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Recognition of Oil and Gas Reservoir Space Based on Convolutional Neural Network

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Abstract: *The accurate identification of oil and gas reservoir space is paramount in the field of oil and gas exploration, as it directly influences the success and efficiency of drilling operations. In recent years, deep learning technology, particularly convolutional neural networks (CNN), has emerged as the most widely adopted artificial intelligence method for image recognition tasks. By leveraging the powerful feature extraction capabilities of CNN, researchers and industry professionals can now identify the type and content of reservoir spaces with unprecedented objectivity and accuracy. This approach not only minimizes human error and subjective interpretation but also significantly reduces labor costs and enhances overall work efficiency. Notably, the application of CNN in the identification of the reservoir space of the Chang 8 oil-bearing group in the Ordos Basin has yielded impressive results, demonstrating its practical value and promotion significance in the oil and gas industry. This technological advancement holds great promise for improving the exploration and development of oil and gas resources worldwide.*

Keywords: *Recognition of Oil and Gas Reservoir Space, Convolutional Neural Network, Chang 8 Reservoir*

1. Introduction

Oil and gas resources play an important role in the world's energy structure today, and their exploration and development play a decisive role in ensuring national energy security and promoting economic development. In this process, the accurate identification of oil and gas reservoir space is particularly critical, as it directly affects the efficiency and economic benefits of oil and gas resource development. Traditional methods for identifying oil and gas reservoir space, such as geological analysis and seismic exploration, can meet the needs of exploration to a certain extent, but are limited by identification accuracy and processing speed, making it difficult to adapt to the current complex and ever-changing exploration environment and the urgent need for high efficiency and high accuracy[1].

With the continuous progress of science and technology, especially the rapid development of artificial intelligence, deep learning technology provides a new solution for the identification of oil and gas reservoir space with its powerful feature learning ability and efficient expression of data. The convolutional neural networkin deep learning has achieved remarkable results in the field of computer vision. It can automatically learn hierarchical features in images, and then achieve accurate recognition and classification of objects. The introduction of this technology is expected to bring revolutionary breakthroughs in the field of oil and gas exploration, improving the accuracy and efficiency of reservoir space identification [1].

Numerous studies have attempted to apply Convolutional Neural Networks to the field of oil and gas exploration. For instance, researchers have developed reservoir identification models based on CNN, which, through deep learning of seismic data, have achieved precise identification and information extraction of seismic response signals from reservoir pore fluids [1]. Other studies have combined CNN with remote sensing image technology for aircraft target detection, an approach that can also provide insights into the identification of oil and gas reservoir spaces [2]. Furthermore, the application of CNN in fields such as fault diagnosis [3], elastic parameter inversion [4], and image hashing algorithms [5] has demonstrated their wide applicability and powerful potential.

Traditional methods for identifying oil and gas reservoir spaces have been unable to meet the current demands of exploration and development, while the emergence of deep learning technology has brought new development opportunities to this field. The method of identifying oil and gas reservoir spaces based on Convolutional Neural Networks is expected to become an important technical means for future exploration and development, and its research holds significant practical and application value. By deeply mining the reservoir information contained in exploration data such as geological data, and improving data utilization and identification accuracy, it is hoped to provide strong support for the efficient development of oil and gas resources.

2. Oil and Gas Reservoir Space Recognition Technology Based on Convolutional Neural Network

2.1 Advantages of Convolutional Neural Networks in Oil and Gas Reservoir Space Identification

Convolutional Neural Networks demonstrate significant advantages in the field of oil and gas reservoir space identification, primarily in terms of feature extraction, generalization ability, model optimization, and practical application effects.

In terms of feature extraction, CNN, with their unique structures of convolutional layers and pooling layers, can automatically extract hierarchical feature information from raw seismic data. This feature information not only includes low-level details such as edges and textures but also encompasses high-level semantic features, providing a rich informational foundation for the accurate identification of oil and gas reservoir spaces. Compared to traditional methods that rely on manually designed features, CNN offer a more automated and efficient approach to feature extraction, capable of adapting to complex and varied geological environments.

Regarding generalization ability, CNN exhibit excellent adaptability and robustness. Due to the significant variations in geological features of oil and gas reservoir spaces across different regions, identification methods must possess strong generalization capabilities. By training on large-scale datasets, CNN can learn the inherent patterns and distributional characteristics of the data, thereby performing well in reservoir space identification tasks across diverse regions. Furthermore, CNN can effectively resist the influence of noise and interference, maintaining the stability of identification results.

In terms of model optimization, CNN provide flexible training and optimization strategies. By adjusting network structures, optimization algorithms, learning rates, and other parameters, the performance of CNN in oil and gas reservoir space identification can be further enhanced. Additionally, with the continuous development of deep learning technology, increasingly advanced optimization algorithms and techniques are being applied to the training process of CNN, such as batch normalization and residual connections. The application of these techniques makes CNN training more efficient and stable.

In terms of practical application effects, CNN have achieved remarkable results in multiple oil and gas exploration and development projects. Compared to traditional methods, CNN demonstrate clear advantages in terms of identification accuracy, processing speed, and automation level. These practical application cases fully demonstrate the effectiveness and practicality of CNN in oil and gas reservoir space identification.

In summary, CNN possess unique advantages in oil and gas reservoir space identification, including powerful feature extraction capabilities, excellent generalization abilities, flexible model optimization strategies, and significant practical application effects. These advantages make CNN a highly potential identification method in the field of oil and gas exploration and development, promising to bring revolutionary changes to future oil and gas resource exploration and development.

2.2 Oil and Gas Reservoir Space Identification Method Based on Convolutional Neural Networks

2.2.1 Data Preparation and Preprocessing

Data collection is the primary task, involving the acquisition of geological thin section data and the organization of corresponding oil and gas reservoir space labels. Geological thin section data, as an important information source reflecting subsurface structures, directly influences the model's ability to learn effective features based on its quality. Therefore, during the collection process, it is essential to ensure the comprehensiveness, accuracy, and representativeness of the geological thin section data. Simultaneously, to train a model with generalization ability, data diversity cannot be ignored, necessitating the inclusion of oil and gas reservoir space samples from various geological conditions and reservoir types.

2.2.2 Model Construction and Optimization

In terms of model construction, this study designs a deep convolutional neural network model tailored for the specific task of oil and gas reservoir space identification. The model consists of multiple convolutional layers, pooling layers, and fully connected layers to achieve feature extraction and classification of seismic data. In the design of convolutional layers, we employ convolution kernels of different sizes to capture feature information at various scales. Furthermore, by increasing the depth of convolutional layers, the model can learn more abstract and high-level feature representations. Pooling layers are utilized to reduce the dimensionality of feature maps, decrease computational load, and enhance the model's robustness.

Regarding model optimization, we adopt multiple strategies to improve model performance. First, for the choice of optimization algorithms, we compare different methods such as Stochastic Gradient Descent (SGD) and Adam, and select the most suitable optimizer for this task based on experimental results. Second, we finely adjust the learning rate, employing a learning rate decay strategy to ensure stable convergence of the model during training. Additionally, to prevent model overfitting, we use L2 regularization techniques to constrain the model's weights and employ dropout strategies to randomly drop some network connections during training, thereby enhancing the model's generalization ability.

2.2.3 Training and Testing

In the training and testing phase, the convolutional neural network model is first trained using the labeled training set data. During training, the network's output is calculated through forward propagation and compared with the true labels to obtain the error. Subsequently, the backpropagation algorithm is used to adjust the network's weight parameters based on the error, aiming to minimize the loss function on the training set. To avoid overfitting and improve the model's generalization ability, a validation set is introduced for cross-validation during the training process.

The validation set primarily serves to monitor the model's performance during training and guide the adjustment of hyperparameters such as learning rate and batch size. Through iterative training and validation processes, the model's structure and parameter settings can be gradually optimized until satisfactory performance is achieved on the validation set.

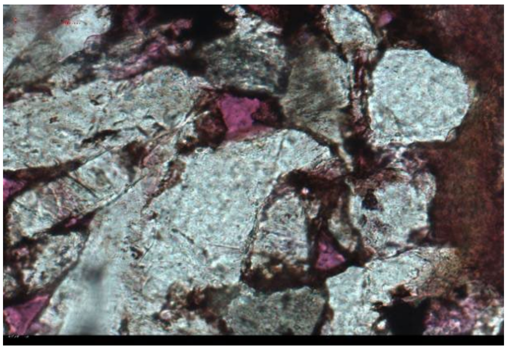
3. Application effect

The Ordos Basin, situated in the central region of the Chinese mainland, covers an area of 250,000 square kilometers, making it the second largest sedimentary basin on land in China. It is abundant in oil, natural gas, and coal resources. Originally part of the North China Plate, the Ordos Basin separated from it after the Indosinian movement and gradually transformed into a large cratonic basin with a rectangular outline [6, 7]. The North China Platform, alternatively referred to as the Sino-Korean quasi-platform by Huang Jiqing, encompasses the entire northern region of China north of the Qinling Mountains, the southern part of northeast China, the Bohai Sea, the North Yellow Sea, and the northern portion of North Korea. It has a generally triangular shape and is delineated from adjacent geological units by deep faults [8-10]. The current structural configuration of the basin is a north-south oriented rectangular basin, characterized by a large asymmetric syncline with a gentle eastern flank and a steep, narrow western flank. The internal structure of the Ordos Basin is relatively simple, with a gentle slope generally less than 1°. The basin has developed a range of low-amplitude nose-like structures due to differential compaction, arranged in an east-west direction, which provide favorable trap conditions for the formation of structural-lithological oil reservoirs. Based on its evolutionary history and current structural morphology, the Ordos Basin is divided into six structural units, including the flexure belt in the west of Shanxi, the Yishan (Northern Shaanxi) slope, the Tianhuan depression, the western margin thrust belt, the Yimeng uplift, and the Weibei uplift.

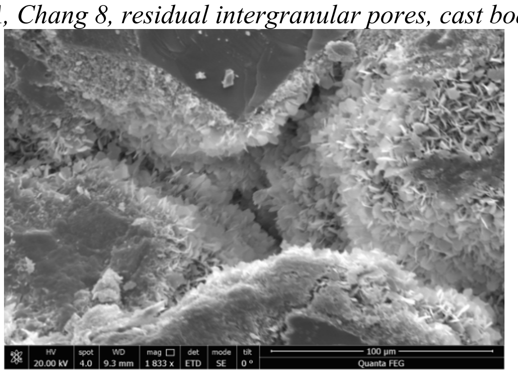
Based on outcrop, drilling, and seismic data, the region has developed extensive Paleozoic and Mesozoic strata, while the Cenozoic strata are relatively thin. Notably, the Silurian, Devonian, Upper Jurassic, Upper Cretaceous, and Lower Tertiary are all absent. The surface is predominantly covered by Quaternary loess. The Mesozoic strata consist of a single river-lacustrine facies coal-bearing sedimentary formation, with the Upper Triassic lacustrine facies deposition being the thickest and most widely distributed, and serving as one of the most significant oil and gas-bearing horizons in the Ordos Basin. The Upper Triassic Yanchang Formation is primarily composed of light gray and brown gray medium- to fine-grained sandstone, dark gray siltstone, gray-black mudstone with black carbonaceous mudstone, shale, and oil shale, occasionally interspersed with thin tuffaceous mudstone, coal seams, or thin coal layers. It is in parallel unconformity with the underlying Middle Triassic Zhifang Formation and the overlying Lower Jurassic Fuxian Formation. Generally, the Yanchang Formation is divided into five lithological assemblages. For the purposes of oil field production and research, the Yanchang Formation is further subdivided into 10 lithological sections, with the Chang 8 section being the focus of this study.

Reconstructed by sedimentation, diagenesis, etc., the reservoir of the Chang 8 member in the study area is tight and its physical properties are poor. The porosity is usually5%~13%, and the air permeability is usually$2\sim18\times10^{-3}\mu m^2$. The lithology is mainly fine sandstone and siltstone. The rock types are mainly lithic feldspar sandstone and feldspar lithic sandstone, followed by lithic sandstone and feldspar sandstone. The pore types are mainly dissolved pores or intergranular pores-dissolved pores. The throat is small, the average median radius is only 0.14μm, and the average displacement pressure is 2.08MPa. The composition and content of clay minerals and other cements also vary greatly, resulting in significant differences in pore structure characteristics and reservoir physical properties in different zones, with strong heterogeneity.

Taking the Chang 8 oil layer group in a block of the Ordos Basin as an example, according to the petrological characteristics of the reservoir, through the analysis and statistics of 100 rock thin slices and 35 scanning electron microscope samples, the reservoir space of the Chang 8 oil layer group in the study area is identified manually. Residual intergranular pores and residual intergranular pores are dominant(see figure 1). Intergranular pores. When particles accumulate, the pore space formed by the particles supporting each other. The degree of development of intergranular pores is closely related to factors such as particle content, size, sortability, arrangement and filling content. The retention of residual primary intergranular pores in the reservoir is a key factor in determining the quality of the reservoir. Intragranular dissolution pores refer to the pores formed by partial dissolution of various carbonate particles due to selective dissolution. When the dissolution spreads to the entire particle to form pores with the same shape and size as the original particle, it can be called mold porosity.



a. Well A, Chang 8, residual intergranular pores, cast body piece



b. Well B, Chang 8, residual intergranular pores, SEM

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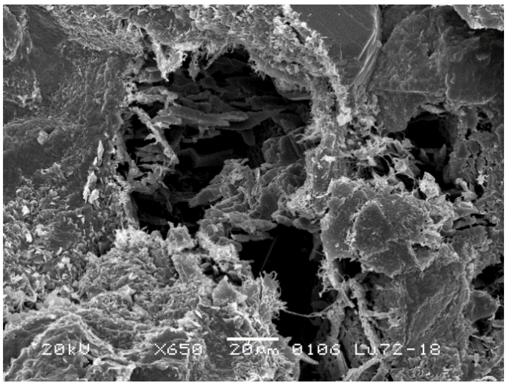
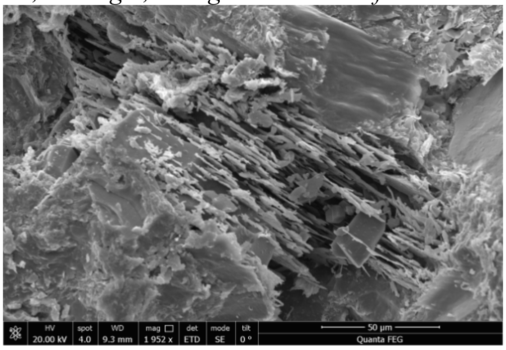


c. Well C, Chang 8, Intergranular hole of dissolution, SEM



d. Well D, Chang 8, soluble hole of feldspar, SEM

Figure 1: Microphotograph of the reservoir space in the study area

The absolute contents of intergranular pores and intragranular dissolved pores were 0.651% and 0.822%, respectively. When employing convolutional neural network-based technology for the identification of oil and gas reservoir spaces, the average error for both types of pores was less than 15%. This level of accuracy meets the required standards (see Table 1).

Table 1: Absolute content statistics of main reservoir space types in the study area

Manual recognition results		Convolutional neural network recognition results		Average error of two pores
Intergranular pores(%)	Intragranular Dissolved pores(%)	Intergranul ar pores(%)	Intragranular Dissolved pores(%)	
0.651	0.822	0.725	0.936	<15%

4. Conclusion

This study delves into the issue of oil and gas reservoir space identification by introducing convolutional neural networks (CNN). After a detailed analysis of the origin, development, structure, and characteristics of CNN, we constructed a specialized CNN model tailored for oil and gas reservoir space identification. Through extensive experimental validation, this model has demonstrated excellent performance on actual geological data.

In terms of feature extraction, CNN, with their powerful feature learning capabilities, can distill features closely related to oil and gas reservoir spaces from complex geological thin section images. This is fully reflected in the experimental results, where the model accurately captures the characteristics of oil and gas reservoir spaces, providing a solid foundation for subsequent classification and identification.

Regarding classification and identification, the proposed CNN model also performs exceptionally well. Through meticulously designed network architecture and optimized training strategies, the model achieves high accuracy in identifying oil and gas reservoir spaces on the test set. This not only proves the vast potential of CNN in the field of oil and gas exploration but also provides powerful technical support for future oil and gas resource development.

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This study also emphasizes the model's generalization ability and adaptability. Experimental validation demonstrates that the model can flexibly handle oil and gas reservoir space identification tasks across different regions, showcasing promising application prospects. This achievement holds significant importance for driving innovation and development in oil and gas exploration technologies.

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