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Research Article

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Classification and Recognition of Underground Tectonic Coal Image based on BCNN

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Abstract: The classification and recognition of underground tectonic coal images can provide information support and technical support for the prediction of coal and gas outburst accidents, the evaluation of underground safety and the construction of intelligent mine engineering. The traditional identification method is greatly affected by the complex environment and personal experience factors in the underground field. Aiming at this problem, an automatic tectonic coal image classification model based on improved bilinear convolutional neural network (B-CNN) is proposed. Firstly, the Retinex image enhancement algorithm is used to enhance the image of the data set, and the data set is expanded to avoid the risk of over-fitting. Then, the lightweight MobileNetV2 network is used instead of the original feature extraction network VGG to improve the extraction ability of the main features of the underground tectonic coal. The attention mechanism is introduced, and the transfer learning is combined to improve the accuracy of image classification. The experimental results show that the model can effectively identify the uneven illumination of underground shooting, and the comprehensive recognition accuracy can reach 93.66%. This method can better identify the type of tectonic coal.

Keywords: coal and gas outburst; coalbed methane; tectonic coal; intelligent identification; image recognition

1. Introduction

The production and utilization of coal plays a dominant role in energy consumption in China and even in the world. China is one of the countries with the largest coal consumption in the world and one of the countries with the most serious coal and gas outburst accidents in the world, often causing casualties and economic losses. In the process of coal mining, how to avoid gas disaster and how to make better use of gas has become the focus of attention. In the process of green mine construction, China’s coal safety situation continues to improve, and the goal of "low accident, low death" has been gradually achieved. However, from the number of coal and gas outburst accidents, the problem is still severe. Due to the complexity of the geological conditions of coalbed methane occurrence and the immaturity of the key technology of coalbed methane development, the production of coalbed methane wells in China is generally low, unstable and decays rapidly. Tectonically deformed coal is one of the important factors that cause coal and gas outburst, and it is also an important factor affecting the development effect of coalbed methane. Under the influence of tectonic stress, tectonic coal presents the characteristics of "three low and one high" with low porosity, low permeability, low pressure and high heterogeneity, which is easy to induce gas disaster. The type of tectonic coal is the key factor in the risk assessment of coal and gas outburst. The adsorption capacity of coal with different failure types to gas is different, and the physical and mechanical properties are quite different. Many typical outburst accident cases surface outburst occurred in tectonic coal seam, a serious threat to coal mine safety production [1]. Therefore, the research on the characteristics of coal structure can provide theoretical support and scientific basis for the prediction of coal and gas outburst accidents and the exploration and development of coalbed methane, so as to realize the co-mining of coal and coalbed methane and inhibit the occurrence of coal and gas outburst accidents.

Due to the obvious macroscopic difference between tectonic coal and primary coal, it is still mainly based on artificial physical observation and identification, which is greatly affected by physical environment and subjective factors, and the efficiency is low. For the complex and harsh underground environment that is difficult for some personnel to reach, the traditional manual identification method is difficult to implement. Therefore, it is particularly important to find a new, more effective and more direct recognition method.

In recent years, many scholars have conducted in-depth research on coal-rock recognition technology and proposed a variety of methods to provide theoretical guidance for the development of coal-rock recognition technology and the intelligent construction of fully mechanized mining face [2]. With the development of machine vision image recognition and deep learning, coal-rock recognition technology based on image processing has gradually become an important research direction to solve the problem of coal-rock recognition [3,4,5]. Based on the analysis of the above research, the current research mainly focuses on the classification and recognition of coal and rock images. Most of them are applied to fully mechanized mining face, and there are few studies in the field of coal mine safety.

The use of intelligent equipment for tectonic coal image recognition can not only reduce the risk of mining personnel and reduce the incidence of accidents but also help to solve the classification needs of personnel who are difficult or unable to reach the mining face, and complete the project needs in a timely and efficient manner. Compared with traditional classification methods, the image classification method based on deep learning can avoid the influence of subjective factors of manual classification, has higher classification accuracy and faster classification speed, and can save manpower cost to a greater extent.

Based on bilinear convolutional neural network and transfer learning method, this paper proposes an improved bilinear convolutional neural network for tectonic coal image classification. The experimental results show that the model can effectively identify the type of tectonic coal, improve the classification accuracy and improve the classification efficiency. It provides new ideas for improving the level of coal mine intelligence and ensuring coal mine safety, and has high theoretical significance and application value.

2. Materials and Methods

A. Data sets and preprocessing

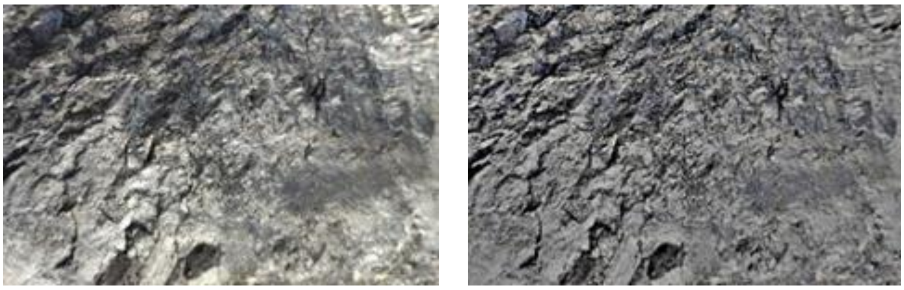
The data set used in this paper uses an industrial camera to take photos of tectonic coal underground. The distribution of various types of data in the data set is shown in Table 1, which is divided into a training set and a validation set in a ratio of 7:3, including Primary structural coal, Destructive coal, Strongly destructive coal, Pulverized coal, fully molded coal5 image data.

Table 1: Specification of Models in stage

Coal body category	Number of pictures
Primary structural coal	450
Destructive coal	482
Strongly destructive coal	398
Pulverized coal	412
Fully pulverized coal	414

In the study of image classification of tectonic coal in underground coal mine, due to the influence of complex and harsh environmental factors in underground coal mine, there will be low quality features such as low illumination, weak edge, uneven illumination and low contrast in image imaging. These factors lead to the characteristics of tectonic coal are not obvious and clear enough.

In order to solve these problems, Retinex image enhancement algorithm will be used. Through comparative analysis, Multi-Scale Retinex with Color Restoration (MRCR) method is finally selected [6]. The data set is processed by MRCR, and the comparison before and after processing is shown in Figure 1.



(a) Artwork *(b) After MRCR treatment*

Figure 1: Comparison chart before and after treatment

B. MobileNetV2 Network Model Structure

MobileNetV2 proposed in 2018, is an efficient and lightweight convolutional neural network architecture designed to provide an efficient balance between performance and model size. Compared with the MobileNetV1 network, the performance and efficiency of the network have been significantly improved. In the experiment, MobileNetV2 shows its excellent performance on tasks such as ImageNet classification and COCO target detection.

The MobileNetV2 model proposes a new hierarchical structure: the inverted residual with linear bottleneck. Firstly, the low-dimensional compression expression of the input data is extended to high dimensions, and the lightweight deep convolution is used for filtering. Then, linear bottleneck is used to map features to low-dimensional compressed expressions. This structure can reduce the number of parameters and computational complexity of the model and maintain high accuracy. At the same time, in order to avoid the possible loss or destruction of information caused by using the ReLU activation function, the last convolutional layer of the bottleneck structure no longer uses the ReLU activation function but uses the linear activation function.

The use of MobileNetV2 network can make the model pay more attention to feature channels and suppress useless information. It not only reduces the size parameters and computational complexity of the network but also reduces the complexity of the network while maintaining high accuracy. It is especially suitable for deployment on mobile and embedded devices.

C. BCNN

The Bilinear Convolutional Neural Network (B-CNN), proposed by Lin et al. in 2015, is an end-toend model [7]. Its structure is mainly composed of two branch networks, which use VGG-A and VGG-B respectively to extract features. After the network performs feature extraction, it will conduct a bilinear pooling operation on the image features extracted by the two branches.

D. Transfer Learning

Training a deep neural network from scratch is an extremely time-consuming task. Transfer Learning is introduced here. The goal of transfer learning is to use the knowledge learned by the model in a certain field. It can be applied to related tasks with only minor changes, which greatly reduces the time cost[8].

In this paper, MoblieNetv2 trained by ImageNet dataset will be used as the underlying feature extraction network, and the underlying features learned in ImageNet will be transferred to the image recognition network as the initialization parameters of the network to learn and construct the model.

3. Results & Discussion

A. Experimental Environment

This experiment was carried out on a computer with CPU model 11th Gen Intel (R) Core (TM) i9-11900F, GPU RTX 4070, and memory (RAM) 32G.

B. Experiment Setting

The epoch of the model training in this experiment was 200 times, the batch-size was set to 32, and the initial learning rate was 0.001. The Adam optimizer was used to train the entire network.

C. Experimental Parameters and Evaluation Criteria

The epoch of the model training in this experiment was 200 times, the batch-size was set to X, and the initial learning rate was 0.001. The Adam optimizer was used to train the entire network.

Accuracy, precision, recall and F1 score are selected as evaluation indexes to measure the classification effect of the model.

D. Experimental Results and Analysis

The loss function and accuracy curve of the model training process are shown in the figure. The accuracy of the final model on the test set reached 93.66 %.

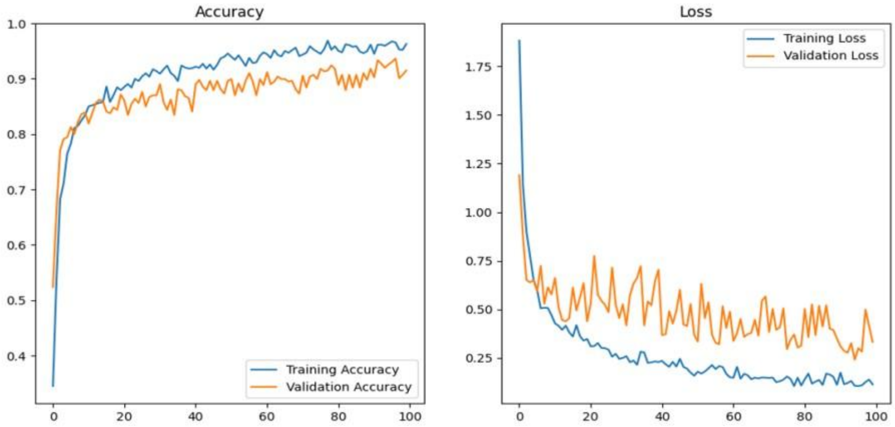


Figure 2: Loss curve and accuracy curve of network training process

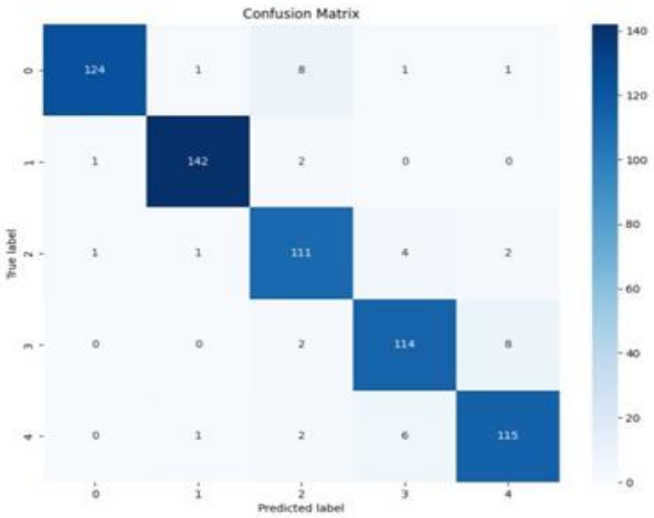


Figure 3: Confusion matrix

In order to better evaluate the classification performance of the model, the confusion matrix is introduced to reveal the classification performance of the improved model. Figure 2 shows the recognition results of the model in the test set. Tags 0-4 represent Primary structural coal, Destructive coal, Strongly destructive coal, Pulverized coal and Fully pulverized coal, respectively.

The confusion matrix is shown in Figure 3.

The experimental results show that the classification accuracy of the model proposed in this paper is 88.8 % and above all kinds of tectonic coal, and the highest can reach 98.41 %. It shows the strong application potential of the model.

4. Conclusion

Aiming at the shortcomings of tectonic coal classification and recognition methods, this paper proposes an image classification method based on improved bilinear convolutional neural network and transfer learning, and establishes an end-to-end tectonic coal image recognition model. The model uses MobileNetV2 as a feature extraction network. In addition, the attention mechanism is introduced to further improve the recognition ability of the model. The experimental results show that the accuracy of the model proposed in this paper reaches 93.66% on the test set, and the classification accuracy of various types of tectonic coal is 88.8 % and above, which can better distinguish different types of tectonic coal.

Tectonic coal image recognition based on deep vices has important application prospects in ensuring coal mine safety production process, but it also faces many challenges. First, the data set scene is simple and the richness is insufficient. Since there are few public data sets specifically for the identification of tectonic coal types, more samples need to be taken in the later stage to further expand the diversity and complexity of the data set and enhance the generalization and robustness of the model. Secondly, the underground environment of coal mine is bad, and the image enhancement technology for mine still needs to be strengthened.

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