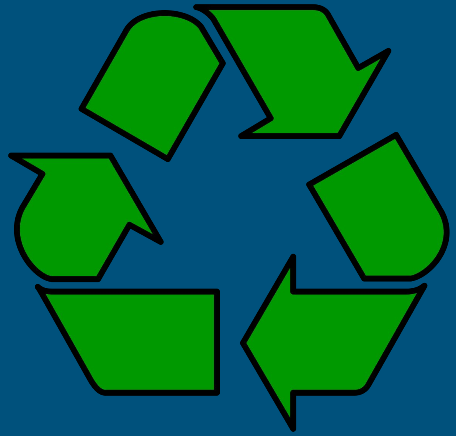
Recycle or Compost?



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Problem and Application Domain

Problem:

- According to the US Environmental Protection Agency, the recycling rate has increased from about 7% to over 32% in the US over the past 60 years
- Even with the progress, over 40% of waste can still be recycled and is trashed instead.
- One of the problems revolving around this issue is that many Americans don't know what to recycle

Goal:

- Develop a model that is easily accessible for the consumer (for example, through an app), so recycling can grow in the home.
- By making an easily accessible model for consumers, we can help minimize the confusion in recycling by addressing the question: "Should I recycle this?"

Environmental Protection Agency. (n.d.). *America Recycles Day*. EPA. Retrieved April 24, 2022, from https://www.epa.gov/recyclingstrategy/america-recycles-day

Morgan, B. (2021, December 10). Why is it so hard to recycle? Forbes. Retrieved April 24, 2022, from https://www.forbes.com/sites/blakemorgan/2021/04/21/why-is-it-so-hard-to-recycle/?sh=5e5966893b77

Related Work- Computer Vision For Recycling by Pratima Kandel

- Student project at the University of Mary Washington
- "RecycleRight" is an Android application that can efficiently aid individuals in identifying recyclable and non-recyclable household items.
- **Purpose:**
  - Designed to develop an application based on a deep learning model that aids users to correctly identify the nature of objects that they deem recyclable and to widen the scope of healthy recycling
- **Method:**
  - Utilizes transfer learning from from VGG-16 pre trained model with frozen weights in the top layers, unfrozen weights on the last layers, and replaced the last layer with a Softmax layer
- **Challenges:**
  - Many different shapes and labels of recyclable household items so just a few examples of each is not a sufficient amount of data.
  - Images that they used for training had white backgrounds so the complex backgrounds in real life can make identification more challenging

Kandel, Pratima, "Computer Vision For Recycling" (2020). Student Research Submissions. 379. https://scholar.umw.edu/student_research/379

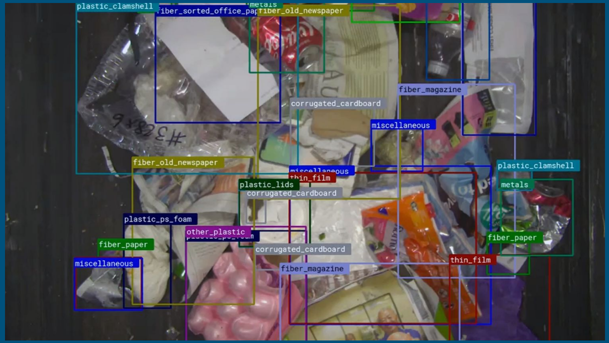
Related Work- Recycleye

- Technology company using advanced machine learning, computer vision and robotics to commodify waste.
- **Goal:**
    - Bring transparency, traceability and efficiency to the global waste management industry
    - Improve plant performance with Recycleye Vision and Recycleye Robotics solutions to enable data-driven strategic decisions and automated operations.
- **2 main products:**
    - Recycleye Vision
        - scans and identifies co-mingled waste materials
        - Classifying each item over 100 times, Recycleye Vision identifies materials to provide real-time composition data
        - Can be used alone or with Recycleye Robotics to pick and sort identified waste.
        - Can detect materials across 28 classes.
            - Can even detect and differentiate colours and shapes, food and non-food grades and packaging and non-packaging materials, even at brand levels
    - Recycleye Robotics
        - performs the physical tasks of picking and placing waste materials, automating manual operations.
        - Capable of successfully delivering up to 33,000 picks from co-mingled waste per 10-hour shift.

About us - recycleye - turning the world's waste into resource. Recycleye. (2022, April 6). Retrieved April 24, 2022, from https://recycleye.com/about-us/

Related Work- AMP Robotics

- Applies deep learning to continuously improve the precise identification and categorization of paper, plastics, and metals by color, size, shape, opacity, form factor, brand, and more, contextualizing and storing data about each item it perceives. A local Louisville company!
- **Goal:**
  - enable automation to accurately recover recyclables, remove contamination and ultimately create high-value raw material for resale
- **Main Products:**
  - **AMP Neuron™**
    - Core AI Technology that applies computer vision to process millions of images to map complex material streams.
    - continuously trains itself by processing millions of material images into data, building upon an ever-expanding neural network that adapts to changes in a facility's material stream.
  - **AMP Cortex**
    - High-speed, intelligent robotics system
    - Guided by AMP's artificial intelligence (AI) technology, their robots intelligently perform physical tasks of sorting, picking, and placing material to achieve 99% accuracy and up to 80 picks per minute.
  - **AMP Clarity**
    - Web-based data portal that provides real-time material characterization and performance measurement throughout key process stages of sorting operations.
    - Can be used to gain insights and adjust processes to improve productivity



AMP neuron. AMP Robotics. (n.d.). Retrieved April 24, 2022, from https://www.amprobotics.com/amp-coretechnology

Dataset

We selected our dataset from Kaggle and it contains images of organic and recyclable objects

Dataset is divided into train data (70%), validation data (20%) and test data (10%)

- Training data - 17600 images
- Validation data- 4964
- Test data - 2513 images

Method - Convolutional Neural Network (CNN)

The main method used was CNN. Because our dataset is comprised of images, computer vision was our choice for the method behind our model.

- CNN has come a long way since just being able to decode digits when it was first developed. New computing resources have enabled researchers to revive CNNs
- 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
- CNN uses filters/kernels on the input image to generate a feature map (another matrix) after its been convolved
- The early features extracted from the images are simple local features like edges or lines, but eventually our output will be a classification of the image (is it recyclable or organic?)
- CNN's have multiple building blocks to help accurately extract data:
    - Convolutional filters (kernels) = each filter has a specialization to detect & detect increasingly more complex features in subsequent neural network layers
    - Padding = keeps an image from shrinking between layers
    - Pooling = takes a convoluted feature after the convolution layer and shrinks it again
    - Max/Avg/Min Pooling = takes the largest/average/minimum number in the filter window to reduce complexity & avoid overfitting

Method - Transfer Learning

We wanted to utilize transfer learning from ImageNet and use pre trained weights to jumpstart our model's ability to identify the objects in our images.

- The universal features shared between images (edges, patterns, gradients) that are learned from Imagenet can be applied/transferred to our dataset to help distinguish and understand the differences between recyclable and organic materials
- One of the general preprocessing steps we took was to format our images input size to match the Imagenet models
- We did see better performance when we adjusted our model to include transfer learning rather than from scratch

Method - Transfer Learning with VGG19

We used VGG19 to start our model off with transfer layers

- VGG19 consists of 19 layers (16 convolutional layers, 3 fully connected layers, 5 maxpool layers, and 1 softmax layer)
- VGG19 can be considered a successor of the AlexNet, but was created by Visual Geometry Group at Oxford (it improves on AlexNet and uses deep convolutional layers to improve accuracy)
- The arguments we included for our problem are:
    - Include_top = False (we did not include the 3 fully connected layers at the top of the network)
    - Weights = imagenet (pre-training on ImageNet)
    - Input_shape = 224, 224, 3 (formatted our image size to VGG19 default)
    - Pooling = None (so the output of the model will be 4D tensor output)
    - We also froze the layers weights from the transfer model

```
vgg19 = VGG19(include_top=False,
              weights='imagenet',
              input_shape=(224,224,3),
              pooling=None)
```

```
[ ] for layer in vgg19.layers:
        layer.trainable = False
```

Code - Path to the Final Model

Below are the basic steps we took after gathering our data:

- After loading the dataset we split and scaled our data into train, validation, and test sets
- Second, we created a basic CNN model from scratch that had 3 convolutional layers and then one dense layer with relu and one with softmax
- Third was a simple transfer learning model off of VGG19 to see how it would generally perform with our data set
- Once we decided on the transfer set to use, we worked on optimizing the model using different techniques and layers. We tried adding different amounts of dropout, normalization, regulators, and different loss functions in the model

Findings

Our Winning Model:

```
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
```

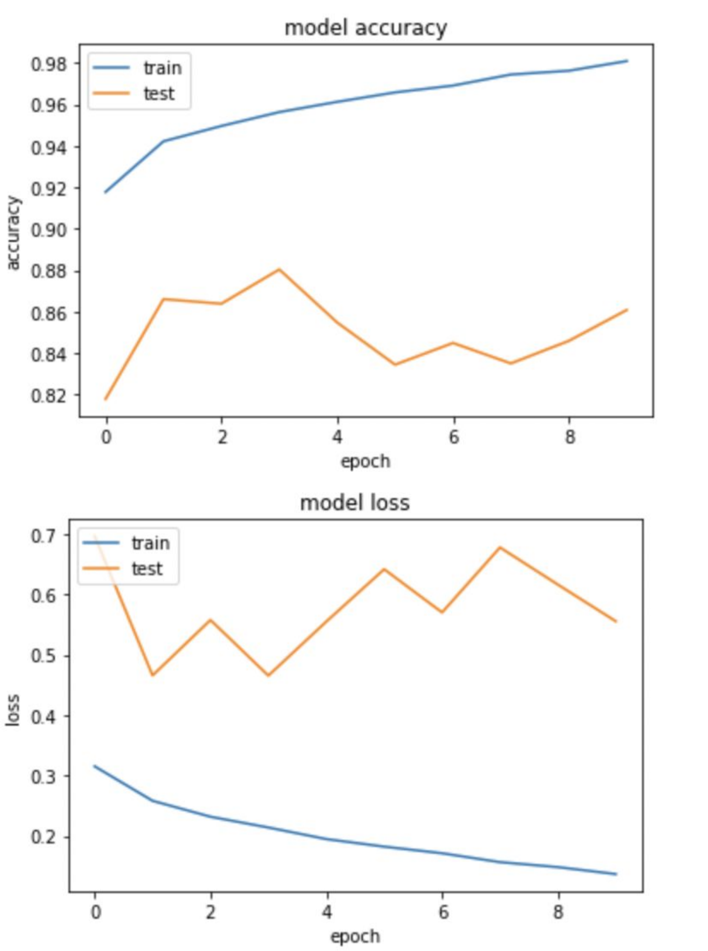
Findings

Results:

- With frozen trainable layers in VGG19: **Accuracy - 87.58%**
- After unfreezing the trainable layers: **Accuracy - 91.60%**

Graph Observations:

- Noise
- Overfitting



Further Improvement

From here, we would recommend taking a more data centric approach to further improve the model

- Data Augmentation - This could be used to provide more images to improve the model.
- Local Investigation - Looking at individual pictures to see what the model found as important to identify them as the model did.
- Global Investigation - Finding the general “What makes an image labeled recyclable or compost?” for this model.

Business and Social Implications

Business

- The global waste recycling industry is valued at $58 Billion in 2021
- It is expected to reach $88 Billion by 2030
- Incorrect waste segregation adds a lot of cost to both the businesses that process recycled waste as well as businesses that compost the waste
- Our proposed model can be used in two different ways
  - At the consumer level
  - At the industry level
- Consumer: By using our model in a mobile application, waste segregation problem can be addressed right at the source
- Industry: Our model can also be used by the waste processing industries for automating the waste segregation resulting in time efficiency and cost savings

Business and Social Implications

Social

- 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
- The more we recycle, the less garbage winds up in our landfills and incineration plants
- Recycling gets down to one person taking action
- It conserves energy, reduces air and water pollution, reduces greenhouse gases, and conserves natural resources.

Conclusion

- We achieved a test accuracy of 91.6% for our best model
- We did observe some noise and signs of overfitting in the final model
- Satisfactory performance to be used in a consumer facing waste segregation application
- With the further suggested improvements, it can also be used in the industrial waste management applications
- Overall, we believe our model can have a real positive impact both for business and for the environment