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Research on Intelligent recognition of Rock samples based on Deep Learning method

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Abstract: Rock sample recognition plays an important role in oil and gas exploration and mineral resources exploration. At present, the main rock sample identification methods are logging, seismic, gravity and magnetism, geochemistry, hand samples and thin slice analysis and so on. In particular, the mainstream thin section analysis requires professionals to analyze the rock slices manually, but manual detection and preparation of rock slices take a long time. In order to reduce the workload and shorten the time period, the image depth learning method is used to establish the model. After the cuttings and core samples are collected by the industrial camera in the mud logging site, the real-time automatic identification and classification of rock samples and the evaluation of oil and gas-bearing properties are realized. In this paper, the file in .JPG format is cut to discard the information that does not contain rock at the edge. Then it was divided into 4* 4, 6*6, 8*8, 10*10 segments. After image enhancement, the transfer learning method is used to train the neural network using Desnet201 in the built-in library of torch, and the Desnet201 network is selected as our neural network framework. Then the last softmax layer is changed into a multi-layer perceptron with three hidden layers, and the improved Desnet201 is used as a model to identify rock types in this paper.

1. Introduction

As an important content in the field of geology, rock classification and identification is an important part of mineral resources exploration. Traditional rock sample identification methods include well logging, seismic, gravity and magnetism, geochemistry, hand samples and thin slice analysis, etc. The production time of rock slices is more than 12 hours, and the grinder and dryer are not easy to carry and are not suitable for rapid identification of rocks in the field. In order to shorten the time period, improve portability and real-time recognition, the image depth learning method is used to establish the model. After the cuttings and core samples are collected by the industrial camera at the logging site, the rock samples can be identified and classified automatically in real time.

In recent years, with the development of computer technology, many scholars use artificial intelligence to recognize images to assist geological exploration [1]. In the aspect of rock meso-structure, Liu Yanbao [2] proposed that through the threshold segmentation method of combining LS-SVM classification and digital image processing, a man-machine combined rock meso-structure image system analysis method was proposed. In terms of rock macrostructure, Laercio B. Gonc, alves proposed a neuro-fuzzy hierarchical classification method based on binary space division [3]. The above early interdisciplinary research is mainly focused on machine learning, which needs to be preprocessed manually according to the characteristics of the sample, which takes a long time. At the same time, human subjective factors also reduce the accuracy of image recognition. In recent years, Cheng Jianguo [4] and others have realized the feature extraction of rock slice images based on convolution neural network. Xu Shuteng and others have established U-net convolution neural network models for microscopic ore recognition based on Tensorflow, and most of these models rely on rock slice images. There are many steps in making rock slices and many materials are used, which leads to some problems, such as difficult for non-professionals to make, lack of real-time access to classified information, inconvenient to carry materials and so on. Therefore, through the traditional digital image processing technology and depth learning algorithm, this paper designs a rock intelligent recognition and classification model based on the field rock sample images, and realizes the rock sample classification.

2. Model building preparation

The characteristic of DenseNet [5] is that the input of each layer comes from the output of all previous layers, and the formula is

$$[H]x_l = H_l([x_0, x_1, x_2 ..., x_{l-1}]) \tag{1}$$

DenseNet establishes the connection relationship between different layers, so that the features can be more fully utilized. The component module DenseNetBlock, DenseBlock of DenseNet consists of k DenseNetblock composed of 1-1 convolution layer and 3-3 convolution layer, as shown in the figure.

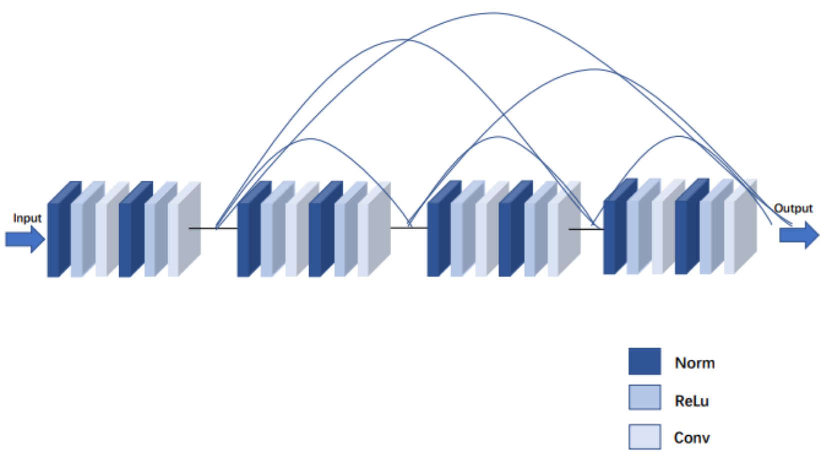

Figure 1: DenseNet201

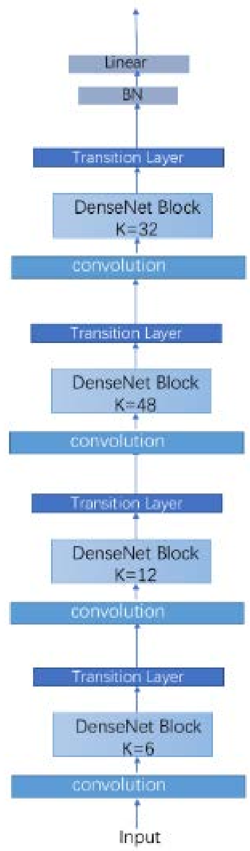

Figure 2: Network structure result

It can be seen that the traditional convolution layer 5 network has only 5 connections, while DenseNet has 10 connections, which enhances the propagation of the feature graph, makes more full use of the feature graph of the previous layer, and greatly reduces the number of parameters. The DenseNetBlock is connected by a Transition layer, and the Transition layer consists of a 1 to 1 convolution layer and an average pooling layer of 2 to 2, which is used to reduce the number of parameters.

After the 7*7 convolution layer with a step size of 2 and the maximum pool layer with a step size of 3-3, the DenseNetBlock, Dense Block structure with 6, 12, 48 and 32 dense block is connected sequentially and the DenseNetBlock is connected by the Transition layer. After the global average pooling of 7-7, the extracted features are classified by the full connection layer, and the network structure is shown in the figure.

3. Lithology identification model

3.1 Data pretreatment

3.1.1 Image of cropping and splitting

In order to prevent the background's recognition capability is greater than the recognition capability of each rock, the data set ROCK number is cropped between 322 to 350, the image data of ".jpg" format, under the premise of removing the background, keep as big as possible Rock image. In order to enhance the training effect, the picture is cut into 4 * 4, 6, 8 * 8, 10 * 10 and name the subfold in the original number Nth, using different cutting methods to train, comparison One item is selected, and the results are shown as shown.

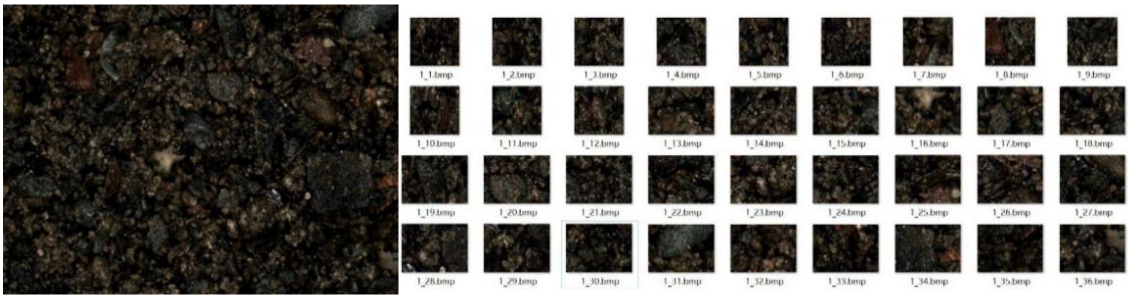

Figure 3: Segmentation result

3.1.2 Data amplification

The original data set has a total of 315 rock pictures, where we expanded to 315 * n ^ 2 by cutting treatment. Import the Transforms function from the TorchVision library. In its structural compose, the cut-cutted original map and the label image are dilated, mainly horizontally and vertically flip images, random angles (30°), and the method expanded to the original 4 times. At the same time, after testing, it was found that the Gaussian noise was unfavorable to the feeding machine, and the contrast and brightness of the data were nearly beneficial.

Table 1: Data set size transformation

Data preprocessing	Raw data	Image cropping	Data amplification
Data set size	315*	$315*N^2$	$4*315*N^2$

3.2 Rock sex identification model

In this paper, DenseNet201 is selected to extract features, and then multi-layer perceptrons are connected to classify the extracted features. The cross entropy function is selected as the loss function, and the update step size is calculated by using the optimizer Adam, and the gamma=0.1 is set, the initial learning rate is 0.001 and the step size is 5. Using the method of transfer learning, the pre-training model of the relevant network on the ImageNet data set is frozen and fine-tuned, and the final model is obtained. The model was evaluated by the accuracy (ACC) and the area surrounded by the axis under the ROC curve (AUC).

In the hardware environment of the experiment, the GPU is TITAN X (Pascal), and the video memory is 12G * 4 and the CPU is TOP.

4. Analysis of experimental process and results

4.1 Super parameter selection

Table 2: Super parameter selection

	After freezing	Before freezing
Risize	256*256	256*256
Batch size	16	16
Iearning rate	0.001	0.001
StepLR	step_size=3,gamma=0.1	step_size=7,,gamma=0.1
epochs	8	32

4.2 Training and testing of lithology recognition model

As shown in the figure, when the epoch is greater than 40, the accuracy of the training set oscillates around 0.96 and the accuracy of the training set oscillates around 0.85. This paper also improves the recognition performance of the model by changing the image size of the input lithology recognition model. As can be seen from the figure, with the thinner the image is cut, the accuracy of the test set is basically stable, while the accuracy of the training set is improved. However, there is little difference between the accuracy of 8: 8 and 10: 10, but the amount of calculation of 10: 10 is larger, so 8: 8 is chosen to segment the image.

5. Conclusion

This paper first introduces the main methods and disadvantages of lithology classification in the field of artificial intelligence at present, expounds the importance of developing a new lithology identification model, and shows the significance and value of this study. For the lithology recognition and classification model, this paper aims at the white light photos and fluorescence photos taken by the industrial camera, uses the transfer learning method to train the neural network using Desnet201 in the built-in library of torch, and chooses the Desnet201 network as our neural network framework. Then the last softmax layer is changed into a multi-layer perceptron with three hidden layers. The improved Desnet201 is used as a model to identify rock types in this paper, and the accuracy of rock classification is up to 0.85. The use of depth learning method can effectively identify all kinds of rocks, shorten the time of rock recognition, simplify the steps of rock identification, and basically meet the requirements of portability and real-time recognition in field observation. After the industrial camera captures the films and core sample photos on the site, the industrial camera is used to automatically identify the classification in real time in rock samples.

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