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Research on Reservoir Lithology Prediction Based on Residual Neural Network and Squeeze-and- Excitation Neural Network

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Abstract**—**Conventional reservoir prediction methods ar not sufficient to explore the implicit relation between seismic attributes, and thus data utilization is low. In order to improve the predictive classification accuracy of reservoir lithology, this paper proposes a deep learning lithology prediction method based on ResNet (Residual Neural Network) and SENet (Squeeze-and-Excitation Neural Network). The neural network model is built and trained by using seismic attribute data and lithology data of Shengli oilfield, and the nonlinear mapping relationship between seismic attribute and lithology marker is established. The experimental results show that this method can significantly improve the classification effect of reservoir lithology, and the classification accuracy is close to 70%. This study can effectively predict the lithology of undrilled area and provide support for exploration and development.

Keywords**—**Convolutional neural network, lithology, prediction of reservoir lithology, seismic attributes.

I. Introduction

WITH the improvement of oil and gas exploration, the conventional oil and gas resources are decreasing, and the exploration objects are gradually changing from structural oil and gas reservoirs to hidden oil and gas reservoirs. However, hidden oil and gas reservoirs are generally characterized by deep burial, complex structure, and great difficulty in exploration and development. Lithology identification is one of the important tasks of well logging reservoir evaluation, which is the basis of reservoir description, formation evaluation, real-time drilling monitoring, reservoir parameter solution and reservoir evaluation [1]. Direct experimental measurement of the core is the most accurate method to identify lithology, but it consumes tremendous time and money, which is limited in practical application [2]. Traditional lithology identification methods, such as crossplot and overlap [3], cannot effectively identify reservoir lithology.

Deep learning has been applied in reservoir prediction and lithology identification. Guohe et al. [4] used depth belief network to predict logging lithology data by taking seismic data from several adjacent sampling points as input, and obtained the predicted lithology profile. Anpeng et al. [5] used natural gamma ray (GR) and other logging data as the input of deep network for lithology prediction, and achieved great results. Jialiang et al. [6] combined PCA principal component analysis and BP network to reduce the dimension of network input data, network parameters and computation.

As an important part of deep learning method, convolutional neural network [7] has made remarkable achievements in image recognition [8] and sound analysis [9], while reservoir prediction is still in the development stage. In this paper, the seismic attribute data of a block in Chengdao of Dongying are extracted and organized, the deep convolutional neural network is built, and the nonlinear mapping relationship between seismic attribute and logging lithology is established by using its powerful feature extraction and nonlinear fitting ability, and a new method of lithology prediction is proposed and verified by experiments.

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II. Research Methods

A. Convolutional Neural Network (CNN)

As an important part of deep learning, CNN provides an end-to-end learning model. The parameters in the model can be trained by the traditional gradient descent method, and the features in the data can be learned by the trained CNN [10]. Since the original information can be directly input, the complicated pre-processing of data can be avoided. Meanwhile, the convolution operation shares weights of the network, which greatly reduces complexity and computation of the model. Consequently, this approach has been widely applied.

The most important part of the CNN is convolution and pooling operation. Each convolutional layer moves on the input feature graph through a convolution kernel to obtain the local information of each step, while the pooling layer mixes the information of adjacent units in the input feature graph through operations such as maximum pooling and average pooling. In recent years, many models based on CNN were proposed, especially in the field of image recognition, including GoogleNet [11], ResNet [12], SENet [13] etc. They have improved the network structure in network depth and information transmission, and have become a popular component of convolutional network model.

a) Convolutional Operation

Convolution is a special mathematical operation. A convolution kernel carries out a convolution operation every step it moves on the input feature graph, and the output result can be obtained by adding bias and activating function [7]. The receptive field of the operation is the same size as the convolution kernel, and each convolution can extract the local features. The convolution process is shown in Fig. 1. The convolution calculation is shown in (1):

$$x_j^l = f(u_j^l)$$
$$u_j^l = \sum_{i \in M_j} x_i^{l-1} \times k_{ij}^l + b_j^l \tag{1}$$

l is the sequence number of the convolutional layer, j is the sequence number of the channel, x_j^l is the output of the JTH channel j of the convolutional layer l, u_j^l is the output of the unactivated function after convolution operation. $f(\cdot)$ can be activation function, generally sigmoid function or ReLU function. M_j is the subset of the input feature graph, x_i^{l-1} is the input of the convolution layer, k_{ij}^l is the convolution kernel matrix, b_j^l is the corresponding bias, "$*$" is convolutional operation.

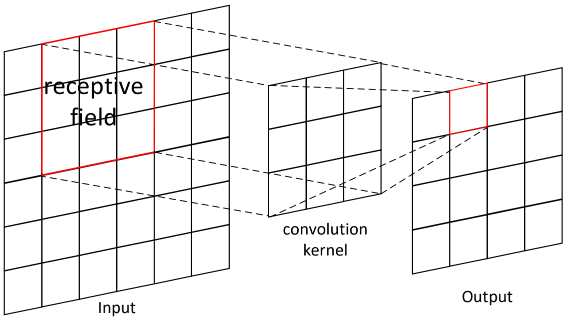

Fig. 1 Convolutional operation

b) Pooling

Pooling can be used to conduct statistics on the features of different positions after convolution operation, and lower resolution statistical representation can be performed on the convolutional layer [14]. Common methods include average pooling, maximum pooling, etc. Pooling layer, also known as sampling layer or feature mapping layer, is obtained by pooling operation and then through activation function, which can effectively reduce the size of the matrix and reduce model parameters. Pooling calculation is shown in (2):

$$x_j^l = f(u_j^l)$$
$$u_j^l = w_j^l \text{pooling}(x_j^{l-1}) + b_j^l \tag{2}$$

w_j^l is the weight of pooling, b_j^l is the bias of pooling.

B. ResNet

As the CNN gradually develops to a deeper level, the main problem facing the network is degradation rather than overfitting. The network performance no longer improves with the increase of depth, and even the performance declines when the network depth further increases [15]. Aiming at this problem, ResNet is designed through an identity mapping to transfer information directly backward, and constitute a Residual block, on the part of the Network learning into the Residual block. Hence, a deep Network can be constructed. The network learns the identity mapping of the residual block in the process of training, and then achieves the suitable depth of the network. The residual structure is shown in Fig. 2. F(X) is the residual function, X is the identity mapping, and the mapping of the residual structure is H(X) = F(X) -X, then F(X) = H(X) -X. It is easier to optimize the residual mapping than the original mapping [12].

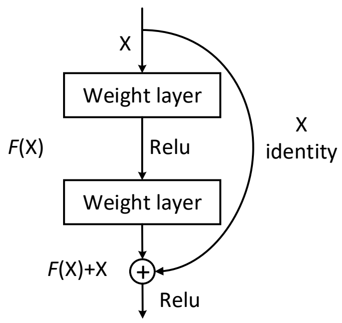

Fig. 2 Residual block

C. SENet

SENet can explicitly model the interdependencies between channels and adaptively recalibrate the characteristic responses of channel directions [13]. It has two main operations: Squeeze and Excitation. The Squeeze operation makes each characteristic of the two-dimensional channel become a real number, which can represent features in response to the global distribution channel while the Excitation operation is similar to the gating mechanism in the LSTM [16], which can generate weights for feature channels and explicitly model the correlation between feature channels. Finally, scale operation is used to scale the original feature graph with the weight obtained. The main structure of SENet is shown in Fig. 3 [13].

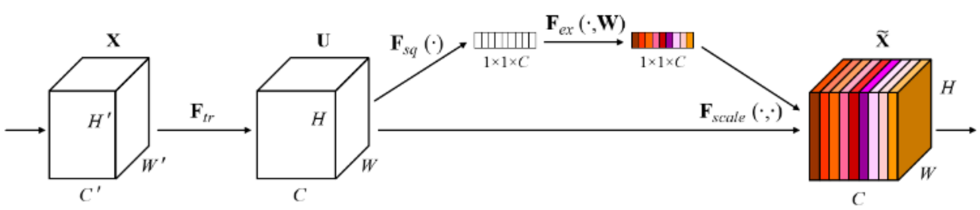

Fig. 3 SENet block

a) Squeeze

To mine the dependencies between channels, we use a global average pooling operation to generate channel-level statistical data, as shown in (3):

$$z_c=F_{sq}(u_c)=\frac{1}{H\times W}+\sum_{i=1}^{H}\sum_{j=1}^{W}u_c(i,j) \tag{3}$$

u_c represents an input characteristic graph, H and W represent dimensions of the feature graph, $z_c \in R^c$ represents statistical data of a channel after Squeeze operation.

b) Excitation

Excitation operation can build dependencies between channel statistical data. Two reduction ratio r full connection layers are used to limit the model complexity, and then we use the ReLU [17] activation function to get the weight of channel level, as shown in (4):

$$s=F_{ex}(z,W)=\sigma(g(z,W))=\sigma(W_1\delta(W_2 z)) \tag{4}$$

δ represents ReLU function, $W_1 \in R^{\frac{C}{r}\times C}$ and $W_2 \in R^{C\times\frac{C}{r}}$ represent the weights of full connection layer. Finally, the final result is obtained by multiplying the original feature graph by the weight of the channel level through the scaling operation as shown in (5):

$$\tilde{x}_c=F_{scale}(u_c,s_c)=s_c u_c \tag{5}$$

III. Res-SE-Net Lithology Prediction Model

A. Model Structure

We propose a method of lithology prediction which combines the advantage of ResNet to deepen the network with the advantage of SENet to mine relationship between channels. This method can construct a flexible lithology prediction model. On the basis of classical convolution neural network, we use ResNet identity to deepen the depth of network, and use SENet Squeeze, Excitation to mine association relationship between channels. The designed network can be composed of multiple similar components, and the main component of the network, "SEidentity_Block", is shown in Fig. 4.

The convolution kernel of 1×1 extracts global features and fuses the features of the previous convolution at the channel level, followed by two convolution kernels of 3×3 to mine local features of the feature map and reduce the network parameters. Because the numerical ranges of various seismic attribute data vary greatly, we add a BatchNormalization layer after each convolution to effectively prevent the gradient from disappearing. Moreover, we use the Squeeze and Excitation to mine the relationship between channels and generate weight. Finally, the identity connection is added at the beginning and end of the structure to realize the idea of ResNet, so that the structure changes from the original mapping of learning to learning residual mapping, which makes learning easier and can increase the depth of the network.

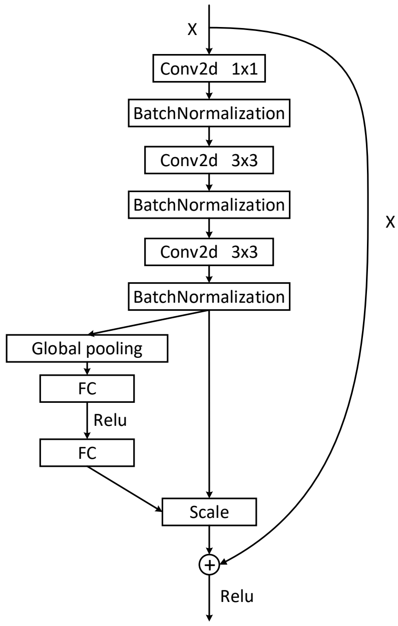

Fig. 4 SEidentity_Block

B. Network Construction

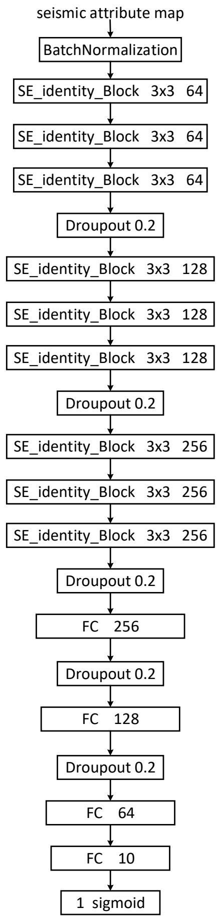

Fig. 5 Model structure

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We use 49 seismic attributes, such as original amplitude, mean square amplitude, instantaneous phase, and instantaneous frequency, to form a 7×7 input matrix, and construct multiple SEidentity_Block, which is followed by a dropout layer to reduce overfitting. Finally, four full-connection layers are connected to a sigmoid layer for dichotomous classification, with sandstone and mudstone as the output labels of {0,1}. The network structure with three "seidentity_blocks" is shown in Fig. 5.

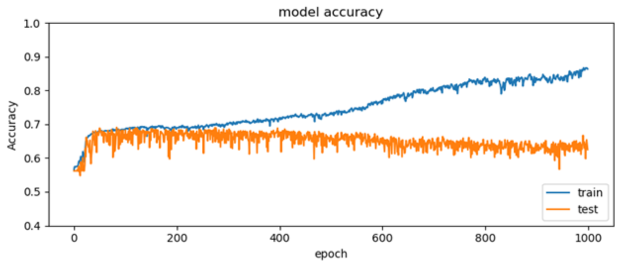

Fig. 6 Accuracy rate of training

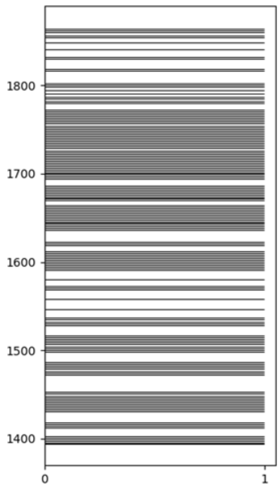

Fig. 7 Prediction result of CB11

IV. Experiment and Analysis

A. Experimental Data

We take a block in Chengdao, Dongying as the research object, and extract SEGY seismic data volume, logging data, logging lithology data, time-depth conversion data and horizon information.

B. Data Processing

a) Seismic Data Processing

We first calculate the location of each line of data in the segy file. For round-trip travel, the range is 1025, the inline range is 627 to 2267, and the CDP range is 1189 to 1852. Since the range of values of each attribute varies greatly, the data are normalized as shown in (6):

$$x' = \frac{x - x_{min}}{x - x_{max}} \quad (6)$$

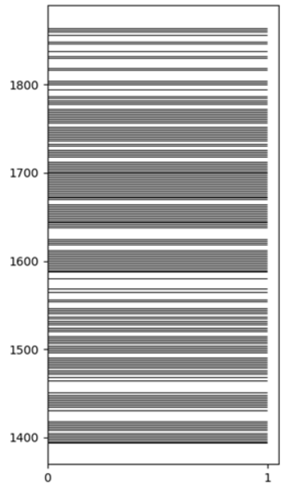

Fig. 8 Real label of CB11

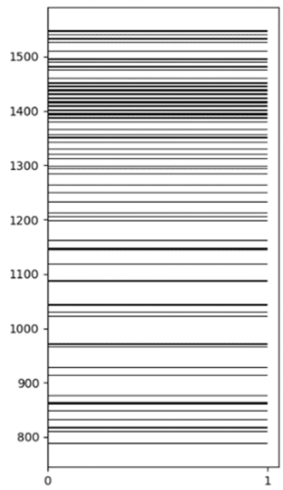

Fig. 9 Prediction result of CB111

b) Lithology Label Data Processing

Lithology markers are mapped to the time-travel scale of seismic data by logging lithology files and time-depth conversion files. The travel time range $[t_1^l, t_2^l]$ of the corresponding seismic attribute is calculated according to each depth range $[d_1^l, d_2^l]$ of the lithology file. Lithological markers $label^l$ of depth range $[d_1^l, d_2^l]$ is the label of each sampling point in $[t_1^l, t_2^l]$, divided into sandstone and mudstone y={0,1}.

C. Comparative Aanalysis of Pprediction Mmethods

We used the network 27-Res-SE-Net with the structure in Fig. 5, and the comparison models were the ordinary convolutional network 27-Conv-Net, the network 27-Res-Net with only ResNet structure, and the network 27-SE-Net with only SENet structure, and conventional machine learning algorithms [18], including SVM, decision tree, KNN algorithm and xgboost algorithm using RBF kernel function.

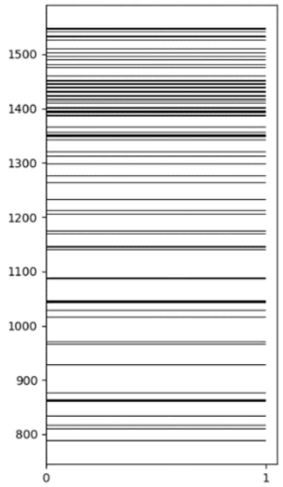

Fig. 10 Real label of CB111

TABLE I
ACCURACY COMPARISON

method	accuracy of training	accuracy of predicting	number of training
27-Res-SE-Net	70.47%	69.72%	200
27-Conv-Net	69.67%	65.41%	800
27-Res-Net	71.99%	66.35%	180
27-SE-Net	71.88	67.92	220
SVM	——	57.90%	——
DecisionTree	——	59.96%	——
KNN	——	60.11%	——
Xgboost	——	64.31%	——

As show in Table I, 27-Res-SE-net has the highest prediction accuracy and fast convergence rate. Ordinary convolutional network 27-Conv-Net has the slowest convergence speed, and it is speculated that the network is too deep, resulting in "degradation" [12]. When the network is shallow, the convergence is faster, but the prediction accuracy rate does not change significantly. 27-Res-Net has the fastest convergence speed. Compared with 27-Conv-Net, it can be seen that ResNet structure can significantly accelerate the convergence speed of deep network. Compared with 27-Res-net, 27-SE-Net has higher prediction accuracy and slower convergence speed, so SENet can also speed up the network convergence speed and significantly improve the accuracy. Combined with the advantages of both, 27-Res-SE-Net has a fast convergence speed and the highest accuracy, which is the model with the best effect. However, after the 27-Res-SE-Net continued training, as shown in Fig. 6, the accuracy of the training set continued to improve, while there was no significant change in the prediction set. It was speculated that overfitting had occurred, and overfitting was still a common problem in the depth model. At the same time, the accuracy of depth model in prediction set is generally higher than that of conventional machine learning model, which shows the advantages of deep learning model over conventional machine learning model.

D.Example Analysis of Borehole Lithology Prediction

The 27-res-se-net model is used to predict the lithology of Wells CB11 and CB111. The results are shown in Figs. 7-10. In Wells CB11 with dense sandstone and CB111 with sparse sandstone, the prediction accuracy was 82.2% and 86.4 respectively.

E. Example Analysis of Profile Lithology Prediction

We use 27-Res-SE-Net model to predict the profile of underground lithologic, taking the inline for sandstone markers imaging data from 1328 and 1368 respectively. The analysis results are shown in Figs. 11 and12.

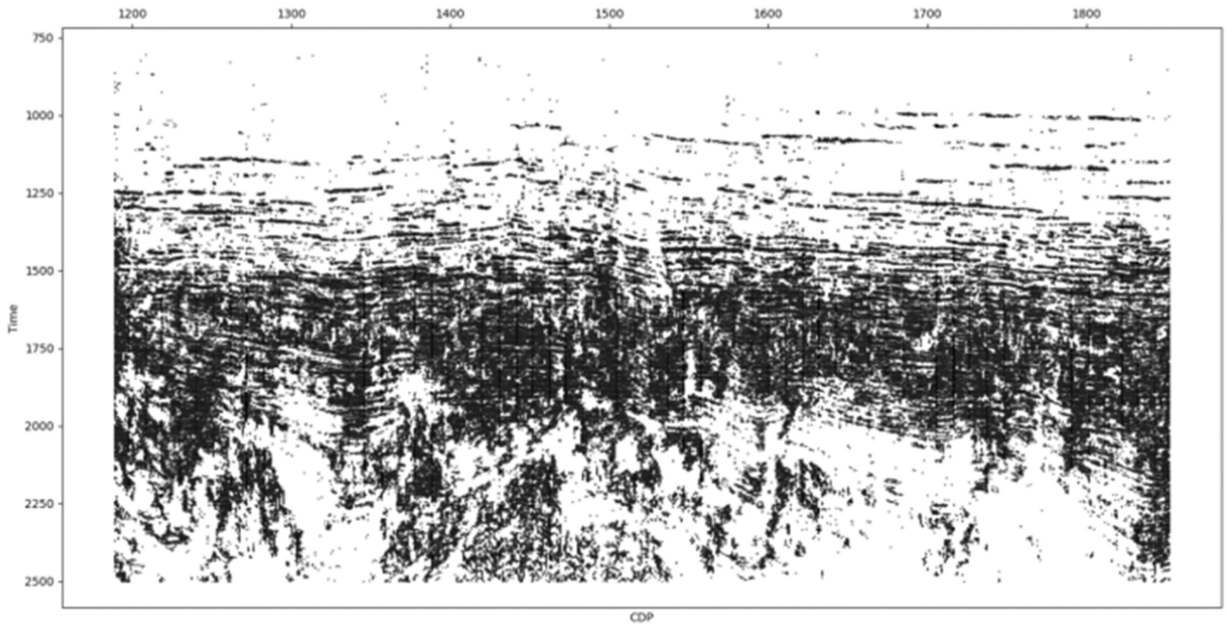

Fig. 11 Prediction result where inline = 1328

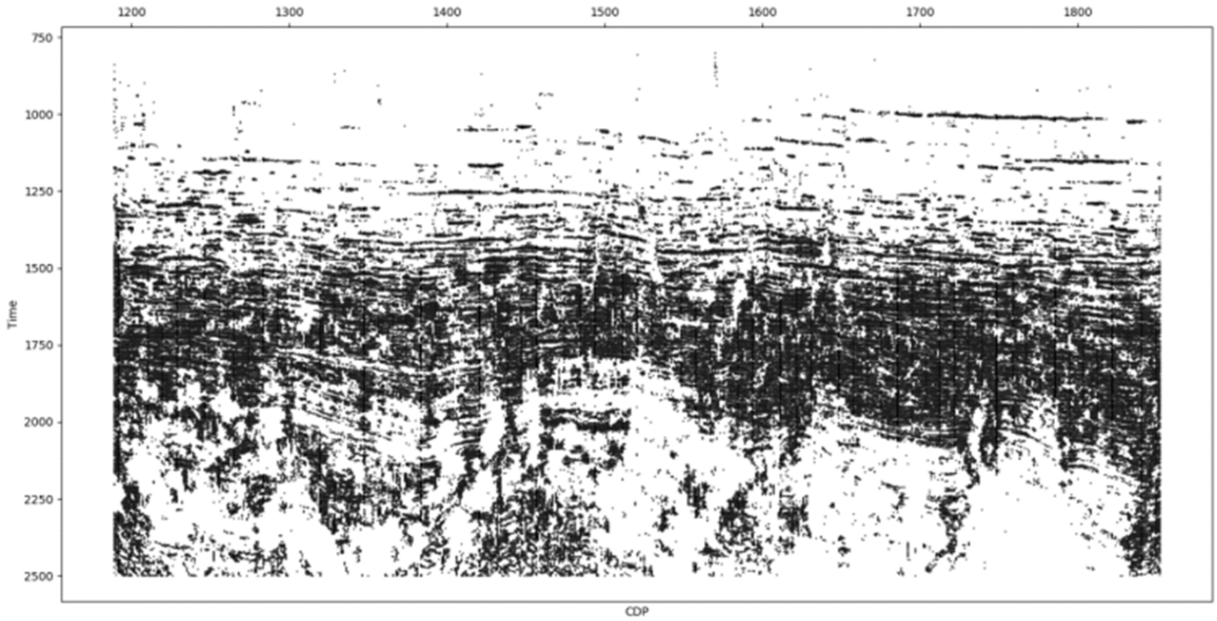

Fig. 12 Prediction result where inline = 1638

V. Conclusion

To improve the accuracy of reservoir lithology prediction, deep learning method is used to build the neural network model. We use the ResNet to add the depth of network, realizing the effective depth of adaptive network. Further SENet is applied after each convolution structure mining the correlation between different channels, in the network training process, to establish the mapping relationship between seismic attributes and lithologic tag. Experimental results in Chengdao area of Shengli oilfield show that compared with conventional reservoir prediction methods and conventional machine learning algorithms, the prediction effect of deep neural network combined with ResNet and SENet is significantly improved, which proves the effectiveness of deep learning and its advanced models in the field of reservoir prediction.

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