

Advanced Trash Classification

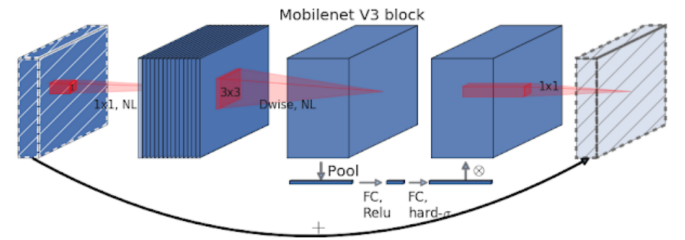
Sai Manoj¹, Eshan Deb² and Gaurav J³

Abstract—The Advanced Trash classifier manage a variety of waste materials automatically. We propose a system developed using NetAdapt for Layer wise search based pre-train (MobilenetV3Large) Convolution Neural Network which has fewer parameters to support the lower capability of embedded systems(CPU) like Raspberry-pi where our solution is likely to be deployed or mobile devices, thus reducing run time. The model is developed on trash image dataset(TrashNet) which was developed by Gary Thung and Mindy Yang, we merged this dataset with Kaggle competition(Garbage Classification). The proposed system achieves a validation accuracy of 96.45% on the dataset we used.

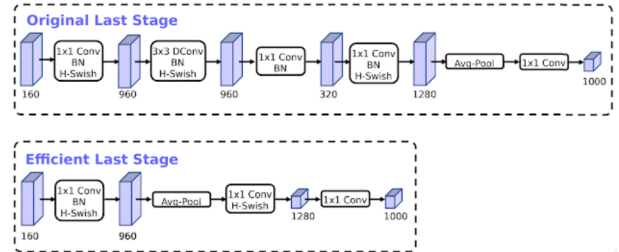
I. INTRODUCTION

The place of recycling in modern society is very important. In recycling process for today, separation of waste with manpower must take place in order to make a series of large filters. People may be confused about how products they consume are considered to be garbage. Within the scope of this study, it was to develop an algorithm for classification of garbage. Our aim is to increase efficiency of waste processing facilities and to identify non-recyclable wastes because garbage separation process is very difficult to separate garbage with a false prediction rate that is at par with the optimal Bayesian error for this task, which is to put simply 0% error rate. The proposed method will be designed not only for environmental benefits but also for saving time and manpower. To counter this problem we can automate the entire process by building an image classifier using convolutional neural network (CNN) based models and thereby decrease the time for the waste segregation and make it cost-effective, In the case of this project the trash is classified into 9 distinct classes namely Aluminum, Carton, Glass, Organic Waste,

Other Plastics, Paper and Cardboard, Plastic, Textiles and Wood. As India has started to apply waste segregation as a compulsory measure under sanitary protocols this project has a growing need and the scope of this project is large. The CNN network used is MobileNetV3Large,



An interesting optimization of MobileNetV3 was the redesign of some of the expensive layers in the architecture in comparison to MobileNetV2. By incorporating some basic optimizations, MobileNetV3 was able to remove three expensive layers of its predecessor architecture without sacrificing accuracy.



this architecture of MobilenetV3 mitigates the drawback of MobilenetV2 which incorporates squeeze-and-excitation blocks as part of the search space which ended up yielding more robust architectures. Thus now MobileNetV3 yields further better performance then it's predecessor

II. RELATED WORK / BASE PAPER(S)

Many different algorithms have been developed for the classification of images, such as RNNs, SVMs, ANN etc, but Convolutional Neural Network which is a Machine Learning algorithm has really performed better than all of them. CNNs

¹Sai Manoj, PES1UG19CS155

²Eshan Deb, PES1UG19CS152

³Gaurav J, PES1UG19CS599

hit the spot when the algorithm was used to win the 2012 image-Net large-scale visual recognition challenge(ILSVRC) which was proposed in [1]. Since 2012 many different CNN architectures have been developed which has solved many image classification problems [2][3][4][5]. Lulea University of technology in 1999 undertook a project, and a system was developed to recycle metal scraps using mechanical shape identifier[6][7] used the features from SIFT and outline shape on the Bayesian computational framework and their system was based on the Flickr material database.[8][9]in 2016 developed an Auto-Trash which was able to differentiate between compost and was recycled with Raspberry Pi, their system was developed using Google's Tensorflow. The short-come of their system was that it was only able to differentiate compost materials. A smartphone application was developed by [10] which was able to roughly identify the hip of garbage in the image. This application enables a person to give information of garbage in their area and obtained a mean accuracy of 85% using AlexNet pre-trained model. base paper[?][?]

III. DATASET

This is a set of merged datasets that contains 5000+ images of waste images that can be used in classification and segmentation problems. The main sources are

A. trashnet data

Currently, the dataset consists of 2527 images: 501 glass, 594 paper, 403 cardboard, 482 plastic, 410 metal, 137 trash. The pictures were taken by placing the object on a white posterboard and using sunlight and/or room lighting. The pictures have been resized down to 512 x 384, which can be changed in data/constants.py (resizing them involves going through step 1 in usage). The devices used were Apple iPhone 7 Plus, Apple iPhone 5S, and Apple iPhone SE.[11]

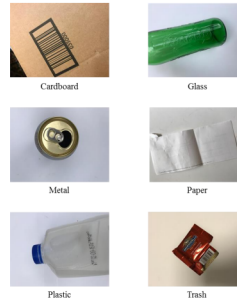
B. Plastic Waste DataBase of Images – WaDaBa

The object were put on the research position and next photographed with first and second type of light. There were series carried out of 10 photographs with differ in the angle of the turnover for every object (in the vertical axis). Next the

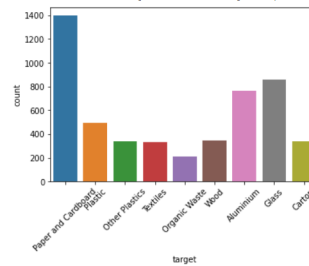
object was damaged to varying degrees: small, medium and large. For each type of destruction have been made 10 photographs. So considering all variants for every object 40 photographs were taken, multiplying it by the number of objects, 4 000 of photographs were created in the database.

The parameters of photographs: size 1920x1277 of pixels, resolution 300 dpi ,colour palette RGB 24 bits, file format JPG[12]

Sample images:



Distribution of the dataset we are using:



IV. METHODOLOGY

A. Baseline Model

We created a first thought model to keep as a guideline for other models to beat. We use just use a basic set with continuous 4 layers of CONV2D + MaxPooling Layer followed a fully connected network passed to a softmax layer for multiclass classification. Loss function: categorical cross entropy, Optimizer: ADAM, epochs: 50, accuracy: 42.56%

```
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d_4 (MaxPooling 2D)	(None, 127, 127, 32)	0
conv2d_5 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_5 (MaxPooling 2D)	(None, 62, 62, 64)	0
conv2d_6 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_6 (MaxPooling 2D)	(None, 30, 30, 128)	0
conv2d_7 (Conv2D)	(None, 28, 28, 256)	295168
max_pooling2d_7 (MaxPooling 2D)	(None, 14, 14, 256)	0
flatten_2 (Flatten)	(None, 50176)	0
dense_4 (Dense)	(None, 512)	25690624
dropout_2 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 512)	262656
dropout_3 (Dropout)	(None, 512)	0
dense_6 (Dense)	(None, 9)	4617

```

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Total params: 26,346,313
Trainable params: 26,346,313
Non-trainable params: 0
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```

B. Fine-tuned Models

We switched our focus to **transfer learning** using pretrained NN - vgg16, resnet50 and mobilenetV3Large.

To pick among the different pretrained architectures we use a preliminary test.

Preliminary Test- Compare Performance without any design optimizations, and number of parameters

we just import the pretrained models excluding the final layer,i.e include_top=false. And we add a softmax layer and train the models(vgg16, resNet50, mobilnetV3Large) on the dataset.

Setup: image size-256*256, batch size-128, epochs=10, weights initialized from **imagenet** , loss function- categorical cross entropy, optimizer ADAM.

Preliminary test results

model	performance	val loss	epochs	total number of parameters
vgg16	82.16	3.215	50	1,50,09,609
resNet50	86.43	2.947	50	4,03,66,217
mobileVnetLarge3	84.555	3.045	50	45,61,801

On inspection, we found that mobileNetV3Large is suitable for our task,

considering it achieves better performance than vgg16 and has very less parameters in comparison to top performing resnet50, so we next apply model design decisions to improve the performance using mobilenetV architecture in mind.

C. improving final model- mobilenetV3Large

In preliminary test we found that train accuracy was increasing but test accuracy was decreasing which shows clearly that the model was overfitting: we have 2 ways to reduce over fitting 1. early stopping, 2. regularization.

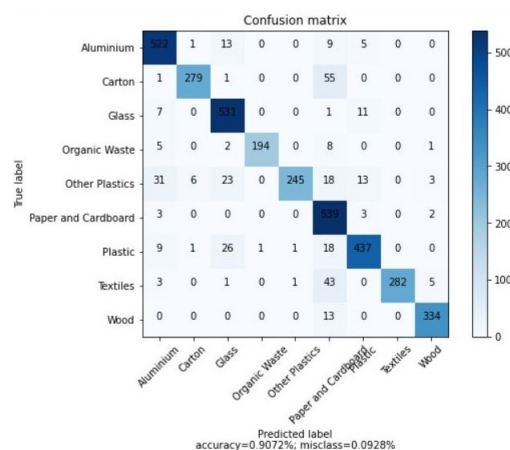
We chose to go with **regularization**:

Initially we go with imagenet weights in all layers , then we set all except 6 layers trainable. We add dropout(p=0.45) to avoid as the first layer after mobilenetV3Large architecture, next AvgPooling to further reduce number of parameters, then add Batch normalization accelerates training, in some cases by halving the epochs or better, and provides some regularization, reducing generalization error. Finally we add regularization layer- l1(0.045), kernel_initializer='he_normal')(x).

So now the result achieved:

accuracy: 0.9427

Confusion Matrix



V. RESULTS

Final Performance attached from notebook

Epoch: 50/50
 2020-11-24 10:00:00 - loss: 2.0460/1.0100 - steps: 3.4707 - accuracy: 0.9075 - val_loss: 3.4402 - val_accuracy: 0.9445

VI. CONCLUSION AND FUTURE SCOPE

A. Conclusion

We have improved trash classification framework for mobile devices with accuracy: 0.9427 and With a run-time(real time test) under 20 seconds. So now we can deploy this service for iot-solutions.

B. Future scope

We are interested in extending our work from classification to object(trash) detection, using Mask R-CNN or EfficientDet-D2 to perform trash recognition tasks(Segmentation task). The task is, given an image with a picture or a garbage(multiple objects unlike the current work, i.e Multi-label) we want to label the objects to the respective classes and also give back the result of the percentage wise distribution of the various categories area(pixels) present in the image and also detect the object with a boundary-box.

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