Final Report: Garbage Sorting

Github link: **https://github.com/xujintao1000/Garbage-Classification**

Team Number：17

Word Count：2081

Date: 2021.4.9

1.0 Introduction

For this project, we are trying to figure out how we can accurately classify garbage. Take GTA as an example, 200,000 tons of waste is found in the recycle bin pre year, but 45,000 tons of that is garbage. The government loses 2 million dollars on re-classifying garbage each year[1]. It is getting increasingly difficult for us to distinguish and categorize garbage. Due to the increased variety of goods, people get confused and overwhelmed about how to categorize and dispose of their waste. Using machine learning, people can confidently and easily separate their waste appropriately. Machine learning is beneficial since it can learn and apply its learning to unknown things, which streamlines the sorting process and makes it easier for the end-user.

2.0 Illustration / Figure

Figure 1 shows the processing of how our model performs. First, we load the images that we took with the camera into our project's local webpage. Second, we wait for the response from our project. Third, our project will return the possible output amount in four categories.

Our project uses the Java Spring MVC framework to separate the front end and back end. Data is passed to the model layer through the controller layer. Then the controller returns the processed data to the view layer. The result of the waste category is shown on the webpage (Figure 1.).

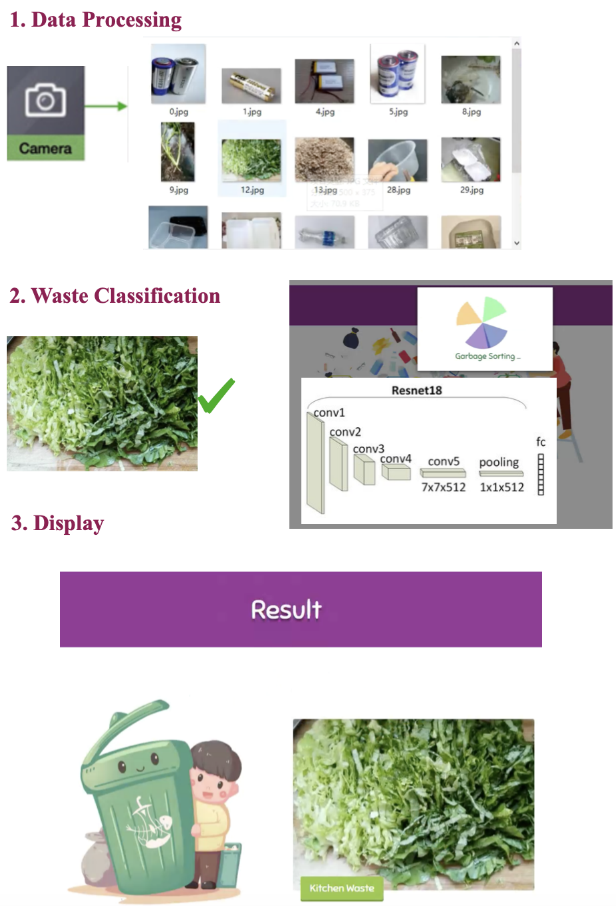

Figure 1. Illustration of the overall idea of the project

3.0 Background & Related Work

The following two existing technologies are currently in use by garbage sorting.

3.1 Alphabet's trashing-sorting robot arm

Alphabet's X team has been using the robots to sort recycling and trash using the computer visions (Figure 2.). The machine learning techniques it used to create the system includes the use of synthetic data from virtual environments with reinforcement learning [2]. The robots learned through practice and were able to reduce waste contamination levels from 20 percent to less than 5 percent [3].

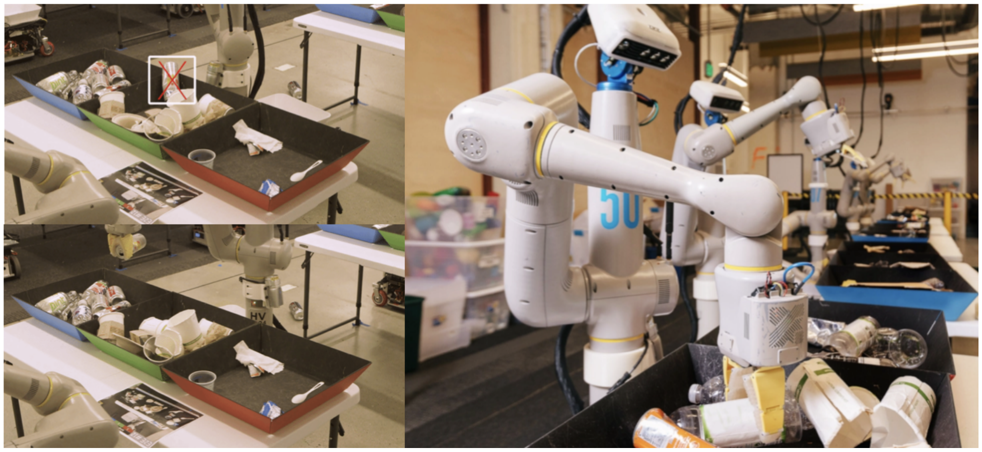

Figure 2. Alphabet’s trashing-sorting robots sort trash at Alphabet’s lab.[3]

3.2 Baidu trash-sorting mini program

It is becoming more popular for people to use apps to help sort out their trash in China. The image-sorting artificial intelligence technology applied on facial recognition now expands to trash sorting [4]. The Baidu applet for waste sorting has a voice search function and a camera search function (Figure 3.). Users can use their mobile phone cameras or microphones to search for different types of garbage. The app can scan items using the cameras on users’ smartphones and displays the classification results — wet or dry waste, recyclable or harmful waste [4].

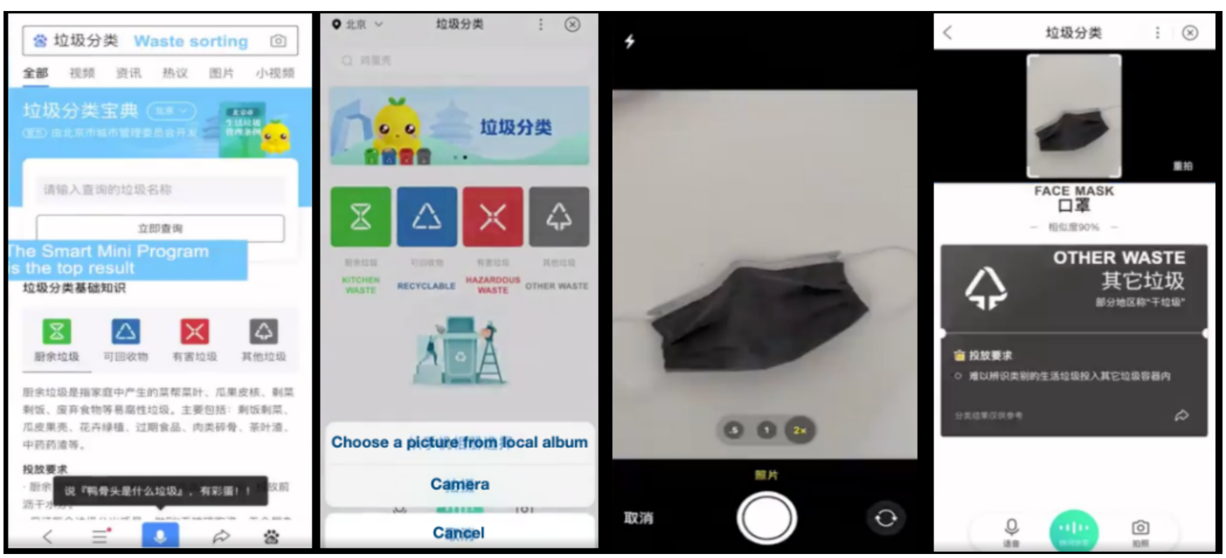

Figure 3. Baidu trash-sorting mini program uses image-recognition artificial intelligence technology.

4.0 Data Processing

4.1 Collecting data

The trash data from Huawei AI contest are made to be our train and validation data(Figure 4.)[5]. In our project, we divided the garbage into four groups: recyclable garbage, kitchen waste, hazardous waste and other garbage. We manually selected 600 common used garbage images as train data for each group and 75 as validation data. Besides, we selected 300 images from the Kaggle website as our test data set and checked that there are not the same images as the train and validation data[6]. Then the ratio for train, validation and test data is 2400:300:300 which is 8:1:1.

4.2 Cleaning and formatting data

For all the train and validation data images, we resized the images to the final image size of 224*224 pixels. Then we made the trash in the center of the cropped region and rotated the images for data augmentation. This makes the training set richer, and the model more generalizable. We also used colorjitter function to randomly change the brightness, contrast and saturation of an image. This could lead the model to a better performance on testing because the trash images we took on the phone might be different at different situations such as the dark or bright environment. At last we normalized the data with mean and deviation that are both 0.5 for increasing converging speed. The whole process is shown below(Figure 5.).

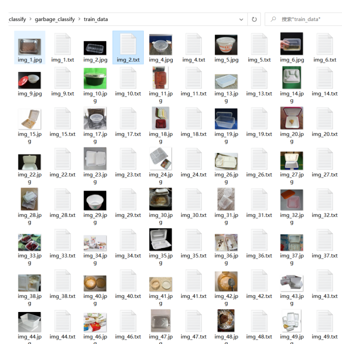

Figure 4. Partial garbage data source[1]

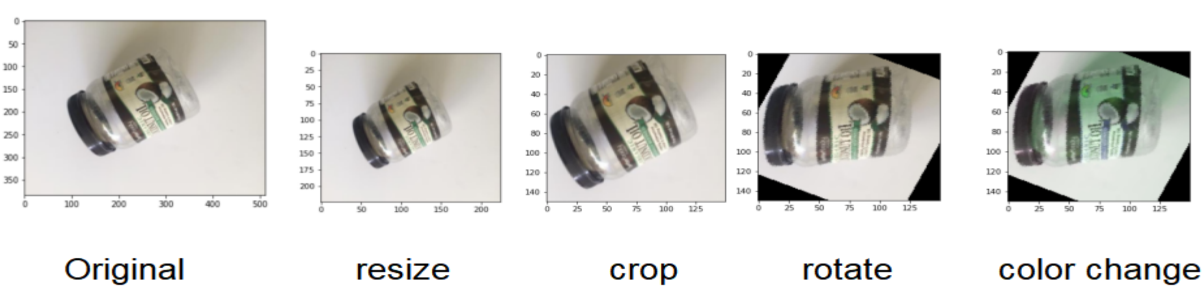

Figure 5. process of cleaning and formatting data

5.0 Architecture

We use transfer learning to test pre-trained CNN models, VGG16 and Resnet18, to determine which one is our primary model since these two models are commonly used for multi-classification. By training accuracy comparison, we chose resnet18 as our final primary model. There are 13 convolutional layers, 5 pooling layers, and 4 fully connected layers to finally generalize the 4 possible outputs in our resnet18 model. The details of the model are shown below(Figure 6.). Next, we fine-tune this resnet18 model by unfreezing the entire model except the last layer and re-training it on the new data with a very low learning rate. This can potentially achieve meaningful improvements, by incrementally adapting the pretrained features to the new data. To avoid overfitting, we added a dropout layer in the fully connected layer. Then we choose CrossEntropyLoss to calculate loss, and Adam as the optimizer, since Adam is converging fast at the beginning. After several times of training the model, the final hyperparameters of the batch size is 32, the learning rate is 1e-4, and the epoch is 10.

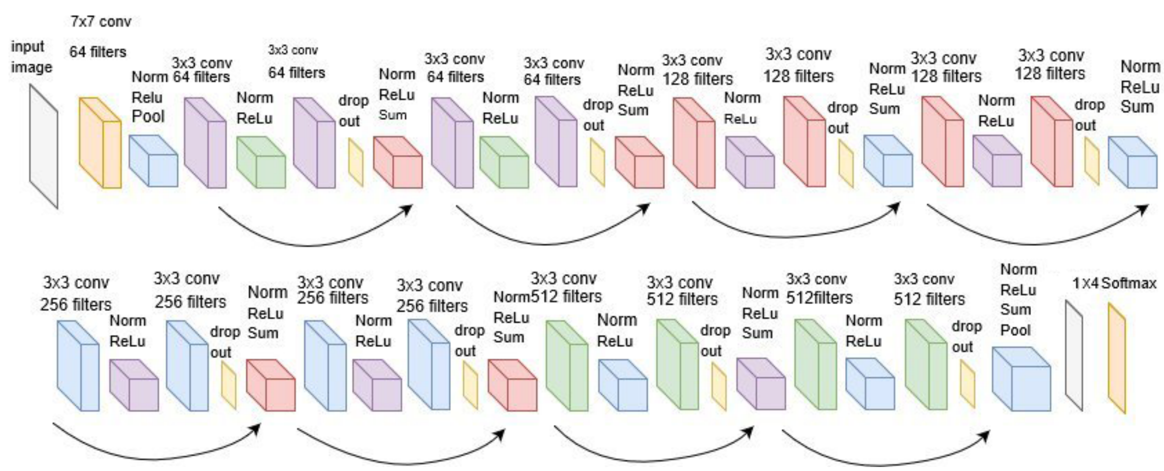

Figure 6. The detail of internal Resnet 18 model

6.0 Baseline Model

We will use Multi Classification Support Vector Machines (SVM) as our baseline model since we need a way to classify our waste images. For image detection, our model needs to tackle the structure and color classification problems. If the model receives the image, it will return the similarity percentages of each waste category based on the structure and color parameter. The model will make a decision to choose the waste category with the highest percentage. Thus, SVM is chosen in view of the fact that each garbage image has properties in its shape and colour, and it would not be affected by the hyperparameter.

7.0 Quantitative Results

Figure 7 shows that our model achieves around 90% accuracy, and this data is close to the probability of the validation accuracy of our training model. To be more specific on how we get the test accuracy, we load every image from the test datasets and send it to the model to get the output of one of four possible garbage categories. Next, we compared the index stored from the image with the model's output, and we will accumulate the accuracy if they match.

Besides, we separated the 300 image test dataset into categories to find the accuracy of each category. Based on this result in Figure 8, we conclude that our model has the highest probability of identifying the recycled garbage, which arrives at 97%. Besides, We should also notice that the "Other garbage" category shows the lowest accuracy,so that our model might not work well on identifying the "Other Garbage" category.

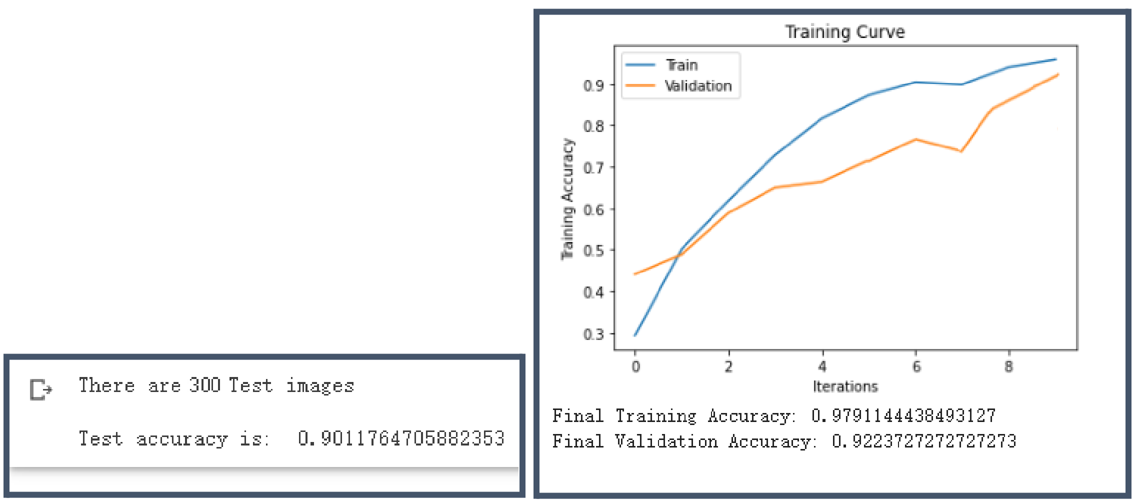

Figure 7. The result of test accuracy, and the validation and training accuracy from primary model

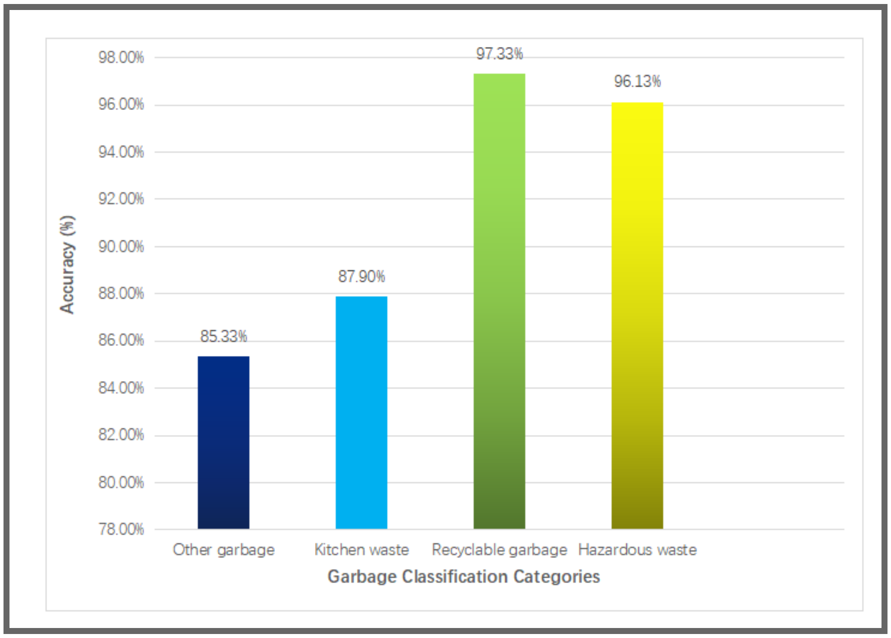

Figure 8. The probability of each category test accuracy

8.0 Qualitative Results

Figure 9 shows the two types of results after we load the image into our project. The first result is the name of the garbage type. To be more specific, if the user puts the battery image into our project, then the output will be "harmful", which means the battery belongs to the "harmful garbage." The second result shows the bar chart, and it is used to show the potential possibilities for every garbage category. The x-axis represents the type of garbage category, and the y-axis represents the probability. Besides, the percentage on the bar charts determines which category the picture will be finally classified into. For example, in Figure 3, plastic food packaging shows almost 100% on "Recycling Garbage", and the remaining shows nearly 0%.

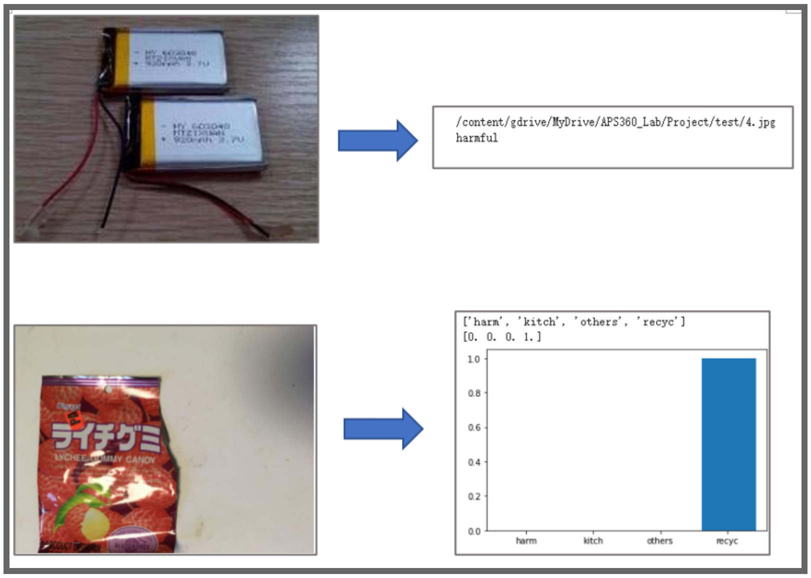

Figure 9. Two types of methods of showing the result

9.0 Evaluate model on new data

The result of the test of accuracy for Resnet18 arrives at 90.12% (Figure 10.). We put the test images into the model, and we get the output by accumulating the accuracy. The validation accuracy is around 92%, which is really close to the test result of our model. It also means that our model is relatively reliable in classifying most of the garbage.

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There are 300 Test images

Test accuracy is:  0.9011764705882353
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Figure 10. Test accuracy of the test dataset from the original dataset

We created a test dataset containing 24 new test images to test the model's performance on new data. The test accuracy of the new test dataset is about 90.64% (Figure 11.). We loaded 16 new test images and used the bar chart to show the potential possibilities for every garbage category. For example on Figure 7, the possibility for the image of batteries to belong to harmful waste is about 80 percent, while the possibilities of the other categories are all below 5% (Figure 12.).

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There are 24 Test images

Test accuracy is:  0.9064264785584357
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Figure 11. Test accuracy of new test dataset

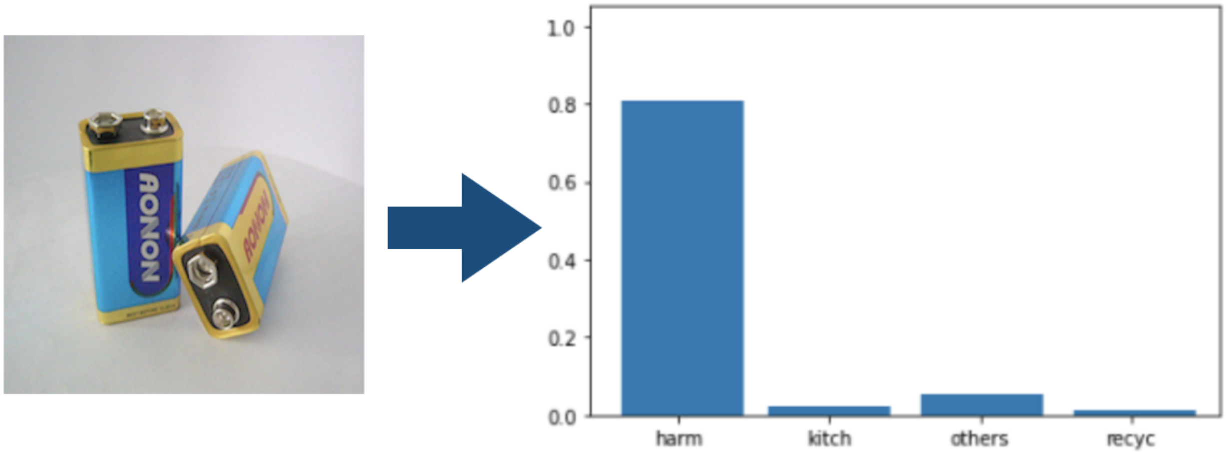

Figure 12. Prediction of the category of the waste

10.0 Discussion

After observing all the results, we think our model is performing very well given the tasks. We knew from the beginning the amount of variations on items of garbage is incredibly large and slight distortion in the photos can cause errors for classification. From our results, we are getting a 90.12% test accuracy, which means that items are being categorized with a 90% efficiency rate. Comparing this to our baseline results which were 53% in accuracy, our project significantly helped sort out recyclable materials from the garbage. With this being said we observed some abnormal results too that we did not expect and it was unusual. We found that our model easily mismatched the image of a cup of glass and the black plastic bag(Figure 13.). The reflection effect caused the image to not be classified correctly, which resulted in the unexpected results.

Something we learned was that it is very important to separate the training data evenly so we don't get any biases in the category classification. We had to ensure we had the same amount of data for each class to eliminate bias.

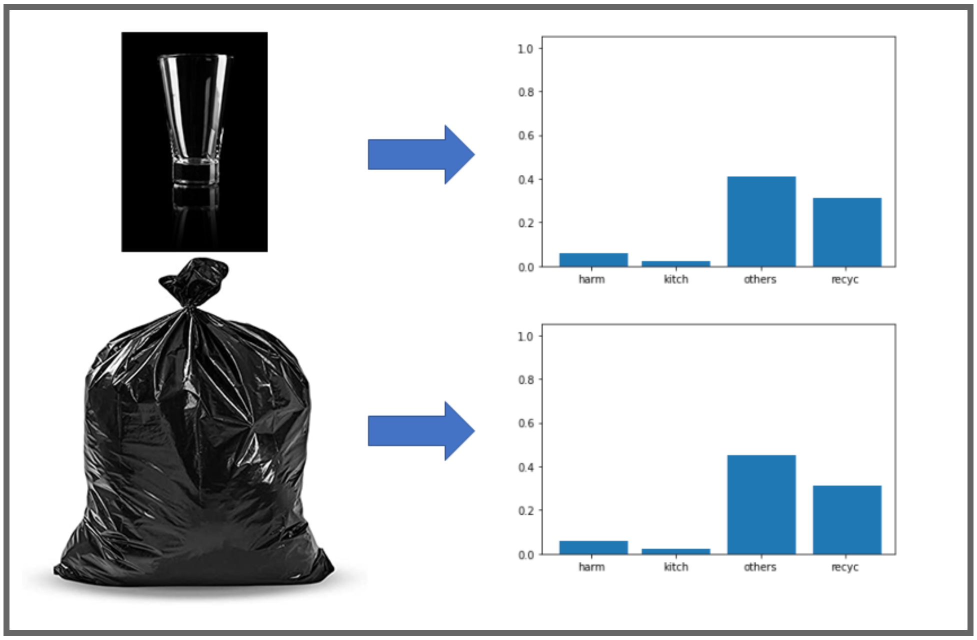

Figure 13. The output distribution of a cup of glass and the black plastic bag

11.0 Ethical Considerations

11.1 Possibility of environmental pollution

The model probably sorts the main object, but it could cause environmental pollution when classifying the special object. For example, lipsticks are contained in the glass. The glass is recyclable waste while the liquid is harmful. The system may detect the lipstick as recyclable garbage, and it would be put in the recycle trash bin with other recyclable garbage together. This leads to environmental pollution when disposing of garbage in the next step of composing.

11.2 Privacy

When we use our phones to scan an object, it could be saved on the phone. Other apps could obtain the picture and analyse our personal preferences based on the large amount of data. Besides, some personal information could be leaked if it is left on abandoned courier boxes. Thus, people's privacy may be leaked to a certain extent.

12.0 Project Difficulty / Quality

Our project is aimed at sorting the various garbage into the correct group. In view of the huge variety of garbage, it is not easy to clarify them with high accuracy. For the data processing, we use data augmentation to get adequate data in order to train the model better. Also, we use transfer learning to test the different models such as VGG16 and Resnet 18, and then we choose Resnet 18 as the final model by comparing the accuracy. Next, we come up with a better model by fine-tuning.

We choose 2400 images as our training data,, and the Resnet 18 itself has 13 convolutional layers with 5 pooling layers, so it takes around 1 hour to train the model every time. The complexity of the model is much higher than that in the lab, and the amount of training data is much larger than the relevant labs. At last we get that the final accuracy of testing is around 0.9. For some recyclable and hazardous waste, the accuracy is almost 100%. Overall, the model meets our expectations because we want to collect the recyclable garbage as much as possible and we do not want the hazardous garbage classified into the wrong groups, which leads to some potential risk when it is mixed with other trash.

Reference

[1] CBC. 2021. *Many Canadians are recycling wrong, and it's costing us millions | CBC News*. [online] Available at: <https://www.cbc.ca/news/technology/recycling-contamination-1.4606893> [Accessed 10 April 2021].

[2] Johnson, K., 2021. *Alphabet’s trash-sorting robots have reduced office waste contamination to ‘less than 5%’*. [online] VentureBeat. Available at: <https://venturebeat.com/2019/11/21/alphabets-trash-sorting-robots-have-reduced-office-waste-contamination-to-less-than-5/> [Accessed 12 February 2021].

[3] Engadget.com. 2021. *Engadget is now a part of Verizon Media*. [online] Available at: <https://www.engadget.com/2019-11-22-alphabet-xlab-everyday-robot.html> [Accessed 12 February 2021].

[4]Li, J., 2021. *In China, facial-recognition technology is being deployed to take out the trash*. [online] Quartz. Available at: <https://qz.com/1667020/in-china-people-are-turning-to-apps-to-sort-out-their-trash/> [Accessed 12 February 2021].

[5] huawei. 2021. *Huawei - Building a Fully Connected, Intelligent World*. [online] Available at: <https://modelarts-competitions.obs.cn-north-1.myhuaweicloud.com/garbage_classify/dataset/garbage_classify.zip> [Accessed 10 February 2021].

[6] Kaggle.com. 2021. *Split Garbage Dataset*. [online] Available at: <https://www.kaggle.com/andreasantoro/split-garbage-dataset> [Accessed 6 February 2021].