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Junk Identification and Sorting Applications Based on Deep Residue Networks

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Abstract: ***With the advancement of technology, people are thinking more and more about technology and life. One of the major problems is the increasing capacity of urban waste disposal, so the policy of waste sorting (that is, the sorting of garbage in a prescribed order of order) has been introduced to demonstrate and realize the maximum economic value of garbage. Therefore, the sorting and recycling of garbage has great research value and significance. Therefore, solving the problem of garbage identification and classification has become our top priority. Based on this, the author designed a classification system based on ResNet18 network structure and transfer learning. Experiments have shown that based on this garbage sorting system model, the accuracy of garbage classification can reach more than 90%, which largely solves the problem of garbage identifying and sorting.***

Keywords: ResNet18; Transfer learning; Deep learning; Dispose of waste.

1. INTRODUCTION

With the current pace of urbanization and intelligent life in China accelerated, people's material living standards were also continuously improved, and the demand for life was constantly increasing, resulting in a steady increase in the total amount of garbage in urban daily life. In recent years, China has developed into one of the countries with the greatest pressure on urban everyday waste disposal work in the world. In media forensics, Jiang et al. (2025) [1] developed LMAT-ND, an enhanced Llama-7B model with meta-attention mechanisms for detecting AI-generated news content. Computer vision research has seen notable contributions including Peng et al. (2023) [2]'s work on source-free domain adaptation for human pose estimation and Zheng et al. (2025) [3]'s DiffMesh framework that integrates motion-aware diffusion models for video-based human mesh recovery. In healthcare analytics, Zhang et al. (2025) [4] investigated machine learning approaches for anomaly detection in biomechanical big data, while Wang (2025) [5] proposed RAGNet, a novel transformer-GNN hybrid model for predicting rheumatoid arthritis risk. Medical imaging research by Chen et al. (2024) [6] introduced Bimcv-R, a benchmark dataset for 3D CT text-image retrieval tasks. Natural language processing advancements include Yu et al. (2025) [7]'s study on transformer-based automatic text summarization using pointer-generator networks. AI applications in economics have been explored by Bi and Lian (2025) [8], who examined digital finance's role in high-tech industry exports, while Chen et al. (2023) [9] developed a self-supervised approach for neuron segmentation using multi-agent reinforcement learning. In financial technology, Pal et al. (2025) [10] presented an AI-driven credit risk assessment system for supply chain finance applications.

For the waste disposal process, it is a prerequisite for automated sorting and disposal when determining the location of waste and identifying the kind of waste. In this premise, the traditional image processing and recognition requires us to extract image features one by one, and is greatly affected by the data set.

2. KNOWLEDGE OF EXPERIMENTAL THEORY

2.1 Garbage _ classify data set

In this model training, we used a garbage _ classify dataset consisting of 14,802 images and 14,802 text documents with corresponding image names and corresponding labels. The picture names and labels in this document are separated by semicolon comma. In the four broad ranges of other waste, kitchen waste, recyclables, and hazardous waste, they are divided into 40 different categories, corresponding to the numbers 0 to 39. The quantitative relationship of the categories is shown in the following diagram:

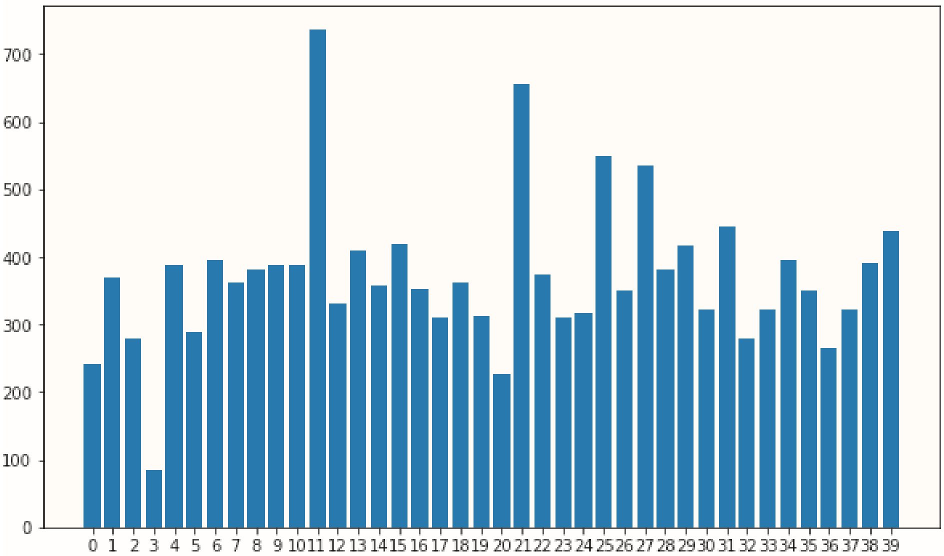

Figure 1: Quantitative relationships of 40 types of garbage

When dividing the data sets, this paper divided the 40 types of pictures into 80 percent training sets and 20 percent test sets.

2.2 Plain networks and deep residual networks

First, let's look at an experiment: the experiment directly stacks the traditional plain network multiple times, that is, doing a diffraction transformation and a nonlinear transformation layer by layer, and then image recognition and testing. The error results of the training set and test set are as follows:

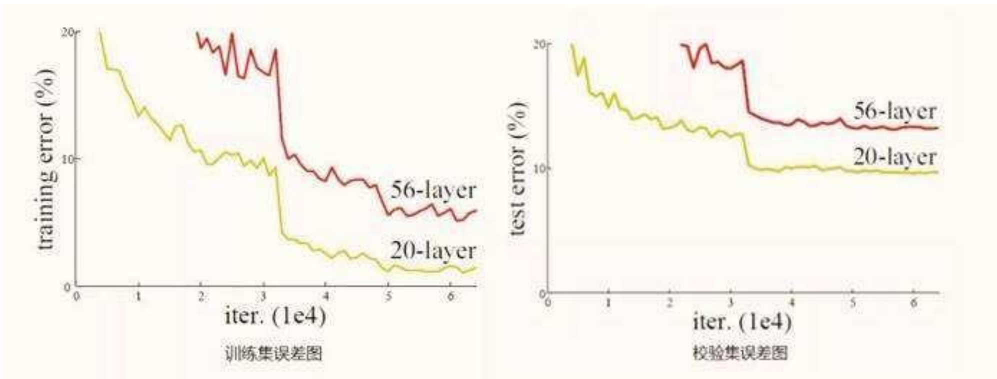

Figure 2: Multiple-Layer Plains Network Training Set Test Set Errors

It can be seen that when the network layer reaches a certain depth, the model effect all decreases and the error rate increases abruptly. At this point, it is not difficult to conclude that the accuracy of the model increases with the number of layers of the network, and the accuracies of both training and test sets rapidly decrease when the network is superimposed to a certain number of levels. It can be seen that when the network layer reaches a certain depth, the various functions of the deep network are reduced, so it becomes more difficult to train [4].

The ResNet (Residual Neural Network) network uses a residual network structure, which we can use when we need to set the number of layers deep. This residual network structure currently allows our network to reach up to more than a thousand layers. The final classification effect achieved by training through such structures is also relatively good. The following diagram shows the basic structure of the network blocks of residual blocks. It goes without saying that the residual building blocks have a jumping structure:

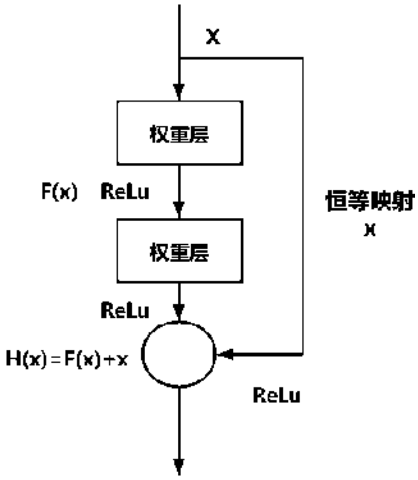

Figure 3: Structure of residual blocks

The advantage of the residual network is that the residual network is easier to learn the identity function, and the added network layer can be regarded as a residual block。[5], using the short circuit mechanism to transform the matrix multiplication of the affine transformation into the addition property, which makes the calculation relatively stable, and the short circuit mechanism can propagate the gradient without loss, the gradient will not be directly transmitted after the weighted layer, thus further inhibiting the gradient decay。The stability of training is greatly improved and the training process is greatly simplified through a comprehensive calculation of suppressed gradient decay and additive nature.

The traditional neural network has an output of the nth layer, which can only be constrained to the input of the next n + 1 layer. This kind of deep residual network can make the output of a layer pass through several weight layers and directly be the input of the weight layer after several layers。[6]In this way, the effect of superimposing multi-layered networks is accomplished without introducing new parameters or increasing computational complexity, which is highly generalizable and greatly solves the problem of multi-layer models losing accuracy at the deep layer. The ResNet18 network used in this article consists of 17 convolutional layers and one fully connected layer.

2.3 Migration Learning

In machine learning, transfer learning is one of the common model training methods. It is a machine learning method that uses existing basic knowledge to analyze and solve problems in different but similar technical fields [7]. Simply put, it is to cite one case in another and deduce new knowledge based on the facts and principles of existing knowledge; In machine learning, then, it is through existing neural network model data to find common ground and figure out how to learn patterns of new models, and the most crucial point is how to find similarities between existing knowledge and new information in neural network models.The main advantage of transfer learning is that it is less dependent on data and labels, and relaxes the independence and distribution constraints [8].

Therefore, the use of transfer learning methods can not only save a lot of time, reduce the computational power we need to use GPUs, but also in various aspects of better performance shortcuts. Especially for scholars new to Deep Learning, it is difficult to train a good model because of their limited knowledge and ability, so we can use transfer learning to migrate the model trained by a previous person, and we can fulfill our needs faster and easier. In general, transfer learning is about taking advantage of the similarities and correlations between source and target domains, migrating some of the parameters or characteristics of the source model to the target model, and adjusting the target model adaptively. Therefore, this paper uses the idea of transfer learning to adjust the structure of ResNet18 model and train 40 kinds of garbage images.

3. SYSTEM IMPLEMENTATION

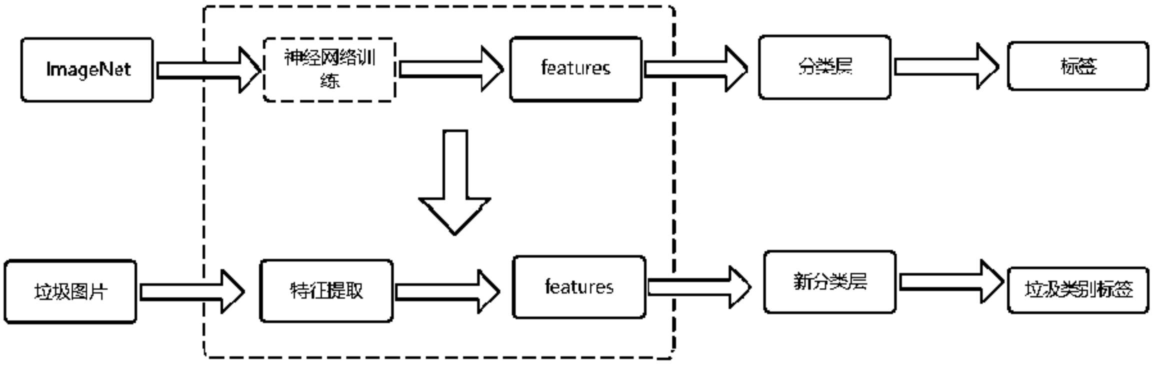

Figure 4: System Process

This paper uses the Pytorch system frame, which is a torch based python machine semester library, open source by Facebook, specifically for GPU-accelerated deep Divine Network (DNN) programming containing tensor computation[9]It is characterized by a scalar computing engine, an automatic guidance mechanism and an advanced neural network interface. The computation in Pytorch is basically based on the tensor, which can be said to be the basic unit of computation in Pytorch. Therefore, this article chooses to use the form of tensor to manipulate the image and to calculate the final accuracy of the experiment. Based on the ResNet18 network model and partially improved on it.

About image processing and enhancement, this paper uses transforms to carry on a series of manipulation processing, The methods of central trimming, random rotation, transformation to tensor and standardization were mainly used to adapt the image to the existing ResNet18 network, and after image data processing, the model generalization capacity improved and the convergence rate increased.

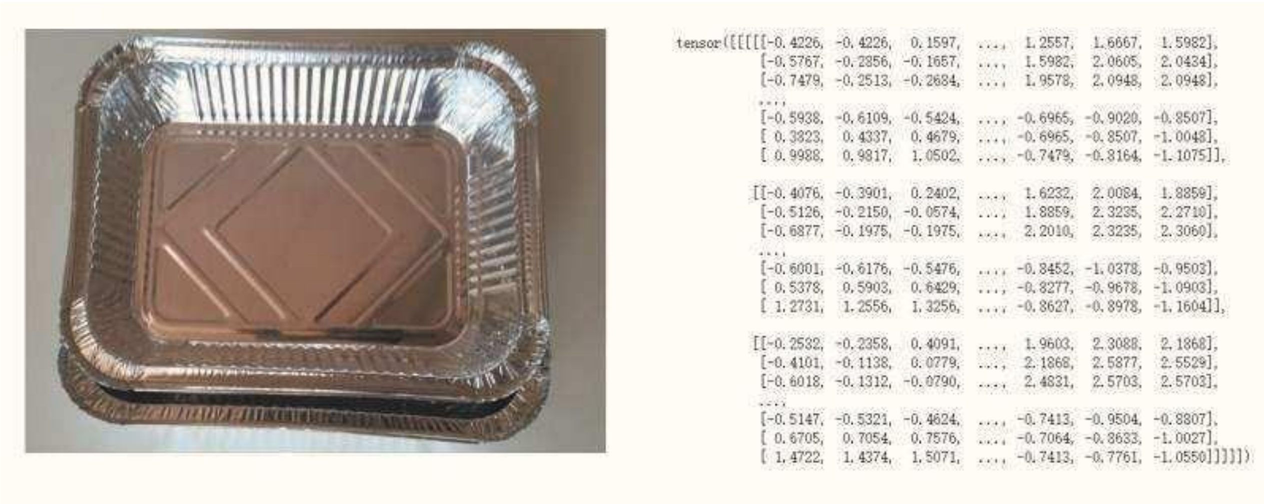

Figure 5: Picture processing

After loading the pre-trained model, the network is frozen. The frozen network is to keep the parameters (that is, the weights) in the specified layer in Pytorch, replace the last full-connectivity layer, and modify the class to a garbage class number of 40. Since the garbage recognition classification task in this article is a multi-class task, we use a cross-entropy loss function. Compare ResNet18 network and GoogLeNet network, and compare Adam and SGD two accelerators in different situations,After different learning rates and batch_size, the combined results found that the ResNet18 network-based migration learning was faster, and the model worked best when the parameters were set to batch_ size = 32, using a SGD accelerator and the learning rate was set to 0.003.

googlenet	batchsize=64 optim=SGD lr=0.003	Train epoch:0 loss:1.6383 acc:0.5489 Test epoch:0 loss:1.1696 test_acc:0.6571 Train epoch:1 loss:1.1440 acc:0.6633 Test epoch:1 loss:1.0161 test_acc:0.7031
resnet18	batchsize=32 optim=SGD lr=0.003	Train epoch:0 loss:1.0020 acc:0.6993 Test epoch:0 loss:0.9544 test_acc:0.7231 Train epoch:1 loss:0.9674 acc:0.7109 Test epoch:1 loss:1.0203 test_acc:0.7045

Figure 6: Compare results between two network models

The processed data is then put into the model for training, and the accuracy rate can reach more than 90% after 10 rounds of training.

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train: acc: 0.9403973509933775    recall: 0.9594594594594594
test: acc: 0.9578947368421052     recall: 0.978494623655914
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Figure 7: Accuracy after 10 rounds of training

4. CONCLUSION

This paper uses ResNet18 structure of deep residual network and transfer learning to realize garbage recognition and classification. During the experiment, we studied the current status and existing problems of garbage sorting, as well as the current state of research in the field of garbage collection. The training set and test set are created, and the image processing and image enhancement are carried out. Compare ResNet18 and GoogLeNet, and find the best model parameters. A slight overfitting occurred later in the training of the model, so further adjustment of the parameters is needed. Because there is no data set that contains the location label of garbage, this paper has completed the identification and classification of garbage. The task of determining the location of garbage is still empty, but labeling requires the researchers to label one by one, which is tedious and time consuming, and cannot be solved at this time. With regard to garbage sorting, I think the focus is not only on whether residents can make correct judgments about garbage, but also on the fact that residents are not actively involved, the government lacks a systematic regulatory mechanism, and the equipment for garbage separation is not convenient and innovative. In the light of the above, human literacy and scientific and technological standards should advance together and keep pace to solve the problem of garbage sorting.

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