The role of artificial intelligence recognition in metallogenic prediction

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Abstract. Artificial intelligence algorithm has developed rapidly in recent years, and deep learning has become the research hotspot of many scholars. Artificial intelligence algorithm is just developing in geology, especially in metallogenic prediction. In this work, the 1:250000 aeromagnetic data image of a certain area is used to predict the gold deposit, and good research results are obtained.

1. Introduction

The prediction of ore deposits by using limited geological data has always been the focus of geologists. With the development of computer technology, the special software and hardware function is becoming more and more powerful, which makes the CPU and GPU computing power have a rapid progress. This also makes it possible to use artificial intelligence algorithm to predict mineralization. At present, the development of artificial intelligence algorithm is changing with each passing day, especially deep learning has become a research hotspot in recent years. Therefore, this paper discusses the role of artificial intelligence algorithm in metallogenic prediction.

The deep learning algorithm used in this paper is GoogLeNet, which was proposed by Christian Szegedy in 2014 [1]. Compared with AlexNet, VGG and other square algorithms, it has higher operation efficiency and can extract more image features, which makes the training result better. The model structure of GoogLeNet is shown in Fig. 1. The specific operation process of this algorithm has been explained in detail in the original text. Therefore, the principle of the algorithm will not be discussed in this paper, but its role in geological work will be studied only. Artificial intelligence geology can have complex forms, but it is also a very meaningful exploration experiment [2]. Zhang Y et al. have applied it to automatic lithology recognition and classification of rock images [3].

2. Experimental design

2.1 Sample data

The image used in the experiment is 1:250000 aeromagnetic data of a certain area in Gansu Province. The image is formed after gridding by Kriging method, and is divided into 42 image samples. There are 9 ore bearing images and 33 non ore bearing images. The ore bearing image is the image containing yellow dots, which reflects that the image contains gold deposits or gold mineralization spots. Six pictures are selected as ore bearing test group, and another six pictures are selected as non ore bearing test group. An example of image training sample is shown in Fig. 2. They were randomly rotated from - 90 ° to 90 ° respectively; 5 to 2 times at random; - 1 to 1 times at
random horizontal translation; 1 to 1 times at random vertical translation. Through the above operation, the original 12 samples were increased several times to 160 models and trained. During the training, 30% is used as the verification data and 70% as the training data, and the Google net model structure is used to train it.

**Figure 1.** Structure of GoogLeNet model

**Figure 2.** Example of image training sample
2.2 Model training and analysis

During the training process, the learning rate was 0.0001, the maximum epochs was 30, and the validation frequency was 5. Because the number of training samples is 12, the mini batch size is selected as 3, that is, three images are called for training each time to ensure that the whole data set can be used in each round of training. Training accuracy refers to the percentage of images that can be accurately trained in all images. After 30 rounds of training, the training accuracy is 92%, the verification accuracy is 75%, and the cross entropy value is 0.05. According to the curve in Fig. 3, the training effect is ideal and the accuracy basically meets the requirements.

![Figure 3. Training process of image recognition (blue line - training accuracy; brown line - cross entropy; black dotted line - test accuracy)](image)

3. The test group images were predicted

The remaining 30 images of the study area are taken as the test group. There are three ore bearing images in the test group, namely test-3, test-11 and test-26. There are 27 non ore bearing images, and some image test samples are shown in Fig. 4. These images are input into the trained model for recognition. The specific recognition results are shown in Table 1.

![Figure 4. Sample of partial image test](image)
We can see from table 1 that 29 out of the 30 images tested have got correct recognition results, and the comprehensive prediction accuracy rate is 97%, of which the recognition accuracy of non ore bearing image is 100% and that of ore bearing image is 67%. The main reason for the low recognition accuracy of ore bearing images is that the number of them is small, and the recognition rate is greatly reduced due to the wrong recognition of one piece. From Figs. 2 and 4, it is difficult for the naked eye to see how the two sets of images are related. The abnormal intensity of the image in Fig. 4 is significantly higher than that in Fig. 2. Even senior experts are difficult to predict ore bearing images by comparing the two groups of images. If more geological data are analyzed in the later stage, with the increase of data dimension, the difficulty of artificial identification will increase gradually, and the recognition accuracy of the results will also decrease accordingly. Deep learning can overcome the shortcomings of artificial recognition, play a good auxiliary role, improve the utilization of data and recognition accuracy.

| Test image | Classification recognition probability ( % ) | Is it mineralized? | Accuracy | Test image | Classification recognition probability ( % ) | Is it mineralized? | Accuracy |
|------------|---------------------------------------------|-------------------|----------|------------|---------------------------------------------|-------------------|----------|
| Test-1     | 0.97                                        | 0.03              | no       | Test-16    | 0.99                                        | 0.01              | no       |
| Test-2     | 0.95                                        | 0.05              | no       | Test-17    | 0.94                                        | 0.06              | no       |
| Test-3     | 0.15                                        | 0.85              | yes      | Test-18    | 0.87                                        | 0.13              | no       |
| Test-4     | 0.99                                        | 0.02              | no       | Test-19    | 0.95                                        | 0.45              | no       |
| Test-5     | 0.99                                        | 0.01              | no       | Test-20    | 0.89                                        | 0.11              | no       |
| Test-6     | 0.96                                        | 0.04              | no       | Test-21    | 0.89                                        | 0.11              | no       |
| Test-7     | 0.99                                        | 0.01              | no       | Test-22    | 0.99                                        | 0.01              | no       |
| Test-8     | 0.96                                        | 0.04              | no       | Test-23    | 0.99                                        | 0.01              | no       |
| Test-9     | 0.99                                        | 0.01              | no       | Test-24    | 0.99                                        | 0.01              | no       |
| Test-10    | 0.99                                        | 0.01              | no       | Test-25    | 0.94                                        | 0.46              | no       |
| Test-11    | 0.11                                        | 0.89              | yes      | Test-26    | 0.01                                        | 0.99              | yes      |
| Test-12    | 0.99                                        | 0.01              | no       | Test-27    | 0.51                                        | 0.49              | no       |
| Test-13    | 0.52                                        | 0.48              | no       | Test-28    | 0.99                                        | 0.01              | no       |
| Test-14    | 0.58                                        | 0.42              | no       | Test-29    | 0.99                                        | 0.01              | no       |
| Test-15    | 0.96                                        | 0.04              | no       | Test-30    | 0.99                                        | 0.01              | no       |

4. Conclusion

This study is based on deep learning algorithm for geological image processing, through the ore bearing image and non ore image learning, to predict other images. After training with googlenet model, the comprehensive image recognition rate can reach more than 97%, which indicates that this algorithm can be used for metallogenic prediction of geological images. Artificial neural network learning depends on a large amount of data for learning, the amount of data used in this work is small, so there are some errors. Through the image enhancement algorithm can be very good for a small amount of data incremental processing, to achieve the purpose of better application.

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