Garbage Classification

Xinmeng Chen
Zhiyue Feng
Ran Ju

Contents

01

Data Preparation

Data Preprocessing

Data Cleaning

Chose 14 classes and selected high quality images

Resize

Resized the size of the images into 256*256

Split & Augment

Split training and test dataset (10:1)

Array

Covert the image into array

Data Cleaning

kaggle

garbage-classification.zip	2020/4/20 10:31	WinRAR ZIP 压缩...	83,955 KB
waste-pictures.zip	2020/4/20 10:49	WinRAR ZIP 压缩...	2,148,962...

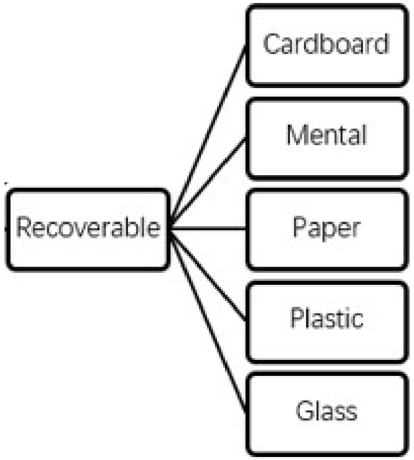
The smaller one has about **2,530** images and the bigger one has about **23,640** images. It has 26 classes in total

bandaid
battery
bowlsanddishes
bread
bulb
cans
carton
chopsticks
cigarettebutt
diapers
facialmask
glassbottle
leaflet
leftovers
medicinebottle
milkbox
nailpolishbottle
napkin
newspaper
XLight

cardboard
glass
metal
paper
plastic
trash

However, when we look at the detail of each dataset…

The smaller one



The larger one

plastic

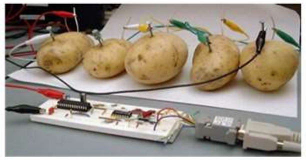
bandaid

carton

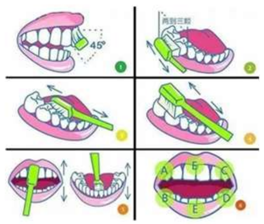
leftovers

rag

battery

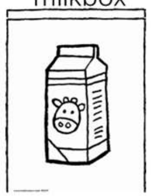


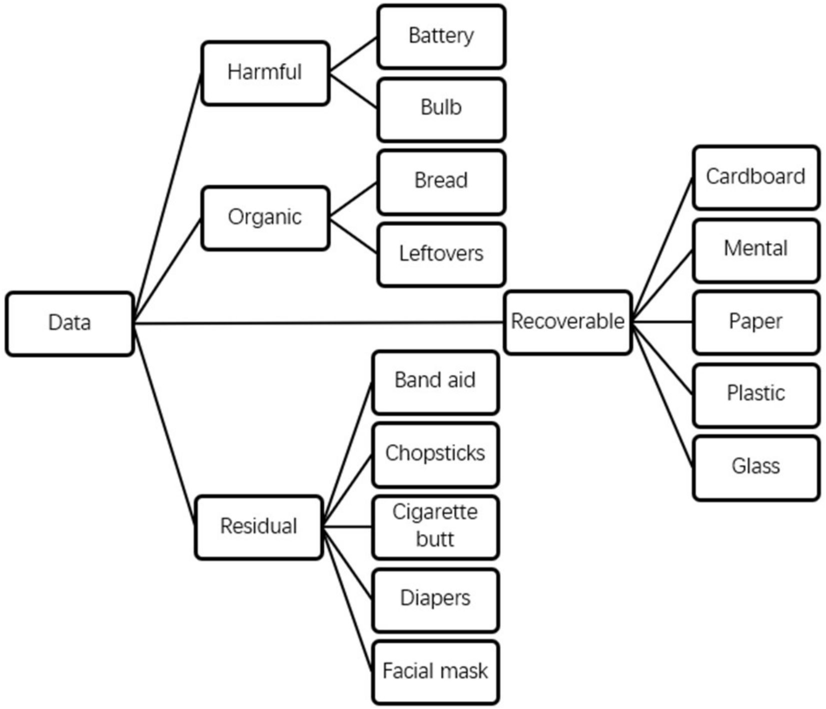
toothbrush



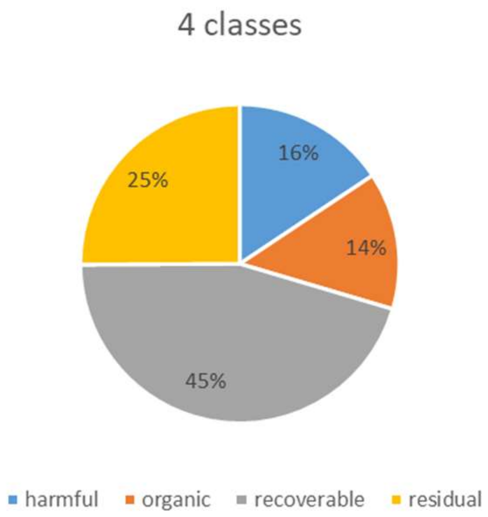
facialmask

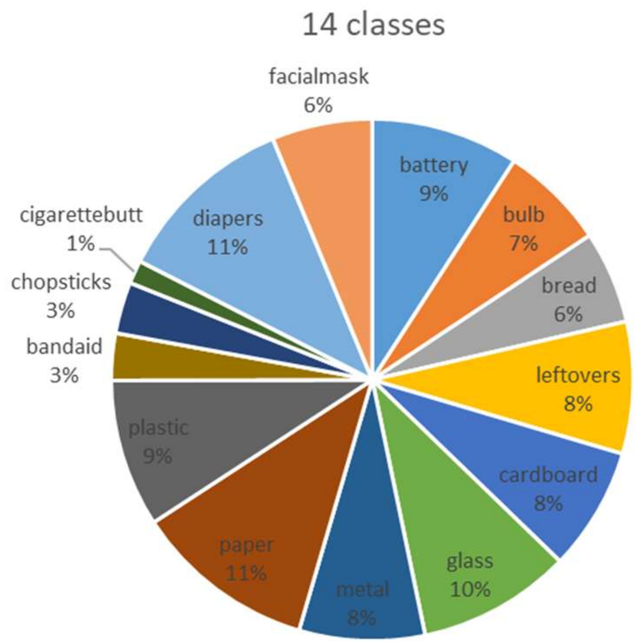
milkbox





4 types of garbage with the total number of 5,071 images


4 classes
16%
14%
45%
25%
harmful
organic
recoverable
residual


14 classes
facialmask 6%
battery 9%
bulb 7%
bread 6%
leftovers 8%
cardboard 8%
glass 10%
metal 8%
paper 11%
plastic 9%
bandaid 3%
chopsticks 3%
cigarettebutt 1%
diapers 11%

For each class training : test= 10 : 1

For training set We did data augmentation to make sure all types has around 450 images

B&W

Gray

RGB

LBP

First Version CNN

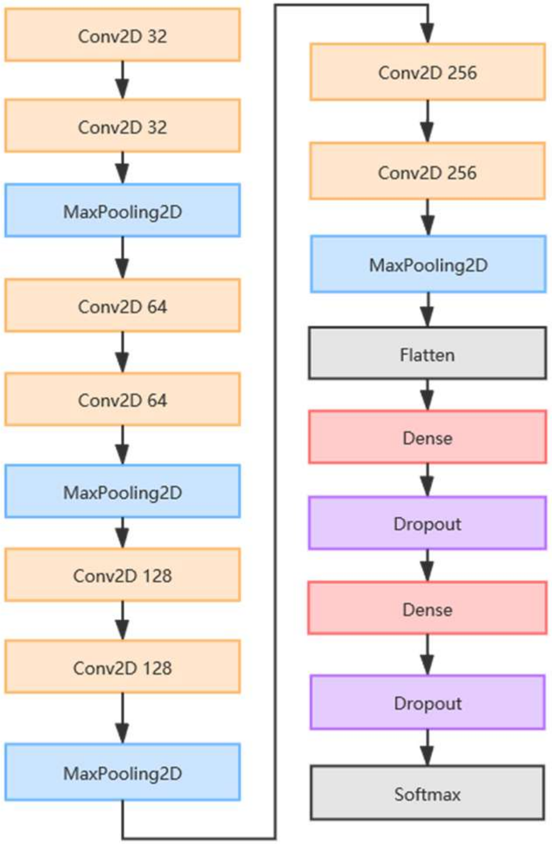
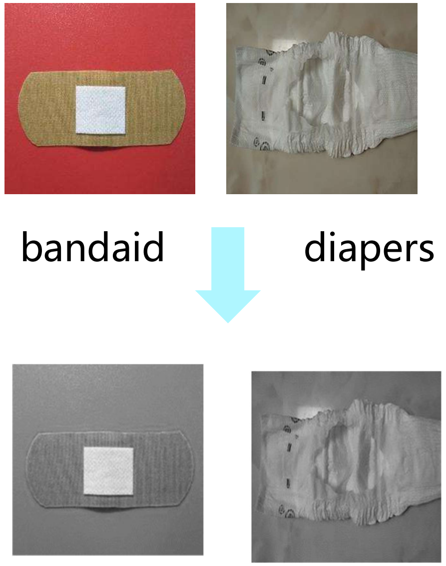


Image	Accuracy
RGB	0.715
B&W	0.61
Gray	0.66
LBP	0.589



02-1

KNN

Easiest network we tried

KNN

Time Consuming

Calculation complexity
Memory complexity
Lots of work of data processing

Calculation Complexity

The number of features are large.
The training set is not small.

Memory Complexity

The number of categories is comparatively large.
The calculation matrix will take lots of memory.

Overfitting and Underfitting

The selection of K using cross validation method is global optimal.

02-2

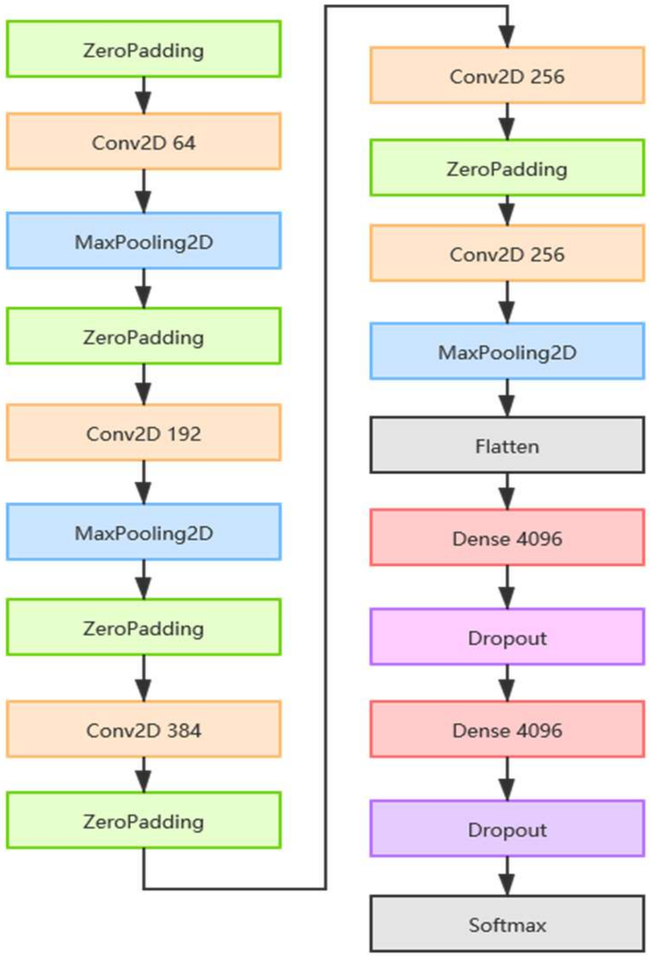
Alex Net

Winner of ILSVRC-2012

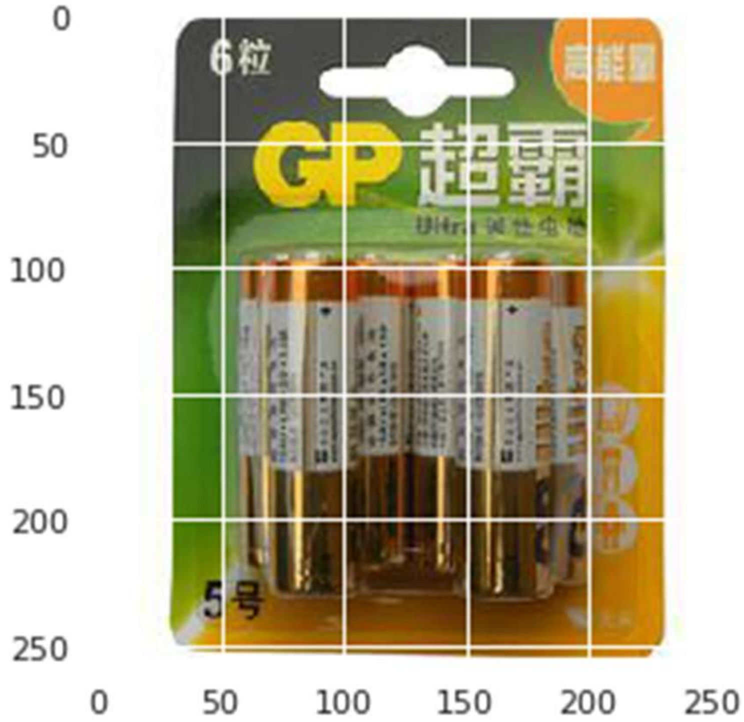
Alex Net

ReLu activation function

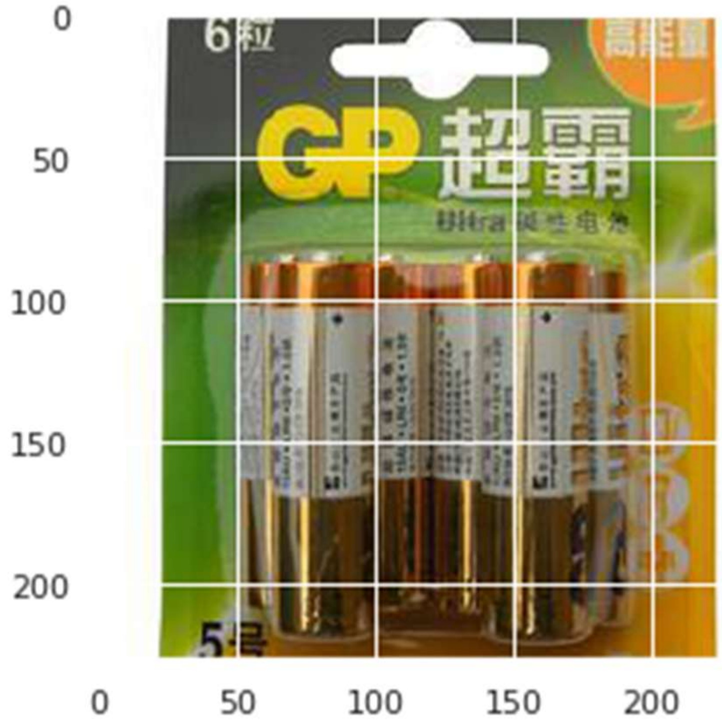
Drop out and data augmentation



The effect of random crop

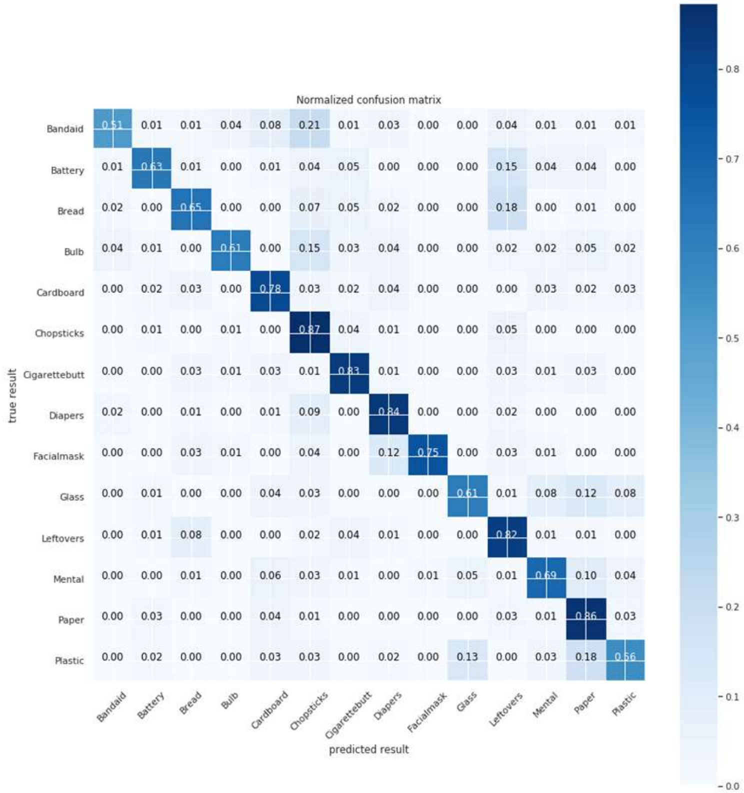


Original image

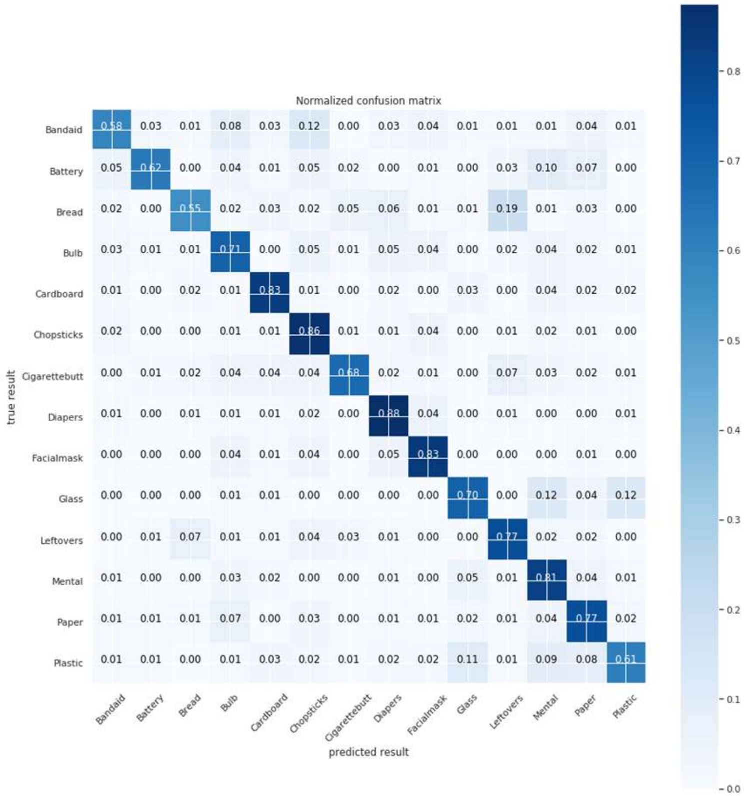


Processed image

The effect of random crop



The confusion matrix without random crop



The confusion matrix using random crop

Performance

	precision	recall	f1-score	support
0	0.80	0.51	0.63	72
1	0.82	0.63	0.71	73
2	0.73	0.65	0.69	88
3	0.91	0.61	0.73	96
4	0.80	0.78	0.79	120
5	0.52	0.87	0.65	79
6	0.73	0.83	0.78	71
7	0.73	0.84	0.78	82
8	0.98	0.75	0.85	68
9	0.77	0.61	0.68	72
10	0.65	0.82	0.73	106
11	0.77	0.69	0.72	105
12	0.59	0.86	0.70	78
13	0.65	0.56	0.60	61
accuracy			0.72	1171
macro avg	0.75	0.72	0.72	1171
weighted avg	0.75	0.72	0.72	1171

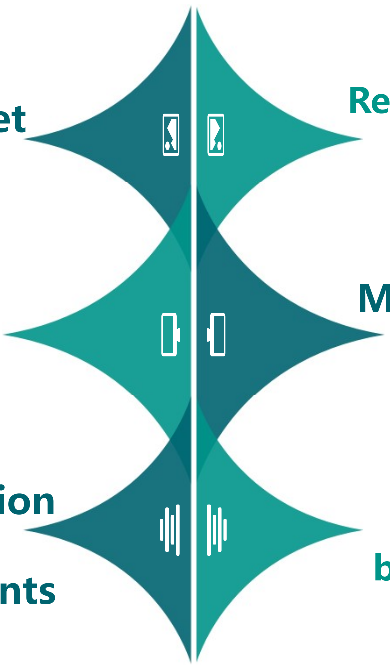
Original

	precision	recall	f1-score	support
0	0.78	0.58	0.67	580
1	0.85	0.62	0.72	455
2	0.77	0.55	0.64	570
3	0.68	0.71	0.69	595
4	0.86	0.83	0.84	760
5	0.68	0.86	0.76	585
6	0.81	0.68	0.74	435
7	0.75	0.88	0.81	560
8	0.74	0.83	0.78	440
9	0.69	0.70	0.70	420
10	0.73	0.77	0.75	700
11	0.71	0.81	0.76	775
12	0.66	0.77	0.71	545
13	0.68	0.61	0.64	380
accuracy			0.74	7800
macro avg	0.74	0.73	0.73	7800
weighted avg	0.74	0.74	0.74	7800

Using random crop

PCA (principle component analysis)

Advantages



- Make the data set easier to use
- Reduce the computation cost
- Remove noises
- Make the results easier to understand
- Eliminates interaction between raw data components
- Not restricted by sample labels

Concerns

- **Ambiguity**
- **Lose important information**

02-3

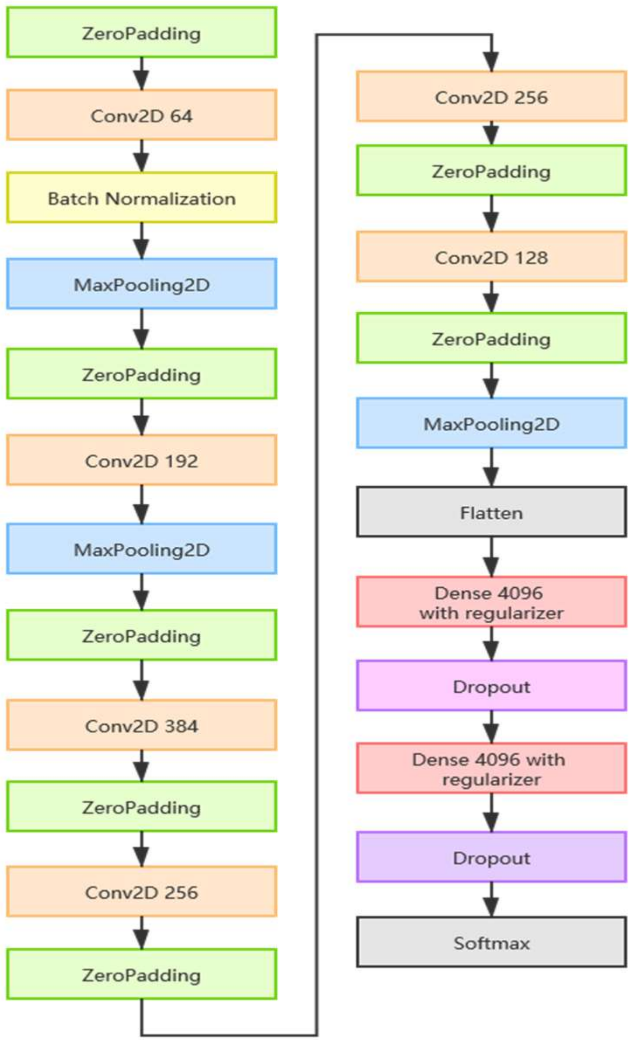
AlexNet+Yolo

Self – designed Network

AlexNet + Yolo

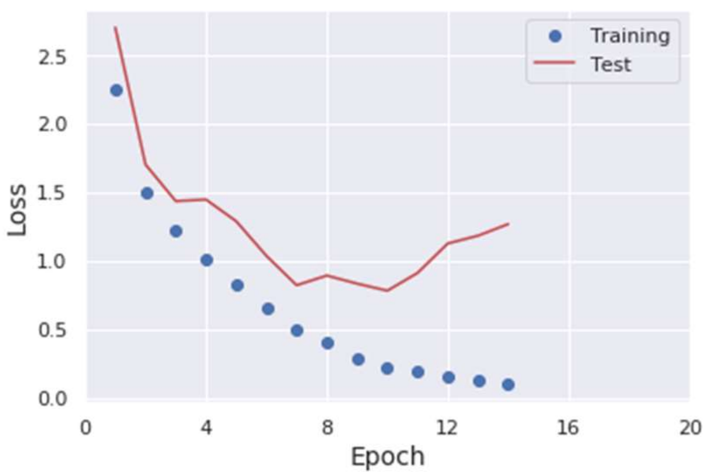
Changes

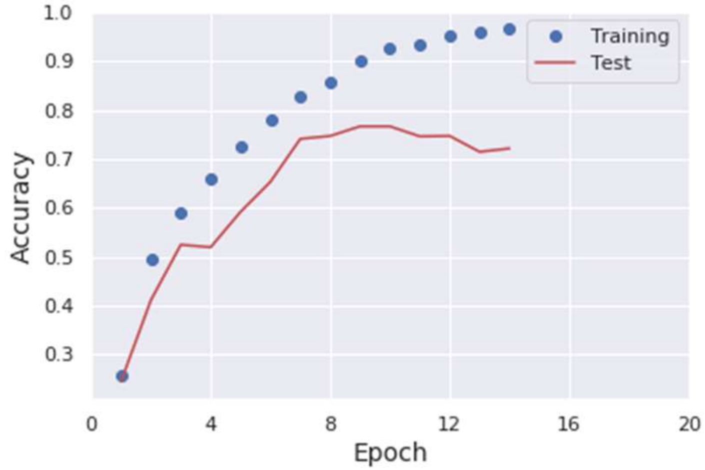
- 01 Regularization
- 02 Zero padding
- 03 More convolutional layer
- 04 Batch normalization

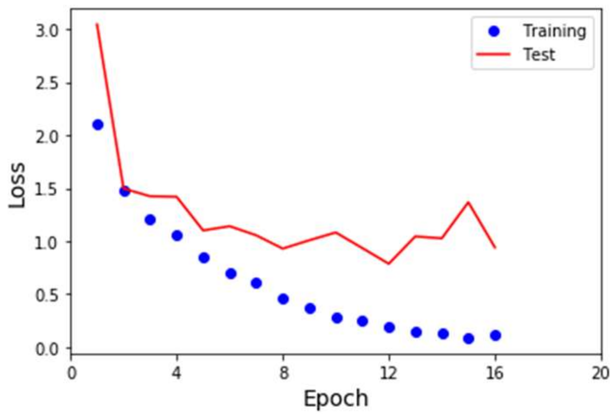


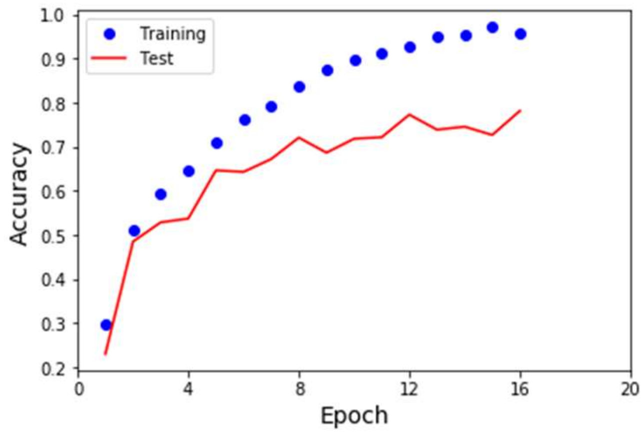
Learning curve

Original



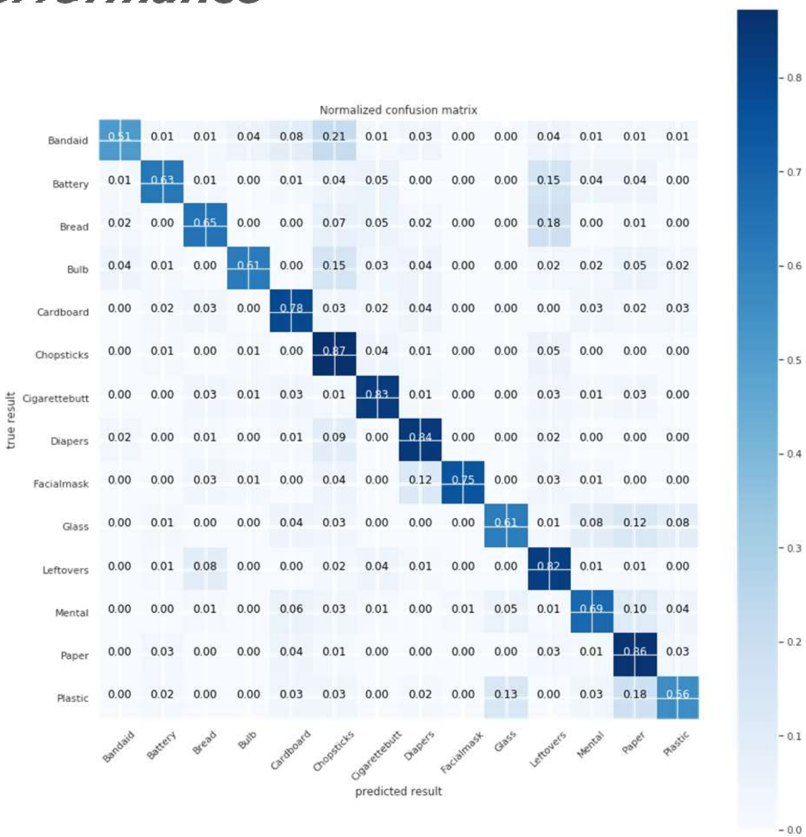




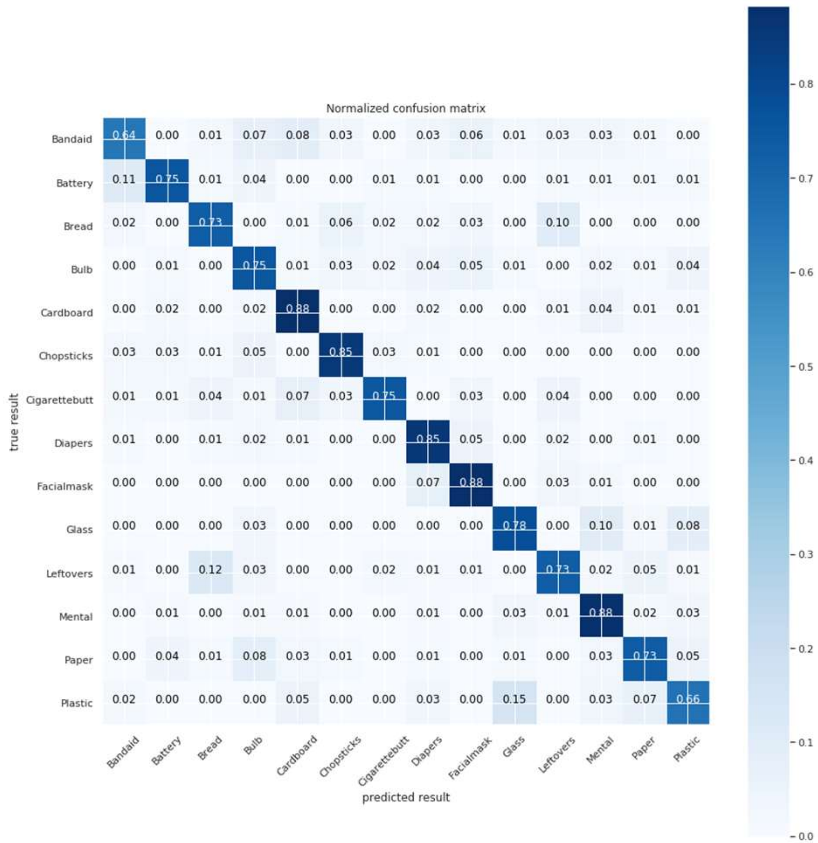


Updated

Performance



Original



Updated

Performance

	precision	recall	f1-score	support
0	0.80	0.51	0.63	72
1	0.82	0.63	0.71	73
2	0.73	0.65	0.69	88
3	0.91	0.61	0.73	96
4	0.80	0.78	0.79	120
5	0.52	0.87	0.65	79
6	0.73	0.83	0.78	71
7	0.73	0.84	0.78	82
8	0.98	0.75	0.85	68
9	0.77	0.61	0.68	72
10	0.65	0.82	0.73	106
11	0.77	0.69	0.72	105
12	0.59	0.86	0.70	78
13	0.65	0.56	0.60	61
accuracy			0.72	1171
macro avg	0.75	0.72	0.72	1171
weighted avg	0.75	0.72	0.72	1171

Original

	precision	recall	f1-score	support
0	0.63	0.83	0.72	70
1	0.87	0.60	0.71	65
2	0.85	0.66	0.74	91
3	0.81	0.76	0.78	83
4	0.83	0.86	0.84	97
5	0.77	0.88	0.82	89
6	0.88	0.69	0.78	75
7	0.76	0.75	0.75	76
8	0.69	0.91	0.79	65
9	0.78	0.60	0.68	70
10	0.81	0.75	0.78	127
11	0.72	0.91	0.80	116
12	0.71	0.87	0.78	78
13	0.80	0.57	0.66	69
accuracy			0.77	1171
macro avg	0.78	0.76	0.76	1171
weighted avg	0.78	0.77	0.76	1171

Updated

02-4

VGGNet

Second price network in ILSVRC, 2014

VGGNet

Difference

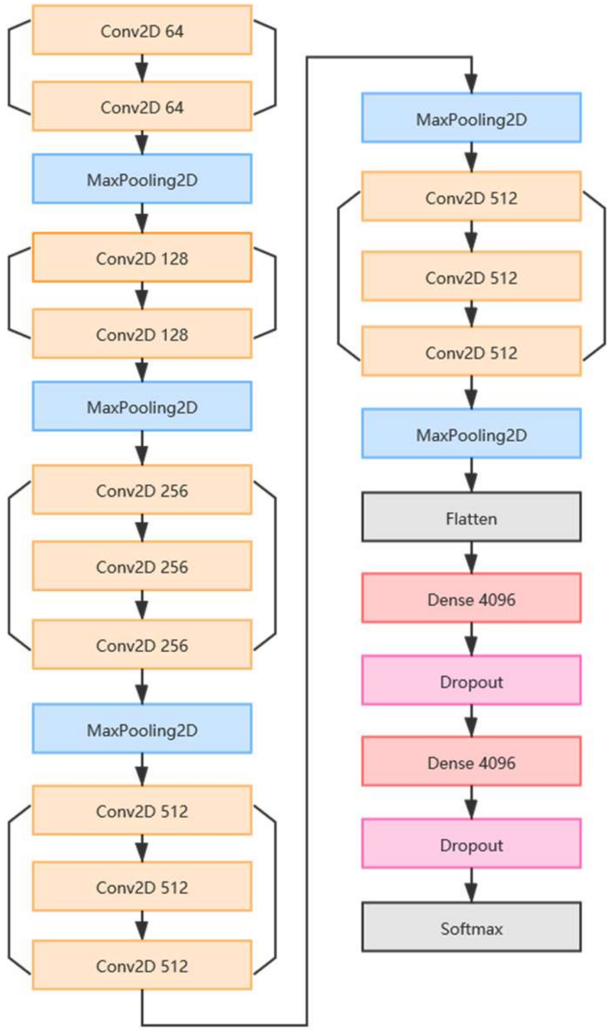
- Conv2D: 3 x 3 and 1 x 1 kernels.
- MaxPooling2D: 2 x 2 kernels.

Pros

- Deeper layers & wider feature map

Cons

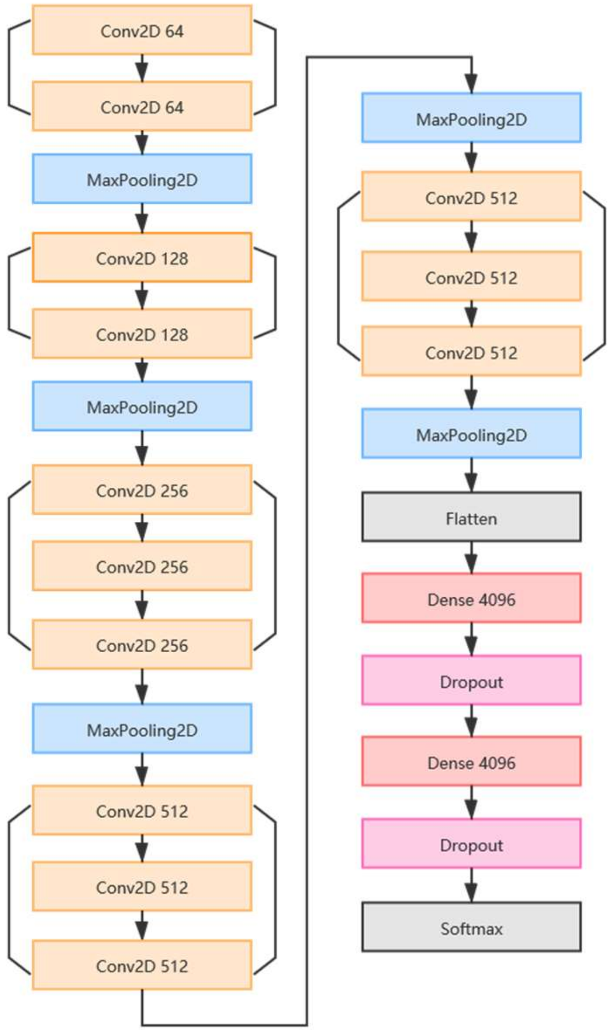
- More parameters & time consuming



VGGNet – Result

Result	Layers	Accuracy	Loss
AlexNet	8	0.721	1.372
AlexNet+ Yolo	9	0.782	1.219
VGG-11	11	0.615	1.421
VGG-16	16	0.623	1.539

Reach saturation accuracy



Confusion matrix

Confusion matrix of VGG

	Bandaid	Battery	Bread	Bulb	Cardboard	Chopsticks	Cigarettebutt	Diapers	Facialmask	Glass	Leftovers	Mental	Paper	Plastic
Bandaid	4	0	0	1	1	0	0	0	1	0	0	0	0	1
Battery	2	24	0	5	4	1	1	0	1	1	2	0	1	2
Bread	0	0	19	0	0	0	0	2	0	0	6	0	1	0
Bulb	2	0	1	12	2	1	1	5	0	2	0	2	2	2
Cardboard	1	2	1	0	25	0	0	1	0	1	1	3	0	2
Chopsticks	1	0	0	0	1	10	0	0	0	0	0	0	0	0
Cigarettebutt	0	0	0	1	0	1	4	1	0	0	0	0	0	0
Diapers	1	0	1	0	3	0	1	47	1	0	0	0	0	0
Facialmask	0	0	0	0	0	0	0	9	21	0	0	0	0	0
Glass	1	1	0	1	1	0	0	1	1	28	0	3	2	7
Leftovers	0	1	5	0	0	1	1	1	0	0	22	0	0	0
Mental	0	1	0	0	2	2	0	4	0	9	0	16	1	3
Paper	2	0	0	3	1	1	1	3	2	3	0	0	38	0
Plastic	5	1	0	1	3	3	2	4	1	3	0	0	4	17

Confusion matrix of AlexNet+Yolo

	Bandaid	Battery	Bread	Bulb	Cardboard	Chopsticks	Cigarettebutt	Diapers	Facialmask	Glass	Leftovers	Mental	Paper	Plastic
Bandaid	7	0	0	0	0	1	0	0	0	0	0	0	0	0
Battery	1	41	0	1	1	0	0	0	0	0	0	0	0	0
Bread	0	0	13	0	1	2	1	1	0	1	6	0	1	2
Bulb	0	0	1	22	1	2	0	1	1	1	0	1	2	0
Cardboard	0	3	0	0	26	0	1	0	0	0	0	0	4	3
Chopsticks	0	0	0	0	0	12	0	0	0	0	0	0	0	0
Cigarettebutt	0	0	0	1	0	1	4	0	0	0	0	0	0	1
Diapers	1	0	1	2	2	2	0	42	4	0	0	0	0	0
Facialmask	0	0	0	0	0	0	1	3	25	0	1	0	0	0
Glass	0	0	0	0	1	0	0	0	0	36	0	5	1	3
Leftovers	0	0	0	0	0	0	0	1	0	0	30	0	0	0
Mental	0	0	0	1	0	3	0	1	0	10	0	17	3	3
Paper	0	0	0	0	5	1	0	0	0	0	0	1	43	4
Plastic	0	1	0	0	5	0	0	0	0	3	0	3	0	32

Confused Data


bread (128).jpg


bread (139).jpg


Leftovers (66).jpg


Leftovers (83).jpg


glass21.jpg


glass27.jpg


metal17.jpg


metal43.jpg


plastic8.jpg


plastic22.jpg

Confusion type 1

Bread & Leftovers

Confusion type 2

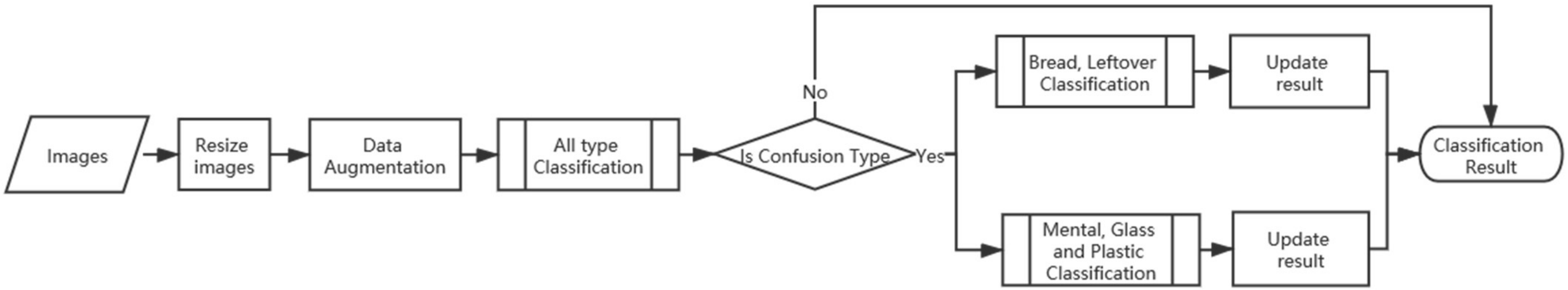
Glass, Mental & Plastic

03

Final Model

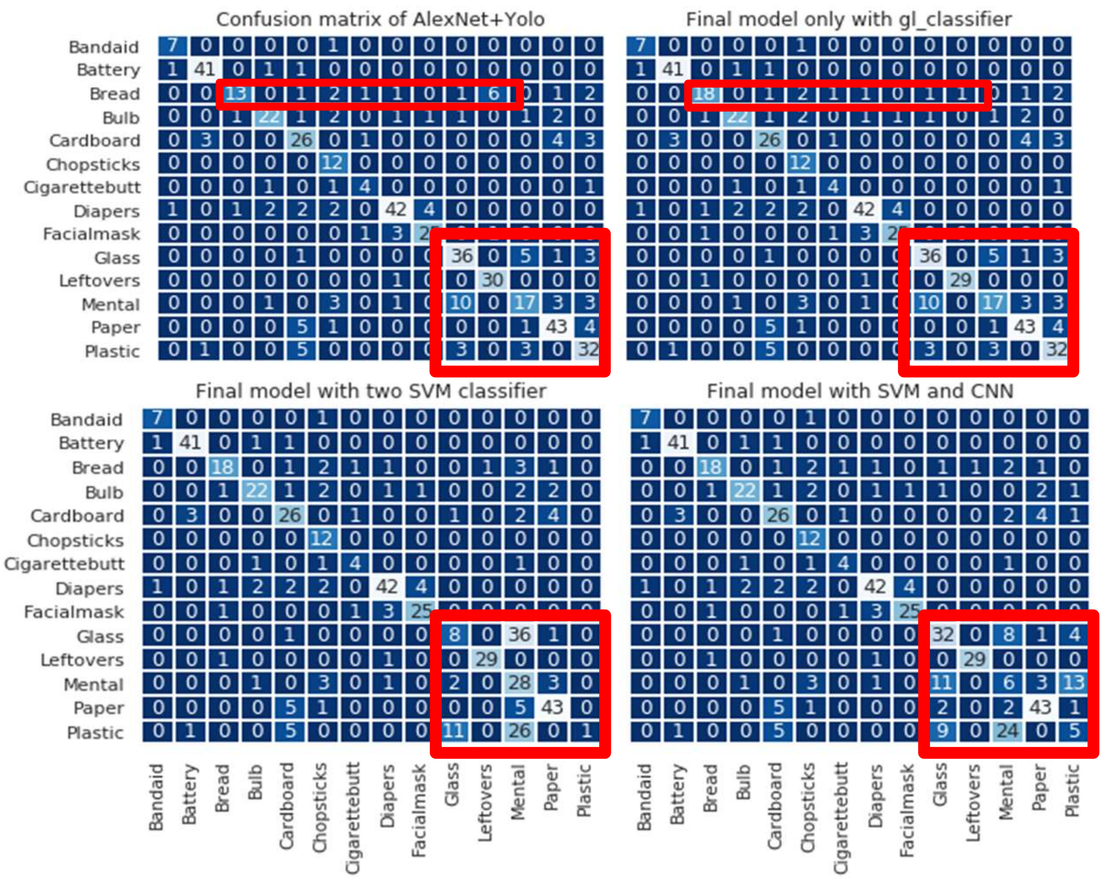
AlexNet + Yolo + Separate Classification

Final Model



All type classification	Bread – Leftovers Classification	Mental – Glass – Plastic Classification
AlexNet + Yolo	SVM	CNN + SVM

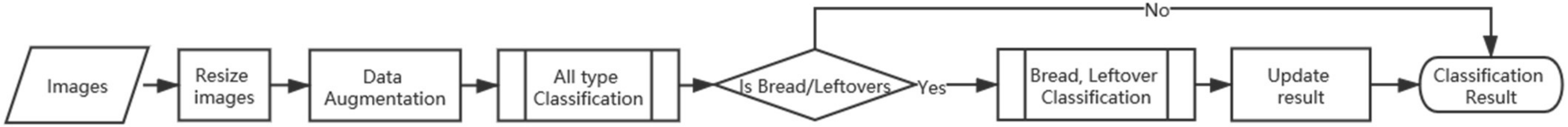
Performance for Confused data Classification



Why perform bad? How to improve?

- Feature Extraction
- Methods
- Physical sensors

Final Model



Accuarcy	
14 small type	0.7613
4 big type	0.9118

This is a cardboard,
It is recoverable.

04

Future

What we can do for next ?

Further Improvement

Complex Background

Multiple Objects

Classification for more types

Q & A

Thanks