Research on Application of Image Enhancement Technology in Automatic Recognition of Rock Thin Section

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Abstract. Artificial intelligence technology has rapidly emerged in various new industries due to its high efficiency and has been successfully used in many fields. However, it has been slow to start in the field of petroleum exploration, under the background of the need for more efficient exploration and development in the petroleum field. In this paper we used the ResNet-18 convolutional neural network to make an attempt to automatically identify rock thin section, and finds that this method can efficiently identify rock thin section and has a higher accuracy rate. In addition, we adopted appropriate image enhancement technology, which can significantly improve the recognition accuracy of the model. It proves that related machine learning technology has broad application prospects in the fields of petroleum exploration and petroleum geology.

1. Introduction
The transformation of petroleum exploration and development from conventional fields to unconventional fields is an inevitable trend of technological development. The era of intelligent oil and gas is coming. How to use advanced artificial intelligence technology [1-3] to replace the tedious tasks of petroleum geologists. This is the most essential issue to improve the efficiency of exploration and development.

In the first stage of petroleum exploration, lithology identification is a necessary and tedious basic work. Petroleum geologists need to use a polarizing microscope to identify and comprehensively name the optical characteristics of the corresponding rock and mineral under the microscope. This method is time consuming and laborious, and requires quite experienced geologists to complete this task.

With the development of computer image recognition, convolutional neural networks have good development prospects in many image recognitions fields, such as transportations and medical treatments. This proves that convolutional neural networks have good versatility and excellent performance in image recognition processing [4]. Moreover, the image enhancement technology in a specific field can increase the sample size, highlight the characteristics of the sample, and also have a better effect in suppressing noise [5].

Therefore, we used a convolutional neural network algorithm (ResNet-18) to realize the automatic recognition of rock thin section. And for the original sample pictures, simple image enhancement processing is performed to obtain more samples. The application of image enhancement technology in the process of automatic identification of rock thin section is comparatively studied.
2. Methods and experiments

2.1. ResNet Convolutional Neural Network

We choose the ResNet-18 architecture [6-7] as the neural network model. In this architecture, 18 layers with parameters are used. The structure is shown in Figure 1.

Among the 18 parameter-containing layers, 17 are convolutional layers and the last is a fully connected layer. The parameters are shown in Figure 1. Each convolutional layer is connected with a batch normalization layer and an activation layer with ReLU as the activation function. For the input element $x \in \mathbb{R}$, the ReLU function outputs $f(x) = \max\{0, x\}$ to provide the deep neural network with stronger nonlinearity. Compared with the traditional activation function, the ReLU function can accelerate the training of the neural network [4]. In addition, after the first convolutional layer and the last convolutional layer, the maximum pooling layer and the average pooling layer are respectively connected. For a detailed introduction of each layer, please refer to related books on deep learning [8]. In order to obtain an intuitive and clear output, we added a SoftMax layer after the fully connected layer to normalize the input of the fully connected layer into a weight distribution. Specifically, assuming that the output corresponding to each category of the fully connected layer $z_i, i \in [K]$ is the score of each category, and the softmax layer is calculated by

$$p_i = \frac{\exp(-z_i)}{\sum_{k=1}^{K} \exp(-z_k)}, \forall i \in [K]$$

(1)

To get the predicted weight $p_i$ for each category.

![Figure 1. The architecture of ResNet-18](image)

Figure 1. The architecture of ResNet-18, the numbers in the layers represent the parameters of each layer. Taking the first convolutional layer as an example: “$7 \times 7$” represents the size of the convolution kernel; “64” represents the number of convolution kernels; and “/ 2” represents the output size halved. For the fully connected layer, “8” indicates the number of output categories.
The prediction process of ResNet can be summarized as follows: the image samples are first input through the convolutional layer and passed through the maximum pooling layer, and then connected to 8 basic modules for residual learning, and finally input through the average pooling layer to the whole connected to the SoftMax layer. Connection layer. The output of the SoftMax layer is the predicted score of each category. For each sample, we can take the category corresponding to the largest score as the final prediction result.

The ResNet-18 neural network and related programs used in this article are implemented using the PyTorch machine learning framework and Python language.

2.2. Test set and original training set

The classification and statistical methods adopted in this subject: A total of eight types of photos under single-polarized and cross-polarized lenses of four types of rocks are collected.

The pictures used in the experiment were collected by the laboratory equipment Nikon Eclipse Lv100 Pol polarizing microscope, the magnification was forty times, and the supporting software was used to automatically white balance and take pictures. Three major rock types are selected: metamorphic rock, volcanic rock, and sedimentary rock. Among them, sedimentary rocks have a greater impact on oil and gas due to their different sedimentary environments, so they are subdivided into two types: carbonate rocks and clastic rocks. A total of 8882 photos were collected in this experiment (Figure 2). Among them, the photos under the cross-polarizer of metamorphic rock accounted for 756, and the photos under the single-polarizer accounted for 564; the photos under the cross-polarizer of volcanic rock accounted for 880, and the photos under the single-polarizer. There are 735 photos; clastic rocks under the cross-polarizer account for 764 photos, and the single-polarizer photos account for 608; the carbonate rocks account for 1,655 photos under the cross-polarizer and 2920 photos under the single-polarizer. The computer randomly selected 20% of the photos of each category in the training set (1803 photos in total) as the test set, and the remaining photos (7079 photos in total) as the training set (Table 1).

Figure 2. Images in the training set belonging to eight classes. (a)—Metamorphic rock image under orthogonal polarized light.(b)—Metamorphic rock image under single polarized light.(c)—Volcanic rock image under orthogonal polarized light.(d)—Volcanic rock image under single polarized light.(e)—Clastic rock image under orthogonal polarized light.(f)—Clastic rock image under single polarized light.(g)—Carbonate rock image under orthogonal polarized light.(h)—Carbonate rock image under single polarized light.

2.3. Image enhancement

Image enhancement is to meet the special needs of the application, highlight the feature information in the image, suppress or remove other interference information, and perform image analysis, training and recognition pre-processing for different applications. The purpose is to transform the original image
feature information to adapt to the computer A series of methods of image recognition [5]. General image enhancement is processed from contrast stretching processing and detail preservation and reproduction [9].

Table 1. Type and size of training set and test set

| Rock type        | Number of photos under crossed polarizer | Number of photos under single polarizer |
|------------------|-----------------------------------------|----------------------------------------|
|                  | Training set | Test set | Training set | Test set |
| Metamorphic rock | 605         | 151      | 452         | 112      |
| Volcanic rock    | 704         | 176      | 580         | 155      |
| Clastic rock     | 612         | 152      | 487         | 121      |
| Carbonate rock   | 1303        | 352      | 2336        | 584      |

This article uses a total of three image enhancement methods:
1) Salt and pepper noise: Using OpenCV (Open Source Computer Vision Library) and Python, the computer automatically selects 1% of the pixels of each photo in the original training set, and replaces the colour pixels with pure white pixels and pure black pixels.
2) Image cropping: Use OpenCV and Python to crop the original training set, and crop all the original pictures into pictures with the shortest side length greater than 300 (pictures are cut into four).
3) Image brightness and exposure adjustment: Use OpenCV and Python to adjust the brightness and exposure of the original training set, and randomly adjust the original image brightness within 30% of the original display brightness value. Randomly adjust the exposure of random points within 15%.

3. Control group
In order to study the role of related image enhancement technology in the automatic identification of rock thin section, this paper made five control groups and used the Resnet-18 model for training. The five control groups are A, B, C, D, E:
A: This training set is the original photo training set. A total of 7079 photos.
B: This is a combination of the original training set and random salt and pepper noise image enhancement of the original training set photos. A total of 14158 photos.
C: This training set is composed of photos cropped from the original training set. 28316 pictures in total
D: This set of training set is a combination of the original training set and the brightness and exposure adjustment image enhancement of the original training set. A total of 14158 photos.
E: This set of training set is composed of the original training set and the original training set with random salt and pepper noise, brightness and exposure adjustment image enhancement. A total of 21237 photos.

4. Results
The above five control groups A, B, C, D, and E are all input into the Resnet-18 model for training, and a total of 16 epochs are performed (each epoch means running through all the pictures in the training set). Each epoch outputs the total recognition accuracy and classification accuracy of the test set once. According to the output correct rate, make a graph of the average correct rate of each epoch of the five control groups (Figure 3), and the correct rate table of all categories of the epoch with the highest correct rate in all the control groups (Table 2).

It can be seen from Table 2 that all the image enhancement control groups have a significant improvement in the recognition accuracy. The average recognition accuracy of the original training set A is 92.2%, the average recognition accuracy of B is 93.0%, the average recognition accuracy of C is 96.3%, the average recognition accuracy of D is 93%, and the recognition accuracy of E is 93.3%. The
recognition accuracy of the cropped image enhancement group is improved the most, increasing by 4.1%. Other image enhancement methods have improved the variance of the correctness rate of each category, and the recognition accuracy rate will not be too low, and it can be maintained above 80%.

From figure 3, it can be seen that the recognition accuracy of the first epoch recognition in groups A and C is low, and the initial accuracy is not more than 70%, while the initial accuracy of groups B, D, and E are all above 80%, and there is a better one in one round of training. Good results. Moreover, the accuracy of group A without image enhancement processing fluctuates greatly with the training rounds, and the accuracy of the group undergoing image enhancement processing fluctuates slightly with training rounds and is relatively stable.

Figure 3. Average recognition accuracy rate of each control group
TABLE 2. In the epochs with the highest correct rate in each control group, the correct rate of various types of rock recognition

| Recognition accuracy rate | A (14epochs) | B (12epochs) | C (9epochs) | D (8epochs) | E (10epochs) |
|---------------------------|-------------|--------------|-------------|-------------|-------------|
| Average correct rate      | 92.2%       | 93.0%        | 96.3%       | 93.0%       | 93.3%       |
| Metamorphic rock image under orthogonal polarized light | 78.15% | 86.09% | 90.73% | 85.43% | 87.42% |
| Metamorphic rock image under single polarized light | 99.11% | 100.00% | 98.21% | 92.86% | 86.61% |
| Volcanic rock image under orthogonal polarized light | 92.61% | 92.61% | 96.02% | 88.64% | 88.64% |
| Volcanic rock image under single polarized light | 95.14% | 96.53% | 100.00% | 91.67% | 99.31% |
| Clastic rock image under orthogonal polarized light | 97.37% | 97.37% | 100.00% | 97.37% | 97.37% |
| Clastic rock image under single polarized light | 97.52% | 97.52% | 100.00% | 99.17% | 99.17% |
| Carbonate rock image under orthogonal polarized light | 81.23% | 89.23% | 96.62% | 87.69% | 90.15% |
| Carbonate rock image under single polarized light | 97.43% | 92.81% | 94.69% | 96.40% | 95.38% |

5. Conclusion
In this paper we used the Resnet-18 convolutional neural network model to automatically recognize four types of rock thin section images under the microscope. It shows that the convolutional neural network algorithm has a strong generalization ability in the field of rock thin section identification, and the recognition accuracy is high. The contrast experiments of image enhancement technology show that the use of appropriate image enhancement technology can improve the recognition accuracy of rock thin slices, and can identify rock types more efficiently. Appropriate artificial intelligence algorithms have good application prospects in the field of petroleum geology, which can greatly improve people's work efficiency, enhance exploration and development benefits, and reduce development costs.

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