

Residual Neural Networks for Gemstone Recognition and Classification

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Abstract: For rapidly and accurately identifying and classifying different gemstones, a residual neural network-based gemstone classification and recognition model is presented using the image feature differences of 15 classes of gemstones. The gemstone image set is firstly established, then the image set is expanded using the data enhancement method, and afterwards the sample data set is obtained using the data cleaning method. The images are divided into training and test sets in the ratio of 8:1, and then the training set is trained using a residual neural network (ResNet 50). Finally, the correctness of the network is evaluated. The experimental results show that the average accuracy of this gem classification and identification algorithm reaches 93.46%, and basic engineering applications can be achieved.

Keywords: Residual Neural Network; Identification; Gemstone

1. Introduction

With the rapid development of computer technology and the improvement of computer hardware performance, deep learning has made great progress [1]. Computer vision technology and pattern recognition technology provide new paths and methods for gemstone identification and classification, and they work well in practical applications. As the number of neural network layers continues to deepen, the difficulty of training the CNN model will gradually increase as well [2]. In response to the difficulty of training deep CNN models, K. He et al. [3] of Microsoft Research Asia proposed the ResNet model in 2015.

Compared with the traditional convolutional neural network, a shortcut-connection was used by the residual building block to skip the convolutional layers, which effectively alleviates the problem of gradient disappearance or gradient explosion caused by increasing depth in the neural networks. [4] Residual Neural Network also has the advantages of deeper layers, less number of parameters, faster convergence, and higher accuracy. At the heart of ResNet lies the use of a residual module to address the problem of model degradation in deep networks.

Therefore, this study proposes constructing a gemstone classification and recognition model based on the deep residual neural network ResNet50 algorithm. The acquired image set is data enhanced and cleaned, and then the images are divided into training and test sets in a ratio of 8:1. The training set was placed in the ResNet50 model for training and tested with a test set to obtain accuracy metrics for the model and illustrate the usefulness of residual neural networks in gemstone classification.

2. Model Algorithm Structure

ResNet gem classification and recognition algorithm research, the main steps include image acquisition, data enhancement, data annotation, ResNet model training, and other measures. Figure 1 will present the exact process.

This study focuses on the use of ResNet 50. A residual neural network (ResNet) is a class of deep transfer learning based on a residual network [5]. One of the basic residual learning modules is shown in Figure 1. x is the system input, $H(x)$ is the system target mapping, and $F(x)$ is the network mapping before summation. The core idea is that instead of learning an ideal target mapping $H(x)$ directly by stacking convolutional networks, the system learns the residual function $F(x) = H(x) - x$ because it is difficult to achieve a mapping from x to $H(x)$ directly. A deep residual neural network is a stack of multiple residual blocks. As residual learning highlights small changes in the learning process and

automatically eliminates some of the redundant layers in the implicit layer, residual mapping is more straightforward to optimize than traditional mapping methods, thus solving the problem of performance degradation in deep networks.

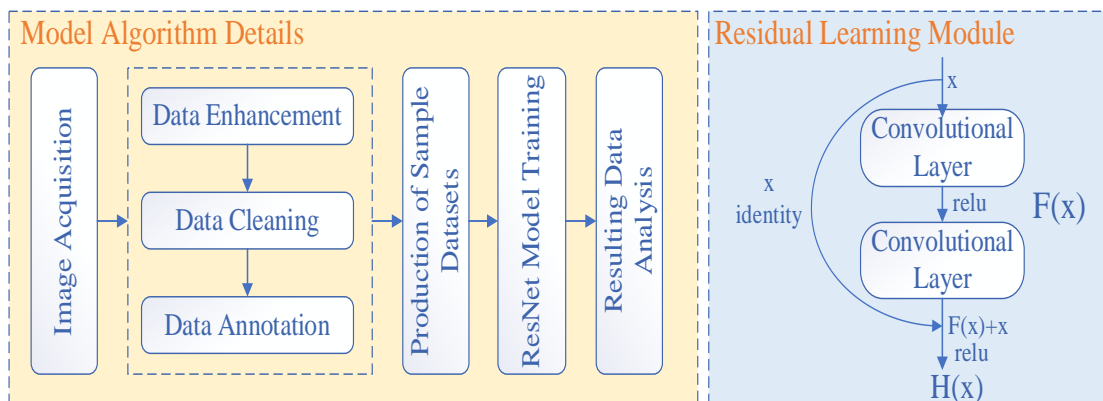


Figure 1: Model Algorithm Details & Residual Learning Module

ResNet 50 contains four large blocks, each with several bottlenecks (3+4+6+3 = 16 bottlenecks in the structure picture), and finally, a fully-connected network is used to complete the classification task. The whole model has a total of 50 convolutional layers. Figure 2 shows the exact structure.

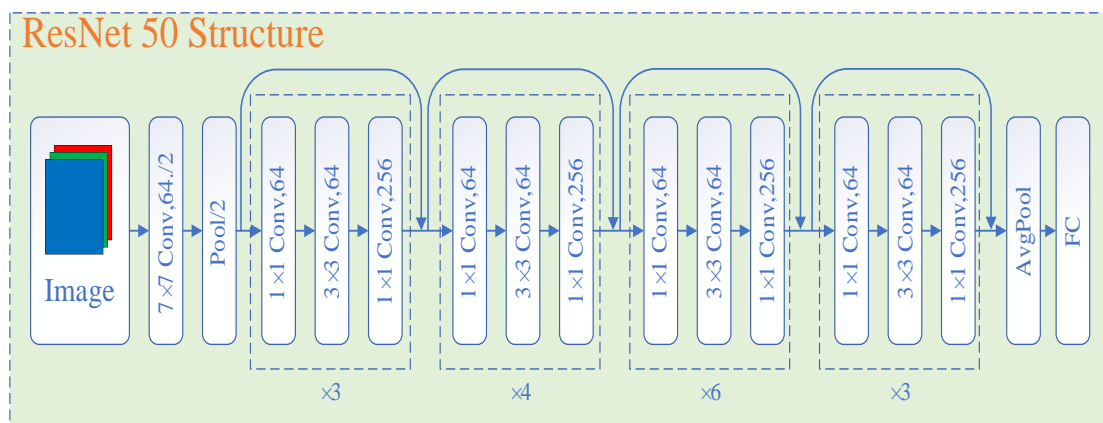


Figure 2: ResNet 50 Structure

3. Sample Image Processing

The primary source of sample data is the open dataset of the Web. However, the number of samples in the public dataset is minimal. Theoretically, the more images of each gemstone, the better, so the sample data was expanded manually to include a total of 1789 images of 15 gems. Since most of the images in the sample database were in JPG and PNG formats, the sample data were batch processed and converted to JPG format.

After converting the format, the images need to be cropped to become $224 \times 224 \times 3$ color images. Then, 1789 images were processed with data enhancement by rotating, panning, and scale transformation to expand the sample to 8156 images.

In order to improve the labeling efficiency and reduce the unevenness of the samples, it is necessary to clean the gemstone image data to exclude a large number of distorted pieces that are impossible to be recognized. In this study, manual cleaning was done, and 7429 images were obtained from 8156 images. The obtained images were divided into data according to the ratio of 8:1. 6605 images from 7429 data were used as the training set, and 824 images were used as the test set. The specific number of images and annotation types are shown in Table 1.

Table 1: Gemstone Data Sheet

Gem Image						
Training Sample	55	57		58	54	52
Test Sample	442	457		464	435	416
Label	0	1		2	3	4
Gem Species	Alexandrite	Almandine		Benitoite	Cats Eye	Carnelian
Gem Image						
Training Sample	54	52		58	56	55
Test Sample	433	416		465	448	442
Label	5	6		7	8	9
Gem Species	Beryl Golden	Danburite		Diamond	Emerald	Fluorite
Gem Image						
Training Sample	54	55		56	55	53
Test Sample	432	441		448	441	425
Label	10	11		12	13	14
Gem Species	Garnet Red	Hessonite		Iolite	Jade	Kunzite

4. Model Training

The network model uses the deep learning open source framework PaddlePaddle. programming and model training are performed using personal laptops. The required software and its development tools include python 3.7.4, paddlepaddle-gpu 2.2.2, scikit-image 16.2, numpy 1.19.3, matplotlib 3.3.4, opencv-python 4.5.5.62, etc.

The model uses the ReLU activation function, The function is represented as follows, the learning rate a is set to 0.1, and the optimizer uses Adam and the default parameters. The model is trained for 100 iterations.

$$\text{ReLU}(x) = \begin{cases} 0, & x < 0 \\ x, & x > 0 \end{cases} \quad (1)$$

5. Results

After nearly 100 iterations, the error values of the training set converge and stabilize. The loss function uses the Cross Entropy Loss Function.

$$L(input, target) = -\log \frac{e^{input[target]}}{\sum_{j=0}^N e^{input[j]}} = -input[target] + \log \left(\sum_{j=0}^N e^{input[j]} \right) \quad (2)$$

The loss function curve and the correctness curve of the residual neural network model training will be shown in Figure 3.

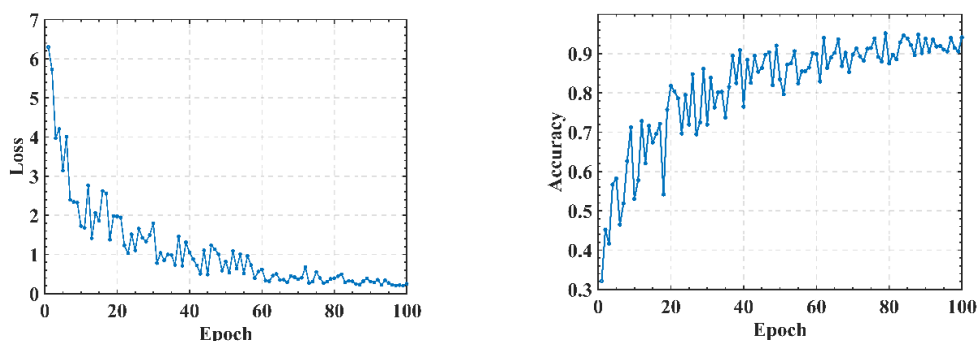


Figure 3: Loss and Accuracy

The neural network weights with the smallest and closest error values between the training set and the test set are selected as the optimal weights, and this optimal set of network weights is the network model obtained from the training.

Table 2: Accuracy Rate Detail Table

Lable	Accuracy	Lable	Accuracy	Lable	Accuracy	Lable	Accuracy
0	89.40%	4	96.41%	8	93.85%	12	92.63%
1	88.91%	5	94.75%	9	94.91%	13	94.02%
2	94.14%	6	95.12%	10	92.31%	14	94.51%
3	94.89%	7	93.51%	11	92.58%	average	93.46%

As can be seen from Table 2, the average recognition accuracy of various gemstones has reached 93.5%. The recognition accuracy of diamond and cat's eye gemstones has been as high as 95.12% and 96.41%, basically meeting the requirements of engineering applications.

6. Conclusion

In this paper, a gemstone image classification and recognition algorithm based on ResNet50 is proposed based on 15 gemstone images, and the following conclusions are obtained.

(1) Alexandrite, Almandine, Benitoite, Beryl, Golden, Carnelian, Cats Eye, Danburite, Diamond, Emerald, Fluorite, Garnet Red, Iolite, Jade, Kunzite gems, Hessonite using ResNet 50, were classified, and the average recognition accuracy has reached 94%. The test results show that it is feasible to organize gemstone images using this method, and it has high detection accuracy, which meets the requirements of engineering applications.

(2) With the continuous development of deep learning, more efficient and accurate neural networks can be applied to the gemstone identification industry to achieve faster and more precise classification and identification.

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