advantage of numerical simulation is that it can solve the production prediction problem without actual production data; however, it requires a large amount of data calculation and high-precision data sources. Moreover, the physical mechanism of fluid motion is very complex. Currently, the most widely used numerical methods include the finite difference method (FDM), finite volume method (FVM), and spectral method. Numerical methods are extensively used in various fields, for example, FEM and FVM, are used in computational fluid dynamics. Reservoir numerical simulation has always been an integral part of reservoir management and is used to estimate production status, and check reservoir parameters. Running a numerical simulation model can take days or even months, and sometimes hundreds of simulations are required to achieve optimal results.

The initial well production is a comprehensive reflection of the geological, reservoir, and engineering parameters. The factors affecting oil well production were selected from aspects of rock structure and pore-throat micro-structure characteristics, and the reservoir characteristics and engineering parameters were fully considered. Finally, the XGBoost algorithm was used to analyze the importance of each parameter and to clarify the main controlling factors of unconsolidated sandstone production.

2 | GEOLOGICAL BACKGROUND

The P oilfield, located east of the Bohai Sea, was developed on the Tanlu fault zone and has a fault anticline structural type that was developed in the background of the paleo-uplift. (Figure 1A). The main oil layers developed in the Neogene Guantao
Formation and the lower member of the Minghuazhen Formation (Figure 1B). The lithology of the reservoir is fluvial terrigenous clastic rock, and that of the target interval is mainly feldspar sandstone. The average porosity of the reservoir was 27%, and the average permeability was 1321 mD. This oilfield is a reservoir with high porosity and permeability. The thickness of the oil layer is 63–151 m, and the length of the oil-bearing area is greater than 50 km². The oil-bearing layer is thick and the reservoir is highly heterogeneous. The reservoir’s crude oil has the characteristics of high density, high viscosity, high gum content, low asphaltene content, low wax content, low sulfur content, and low freezing point. The properties of the crude oil gradually improve as the depth of the reservoir increases. On the plane, the fluid properties showed good central body regions and relatively poor wing portions (Figure 1C).

The initial production (6 months of production) of 100 oil wells is shown in the following table (Table 1):

### MATERIALS AND METHODS

Two main problems are required to be solved in this study: (1) the optimization of the representative reservoir parameters, and (2) the optimization of the fitting
accuracy of the DNN model. The specific steps toward realizing these are illustrated in Figure 2. The solution is further explained by analyzing a case of the study area.

Step 1: Parameter selection. Representative reservoir parameters were selected using data mining methods, such as correlation analysis and principal component analysis (PCA).

Step 2: Data preprocessing. Preprocess data for computational efficiency.

Step 3: DNN hyperparameters setting. The hyperparameters of the model are optimized, and the best parameters are selected to train the model.

Step 4: Oil well production forecast and evaluation of key controlling elements. The initial production prediction of the actual production well is conducted to verify the reliability of the DNN. The DNN is combined with the XGBoost algorithm to clarify the main control factors.

3.1 Parameter optimization and data processing

Data from a total of 100 production wells were collected for this study, including the fluid properties and geological, engineering, and production performance parameters (Table 2). The parameters were porosity, permeability, pore throat radius at 35% mercury saturation (R35), flow zone indicator (FZI), reservoir quality index (RQI), median grain diameter (Md), shale content (Vsh), mature mineral composition degree, crude oil viscosity, well completion method, and specific oil recovery index. The geological parameters were obtained from the weighted average of the thicknesses of the perforation section, which were obtained from logging interpretation results and core tests. The crude oil viscosity was obtained from an analysis and laboratory data, the engineering parameters were obtained through a completion method, and the dynamic parameters were obtained from the initial stage of production. The specific oil recovery index during the stable period was approximately 6 months.

3.1.1 Production impact parameter

Reservoir microscopic characteristic parameters

The microscopic characteristics of a reservoir directly affect its storage and seepage capacities, which are of great significance in management of the reservoir. Currently, there is no unified definition of the microscopic characteristics of reservoirs. In this study, aiming
Step 1. Generation of dataset

1) Reservoir microscopic characteristic parameters

Correlate core test data with logging curves

2) Fluid property parameter

Features of crude oil

| Parameter | Setting range | Optimal value |
|-----------|---------------|---------------|
| Oil density (g/mL) | 0.9-0.95 | 0.93 |
| Dilution factor (ppm) | 50-100 | 75 |
| Pouring point (°C) | -30-12 | -5 |
| Paraffin content (%) | 0-10 | 2 |
| Asphalt content (%) | 1-5 | 3 |

3) Engineering parameters

Well completion method

- 1 Open hole screen
- 2 Coiled tubing
- 3 Frac and pack
- 4 High speed water

Step 2. Data processing and parameter optimization

1) Normalization

\[ X^* = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \]

2) Parameter optimization

Step 3. Deep learning

1) Flow chart of DNN

2) Training

3) Forecasting

Step 4. XGBoost

1) Parameter optimization

| Parameter         | Setting range | Optimal value |
|-------------------|---------------|---------------|
| Iterations        | 1-200         | 200           |
| Tree height       | 1-7           | 4             |
| Learning rate     | 0.01-0.50     | 0.035         |
| Training samples proportion | 0.50-0.90 | 0.85 |
| Iteratively select feature scale | 0.50-0.90 | 0.85 |

2) Feature importance analysis

FIGURE 2 The workflow of the DNN model and XGBoost for production prediction and main controlling factor analysis. DNN, deep neural network.
at the basic characteristics of the loose sandstone, the microscopic characteristics of the reservoir are defined as the comprehensive attributes of the heterogeneity of the reservoir rock structure and composition and the pore-throat structure. Based on the above definitions, some representative reservoir micro-characteristic parameters were selected.

1. Pore structure characteristics

(1) Porosity and permeability

Porosity plays a significant role in the reservoir evaluation system \(^{32,33}\) by representing the reservoir capacity and establishing a relationship with the logging curve. The formulas are as follows:

\[
\phi_t = \frac{\rho - \rho_{ma}}{\rho_{ma}}, \quad (1)
\]

\[
\phi_e = \phi_t - V_c \cdot V_{cbw}, \quad (2)
\]

where \(\phi_t\) is the total porosity (decimal fraction), \(\phi_e\) is the effective porosity (decimal fraction), \(\rho\) is the logging density value (g/cm\(^3\)), \(\rho_{ma}\) is the pure sandstone density value (2.65 g/cm\(^3\)), \(\rho_{fluid}\) is the formation water density value (1.0 g/cm\(^3\)), \(V_c\) is the clay content (decimal fraction), and \(V_{cbw}\) is the bound water content of the clay (decimal fraction).

Permeability has always been a difficult point in logging interpretation, \(^1\) which has established eight lithofacies constraint standards in the P oilfield to explain permeability (Table 3). The correlation was found to be good. The log permeability is closely related to the core permeability. The relative standard deviation is 1.76%.

(2) R35

Coring is difficult in offshore fields and pore-throat parameters are difficult to obtain based on mercury injection tests in all wells. Geophysicists have introduced empirical formulas that relate the pore-throat radius to porosity and permeability (which are readily available and inexpensive to measure). \(^{29,34-36}\) The defined R35 can be used to characterize the reservoir's effective pore-throat radius, but it must be calibrated based on the reservoir characteristics. A study of a sample of the research region to carry out a porosity, permeability, and capillary experiment, Pittman's method, \(^{36}\) was applied to fit the pore throat radius, porosity, and permeability relationship, obtaining a series of corresponding mercury saturation values of 10%–75% of the pore-throat radius (Table 4). The correlation at 35% is the best, and R35 has a good correlation with other mercury injection
characteristic parameters (Figure 3A) and can better represent the mainstream pore-throat radius than R50 (Figure 3B). Therefore, R35 was selected as a comprehensive parameter to represent the pore-throat structure of the reservoir.

(3) FZI and RQI

Amaefule et al. first introduced the FZI and RQI concepts to characterize the pore structure of clastic rocks and divide the flow units. Subsequently, these parameters were widely used in reservoir research. The FZI and RQI values can be used to differentiate pore structure types with different seepage characteristics. The derivation process is as follows:

\[
RQI = 0.0314 \times \sqrt{K/(\phi)},
\]

\[
\phi = \phi_{He}/(1 - \phi_{He}),
\]

\[
FZI = \frac{RQI}{\phi} = \left(0.0314 \times \left(\frac{k}{\phi}\right)^{1/2}\right)/(\phi_{He}/(1 - \phi_{He})),
\]

where \(k\) is the permeability (mD), \(\phi_{He}\) is the effective porosity (%), and \(\phi\) is the ratio of pore volume to particle volume.

| Lithofacies | Lithology | Regression formula | Correlation coefficient | Poro. % | Perm. mD |
|-------------|-----------|--------------------|------------------------|--------|---------|
| A           | Pebble sandstone | \(\lg K_1 = 10.58630 + 12.96300\lg \phi\) | 0.9253 | 23.5 | 460.3 |
| B           | Middle-fine sandstone | \(\lg K_1 = 8.07398 + 9.55263\lg \phi\) | 0.9653 | 28.8 | 1130.1 |
| C           | Fine-very fine undulating bedded sandstone | \(\lg K_1 = 8.10118 + 11.32530\lg \phi\) | 0.9158 | 27.3 | 765.2 |
| D           | Fine-very fine argillaceous sandstone | \(\lg K_1 = 3.12483 + 3.63815\lg \phi\) | 0.8236 | 23.7 | 172.6 |
| E           | Fine to very fine sandstone (carbonaceous clasts) | \(\lg K_1 = 2.12723 + 4.63815\lg \phi\) | 0.8156 | 21.1 | 268.4 |
| F           | Argillaceous sandstone | \(\lg K_1 = 10.58630 + 12.96300\lg \phi\) | 0.8031 | 19.7 | 102.9 |
| G           | Siltstone | \(\lg K_1 = 10.58630 + 12.96300\lg \phi\) | 0.8739 | 18.1 | 53.2 |
| H           | Grayish green mudstone light red mudstone | \(\lg K_1 = 10.58630 + 12.96300\lg \phi\) | 0.7928 | 13.9 | 12.7 |

| Mercury saturation(%) | Fitting formula \((\phi, \% ; K, \text{mD})\) | Correlation coefficient \((R^2)\) |
|------------------------|-----------------------------------------------|-------------------------------|
| 10                     | \(\lg R10 = 0.992 + 0.533\lg K - 0.928\lg \phi\) \((N = 41)\) | 0.72 |
| 15                     | \(\lg R15 = 0.977 + 0.570\lg K - 1.048\lg \phi\) \((N = 41)\) | 0.85 |
| 20                     | \(\lg R20 = 0.875 + 0.587\lg K - 1.053\lg \phi\) \((N = 41)\) | 0.90 |
| 25                     | \(\lg R25 = 0.677 + 0.632\lg K - 1.050\lg \phi\) \((N = 41)\) | 0.91 |
| 30                     | \(\lg R30 = 0.490 + 0.698\lg K - 1.098\lg \phi\) \((N = 41)\) | 0.91 |
| 35                     | \(\lg R35 = 0.321 + 0.791\lg K - 1.227\lg \phi\) \((N = 41)\) | 0.92 |
| 40                     | \(\lg R40 = 0.581 + 0.919\lg K - 1.725\lg \phi\) \((N = 41)\) | 0.86 |
| 45                     | \(\lg R45 = 0.110 + 1.018\lg K - 1.684\lg \phi\) \((N = 41)\) | 0.80 |
| 50                     | \(\lg R50 = -0.044 + 0.991\lg K - 1.606\lg \phi\) \((N = 40)\) | 0.77 |
| 55                     | \(\lg R55 = 1.146 + 1.117\lg K - 2.779\lg \phi\) \((N = 40)\) | 0.70 |
| 60                     | \(\lg R60 = 2.429 + 1.233\lg K - 4.025\lg \phi\) \((N = 40)\) | 0.60 |
| 65                     | \(\lg R65 = 2.914 + 1.155\lg K - 4.335\lg \phi\) \((N = 37)\) | 0.45 |
| 70                     | \(\lg R70 = 4.061 + 1.166\lg K - 5.339\lg \phi\) \((N = 37)\) | 0.34 |
| 75                     | \(\lg R75 = 0.222 + 0.794\lg K - 2.156\lg \phi\) \((N = 32)\) | 0.18 |
2. Rock structure and composition parameters

(1) Shale content and the medium grain diameter

The median grain diameter (Md) corresponds to the point where the particle content is 50% on the probability cumulative curve drawn according to particle size sieve analysis data and is generally expressed in millimeters (or the \( \phi \) value). The thicker the sediment, the more its hydrodynamic effect. Given the loose reservoir of unconsolidated sandstone, shale particles easily fall off and migrate during the development process, blocking the throat and adversely impacting the development. Therefore, shale content (Vsh) was selected as an evaluation parameter. Generally, a linear correlation exists between the logarithms of Md and Vsh. In this study, using laser particle size analysis data, the statistical relationship between median particle size, shale logging value, and regression analysis, that is, the regression formula of median particle size is established as follows (Figure 4A):

\[
\log \text{Md} = 3.0254 + 0.0197\text{Vsh}, \quad R^2 = 0.80,
\]

where Md is the median grain diameter (mm) obtained by the laser particle size analysis experiment, and Vsh is the argillous content (%) obtained by logging interpretation.

(2) Shale content and medium grain size

Mineral composition maturity refers to the relative content of the most stable components in clastic rocks that mark the maturity of its composition: composition maturity \( = (\text{quartz})/(\text{feldspar} + \text{cuttings}) \). The lower the relative value, the purer the lithology of the reservoir, the greater the compositional maturity index, and the better the general physical properties. The composition maturity index was calculated from cast thin-section data. However, the coring well was limited and the coring interval was greater. Consequently, the corresponding thin-section data are minimal. To obtain a longitudinally continuous composition maturity index value, logging data is required.
Logging curves that are highly sensitive to reservoir lithology include gamma ray (GR), spontaneous potential (SP), and photoelectric index (Pe). Lai et al. defined the lithology index \( LI = \frac{\text{GR}}{\text{Pe}} \) (where the GR unit is API, and the unit of Pe is barns per electron, b/e) and is a suitable parameter for characterizing the maturity of the reservoir composition (Figure 4B). Generally, the smaller the LI value, the higher the content of quartz and feldspar, and the lower the content of rock debris, which means the purer the lithology of the reservoir, the higher the composition maturity index, and the better the physical properties of the reservoir. Thus, LI was used to characterize the composition maturity index of the reservoir.

**Engineering parameters**

Completion methods also strongly influence the development capability of oil wells. Commonly used completion methods in the study area are open-hole screens, fracturing and packing, high-speed water and frac pack, and casing perforation. Sand is produced during the production process. Fracturing and packing are commonly used to stimulate and control sand. The different types of completion methods have specific impacts on the output of the oil well at the initial stage of production. In this study, a completion method was selected as an engineering parameter (Table 2).

**Fluid property**

In the study area, the oil interval is long, the reservoir highly heterogeneous, and the fluid properties varied greatly in the vertical direction (Table 5). Fluid properties have a strong impact on oil-well production. In this study, we attempted to establish a DNN model with and without crude oil viscosity (Figure 5). The final neural network model without crude oil viscosity had low prediction accuracy. Therefore, the crude oil viscosity was selected to characterize the properties of the reservoir fluid. Data were obtained using sampling assays.

### Table 5

| Horizon                        | Oil density (20°C)/(g cm\(^{-3}\)) | Oil viscosity (50°C)/(mPa s) | Freezing point (°C) | Paraffin content (%) | Colloid content (%) | Asphalt content (%) |
|-------------------------------|-----------------------------------|------------------------------|---------------------|---------------------|--------------------|---------------------|
| Lower Member of Minghuazhen Fm. | 0.953–0.961                       | 193.2–558.6                  | −33 to −12          | 1.11–2.70           | 15.94–18.81        | 1.53–5.92           |
| Guantao Fm.                   | 0.912–0.953                       | 35.2–198.5                   | −35 to −15          | 1.11–8.83           | 2.86–21.84         | 1.03–13.92          |

3.1.2 | Production parameter

The oil production index refers to the daily liquid production volume under a unit difference in production pressure. The calculation formula is as follows \(^{44} J = \frac{Q}{P_e - P_{oil}}, \)

(Figure 5) (A) DNN prediction results considering crude oil viscosity and (B) DNN prediction results without considering crude oil viscosity. DNN, deep neural network.
where \( J \) is the fluid production index \((t/(\text{day MPa})\), \( Q \) is the daily fluid production \((t/\text{day})\), \( P_e \) is the reservoir static pressure \((\text{MPa})\), and \( P_\omega t \) is the reservoir flow pressure \((\text{MPa})\).

The specific oil recovery index refers to the oil recovery index per meter of oil-well thickness with a unit production pressure difference. The calculation formula is as follows:

\[
J_h = \frac{J}{h},
\]

where \( J_h \) is the specific oil recovery index \((t/(\text{day MPa)/m})\), and \( h \) is the oil layer thickness \((\text{m})\).

### 3.1.3 Data preprocessing

1. Data normalization

Data preprocessing was used to normalize the input data. The various parameters have features of multiple sources, dimensions, and formats, and using their data directly will cause problems in the calculation process. Therefore, it is necessary that these data be normalized through preprocessing. In data preprocessing, all features are mapped between 0 and 1 through mathematical calculations, thereby improving the operation efficiency. The formula used in this study is as follows:

\[
x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}},
\]

where \( x_{\max} \) is the maximum value and \( x_{\min} \) is the minimum value.

2. One-Hot Encoding

The engineering parameters are not continuous numerical variables, but discrete categories, whereas the artificial neural network (ANN) training process is based on numerical values. Therefore, discrete categorical variables should be converted into numerical values to train neural network models. One-hot encoding solves this problem by mapping discrete categorical data into a column of binary vectors with at most one value.\(^{45}\) One-hot encoding treats each feature category as a new one. Taking the completion method as an example, after encoding, the data of the completion method were converted into the following format (Table 6):

### 3.2 Deep neural network

The principle of ANN is a machine learning technology created by imitating the neurons of the human brain. In the neural network, output results are obtained by obtaining the sum of the weights assigned to neurons between the input and output, and the model is modified by changing the weights and thresholds of the neurons according to a defined loss function. Figure 6 shows a schematic of two neural networks. No unified distinction exists between the two neural networks, but most scholars believe that the number of hidden layers is the difference between the two types of neural networks.\(^{45}\) An activation function enables a neural network to process nonlinear functions, which represent the curves. Under the premise of using activation functions, the more layers of neural networks, the more complex the problems that can be solved. The principle of the ANN is to apply the following formula:

\[
z_i = \sum_{j=1}^{n} \omega_{ij} x_i + b_i,
\]

where \( \omega_{ij} \) is the weight, \( b_i \) is the threshold, \( x_i \) is the input eigenvector, and \( z_i \) is the predicted result.

### 3.2.1 Activation functions

Without an activation function, the ANN model is purely a linear model, regardless of its number of hidden layers; it can only solve linear problems. Given the limitation of linear representation, many features of the initial input

| Well number | Well completion       | Well number | Open hole screen | Casing perforation | Frac and pack | High speed water + Frac and pack |
|-------------|-----------------------|-------------|------------------|-------------------|---------------|----------------------------------|
| 1           | Open hole screen      | 1           | 1                | 0                 | 0             | 0                                |
| 2           | Casing perforation    | 2           | 0                | 1                 | 0             | 0                                |
| 3           | Frac and pack         | 3           | 0                | 0                 | 1             | 0                                |
| 4           | High speed water + Frac and pack | 4 | 0 | 0 | 0 | 1 |
cannot be preserved. Therefore, all nonlinear functions, such as an activation function, should be introduced into the neural network. The following Table (Table 7) lists commonly used activation functions and their expressions.

The sigmoid\(^{46,47}\) and tanh\(^{48,49}\) functions were common activation functions in the early days. Their function curves are shown in Figure 7. When the input value of the sigmoid function has a positive or negative infinity tendency, the gradient approaches zero, that is, the gradient dispersion phenomenon occurs. As shown in Figure 7, the shapes of the tanh and sigmoid functions are similar. The output value of the sigmoid function is between 0 and 1, and the output value of tanh is between \(-1\) and 1. Therefore, tanh is more efficient than the sigmoid function. However, the disadvantage of these two activation functions is that the amount of input data significantly affects the learning speed of the neural network. To solve this problem, a new activation function, rectified linear unit (ReLU), has been proposed.\(^{50,51}\) ReLU is the activation function selected in this study. When the input of the ReLU function is positive, the output has a linear relationship with the input, the derivative is always 1, and no gradient dispersion occurs, thereby addressing the problems of the previous sigmoid and tanh functions. The operation speed is significantly improved compared with that of the exponential operation of the sigmoid and tanh functions owing to its linear calculations.

### 3.2.2 Adam optimizer

Computer scientists have developed many optimization algorithms in the history of artificial intelligence development; however, many algorithms can only be applied to certain types of neural networks. Homik et al. proposed the gradient descent with momentum (GDM) algorithm,\(^{52}\) which can be applied to various neural network structures. Csáji\(^{53}\) proposed the root-mean-square propagation (RMSprop) method. An optimizer applies an adaptive learning efficiency to avoid over-the-mouth points. Adam is a learning rate-adaptive optimization algorithm that combines root mean squared propagation (RMSprop) and GDM and is currently the most commonly used optimization algorithm.\(^{54}\) Its iterative formula is as follows:

\[
\Delta x_t = -\frac{\eta}{\sqrt{\sum_{i=1}^{t}g_i^2}}g_t,
\]

where \(\eta\) is the initial learning rate, \(g_t\) is the gradient of the parameters in the \(t\)th iteration, and \(\Delta x_t\) is the change in the parameters in the \(t\)th iteration. The denominator is the \(L^2\) norm for all gradients in each dimension.\(^{54}\)

### 3.3 Principal component analysis

The principal component analysis is a data analysis method used for dimensionality reduction,\(^{55,56}\) which can convert multiple variables into a small number of
principal components. Each target parameter is transformed into a principal component through linear change, and the premise of the nonlinear correlation between the original variables is satisfied. The advantage of this method is that the data dimension can be reduced, and the data can also be classified. This study analyzed the meaning of each type of parameter and classified the parameters using PCA. The calculation steps are as follows:

Step 1. Normalize the raw data.
Step 2. Build the covariance matrix from the normalized data matrix.
Step 3. Calculate the eigenvalues according to the covariance matrix and obtain the principal component and cumulative variance contribution rates.
Step 4. Build the factor loading matrix and calculate the principal components.

3.4 | XGBoost

The XGBoost algorithm is an improved ensemble learning algorithm for gradient boosting decision trees (GBDTs). It adopts the gradient boosting idea of the GBDT and the regression tree generation algorithm and has been improved in many aspects (Figure 8). The advantages of XGBoost are as follows:

1. The XGBoost algorithm performs a second-order Taylor expansion on the loss function and simultaneously uses the first- and second-order derivatives to improve prediction accuracy.
2. The XGBoost algorithm also supports linear classifiers.
3. The XGBoost algorithm saves the data as a block structure so that the gain calculation of each feature can be performed in multiple lines, improving the efficiency and accuracy of the operation.
4. The XGBoost algorithm can obtain the importance ranking of feature variables through statistics. The importance is generally expressed as a score. The importance of each decision tree is calculated by the number of improved performance measures at each attribute segmentation point. Then, the feature importance of all decision trees in the model is averaged. This provides a new idea for data reduction and main control factor analysis.

4 | RESULTS AND DISCUSSION

4.1 | Parameter optimization

According to the reservoir characteristics, many parameters affecting productivity were selected from the aspects of the reservoir's microscopic characteristics, fluid properties, and engineering parameters. However, the calculation methods for some of these parameters are quite similar; for example, R35, RQI, and FZI are obtained indirectly through porosity and permeability owing to the lack of cores. Therefore, through correlation and principal component analyses, representative parameters were simplified and selected for the quantitative evaluation of productivity factors.

4.1.1 | Principal component analysis

Generally, the cumulative contribution rate must exceed 85% for categorization into a class of principal components. In this study, through PCA, a large number of selected characteristic parameters were divided into mutually independent types (Figure 9). The cumulative contribution rate of the first three principal components in the study area reached 85.97%, which provides a good overview of the original variables. The first principal component had high positive loadings for the original variables of porosity, permeability, R35, RQI, and FZI, where R35 represents the effective pore throat radius of the reservoir, and FZI and RQI characterize the seepage capacity of the reservoir. Thus, the first principal component is called the pore-structure component. The second principal component has a high positive load on the median grain size and lithological structure parameters, and a large load on the argillaceous content. The second principal component was called the rock structure and composition. The third principal component has a large positive load on oil viscosity and can be called a fluid property component. The rationality of extracting the various parameters was also verified by PCA.

4.1.2 | Correlation analysis

The parameters were divided into three categories through PCA; however, there were strong correlations between the various parameters.

1. Reservoir pore structure characteristic parameters

Figure 9 shows that porosity, permeability, R35, and RQI have high correlations among the parameters, and FZI has a weak correlation with the above parameters. The FZI and R35 were finally selected for characterizing the pore structure.

2. Rock texture and fabric parameters

The correlation between shale content and median particle size was strong, and the lithology index was

![Figure 9](image)

**Figure 9** Principal component analysis (PCA) result diagram. (A) Rotated component matrix and cumulative contribution rate of principal components and (B) principal component classification.
weakly correlated with other parameters. Finally, the median grain size and lithology index were selected to characterize the rock combination and composition (Figure 10).

3. Fluid properties

The viscosity of crude oil was selected to characterize the properties of the reservoir fluid (Figure 10).

4. Engineering parameters

The well completion method was selected as the engineering parameter (Figure 10).

Figure 11 shows the characterization results of the optimized evaluation parameters in well P-9. We have established the matching relationship between the core test and the logging curve, which can intuitively characterize the distribution characteristics of various parameters. Then, the parameters of each well are calculated by means of the weighted average of sandstone thickness.

### 4.2 DNN hyperparameter optimization

Before the final establishment of the DNN model, hyperparameters, such as the optimizer, learning rate, dropout of the DNN, and number of hidden layers were optimized using the specific oil recovery index of 100 oil production wells. The hyperparameters are listed in Table 8.

The optimizer determines how the parameters are updated during the neural network backpropagation process, which has a significant impact on the model's predictive performance. The optimization was carried out using commonly used optimizers, such as the stochastic gradient descent (SGD), Adam optimizer, and root mean squared propagation (RMSprop) (Figure 12). The number of neurons and layers determines the scale of the network (Figure 13). Different scales of deep neural networks have different learning capabilities, which has a decisive impact on the prediction accuracy of the DNN. In the parameter table (i.e., Table 8), for the number of neurons row, each bracket represents the network size, and the elements in the brackets represent the number of neurons in the DNN. The learning rate indicates the size of the parameter update during the backpropagation process. If the learning rate is extremely large or small, the network will experience difficulty in updating the parameters and converging (Figure 14). Consequently, the global minimum point cannot be determined, and the network cannot achieve an improved prediction performance. Dropout was used to solve the issue of neural network overfitting, which is a common problem in machine learning and should be considered (Figure 15).

The mean square error (MSE), a common regression evaluation index, was used to measure the prediction performance of the specific oil recovery index of the depth neural networks at different depths. The MSE and RMSE are defined as follows:

\[
MSE = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2, \tag{12}
\]

\[
RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2}, \tag{13}
\]

where \(y_i\) and \(\hat{y}_i\) are the actual and predicted specific oil recovery indices, respectively.

Based on the above analysis, the optimized hyperparameters are listed in Table 9.

---

**Table 8**

| Hyperparameter | Values |
|---------------|--------|
| Optimizer     | SGD    |
| Learning Rate | 0.01   |
| Dropout       | 0.5    |
| Number of Neurons | 100   |

**Table 9**

| Hyperparameter | Values |
|---------------|--------|
| Optimizer     | SGD    |
| Learning Rate | 0.01   |
| Dropout       | 0.5    |
| Number of Neurons | 100   |

---

**Figure 10** The plot of the parameter correlation coefficient matrix
In this study, data from 100 wells were collected at the initial stage of production (6 months), and the samples were divided into 10 parts using cross-validation technology. One part was selected as the test set, and the remaining 9 were used as the training set.

### Table 8: DNN model hyperparameter analysis range

| Hyperparameter       | Subdivision                                           |
|----------------------|-------------------------------------------------------|
| Optimizer type       | SGD, Adam, RMSprop                                    |
| Number of neurons    | [5,10,1], [5,10,5,1], [5,10,20,10,1]                 |
| Learning rate        | 0.001, 0.0025, 0.01, 0.05                             |
| Dropout              | With or without                                       |

### Figure 11: Characterization results of evaluation parameters in well P-9

### Figure 12: The effect of optimizer type on the DNN. DNN, deep neural network.

### Figure 13: The effect of the number of neurons on the DNN. DNN, deep neural network.

### 4.3 Prediction results of the DNN model

In this study, data from 100 wells were collected at the initial stage of production (6 months), and the samples were divided into 10 parts using cross-validation technology. One part was selected as the test set, and the remaining 9 were used as the training set. The root mean
square error (RMSE) is 0.14 indicating that the predicted value is consistent with the actual value (Figure 16).

The deep neural network model has significant advantages over traditional methods (such as numerical simulation and logging interpretation). First, compared with the traditional linear fitting direction, a neural network can deal with complex nonlinear data relations, thereby making the prediction results highly accurate. Second, compared with the numerical simulation method, a reservoir model needs not be constructed. Rather, only data mining is required, which is easy to implement. Third, the model is easy to update; the data of old wells can be updated, and that of new wells can be added, indicating good adaptability and easy implementation.

4.4 | Analysis of main control factors

First, the parameters of the XGBoost algorithm are optimized to determine the optimal parameter combination. The optimal number of iterations and tree height of the XGBoost algorithm is mainly adjusted using the grid search (Grid SearchCV) method. The other parameters were adjusted in sequence by step size within the set parameter adjustment range. The final adjustment parameters were as follows (Table 10).

The feature importance ranking was obtained based on the XGBoost, and the importance scores of the feature variables followed the order R35, crude oil viscosity, Md, LI, well completion method, and FZI. Figure 10 shows that the pore structure characteristics, crude oil viscosity, and rock structure parameters had the greatest impact on production. The pore structure parameters directly controlled the seepage capacity and storage space of the reservoir.62,63 Crude oil viscosity has a significant influence on oil well productivity. The rock structure parameters indicate the sedimentary facies change of the reservoir and differences in rock and mineral types. The cementation was loose, and the shale particles migrated easily during development and blocked the pore throats. Therefore, the shale content and median particle size also have a significant influence on the productivity of the oil well. The importance of the evaluation parameters is in keeping with the previous geological understanding (Figure 17).

| Hyperparameter         | Value      |
|------------------------|------------|
| One-hot encoding       | Used       |
| Optimizer type         | Adam       |
| Number of neurons      | 1, 5, 10   |
| Learning rate          | 0.01       |
| Dropout                | Not used   |
| Activation function    | ReLU       |

Abbreviation: DNN, deep neural network.

![FIGURE 14](image14.png) The effect of learning rate on the DNN. DNN, deep neural network.

![FIGURE 15](image15.png) The effect of Dropout on the DNN. DNN, deep neural network.

![TABLE 9](table9.png) DNN model hyperparameter optimization results

![FIGURE 16](image16.png) Prediction error of specific oil recovery index in the study area
Unconsolidated sandstone heavy oil reservoirs are distributed in major oil-producing regions worldwide (Table 11), mainly in Tertiary strata, and the sedimentary type is mainly a fluvial-delta sedimentary system. Such reservoirs have the characteristics of a shallow burial depth (<1800 m), high porosity and permeability, loose cementation, and large changes in crude oil properties. The research methods and optimal evaluation parameters adopted in this study also have reference significance for other unconsolidated sandstone reservoirs.

**TABLE 10** XGBoost parameter tuning

| Parameter            | Setting range | Optimum value | Step |
|----------------------|---------------|---------------|------|
| Iterations           | 1–200         | 200           | 1    |
| Tree height          | 1–7           | 4             | 2    |
| Learning rate        | 0.01–0.1      | 0.035         | 0.01 |
| Training samples proportion | 0.50–0.90 | 0.85          | 0.05 |
| Iteratively select feature scale | 0.50–0.90 | 0.85          | 0.05 |

**FIGURE 17** Feature importance distribution

**TABLE 11** Typical unconsolidated sandstone oilfields and their burial depths

| Country  | Region            | Oil field           | Buried depth (m) |
|----------|-------------------|---------------------|------------------|
| China    | Bohai Bay Basin   | Gudao Oilfield      | 1120–1350        |
|          |                   | Qinhuangdao Oilfield| 950              |
|          | Nanxiang Basin    | Jinglou Oilfield    | 100–830          |
|          |                   | Gucheng Oilfield    | 150–1047         |
| Sudan    | Muglad Basin      | Fula Oilfield       | 1200–1500        |
| Canada   | Eastern Alberta   | ColdLake Oilfield   | 330–500          |
|          |                   | Lloyminster Oilfield| 400–500          |
|          |                   | FrogLake Oilfield   | 424–600          |
| Eastern Alberta | Gulf of Mexico | KernRiver Oilfield | 220–420          |

**5 | CONCLUSIONS**

Based on the definition of the microscopic characteristics of a subject reservoir, this study proposes a deep neural network production prediction method and combines it with the XGBoost algorithm to itemize the main controlling elements affecting oil well production. The data set includes pore structure characteristics, rock structure, and fabric characteristics, fluid properties, and engineering parameters. The results of this study are summarized as follows.

1. The microscopic characteristics of the unconsolidated sandstone reservoir, that is, the comprehensive attribute parameters, quantitatively describe the heterogeneity of the reservoir rock structure and composition and the pore-throat structure parameters. According to the above definition, the reservoir micro-characteristic parameters were selected from the aspects of rock structure and pore-throat micro-structure characteristics, and combined with the reservoir and engineering parameters to obtain good prediction results.

2. Through sensitivity analysis of hyperparameters, a deep neural network model with improved
predictability was established. The results of the neural network hyperparameter optimization show that dropout has a low impact on this model. When the hidden layer is 2, the absolute error function is the smallest; the activation function adopts ReLU, the learning rate is 0.01, and the Adam optimizer is used. Hyperparameters have a significant impact on the accuracy of neural networks, therefore, deep neural network models should be tuned before they are used to produce predictions.

3. Identifying independent variables that have a significant influence on the initial production of oil wells based on the XGBoost algorithm and calculating the feature importance ranking of variables has practical benefits. The results show that the microscopic pore structure, crude oil viscosity, and median particle size are key parameters, further indicating that the microscopic characteristics of the reservoir have a significant impact on the production of oil wells. The viscosity of crude oil in the oil layer in heavy oil reservoirs varies significantly, and both static and fluid property evaluation parameters must be fully considered to reflect actual reservoir performance.

ORCID
Zhao Wang http://orcid.org/0000-0001-8754-6564
Hongming Tang http://orcid.org/0000-0002-1130-9009

REFERENCES
1. Liu Y, Luo X, Kang K, et al. Permeability characterization and directional wells initial productivity prediction in the continental multilayer sandstone reservoirs: a case from penglai 19-3 oil field, bohai bay basin. Petrol Explor Dev. 2017;44:97-104. doi:10.1016/S1876-3804(17)30012-5
2. Hao F, Zhou X, Zhu Y, Bao X, Yang Y. Charging of the Neogene Penglai 19-3 field, Bohai Bay Basin, China: oil accumulation in a young trap in an active fault zone. Am Assoc Pet Geol Bull. 2009;93:155-179. doi:10.1306/09080808092
3. Zhou S, Zhang F, Sun F. The typical development practice of Chinese offshore oilfield[M]. Beijing: Petroleum Industry Press; 2009:28-29.
4. Xue Ya, Deng Y, Wang D, Yang H, Lv D, Kang K. Hydrocarbon accumulation conditions and key exploration and development technologies for PL 19-3 oilfield. Petrol Res. 2019;4:29-51. doi:10.1016/j.ptlrs.2019.01.003
5. Wang M, Tang H, Tang H, et al. Impact of differential densification on the pore structure of tight gas sandstone: evidence from the Permian Shihzei and Shanxi Formations, Eastern Sulige Gas Field, Ordos Basin, China. Geoﬂuids. 2019;2019:4754601-4754625. doi:10.1155/2019/4754601
6. Fan C, Li H, Qin Q, He S, Zhong C. Geological conditions and exploration potential of shale gas reservoir in Wufeng and Longmaxi formation of southeastern Sichuan Basin, China. J Petrol Sci Eng. 2020;191:107138. doi:10.1016/j.petrol.2020.107138
7. Wang M, Tang H, Zhao F, et al. Controlling factor analysis and prediction of the quality of tight sandstone reservoirs: a case study of the He8 Member in the eastern Sulige Gas Field, Ordos Basin, China. J Nat Gas Sci Eng. 2017;46:680-698. doi:10.1016/j.jngse.2017.08.033
8. Vishal V, Mahanta B, Pradhan SP, Singh TN, Ranjith PG. Simulation of CO2 enhanced coalbed methane recovery in Jharia coalfields, India. Energy. 2018;159:1185-1194. doi:10.1016/j.energy.2018.06.104
9. Zhang J, Feng Q, Zhang X, et al. Multi-fractured horizontal well for improved coalbed methane production in eastern Ordos basin, China: field observations and numerical simulations. J Petrol Sci Eng. 2020;194:107488. doi:10.1016/j.petrol.2020.107488
10. Peaceman DW. Fundamentals of Numerical Reservoir Simulation. Elsevier; 2000.
11. Geiger S, Roberts S, Matthäi SK, Zoppou C, Burri A. Combining finite element and finite volume methods for efficient multiphase flow simulations in highly heterogeneous and structurally complex geologic media. Geoﬂuids. 2004;4:284-299. doi:10.1111/j.1468-8123.2004.00093.x
12. Zidane A, Firoozabadi A. Higher-order simulation of two-phase compositional flow in 3D with non-planar fractures. J Comput Phys. 2020;402:108896. doi:10.1016/j.jcp.2019.108896
13. Antonietti PF, Facciolà C, Russo A, Verani M. Discontinuous galerkin approximation of flows in fractured porous media on polytopic grids. SIAM J Sci Comput. 2019;41:A109-A138. doi:10.1137/17m1138194
14. Ma T, Zhang K, Shen W, Guo C, Xu H. Discontinuous and continuous Galerkin methods for compressible single-phase and two-phase flow in fractured porous media. Adv Water Resour. 2021;156:104039. doi:10.1016/j.adewaterres.2021.104039
15. Shen J, Tang T, Wang L-L. Spectral Methods: Algorithms, Analysis and Applications. Vol 41. Springer Science & Business Media; 2011.
16. Boyd JP. Chebyshev and Fourier Spectral Methods. Courier Corporation; 2001.
17. Souissi A. Numerical Simulation of One-Dimensional and Two-Dimensional Mass Transport in Groundwater, Using Galerkin, Petrov-Galerkin and Localized Adjoint Methods. Ph.D., The University of Arizona; 1991.
18. Epshteyn Y, Rivière B. Fully implicit discontinuous finite element methods for two-phase flow. Appl Numer Math. 2007;57:383-401. doi:10.1016/j.apnum.2006.04.004
19. Marcondes F, Sephnoorii K. An element-based finite-volume method approach for heterogeneous and anisotropic compositional reservoir simulation. J Petrol Sci Eng. 2010;73:99-106. doi:10.1016/j.petrol.2010.05.011
20. Muradkhani L. Neural networks for prediction of oil production. IFAC-PapersOnLine. 2018;51:415-417. doi:10.1016/j.ifacol.2018.11.339
21. Baneshi M, Behzadijo M, Rostami M, Schaffie M, Nezamabadi-pour H. Using well logs to predict a multimin porosity model by optimized spread RBF networks. Energy Sources A Recovery Util Environ Eff. 2015;37:2443-2450. doi:10.1080/15567036.2011.628362
22. Cao S-Y, Liang C-S. The application of BP neural network in reservoir prediction. Prog Geosci. 2002;17:84-90.
23. Hinton GE, Salakhutdinov RR. Reducing the dimensionality of data with neural networks. Science. 2006;313:504-507. doi:10.1126/science.1127647
24. Liu J-J, Liu J-C. Integrating deep learning and logging data analytics for lithofacies classification and 3D modeling of tight sandstone reservoirs. Geosci Front. 2022;13:101311. doi:10.1016/j.gsf.2021.101311
25. Tewari S, Dwivedi UD. Ensemble-based big data analytics of lithofacies for automatic development of petroleum reservoirs. Comput Ind Eng. 2019;128:937-947. doi:10.1016/j.cie.2018.08.018
26. Wang S, Chen Z, Chen S. Applicability of deep neural networks on production forecasting in Bakken shale reservoirs. J Petrol Sci Eng. 2019;179:112-125. doi:10.1016/j.petrol.2019.04.016
27. Allen MB, Macdonald DIM, Xun Z, Vincent SJ, Brouet-Menzies C. Early Cenozoic two-phase extension and late Cenozoic thermal subsidence and inversion of the Bohai Basin, northern China. Marine Petrol Geol. 1997;14:951-972. doi:10.1016/S0264-8172(97)00027-5
28. Liang J, Wang H, Bai Y, Ji X, Duo X. Cenozoic tectonic evolution of the Bohai Bay Basin and its coupling relationship with Pacific Plate subduction. J Asian Earth Sci. 2016;127:257-266. doi:10.1016/j.jseaes.2016.06.012
29. Winland H. Oil accumulation in response to pore size changes, Weyburn field, Saskatchewan. Amoco Production Research Report No. F72-G25; 1972.
30. Amaefule JO, Altunbay M, Tiab D, Kersey DG, Keelan DK. Research progress on evaluation methods and factors controlling oil accumulation in tight reservoirs. J Petrol Sci Eng. 2019;178:723-735. doi:10.1016/j.petrol.2019.04.007
31. He J, Zhu S, Shi X, et al. Characteristics of lithofacies in deep shale gas reservoirs in the southeastern Sichuan Basin and their influence on pore structure. Front Earth Sci. 2022;10:10. doi:10.3389/feart.2022.857343
32. Li H. Research progress on evaluation methods and factors influencing shale brittleness: a review. Energy Rep. 2022;8:4344-4358. doi:10.1016/j.egyr.2022.03.120
33. Li H, Tang H, Qin Q, et al. Characteristics, formation periods and genetic mechanisms of tectonic fractures in the tight gas sandstones reservoir: a case study of Xujiawe Formation in YB area, Sichuan Basin, China. J Petrol Sci Eng. 2019;178:723-735. doi:10.1016/j.petrol.2019.04.007
34. Spearing M, Allen T, McAulay G. Review of the Winland R35 method for net pay definition and its application in low permeability sands. Proceedings of the 2001 International Symposium of the Society of Core Analysts. 2001.
35. Nabawy BS, Géraud Y, Rochette P, Bur N. Pore-throat characterization in highly porous and permeable sandstones. Am Assoc Pet Geol Bull. 2009;93:719-739. doi:10.1306/03160908131
36. Pittman ED. Relationship of porosity and permeability to various parameters derived from mercury injection-capillary pressure curves for Sandstone1. Am Assoc Pet Geol Bull. 1992;76:191-198. doi:10.1306/bdf87a4-1718-11d7-8645000102c1865d
37. Li X, Huang H, Lu H. Improving the accuracy of permeability prediction modeling based on flow units: an example from the Khasib Limestone Reservoir of Ahdeb Oil Field, Iraq. Proceedings of the 2018 SEG International Exposition and Annual Meeting. 2018.
38. Farouk S, Sen S, Ganguli SS, Abuseda H, Debnath A. Petrophysical assessment and permeability modeling utilizing core data and machine learning approaches—a study from the Badr El Din-I field, Egypt. Marine Petrol Geol. 2021;133:105265. doi:10.1016/j.marpetgeo.2021.105265
39. Shehata AA, Osman OA, Nabawy BS. Neural network application to petrophysical and lithofacies analysis based on multi-scale data: an integrated study using conventional well log, core and borehole image data. J Nat Gas Sci Eng. 2021;93:104015. doi:10.1016/j.jngse.2021.104015
40. Rebeiro TB, Batezzelli A, Mattos NHS, Leite EP. Flow units in complex carbonate reservoirs: a study case of the Brazilian pre-salt. Marine Petrol Geol. 2022;140:105639. doi:10.1016/j.marpetgeo.2022.105639
41. Shan L, Cao L, Guo B. Identification of flow units using the joint of WT and LSSVM based on FZI in a heterogeneous carbonate reservoir. J Petrol Sci Eng. 2018;161:219-230. doi:10.1016/j.petrol.2017.11.015
42. Sen S, Abioui M, Ganguli SS, et al. Petrophysical heterogeneity of the early Cretaceous Alamein dolomite reservoir from North Razzak oil field, Egypt integrating well logs, core measurements, and machine learning approach. Fuel. 2021;306:121698. doi:10.1016/j.fuel.2021.121698
43. Lai J, Wang G, Huang L, et al. Brittleness index estimation in a tight shaly sandstone reservoir using well logs. J Nat Gas Sci Eng. 2015;27:1536-1545. doi:10.1016/j.jngse.2015.10.020
44. Zhang W, Mehrabian A. Poroelastic solution for the nonlinear productivity index of wells in stress-sensitive reservoir rocks. SPE J. 2021;26:68-82. doi:10.2118/195947-pa
45. Schmidhuber J. Deep learning in neural networks: an overview. Neural Net. 2015;61:85-117. doi:10.1016/j.neunet.2014.09.003
46. Yin X, Goudriaan J, Lantinga EA, Vos J, Spiertz HJ. A flexible sigmoid function of determinate growth. Ann Botany. 2003;91:361-371. doi:10.1039/aobmc9029
47. Ito Y. Representation of functions by superpositions of a step or sigmoid function and their applications to neural network theory. Neural Net. 1991;4:385-394. doi:10.1016/0893-6080(91)90075-G
48. Kalman BL, Kwasny SC. Why tanh: choosing a sigmoidal activation by sparse regularization. Proceedings of the 2017 International Joint Conference on Neural Networks (IJCNN), 2017:268-2691.
49. Feng J, Lu S. Performance analysis of various activation functions in artificial neural networks. J Phys Conf Ser. 2019;1237:022030. doi:10.1088/1742-6596/1237/2/022030
50. Schmidt-Hieber J. Nonparametric regression using deep neural networks with ReLU activation function. Ann Stat. 2020;48:1875-1897.
51. Ide H, Kurita T. Improvement of learning for CNN with ReLU activation by sparse regularization. Proceedings of the 2017 International Joint Conference on Neural Networks (IJCNN), 14-19 May. 2017:2684-2691.
52. Hornik K, Stinchcombe M, White H. Multilayer feedforward networks are universal approximators. Neural Net. 1989;2:359-366. doi:10.1016/0893-6080(89)90020-8
53. Csapó BC. Approximation With Artificial Neural Networks. Vol 24. Faculty of Sciences, Eötvös Loránd University; 2001:7.
54. Kingma DP, Ba J. Adam: a method for stochastic optimization. arXiv preprint arXiv:1412.6980; 2014.
55. Abdi H, Williams LJ. Principal component analysis. WIREs Comput Stat. 2010;2:433-459. doi:10.1002/wics.101
56. Ringnér M. What is principal component analysis. Nat Biotechnol. 2008;26:303-304. doi:10.1038/nbt0308-303
57. Chen T, Guestrin C. Xgboost: a scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2016;785-794.
58. Wang M, Liu S, Zeng M, et al. Diagenesis and diagenetic facies distribution prediction of Chang 8 tight oil reservoir in Maling area, Ordos Basin, NW China. Turkish J Earth Sci. 2019;28:457-469. doi:10.3906/yen-1809-13
59. Bottou, L. Stochastic gradient descent tricks. In: Montavon G, Orr GB, Müller KR, eds. Neural Networks: Tricks of the Trade. Lecture Notes in Computer Science, Vol 7700. Springer; 2012: 421-436.
60. Tieleman T, Hinton G. Lecture 6.5-rmsprop: divide the gradient by a running average of its recent magnitude. COURSERA Neural Netw Mach Learn. 2012;4:26-31.
61. Srivastava N, Hinton G, Krizhevsky A, Sutskever I, Salakhutdinov R. Dropout: a simple way to prevent neural networks from overfitting. J Mach Learn Res. 2014;15:1929-1958.
62. Li J, Li H, Yang C, Wu Y, Gao Z, Jiang S. Geological characteristics and controlling factors of deep shale gas enrichment of the Wufeng-Longmaxi formation in the Southern Sichuan Basin, China. Lithosphere. 2022;2022:4737801. doi:10.2113/2022/4737801
63. Fan C, Xie H, Li H, et al. Complicated fault characterization and its influence on shale gas preservation in the southern margin of the Sichuan Basin, China. Lithosphere. 2022;2022:8035106. doi:10.2113/2022/8035106

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