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Research on Image Classification of Recyclable Garbage Based on Transfer Learning

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Abstract

In order to identify and classify recyclable garbage more efficiently, this paper proposes a recyclable garbage image classification model based on transfer learning. This model uses ResNext101 as a neural network model and uses transfer learning methods to identify and classify garbage. The data set is manually divided into five categories: cardboard, waste paper, plastic, glass and metal. In each classification, 80% of the samples are randomly selected as the training set of the experiment, and the remaining 20% are used as the test set of the experiment. Under the Pytroch deep learning framework, migration learning is performed on the ResNext101 pre-training model based on the training set to form a new ResNext101 classification model. The experimental results show that the accuracy rate of garbage image classification using this model method has reached more than 90%.

Keywords

Transfer Learning; Garbage Classification; Deep Learning.

1. Introduction

The current recycling plants for recyclable garbage mainly use physical methods to sort the recyclable garbage. Methods include size screening, bounce sorting, air sorting, liquid flotation, eddy current sorting and other technologies. Manual sorting is even more of an indispensable link. Manually can be used to select those large-size targets that cannot be identified by mechanical sorting, as well as further quality control after various mechanical sorting processes. In order to solve this problem, this paper proposes a recyclable garbage image classification model based on migration learning to achieve accurate identification and classification of recyclable garbage targets. Deep learning is an important breakthrough in the field of artificial intelligence in the past decade. It has achieved great success in many fields such as image and video analysis, speech recognition, computer vision, natural language processing, and multimedia. Using deep learning solutions such as convolutional neural networks can gradually replace traditional image processing tasks based on algorithm descriptions[1]. Deep learning, with its super-high prediction accuracy in recognition applications, is bound to bring about profound changes in many traditional industries, including garbage classification. According to my country's current standards, it can be divided into food waste, recyclable garbage, hazardous garbage, and other garbage. Recyclable garbage can be further divided into waste paper, waste plastic, waste electronic products, waste fabric, waste metal, waste glass, etc.

2. Transfer learning

The so-called deep learning is actually a broader type of machine learning based on artificial neural networks. The deep learning architecture includes convolutional neural networks, deep neural networks, and recurrent neural networks. Deep learning imitates the human brain and works by

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learning data representation. This requires training through a large amount of data. Through high-quality and sufficient data training, more comprehensive image features can be learned, thereby enhancing the robustness of the model And generalization[2].

2.1 Selection of Deep Learning Framework

The commonly used frameworks now include Tensorflow, Pytorch, and Keras. Because the Pytorch framework has powerful GPU-accelerated tensor calculations and supports dynamic neural networks, Pytorch was finally selected as the framework. In the actual application of garbage classification, due to the large differences in garbage morphology and background changes, it is not conducive to effective classification, so it is particularly important to select an appropriate backbone network. Convolutional neural networks need a backbone network with an appropriate number of network layers and efficient to obtain feature information[4].

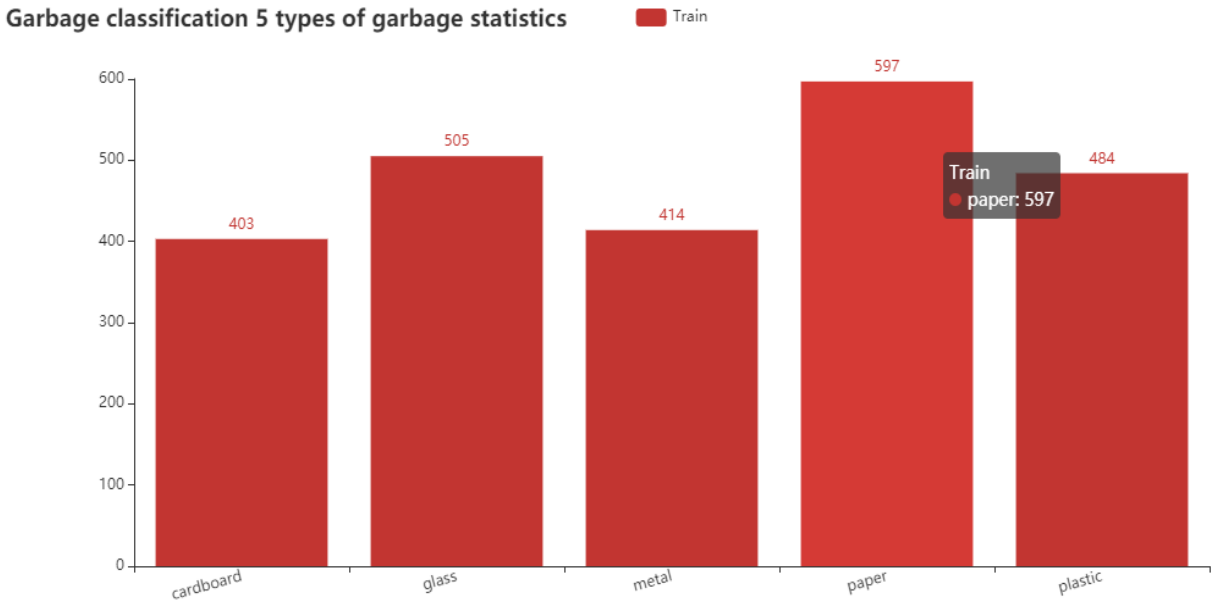

Figure 1. Data set distribution

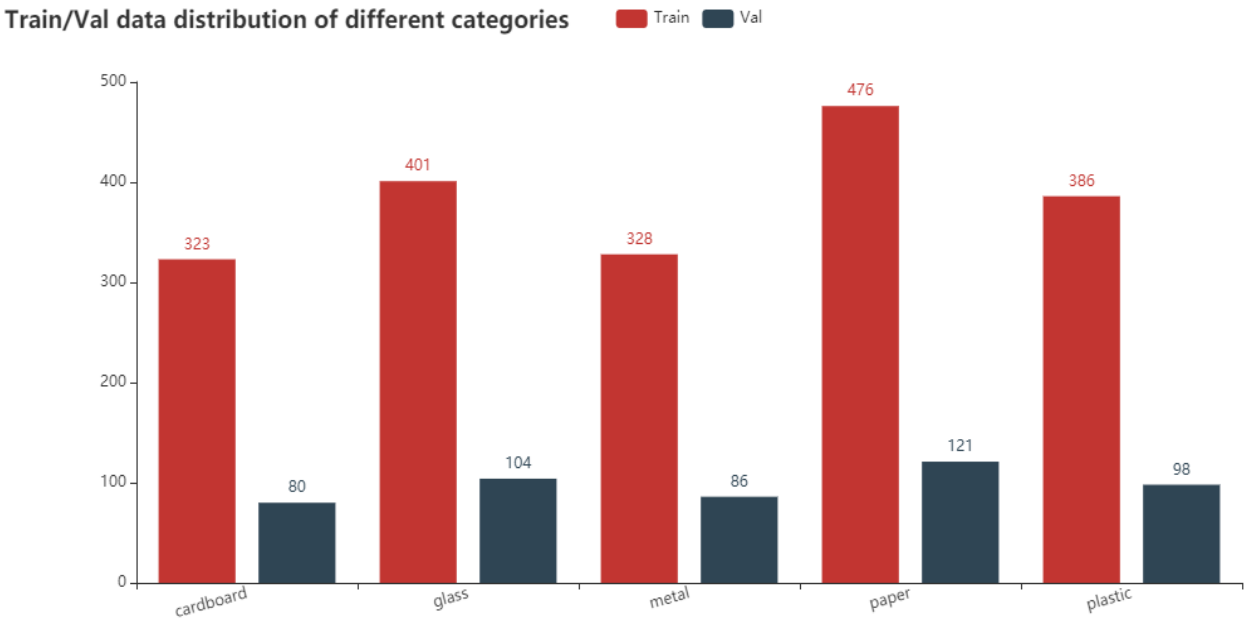

Figure 2. Training and test data set distribution

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2.2 Selection of Data Set

The image data set of this research is based on the garbage image data set created by GaryThung and MindyYang. The data set consists of 1989 pictures, divided into 5 categories: glass, paper, plastic, metal, and cardboard. The size of all picture pixels Adjust to 512×384[5]. These images can better express the state of domestic garbage when it is recycled, such as deformed bottles, wrinkled paper, etc. There are about 300-400 images in each category, and the lighting and posture of each photo are different, and each image has implemented image enhancement technology. These techniques include random rotation of the image, random brightness control, random translation, random zoom and random cropping. The purpose of choosing the transformed image is to consider the different directions of the recycled material and to maximize the size of the data set. Figure 1 is the distribution of the data set, and Figure 2 is the distribution of the data set after dividing the training data and the test data.

2.3 Transfer learning model

In the absence of large-scale data annotation data sets, this paper designs using migration learning to obtain a CNN network capable of extracting features, using the neural network ResNeXt-101-32x16d-wsl pre-training model, which is a model for Instagram (940 million) The data set is weakly supervised training, and there are 1000 kinds of output parameters[6]. The model designed in this paper first determines the neural network structure according to the number of categories of images in the existing recyclable garbage data set, cleans and enhances the acquired data, determines the hyperparameters, starts training the neural network, and records the loss function during the training process The value and the pass rate of the validation set are used for parameter tuning.

3. Experiments and results

Model training and testing are done under Pytorch's deep learning framework. Hardware environment: AMD Ryzen5 3600x@3.79GHz, 16GB memory, Nvidia RTX3060ti GPU, 8GB video memory. Software environment: CUDAToolkit11.0, CUDNNV11.0, Pytorch1.7.1, Windows10 64bit operating system. Model training and testing are accelerated by GPU. For migration learning model training, there are mainly Epoch, Batch Size and Learning Rate parameters.

1) Epoch: An Epoch refers to the process of sending all data into the network to complete a forward calculation and back propagation. As the number of Epoch increases, the number of weight update iterations in the neural network increases.

2) Batch Size: Batch is the data sent to the network for training each time, and Batch Size is the number of training image samples in each batch. In order to find the best balance between memory capacity and memory efficiency, Batch Size should be carefully adjusted to optimize the performance of the network model and the speed of training.

3) Learning Rate: It is an important parameter in deep learning, which determines the recognition accuracy of training samples. A suitable Learning Rate can make the recognition accuracy of training samples reach an ideal value in a suitable time[7].

Randomly divide 80% of each category of pictures in the recyclable household garbage data set into the training set, and the other 20% as the test set. When the above three parameters take different values, a total of 18 experiments are completed, and the training accuracy and test accuracy of the model in each experiment are shown in Table 1. In order to comprehensively evaluate the effect of each parameter combination, the accuracy is normalized and used as the final model score. The training accuracy score and test accuracy score of the model are weighted and averaged by 0.6 and 0.4 respectively to obtain a comprehensive score. According to the comprehensive score, it can be seen that when the parameter combination of Epoch, Batch Size and Learning Rate is set to (10, 32, 0.001), the effect of transfer learning is the best.

Perform 500 trainings on this parameter to get the data in Figure 3. Evaluate the best model trained under the parameters to get the confusion matrix. From the confusion matrix table 2 we can see that

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the average accuracy of the model is 89.27%, and the prediction accuracy from high to low is glass, waste paper, cardboard, plastic, and metal. From the confusion matrix, the main misjudgment errors are: cardboard And waste paper, between glass, metal and plastic. Because the glass, metal and plastic in the data set may be misjudged due to the reflective surface at a specific time.

Table 1. Experimental data

Epoch	Batch Size	Learning Rate	Training/%	Prediction/%	score
5	8	0.001	86.99	87.12	87.068
5	8	0.0001	82.55	88.96	86.396
5	16	0.001	89.91	86.50	87.864
5	16	0.0001	82.23	83.84	83.196
5	32	0.001	83.70	83.84	83.784
5	32	0.0001	80.77	82.61	81.874
10	8	0.001	90.75	89.37	89.922
10	8	0.0001	88.35	86.71	87.366
10	16	0.001	92.11	88.55	89.974
10	16	0.0001	88.04	88.55	88.346
10	32	0.001	94.62	89.37	91.470
10	32	0.0001	90.02	86.91	88.154
20	8	0.001	86.73	89.57	88.434
20	8	0.0001	83.65	86.71	85.486
20	16	0.001	84.33	87.53	86.250
20	16	0.0001	92.52	87.93	89.766
20	32	0.001	86.10	86.30	86.220
20	32	0.0001	87.25	86.50	86.800

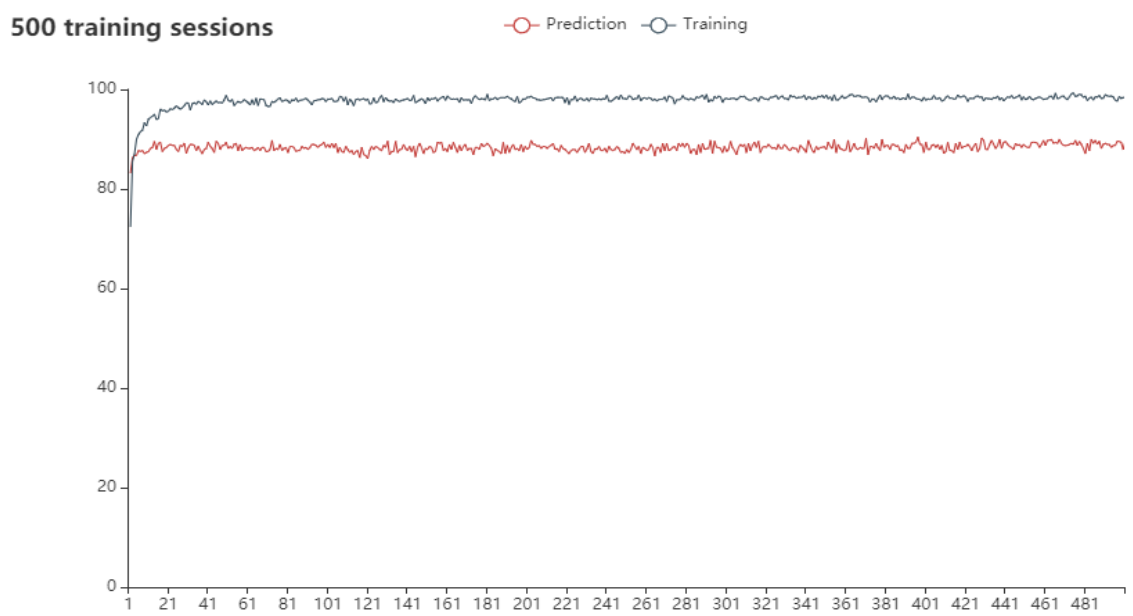

Figure 3. (10,32,0.001)500 training sessions

Table 2. Confusion matrix

Real category	Predictive category					test numbers	Forecast accuracy
	Cardboard	Glass	Metal	Paper	Plastic		
Cardboard	72	1	0	6	1	80	0.9000
Glass	0	97	4	1	2	104	0.9327
Metal	0	9	71	3	3	86	0.8256
Paper	5	0	3	111	2	121	0.9174
Plastic	0	8	2	1	87	98	0.8878

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4. Conclusion

Aiming at the existing recyclable garbage classification methods mostly physical classification, this paper proposes a recyclable garbage image classification model based on migration learning. This paper uses the migration learning method to adjust the network structure and parameters of the ResNet101 pre-training model, and conducts classification experiments on recyclable garbage image recognition. Finally, the accuracy of garbage classification and recognition reaches more than 90% in complex scenes. Although there are still a few misrecognitions and missed detections, due to the low cost of hardware used in deep learning and high recognition accuracy, it meets the requirements of the existing actual scene garbage classification, which makes the artificial intelligence high-speed sorting using this method The equipment has achieved high practical value and economic value.

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