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Application of Neural Networks in Reservoir Classification of the Luliang Oil Field

Zhuo Feng, Yupeng Zhuang, Zhifa Kang and Te Yan

School of Petroleum Engineering, XI'AN SHIYOU University, Shanxi 710065, China

ABSTRACT

To address the reservoir classification requirements of the Hutubihe Formation in Luliang Oilfield, this paper constructs an intelligent classification model based on deep neural networks. By automatically learning the complex nonlinear relationships among seven parameters—porosity, permeability, gamma ray, resistivity, oil saturation, density, and thickness—the deep neural network replaces traditional manual weight assignment methods and achieves multi-parameter collaborative characterization of reservoir properties. Based on the data-driven concept, an adaptive deep neural network architecture is adopted to realize intelligent reservoir classification. The accuracy of this method is verified through core analysis and neural network methods. Finally, the classification results are presented in radar charts, significantly improving the objectivity and accuracy of reservoir classification. Research shows that the deep learning model can automatically extract deep features from reservoir parameters. Core experiments indicate that the matching degree between reservoir categories and pore structure and flow capacity exceeds 90%, while the classification error of key parameters (porosity and permeability) is less than 5%. This method breaks through the limitations of traditional classification methods, achieves intelligent and precise classification of multi-layer reservoirs in Luliang Oilfield, and provides a more reliable decision-making basis for optimizing development adjustment plans. It verifies the superior performance of deep learning algorithms in complex heterogeneous reservoir classification and demonstrates significant practical value for refined residual oil potential tapping and intelligent development decision-making in mature oilfields.

KEYWORDS

Reservoir Classification; Neural Network Model; Multi-Parameter Synergy.

1. INTRODUCTION

The Luxi area, located in the central part of the Junggar Basin, represents a typical water-flooded sandstone reservoir in the Xinjiang Oilfield and possesses significant hydrocarbon exploration and development potential [1]. This region features the development of a highly productive reservoir belt in the middle-shallow layers, encompassing the Luliang-Shinan-Xiayan reservoirs, with up to 42 oil-bearing layers, among which the main layers account for 15%. To date, the cumulative oil production has exceeded 17 million tons, with a recovery factor of 26.4%, and the remaining recoverable reserves amount to 50 million tons, demonstrating substantial development potential. However, the current reservoir classification criteria—based on medium-high permeability, main/non-main reservoirs, homogeneity, and well pattern arrangement—fail to achieve precise classification for oil layers with significant variations in porosity (8-25%) and permeability (10-2000 mD), such as J2x4 and K1h27-4. This leads to inadequate adaptability in well pattern infilling plans. Therefore, there is an urgent need to develop a novel multi-factor reservoir classification method based on flow capacity differences to address the challenges of evaluating heterogeneous reservoirs.

Research on reservoir classification has evolved through three stages: early lithology-based methods (e.g., sandstone/carbonate rock) suffered from low engineering applicability due to interference from depositional-diagenetic processes [2]; subsequent petrophysical parameter classification systems (porosity, permeability, saturation) improved scientific rigor but relied on manual core analysis, exhibiting strong subjectivity and low efficiency [3]. Currently, machine learning techniques can achieve intelligent reservoir classification by Dig non-linear relationships among well logging, petrophysical, and dynamic data, providing new methods and insights for complex reservoir classification [4]. Particularly in multi-layered, highly heterogeneous reservoirs like the Luxi area, constructing a data-driven flow unit classification model can not only accurately identify preferential flow pathways but also optimize injection-production structures, thereby playing a crucial role in enhancing oil recovery and tapping into remaining oil potential.

This study addresses the characteristics of reservoirs in the Luxi area by innovatively integrating flow unit theory and machine learning algorithms, aiming to establish a multi-dimensional classification standard based on seepage capacity differences. This will provide theoretical support and technical pathways for the secondary development of mature oilfields. The research findings will promote the transition of reservoir classification from "empirical thresholds" to "intelligent decision-making," offering technical support for cost reduction, efficiency improvement, and sustainable development in oilfield operations.

2. SELECTION OF RESERVOIR CLASSIFICATION METHODS

Common reservoir classification methods primarily include five categories: geological empirical methods, mathematical clustering methods, "facies-controlled" classification methods, flow capacity classification methods, and machine learning/deep learning methods.

The geological empirical method, also known as core analysis, is the most fundamental and traditional means of reservoir evaluation [5]. This method relies on the long-term accumulated practical experience and geological theories of researchers. Key petrophysical parameters such as porosity, permeability, and oil saturation obtained through core analysis are selected, and classification thresholds are manually set (e.g., classifying reservoirs with porosity greater than 15% as Class I) to identify and classify reservoir "sweet spots." The advantages of this method lie in its simple principles, clear geological significance, and close integration with actual exploration and development practices. However, its drawbacks include significant influence from subjective factors, relatively fixed classification boundaries, and difficulty in accurately capturing complex nonlinear relationships between parameters. As a result, its classification effectiveness is often inadequate in highly heterogeneous reservoirs.

Neural network methods employ unsupervised learning strategies to identify potential grouping structures within data [6]. Hierarchical clustering (HC) recursively constructs dendrograms by calculating sample distances, offering an intuitive process but suffering from low computational efficiency and susceptibility to noise interference. DBSCAN identifies clusters of varying shapes and filters out noise points based on sample density distribution, without requiring pre-specification of the number of categories. However, its classification performance is easily affected by the setting of the neighborhood radius ε and the minimum number of samples, and it performs poorly with high-dimensional data [7]. Spectral clustering (SC) relies on the eigenvalue decomposition of the graph Laplacian matrix to achieve data dimensionality reduction and partitioning, making it suitable for non-convex distributed datasets. Nevertheless, it incurs high computational costs, and the kernel function parameters significantly influence the classification results [8]. As a classic partitioning clustering method, K-means offers high execution efficiency but requires pre-determination of the number of clusters, is sensitive to the selection of initial center points, and adapts poorly to non-spherical clusters and outliers [9].

The "facies-controlled" classification method is based on geological genetic analysis. This approach uses geological facies types, such as sedimentary facies, diagenetic facies, or lithofacies, as classification units and further subdivides reservoirs within each facies zone based on petrophysical parameters [10]. The guiding principle of this method is that "facies" control reservoir characteristics, and reservoirs within the same facies zone share similar geological attributes and distribution patterns. Its advantage lies in the fact that the classification results align with geological laws, effectively reflecting the formation mechanisms and spatial distribution characteristics of reservoirs, and maintaining high consistency with geological understanding. However, the accuracy of the classification largely depends on the precise determination of sedimentary or diagenetic facies boundaries, which often involves multiple interpretations and uncertainties. In areas with low facies interpretation accuracy, the reliability of the classification results significantly decreases.

The flow capacity classification method primarily relies on the seepage characteristics of reservoir fluids as the basis for classification. It is a functional classification approach from the perspectives of reservoir engineering and fluid dynamics [11, 12]. This method uses indicators such as the Flow Zone Index (FZI), Rock Physics Index (RPI), or pore structure parameters to quantitatively evaluate the seepage capacity and storage performance of reservoirs, thereby achieving dynamic classification. Its advantage lies in the close correlation between classification indicators and reservoir productivity and development dynamic responses, making it particularly suitable for production practices such as water-flooding development, productivity evaluation, and numerical simulation. However, this method requires high-quality and complete core and well logging data, involves relatively cumbersome calculation processes, and necessitates the integration of multi-scale geological parameters. Its applicability is limited in areas with poor data foundations or extremely strong reservoir heterogeneity.

Machine learning and deep learning methods provide a new data-driven approach to reservoir classification [13]. These methods use algorithms to automatically learn the complex relationships between high-dimensional features extracted from well logging, seismic, and core data and reservoir types. Traditional machine learning methods (e.g., random forest, support vector machine) still rely on manual feature construction and selection, while deep learning methods (e.g., convolutional neural networks, long short-term memory networks) can adaptively extract high-level features in an end-to-end manner, thereby improving classification accuracy for complex heterogeneous reservoirs [14]. Their advantages include strong capability in handling high-dimensional and nonlinear data, high classification accuracy, and the ability to integrate multi-source heterogeneous data, reducing reliance on human experience.

This study involves a large amount of reservoir data that has been systematically preprocessed. To improve data processing efficiency and classification accuracy, this paper employs neural network algorithms to achieve reservoir classification.

3. STEPS FOR RESERVOIR CLASSIFICATION

3.1. Data Preprocessing

Data standardization is a commonly used technique in machine learning and data preprocessing [16]. Its purpose is to adjust the scale or distribution of data to make it more suitable for model training requirements. Common standardization methods include: Z-score standardization, which transforms data into a distribution with a mean of 0 and a standard deviation of 1 by subtracting the mean and dividing by the standard deviation; Min-Max standardization, which linearly maps data to a specific range (e.g., [0, 1]);Max-Abs standardization, which scales data to the range [-1, 1] by dividing by the maximum absolute value;Log transformation, which improves skewed distributions through logarithmic operations to make them closer to a normal distribution; Robust standardization, which uses the median and interquartile range (IQR) for scaling and is suitable for datasets containing outliers. Selecting an appropriate standardization method based on the characteristics of the data distribution and practical requirements helps improve model training efficiency and final performance.

To eliminate dimensional differences among multi-source reservoir parameters (e.g., porosity, permeability) and preserve data integrity to the greatest extent, this study adopts Z-score standardization. The standardization formula is as follows:

$$X_{scaled} = \frac{X-\mu}{\sigma} \quad (1)$$

where μ is the mean value of the feature and σ is the standard deviation of the feature. After standardization, each feature parameter is transformed into a distribution with a mean of 0 and a standard deviation of 1. By processing variables such as porosity, permeability, gamma value, resistivity, oil saturation, density, and thickness, the comparability among these variables is ensured, thereby providing a more reliable data foundation for subsequent analysis.

3.2. Neural Network Model Construction

To account for the characteristics of datasets of different sizes, this study designed an adaptive-depth neural network architecture to optimize model performance and enhance its generalization capability. The model structure is dynamically adjusted based on the number of training samples (Table 1), ensuring that the network complexity matches the data scale.

Table 1 Adaptive Neural Network Structure Configuration

Data Size	Network Structure	Dropout Rate	Learning Rate	Batch size
<500 samples	32-16 neurons	0.4-0.3	0.0005	8
500-1500 samples	64-32 neurons	0.3	0.001	16
>1500 samples	128-64-32 neurons	0.2	0.001	32

3.3. Neural Network Model Training and Optimization

To prevent model overfitting, an early stopping mechanism was introduced. This mechanism continuously monitors the change in validation set loss. If the loss does not decrease for 20 consecutive iterations, the training is automatically terminated. During training, the changes in loss function and accuracy with respect to epochs were fully recorded (as shown in Figure 2). The training curves were used to evaluate the model's convergence status and generalization ability. After training, the model performance was systematically evaluated using the validation set. A classification report including metrics such as precision, recall, and F1-score was generated. Additionally, a confusion matrix was plotted (as shown in Figure 1) to comprehensively analyze the model's classification effectiveness across different reservoir categories.

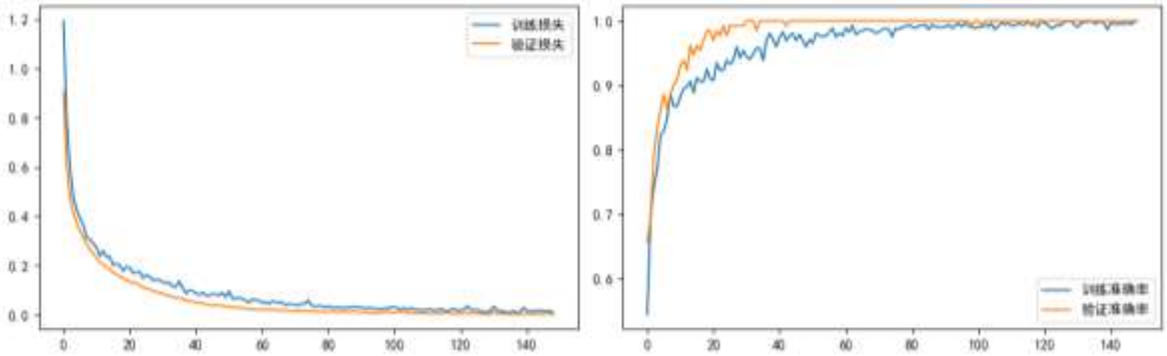


Figure 1 Variation of Loss Function and Accuracy with Epoch

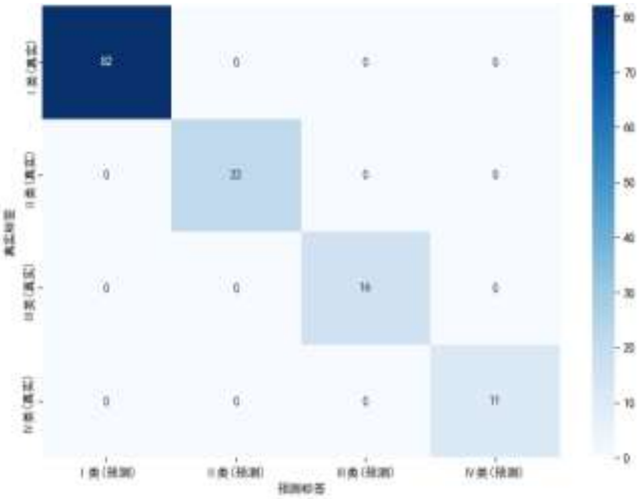


Figure 2 Confusion Matrix

3.4. Prediction and Application of Neural Network Model

The trained model was used to predict reservoir types for all well section data. Based on the prediction results, quantitative statistics and visual analysis of reservoir category distribution were further conducted (as shown in Figure 3), clarifying the spatial distribution patterns of various reservoir types. This provides direct data support for development well pattern deployment and optimization of treatment measures in the target formation of the study area. This method significantly reduces human subjectivity in the classification process and enhances the efficiency and objectivity of reservoir evaluation workflows.

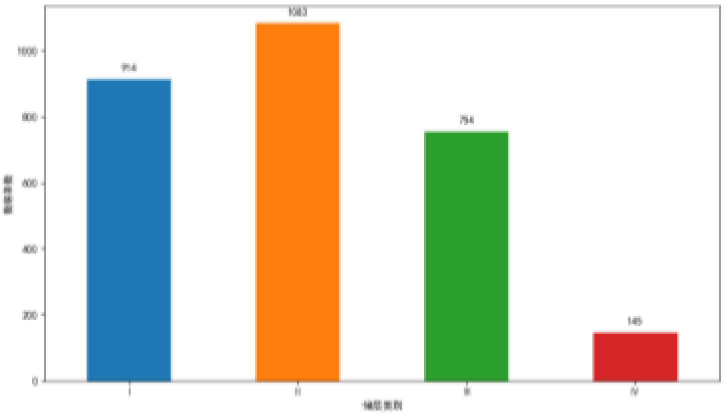


Figure 3 Analysis of Prediction Results

4. RESERVOIR CLASSIFICATION RESULTS AND ANALYSIS

4.1. Application of Reservoir Classification

The model predicted a total of 2,896 data points, with Class I reservoirs accounting for 31.6%, Class II for 37.4%, Class III for 26.0%, and Class IV for 5.0%. The reservoir types represented by wells in the same well section were plotted on the well location map of the LU9 block, revealing reservoir heterogeneity and spatial distribution patterns. By quantitatively characterizing key physical parameters such as porosity and permeability, the complex reservoir was divided into several units with relatively uniform internal structures, laying the foundation for building a high-precision 3D geological model. Based on these results, the classification directly guides development and production practices: on one hand, it provides a scientific basis for optimizing development well pattern placement, ensuring that high-efficiency wells are located in areas with superior Class I and

II reservoirs; on the other hand, it supports the formulation of differentiated development strategies and stimulation measures. For example, efficient extraction is implemented for high-quality reservoirs, while economically targeted potential tapping technologies are adopted for Class III and IV reservoirs, thereby maximizing reservoir potential and optimizing development benefits.

In the LU 9 Well Block of the Luliang Oilfield, high-quality reservoirs such as Class I and II in the K1h23-4 layer are primarily concentrated in the central and western parts of the study area, exhibiting a ring-shaped distribution pattern characterized by "thicker central zones and thinner edge zones." To further elucidate the main controlling factors of high-quality reservoir distribution, it is necessary to integrate the reservoir classification map with basic geological maps such as sedimentary facies distribution, structural morphology, and fracture prediction within the study area. This comprehensive overlay analysis will clarify the control mechanisms of sedimentary environment, diagenesis, or structural fractures on the development of high-porosity and high-permeability reservoirs. Based on this analysis, the effectiveness and rationality of the existing development well pattern in controlling high-quality reservoir areas can be systematically evaluated. This will identify underutilized potential zones and areas with well pattern deficiencies, thereby providing a reliable geological basis for optimizing infill well placement, adjusting injection-production structures, and formulating differentiated development strategies.

4.2. Validation of Classification Results by Core Analysis

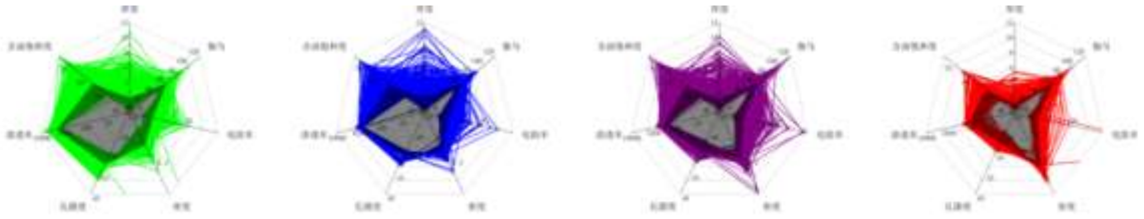
Core analysis validation demonstrates that neural networks achieve high accuracy in classifying key parameters such as porosity and permeability, exhibiting significant advantages in handling complex heterogeneous reservoirs. The neural network precisely matches reservoir categories with pore structure and flow capacity characteristics, successfully identifying the flow properties of different reservoir intervals. In most cases, the consistency between reservoir categories and physical parameters exceeds 85%. These results verify the feasibility and application value of machine learning classification methods in oilfield development [17].

Taking the porosity and permeability of the Hutubihe Formation as an example, the parameter ranges determined by core analysis and neural network methods show minimal differences. However, the neural network method provides more precise parameter ranges with higher decimal precision, typically maintaining errors within 5%, demonstrating significant scientific advantages. Traditional methods are susceptible to human factors and struggle to adapt to complex reservoir variations, while the neural network method employs data-driven classification criteria to automatically identify reservoir characteristics. This approach reduces manual intervention, improves classification efficiency and accuracy, aligns better with mathematical logic, avoids errors from subjective weighting, and more effectively meets practical development needs.

Table 2 Comparison between Core Analysis Method and Neural Network Method Results

Reservoir Classification	Cumulative Percentage	Porosity (%)	Permeability (mD)	Saturation (%)
Class I Reservoir	＜30%	>32	>1000	>55
Neural Network		>32.1	>1000	＞59
Class II Reservoir	30%~60%	30-32	500-1000	51-55
Neural Network		30.2-32.1	600-100	56-59
Class III Reservoir	60%~90%	28-30	200-500	49-51
Neural Network		28.4-30.2	200-600	54-56
Class IV Reservoir	＞90%	24.6-28	11.1-200	37.5-49
Neural Network		<28.4	<200	＜56
Class V Reservoir		<24.6	<11.1/0	<37.5

As shown in Figure 4, the radar chart of reservoir parameters clearly reveals the differences in physical and electrical properties of different reservoir categories. The chart shows that high-quality reservoirs (e.g., Class I and II) exhibit higher porosity, permeability, and oil saturation, indicating excellent storage and flow capacity. In contrast, lower-quality reservoirs (e.g., Class III and IV) generally display lower density and resistivity values, reflecting their poorer lithology and physical properties. This distribution pattern not only confirms the typical physical property combination of "high porosity, high permeability, and high oil saturation" in high-quality reservoirs but also reveals the correlation between low resistivity, low density, and declining reservoir quality from the perspective of electrical responses. This regularity provides an important basis for rapid reservoir evaluation and classification using well logging data, further clarifying the geophysical identification markers for different grades of reservoirs.



Ⅰ类储层 Ⅱ类储层 Ⅲ类储层 Ⅳ类储层

Figure 4 Radar Chart of Various Reservoir Categories

5. SUMMARY

This study constructs an intelligent classification model based on a deep learning neural network. The deep neural network automatically learns the complex nonlinear relationships among seven parameters—porosity, permeability, gamma ray, resistivity, oil saturation, density, and thickness—replacing traditional manual weight assignment methods and achieving multi-parameter collaborative characterization of reservoir properties.

Experimental results show that after reservoir classification using the intelligent deep learning neural network model, Class I reservoirs account for 31.6%, Class II for 37.4%, Class III for 26.0%, and Class IV for 5.0%. Compared with the core analysis method, the neural network method demonstrates higher accuracy, significantly enhancing the geological rationality of the classification results. It avoids the impact of similarly characterized parameters on the classification outcome and breaks through the limitations of traditional single-parameter thresholds. For the first time, the neural network method achieves dynamic weight-based grading of multi-layer reservoirs in the Luliang Oilfield, providing a data-driven decision-making basis for well pattern optimization.

The research results validate the applicability of machine learning algorithms in classifying complex homogeneous reservoirs and provide important practical value for residual oil potential tapping and development plan adjustments in mature oilfields. This method not only improves the efficiency of reservoir classification but also offers robust technical support for decision-making optimization in oilfield development, demonstrating significant theoretical importance and practical application prospects.

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