Report: Detecting Compostable and Non-Compostable Waste from Images

Dakota McNealy
dmcnealy@stanford.edu

1 Problem Motivation

The intent of my research is to build a model that will be able to detect whether or not an object of waste is of organic material or not. The motivation is to make our waste management more efficient and effective. As the world looks to become more environmentally friendly, it will move more towards strictly recyclable or compostable waste. One of the biggest downfalls of implementing a comprehensive recycling system in communities is the human error aspect during disposal.

Accuracy is extremely important in this problem. For example, a bag of recycling with all recyclable materials except for one misplaced item, may be sent to landfill, which has very unsatisfactory and self-defeating environmental effects. Many compostable and non-compostable items look alike (for example plastic vs corn-based 1-use silverware). The goal of this project was to eclipse 80% accuracy in waste identification.

The simplest case that I will be trying to apply my model to is a Wet and Dry recycling system, where all compostable and non-recyclable materials are placed in one bin, and all recyclable, non-decaying materials are placed in the other. It is unfortunately easy for even the most educated to accidentally dispose waste in the incorrect bin. But even having a simple camera system deployed in some community locations giving instant feedback to the disposing person, could have lasting effects on human accuracy in disposing waste correctly, leading to cost savings and a smaller footprint in the waste management industry.

Previously, this problem has been attempted, however, the lack of and difficulty of collecting data has held back research. In the *Classification of Trash for Recyclability Status* paper by Thung and Yang [3], their SVM model performed significantly better than their neural network approach, yet only managed 63% accuracy on their training set. A different paper, titled *Smart Trash Net: Waste Localization and Classification* by Awe, Mengistu and Sreedhar attempted to solve the waste classification problem using and region proposal convolutional neural network. However, their overall accuracy on their data overall never eclipsed 75% for a single class of waste, and overall accuracy never greater than 69%, They attributed this partly due to computing power restrains that kept them from further experimenting with hyper-parameters. Unfortunately, accuracy below 70% in each of these studies leaves more to be desired for a system that may be applied in the real world.

3 Dataset

The primary dataset I chose to use is the Waste Classification Dataset [1]. It contains a test and training set of images in 3 labeled categories, O (organic material), R (recyclable material), and N (non-recyclable material). In total Each image depicts one particular type of (O, R, or N) material. The dataset was organized to have the N portion of the dataset to represent recycled plastic bottles as non-recyclable. In total, there are more than 25,000 images within this dataset, making it sufficient to train a complex model such as a neural network. While I did have the option to use an additional dataset that classified images into 6 classes (cardboard, glass, metal, paper, plastic, and trash)[2], I decided to focus my efforts on the 3 class dataset, as I thought it more closely resembled a waste management systems that is easier to implement in communities.

4 Preprocessing and Model Approaches

The Waste Classification Dataset is large, organized, and complete, but for the purposes of the problem I am trying to solve, I modified the groups of classification in the training and test set. The creator of the dataset created a whole class of disposed bottles, labeling them as non-recyclable, or "N." I initially trained my model on the separated 3 class dataset, but the majority of my testing was done on a combined 2 class version of the dataset – I narrowed the classes from "N", "O", and "R" to "O" and "R" (organic and recyclable) by merging the "N" class of bottles into the recyclable group "R". Since many places that use 3 class waste disposing systems, including Stanford, identify almost all glass and plastic bottles as recyclable material, and some still use the two class system of wet and dry. Not all of the images are of the same size, but I chose to use Pytorch's RandomCrop() function with constant padding to ensure 500 by 500 pixel size for all pictures in the dataset. Additionally, I experimented with random rotations of the dataset to see if that could possibly improve my performance.

The model I chose apply was a Convolutional Neural Network. CNN's are adept at interpreting high to definition input. Convolutional Neural networks require a large dataset, but my combined dataset consists of more than 25 thousand images.

Throughout my experimentation, I used cross-entropy loss. My initial working model consisted of only 6 layers – three convolutional layers, with 3 linear layers, along with two applications of pooling. I later increased this number to 4 convolutional layers, 2 pooling layers, and 4 linear layers.

I also experimented with two forms of optimization, the first being simple stochastic gradient descent, and the second being Adam Optimization. Additionally, I experimented with how many times I looped over my data during training.

Finally, once I was able to standardize the size of my images using Pytorch's RandomCrop() method in preprocessing, I could experimenting with different training batch sizes.

5 Results

Model 1: 3 Conv Layers,, Batch Size 1, SGD optimizer, 3 class

Overall Accuracy on Training Dataset: 69%
Overall Accuracy on Test Dataset: 70%

Test accuracy of N : 18 %
Test accuracy of O : 84 %
Test accuracy of R : 71 %

Model 2: 3 Conv Layers,, Batch Size 1, SGD optimizer, 3 Class, 2 Training Epochs

Training Loss:

On Epoch 1:
example 2000 loss : 1.016
example 22000 loss : 0.764

On Epoch 2:
example 2000 loss : 0.766
example 22000 loss : 0.748

Model 3: 4 Conv Layers,, Batch Size 1, SGD optimizer, 3 Class

Final training loss: 0.733

Accuracy of the network on the training images: 71 %
Accuracy of the network on the test images: 71 %

Test accuracy of N : 0 %
Test accuracy of O : 98 %
Test accuracy of R : 62 %

	('N', 'O', 'R')
N misinterpreted as	[0. 152. 242.]
O misinterpreted as	[0. 0. 25.]
R misinterpreted as	[0. 421. 0.]

Model 4: 4 Conv Layers,, Batch Size 1, SGD optimizer, 2 Class

Final training loss: 0.593

Accuracy of the network on the training images: 74 %

Accuracy of O : 97 %
Accuracy of R : 46 %

Accuracy of the network on the test images: 71 %

Accuracy of O : 99 %

Accuracy of R : 44 %

Model 5: : 4 Conv Layers, Batch Size 1, Adam optimizer, 2 Class
Final training loss: 0.493

Accuracy of the network on the training images: 80 %
Accuracy of O : 84 %
Accuracy of R : 74 %

Accuracy of the network on the test images: 84 %
Accuracy of O : 95 %
Accuracy of R : 73 %

Model 6: 4 Conv Layers, Batch Size 1, Adam optimizer, 2 Class, Batch Size 200
Final Training loss: 0.531

Accuracy of the network on the training images: 73 %
Accuracy of O : 75 %
Accuracy of R : 71 %

Accuracy of the network on the test images: 81 %
Accuracy of O : 88 %
Accuracy of R : 74 %

Model 7: 4 Conv Layers, Batch Size 1, Adam optimizer, 2 Class, Batch Size 200, Random Rotation
Final training loss: 0.658

Accuracy of the network on the training images: 55 %
Accuracy of O : 100 %
Accuracy of R : 0 %

Accuracy of the network on the test images: 48 %
Accuracy of O : 100 %
Accuracy of R : 0 %

7 Analysis and Insights

My model initially performed very poorly when trying to identify the "N" in the three class application. The raw dataset's "N" class is composed of strictly recyclable plastic and glass bottles. Even after adding additional model layers, and looping over the training data an additional time, only modest improvements were seen at best – no significant improvement in training loss when looping over the training data twice, and only modest 1% accuracy improvement when adding additional layering to my model.

Next, I trained the deeper network on a combined 2 class dataset that combined the previous dataset into one of two classes Non-rcyclable ("N") and Organic ("O"). This showed a small performance increase of the model, however, 2 class prediction in theory should increase model accuracy for most predictors compared to 3 class prediction.

Finally, the best results I achieved was when I switched to Adam Optimization. This brought the accuracy of the model to 84% in testing.

I further experimented with increasing batch size, as well as manipulating my data through random rotations, but neither seemed to improve my model's performance. The model trained best with batches of size 1.

While Adam, and more layering helped improve the matter, there was a constant discrepancy between the Organic class and all others, especially the "N" class in the 3 class dataset throughout the testing of all my models. While this could be due to the nature of my classing or training, it may be due to the nature of the dataset contents themselves. Especially for the context of the problem, it may be beneficial time permitting to collect data of actual trash/waste, instead of simply representative images as were present in this dataset. Additionally, further experimentation of different optimizers, loss functions and layering strategies may still be very fruitful,

However, to conclude, my experimentation has shown that a neural network, specifically a Convolutional Neural Network is suitable to the task of waste classification with minimal data preprocessing. I was able to identify the organic and non-organic materials with up to 84% accuracy. It leads me to believe that further research in the area of neural networks and waste classification could lead to valuable results for real world applications.

8 References

[1] (2019, November). Waste Classification Data v2. Retrieved January 21, 2020 from https://www.kaggle.com/sapal6/waste-classification-data-v2.

[2] (2019, January). Garbage Classification. Retrieved January 21, 2020 from https://www.kaggle.com/asdasdasasdas/garbage-classification#cardboard1.jpg.

[3] Gary Thung Mindy Yang. Classification of trash for recyclability status. CS229 Project Report
2016, 2016.

[4] Oluwasanya Awe Robel Mengistu Vikram Sreedhar. Final Report: Smart Trash Net: Waste Localization and Classification, 2017.