



MSBA7011  
Managing and Mining Big Data

# **Garbage Classify**

## **Image Classification Based on Deep Learning**

April 2020

### **Group A9**

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# 1. Executive Summary

At present, garbage classification is usually handled by human labor. It would be more efficient to develop an image classifier to classify garbage. To be specific, given a picture of garbage, the classifier would help sort trash before disposal. This requires deep learning to classify the garbage and tell the user what type of trash it is. Using 14802 garbage images downloaded online, we train a convolutional neural network to classify the garbage into 40 classes (sub-categories) and could achieve 87.18% accuracy on the test data.

As a digital marketing firm in Shenzhen, mobile application design is one of the main services provided by us, and our project could be used to develop a new app or platform for the government aiming to help citizens classify garbage before throwing it out in the garbage station. By cooperating with government and contributing to environmental protection, our firm can earn a higher reputation as well as maintaining steady revenues.

## 2. Introduction

Nowadays, garbage classification has become a hot topic in society. Large cities in China such as Shanghai, Shenzhen, Guangzhou and Hangzhou already piloted a shift to make garbage classification compulsory, instead of voluntary. By 2022, every city in China at the prefecture level and above should have at least one district where all household garbage is classified, and by 2025 they should have their own household garbage sorting and disposal systems. Garbage classification has become a common topic that people would encounter in their everyday life.

When the garbage classify rule is firstly published, the citizen may have difficulty distinguishing the garbage type and so are reluctant to obey the rule. Besides, at present, artificial garbage classification is the first part of garbage treatment, and most domestic waste treatment plants are using the method of manual assembly line to sort garbage, which has the disadvantages of poor working environment, high labor intensity and low sorting efficiency. In the face of massive garbage, manual sorting can only sort out a very limited part of recyclable and hazardous garbage, and most of the garbage goes to landfills, which can cause great waste of resources and environmental pollution risk. Another huge problem is recycling contamination, it occurs when waste is incorrectly disposed of - like recycling a medicine box with residual drugs in it; or when waste is correctly disposed of but incorrectly prepared - like recycling unrinsed jam jars. Contamination is a huge problem in the recycling industry that can be mitigated with automated waste sorting.

Since our firm is in Shenzhen, our project aims to solve these problems by building an image classifier to sort different kinds of garbage according to rules of Shenzhen government. The original goal of the waste classifier is to create an in-house tool that would help people sort their trash before throwing it out. Specifically speaking, we train a convolutional neural network to classify an image into one garbage class among 40 sub-categories. The model is trained using ResNet. In the future we will embed this model in new app and platform. We believe our model can greatly help government promote the policy, improve the efficiency of garbage sorting, and reduce contamination in the recycling industry.

The rest of this report is organized as follows. In section 3, we will introduce our data source and give some summary statistics of data. In section 4, we will go over different models that we tried in this project, and compare them to give the best choice. In section 5, we will state our conclusion and some future work that might be taken.

## 3. Data

### 3.1 Data Source

We use data from a Huawei AI competition<sup>1</sup>. The train data ([https://modelarts-competitions.obs.cn-north-1.myhuaweicloud.com/garbage\\_classify/dataset/garbage\\_classify.zip](https://modelarts-competitions.obs.cn-north-1.myhuaweicloud.com/garbage_classify/dataset/garbage_classify.zip)) includes “train\_data” folder and a JSON file which states the classify rule. The test data are provided as supplement from Baidu Cloud ([https://pan.baidu.com/s/1SulD2MqZx\\_U891JXeI2-2g](https://pan.baidu.com/s/1SulD2MqZx_U891JXeI2-2g) password: epgs). After downloading, we manually rename the data folder as “test\_data” and move to “garbage\_classify” folder.

### 3.2 Training and test dataset

Training dataset contains 14802 garbage images and corresponding label files (.txt).

Testing dataset contains 4165 garbage images and corresponding label files (.txt). The percentage of test size is 22%.

The classification rule is clarified in “garbage\_classify\_rule.json” file. We have 4 categories of garbage, and 40 sub-categories or classes. The list of classes are shown in Appendix.

### 3.3 Data Visualization

We read the labels of each images from text file by python. And then plot the distribution of quantity of garbage images of each classes and categories are as below. As we can see, the recoverable garbage is most and hazardous garbage is least.

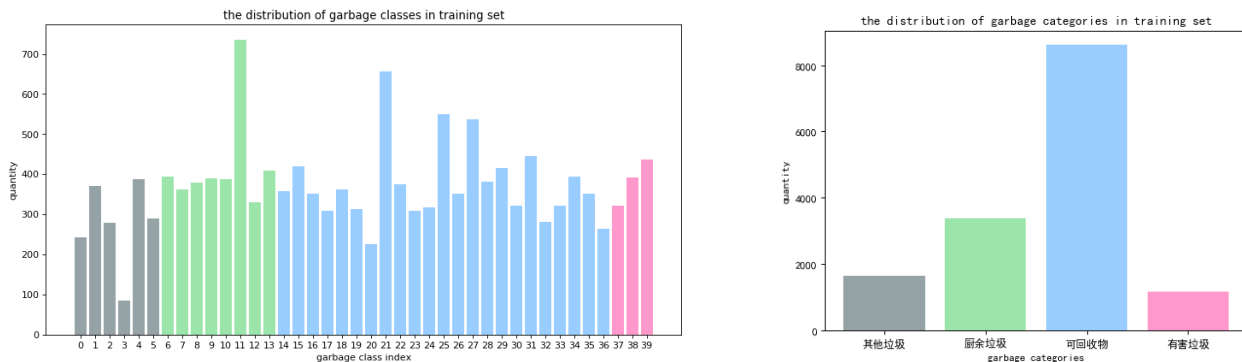


Figure 1 - The Distribution of Garbage Classes and Categories in Training Set

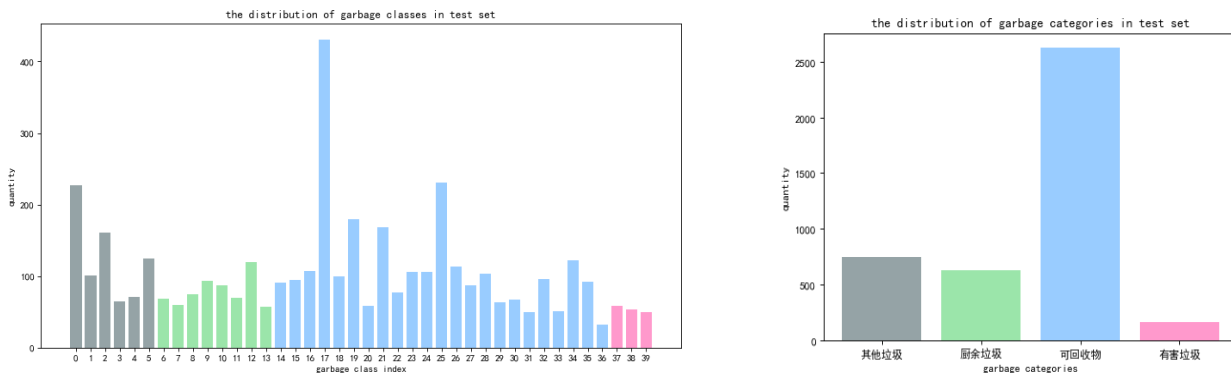


Figure 2 - The Distribution of Garbage Classes and Categories in Testing Set

<sup>1</sup> <https://competition.huaweicloud.com/information/1000007620/introduction?track=107>

## 4. Analysis

### 4.1 Method and Platform

We plan to use pytorch in Python to train and test our convolutional neural network. Specifically, we choose to try transfer learning of Resnet18, Resnet50 and ResNext50(32x4d) because of their low operations and high accuracy. Limited by our laptop hardware, we use Google Colab (GPU mode) to load images and train above models after data preparation.

### 4.2 Data Preparation and Loading

As for now, photos of all types of trash are stored in one folder. To adapt the data for ImageFolder() to load images efficiently, we use Python to automatically create 40 folders denoted as 40 classes of trash for training and testing dataset respectively, and automatically move the images to corresponding folders.

Before loading images, we also adopt Data Augmentation. For training photos, we process them by following steps: randomly crop the them into size 256; flip part of them; crop them into size 224; convert them into tensor type; make normalization. Augmentation for testing photo is simpler: resize and crop them into size 256 and 244 respectively, then make conversion and normalization.

Setting a batch size of 128, finally we obtain the input with shape [128, 3, 224, 224] of one batch.

### 4.3 Model Selection and Parameters Tuning

We are going to select the best network among ResNet18, ResNet50 and ResNext-50. By transfer learning, we initialize the network with a pretrained network. In order to be more efficient, we freeze the parameters firstly.

For each network, we improve the performance by tuning optimizer and learning rate parameters, fixing weight decay =  $5e-4$ .

Model	ResNet-18/ResNet-50/ResNext-50					
Optimizer	Adam			SGD		
Learning rate	0.01	0.001	0.0001	0.01	0.001	0.0001

Figure3 Parameters Tuning

After selecting the best network, then we try finetuning the convnet (not freeze the parameters).

### 4.4 Training and Results

After freezing the parameters and training the models, we get results of 14 models, the test accuracy is shown in below tables. On the one hand, we measure a model by test accuracy, on the other hand, we also check the accuracy curves and loss curves to see whether the model is overfitting. We observe that ResNext-50 has the best performances, with test accuracy of around 85%, and the curves converge well with no obvious overfitting. It makes sense because ResNeXt-50 has the most complex network, and the top-1 error of ResNeXt-50 is slightly lower than that of ResNet-50. ResNet-18 performs much worse than ResNet50 and ResNeXt-50, with test accuracy of around 80%. Besides, we learn that the Adam and SGD optimizer perform similarly on these three network and our datasets, but learning rate 0.0001 is more appropriate for Adam, and 0.001 for SGD.

Model	ResNet-18					
Optimizer	Adam			SGD		
Learning rate	0.01	0.001	0.0001	0.01	0.001	0.0001

Testing accuracy (%)	78.06	80.58	<b>79.11</b>	81.01	<b>79.06</b>	72.89
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ResNet-50						
Model	Adam			SGD		
Optimizer	Adam			SGD		
Learning rate	0.01	0.001	0.0001	0.01	0.001	0.0001
Testing accuracy (%)	80.93	84.48	<b>84.93</b>	N/A	84.22	<b>84.98</b>

ResNeXt-50						
Model	Adam			SGD		
Optimizer	Adam			SGD		
Learning rate	0.01	0.001	0.0001	0.01	0.001	0.0001
Testing accuracy (%)	N/A	84.43	<b>84.98</b>	N/A	<b>84.73</b>	N/A

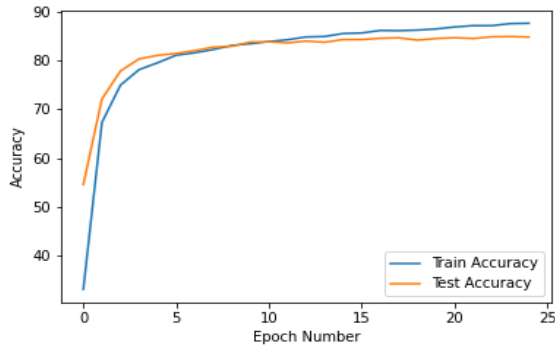


Figure4 ResNeXt50 (SGD, learning rate=0.001)

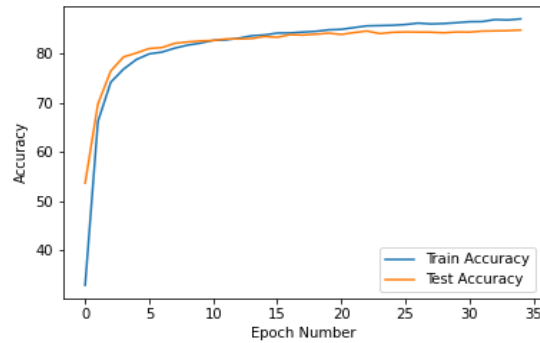


Figure5 ResNeXt50 (Adam, learning rate=0.0001)

Then we try finetuning the convnet on ResNext50. This time Adam performs worse than SGD optimizer. Finally, we get our best model which is shown below. The test accuracy reaches 87.18%.

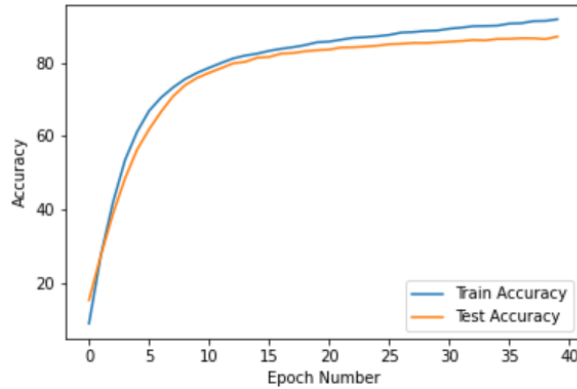
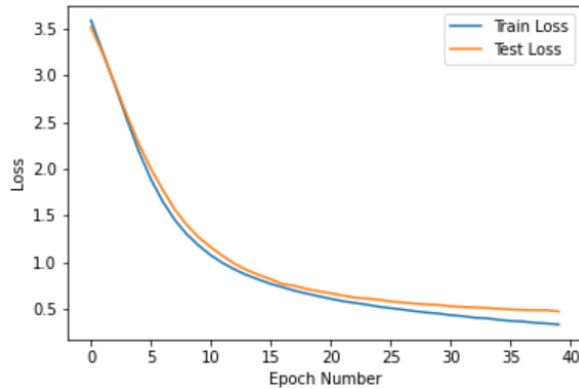
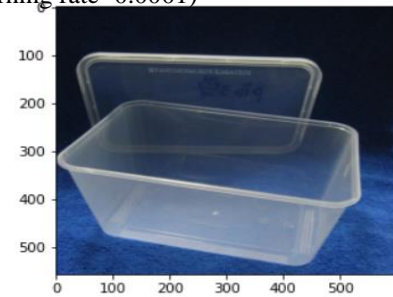


Figure6 ResNeXt50 (SGD, learning rate=0.0001)

Model	ResNext50(32x4d)
Optimizer	SGD
Scenarios	Finetuning the convnet
Learning rate	0.0001
Weight Decay	5e-4
Epoch	40
Testing accuracy (%)	87.18%



Prediction in progress  
0 其他垃圾/一次性快餐盒

Figure7 A Prediction Example

Then we save the model parameters as ‘pth’ file for future prediction. The Google Drive link of the final model is attached in Appendix.

The prediction is much simpler. We load the image which we want to predict and input to the saved model, and map the output class index to the class name. An example is as above figure7.

## **5. Conclusion**

### **5.1 Benefits**

Firstly, we could design an app using the model helping government instruct citizens to classify garbage. Instead of searching the rules online or getting confused of the statement of each class, people just need upload an image of trash and our app could tell the exact class a few seconds later. Government could update the rules in the app without extra promotion on media and citizens could adopt to the real time update without effort on understanding.

Secondly, using the image classification model, we actually could classify garbage given different classification standards other than the one used in the current model. Therefore, it is possible that governments in different areas or countries could use their local standards, making our app go to the global market.

Thirdly, by establishing a long-term cooperative relationship with the governments, we will also offer long-term maintenance and update service of the app. Mainly include the update of garbage types and images, and the maintenance and management of the daily operation of the app.

### **5.2 Limitations and Future Work**

Firstly, since we just give one output with one image, we can not assess the picture with more than one kind of garbage and try to classify them separately. For example, if an image of a milk tea bottle is given, we cannot separate the plastic lid and the paper made bottle.

Secondly, the classification accuracy may be disturbed by other items in the picture, because currently our dataset is all images of only one garbage without any interference.

Given more time, we could use image recognition to further implement garbage classification and to lower the requirement of image input by customers.

Thirdly, we could not test more complicated models because of the limitation on the computer hardware. Given more resources and time, we are confident to explore a more accurate model to improve the performance of garbage classification.

## **6. Duties**

After deciding the project topic, Tang Xiaojun did some search for data source and paper reading, and tried coding though the performance was not so good. Later for data processing, data preparation, coding and training model part, Chen Jiaojiao and Xie Siyang are mainly responsible, and paid a lot of efforts fixing the problem of laptop’s memory limitation and figuring out to correctly use Colab. Tang Xiaojun, Wang Yang, Yan Shujie and Zhang Xiao wrote the report, made the PPT slides. Chen Jiaojiao modified the report and formatting the report. Xie Siyang and Chen Jiaojiao further sorted out the data, code and other files together.

# Appendix

## Appendix 1. Garbage Classes and Categories

"0": "其他垃圾/一次性快餐盒"	"11": "厨余垃圾/菜叶菜根",	"21": "可回收物/插头电线",	"31": "可回收物/调料瓶",
"1": "其他垃圾/污损塑料"	"12": "厨余垃圾/蛋壳",	"22": "可回收物/旧衣服",	"32": "可回收物/酒瓶",
"2": "其他垃圾/烟蒂",	"13": "厨余垃圾/鱼骨",	"23": "可回收物/易拉罐",	"33": "可回收物/金属食品罐",
"3": "其他垃圾/牙签",	"14": "可回收物/充电宝",	"24": "可回收物/枕头",	"34": "可回收物/锅",
"4": "其他垃圾/破碎花盆及碟碗",	"15": "可回收物/包",	"25": "可回收物/毛绒玩具",	"35": "可回收物/食用油桶",
"5": "其他垃圾/竹筷",	"16": "可回收物/化妆品瓶",	"26": "可回收物/洗发水瓶",	"36": "可回收物/饮料瓶",
"6": "厨余垃圾/剩饭剩菜",	"17": "可回收物/塑料玩具",	"27": "可回收物/玻璃杯",	"37": "有害垃圾/干电池",
"7": "厨余垃圾/大骨头",	"18": "可回收物/塑料碗盆",	"28": "可回收物/皮鞋",	"38": "有害垃圾/软膏",
"8": "厨余垃圾/水果果皮",	"19": "可回收物/塑料衣架",	"29": "可回收物/砧板",	"39": "有害垃圾/过期药物"
"9": "厨余垃圾/水果果肉",	"20": "可回收物/快递纸袋",	"30": "可回收物/纸板箱",	
"10": "厨余垃圾/茶叶渣",			

## Appendix 2. Final Model Files

Google Drive Link:

<https://drive.google.com/drive/folders/10CaEmUnxRJE1ttxmOOZtGyZKatUKhhX6?usp=sharing>

(All other links please see attached ReadMe.txt.)

## Appendix 3. References

Car classification using resnet50 ([https://www.jianshu.com/p/b935e108ba7d?utm\\_campaign=hugo](https://www.jianshu.com/p/b935e108ba7d?utm_campaign=hugo))

Transfer learning of pytorch (ResNet18) ([https://blog.csdn.net/weixin\\_40123108/article/details/85238355](https://blog.csdn.net/weixin_40123108/article/details/85238355))

Comparison of ResNext50 and ResNet50 (<https://www.cnblogs.com/bonelee/p/9031639.html>)

Teach you how to build an image classification model from scratch with PyTorch

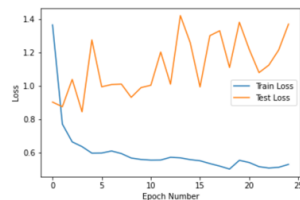
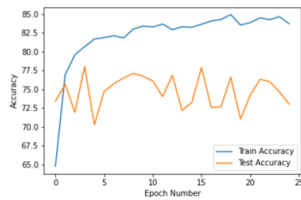
(<https://blog.csdn.net/gaotihong/article/details/80763813>)

resnet18 50 network structure (<https://www.jianshu.com/p/085f4c8256f1>)

## Appendix 4. Training Results

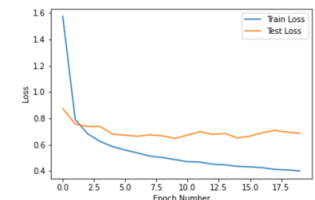
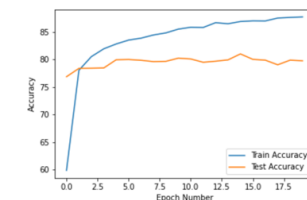
Resnet18 Adam(freeze) 0.01 25

78.055% epoch4



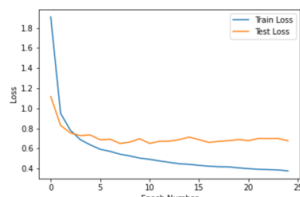
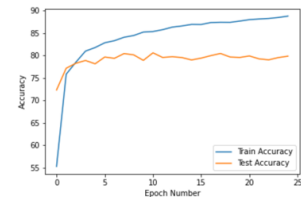
Resnet18 SGD(freeze) 0.01 20

81.008% epoch15



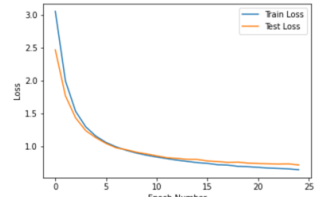
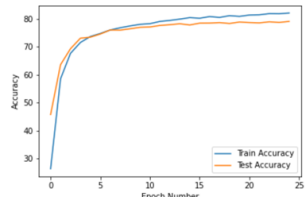
Resnet18 Adam(freeze) 0.001 25

80.576% epoch11



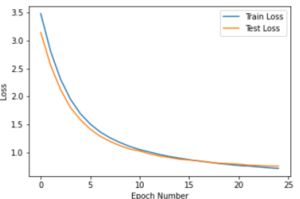
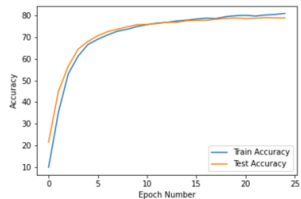
Resnet18 SGD(freeze) 0.001 25

79.064% epoch25



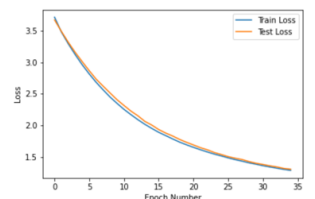
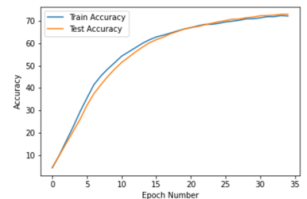
Resnet18 Adam(freeze) 0.0001 25

79.112% epoch23



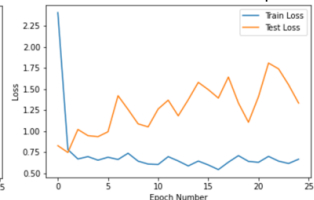
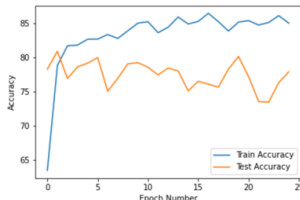
Resnet18 SGD(freeze) 0.001 35

72.893% epoch35

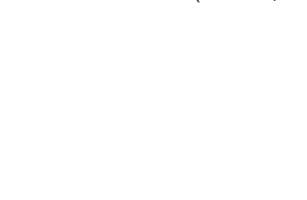


Resnet50 Adam(freeze) 0.01 25

80.934% epoch2

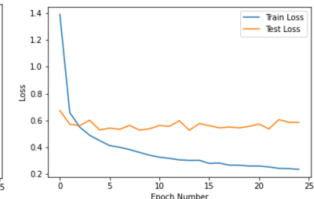
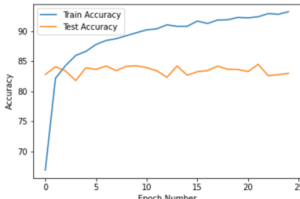


Resnet50 SGD(freeze) 0.01 20



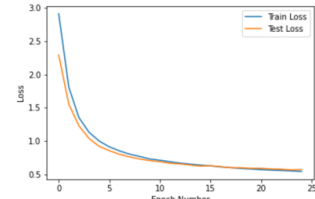
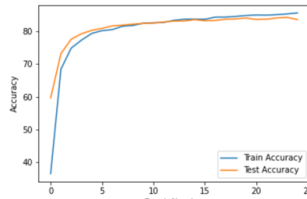
Resnet50 Adam(freeze) 0.001 25

84.479% epoch22



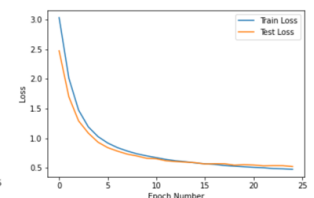
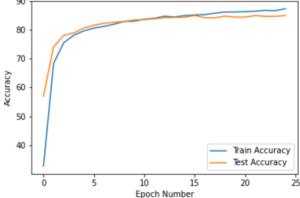
Resnet50 SGD(freeze) 0.001 25

84.216% epoch24



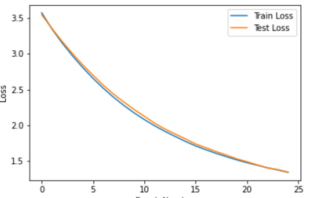
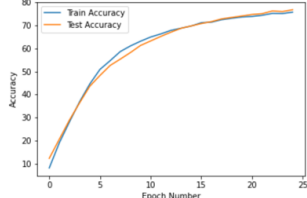
Resnet50 Adam(freeze) 0.0001 25

84.934% epoch16



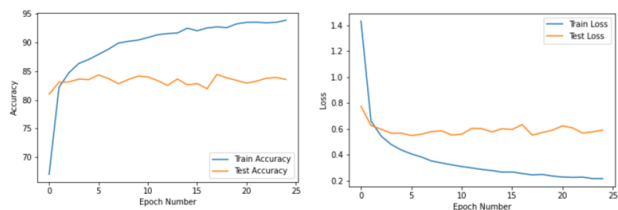
Resnet50 SGD(freeze) 0.0001 25

84.982% epoch24

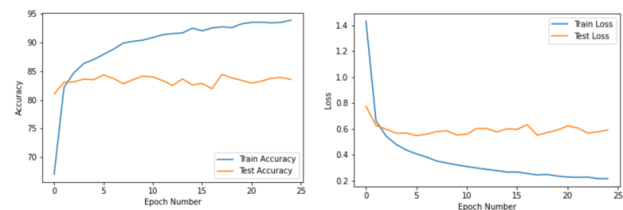




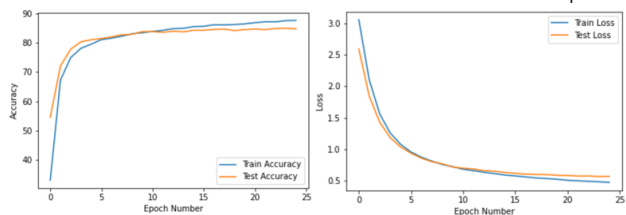
Resnext50 Adam(freeze) 0.01 25



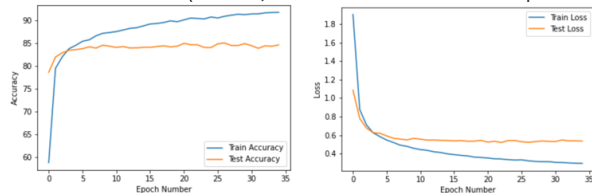
Resnext50 Adam(freeze) 0.001 25 84.431% epoch18



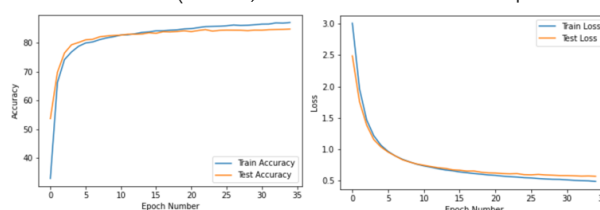
Resnext50 Adam(freeze) 0.0001 25 84.982% epoch24



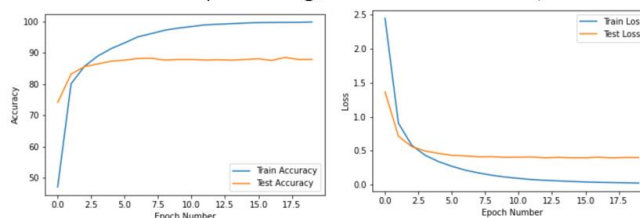
Resnext50 SGD(freeze) 0.005 35 85.066% epoch27



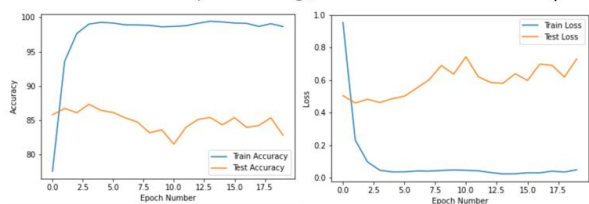
Resnext50 SGD(freeze) 0.001 35 84.730% epoch35



Resnext50 SGD(finetuning) 0.001 20 88.475% epoch18



Resnext50 Adam(finetuning) 0.0001 20 87.323% epoch4



Resnext50 SGD(finetuning) 0.0001 40 87.179% epoch40

