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# Seismic Facies Recognition of Ultra-Deep Carbonate Rocks Based on Convolutional Neural Network

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**Abstract:** Seismic facies is a seismic reflection unit defined by specific seismic reflection characteristics, that is, the seismic responses of sedimentary facies or geological bodies, whose accuracy will directly affect the reliability of oil and gas exploration results. Currently, seismic facies is generally recognized depending upon the differences between certain single trace seismic attributes (waveform, frequency spectrum, and amplitude, etc.) and adjacent units to conduct cluster analysis. Such methods, however, have ambiguity in identifying special reflective structures with continuous waveforms (e.g. massive carbonate deposits). In order to solve this problem, this paper incorporates artificial intelligence (AI) technology into automatic recognition of seismic facies with special reflection structures. Firstly, a 2D seismic facies classification sample label set is designed and formed. Then, a seismic facies prediction model is designed and constructed using a multi-layer convolutional neural network (CNN). Finally, the trained model is used to automatically track the seismic facies in the study area. This method was applied to seismic facies recognition for the Sinian Dengying Formation in an area of the Sichuan Basin, and the seismic facies recognized were compared with artificially interpreted ones. It is confirmed that the proposed method provides a better effect than artificial interpretation, with greatly improved accuracy and efficiency.

**Keywords:** Artificial Intelligence, Convolutional Layer, Seismic Facies, Label, Model

## 1. Introduction

The term "seismic facies" is derived from sedimentary facies and can be understood as the sum of the manifestations of sedimentary facies in a seismic data volume. It is a comprehensive reflection of sedimentary body shape, lithology difference, and stacking style of stratigraphic assemblage in space. Accurate recognition of seismic facies is of great significance for sedimentary facies research and hydrocarbon resource exploration and development [1-3]. Based on the recognition and division of sequence boundaries from regional seismic data, seismic facies types are identified according to the internal structure and external morphology of seismic reflections, and then the seismic facies are mapped [2]. In previous studies, if it is possible to establish corresponding relations between different types of seismic facies and simple seismic attributes (e.g. seismic waveform, amplitude, and frequency), then seismic facies can be recognized through clustering methods. However, for seismic facies types that must be distinguished through global spatial distribution information such as special reflection structures and waveform continuity, the application of conventional clustering methods generally cannot achieve good results [3]. Currently, geologists still rely on their personal experience to identify seismic facies by physiognomy method through many seismic sections one by one, which has worse repeatability and lower efficiency, making it difficult to objectively depict seismic facies [4].

Artificial intelligence (AI) technologies are widely used in various industries [5-8], and they are especially advantageous in image feature recognition. If AI technologies can be used instead of manual labor to achieve automatic recognition of seismic facies with special reflection structures, they will greatly improve the efficiency and accuracy of interpretation. Currently, there are two major types of methods for seismic facies recognition: one is the patch-based model, and the other is the encoder-decoder model [5-6]. The former is to input a seismic image patch (for example, in size of 64×64×3), and output the classification of the entire image after processing (with only one value, such as whether it is a salt dome or a river channel, marked at the center of the image). The latter inputs the entire seismic section and outputs the classification on each sample point (pixel point) on the entire image after processing. Considering the application limitations, the first method is considered to be more practical. Therefore, this paper adopts the first method for subsequent research.

The application bottlenecks of these methods are mainly found in two aspects. One is the training of universal model, because the types of seismic facies that are concerned in different regions vary greatly, and trained models are often only sensitive to specific reflection features. The other is the quick creation of a sample set for model training. This paper proposes the targeted training of AI model for some blocks in the study area and then promotes it in the same study area or adjacent areas (the same subfacies zone), which avoids the problem of model generalization, and directly creates sample labels using existing interpretation results.

## 2. Methodology

### 2.1. Design and Making of Sample Set and Labels

Machine learning technologies can be classified to three categories according to label types [1], namely, clustering methods that do not require sample labels, classification methods that require labels, and reinforcement learning methods with delayed label types. In AI model training, mainstream technologies still need a large number of data labels. The sample set is used for the input of the AI model, and the label is the expected output of the model. As shown in Figure 1, depending upon the actual data characteristics of the study area, the sample set is made using multi-trace data from the inlines and crosslines of the sample point locations of the target layer, and the artificially interpreted seismic facies type of the sample point location is used as the sample label. As shown in Figure 5, the overall data (3200 $km^2$) is divided into a training set, a validation set, and an application set. The training set is located in the red box for model training; the validation set is located in the black box to verify the accuracy of the trained model in this area; and the application set is located in a colorless area (no label) and is the data for promoting application in this area.

### 2.2. Design and Training of AI Model

In this study, a combination of 5-layer CNN (convolutional layer) and 2-layer FCN (fully-connected layer) is adopted (Figure 2).

Input layer: It is used to receive model input data. The CNN+FCN model is adopted here, so the model input is required to be seismic data with fixed size. Moreover, in order to improve the adaptability of the model to different data, the input samples are normalized.

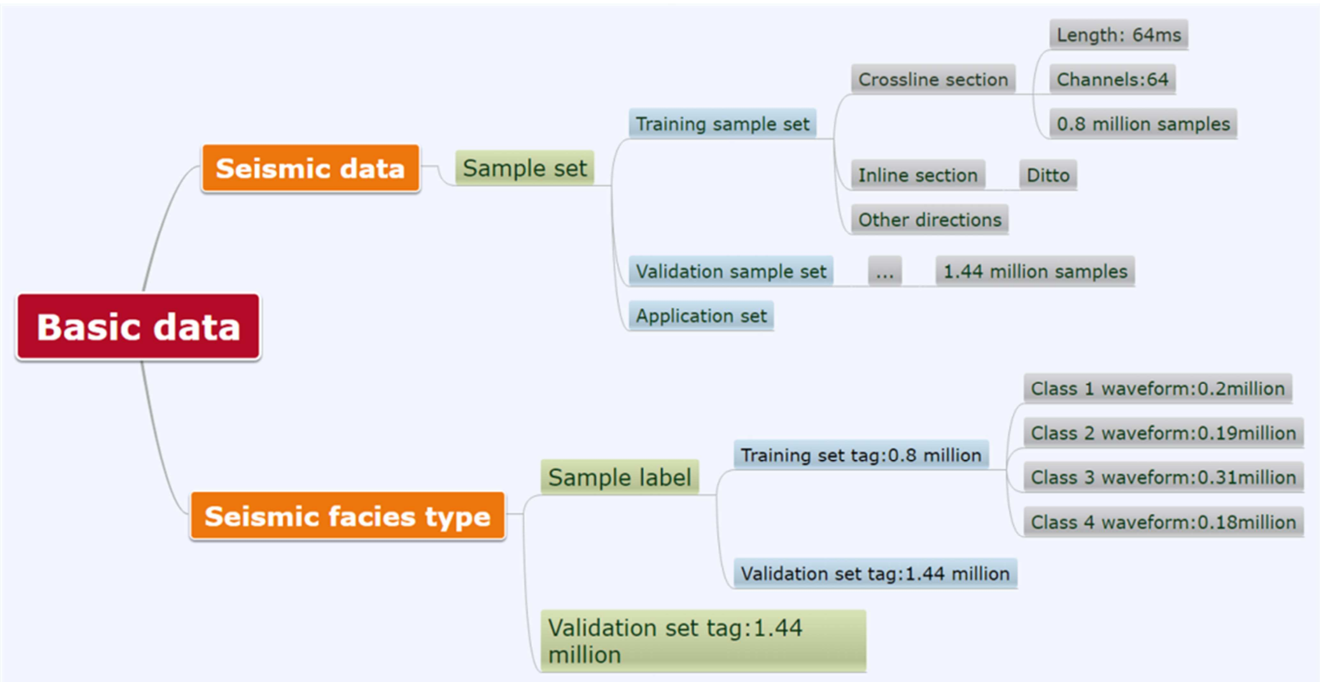



***Figure 1.*** *Process of making sample sets and labels.*

Convolutional layer: The convolutional kernel is used for feature mapping and feature extraction. The shared weight feature greatly reduces the number of model parameters, and improves the trainability and the demand for sample size. The activation function RELU layer is used to map the output of the convolutional layer nonlinearly to improve the recognition ability of nonlinear features. The pooling layer (MAXPOOL) is applied to perform dimensionality reduction on input samples and improve the view of the convolutional kernel layer by layer, making it capable of extracting global features.

Fully-connected layer: It is mainly used to re-fit and comprehensively analyze the features extracted from the convolutional layer. The normalized layer is used for preprocessing in the middle of the neural network layer, that is, the input from a layer is normalized before entering the next layer, which can effectively prevent "gradient dispersion" and accelerate network training. DROPOUT is used to improve the generalization ability of a model. DROPOUT refers to temporarily discarding a portion of neural network elements from the network according to a certain probability during the training process of a deep learning network. This is equivalent to transforming a large neural network into a combination of multiple small networks, which can significantly improve the generalization ability of the model.

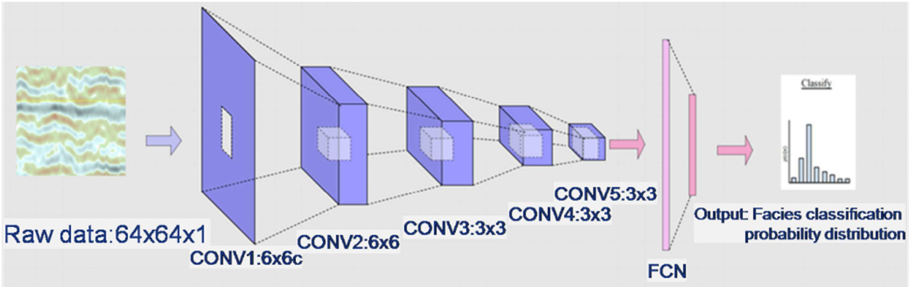



***Figure 2.*** *Structure of the proposed AI model.*

Output layer: It is used to output the facies type judgment results of input samples, which can be facies classification or probability distribution.

Two aspects are mainly considered in the model training process. One is random breaking up of sample data. The large amount of data in the sample set can only be loaded in the model in batches for training in turn. If the original sample set is not randomly broken up, the same batch of data may derive similar characteristics, which will lead to fluctuations in the prediction accuracy of the model. The other is facies type weighting coefficient. Innovatively, different weighting coefficients are set for different facies types in the model training process to balance the difference in the number of samples of different facies types in the sample set.

## 3. Application

The Sichuan Basin is a large superimposed basin developed on the basis of the Upper Yangtze craton [9-12]. It has experienced the evolution of marine basin in the Late Proterozoic–Middle Triassic period and continental basin in the Late Triassic–Cenozoic period. The Dengying Formation is the first set of basin-wide marine sedimentary strata after the deposition of the Doushantuo Formation in the basin. It is lithologically composed of algal limestone and dolomite, with quartz sandstone and mudstone locally. The study area is located in central Sichuan Basin. From the perspective of sedimentary paleogeography, the Dengying Formation is discovered in the east platform of the platform margin facies belt in the Deyang-Anyue rift trough [13-16]. It is a set of carbonate platform sedimentary system, belonging to the facies belt with relatively calm water body within the platform. Sedimentary facies belts such as grain shoal, algal mound, intershoal sea and lagoon are developed, and grain shoal and algal mound microfacies are relatively developed, with platform margin and open platform sediments in dominance.

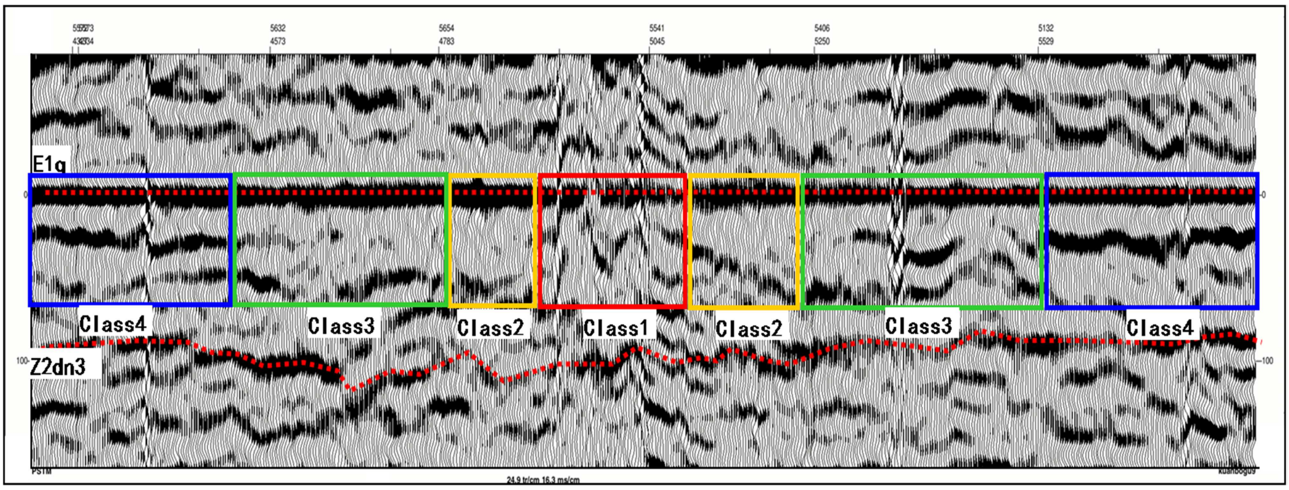



***Figure 3.*** *Classification and interpretation section of four seismic facies models in Deng 4 Member inside platform in central Sichuan Basin.*

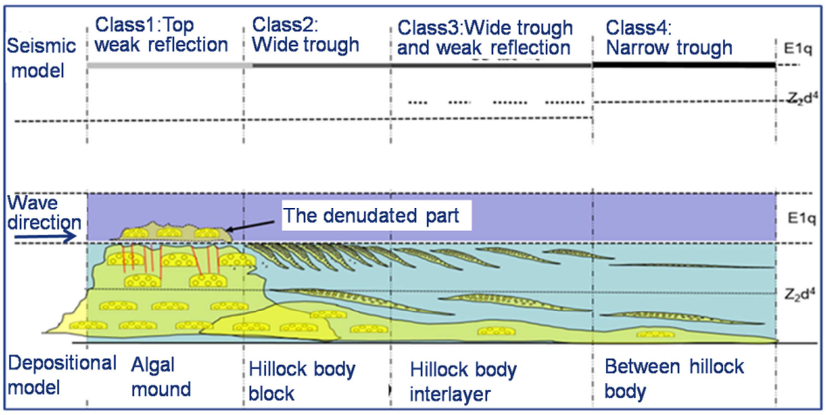



***Figure 4.*** *Four seismic facies models and their corresponding relations with sedimentary facies in Deng 4 Member.*

According to the known drilling and seismic reflection characteristics (Figure 3), and considering that the seismic reflection parameters in the facies change zone are different from those in adjacent units [7], the corresponding relations between four seismic facies models and sedimentary microfacies in the upper part of the fourth member of Dengying Formation (Deng 4 Member) of Sinian are preliminarily established (Figure 4). It is indicated that the weak top reflection structure in Model I represents the deposit of algal mound, the wide trough reflection structure in Model II represents the deposit of blocky mound beach, the intermittent peak reflection structure in Model III represents the interbedded deposit of mound beach, and the continuous peak reflection in Model IV represents the deposit of low-lying zone between algal mounds.

Based on the waveform section characteristics of four seismic facies models, seismic facies are identified and extracted artificially on individual seismic section. The manually mapped seismic facies model distribution provides basic data for subsequent research (Figure 5).

In the model training process, the prediction errors of the training and validation sets are monitored in real-time. As shown in Figure 6, the error of the training set decreases rapidly; the partial error of the validation set first decreases and then maintains a stable level, and no obvious over-fitting occurs. This indicates that the model structure set parameters are reasonable.

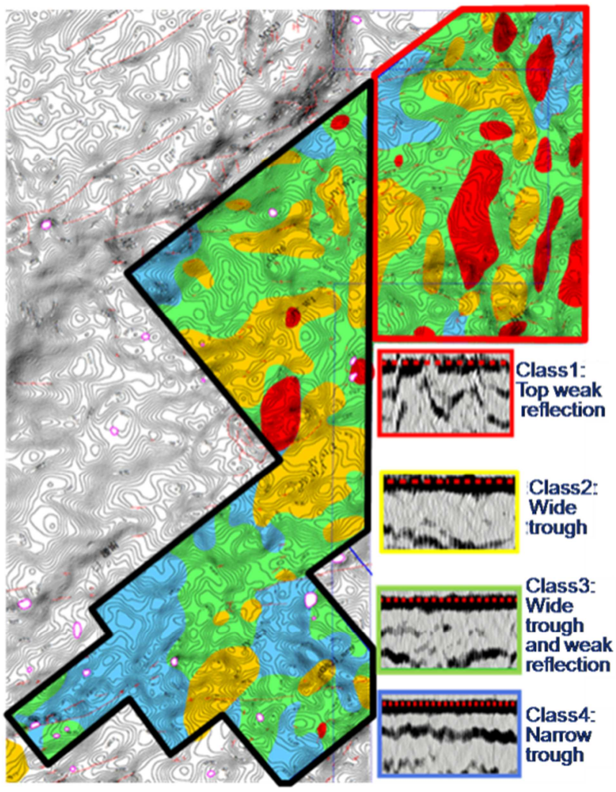
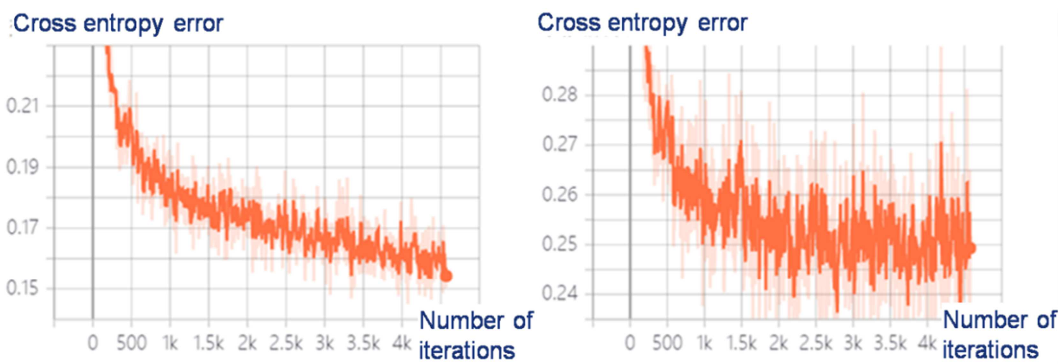



***Figure 5.*** *Artificially interpreted seismic facies map.*




a. Error monitoring for training set b. Error monitoring for validation set

***Figure 6.*** *Error monitoring during training.*

Figure 7 shows the predicted seismic facies by the AI model, displaying stable and continuous distribution. The predicted results are consistent with the artificially interpreted results in trend, except some differences in local regions.

In the training area and the validation area, regions with significant differences between model prediction and artificial interpretation are selected for detailed comparison on section (Figure 8). After careful recognition of the section, the B-C segment in the training area should be interpreted as intermittent peak of Model III, which is considered to be an artificial interpretation error. The E-F segment in the validation area should be intermittent peak and the F-G segment should be wide trough, which are considered as errors in artificially identified boundaries. The H-I-G-K segment in the application area has higher prediction accuracy through precise section recognition.

## 4. Conclusions

The AI solution is proposed for automatic seismic facies recognition. Practical application verifies that the method can effectively recognize seismic facies with special reflection structures, indicating that special seismic facies or seismic attributes can be quickly recognized through artificial intelligence.

Most of the artificially interpreted seismic facies in the study area are compared with the prediction results by AI model, confirming that the latter is superior. Artificial intelligence can eliminate significant errors in artificial interpretation and improve interpretation accuracy.

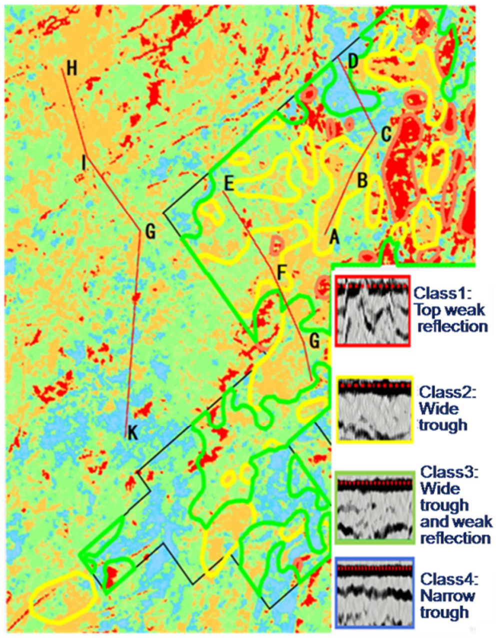



*Figure 7. Classification of seismic facies predicted by AI model.*

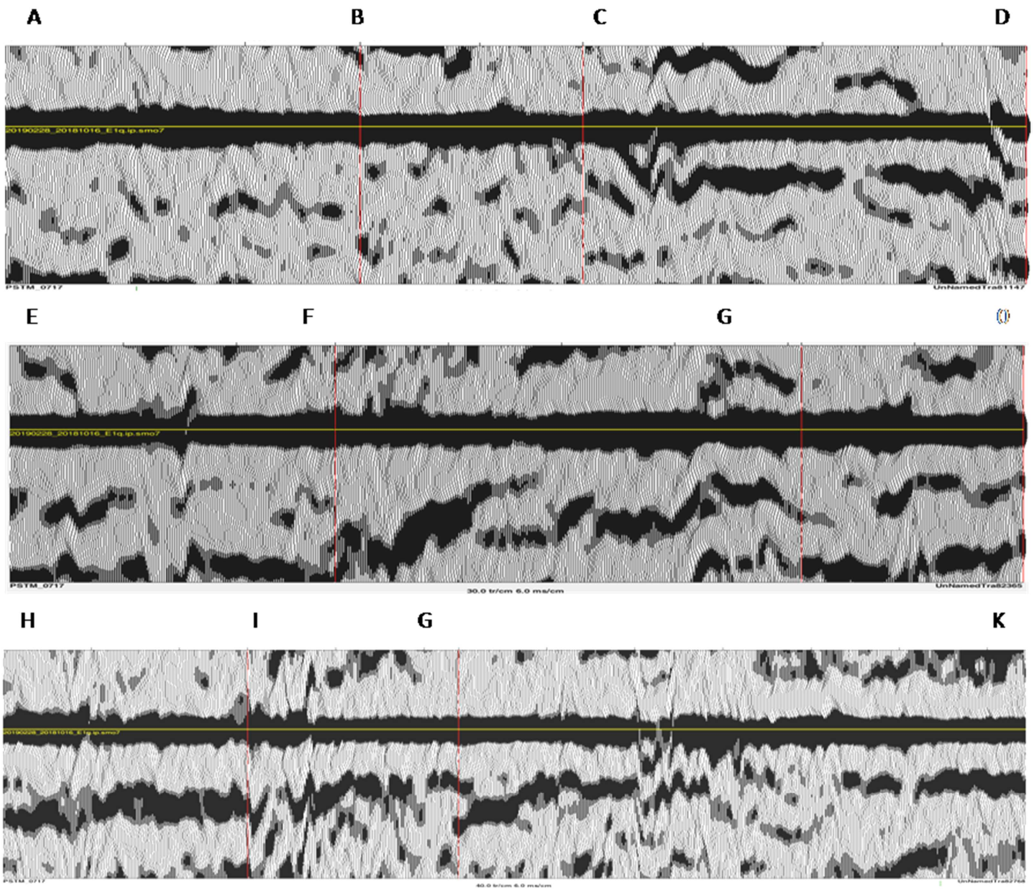



*Figure 8. Analysis and revision of model prediction accuracy.*

In the same study area, AI technologies are used to achieve small-scale, real-time training for the special needs of an interpretation and depending upon partial interpretation results, thereby achieving automatic seismic facies recognition across the area. This application is verified to effectively compensate for the inadequate generalization ability of AI model in the promotion.

After fine and artificial interpretation in small areas, the application of artificial intelligence's fast and accurate learning ability can quickly promote the results of artificial interpretation in small areas to nearby areas. While maintaining consistency in seismic data quality, it can greatly improve interpretation efficiency and reduce the labor intensity of interpreters, which is worthy of promotion.

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# Biography

**Yan Zhenhua** (1985-), male, master, senior engineer, is engaged in research on seismic data interpretation methods.