

A Deep Convolutional Neural Network Based Domestic Garbage Classification Model

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Abstract: Garbage classification is of great significance to maximize recycling and disposal of domestic garbage. In this paper, we propose deep convolutional neural network (CNN) based domestic garbage classification model. Although deep learning has been applied in the field of image recognition and classification with great success, it requires very large and comprehensive training dataset to classify images accurately. The robustness of deep learning model is significantly affected for domestic garbage where the amount and types of data are small to meet the needs of deep learning model training. To solve this problem, we propose a method based on Deep Convolutional Generative Adversarial Network (DCGAN) to enhance the domestic garbage dataset. We validate the proposed domestic garbage classification approach experimentally and compare it with exiting approaches. The experimental results show that the proposed method can effectively expand the data set and significantly improve the classification accuracy, compared with the exiting data enhancement methods based on geometric transformation image operation. In detail, the improvement of data size of training set is up to 81.7% compared with the original training set. And then the improvement of the average accuracy of classification is 7.27% in comparison with no data enhancement method.

1. Introduction

Efficient household waste classification, in addition to collection, is crucial in achieving higher recycling rates. A possible solution to this problem is to use machine learning based solutions to automatically classify garbage type from images. As a result, a flurry of automatic classification methods of garbage has recently appeared, especially the use of neural networks [1, 2] and deep learning [3]. Deep learning-based approaches require a large amount of labeled data for classification. However, the availability of sufficient data for waste classification is a major problem [4]. When the data is scarce, the neural network is prone to overfitting, which is especially obvious on small-scale data sets. These problems bring serious performance damage to the deep convolutional neural network, which affects the convergence of the model in the training phase and the test set. Therefore, a better approach to address this problem is necessary.

The proposed approach, based on the image of the domestic garbage, classifies the household waste into different categories. Although extensive research on waste management has been undertaken [5], few studies have used CNNs to classify domestic garbage from images [3]. This is mainly due to the insufficient domestic garbage datasets to train CNN, which poses significant challenges to classify domestic garbage efficiently. Existing work used small dataset with limited types of garbage in the data set, which cannot be used in real life at all. Although the CNN models trained with large sample training dataset performs well in image classification, there is still a serious problem for small training datasets [4]. To address this problem, this paper presents a novel data enhancement strategy, which is based on Deep Convolutional Generative Adversarial Network (DCGAN), to increase the accuracy of the CNN model and improve generalization ability. The contribution of this paper can be summarized as follows:

(1) We propose a deep learning-based image classification method for classifying domestic garbage. The proposed approach, based on the image of the domestic garbage, classifies the garbage into different categories.

(2) we propose a method based on Deep Convolutional Generative Adversarial Network (DCGAN) to enhance the domestic garbage dataset.

(3) We validate the proposed garbage classification methods experimentally.

The paper is organised as follows. We describe the problem overview and the current work regarding waste classification in Section 2 and Section 3 respectively. The proposed domestic garbage classification is presented in Section 4. We evaluate and discuss our results in Section 5. Finally, the conclusion and the work planned to be performed in future are highlighted in Section 6.

2. Problem overview

This paper focuses on domestic garbage, which is the waste generated by households as the result of the ordinary day-to-day use of a domestic premise. Figure 1 shows some frequent domestic waste item categories, which include food items, cigarette butts, garbage bags, toothpicks, plastic, and dishes.

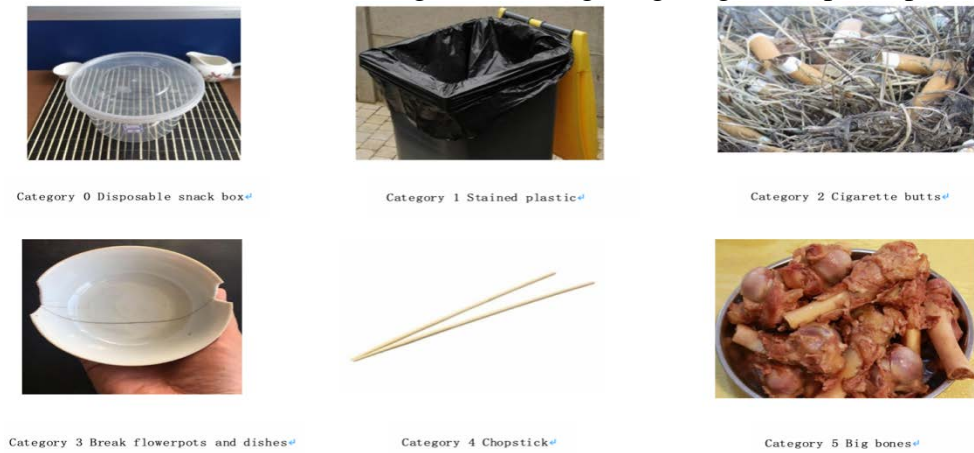


Figure 1. Example of domestic garbage categories

Given a set of domestic garbage image data consisting of several classes on different garbage types, the challenge is how to classify the domestic garbage efficiently and accurately into proper categories with the aims of maximizing recycling and proper disposal. Image classification is a classic problem and there have been many image classification research projects based on support vector machines (SVM) [6] and neural networks [7], but few researches on household waste image classification exists. The traditional machine learning models such as SVM require the training and testing datasets to be from the same domain and identical feature space. However, obtaining the training data and matching the feature data to the test data in the real world is extremely difficult. An alternative approach is to use deep learning, which has a good success in image recognition and classification [8]. However, in the absence of dataset samples that are large enough to train the deep learning model problems such as over-fitting could occur, which affects the classification accuracy of the model in a negative way. Also, collecting and assembling large sample waste images is a difficult process [9], and thus research on garbage classification based on deep learning with small benchmark datasets is very limited. These inherent limitations have hampered the widespread adoption of deep learning in domestic garbage classification studies. This paper aims to address these challenges and propose a novel data enhancement method and a deep learning-based domestic garbage classification method, based on the image of the domestic garbage.

3. Proposed Domestic Garbage Classification Method

In this section, we present the proposed approach for classifying domestic garbage through image classification using deep learning. The proposed model is divided into two stages, as shown in Figure

2. The first stage is the data generation stage. In this stage, the Deep Convolutional Generative Adversarial Networks (DCGAN) [10] is used. DCGAN is a generative confrontation network, which replaces the original perceptron layer by introducing step-size convolution, which enhances the training stability and the quality of generated samples. The first step will generate additional images that will complement the original domestic garbage images. The second stage is the classification training stage. After the first stage of training is completed, DCGAN has learned the distribution of real data. Therefore, at this stage, DCGAN will no longer be trained, just as a data provider, and the generated data and real data will train the classification network together. In the following subsections, these two steps will be described in detail.

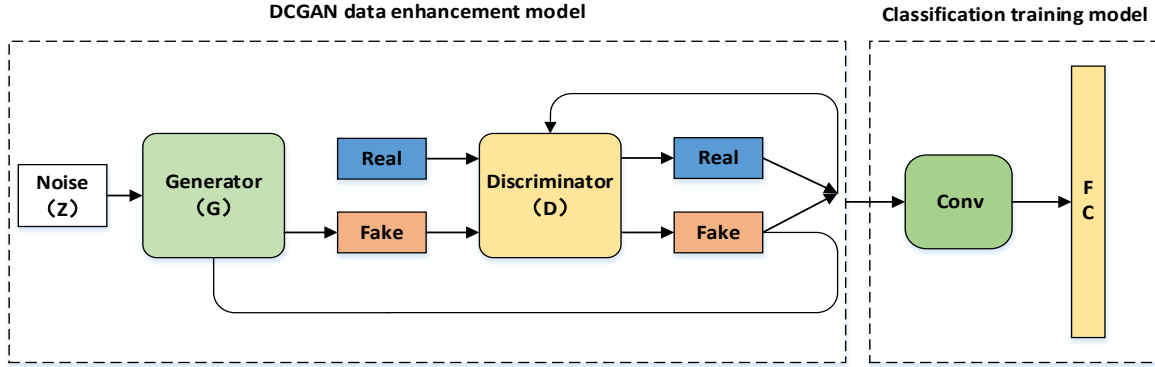


Figure 2. The used model

3.1 Data enhancement network based on DCGAN

DCGAN uses convolutional neural networks to construct generator (G) and discriminator (D) respectively. The generative model G is responsible for generating pictures, using random noise as input, and generating pictures through the noise. Ideally, the generated samples are as close to the real samples as possible. The discriminator D is in charge of determining whether or not a picture is real. The model can distinguish the fake samples as much as possible by calculating the probability that a sample comes from the training data rather than the data generated by model G.

The objective function of GAN optimization is defined as formula (1). Suppose that the probability distribution to be learned is p . To understand the distribution of the generator on the data p_{data} . The generator G creates a mapping from the prior noise distribution $p_z(z)$ to the data space $G(z)$. The discriminator $D(x)$ generates a single value that represents the probability that x comes from the training dataset instead of $p_z(z)$. G and D train at the same time: For G, adjust the parameters to maximize $D(G(z))$, that is to minimize $\log(1 - D(G(z)))$. For D, adjust the parameters to maximize $D(x)$, At the same time, $D(G(z))$ is minimized, that is, $\log(1 - D(G(z)))$ is maximized. When optimizing D is to make $V(D, G)$ the largest, when optimizing G is to make $V(D, G)$ the smallest.

$$\min_G \max_D V(D, G) = E_{x \sim P_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))] \quad (1)$$

This article uses convolutional neural networks to construct generator G and discriminator D respectively. Among them, the discriminator D uses 5 layers of convolutional layers with Batch Normalization and Relu activation functions and 1 layer of fully connected layers to perform feature extraction on the input images; the generator G uses 5 layers with Batch Normalization and LeakeyRelu The deconvolution layer of the activation function will use the noise generated by the Gaussian distribution to generate false sample pictures with the same width and height as the input picture through deconvolution. The deconvolution performs the reverse process of the convolution operation, which can expand the picture through upsampling, and generate a larger-scale feature map from a smaller-scale feature map. Table 1 lists the specific network structure.

Table 1. DCGAN network structure

Generator G			Discriminator D		
Layer	Filter/stride/padding	Output size	Layer	Filter/stride/padding	Output size
DeConv1	7*7/1/0	7*7*1024	Conv1	4*4/2/1	112*112*64
DeConv2	4*4/2/1	14*14*512	Conv2	4*4/2/1	56*56*128
DeConv3	4*4/2/1	28*28*256	Conv3	4*4/2/1	28*28*256
DeConv4	4*4/2/1	56*56*128	Conv4	4*4/2/1	14*14*512
DeConv5	4*4/2/1	112*112*64	Conv5	4*4/2/1	7*7*1024
DeConv6	4*4/2/1	224*224*3	Conv6	7*7/1/0	1

In the training process, the weight of one of the parties is fixed, and the network weight of the other party is updated through training and learning at the same time, and the process is constantly alternated to iteratively optimize the two networks. The goal of the generative model G is to deceive the discriminator D by generating as many real pictures as possible, and the discriminator D's goal is to distinguish the generated pictures from the real pictures as much as possible. In this way, the generator G and the discriminator D constitute a dynamic "game", after continuous training and learning, the Nash equilibrium is finally reached.

3.2 Classification training

We used the following three types of deep convolutional neural networks for classification training: (1) AlexNet variant. AlexNet won the 2012 ImageNet competition and is one of the most used deep networks in classification tasks. AlexNet successfully applied the Relu activation function and verified that its effect surpassed Sigmoid in the deeper network and solved the gradient dispersion problem of Sigmoid in the deeper network. It is also proposed to use Dropout to randomly ignore some neurons during training to avoid overfitting. In this study, we use a variant of AlexNet and add a BN layer after the Relu activation function; (2) VGG16 network. The VGG [1] model was the second place in the 2014 ILSVRC competition. VGG replaced all convolution boxes with 3*3, and all used 2*2 pooling boxes. Compared with AlexNet's 3*3 pooling box, calculating the amount has dropped a lot, and the stacking of multiple small convolution boxes has a certain improvement in accuracy than a single large convolution box. In this research we use the VGG16 network structure; (3) Deep residual network Resnet [2]. Resnet is the champion of the 2015 ILSVRC competition. The deep residual network solves the problem of fusion of low-level features and high-level features and difficulty in convolution box training and can avoid problems such as gradient dispersion while increasing the depth of the network.

4. Experiments and Results

In this section, we discuss the performance of the proposed domestic garbage classification and discuss the results. We also compare the proposed model with other models.

4.1 Data set introduction and analysis

Domestic garbage classification is a challenging problem. Not only does it require a large number of garbage types in the data set, but also a large enough number of pictures of each type of garbage. After comparison and research, we finally use the garbage_classify dataset proposed by Huawei [11].

The data set contains 40 types of domestic garbage, with a total of 14,683 pictures. Figure 3 shows the distribution of the number of garbage types. The horizontal axis shows the image category, and the vertical axis shows the number of images. It can be seen that the image category data is unbalanced. Among them, the smaller amount of data is category 3 (toothpicks), and the larger ones are category 11 (cauliflower root) and category 21 (plug wire). The data set contains rich types of garbage, basically including common household garbage types, but the number of samples for each category is small, and the data distribution is unbalanced. If there is no data enhancement, the direct use of convolutional

neural network for training will result in insufficient training of the network, and over-fitting are extremely likely to occur.

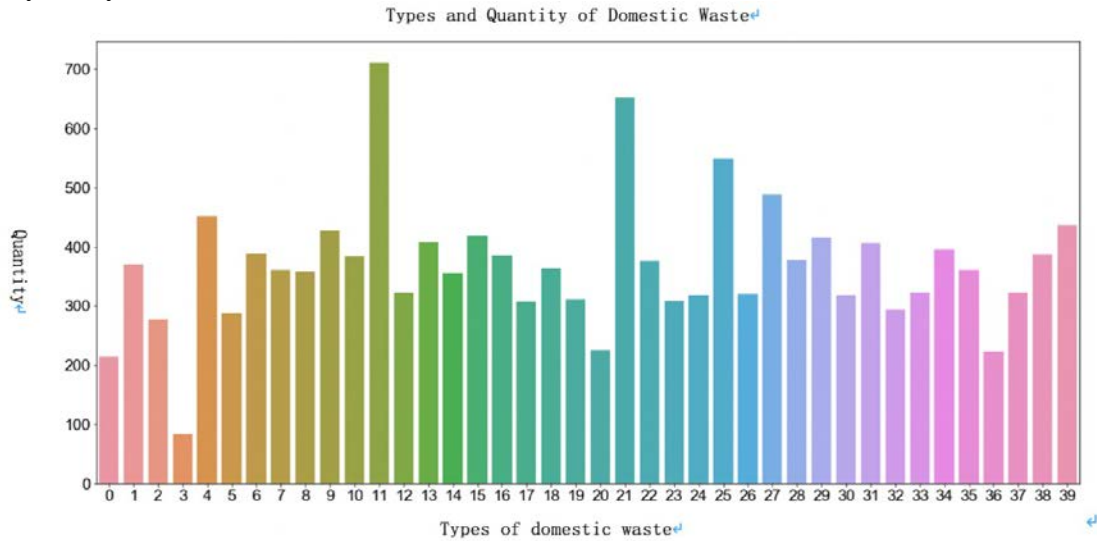


Figure 3. Distribution map of garbage types

4.2 Comparison on data size

In order to verify whether the samples generated by DCGAN can improve the accuracy of household waste classification, we used AlexNet, VGG, and Resnet50 as three classification networks for testing. The experiment mainly compares the following different data enhancement methods:(1)No data enhancement method (C); (2) Traditional data enhancement method based on geometric transformation image operation(C_aug); (3) The method proposed in this paper (DCGAN); (4) The method proposed in this paper is combined with the traditional data enhancement method (DCGAN_aug). The data set size used by each method is shown in Table 2.

Table 2. Data set sample size

method	Training set	Test set
C	10279	4404
C_aug	10279*4	4404
DCGAN	18679	4404
DCGAN_aug	18679*4	4404

Figure 4 shows a sample of generated garbage bags and toothpicks. We select 8400 pictures from the generated pictures. It is impossible for the neural network to distinguish whether these pictures are fake or real, so these pictures can be used as enhanced data for the network to train.

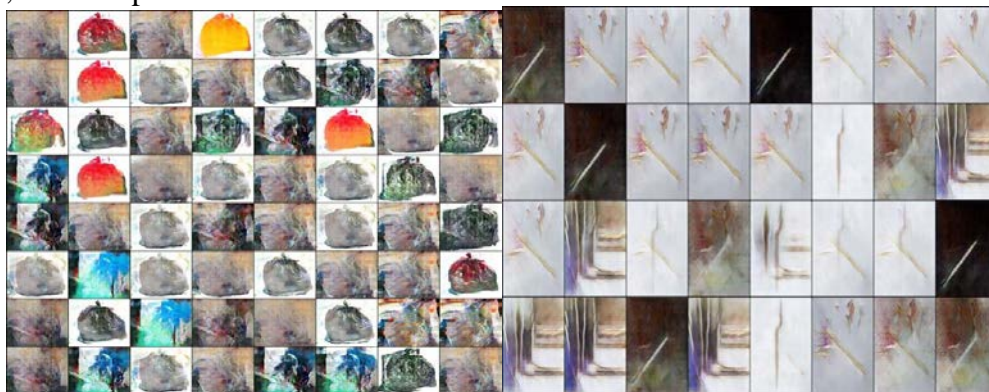


Figure 4. Example diagram of using DCGAN to generate garbage bags and toothpicks

4.3 Comparison on classification accuracy

In the classification stage, we use AlexNet, VGG16, and Resnet50 to train from scratch. The optimizer chooses Adam and the learning rate is 0.001. The experiment compares the classification accuracy (Acc) of the classifier trained under different enhancement methods on the test set, and the results are shown in Table 3.

Table 3. The classification accuracy of the classifiers trained by the three networks under different data enhancement methods on the test set

Model	Test set accuracy	Optimizer	Data enhancement method	Epoch
Alexnet	50.2%	Adam	C	100
Alexnet	53.3%	Adam	C_aug	100
Alexnet	54.1%	Adam	DCGAN	100
Alexnet	58.5%	Adam	DCGAN_aug	100
Vgg16	58.4%	Adam	C	100
Vgg16	61.9%	Adam	C_aug	100
Vgg16	63.3%	Adam	DCGAN	100
Vgg16	65.1%	Adam	DCGAN_aug	100
Resnet50	74.2%	Adam	C	100
Resnet50	76.3%	Adam	C_aug	100
Resnet50	78.3%	Adam	DCGAN	100
Resnet50	80.9%	Adam	DCGAN_aug	100

Here we take Resnet50 as an example. Figures 5 and 6 show the confusion matrix of Resnet50 using C method and DCGAN method respectively. The ROC curve of Resnet50 is shown in Figure 7.

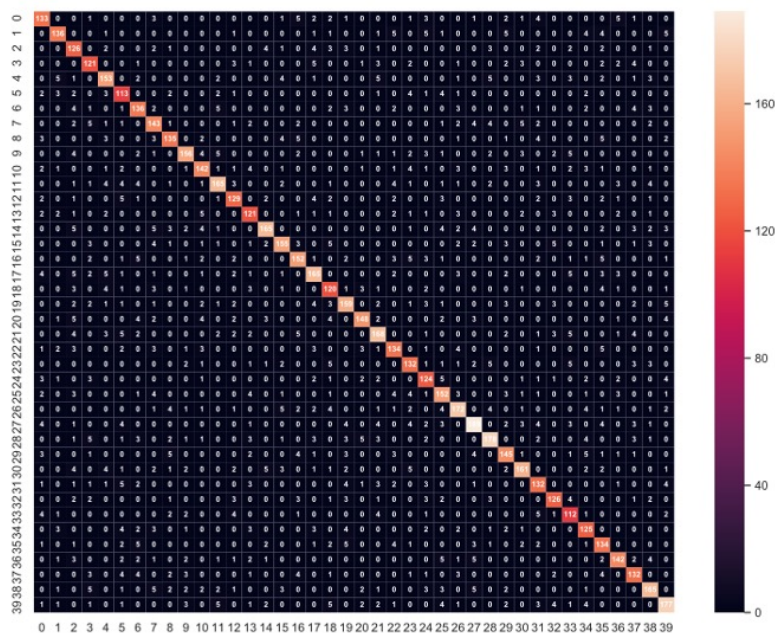


Figure 6. Confusion matrix after Resnet50 uses C method

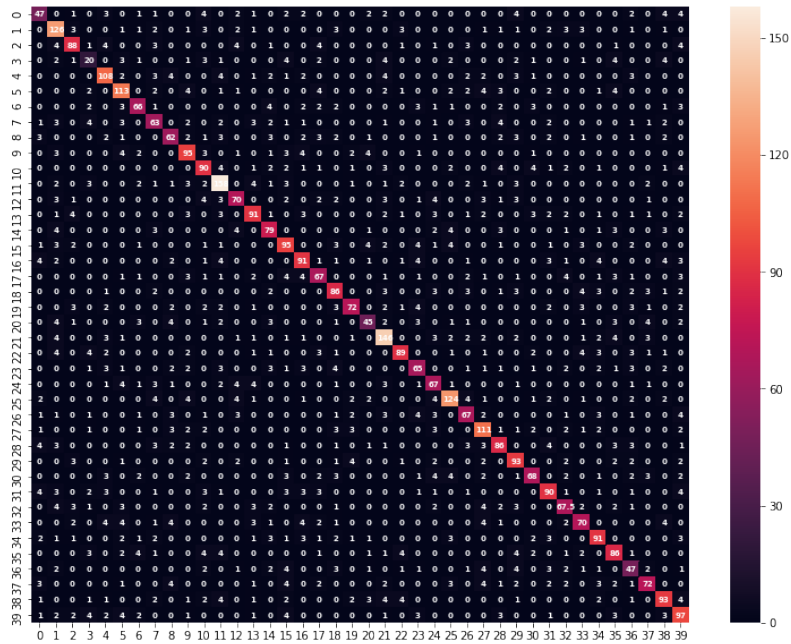


Figure 7. Confusion matrix after Resnet50 uses DCGAN_aug method

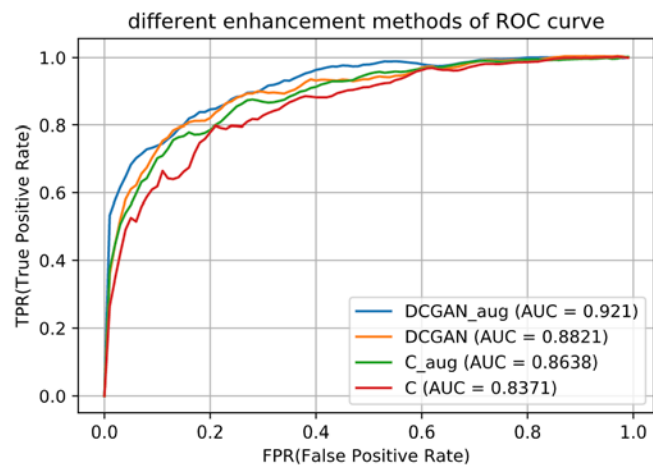


Figure 8. ROC curve based on different enhancement methods of Resnet50

It can be seen from the experimental results that the DCGAN_aug data enhancement method improves the accuracy of the classifier most significantly from table 4. And from Figure 6, Figure 7, Figure 8, it can be seen that when Resnet50 is used as the classification model, the DCGAN_aug data enhancement method can improve the performance of the classifier. This shows that in the case of limited data sets, the use of DCGAN for data enhancement has certain effectiveness and reliability. It also shows that the pictures generated by proposed method and the original pictures have the same semantics and show diversity in content. The method proposed in this paper can further improve the performance of the model on the basis of traditional data enhancement, solve the problem of data imbalance, and effectively expand the training sample.

We summarize that the average improvements of our proposed DCGAN_aug about accuracy compared with C and C_aug on three models are up to 7.72% and 4.09%, respectively.

Table 4. Improvement of DCGAN_aug about accuracy compared with C and C_aug on three models

compared method	Improvement on Alexnet	Improvement on Vgg16	Improvement on Resnet50	Average Improvement
C	8.32%	6.71%	6.78%	7.27%
C_aug	4.41%	3.24%	4.63%	4.09%

5. Conclusions and Future Work

Ultimately, effective garbage recycling and disposal process relies on effective classification of the garbage into proper categories. To this end, we proposed an automatic domestic garbage classification model based on deep convolutional neural networks. We also presented an approach, based on Deep Convolutional Generative Adversarial Network (DCGAN), to address the typical problem of small dataset sample and types that affect the efficiency of deep convolutional neural networks. We validated the proposed models with extensive experiments. Through a large number of experiments and comparisons with other models, it is verified that the proposed method can effectively expand the data set and significantly improve the classification accuracy of the classifier. In detail, the improvement of data size of training set is up to 81.7% compared with the original training set. And then the improvement of the average accuracy of classification is 7.27% in comparison with no data enhancement method. In the future, we will combine the advantages of the three (C_aug, DCGAN and DCGAN_aug), and learn from the research results of the attention mechanism in the neural network to improve the garbage classification algorithm. We will do some research on how identification will fare in a less than ideal environment, and how can 3d modelling be used to further enhance the data.

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