Lithology recognition of complex carbonatite by deep learning

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Abstract. The formation of carbonate reservoirs is affected by many factors such as sedimentation, diagenesis, and tectonic evolution. The rock composition and pore structures are complex, which brings challenges to the interpretation of reservoir lithology. Therefore, a novel approach of one-dimensional convolutional neural network architecture (1DCNN) based on the optimization of gradient descent algorithm for lithology identification is proposed. By fully combining logging physical parameters and vertical structure sequence context information, the deeper intrinsic rules between reservoir lithology and wireline logs can be found. With feature extracting of multi-scale deep feature extraction from multivariable wireline logs, the ability of wireline logs to express lithological features is improved, and the accuracy of lithological identification is further improved. In order to illustrate the prediction effect, the carbonate reservoir of the Majiagou Formation in Block 41-33 in Sulige Gas Field is taken as an example. The results reveal that 1DCNN improves the accuracy of carbonate lithology identification by 0.95% to 11.16%, which provides a new idea for the recognition of complex carbonate lithology.

1. Introduction

Lithology identification is the basis of formation evaluation, reservoir description, and reservoir geologic modeling. The fine division is a reliable basis for determining the spatial distribution of stratigraphic lithology[1]. It is the most direct and effective measure to finely characterize the formation lithology by core drilling. The use of coring technology to finely characterize the formation lithology is the most direct and effective method, but the cost is too high to meet the actual production requirements. Geophysical log data is one of the important sources of subsurface rock information. Due to its advantages of high vertical resolution, good continuity and convenient acquisition, the integration of multiple logging parameters can better characterize the lithological distribution of subsurface reservoirs. Therefore, it is the main direction of current lithology identification research to establish a mathematical model to characterize the lithologic characteristics and identify the formation lithology based on log data.

At present, many scholars have carried out related studies on lithology recognition with different methods (e.g., Nearest Neighbor algorithm, Naive Bayesian, Decision tree, Support Vector Machine, Convolutional Neural Network[2-7], etc.). Based on the analysis of diagenetic process and log data of carbonate strata, these methods have some limitations: (i) Most of the traditional methods identify single lithology from the distribution of multi-parameter spatial structure of log data but ignore the correlation of adjacent lithology in vertical space during the diagenetic process; (ii) It is difficult to further
accurately and quantitatively evaluate heterogeneous lithology with complex formation composition by logging interpretation methods suitable for homogeneous lithology.

We explored the characteristic changes of vertical spatial stratum lithology and log data, as well as the relationship between log data multi-dimensional variables and rock complex composition. Then the correlation is analyzed between different lithology logging variable dimensions and vertical spatial dimensions, and we further determined the approximate range of stratigraphic lithology affected by vertical space. On this basis, a one-dimensional convolutional neural network architecture (1DCNN) optimized by gradient descent method is proposed to realize high precision recognition of lithology in complex carbonate log data.

2. Data background and characteristic analysis
The dataset came from block 41-33 in Sudong area of Sulige gas field[8], which belonged to the Lower Paleozoic Ordovician Majiagou Formation and belonged to the North China Sea sediments. The main rock type was carbonate rock. The early diagenetic characteristics of carbonate rocks made most of the formed stratum thicker and mostly block-like structures, which resulted in a complex reservoir lithology[9]. Through the analysis of core samples and wireline logs, six kinds of wireline logs, including AC, GR, PE, DEN, RLLD, CNL, were selected, which were sensitive to the lithologies[10]. And we used the six kinds of wireline logs to perform a comprehensive inversion of the lithology of six carbonate rocks such as limestone (LS), dolomitic limestone (DL), argillaceous limestone (AL), dolomite (DM), calcareous dolomite (CD), argillaceous dolomite (AD).

2.1. Attribute characteristic
Carbonate rocks were well known for complex lithology and pore systems, which made them heterogeneous strongly and difficult to lithology interpretation. Therefore, improving the lithology recognition accuracy of complex carbonate rocks was an important task for reservoir evaluation in the research area.

Based on the crossplots of conventional logging parameters, different lithologies had various distributions in attribute characteristic, as shown in Figure 1. There was an obvious aliasing phenomenon in the values of single logging attributes in different lithology, but some difference in the values of different logging attributes. Moreover, the specific lithologies could be distinguished by a simple distribution of a single parameter.

![Figure 1. Crossplot between attributes with lithologies.](image)

2.2. Sequence characteristic
The lithology of carbonate rock was the product of sediments undergoing a certain diagenesis and evolution stage, and there was a certain correlation between the vertical spatial rock lithology in its
adjacent strata. The characteristics of log data in vertical spatial structure mainly included the lithologic transition characteristics and the correlation and anisotropy of attribute data in the vertical direction. By calculating the autocorrelation coefficient of different strides logging parameters in the vertical space, the similarity and stability of log data could be characterized. Then the internal relation of each logging parameter in the vertical space would be explored. As shown in Figure 2, RLLD showed high similarity under different strides; CNL gradually stabilized with the increase of stride size, which reflected this attribute was more stable in vertical space; GR, PE, AC, and DEN had similar structure distribution in vertical space, and this showed that the correlation between these parameters and their nearest neighbor vertical data was quite high. As the stride increased, the similarity decreased. It could also be concluded that the characteristics of carbonate log data were complex in vertical space and multi-parameter attribute space. The lithologic distribution was variable, and there was a strong correlation between the vertical log data in the neighborhood. Therefore, it’s necessary to consider not only the multi-parameter attribute space but also the vertical space when performing complex carbonate lithology recognition.

3. 1DCNN model
In order to solve the problem that the logging parameters of different lithologies were similar, and the traditional machine learning methods couldn't recognize well. A one-dimensional convolutional neural network architecture (1DCNN) that integrated multi-dimensional logging parameter information and logging vertical spatial information was proposed. The model could fully mine the more abstract and deep features in the original data by processing the log data and realized a high-precision identification of carbonate lithology.

3.1. Basic network architecture
The basic network architecture in deep learning consisted of a convolutional layer, pooling layer, and fully connected layer. In this model, the overall network model was also based on these basic architectures. Firstly, the convolutional layer performed convolution operations on the input vector through a defined set of convolution kernels to obtain the output feature vector, as in equation (1):

\[ F = (f_i, f_2, \ldots, f_k) = g(X \cdot \Sigma) \]  

where \( X \) is the input vector, \( \Sigma \) is the convolution kernel, \( F \) is the output vector, and \( g \) represents the ReLU activation function.
Then, the pooling layer was connected after the convolutional layer, and the multiple feature vectors obtained by the convolution are down-sampled. We used the maximum pooling filter with a length of 2 and a step size of 2 to pool the feature vector, as in equation (2):

$$h'_j = \max\left(f_{2i-1}, f_{2i}\right)$$  \hspace{1cm} (2)

where $h'_j$ is the j-th value in the i-th feature vector of the pooling layer, $i \in [1, d]$, and j is half the length of the feature vector.

Then the full-connection layer could realize the nonlinear optimization combination of high-order features by nonlinear mapping the extracted high-order features into a fixed size one-dimensional vector. The feature vectors were transferred to the Softmax classifier to calculate the prediction probability that the data belonged to each category through the nonlinear mapping of the two full connection layers, and finally would be recognized and classified. The specific formulas were as follows:

$$y_k = f\left(w_k y_{k-1} + b_k\right)$$  \hspace{1cm} (3)

$$p(\hat{y} = j | x) = \frac{\exp\left(w_j^T x + b_j\right)}{\sum_{j=1}^{K} \exp\left(w_j^T x + b_j\right)}$$  \hspace{1cm} (4)

where $w_k$ is the weight coefficient corresponding to the k-th value, $b_k$ is the bias term, $y_{k-1}$ is the output of the previous layer, and $f\left(\cdot\right)$ is the ReLU activation function. $p(\hat{y} = j | X)$ is the probability that data $X$ is predicted as category j, $w_j$ and $b_j$ are the weight and bias parameters of the corresponding j-th category, and $K$ is the total number of attribute categories.

### 3.2. The 1DCNN model

The basic network architecture of the 1DCNN model proposed in this paper was shown in Figure 3, which consisted of one input layer, two convolutional layers with ReLU structure, two maximum pooling layers, and three fully connected layers. The sample-patch consisted of 31 data points from the center point and its 15 adjacent points.

![Figure 3. Schematic diagram of network model architecture.](image)

The size of the 1D convolution kernel in the first convolution layer was $7 \times 1$, and the number of convolution was 64. The size of the 1D convolution kernel in the second convolution layer was $3 \times 1$, and the number of convolution was 256, which could realize the diversified feature capture of multi-dimensional vertical log data from different scales. The pooling layer was the Max pooling layer with a size of $2 \times 2$. Kept the number of feature channels unchanged, and removed redundancy by reducing the sparsity of the feature map, so that important feature information could be emphasized and the amount of calculation of the network model would also be reduced. Through the nonlinear mapping of the three
fully connected layers, one-dimensional vectors from 1024 to 256 sizes were obtained. So that the shallow features were transformed into deep abstracted features, and the effective differentiated information could be extracted. Finally, the feature vector obtained from the fully connected layer was connected to the Softmax classifier to identify the lithology of the log data.

According to the characteristics of the network architecture, we chose the SGD optimizer in the model, and in order to avoid the phenomenon of over-fitting, we also adopted the Dropout mechanism.

4. Experiment
The experiment took the Sudong 41-33 block of the Sulige gas field as an example and obtained the carbonate log data from 88 wells. The true lithology of the sample was determined by the drilling core data, which fully guaranteed the authenticity of the data's reliability. We used the proposed model (1DCNN) for lithology recognition, and chose the machine learning methods: KNN, NB, DT, SVM, BP as the comparison model. Combined with the analysis of actual log data, the effect of various methods on lithology identification of carbonate log data was evaluated.

4.1. Experimental setup
The computer configuration and software environment used in the proposed model is Intel® Core™ i7-7700 CPU @ 3.60GHz. The system is Windows 10 (64-bit), the programming language version is Python 3.8.10, and the deep platform is version 1.9.0 of the PyTorch. The detailed steps of the experiment are as follows:

Step 1. Use standard deviation standardization to normalize the data. Integrate sample data according to wells, then fuse logging vertical sequence information and attribute information to generate a dataset. Set the random seed (Seed) to 32, and divide the data into a train set and test set according to the ratio of 4:1.

Step 2. Build a 1DCNN network architecture. Determine the basic parameters of each layer in the network based on the characteristics of the log data.

Step 3. Initialize model parameters. The network model batch size (Batch Size) is set to 64, the number of iterations (Epoch) is set to 300. Then we select the cross-entropy function as the loss function and test it every 10 times of training. The dropout parameter is set to 50%, and the SGD algorithm is introduced to optimize the model.

Step 4. The train set of log data is used to iteratively train the network, and then the test set is used to obtain the lithology recognition accuracy of the 1DCNN network.

4.2. Results and analysis
Compared the recognition effects of various lithologies on log data by different methods, as shown in Table 1. It can be seen that the recognition accuracy of KNN and NB methods was mostly less than 90%, which indicated that the extracted features were relatively simple, and the aliasing structures that existed in different lithologies in the logging attribute space wouldn't be effectively distinguished. However, using DT, SVM, BP methods would achieve good recognition results on individual lithology. The 1DCNN network architecture proposed in this paper performs well in most lithologies. It had obtained the best recognition accuracy on LS, DL, DM, and CD. Especially in DM, the recognition accuracy rate was the most significant improvement compared with other methods. The highest recognition accuracy rate reached 97.07%, which proved the effectiveness of this method in the recognition of complex carbonate lithology.

Taking the lithology of Well 57-04 in Sudong Block 41-33 in Sulige Gas Field as an example, the comparison diagrams of prediction and interpretation of different methods was drawn, as shown in Figure 4. Through analysis, it can be seen that the recognition effect of 1DCNN network architecture was better than other methods in the continuous and single vertical lithologic distribution. In vertical areas where lithology changed drastically, the recognition results of the 1DCNN network were basically consistent with the original lithology distribution, while the recognition results of other methods showed a larger difference from the original lithology distribution. The 1DCNN network was also more accurate.
in identifying the CD and DM with fewer samples, which reflected the 1DCNN architecture's superiority and high accuracy in the recognition of complex carbonate log data.

### Table 1. Lithology recognition results of different methods.

| Lithology | Methods | KNN | NB  | DT  | SVM | BP  | 1DCNN |
|-----------|---------|-----|-----|-----|-----|-----|-------|
| LS        |         | 60.98 | 43.75 | 77.51 | 62.65 | 95.34 | 96.10 |
| DL        |         | 93.54 | 90.51 | 94.65 | 95.09 | 90.6  | 96.32 |
| AL        |         | 89.47 | 87.11 | 95.78 | **97.93** | 93.03 | 96.90 |
| DM        |         | 31.68 | 42.86 | 72.54 | 81.82 | 95.69 | 96.10 |
| CD        |         | 82.04 | 87.43 | 96.54 | 94.30 | 94.39 | 95.45 |
| AD        |         | 90.12 | 91.24 | 98.25 | 95.51 | 93.91 | 98.34 |
| Overall Accuracy(%) | | 87.32 | 85.92 | 95.68 | 96.12 | 94.51 | **97.07** |

**Figure 4.** Interpretation and comparison of recognition results by different methods for well 57-04.
5. Conclusion
Starting from the intrinsic properties of complex carbonate rocks, this paper proposed a one-dimensional convolutional neural network architecture (1DCNN), which combined the vertical multi-parameter information of log data. Based on the three basic characteristics: multi-dimensional parameter data distribution, autocorrelation, and lithologic transition probability, this paper comprehensively described the overall distribution of carbonate log data, revealed the difference and connection of carbonate lithology in parameter and vertical space, and deduced the lithologic transformation mode of stratigraphic rocks in the process of deposition and diagenesis. While reducing information loss, this architecture used convolutional stacking to achieve the feature diversity, multi-scale and deep-level capture of log data. Compared with traditional lithology recognition methods, 1DCNN model could obtain richer feature information, which effectively solved the problems of traditional methods that wouldn’t consider the vertical spatial characteristics of log data, the extraction features were single, and the classification and recognition effect was not good. The 1DCNN model could satisfy actual production needs and provided a new way for complex carbonate lithology recognition.

In summary, it could be confidently stated that the 1DCNN model provided a more accurate result compared to the traditional lithology recognition methods studied in this paper. Accordingly, it is expected that the model can be used for lithology identification of different types reservoirs in oil and gas fields, and can even be extended to quantitative prediction of reservoir properties.

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