Open Journal of Applied Sciences, 2026, 16(1), 198-208
https://www.scirp.org/journal/ojapps
ISSN Online: 2165-3925
ISSN Print: 2165-3917

Research on the Identification Method of Fluvial Sandstone Reservoirs Based on U-Net Networks

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How to cite this paper: Wang, F.M., Yu, W.W., Wu, F.F., Li, Y., Yang, Q. and Yuan, X.G. (2026) Research on the Identification Method of Fluvial Sandstone Reservoirs Based on U-Net Networks. *Open Journal of Applied Sciences*, **16**, 198-208.
https://doi.org/10.4236/ojapps.2026.161012

Received: November 19, 2025
Accepted: January 12, 2026
Published: January 15, 2026

Abstract

With the deepening of oil and gas exploration, the exploration targets have gradually shifted from structural oil and gas reservoirs to lithological oil and gas reservoirs. The fluvial sandstone reservoir is an important type of lithological oil and gas reservoir. The fluvial sandstone presents characteristics in seismic data, such as the uneven thickness that is difficult to distinguish, the poor lateral continuity, and the strong subjectivity in tracking and interpretation, which pose great challenges to seismic interpretation work. To solve this problem, this study proposes a method for identifying channel sand bodies based on convolutional neural networks using the image semantic segmentation idea. This method mainly adopts the U-Net network structure, which can effectively combine low-resolution information and high-resolution information. The actual application effect shows that compared with traditional manual interpretation, this method has higher efficiency and accuracy.

Keywords

Lithological Oil and Gas Reservoirs, Fluvial Facies, Convolutional Neural Networks, U-Net

1. Introduction

The exploration and development of oil and gas resources worldwide have mostly been guided by structural traps and have gradually developed towards the exploration of lithological oil and gas reservoirs. As a typical representative of lithological oil and gas reservoir types, the fluvial sandstone reservoir plays an important role in domestic oil and gas exploration and development dominated by terrestrial sedimentary environments. As is well known, there are complicated processes in channel deposits such as frequent diversion and migration, lateral accumulation, and multi-stage stacking, which result in the characteristics of rapid lateral lithology change and complex heterogeneity, and so on. The seismic response law corresponding to channel sand bodies is therefore very complex. The uneven thickness and poor lateral continuity of sand bodies, coupled with the inherent limitations of seismic data resolution, make it very difficult to finely carve, identify the continuous boundaries of the channel, and predict the planar distribution characteristics. Therefore, the development of effective prediction techniques for fluvial sandstone reservoirs is of great significance for the exploration and development of such lithological traps.

In recent years, deep learning has swept all walks of life and become a compelling research focus [1]. Compared to traditional neural network methods, deep learning has stronger nonlinear modeling capabilities and can discover and extract intrinsic features of complex data in a hierarchical manner. Most problems in the field of seismic exploration belong to complex nonlinear problems, which have a good fit with the advantages of deep learning theory in nonlinear modeling. Therefore, many scholars are constantly trying to apply deep learning theory to the actual field of seismic exploration processing and interpretation. In terms of seismic processing, deep learning applications mainly focus on noise processing [2]-[4], first break picking [5] [6], data reconstruction [7], etc. In contrast, the application of deep learning in the field of seismic interpretation is mainly represented by fault identification [8], horizon tracking [9], and seismic facies analysis [10]-[12], etc. Although deep learning theory has brought unlimited opportunities for the development of seismic exploration, there are still many challenges to be solved in practical applications. For example, training label data production and network structure will have a significant impact on the final application effect.

In this study, aiming at the problems of effectively characterizing fluvial sandstone reservoirs in seismic data caused by poor vertical and lateral continuity and strong heterogeneity, a novel method for identifying channel sand bodies based on the convolutional neural network (CNN) is proposed by using image semantic segmentation. The application results of actual data show that this method has good feasibility and effectiveness.

2. Data Preparation

To characterize channel sand bodies using the CNN method, it is necessary to first prepare the training data, as the quality of training data preparation directly affects the training effect. In this study, the training data preparation includes the preprocessing of initial training seismic data and the production of a label dataset.

Seismic data preprocessing is necessary because the amplitude change range of conventional seismic data is large, which is not conducive to the rapid convergence of the network model. Therefore, seismic data is standardized, which is also the general process of data preparation in most deep learning methods. Seismic data standardization adopts the Z-score standardization method, which is a data standardization method based on the mean and standard deviation of the original data. Its specific formula is as follows:

$$S' = \frac{S - \mu(S)}{\sigma(S)} \tag{1}$$

where S' represents the standardized seismic data, S represents the original seismic data, $\mu(S)$ represents the mean value of the original data, and $\sigma(S)$ represents the standard deviation of the original data. Z-score standardization does not change the original data distribution, and the preprocessed seismic data has a mean value of 0 and a variance of 1, which improves the data comparability and enables better robustness and generalization performance in model training.

The production of label data is crucial for the whole model training process. The core idea of this CNN-based method for identifying channel sand bodies is to transform the characterization of channel sand bodies on seismic profiles into image semantic segmentation in the field of computer vision. Image semantic segmentation is based on pixel-level understanding of images to realize the division of pixels of the same category.

In this study, the training datasets are produced using the well-tie profiles, which ensures the accuracy and representativeness of the training data. According to the reflection characteristics of channel sand bodies and the analysis of well-side records, the channel sand bodies are labeled along the interest interval of the well-tie profiles. Thus, the label data corresponding to the well-tie profiles is obtained. The label data contains only two categories, namely channel sand bodies and non-channel sand bodies (with values of 1 and 0). Taking the well-tie profile shown in **Figure 1** as an example, its corresponding label data is shown in **Figure 2**. The value of the yellow part in the figure is 1, representing the channel sand bodies, and the values of the other parts are 0, representing the non-channel sand bodies. In terms of the entire seismic profile, the amount of information contained is too large, and the computational cost is also too high. Therefore, the entire seismic profile is not suitable to be directly used as a training dataset. Drawing inspiration from the concept of image sets in the field of computer imaging, seismic profiles are segmented into equally sized small datasets. Taking into account factors such as computational cost, effective information of a single dataset, and the number of training datasets, a sliding window of 64 × 64 is set to continuously slide along the seismic profile to obtain small datasets of corresponding size. According to the above process of creating small datasets, use a sliding window to scan the original seismic profiles and corresponding label data to generate matching small seismic datasets and label datasets. These small datasets are all 64 × 64 in size, and **Figure 3** shows the small seismic datasets and corresponding label datasets. Considering the amount of training data and the cost of training time, five arbitrary well-tie profiles from different directions and well positions were selected to create training datasets. Given the non-uniformity of the distribution of channel sand bodies, those with a proportion of channel sand body labels below the set threshold on the small datasets were discarded to ensure training stability.

In addition, to expand the training datasets and improve the generalization and robustness of the model, data enhancement processing is conducted on the training datasets.

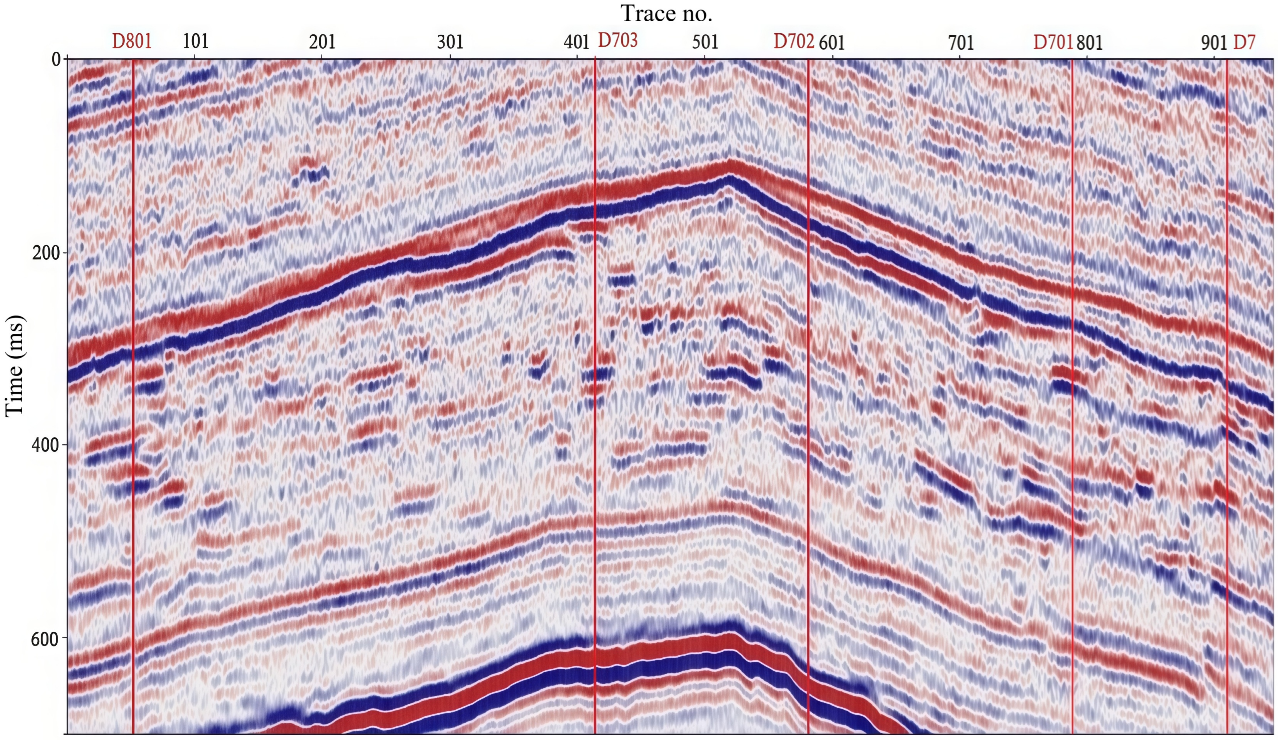

Figure 1. A well-tie profile.

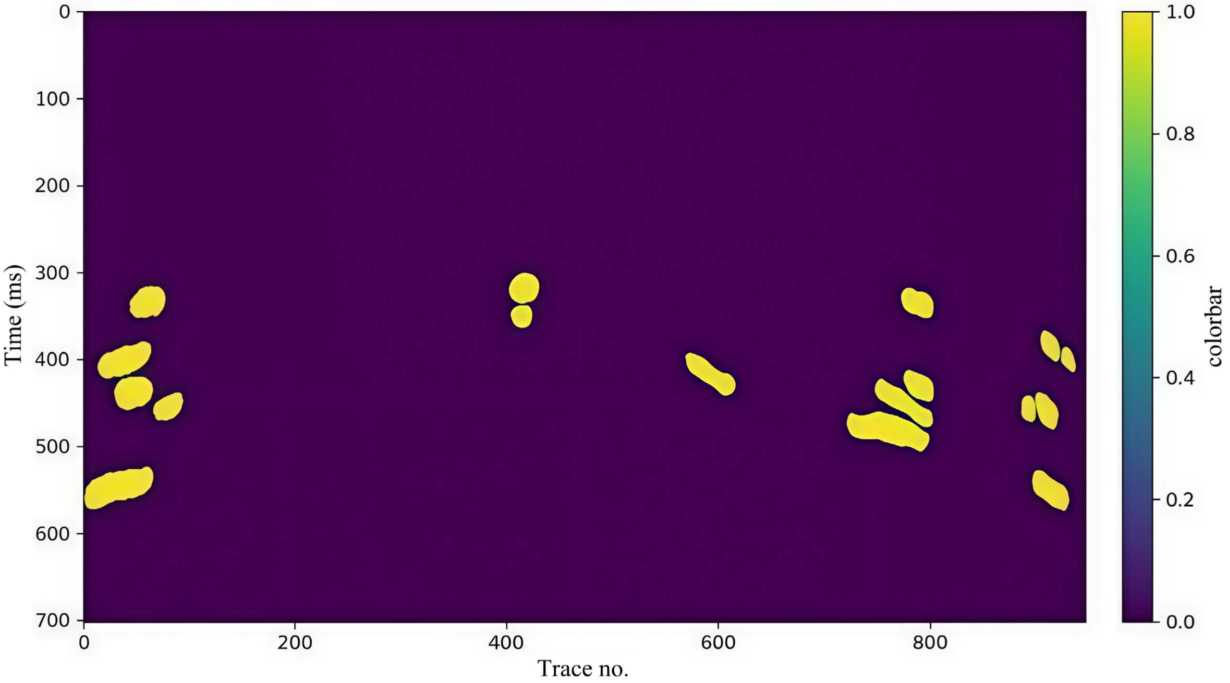

Figure 2. Label data corresponding to the well-tie profile in **Figure 1**.

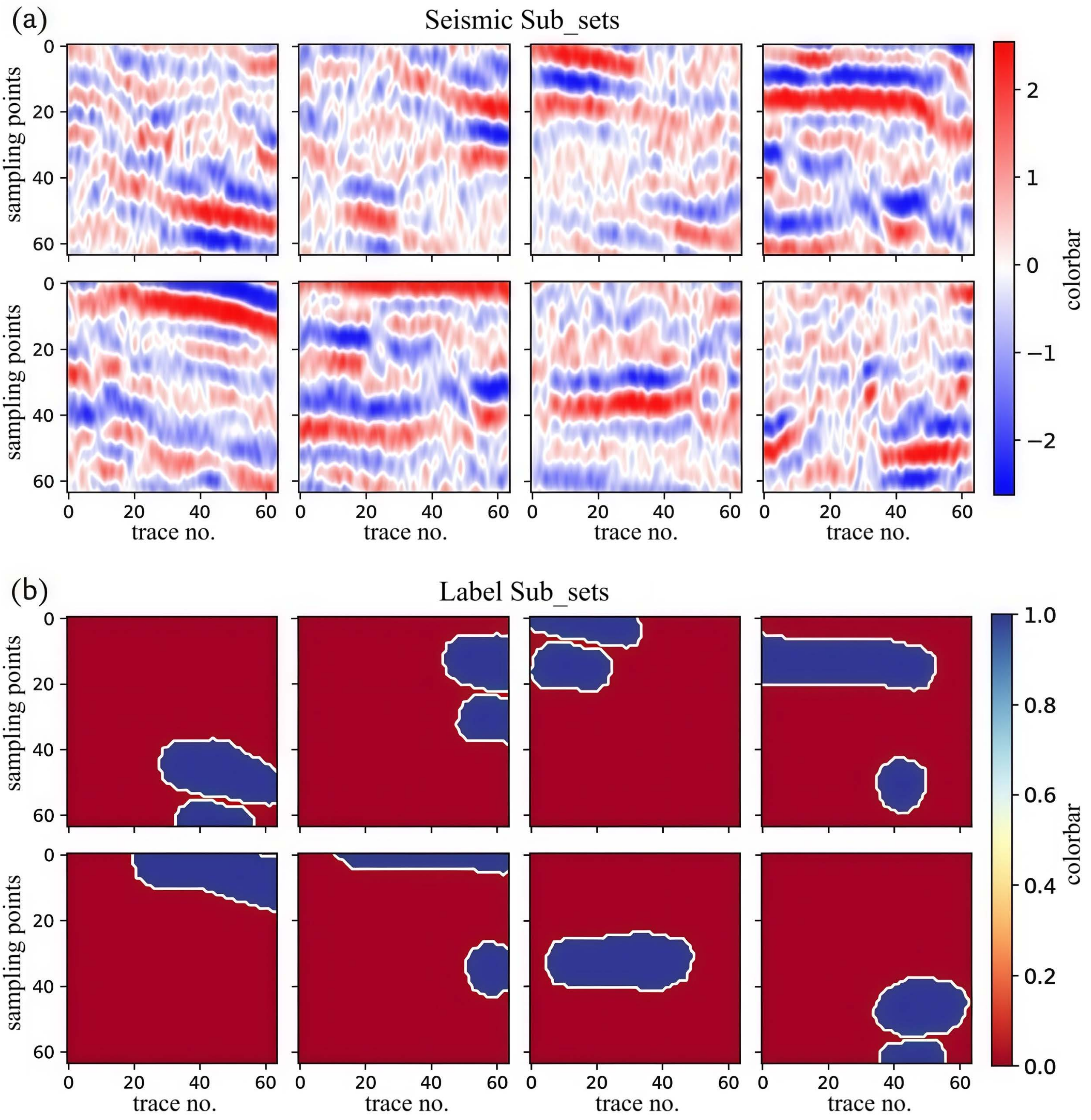

Figure 3. Seismic training datasets: (a) small seismic datasets; (b) corresponding label datasets.

3. Model Training

Deep learning network models always have more network layers, which means they have stronger feature learning and expression capabilities than traditional neural networks. However, this advantage also brings other problems, such as low efficiency due to too many parameters, difficulty in training, and model overfitting. Compared to traditional neural networks or other deep learning network structures, the essential difference of CNN lies in its network structure design, which adopts three strategies: local connection, parameter sharing, and pooling processing. These strategies can greatly simplify the complexity of the model, effectively reduce the number of weight parameters, and improve the stability and generalization of the model. Therefore, in this study, CNN was selected to achieve recognition and characterization of channel sand bodies, and the widely used U-Net network structure in the field of image semantic segmentation was chosen. The U-Net network initially achieved good application results in medical image segmentation [13], mainly because it can effectively combine low-resolution information and high-resolution information. Shallow high-resolution information can accurately segment images with blurred boundaries, while deep low-resolution information can provide more contextual information that is conducive to accurate pixel classification.

After multiple experiments, it was found that the original U-Net network structure could not obtain effective prediction results. In order to better match the needs of the task in this study, the original U-Net network structure was modified and tested. After repeated modifications and experiments, the final network structure model is shown in **Figure 4**. Compared to the original U-Net, this network model consists of seven convolutional modules and one prediction convolutional layer, with the left half called the contracting path and the right half called the expanding path. The contracting path contains four convolutional modules, each consisting of two 3 × 3 convolutional layers (with a stride of 1) and a 2 × 2 max pooling layer (with a stride of 1). The number of convolution kernels in both convolutional layers of the first convolutional module on the contracting path is 64, and the number of convolution kernels increases sequentially to 512. The output feature map size of the input training data processed by each module is halved (for example, the output size after the first module is 32 × 32), but the corresponding number of channels gradually increases (from 64 to 512). The expanding path contains three convolutional modules, each consisting of a 2 × 2 upsampling layer (with a stride of 1) and two 3 × 3 convolutional layers (with a stride of 1). The number of convolution kernels in both convolutional layers of the first convolutional module on the expanding path is 256, and then decreases to 64 in sequence. In contrast to the contracting path, the output feature map size of each convolution module on the expanding path doubles, but the corresponding number of channels gradually decreases (from 256 to 64). The last convolutional layer is to convert the extracted features into the probability of predicted categories. The number of convolution kernels in the convolutional layer of each module on the contracting path gradually increases, and each module is immediately followed by a pooling layer at the end, which is used for feature down-sampling (red arrow in the figure), removing redundant information, compressing features, reducing the number of parameters, and thus reducing the risk of model overfitting. Then the extraction of deep feature information is conducted in the following expanding path. Compared to the contracting path, the expanding path mainly involves the feature up-sampling process (blue arrow in the figure). The unique skip connection structure of the U-Net network (green arrow in the figure) can effectively fuse shallow and deep feature information by concatenating feature maps of the same dimension on the contracting path and expanding path, allowing the network to retain more high-resolution detail information and improve semantic segmentation accuracy.

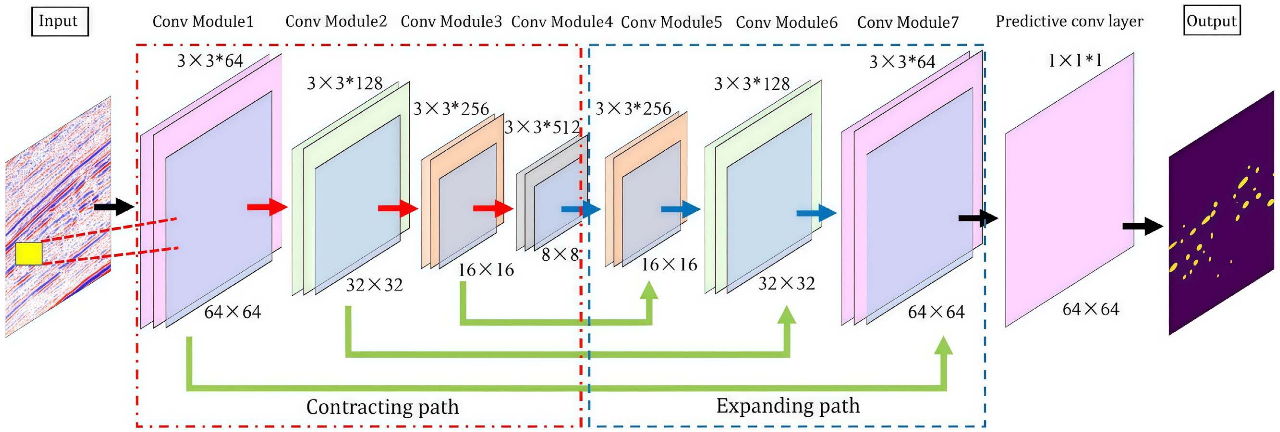

Figure 4. Schematic diagram of the U-Net model.

In order to maintain the same size of input and output data before and after the convolution operation, boundary padding is applied to the input data. In addition, the initialization of network model parameters adopts the He initialization method, and the ReLU function is selected as the activation function after each convolutional layer. However, the Sigmoid activation function is used in the last convolutional layer, which can normalize the final output to a probability size of 0 - 1 for identifying channel sand bodies. The binary cross-entropy loss function is selected as the loss function during the model training to calculate the error between the predicted results and the true values. The small batch gradient descent algorithm is chosen as the optimization strategy for solving the loss function, while the Adam algorithm is used to optimize the gradient descent process. Considering the configuration of computer hardware, the batch size here is selected as 128, which means that 128 small datasets among the entire training data will be fed into the model each time during the model training. After traversal, the iteration will be repeated until the set number of times is reached to stop training. In order to improve the robustness and generalization of the model, batch normalization processing and the Dropout mechanism were also added to the model.

When using the training datasets for model training, it is generally necessary to reserve a small portion of the training datasets as the validation dataset. Here, 10% of the training datasets will be used as the validation datasets to check the correctness of the model, verify the generalization of the model, and, most importantly, adjust the hyperparameters of the model training, such as the model learning rate and batch size in the gradient descent algorithm. If the learning rate of the model is too small, it will cause a decrease in the gradient update speed and the convergence speed of the model in the gradient descent algorithm. If it is too large, the model may fail to converge. In this study, it is set to 0.0001. Similarly, the batch size needs to be chosen appropriately. Setting a large batch size can reduce training time and improve model robustness, but setting it too large can lead to a decrease in model generalization. The numerical curves of the loss function for the training and validation datasets during the model training are shown in **Figure 5**.

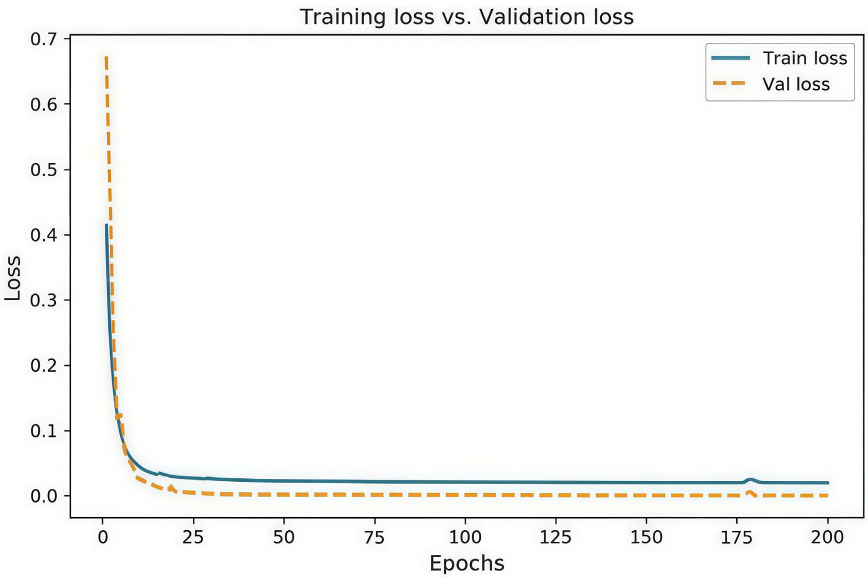

Figure 5. The curves of training error versus verification error.

From the figure, it can be seen that in the early stage of model training, the loss function values on the training datasets and validation datasets are relatively large, but then rapidly decrease, indicating that the model has good learning ability. As the number of training iterations increases, the loss function values tend to stabilize. At the end of model training, the loss function values basically reach the minimum, and the model performance basically reaches the optimal state. In addition, it can be seen that the curves of the loss function on the training datasets and validation datasets are basically consistent, indicating the good generalization of the model.

4. Application Effect

Finally, the actual data application using the trained and saved network model is conducted. In actual data prediction, it is also necessary to cut the seismic profile into small datasets of the same size as the training datasets, and then feed these datasets into the trained model for prediction. In fact, the prediction result is the probability value of determining the category, and the final category is determined by the value of the output probability. The actual data prediction results are shown in **Figure 6**. From the comparison between the actual profile and the predicted profile, it can be seen that the reflection characteristics of channel sand bodies on the seismic profile have been well characterized on the predicted profile, and some sand body responses with weaker reflection characteristics have also been well predicted. From the position relationship of the seismic event reflection characteristics, it can be seen that the predicted results have a good correspondence with the reflection characteristics of channel sand bodies presented in the seismic profile. In addition, the distribution of most channel sand bodies is basically identified, and the lateral discontinuity of channel sand bodies is well characterized, indicating that this method is effective and feasible.

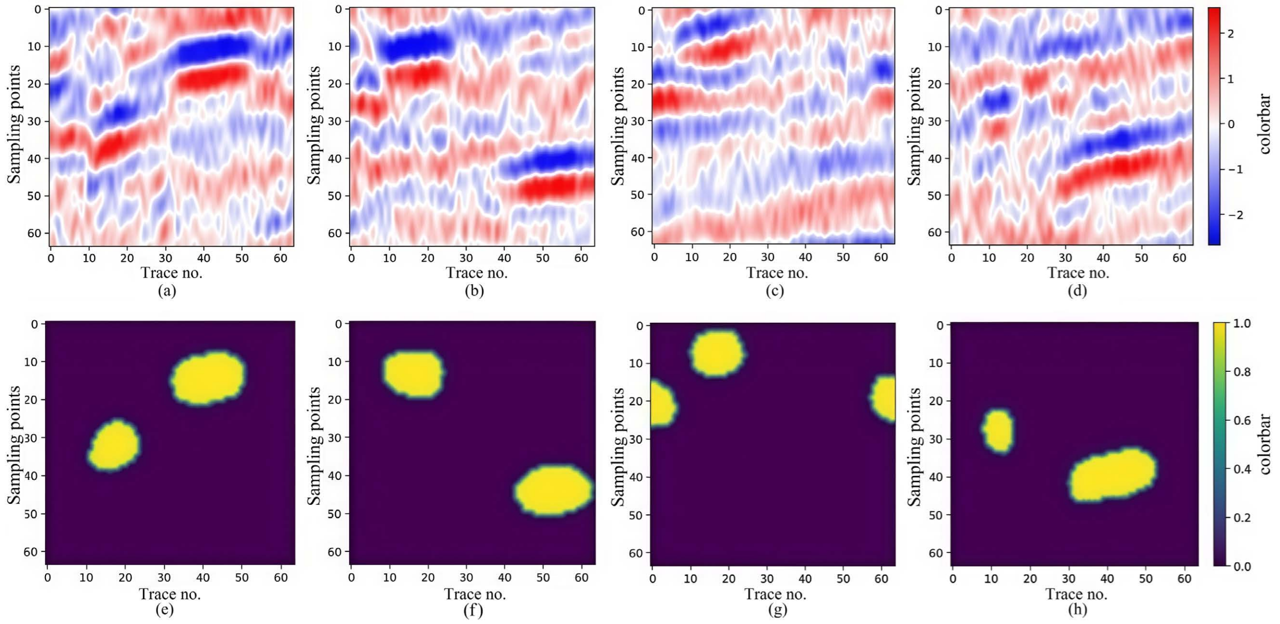

Figure 6. Actual data and corresponding prediction results: (a)-(d) are the actual seismic data, and (e)-(h) are the prediction results corresponding to the actual data.

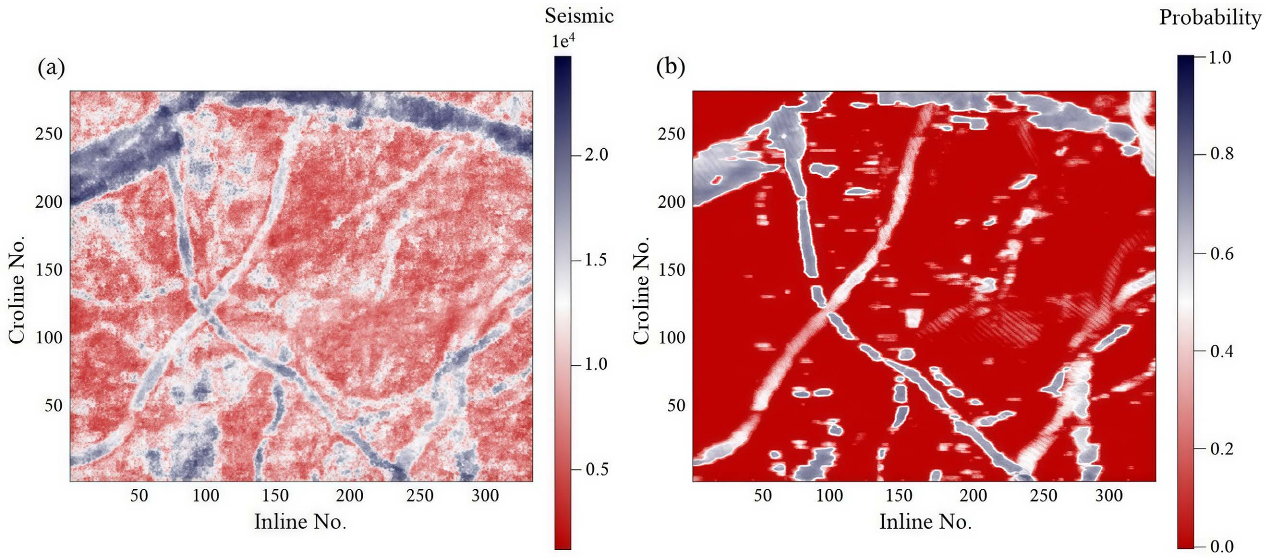

Figure 7. RMS attributes of seismic data and predictions for channel sand bodies using CNN: (a) seismic data; (b) predictions for channel sand bodies using CNN.

In order to analyze the planar distribution of channel sand bodies, taking the target layer t3 as an example, the root mean square (RMS) attribute of the predictions is extracted. For the convenience of calculation, a small-scale 3D data volume within the research area was selected for prediction. The RMS attribute obtained along the layer t3 from the 3D data and corresponding predictions are shown in Figure 7. It can be seen that the RMS attributes of the predictions based on the CNN method and the actual seismic data have a good agreement in terms of the distribution characteristics of the main channel sand bodies, which further verifies the effectiveness and accuracy of the predictions by this method. Specifically, the channel boundary is clearly shown in Figure 7(b), and the continuity of the channel planar extension is also well characterized.

5. Conclusion

This study proposes a CNN-based method for identifying channel sand bodies to tackle the challenge of characterizing fluvial sandstone reservoirs. The CNN model has strong feature extraction capabilities and is widely used in computer vision. Drawing on the experience of CNN in visual processing, this paper converts the characterization of channel sand bodies into image semantic segmentation. The production of label data and the selection of network structures are crucial for the effectiveness of deep learning applications. For the production of label data, based on clarifying the correspondence between the channel sand bodies and reflection characteristics along the well-tie profile, the channel sand bodies were labeled along the interest interval, thereby ensuring the quality of label data production. For the network structure, the widely used U-Net structure in the field of image semantic segmentation is selected as the network model. Based on the small training datasets, the U-Net network structure is repeatedly adjusted and modified to meet the target of identifying channel sand bodies in this study. The application effect of actual data has verified the effectiveness and accuracy of this CNN-based method, indicating that this method has good feasibility for characterizing fluvial sandstone reservoirs.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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