Recycle_NN: Recycalability Prediction using Deep Neural Networks

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Abstract

With the ever-growing issue of climate change impacting our world, being able to quickly and accurately recycle waste materials is suddenly a very important issue. This has effects on saving energy and materials that help our planet. In many cases, recyclable objects will be intermixed with non-recyclable objects which forces the need for a reliable system to classify and identify. This paper proposes a convectional neural network (CNN) model implementation using Tensorflow and Keras to combat this idea. We use pre-trained models to accelerate our results on a database of objects and compare these models' performance.

Introduction

The problem we are trying to solve is that of maximizing the recycling of waste materials provided to a waste management system. Recycling is important in today's society because of its conservation benefits in energy, pollution, and natural resources. As the issue of climate change becomes closer and closer to a critical mass our generation will be tasked with solving this problem.

One way we feel that this problem can be solved is via reliable and accurate systems to maximize recycling. If we can generate a system to classify this task we can apply it to waste management systems processing lines and reroute items that are recyclables away from the non-recyclables it is often mixed with. This will increase the throughput of recyclables by making it easier and simpler for people to do the task, as separating and maintaining items manually in the home often becomes tedious and space-intensive which acts as a large deterrent. As the generation tasked with solving this global issue of climate change, anything that can aid the quest while maintaining people's limited interaction should be prioritized and maximized which is what our system aims to do.

In recent years the field of computer vision has accelerated dramatically thanks to the use of convolutional neural networks (CNNs). There has been a dramatic shift in facial recognition systems, autonomous vehicles, and handwriting recognition, but to this date, there has been a minimal impact in the environmental space. The ability to recycle objects quickly and correctly is a pure image-based task, where CNN's and specifically pre-trained models make the greatest impact.

Related Work

In this section, we review existing work related to our study. In 2016, Yang and Thung (Yang and Thung 2016) collected the waste image dataset, which is named TrashNet. It consists of six classes: glass, paper, cardboard, plastic, metal, and trash. Various models are proposed to improve the accuracy of classifying these waste images. Aral et al. (Aral et al. 2018) compared the performance of Densenet 121, DenseNet169, InceptionResnetV2, MobileNEt and Xception on Trashnet dataset. The authors also apply the data augmentation process to improve image classification accuracy. Bircanoglu et al. (Bircanoğlu et al. 2018) proposed RecycleNet, a light-weighted deep convolutional neural network architecture, which can significantly reduce the number of parameters and produce satisfactory performance. Ruiz et al. (Ruiz et al. 2019) compare different deep learning architectures for automatic garbage types classifications. They found ResNet-based model can produce the best classification results. Besides these models proposed specifically to deal with the waste classification, there are several famous CNN models such as ResNext (Xie et al. 2017), ImageNet (Krizhevsky, Sutskever, and Hinton 2012), VGG (Simonyan and Zisserman 2014) for images classification which can be used to do waste classification tasks. In our project, we select a dataset of recyclables and non-recyclables with more variability than TrashNet from Kaggle. We plan to utilize CNN as the base model and combine transfer learning approach to propose a model which can lead to significant accuracy improvements for classification.

Societal Problem

Waste collection and recycling is significant task for modern society. According to the Environmental Protection Agency, 75% of waste produced by the American people is recyclable, but only 30% of it can indeed be recycled. Most wastes are processed by landfills, which will lead to a lot of environmental problems, such as eutrophication, land pollution, water pollution, air pollution, and so on. With the decrease of natural resources and the increase of different types of garbage, the recycling problem becomes an urgent problem that needs

(a) Waste (b) Recyclable

Figure 1: The examples of waste and recyclable images.

to be solved to reduce pollution and health problems for citizens. For now, most of the recycling process still relies on people to classify the waste, which is time-consuming and harmful for these workers' health. What's more, this waste separation must be completed as soon as possible to reduce the contamination of waste by other materials (Sakr et al. 2016).

To improve the efficiency of the recycling process, intelligent garbage classifiers (Salmador, Pérez Cid, and Rodríguez Novelle 2008) were produced, which use technologies and devices such as smart sensors, cloud platforms to automatically classify the waste and make them located in the right place. Computer vision is an important part of these automatic garbage recycling systems. It can analyze the images or videos captured of the waste and determine which kind of objects are present in the mixed waste. The accuracy of this step directly determines the intelligent garbage classifiers' performance.

In this project, we utilized a new dataset of recyclables and non-recyclables from Kaggle. There are thousands of images of different objects. Our target is to build the model to classify these objects as recyclable The filename of each image in the datasets can match with the recognition results of Google Cloud Vision's Object Recognition API. We split the datasets by 8/1.5/1 ratio to do training/validation/testing.

Approach

Our approach for the project involved training convolutional neural networks (CNN) to train the model to predict whether or not an image would be classified as waste or recyclable. The images in Figure1 are examples of waste and recyclable respectively used as inputs for our model.

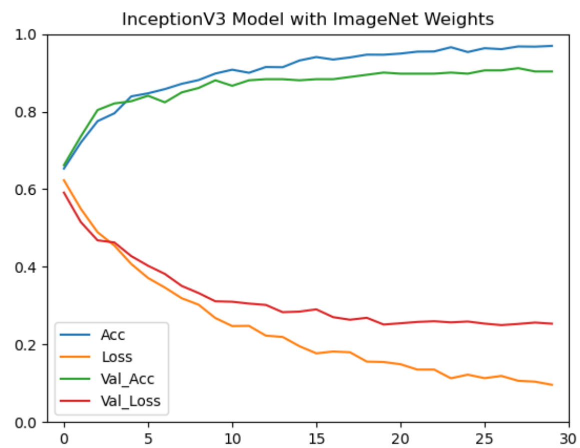
The initial approach to a baseline model involved training a 3x3 CNN after reducing the images to 200 x 200 pixels. The binary classifier achieved a training accuracy of 75%, validation accuracy of 69%, and test accuracy of 56%. The test results were our primary focus, as this shows how the model will perform in a real-world environment where it has most likely never seen the images prior.

We used this model as a baseline to compare against our future work which involved fine-tuning a transfer learning model. This transfer learning model involves using different pre-trained models and weights available via Keras as a convolutional base and then adding our specific classifier on top of that pre-existing model. The concept is that since the pre-trained classifiers have been trained on millions of images of different categories that they could potentially perform well on other tasks as well. We decided to train six pre-trained models using imagenet weights to classify the images. The results from these models will be compared against our baseline model as well as each other to determine which model would perform best for our given use case.

Results

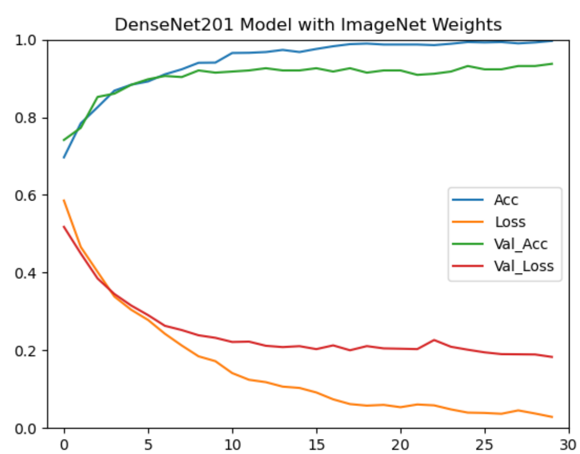
The following graphics are the accuracy and loss of our pre-trained models for waste classification.

A. InceptionV3



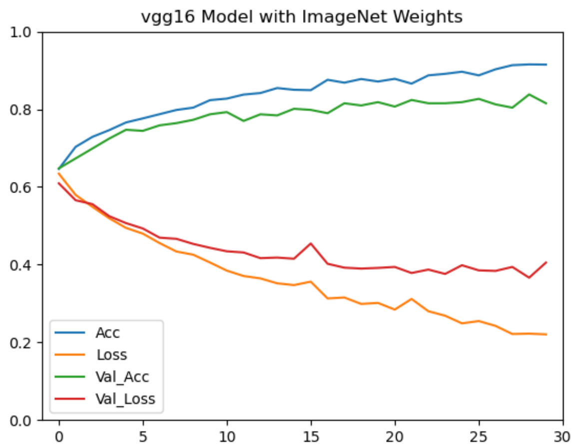
InceptionV3 achieved 96.78%, 91.19%, and 91.54% accuracy scores for training, validation and test respectively.

B. DenseNet201



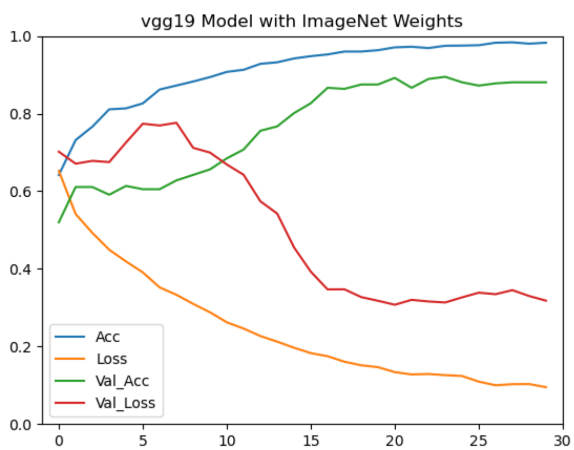
DenseNet201 achieved 99.65%, 93.75%, and 90.77% accuracy scores for training, validation and test respectively.

C. VGG16



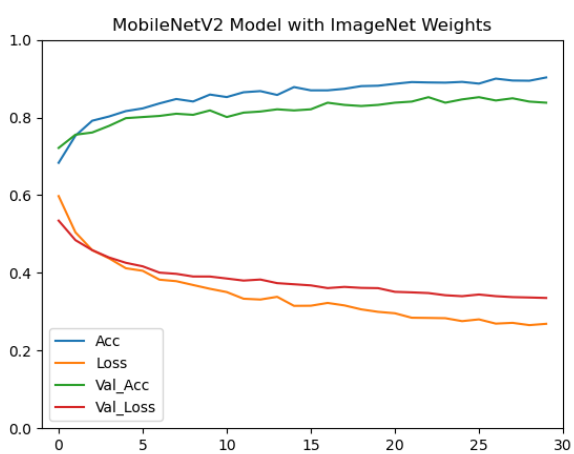
VGG16 achieved 91.54%, 83.80%, and 87.69% accuracy scores for training, validation and test respectively.

D. VGG19



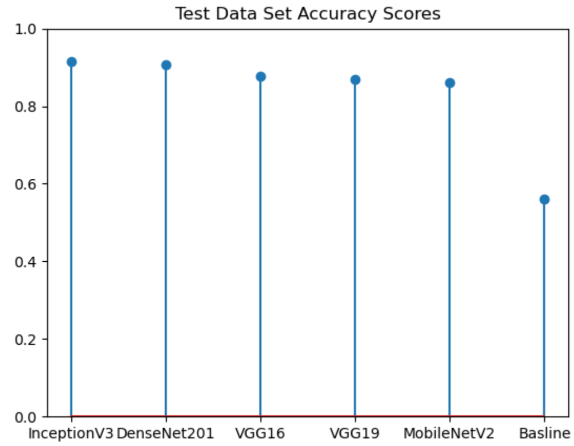
VGG19 achieved 98.36%, 88.07%, and 86.92% accuracy scores for training, validation and test respectively.

E. MobileNetV2



MobileNetV2 achieved 90.30%, 85.22%, and 86.15% accuracy scores for training, validation and test respectively.

F. Comparison



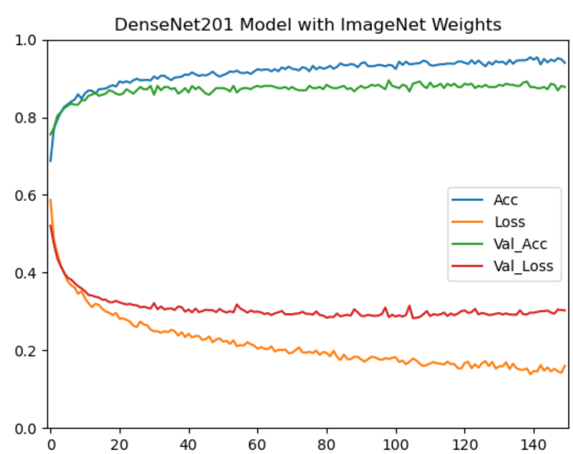
All of the models performed better than our baseline model that was trained without a pretrained model. Every Model scored at least 86.15% Accuracy on data that it had never seen (test dataset) compared to 56% from our baseline model.

This graphic demonstrates the drastic difference when looking at unseen data between our pretrained models and the baseline CNN we created in the first experiment. Every model performed at least 30% better than the baseline model.

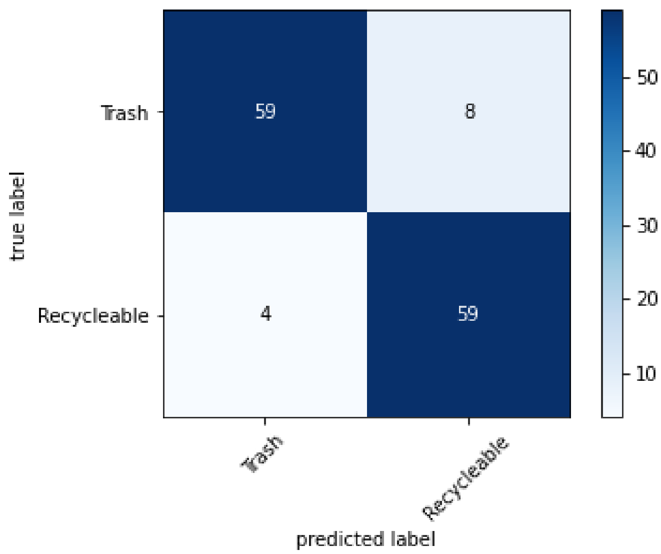
G. Models Trained for More Epochs

After running all five pretrained models, InceptionV3 and DenseNet201 performed the best. We decided to train all five for 30 epochs to compare them all in this stage. The goal was to fine tune the model that performed the best and train it for a longer period of time to see if our test accuracies improved even further.

i. DenseNet201 for 150 Epochs

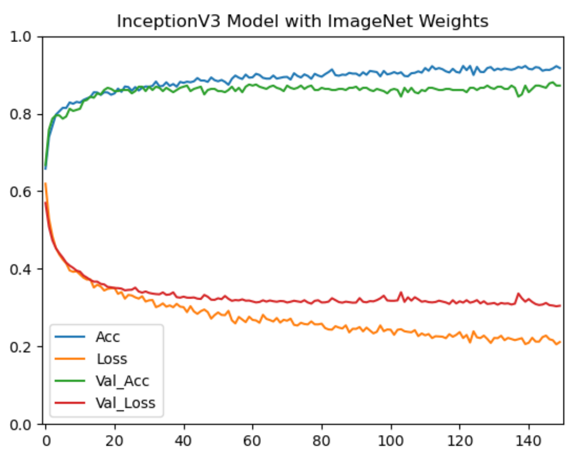


DenseNet201 achieved 95.44%, 89.20%, and 90.77% accuracy scores for training, validation and test respectively. The model did not improve when trained for more epochs. Our thought is that that the model was stuck in a local minima during this training experiment, which is why it produced similar results compared to the same model trained for 30 epochs.

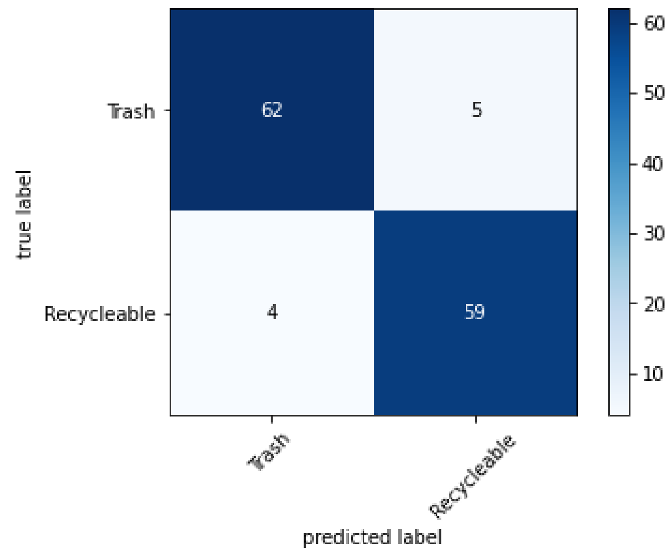


Confusion Matrix for testing the DenseNet201 model after 150 Epochs.

ii. InceptionV3 for 150 Epochs



InceptionV3 achieved 92.23%, 88.06%, and 93.07% accuracy scores for training, validation and test respectively. The model did improve on the test dataset accuracy score, but the training and validation did not improve over the duration of the experiment. There is a chance that our inital models quickly overfit, which is why the results were better in those experiments.



Confusion Matrix for testing the Inception V3 model after 150 Epochs.

F. Future Work

Both of these models performed quite well in determining whether an image should be classified as recyclable or not. The model is limited to the types of images that we had. We would like to get additional images for the model to train on and recognize as well as images that might not be as clear and dry as a staged picture of a light bulb. The models should be further fine tuned for better results on current images as well, due to time constraints we were not able to adjust the model iteratively enough to achieve the best possible results.

Societal Impact Discussion

According to the EPA, in 2018 292 million tons of municipal solid waste was generated in the United States, of that 69 million tons were recycled and 25 million tons were composted. Which accounts for around 35 percent of the total amount.(EPA 2017) These numbers sound impressive until you read National Geographic's numbers that 91 percent of all recyclable plastic is not recycled (Parker 2019). The EPA resources support this fact.

A reliable and accurate system to correctly identify a larger portion of recyclable materials at waste management services would significantly reduce that amount. If we insert the system on the waste management system line to detect and separate these recyclable materials from landfill materials we can significantly help the issue described by National Geographic. The EPA stated that the total number of plastics entering through the system is 36 million tons.

An increase in our system detecting just 1 percent extra plastic would generate an additional 360,000 tons of recycled material. That is around the same weight as the Empire State Building (ESB 2014-04-09). That number is only the amount of waste sent to be recovered for one type of material on a very small increase. Our system would likely develop more results than this. But even the tiniest amount recovered would save a skyscraper amount of material from entering wastelands.

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