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Weather Recognition Algorithm based on Convolution Neural Network

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Abstract: With the development of deep neural network, its excellent performance in the field of vision has attracted the attention of scholars at home and abroad. The method based on convolutional neural network (CNN) has become the most important tool to solve related tasks in the field of vision. In this paper, the weather recognition algorithm based on CNN is studied. This paper first analyzes the structure and characteristics of CNN. Aiming at the problems of low accuracy of existing weather image classification methods and slow model training speed, transfer learning method is introduced on the basis of deep CNN, which can greatly shorten the model training time and obtain better classification effect.

1. Introduction

Weather recognition is a relatively new research direction in the field of mechanical vision. Compared to the general image sorting tasks, the difficulty of weather phenomenon recognition lies in the unique attributes of weather. The same target elements may exist in different categories of weather images, which makes the traditional feature extraction methods such as SIFT and HOG unable to extract effective features from weather images for weather recognition [1-2]. In recent years, with the development of deep learning technology, various universities and research institutes have been putting forward image restoration algorithm framework based on neural networks, from combining with traditional methods to end-to-end restoration network, from shallow network to deep residual network, making the field of image restoration gradually become a hot research direction [3]. For the field of weather image restoration, there are many excellent open source datasets, including rainy, foggy and snow days, etc. Some datasets are also labeled with relevant detection labels to verify the effect of restored images on advanced visual tasks [4]. However, there are still a lot of problems in the current algorithm. For weather recognition, classification is mostly based on static weather, while few scholars have studied the dynamic capture weather recognition, and there is no relevant open source data set to provide training [5].

Different weather conditions, such as fog, rain and snow, will destroy the visual effects on the image, which will seriously damage the performance of the outdoor vision system, resulting in the failure of the image and video based object detection, tracking, recognition and scene analysis system. In order to solve these problems, weather image restoration has been proposed and received great attention [5-6]. Early weather classification methods only divided a given image into sunny or cloudy days, while some later studies gradually expanded the weather classification labels to rainy, foggy and snowy days [7]. A key to weather recognition or classification is how to extract recognition features. In order to solve this problem, some manual feature extraction methods have been proposed [8]. With the rise of CNN in computer vision tasks, and a large number of studies have shown that Neural Networks play a very effective role in vision tasks. Some methods based on CNN model have also been designed for weather recognition [9]. Specifically, some scholars first proposed to use AlexNet network to recognize two types of weather images (sunny day and cloudy day), and the accuracy could reach 94.5% through automatic extraction of recognition features by CNN [10]. Compared with the traditional manual feature extraction method, it has a good robustness to multiple weather categories. Specifically, the AlexNet network pre-trained on ImageNet is first used. The modified network is then trained on two kinds of weather datasets.

Recognition algorithm based on the current weather phenomenon existing problems and challenges, in this study, the main variety of deep learning weather pattern recognition algorithm, based on the classical model of CNN and migration to improve the learning methods, put forward a kind of also have higher recognition accuracy and faster speed of CNN model, and can be applied to real life.

2. Weather Recognition Algorithm based on CNN

2.1. CNN Model

Image classification is the most basic and common task in the field of computer vision. Generally speaking, it is to give an image and then correctly give the category to which the image belongs [11]. When solving the image classification task, traditional machine learning methods generally use feature description algorithm to extract features first, and then send the extracted features to the classifier for image classification. These two stages are completely independent, and the performance will affect each other [12]. CNN is developed through the study of the cognitive principle of human brain, especially the visual principle [13-14].

FIG. 1 shows the local link structure diagram of convolutional layer.

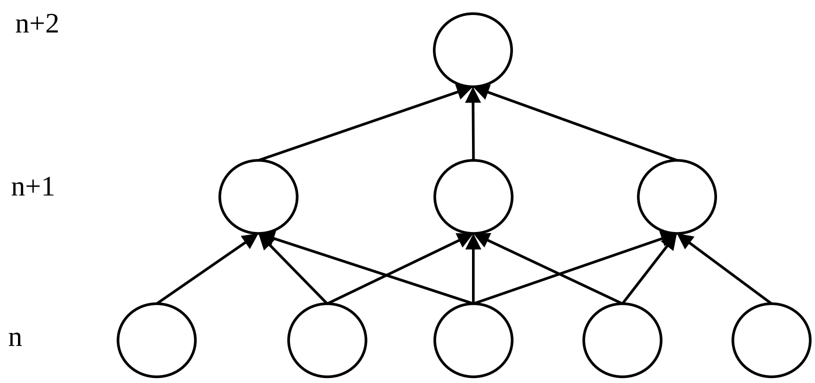

Figure 1. Local connection structure diagram

The convolution kernel is also known as the filter, and the features of the image can be extracted by convolution operation of the input image using the convolution kernel [15-16]. The confusion core slides into the input image. The pixel value in the area whose position size is equal to the convolution kernel size in the input image is multiplied by the value in the corresponding convolution kernel and then added [17-18]. The formula for the convolutional layer is:

$$z_i^k = f(W_i^k * Z_{i-1}^k + b_i^k) \tag{1}$$

Where Z represents the mapping of layer I characteristics, W represents the confusion nucleus and B represents the displacement value.

2.2. Optimal CNN Model Based on Transfer Learning

In the study of weather phenomenon recognition, it is very difficult to ensure the effectiveness and generalization of the model if we build our own deep network model at the beginning. Because the construction of deep network model requires a large sample size for training, millions of network parameters will also be generated, which is a great test for model design and hardware equipment. Therefore, based on the transfer learning algorithm, the previous trained image recognition network model is used to verify the weather phenomenon recognition effect, which builds a good foundation for the subsequent work.

In order to verify the effect of deep learning application in weather phenomenon recognition, transfer learning idea based on shared model is selected to test the effectiveness of deep learning. The CNN model trained by previous studies on large-scale data sets is used as a pre-trained model to learn the weather data, and the excellent network parameters and powerful feature extraction ability of the model are used to mine information. Then the model is fine-tuned to transfer its recognition ability to the weather data. Finally, the effect is tested.

In this paper, DenseNet model is selected as the learning object, which is a relatively new algorithm in the field of image recognition. Through training on four public datasets, CIFAR-10, CIFAR-100, SVHN, ImageNet ILSVRC2012, The network has adjusted the parameters with good generalization, strong feature extraction ability and good recognition effect.

The DenseNet network structure is used as a pre-training model for weather phenomenon recognition, and its structure and characteristics are retained to mine the features of weather images. A small amount of weather data is used to test the recognition effect of the model. The network consists of input volume layers, 4 densely connected dense blocks, 3 pooled and balanced Transition layers and a classification Layer:

Three Dense blocks are set. The nonlinear function of each layer in the model is composed of batch normalization operation, ReLU activation function and 3×3 convolution to ensure the same size of the feature maps in each Dense Block.

Add Transition Layer in Dense Block for pooling and dimensionality reduction operation.

The model uses 224×224 RGB image 3-channel input, and the first layer of convolution uses 7×7 convolution kernel to extract image features.

Dense Block 3×3 convolution before adding 1×1 convolution, because the input of each layer and all the layers in front are connected, will cause a burden to the network, so in order to ensure the characteristics of each channel while dimensionality reduction;

In the Transition Layer, 1×1 convolution is added to further compress parameters, and average pooling is selected to retain more background information corresponding to weather phenomena.

The moving step of all convolution layers is 1, and the edges are filled with zeros. The step of all pooling layers is 2, and no zeros are filled.

Finally, a Softmax layer is connected to classify the data.

The last layer of the network layer has been modified, Softmax is the logistic regression of the problem of multiple classification, which acts as a classifier. That is, for input X, the test result is one of the categories, as shown in Formula (2) :

$$p(y=k/x), y^{(i)} \in \{1,2,...,k\} \tag{2}$$

Where x is the input, y is the classification label, and K is the classification category. In the original model, this layer is used to classify and identify 1000 types of images in the ImageNet database. Since this topic is used to identify six types of weather phenomena, such as haze, dust, rain, snow, frost and dew, Softmax is designed to perform regression on six types of data.

3. Model Experiment Setup

3.1. Experimental Environment

The experimental hardware platform of this work is presented in Table 1.

Table 1. Environment configuration

Experimental	Configuration instructions
CPU	Intel Core i7-7820x
GPU	NVIDIA RTX 2080
Memory	32G
System	Ubuntu

3.2. Experiment Content

In order to explore the influence of transfer learning method on weather image recognition, the network model trained with transfer learning method and the network model trained without transfer learning method are respectively tested, and the accuracy and loss function value change curves are drawn respectively.

In order to demonstrate that the method based on transfer learning is effective, the performance of the proposed method is compared with other common CNN models.

4. Analysis of Experimental Results

4.1. Weather Recognition Experiment

As shown in Figure 2 and Figure 3, compared with the network model without transfer learning method, the network model with transfer learning method has higher initial accuracy, and can quickly reach a relatively high accuracy and converge, and the fluctuation range of the accuracy change curve is small. The loss function value of the network model using transfer learning method decreases to a small value in a short time and remains unchanged gradually. However, the loss function value of the network model without transfer learning method fluctuates up and down and gradually converges after a long time. It can be seen from the above analysis that using the transfer learning method to train the model can improve the performance of the model, speed up the model training process and make the model acquire higher classification accuracy in a short time.

Figure 2. Comparison of network model accuracy before and after transfer learning

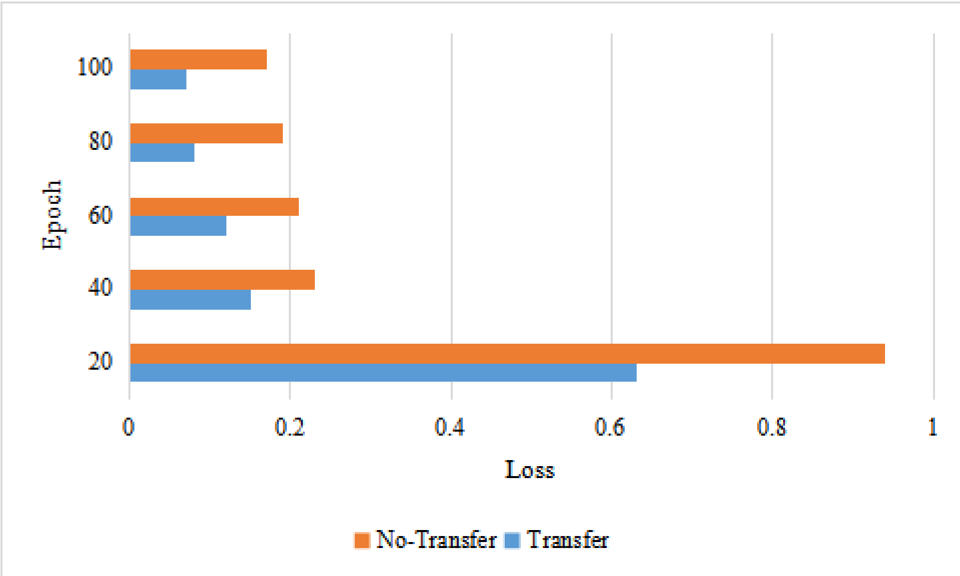

Figure 3. Comparison of network model loss changes before and after transfer learning

4.2. Performance Comparison of Different Models

Table 2. Performance comparison of multiple models

Model	Accuracy	Time(h)
AlexNet	75.21%	2.7
VGG19	81.05%	3.8
GoogLeNet	89.53%	4.4
Transfer	93.17%	2.0

From Table 2, we can see that the classification accuracy of the network model based on transfer learning proposed in this paper is the highest. Meanwhile, in terms of training time, the network model based on transfer learning only takes 2 hours to complete the model training, which is much faster than other network models.

5. Conclusion

The field of autonomous driving, or UAV, is highly susceptible to the influence of weather conditions, and how to effectively identify the weather is an extremely important part of the subsequent recovery task. Aiming at the problems of low recognition accuracy and slow modeling speed of existing weather image classification methods, this paper sorts weather images based on transport learning. The network model trained based on transfer learning method is compared with other models. In this paper, CNN, transfer learning and other related technologies are carefully studied to realize the classification of basic weather types. However, there are still many shortcomings and can be done better: The network model used in this paper still occupies too much memory to be well deployed on mobile devices for practical application. Therefore, we will consider using model compression technology to reduce the size of the model in the later stage, so that it can be better deployed on mobile devices.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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