Classification of Trash for Recyclability Status

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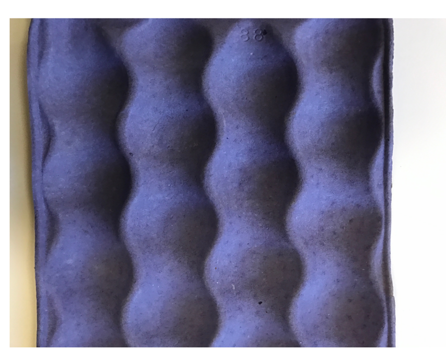
Problem

The current recycling process often requires recycling facilities to sort by hand. Consumers can also be confused about the correct way to recycle materials. By using computer vision, we can predict the category of recycling of an object based on an image of it.

Data Collection & Dataset

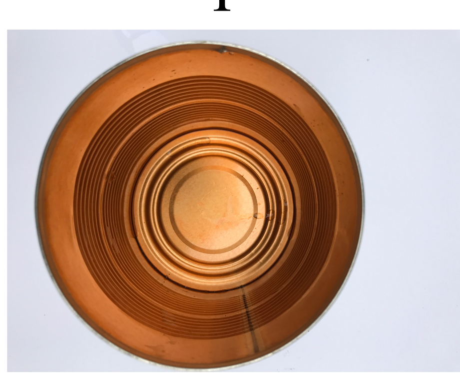
The dataset contains images of recycled objects across six classes with about 500 photos each. The data was hand collected.



Paper

Glass

Plastic



Metal

Cardboard

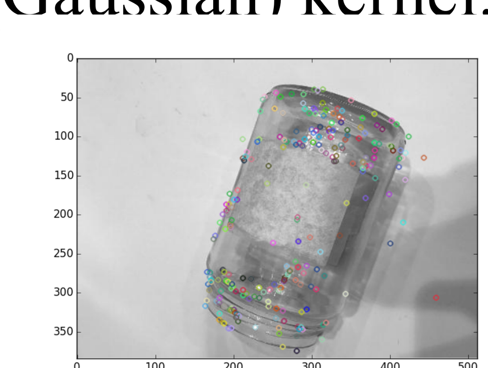
Trash

Together, these recycling classes account for over 99% of all recycled material.

Models

Because the dataset consisted of only images, we figured the best approaches to use are a multiclass SVM and a convolutional neural network.

First, we experimented with running an SVM using SIFT features on all images. SIFT extracts scale invariant, local features. In addition, the SVM used a radial basis function (Gaussian) kernel.



Data augmentation techniques were performed on each image because of the small size of each class. These techniques included random rotation of the image, random brightness control of the image, random translation of the image, random scaling of the image, and random shearing of the image. These image transformations were chosen to account for the different orientations of recycled material and to maximize the data we collected. We also performed mean subtraction and normalization.

For the neural network, “TrashNet”, we used an architecture similar to AlexNet but smaller in filter quantity and size. We chose to emulate AlexNet as it is a proven architecture. The network used Adam gradient descent optimization to achieve faster and best results.

Initial Results

The SVM achieved better results than the Neural Network. It achieved an accuracy of 63% using a 70/30 train/test data split.

After running 50 epochs of training with a 0.0075 learning rate and batch size of 25 on our neural network with a 70/30 train/test split, we achieved a testing accuracy of 27% (and 23% training accuracy). The loss graph is depicted above.

Further Results

We ran another neural network training with 50 epochs, a learning rate of 0.01, and batch size of 25 and got a similar testing accuracy of 25%.

These results are not as good as we expected, but it shows promise of learning and we are still spending time tuning the parameters (batch size and learning rate) to find values that lead to a good model.

Discussion

We gained a new found respect for all of the publicly available datasets. The dataset collection was extremely tedious and at times dirty. We will be gathering some more images and releasing our dataset for public use.

In order to improve our neural net results, we could have collected much more data if the time frame was longer. We attempted to maximize the data we had through augmentation and cross validation.

Future Work

In the future, we would like to extend this project to identify and classify multiple objects from a single picture or video data. This could help recycling facilities more by processing a stream of recycling rather than single objects.

References

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[2] ”Frequent Questions — Paper Recycling.” EPA. Environmental Protection Agency, n.d. Web. 20 Nov. 2016.

[3] Gaurav Mittal, Kaushal B. Yagnik, Mohit Garg, and Narayanan C. Krishnan. 2016. SpotGarbage: smartphone app to detect garbage using deep learning. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp ’16). ACM, New York, NY, USA, 940-945. DOI: http://dx.doi.org/10.1145/2971648.2971731