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Research on Garbage Image Classification Method Based on ResNet-34 Deep Network

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ABSTRACT

In recent years, with the improvement of living standards, the total amount of household refuse is also rising. However, the classification capability of household refuse is relatively backward, and the traditional manual sorting garbage has low efficiency, heavy workload and high difficulty. At present, the machine is gradually replacing the manual, but it mainly uses the traditional image processing method, which is inefficient and inaccurate. The methods of using deep learning network to solve garbage image classification are increasing gradually. The early classification methods mainly include gray image segmentation, threshold segmentation, FCN semantic segmentation and so on. Such methods generally have problems such as low accuracy, complex models, poor robustness, and difficulty in feature extraction. Therefore, this paper proposes to use a deconvolution layer, a maximum pooling layer and a fully connected layer that meets the classification requirements of this article instead of fully connected layer of ResNet-34 to realize the accurate classification of garbage images. By using Fastai, a top-level framework based on PyTorch, as the writing framework, this article greatly reduced the workload. The improved ResNet-34 model based on the Fastai framework is proved by experiments. The recognition accuracy of our improved model is 98.23%, which fully proves that it has effective classification ability on garbage images, and it has the advantage of low time complexity.

1. Introduction

Nowadays, with the growth of population and the development of industry, the world produces 2.01 billion tons of Municiple Solid Waste (MSW) every year. All kinds of MSW cannot be treated in the same way, so it is necessary to classify MSW. Recycling is becoming an integral part of a sustainable society. When garbage is not classified properly, it will lead to garbage accumulation and difficult to deal with. Although it is possible to classify rubbish artificially, it is sometimes difficult to correctly distinguish the types of rubbish in the face of various types of rubbish. Now is the era of artificial intelligence, a variety of image classification algorithms, timely born, not only has an impact on the environment, but also a beneficial impact on the economy.

In recent years, the research on garbage classification mainly starts from the following seven aspects: the evaluation of artificial garbage classification(Fukuyama, 2000; Zeng Libo et al., 2020; Jiang Hui, 2018; Kong Weiwei, 2020; Zhao Fangyuan and LIU Honghao, 2020), garbage classification circulation system(Yuan Jiewen and Chu Leifang, 2020), garbage speech recognition classification(Deng Jiangyun and LI Sheng, 2020; Meng Tianyu et al., 2019; Wang Hua et al., 2020;Wang Zhi et al., 2020a;Wang Zhi et al., 2020b;Yoon Po-wan, 2019), garbage image recognition classification(Aral et al., 2018; Cao and Xiang, 2020; Kang et al., 2020; Ma et al., 2020; Meng and Chu, 2020; Ozkaya and Seyfi, 2019; Rabano et al., 2018; Setiawan et al., 2017; Shi et al., 2020; Wang, 2020; Xiong et al., 2019; Yang and Li, 2020; Zeng et al., 2020; Dong Ziyuan and Han Weiguang, 2020;Gaoming et al., 2020;Kang Zhuang et al., 2020;Ma Wen et al., 2020;Peng Xinyun et al., 2019;Wu Xiaoling et al., 2020;Wu Zhangjing et al., 2020;Yang Huiling et al., 2020;Yuan Jianye et al., 2020a;Yuan Jianye et al., 2020b;Zheng Longhai et al., 2019;Zhu Chaokun and Wei Lunsheng, 2020), garbage sensor classification(Chung et al., 2018; Chung et al., 2020; Shan Hongyu et al., 2018), garbage classification hardware and software system(Chen et al., 2019; Liu Pan and Ding Huaibao, 2020;Lu Chengxi, 2019;Lu Wenjie et al., 2020;Meng Tianyu et al., 2019;Yu Dong and Jing Chao, 2020) and garbage classification robot(Qin Nanqiang et al., 2020;Zhang Fangchao et al., 2019). The main work of this paper is garbage image classification.

Tab.1 .Recent achievements in garbage classification

2 categories	Model	svm	deep-CNN	yolov3-darknet	SIFT
	ACC	100%	84.01%	94.8%	89.9%
	Dataset	self-build	ImageNet	self-build	self-build

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3 categories	Model	SSD			
	ACC	94%			
	Dataset	self-build			
4 categories	Model	TensorFlow	GANet	GCNet	PublicGarbageNet
	ACC	95%-98%	90%	96.73%	96.35%
	Dataset	self-build	HuaWei	HuaWei	self-build
	Model	Inception-v3	VGG16		
	ACC	93.2%	81.1%		
	Dataset	self-build	self-build		
5 categories	Model	improved-Faster R-CNN	L-SSD		
	ACC	81.77%	83.48%		
	Dataset	self-build	self-build		
6 categories	Model	inception-v4	CSMobileNet -18	MAPMobi leNet-18	improved-DenseNet 121
	ACC	90%	89%	86%	95%
	Dataset	self-build	CAS	CAS	Trashnet
	Model	GoogleNet+SV M	WasNet	M-b Xception	MobileNet
	ACC	97.86%	96.1%	94.34%	87.2%
	Dataset	Trashnet	Trashnet	Trashnet	self-build
	Model	ResNet-50			
	ACC	91.40% - 95.35%			
	Dataset	Kaggle			
other	Model	CNN	Inception-v3	ResNet-34	
	ACC	80%	99%	99%	
	Dataset	NULL	self-build	self-build	

The following Table1 shows the classification effect of different algorithms for more garbage categories, such as dichotomy, triple classification, etc.

As shown in Figure 1, the schematic diagram of garbage classification business is shown. Firstly, the images are flipped through the data processing library in Fastai to achieve the effect of expanding the dataset. Then, the ResNet-34 is improved to remove the final fully connected layer, and add transpose layer, maximum pooling layer and fine-tuning fully connected layer. Then we use Fastai to find the best learning rate function and learning rate strategy one-cycle-policy to continuously find the optimal solution, so as to complete the training of amplified data on the improved ResNet-34, and finally get the results.

2. Design of image classification model

The structure of convolutional neural network is very important in feature learning. It is generally believed that the deeper the network design, the better. However, the deeper the actual network is, more problems will be encountered. The main problems are gradient disappearance and gradient explosion(Deng et al., 2009). The latest generation of convolutional neural network (residual neural network) is introduced into residual connection, which can solve the problem of performance degradation in deep-seated convolutional neural network training. The residual connection can accelerate the convergence of the depth network, and maintain the accuracy by greatly increasing the depth of the network. The basic structure of ResNet is shown in Figure 2.

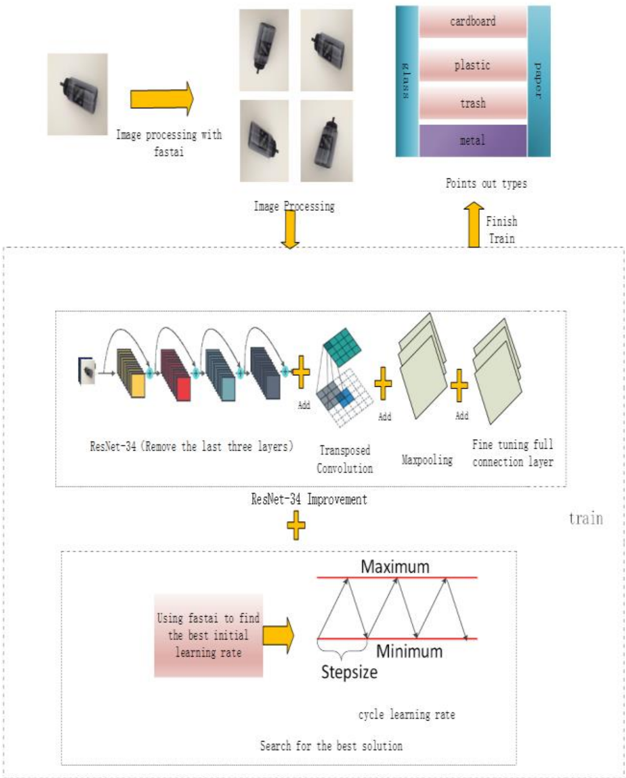

Fig. 1. Waste classification business diagram

The basic idea of the ResNet model is to propose a residual learning structure, which changes the original function F(x) to F(x) + x. The solution of this kind of fitting function is simpler than that of F(x). According to the residual vector coding in the image, a problem is decomposed into a multi-scale residual problem through a remake, so as to solve the difficult problem of deep network training optimization. Therefore, compared with the previous CNN network, ResNet network has improved the network performance while increasing the depth(He et al., 2016). Therefore, this paper uses ResNet-34 to design the garbage classification model.

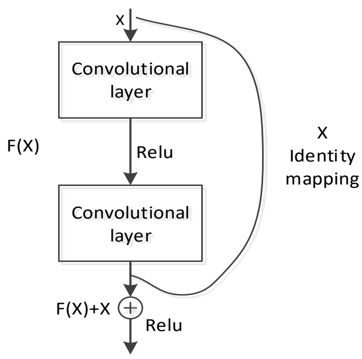

Fig. 2. ResNet basic structure

3. Improve ResNet-34 network

TensorFlow already has Keras, PyTorch also has a high-order encapsulation library for benchmarking, so Fastai came into being. Fastai does not simply encapsulate PyTorch, but is similar to the relationship between Keras and TensorFlow. Keras is a high-level API built on TensorFlow, which is much easier to use than TensorFlow. Fastai is also the same, on the basis of PyTorch, developers can quickly use PyTorch backend for development, not only for research, even production is easy. Similarly, PyTorch also supports GPU for hardware acceleration. Fastai library provides advanced API for creating deep learning models for many different applications, including text generation, text analysis, image classification and image segmentation. Fastai library has become a powerful toolbox, which can quickly load some of the latest algorithms, such as stochastic gradient descent algorithm with restart, differential learning rate and test time augmentation and so on.

Fastai is different from Keras in model construction. Keras makes it easier to build models (build basic models), while Fastai makes deep learning more simple and convenient (transfer learning). Nowadays, there are many mature neural networks, such as ResNet and VGG. Fastai can directly call these mature neural networks for training with a line of code, and support training visualization and the import and export of models, which greatly facilitates the selection of models. This article uses Fastai as the writing framework.

In the second section, the basic structure of ResNet-34 network is introduced and improved. Before improvement, it is necessary to analyze whether the whole network structure conforms to the dataset used in this paper. The garbage image dataset used in this paper is a simple background, and the deconvolution can be introduced to enlarge image features. According to reference(Noh et al., 2015), deconvolution enlarges the most important features according to the information of convolution kernel, which makes classification more accurate. After deconvolution, the features are magnified, and the maximum pooling layer is introduced to highlight the main features of the image. The ResNet called in Fastai is trained on ImageNet. It aims at 1000 categories, but this paper only classifies 6 categories, so it needs to change the fully connected layer. After analyzing the structure, use the create_cnn_model() function in the Fastai to build the model. First, the cut parameter of the function is used to cut out the main part of the network (the trunk part will be retained), and then use create_cnn_model() to add a subnet to extract the modified part. In this paper, we extract the structure after the avgpool layer, and use split parameter to add deconvolutional layer, maximum pooling layer and fully connected layer (six categories) to the main network, and check whether the forward propagation sequence is reasonable, and complete the improvement of ResNet-34 network model.

(1) The purpose of adding transpose convolution layer: after a series of convolution operations, the resolution of feature image is very small, so transpose convolution is used to increase the size of feature map. The feature matrix is sampled to increase the dimension of the matrix.

Transposed convolution is actually the inverse process of convolution, but transposed convolution can not reduce the image before convolution by deconvolution, but can only restore the size of the image before convolution. Figure 3 shows a convolution process, in which 4*4 images are convoluted images, 3*3 shadow images are convolution kernels, and 2*2 images are images after convolution calculation. The input and output relations of the characteristic graph in the convolution process are as follows:

$$o = \left\lfloor \frac{i + 2p - k}{s} \right\rfloor + 1 \qquad (1)$$

In formula (1)o is the output,i is the input, p is the filling, k is the convolution kernel size, and s is the step size.

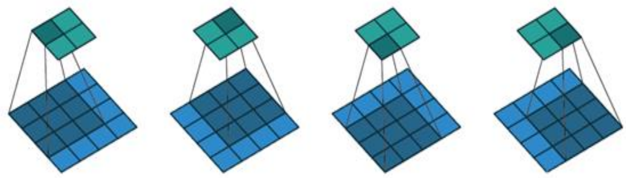

Fig. 3. Convolution process

Figure 4 shows the deconvolution process. It can be seen from the figure that the deconvolution process is very similar to the convolution process. The main difference is that the size of the input image will be smaller than the size of the output image of the deconvolution, which can be completed by increasing the p. In the figure, the input image is the blue part of 2 * 2, the convolution kernel is the shadow part of 3 * 3, and the output is the green part of 4 * 4. The step size of Figure 6 is 1. The input and output relations of the feature map in deconvolution are as follows:

$$o' = (i' - 1)s + k - 2p \qquad (2)$$

In formula (2), o' is the output, i' is the input, p is the padding, k is the size of the convolution kernel, and s is the stride.

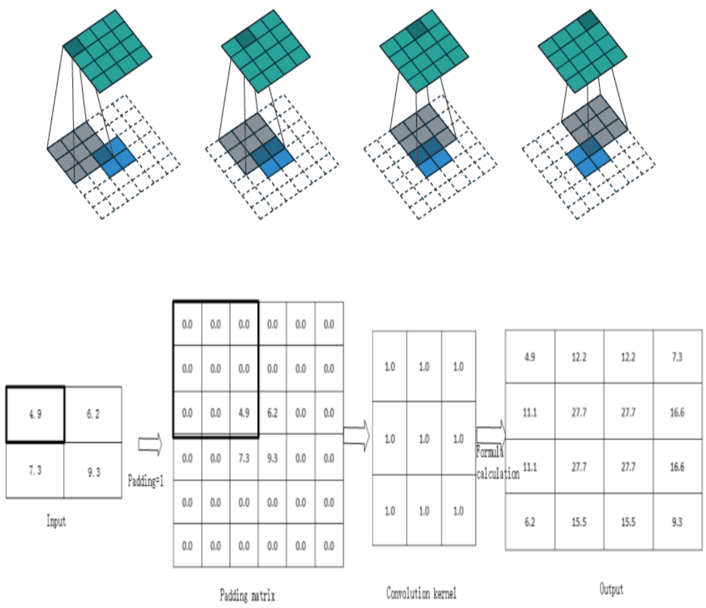

Fig. 4. Deconvolution process

(2) The purpose of adding the maximum pooling layer: the forward propagation of the maximum pooling layer is to pass the maximum value in the patch to the next layer, while the values of other pixels are directly discarded. Then back propagation is to pass the gradient directly to one pixel in the previous layer, while other

pixels do not accept the gradient, that is 0. Because the background of the dataset is single, it has little influence on the classification, so the maximum pooling layer is added to extract the largest feature points in the neighborhood, which reduces the offset of the estimated mean value caused by the parameter error of the convolution layer, and retains the texture features to the maximum extent. As shown in Figure 5, pooling is performed by a matrix of 2×2, which splits the input of 4×4 into four regions and outputs the largest element of each region.

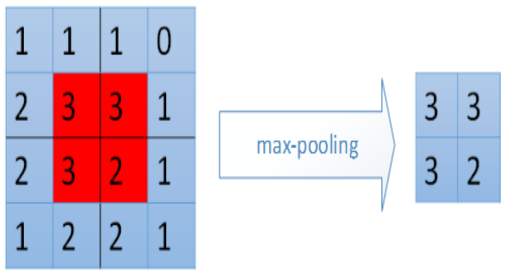

Fig. 5. Maximum pooling process

(3) The purpose of fine tuning fully connected layer(FClayer): since the ResNet-34 neural network model pre-trained in Fastai is carried out on ImageNet dataset, there are too many categories in the dataset, while only six categories are classified in this experiment. Therefore, the fine tuning of fully connected layer (adjusted to full connection layer for six classes) meets the requirements of this experiment, so as to reduce the parameter input and improve the operation speed, and reduce the risk of over fitting. The improved network is shown in Figure 6.

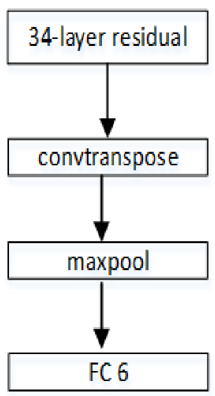

Fig. 6. Improved ResNet-34 network structure

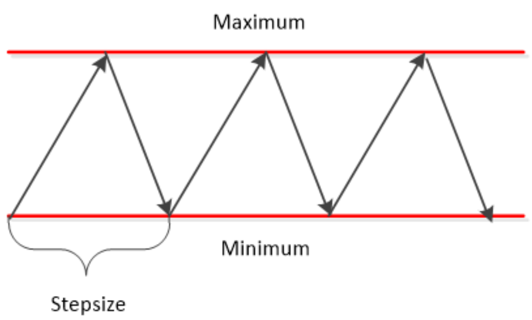

Fig. 7. Cycle learning rate

Because ResNet has a deep network structure, the performance of the model is greatly affected by the search of learning rate during training. Using learn_lr_find directly in Fastai can find the best initial learning rate. After finding the initial learning rate, use the learning rate strategy one-cycle-policy to train the model and start the training. A cycle contains two stages: one stage from a lower learning rate to a higher learning rate, and the other stage to return to the minimum learning rate. As shown in Figure 7, the length of this cycle should be less than the total number of epochs.

The way to find the maximum learning rate is to increase the learning rate from a very low level to a very high level, and stop when the loss begins to lose control. The relationship between learning rate and loss is shown in Figure 8, and a value is selected before the minimum value, and the loss is still in the trend of decreasing. The learning rate in Figure 8 should be between 1e-03 and le-02, and the value should be the maximum learning rate. The minimum value can be dozens of times lower and the learning rate can be reduced by several orders of magnitude from the minimum at the end of training.

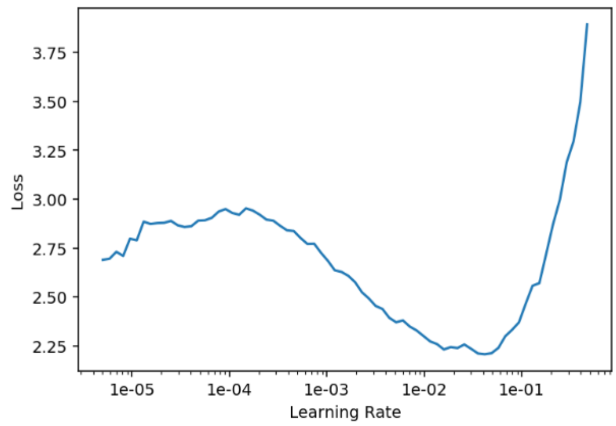

Fig. 8. Relationship between loss and learning rate

In the middle of the period, the high learning rate enables the model jump out of the local lowest point and saddle point during the training process to prevent the network from over fitting. At the end of the training, the loss is smooth, but as the learning rate decreases to annihilation, this will make the loss value reach the local minimum at this time. With a high learning rate, we can learn faster and prevent over fitting. Until the learning rate is annihilated, the difference between validation loss and training loss remains extremely low. This phenomenon is super convergence (Smith and Topin, 2019).

4. Experiment

4.1 DataSet

The experimental dataset of garbage classification is used in this paper. The garbage classification data is derived from the domestic garbage image data set manually collected by Gary Thung and Mindy Yang. The garbage is divided into six categories: cardboard, glass, metal, paper, plastic and trash. The total image data is 2527, as shown in Figure 9.

Fig. 9. Garbage data set

4.2 Dataset Preprocessing

Fastai is very powerful in data processing. Fastai provides many transform functions, which can transform images directly, such as image shading, contrast, clipping, rotation, scaling, horizontal flipping, etc. 2527 images were enhanced (rotated) to expand the dataset to 10108. The data set is divided into training set, validation set and test set, the proportion is 50-25-25. The information statistics of garbage dataset is shown in Table 2, and garbage data enhancement dataset is shown in Table 3. In this paper, RGB three channels are used, and the unified height and width of pictures are 384 * 512. The uniform size images are normalized to accelerate the training speed (speed up the gradient descent speed). First of all, zero average processing is carried out, $\mu=\frac{1}{m}\sum_{i=1}^{m}x^{(i)}$,subtract μ from each training data x. The training set is moved until it is zero mean, and then normalized variance is processed: $\sigma^2=\frac{1}{m}\sum_{i=1}^{m}(x^{(i)})^2$ Divide all the data by the vector σ^2 The normalized variance was processed. The processing method of flower dataset is the same except for data enhancement.

Tab.2 . Statistics of garbage dataset information

Dataset	Total	Train	Valid	Test
Garbage dataset	2,527	1,265	631	631

Tab.3 . Statistics of garbage enhanced dataset information

Dataset	Total	Train	Valid	Test
Enhanced dataset	10,108	5,051	2527	2527

4.3 Training

ResNet-34 model improves the final layer of ResNet-34 neural network after ImageNet pre-training to get better weight, adds transposed convolution layer, adds maximum pool layer, fine-tuning FClayer, and trains again, training only the last improved network layer. Because the Fastai framework is very easy to train for training ResNet-34 models, this is the advantage of integrating most of the applications of deep learning, which can easily achieve transfer learning. Fastai is also extremely easy to find the best learning rate, because there is a class in Fastai, namely, ConvLearner class, which has a function learn.lr_function that automatically finds the optimal learning rate, as shown in Figure 10.

From this figure and previous training experience, we can see that the optimal learning rate is 5.13e-03. After finding the optimal learning rate, we use the learning rate strategy one-cycle-policy to train the model, optimize the improved ResNet-34 neural network to get the optimal solution, complete the training. The training is set to 20 rounds, and the CPU is used for training. Each round of training takes about 74 seconds. The results are shown in Table 4. It is obvious that the learning rate decreases with time, which is closer to the optimal value.

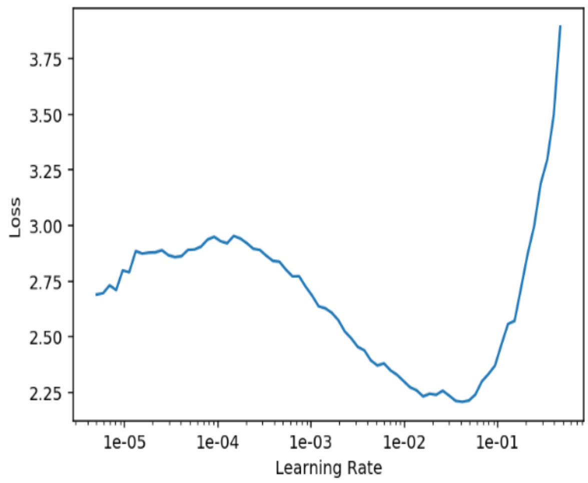

Fig. 10. Learning rate

Tab.4. Training performance

Epoch	Train_loss	Valid_loss	Error_rate	time
0	1.707227	0.753794	0.279365	01:15
1	1.030385	0.473211	0.163492	01:14
2	0.893213	0.574722	0.155556	01:15
3	0.793868	0.649234	0.192063	01:14
4	0.777746	0.983689	0.265079	01:15
5	0.833125	0.501379	0.171429	01:14
6	0.763078	0.620075	0.184127	01:15
7	0.815045	0.739687	0.219048	01:15
8	0.685278	0.476323	0.157143	01:16
9	0.546965	0.406157	0.125397	01:13
10	0.520540	0.301586	0.106349	01:15
11	0.456806	0.423904	0.139683	01:14
12	0.390972	0.278455	0.084127	01:14
13	0.377743	0.358326	0.123810	01:14
14	0.276973	0.229627	0.073016	01:14
15	0.214607	0.240266	0.068254	01:14
16	0.227076	0.240319	0.076190	01:14
17	0.183862	0.215160	0.069841	01:14
18	0.165982	0.196336	0.057143	01:14
19	0.181024	0.213317	0.068254	01:14

4.4 Model Prediction

Start to predict the test data. The function learn.get_preds in the Fastai can predict the picture in batches. The function is used to predict the previously divided test set. After the prediction, the function will generate a vector matrix of tensor, as shown in Figure 11, where the value represents the probability of each image. After the tensor is obtained, the prediction probability in the tensor is transformed into the vector of the category.

```
tensor([[9.9930e-01, 7.4508e-06, 5.8474e-06, 5.7658e-04, 1.5041e-05, 9.0718e-05],
        [9.9295e-01, 1.3228e-05, 6.9960e-06, 2.4118e-05, 1.0447e-03, 5.9644e-03],
        [9.9950e-01, 3.8285e-07, 2.3409e-07, 5.4455e-05, 1.1566e-06, 4.3921e-04],
        ...,
        [8.5862e-05, 2.3456e-04, 3.2881e-05, 6.6785e-01, 2.0749e-03, 3.2972e-01],
        [3.0428e-05, 5.0031e-06, 1.1686e-07, 7.0935e-01, 5.4474e-06, 2.9061e-01],
        [1.3405e-02, 9.7993e-03, 7.0176e-03, 1.4549e-01, 4.9926e-02, 7.7436e-01]])
```

Fig. 11. Vector matrix of tensor

In order to verify the prediction accuracy, the prediction tag is extracted and compared with the test set label in the actual dataset, and the accuracy is 93.23%. The accuracy obtained is satisfactory. In order to improve in the future, we need to know which categories are confused, and draw the confusion matrix diagram, as shown in Figure 12. It can be clearly seen that those categories produce confusion and the number of confusion, which provides a reference for future model improvement.

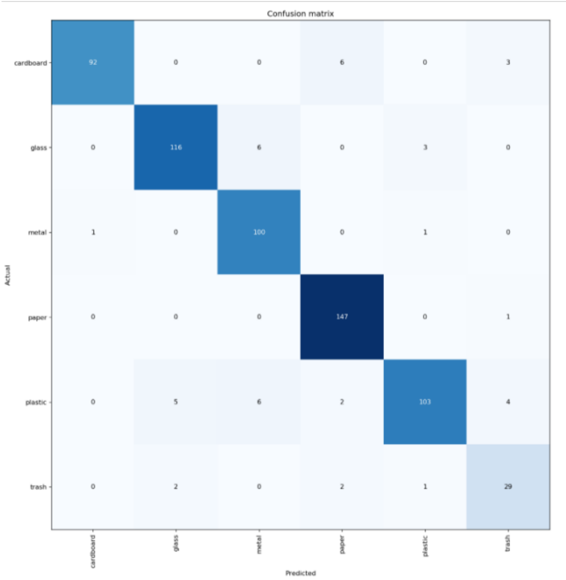

Fig. 12. Confusion matrix

4.4 Analysis of Results

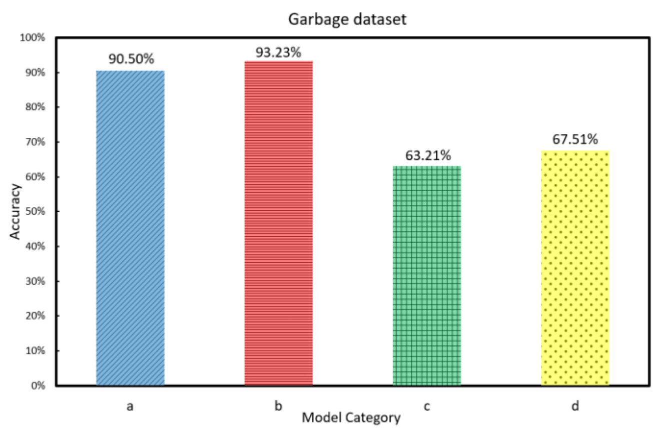

Fig. 13. Accuracy of models in garbage classification data set

In the fourth part, the improved model is trained and predicted. In order to prove the model has good performance, three groups of experiments are compared, Two groups of comparative experiments are carried out by using Fastai based ResNet-34 model (a), Fastai based improved ResNet-34 model (b), TensorFlow image classification network model (4 convolution layers, 4 fully connected layers) (c) and VGG-16 model (d) based on Keras. The first experiment is: garbage classification of all the above models based on garbage dataset. The second set of experiments is: all models except b models are based on the classification of flower datasets. The third group of experiments is to classify the data enhanced garbage dataset and the data unenhanced garbage dataset on the improved model.

The first set of experiments: the accuracy of each model based on the garbage classification dataset is shown in Figure 13.

The accuracy of the model in the figure is 90.56%, 93.23%, 63.21% and 67.51% from left to right. It is obvious that the improved ResNet-34 model based on Fastai framework has better accuracy.

The average training time of each model is shown in Figure 14. he time consumption from left to right is 76s, 74s, 55s and 82s. The improved ResNet-34 model based on Fastai framework is slightly faster than VGG-16 model based on Keras.

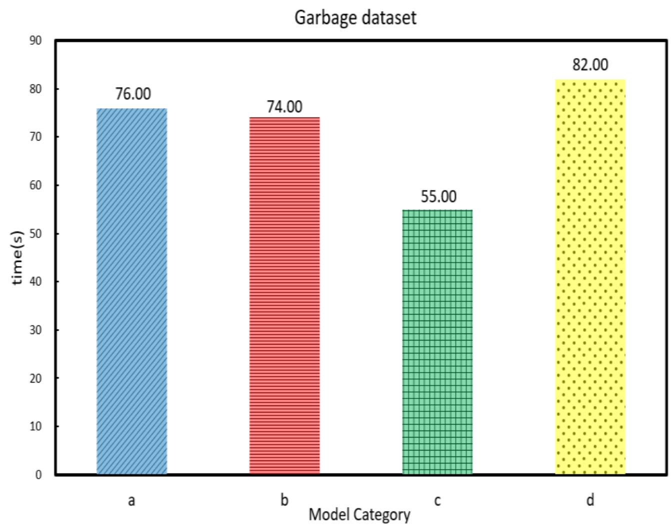

Fig. 14. Time of single round training for each model

Considering the time complexity and accuracy, the improved RsNt-34 model based on Fastai framework is better.

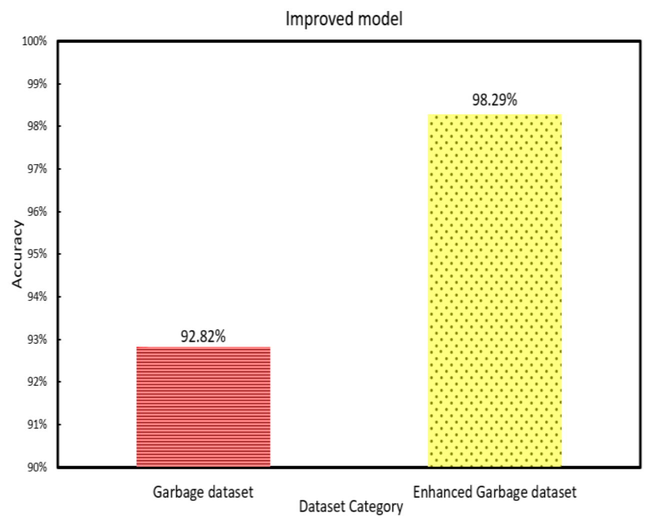

Fig. 15. The accuracy of two data sets on the improved model

The second set of experiments: The accuracy of the improved model in the data enhanced dataset and the dataset without data enhancement is shown in Figure 15. After data enhancement, the accuracy is almost increased by 7%, which proves that the improved model has no over fitting phenomenon when the amount of data increases.

In order to verify whether the model has certain robustness, another set of experiments are added to explore whether the improved model has excellent performance under other datasets. The experimental dataset is from flower dataset. The dataset of photos can be divided into five categories: daisy, dandelion, roses, sunflowers and tulips, with a total of 3670 pictures, as shown in Figure 16. The preprocess method of flower dataset is the same as that of garbage image dataset. The statistics of flower dataset is shown in Table 5.

Tab.5 . Statistics of garbage dataset information

Dataset	Total	Train	Valid	Test
Flower dataset	3,670	1,836	917	917

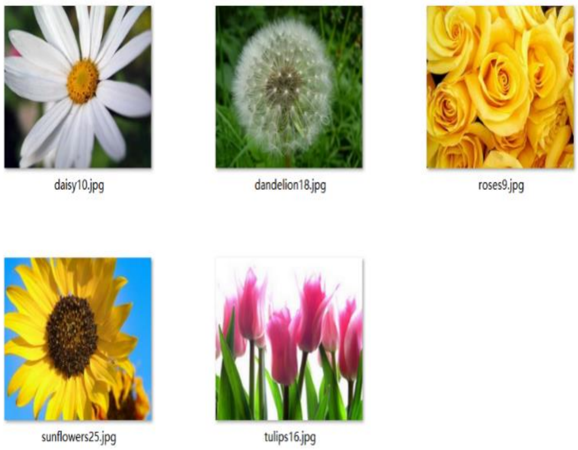

Fig. 16. Flower dataset

Experiment: the accuracy of each model based on flower dataset is shown in Figure 17. The accuracy in the figure from left to right are 92.82%, 59.46% and 71.52%.

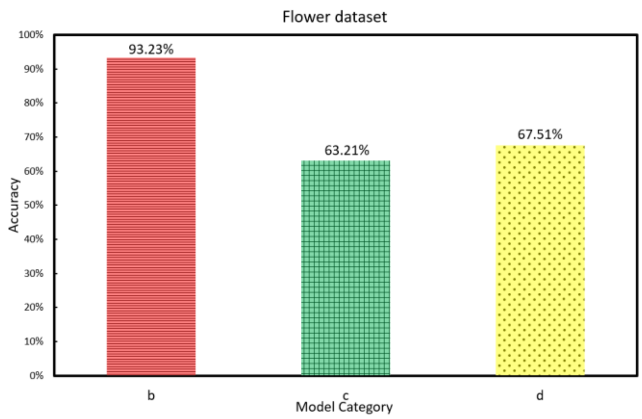

Fig. 17. The accuracy of each model of flower data set

The average time consumption of each model based on flower dataset is shown in Figure 18, and the time consumption from left to right is 96s, 76s and 112S. As the dataset capacity becomes larger, the consumption increases in turn.

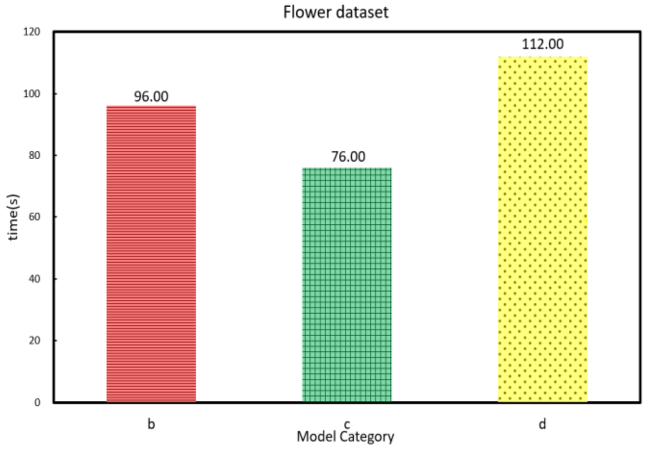

Fig. 18. Single round average time consumption of each model in flower data set

According to this set of experiment, it can be seen that the model in this paper still has higher accuracy and faster training speed on the flower dataset, and the model has certain universality and robustness.

5. Conclusion

In this paper, we use Fastai as the model framework. Through experiments, we can see that the deep learning model using Fastai framework is more efficient and time-consuming. In terms of code amount, the model under Fastai framework is far less than the deep learning model under Keras framework. Using Fastai framework makes the training more accurate and fast, which provides a direction for the selection of image classification framework in the future. Through the work done in this paper, it is proved that Fastai has great advantages in image processing, network construction and optimal value searching with less code, less parameter input, faster speed and complete tool integration, which provides a new choice for image processing framework. In this paper, we delete the final fully connected layer of ResNet-34 model, and add transpose layer, maximum pooling layer and fine-tuning fully connected layer. By comparing the accuracy of improved ResNet-34 model with ResNet-34 and VGG-16, it is proved that the improved ResNet-34 model has higher accuracy, better feature extraction ability and more simplified model structure. The experiment shows that it has certain applicability on the flower dataset.

With the development of urban garbage classification, more and more effective methods to solve the problem of garbage identification are needed. In this paper, the garbage classification and deep learning are combined to propose a garbage classification model. The experiment shows that the improved ResNet-34 model based on Fastai framework can classify garbage more accurately and quickly. The model also has some classification confusion problems, part of the reason is that the amount of data is too small, the other part is the influence of image background, exposure and other issues. Since the dataset with single background is less affected by noise, the next stage is to solve the problem of garbage classification in complex background, which provides a direction for the improvement of the model in the future.

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