Recycle or Compost

Prafulla Adusumalli
University of Colorado, Boulder
prafulla.adusumalli@colorado.edu

Danielle Allen
University of Colorado, Boulder
danielle.allen-1@colorado.edu

Elena Heiner
University of Colorado, Boulder
elena.heiner@colorado.edu

Morgan Likens
University of Colorado, Boulder
morgan.likens@colorado.edu

Abstract

According to the US Environmental Agency, the recycling rate has increased from about 7% to over 32% in the US over the past 60 years but even with that progress over 40% of waste that could still be recycled is thrown in the trash instead. One of the problems that is preventing additional recycling is that many Americans are unsure of what can be recycled. Our project looks to address this problem with an easily accessible model that consumers could utilize to identify recyclable materials. Making the identification of recyclable materials easier will help to minimize recycling confusion.[3]

1. Introduction

Recycling is an integral component of protecting our environment and is reliant on the participation of individuals. In the US the recycling rate has only increased from 7% to 32% in the past 60 years leaving over 40% of waste that could be recycled thrown into the trash. This leaves a lot of room for improvement over our current recycling practices.

Alongside environmental implications recycling also has strong economic benefits. A study performed by the EPA found that in one year recycling activities accounted for 681,000 jobs and $37.8 billion in wages. This results in about 1.17 jobs per 1000 tons of recycled items.

While increasing the amount of recycling is critical it is also very important that we increase knowledge around how to recycle correctly. Not all materials can be treated equally when it comes to recycling so it is critical that individuals learn what can actually be recycled. This is a barrier to increasing the percentage of recyclable waste being appropriately disposed of. Our project addresses this by designing an easy to use model that an individual could utilize in the home to determine if a material is recyclable or not. [3]

2. Related Work

There are currently many related projects and research so we have selected 3 that are closely related to our work and apply at both the individual and waste facility level.

2.1. RecycleRight

The first of these is a research project from a student at University of Mary Washington. They have developed an Android application called “RecycleRight” that efficiently helps individuals identify recyclable materials. They utilized transfer learning from the VGG-16 pre-trained model with frozen weights in the top layers and unfrozen weights in the last layers as well as replacing the last layer with a Softmax layer. Some of the main challenges that they encountered during their research were that there are many different shapes of and labels for recyclable household items. As a result, if they only had a couple examples of a product, they would not have a sufficient amount of data to correctly train the model. This could have been resolved by collecting additional data or performing data augmentation. They also ran into issues with the training images having solid white backgrounds so the more complex backgrounds that exist in an users image may make identification of the product more challenging because of the additional noise that is introduced. [4]

2.2. RecycleEye

The second is a company called RecycleEye. They are a technology company using advanced machine learning, computer vision, and robotics technologies to improve recycling. Their goal is to bring more transparency and efficiency to recycling while also improving recycling plant performance with their products.

The main products that they provide are RecycleEye Vision and RecycleEye Robotics. RecycleEye Vision is a computer vision product that scans and identifies different types of waste once it reaches the recycling plant. As the materials are classified the program also provides real time composition data by classifying each item over 100 times. RecycleEye can detect 28 different classes of materials and can even detect different colors, shapes, and even brand labeling. This product can be used on its own for waste classification or can be used in combination with RecycleEye Robotics. Recycleye Robotics is designed to perform the manual part of waste sorting in combination with recycleye vision. It is capable of doing 30,000 waste picks from commingled waste in a 10 hour shift. [1]

2.3. AMP Robotics

The third is a company called AMP Robotics that is local to Louisville, CO. They apply deep learning to identify and categorize different types of waste. Their goal is to enable automation for the process of recovering recyclables from waste and also creating high value raw materials for resale.

They have 3 core products called AMP Neuron, AMP Cortex, and AMP Clarity. AMP Neuron is their core AI technology that uses computer vision to process images and map complex waste streams. It also continuously trains itself by processing millions of images into data and building its ever expanding neural network so that it can adapt to changes in the stream of waste it is exposed to. AMP Cortex is a high speed robotics system that works in tandem with their AI technology. Their robots are able to perform the traditionally manual task of sorting the waste and have attained 99% accuracy with up to 80 waste picks per minute. AMP Clarity is their web based data portal; that enables sorting operations to see real time material data. This can be used to measure performance during the sorting operations as well as to gain insights into how their processes are working and if adjustments need to be made. [2]

3. Data

We selected the Waste Classification dataset from Kaggle and it contains jpeg images of organic and recyclable objects that are labeled accordingly. In total the dataset is 448 MB and is updated annually. The dataset came with a training and testing data set so we split up the data to create a validation data set as well. We chose a 70/20/10 split for our training, validation and testing sets. The training dataset contains 17600 images, the validation set contains 4964 images and the test set contains 2513 images.

4. Empirical Applications

Based on the previous work explained above, since we were deciding to approach this problem from an individual perspective, that is, helping individuals identify where they should recycle or compost objects, we decided to follow the path that RecycleRight created using VGG16.

After a test, comparing a Convolutional Neural Network made from scratch against a model using transfer learning with VGG19 (an updated version of VGG16, used by RecycleRight), we confirmed that using transfer learning with VGG19 would be best moving forward.

The results of the Convolutional Neural Network and the basic transferred learning of VGG19 are as follows:

The accuracy of the CNN made from scratch ended up with and accuracy of 86.75% and the accuracy of the transferred learning of VGG19 was 85.99%

Although this may show that the CNN from scratch does give a higher accuracy, it seemed that the difference was of variation, instead of a true improvement. Therefore, we decided to use the method of transfer learning to follow a similar path as RecycleRight, allowing for the model to have pretrained weights before starting with our data.

5. Experiments

As explained above, we first experimented with the CNN model from scratch and the use of transfer learning with VGG19 and had determined that the use of transfer learning with VGG19 would be best.

And so, we experimented with several different ways to use VGG19 with other added layers following the model.

5.1. Model 1

For our first model, we experimented with the following layers using a sequential model:

1. VGG19 - with the include_top as False, weights as ‘imagenet’, input_shape as (244,244,3), pooling as max, and frozen trainable layers
2. Flattened layer
3. Dropout layer - of value 0.4
4. Prediction layer - dense layer with a softmax activation
5. Complied with an adam optimizer and categorical_crossentropy loss

The accuracy of this model ended up approximately 88.79%, better than the first 2 models experimented with. We still observed some noise and overfitting with this model and so decided to experiment with other sequential layers.

5.2. Model 2

In the second model, we implemented the following sequential layers:

1. VGG19 - with the include_top as False, the weights as ‘imagenet’, the input_shape as (244, 244, 3), and the pooling as none
2. Batch Normalization layer

3. Dropout layer - of value 0.5
4. Dense layer - value 64, with kernel regularizer L2 of value 0.01
5. Flattened layer
6. Dropout layer - value of 0.5
7. Prediction layer - dense layer of 2 with a softmax activation and kernel regularizer of l2, value of 0.01
8. Complied with an adam optimizer and categorical_crossentropy loss

The results for this model came to an accuracy of 89.34%. This was not significantly higher than the results obtained in Model 1, and so we decided to apply a new process to both of the models to compare again.

This new process will be further explained in section 6.4. Freezing/Unfreezing VGG19 Weights. For now, we will explain these previous methods and go further into why we used them.

6. Explanation of Methods

The following will cover several methods that were experimented with and/or used in the final model.

6.1. Convolutional Neural Network

With the goal of building a model that can differentiate between goods that are recyclable or organic based on an image of the object, it was decided that the best method would be to approach this with a Convolutional Neural Network (CNN). CNN started as a method used to decode handwritten digits when it was first developed. It has now grown into the role of "decoding" images in a sense, as a result of new computing resources, allowing researchers to revive them.

CNN's are a class of deep neural networks that work with a matrix of pixels whose channels are decided by the amount of color in an image. After receiving an image as the input, the CNN will use a mix of filters and kernels to generate another matrix, called a feature map, after it has been convolved. Here are examples of some filters and kernels that are used in CNN:

1. Convolutional Filters (kernels) - where each filter has a specialization to detect increasingly more complex features in subsequent neural network layers
2. Padding - a filter that keeps an image from shrinking between layers
3. Pooling - a filter that takes a convoluted feature after the colcolutional layer and shrinks it again
4. Max/Avg/Min Pooling - filters that take the largest/average/minimum number in the filter window to reduce complexity and avoid overfitting

The early features extracted from the images are simple local features like edges or lines, but eventually mold into the output of an image classification. In this case, classifying an image as recyclable or organic.

6.2. Transfer Learning

The second method that was utilized for this model was transfer learning.

Because our training dataset contains about 17,600 images, it was decided that it would be best to use pre-trained weights to jumpstart our model's ability to identify the objects in our images appropriately.

By using transfer learning, the universal features found in all photos, including but not limited to edges, patterns, and gradients, are learned from ImageNet and are transferred to our dataset. This allows for the model to better distinguish and understand the differences between recyclable and organic materials.

In order to use this method of transfer learning from ImageNet, we preprocessed our images by formatting them into the same input size as the ImageNet's inputs. This way, the model could similarly read the new input, without error.

By using this transfer learning method, the model was able to increase accuracy, showing overall better performance.

6.2.1. Transfer Learning with VGG19

The pretrained model that was extracted from ImageNet was the VGG19 package.

VGG19 contains 19 layers total, including 16 convolutional layers, 3 fully connected layers, 5 maxpool layers, and 1 softmax layer.

VGG19 was created by the Visual Geometry Group at Oxford, and can be considered a successor of the AlexNet, but is more of an improvement on AlexNet, using deep convolutional layers to improve accuracy.

The following are the arguments we included for our VGG19 model:

1. Include_top = False
   - Showing that we chose to exclude the 3 fully connected layers at the top of the network
2. Weights = imagenet
   - Showing the chosen pre-trained model
3. Input_shape = 224, 224, 3
   - Reformatting the image size of our data to VGG19 default
4. Pooling = None
   - Allowing the output of the model to be 4D tensor output

5. Layer.trainable = False
    - Freezing the original layer weights from the transfer model

6.3. Normalization Techniques

After applying the previous methods to the data, we observed some noise and overfitting in the results of the accuracy of the model, and so decided to apply the following techniques:

1. Batch Normalization - used directly after the VGG19 model to normalize the inputs
2. Dropout - a process to randomly drop nodes, combatting overfitting and noise
3. L2 Kernel Regularizers - in our model, used in the Dense and Prediction layers to help combat overfitting in results

By adding these Normalization Techniques, we were able to see an increase in the accuracy of the model.

6.4. Freezing/Unfreezing VGG19 Weights

Freezing and unfreezing trainable weights can also cause a change in the overall results and accuracy.

When freezing the weights, you are taking the weights of the transferred model, in our case the VGG19 model from ImageNet, and using the weights that they had gained from their data. In this case, because we wanted to optimize our results, we found that transferring those weights from ImageNet would be best first.

However, after some experimentation, we found that the following process produced better results:

1. Run the model with untrainable layers.
2. Reset the training and validation generators.
3. Unfreeze the trainable layers.
4. Run the model again.

By doing this, we were able to improve the results and were able to find our final model.

7. Findings

In the following, we will review the final model chosen, the reason for choosing accuracy as the metric, our results, and suggestions for further improvement.

7.1. The Final Model Chosen

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg19 (Functional)          (None, 7, 7, 512)         20024384

 batch_normalization (BatchN  (None, 7, 7, 512)        2048
 ormalization)

 dropout1 (Dropout)          (None, 7, 7, 512)         0

 dense (Dense)               (None, 7, 7, 64)          32832

 flattened (Flatten)         (None, 3136)              0

 dropout2 (Dropout)          (None, 3136)              0

 predictions (Dense)         (None, 2)                 6274

=================================================================
Total params: 20,065,538
Trainable params: 40,130
Non-trainable params: 20,025,408
```

As seen above, we chose to continue with the second Model that we experimented with. Our final model included the VGG19 model, a batch normalization layer, dropout1 of 0.5, dense layer with an L2 kernel regularizer, a flattened layer, dropout2 of 0.5, and the predictions layer with another L2 kernel regularizer.

As explained above, these added layers were able to improve the model, giving the following results.

7.2. Accuracy Metric

When approaching the problem of “Is this object recyclable or compostable?”, it was determined that accuracy would be the best metric to measure the models.

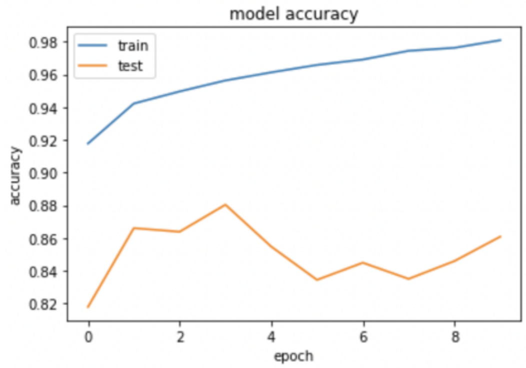
The reason accuracy is the best metric is because it's important to minimize the false positives and false negatives while improving the amount of true positives and true negatives.

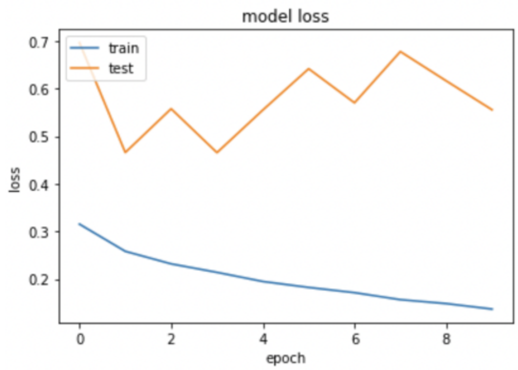
That is, in this context, recyclable and compostable objects are not the same and cannot be treated the same. In fact, if you cannot differentiate them apart when disposing of an object, you could contaminate the entire bin, causing the whole thing to go to a landfill instead.

But on the other hand, you also want to make sure you don’t miss anything that you could recycle or compost. And so, accuracy was determined to be the best measure.

Using the accuracy metric, we will now review our results.

7.3. Results





When working with the first instance of freezing the weights of the VGG19 model, we found the accuracy to be 87.58%. But once we went through the process explained above, and had unfreezed the weights, the new accuracy had increased to 91.60%. However, you do still see some amount of noise and overfitting in the data still, showing there is more room for improvement.

7.4. Suggestions for Further Improvements

Although we experimented with multiple models and multiple parameters to increase our results, we found that the accuracy only improved so much. We had approached this model with a model-centric approach, focusing on the layers within the model first and foremost, in order to achieve convergence.

For further improvement, it is recommended to take a more data-centric approach to further improve the model. Some suggestions include but are not limited to:

1. Data Augmentation - to increase the amount of data
2. Local Investigation - looking at individual images to see what the model found as important aspects to classify the data
3. Global Investigation - to find the general, “What makes an object compostable?” or “What makes an object recyclable?” in this model

By further investigating these, it is believed that the model will improve further, and be better equipped to answer the question, “Is this recyclable or compostable?”.

8. Business and Social Implications

Waste management and recycling is a huge industry worldwide. To quote some numbers, the global waste recycling industry is valued at 58 billion dollars in 2021 alone and it is expected to reach 88 billion dollars by the year 2030. That is more than a 50% increase in 9 years.

Waste segregation is a key step in the waste recycling business that has a direct impact on the cost of waste processing for these companies. Incorrect waste segregation has two impacts - 1. Additional overhead in the waste recycling process if a non-recyclable waste ends up in the recycle category. 2. If the recyclable waste is incorrectly categorized into compost category, it leads to more environmental pollution which could have been avoided.

Our proposed model has the potential to address this challenge both at the consumer level, which is the source, and also at the industry level by using it in the automated waste segregation processes. [6]

The social impact of waste segregation is much more important than the business impact.

The world has changed a lot in the past century. From individually packaged food servings to disposable diapers, more garbage is generated now than ever before. The average American discards seven and a half pounds of garbage every day. This garbage, the solid waste stream, goes mostly to landfills, where it's compacted and buried. As the waste stream continues to grow, so will the pressures on our landfills, our resources, and our environment.

The more we recycle, the less garbage winds up in our landfills and incineration plants. By reusing aluminum, paper, glass, plastics, and other materials, we can save production and energy costs, and reduce the negative impacts that the extraction and processing of virgin materials has on the environment.

It all comes back to us. Recycling gets down to one person taking action. New products can be made from your recyclable waste material.

Everyone knows recycling means less trash going to our landfills but the greatest environmental benefit of recycling is the conservation of energy and natural resources and the prevention of pollution that is generated when a raw material is used to make a new product.

Composting can also have a large impact on our social structures. Especially on a smaller scale, neighborhoods have started sharing compost for gardens on sites like Nextdoor. By including our community in our composting practices people are building neighborhood networks, and being more thoughtful about what they do with their compostable products. Because compost can be beneficial in so many ways, the application would be very helpful to weed out products that don't need to be included in our recycling at all and can be repurposed in our homes. It's nice to see such a simple task can both help the environment and communities.

With composting taking away from recyclable products, it can help save on disposal costs for Waste Management Companies. There will be overall less transportation and storage costs if it is kept local to your own home, or if you can connect with a local company that can pick up your compost (like Compost Colorado). Decreasing the amount of products that are sitting in landfills unnecessarily would help the shortage of landfill capacity that we could be facing. We can help our products be more regenerative to the environment in the long term. [7]

9. Conclusion

In conclusion, we achieved a test accuracy of 91.6% for our best model, which uses VGG19 with unfrozen trainable layers.

We did observe some noise in the final model output and also some signs of overfitting. We believe this is a satisfactory performance for the proposed application of using it in a consumer facing application for waste segregation at the source.

With the further suggested improvements of augmenting the data and deeper investigation, we believe the accuracy of the model can be increased to make it suitable for even the industry grade applications.

Proper disposal of waste has shown to have a large impact on our environment. If people could utilize an app like this to easily sort the trash that is able to be reused, repurposed, or recycled, we could give some trash a second life.

More importantly, we believe our model has the potential to make a real positive impact on businesses, everyday people, as well as the environment.

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