Rock Image Intelligent Classification and Recognition Based on Resnet-50 Model

Jinzi Liu1,a*, Wenying Du2,b, Chong Zhou3,c and Zhiqing Qin4,d
1 School of Mathematics and Statistics, Northeast Petroleum University, Daqing, Heilongjiang, 163318, China
2 School of Physics and Electronic Engineering, Northeast Petroleum University, Daqing, Heilongjiang, 163318, China
3 School of Electrical Information Engineering, Northeast Petroleum University, Daqing, Heilongjiang, 163318, China
4 School of Computer and Information Technology, Northeast Petroleum University, Daqing, Heilongjiang, 163318, China
a*Corresponding author’s e-mail: liujinzi@nepu.edu.cn, bemail: 2876939658@qq.com, cemail: 383213881@qq.com, demail: 980755568@qq.com

Abstract: Machine learning algorithms becomes popular for intelligent classification of rock images. In this paper, it selects Resnet 50 neural network model to divide the data sets based on the rock pictures taken under the white light lamp. By continuously adjusting the parameters of each layer, the intelligent classification of rocks is carried out. The training final validates accuracy reached 94.12%.

1. Introduction
In oil and gas exploration, rock images identification is the basic and important foundation. In the exploration of mineral resources, especially solid metal mineral resources, rock images identification also plays an immeasurable role. The identification and classification of rock images are very important for geological analysis. Long-standing mainly adoption methods of rock images recognition include gravity and magnetism, well logging, seismic, remote sensing, electromagnetism, geochemistry, hand specimen and thin section analysis methods, etc. Nowadays, it is one new way to establish automatic rock sample set recognition and classification model by using image deep learning method [1-5].

The classification and identification of rock samples image always judges based on manual observation, which is time-consuming, low accuracy and subjective influence. In recent years, with the popularity of machine learning, many researchers do lots of work on intelligent algorithm of rock sample image classification and recognition. However, there are still some disadvantages. The commonly uses intelligent algorithms, such as support vector machine or neural network algorithm, all have the problem of relying on artificial feature extraction in image classification. It makes the final effect greatly affected by human subjectivity and uncertainty [6-12].

Resnet-50 algorithm has distinct characteristics of jump connection and residual learning structure. It can better solve problems of deep network training, gradient disappearance, and gradient explosion. In this paper, it choose the algorithm to rock image classification and recognition.
2. Materials and Methods

2.1. Dataset description
The cuttings and core samples obtained by industrial cameras at logging site, and the white light images shoot in dark box. The data set includes seven rock categories are respectively gray fine sandstone, dark gray silty mudstone, light gray fine sandstone, gray argillaceous siltstone, gray black mudstone, dark gray mudstone, and black coal.

The basic data set consists of 300 images, each image was cut into 9 small pieces, change into 2700 small images as enhanced dataset. The above data sets divides into training set and verification set. The division ratio is 8:2. The training set is use for model training; the verification set is use for model parameter tuning. All images are standard and compress to 64×64 scale, as data pre-treatment in this study.

2.2 Resnet-50 model details
As Network structure depth increases, the first problem is gradient explosion/dissipation. Because as number of layers increases, gradient's back propagation becomes unstable with multiplication in the network, especially becomes very large or very small. Gradient dissipation is most common and serious problems.

To solve problem of gradient dissipation, batch normalization, conversion of ReLU activation function, and initialization are adopted. It can be said that the gradient dissipation is better solved. Another problem with network deepening is degradation, its performance of network deteriorates as increase in depth. Based on lots of practical experience, the depth of network structure is critical to performance of training model. As number of layers increases, the network carries out more complex feature pattern extraction. Theoretically, network deeper, the better end results.

However, experiments find that deep network architecture is degrading. With the increase of depth, the accuracy of network tends to be saturated or even decreases. The accuracy of training set will reduce. We can be sure that this is not due to overfitting. Because in the case of overfitting, the accuracy of training set should be very high. Reset networks were designed to solve this problem, and the depth of network was increases by several orders of magnitude.

ResNet presents two mappings. one is the identity mapping, as "Jump connection Polyline" in Figure 1. The other is the residual mapping-ping, as final output is y = F (x) + x. The identity map, as one name implies, refers to itself, the formula for x, and the residual map refers to "different", as residual refers to F(x)+x. The representation of residuals makes more easier to approximate multi-layer network. If the equivalent function can be approximated optimally, then the weight of the multi-layer network is simply approximated to zero, as achieve equivalent mapping.

Resnet-50 performs convolution operation on the input, then remaining four blocks, and finally the full join operation for the sorting task.

The network structure of Resnet-50 is shown in Table 1, which has 50 Conc2D operations. ResNet-50 structural networks are divided into five parts respectively conv1, conv2_x, conv3_x, conv4_x, and conv5_x. Its structure is relatively fix, only the number of channels determined according to specific input demand.

Special attention the last Average pool of ResNet50 is convert each feature map into one feature. So the pooled field size is the feature map size. For example, if the last output bit is 512x7x7, then the pooled field size is 7.
Table 1. ResNet-50 Structural parameters.

| Layer name | Output size  | 50-Layer |
|------------|--------------|----------|
| Conv1      | 112×112      | 7×7,64,stride 2 |
| Conv2_x    | 56×56        | 3×3 max pool,stride 2 |
|            |              | 1×1 64 |
|            |              | 3×3 64,×3 |
|            |              | 1×1 256 |
| Conv3_x    | 28×28        | 1×1 128 |
|            |              | 3×3 128,×4 |
|            |              | 1×1 512 |
| Conv4_x    | 14×14        | 1×1 256 |
|            |              | 3×3 256,×5 |
|            |              | 1×1 1024 |
| Conv5_x    | 7×7          | 1×1 512 |
|            |              | 3×3 512,×3 |
|            |              | 1×1 2048 |
|            | 1×1          | Average pool, 1000-d fc, softmax |
| Flops      | 3.8×10⁹      |          |

2.3 Model Optimization Parameters

In this paper, the optimization technology is composed of Residual block and ReLU. ReLU is piecewise linear, which makes its forward, reverse and derivative piecewise linear and easier optimize. The traditional sigmoid function is easy to lose information due to the saturation of both ends in the process of propagation. ReLU can make some neurons output to 0, thus leading to the sparsity of the network, reducing the interdependence among parameters, and alleviating the problem of overfitting. Some other parameters are shown in Table 2.

Table 2. Parameters for model training utilizing neural networks

| Parameters                  | Value |
|-----------------------------|-------|
| Learning rate               | 0.001 |
| Batch size                  | 64    |
| Dropout rate                | 0.2   |
| Epoch                       | 100   |
| Number of samples           | 2700  |

2.4 Model Evaluation

ACC(Accuracy) is the proportion of corrected prediction. It defines as:

\[
ACC\% = \frac{TP + TN}{TP + FP + TN + FN}
\]  

(1)

TP (true positive) is the number of positive classes identify by the model; TN (true negative) is the number of negatived classes identify by the model. FP (false positive) is the number of false positive classes predict by the model, that is, the number of positive classes predict by negatived class image, and FN (false negative) is the number of missing positive classes unidentify by the model.
When the calculation is completed, the model needs to be evaluated by statistical evaluation indicators, to verify the model. This paper used some error evaluation criteria to study the accuracy of model results. These methods include average relative deviation (ARD), average absolute relative deviation (AARD) and root mean square error (RMSE) as follows:

\[
ARD\% = \frac{100}{N} \sum_{i=1}^{N} \left( \frac{X_i^{\text{real}} - X_i^{\text{predict}}}{X_i^{\text{real}}} \right)
\]

\[
AARD\% = \frac{100}{N} \sum_{i=1}^{N} \left( \frac{X_i^{\text{real}} - X_i^{\text{predict}}}{X_i^{\text{real}}} \right)
\]

where \(N\) represents total amount of data in each set. \(X_i^{\text{real}}\) is the real value we expected from each set, and \(X_i^{\text{predict}}\) is the corresponding predicted value calculated by the neural network.

Loss function choose Mean square variance formula (RMSE).

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( X_i^{\text{real}} - X_i^{\text{predict}} \right)^2}
\]

3. Results & Discussion
The model training process use Deep Network Designer Toolbox of MATLAB. This toolbox directly visualizes training process. Final optimal parameters as input adjustment value are shown in Table 2. After 200 iterations, the accuracy of training set is 97.83%, the accuracy of verification set is 94.12%, and the loss reduction is less than 0.1, in Figure2.

![Figure2](image)

Figure2. Training process accuracy and loss decline process chart

4. Conclusions
Aiming at the problem of rock images classification, this paper adopts effective ResNet-50 residual network, and verifies the data set. The experimental results show that it has obvious effect in terms of average recognition accuracy and loss reduction.

In the future research, we will try to improve Resnet50 residual network model, strengthen performance of multi-layer forward-feed neural network. It continues to optimization improve the accuracy of rock image classification.

Acknowledgments
This work was supported by the State Key Program of National Natural Science Foundation of China (Grant No.51834005), and the Guiding Innovation Fund Project of Northeast Petroleum University (Grant No. 2020YDL-01; Grant No. 2020YDL-06).
References

[1] Yuxuan X., Xu Y. X., Dai Z. Y., Luo Y. X. (2020) Research on Application of Image Enhancement Technology in Automatic Recognition of Rock Thin Section. IOP Conference Series: Earth and Environmental Science, 605(1): 1-7.

[2] Singh A., Regenauer L. K., Mostaghimi P. (2019) Investigating rock micro-structure of sandstones by pattern recognition on their X-ray images. ASEG Extended Abstracts, (1): 1-3.

[3] Yan L., Danling S., Fengju B. (2019) Automatic Recognition of Rock Images Based on Convolutional Neural Network and Discrete Cosine Transform. IIETA, 36(5): 463-469

[4] Wei X. S., Qin X. H., Rong C. L., et al. (2014) Image Classification Recognition for Rock Micro-Thin Section Based on Probabilistic Neural Networks[J]. Applied Mechanics and Materials, 602-605: 2147-2152.

[5] Mariusz M., Andrzej G., Bartłomiej Ś. (2013) The application of pattern recognition in the automatic classification of microscopic rock images. Computers and Geosciences, 60: 126-133

[6] Li B., Lima D. (2021) Facial expression recognition via ResNet-50. International Journal of Cognitive Computing in Engineering, 2: 57-64.

[7] Ramkumar M. O., Sarah Catharin S., Ramachandran V., Sakthikumar A. (2021) Cercospora Identification in Spinach Leaves Through Resnet-50 Based Image Processing. Journal of Physics: Conference Series, 1717: 1-7.

[8] Deng Y. J., Yin J. T., Wang Y., Chen J. G., Sun L., Li Q.L. (2021) ResNet-50 based Method for Cholangiocarcinoma Identification from Microscopic Hyperspectral Pathology Images. Journal of Physics: Conference Series,1880(1): 1-7.

[9] Li M. Ch., Fu J. k., Zhang Y. Liu Ch. Zh. (2020) Intelligent recognition and analysis method of rock lithology classification based on coupled rock images and hammering audios. Chinese Journal of Rock Mechanics and Engineering, 39(5): 996-1004.

[10] Zhu Sh. Sh., Yang W.Y., Hou G. Sh., Lu B. B., Wei Sh. P., (2020). An intelligent classification and recognition method of rock slice . Acta Mineralogica Sinica, 40(1): 106.

[11] Long Wen, Xinyu Li, Liang Gao.(2020) A transfer convolutional neural network for fault diagnosis based on ResNet-50. Neural Computing and Applications, 32: 6111-6124.

[12] Lima R., Duarte D., Nicholson C., et al. (2020) Petrographic microfacies classification with deep convolutional neural networks[J]. Computers & Geosciences, 142: 104481.