Categorizing Unsorted Recyclables

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Introduction

- **Problem**:
  - The recyclables sent to a recycling center:
    - Are contaminated with trash
    - Are unsorted or sorted incorrectly
  - Manual sorting is troublesome
- **Potential Solution**:
  - Convolutional neural network

Background – Convolutional Neural Net

- A convolutional neural network was chosen in order to detect distinguishable features in images
  - The CNN uses a kernel size of 3x3 for the convolutional layers
- CNNs recognize images in components, making them ideal for detecting differences between item categories

Methods - Dataset 1

- Previous dataset from TrashNet project
- 6 categories: metal, glass, paper, plastic, cardboard, trash
- 2000+ images:
  - Around 400 to 500 each for first five categories
  - 137 for trash
- Varied rotations and pictures of features for each category

Methods - Dataset 2

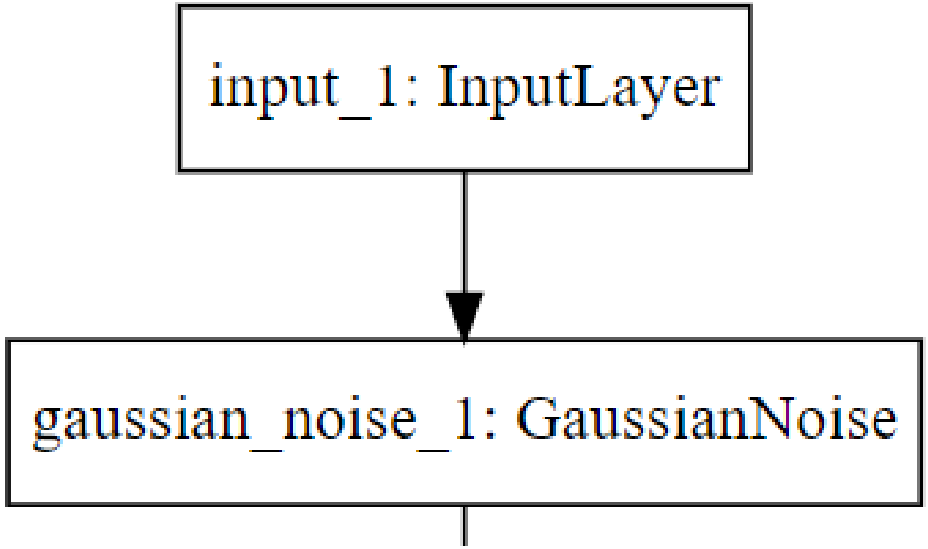
- 4 categories: plastic bottles, glass bottles, cardboard, soda cans
- 1300+ images:
    - Around 350 for glass, cardboard, cans
    - 270 for plastic
- Varied rotations and pictures of features for each category

Methods - Preprocessing

- Resized images to 100 x 100
- Placed in numpy arrays for each category
- Mean subtraction
- One-hot encoding by using labels.csv
- Shuffled images in each category
  - Split images: ½ for training and validation, ½ for testing

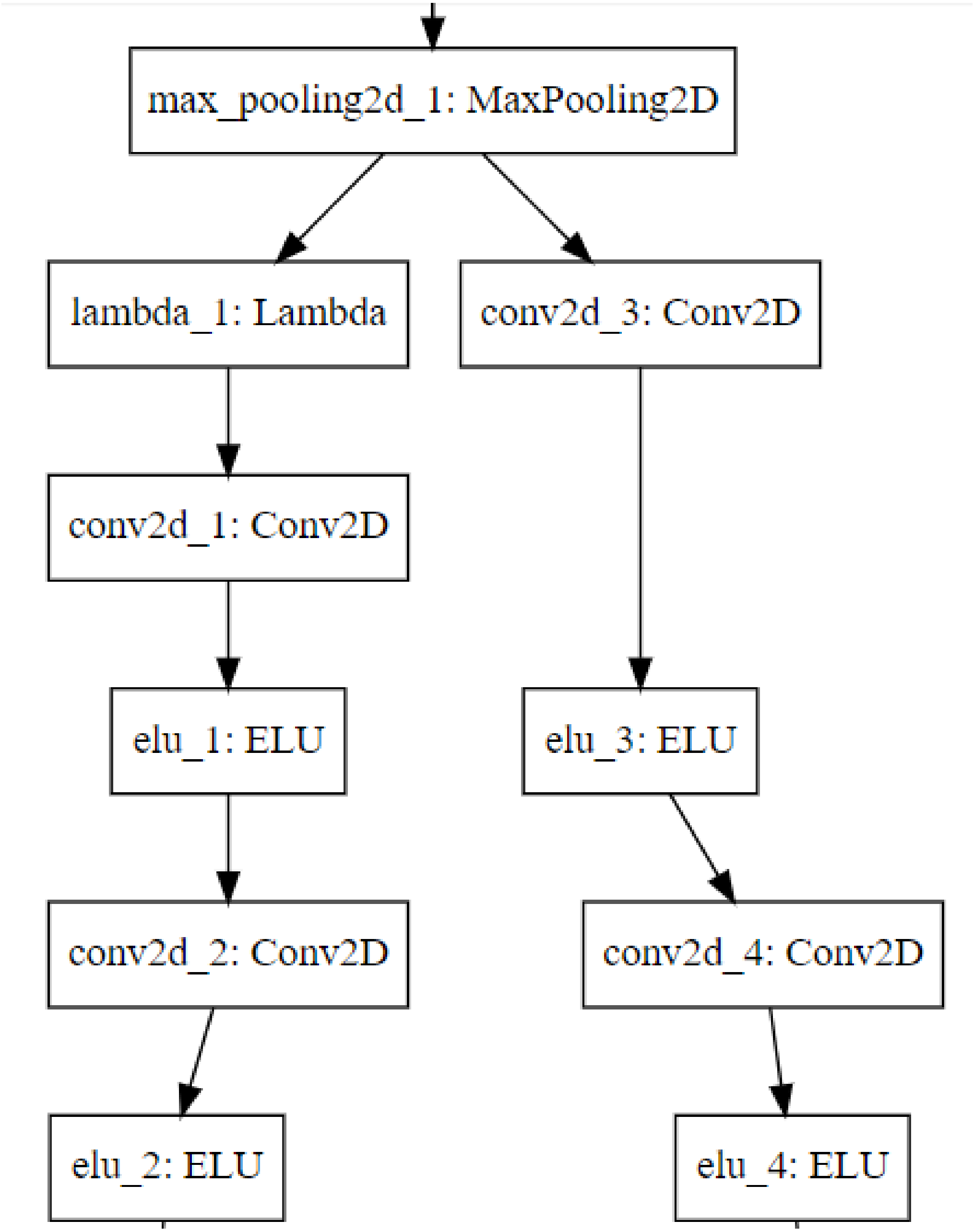
Methods - Model

- Gaussian noise layer
  - Prevents overfitting
  - General features instead of specific features



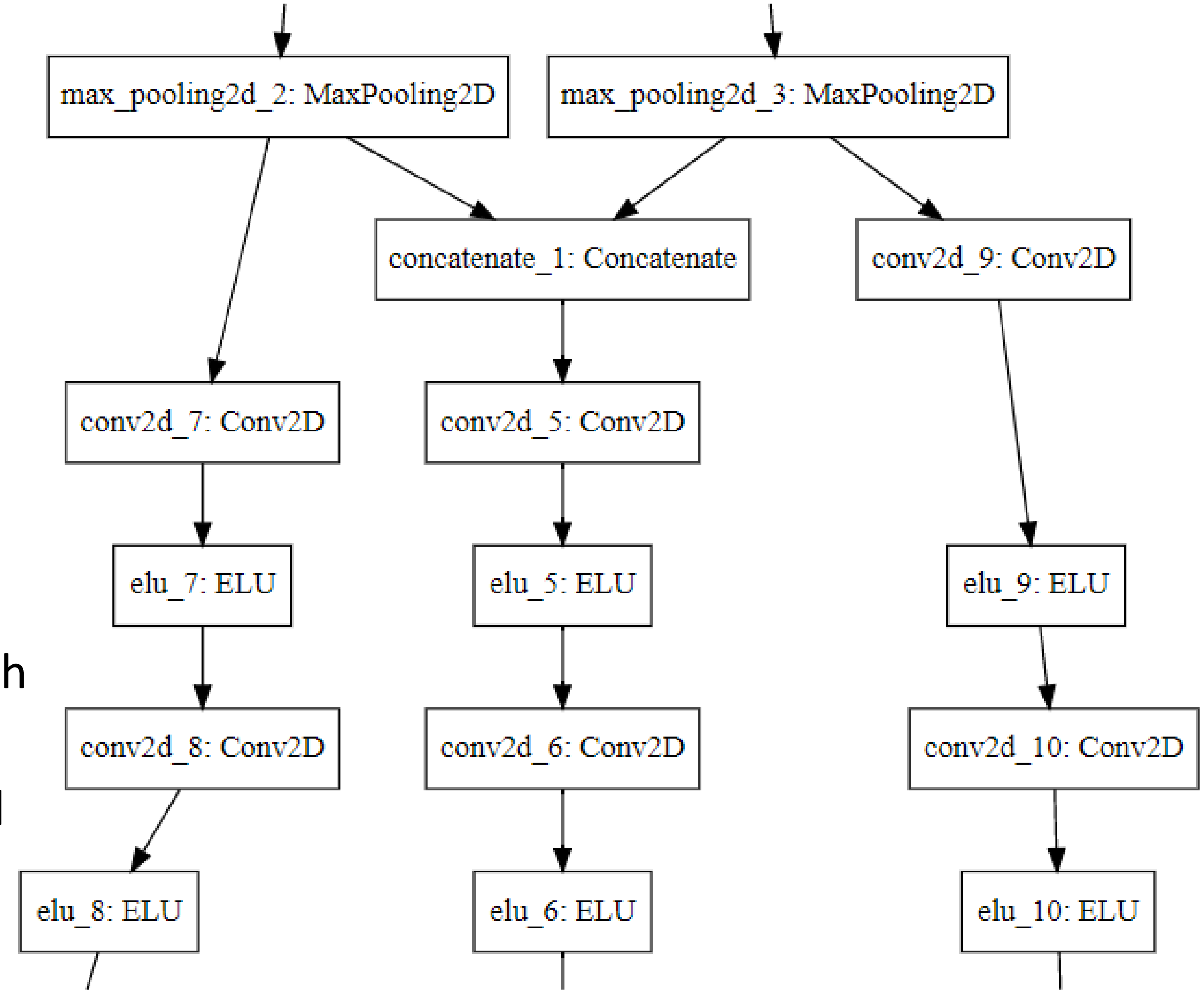
Methods - Model

- Pools previous input branch
  - Reduces parameters
- Left branch
  - Converts all images to grayscale
- Right branch
  - Retains color of all images
- Layers:
  - Lambda – function to convert to grayscale
  - Conv2D
  - ELU – exponential nonlinearity



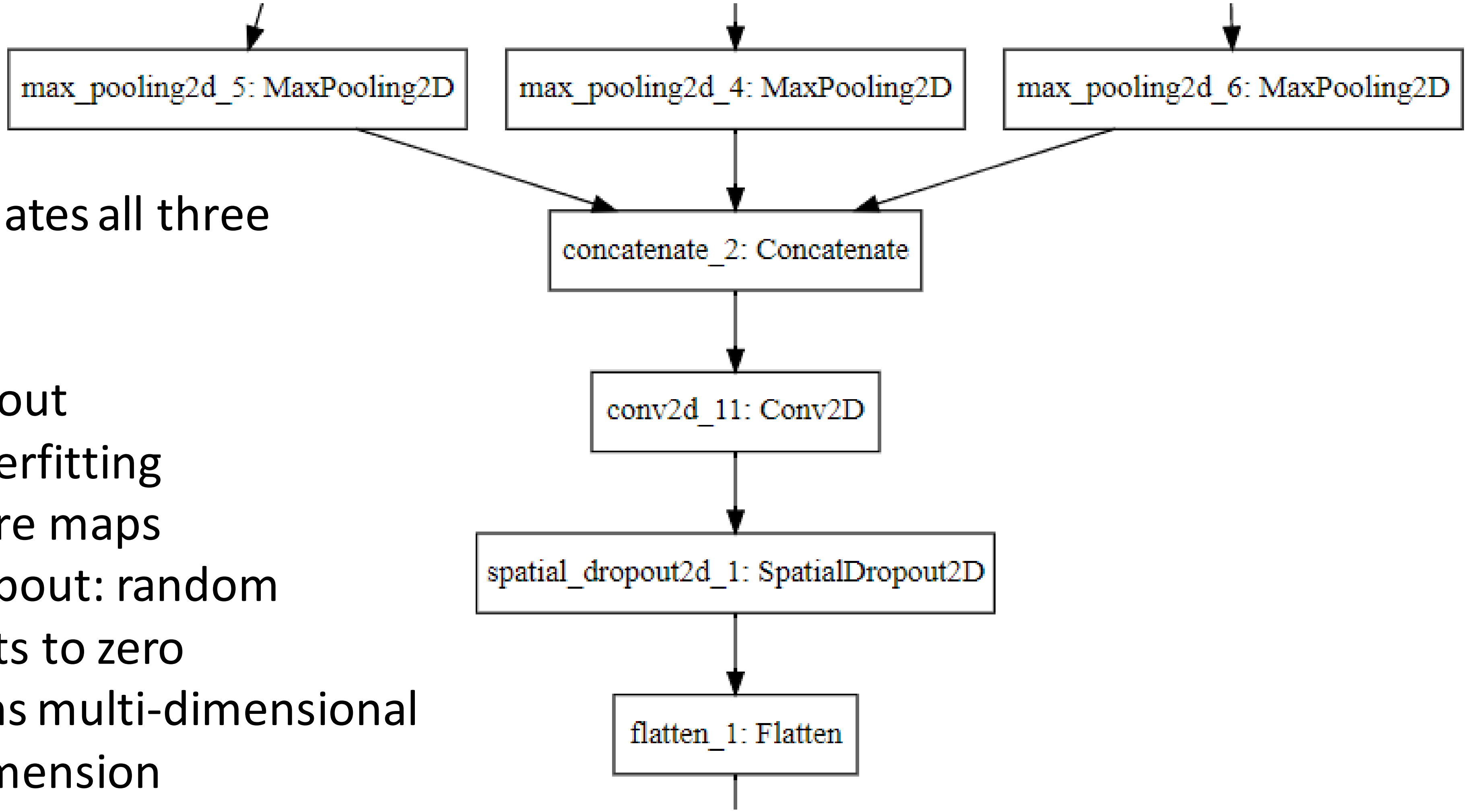
Methods - Model

- Pools previous two branches
- Left
  - Continuation of greyscale branch
- Right
  - Continuation of color branch
- Middle
  - Concatenates grayscale and color branches



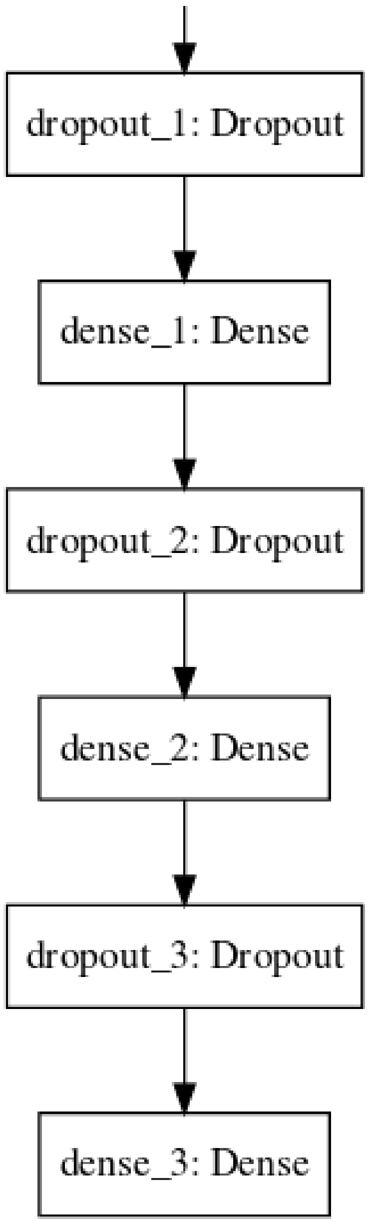
Methods - Model

- Pools and concatenates all three branches
- Layers:
    - Spatial 2D Dropout
        - Prevents overfitting
        - Drops feature maps
        - Regular dropout: random singular units to zero
    - Flatten – flattens multi-dimensional input to one dimension

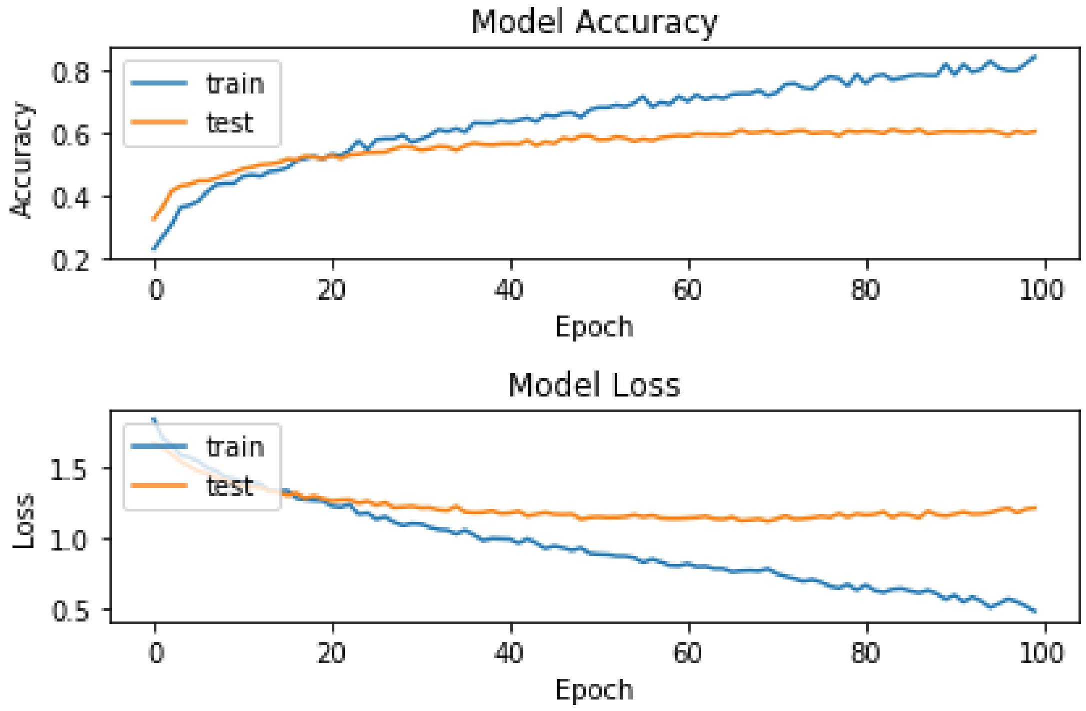


Methods - Model

- Series of dense layers
- Intermixed dropout
  - Reduces unnecessary connections
  - Limits overfitting
- Produces results that can be mapped to the one-hot encodings
- Bottleneck



Results - Dataset 1



- 60% testing accuracy
- Original – 75% accuracy
  - Larger image size (Higher resolution)

```
Breakdown of network predictions for testing set:
------------------------
Glass: 251 images
Network predictions given an image of Glass:
        Glass: 71.71%
        Paper: 3.59%
        Cardboard: 4.38%
        Plastic: 6.37%
        Metal: 8.76%
        Trash: 5.18%
```

Glass: 72%

```
Paper: 297 images
Network predictions given an image of Paper:
        Glass: 12.46%
        Paper: 76.09%
        Cardboard: 3.03%
        Plastic: 1.68%
        Metal: 5.39%
        Trash: 1.35%
```

Paper: 76%

```
Cardboard: 202 images
Network predictions given an image of Cardboard:
        Glass: 15.84%
        Paper: 5.94%
        Cardboard: 66.34%
        Plastic: 3.96%
        Metal: 5.45%
        Trash: 2.48%
```

Cardboard: 66%

```
Plastic: 241 images
Network predictions given an image of Plastic:
        Glass: 24.48%
        Paper: 10.37%
        Cardboard: 8.3%
        Plastic: 46.89%
        Metal: 9.13%
        Trash: 0.83%
```

Plastic: 47%

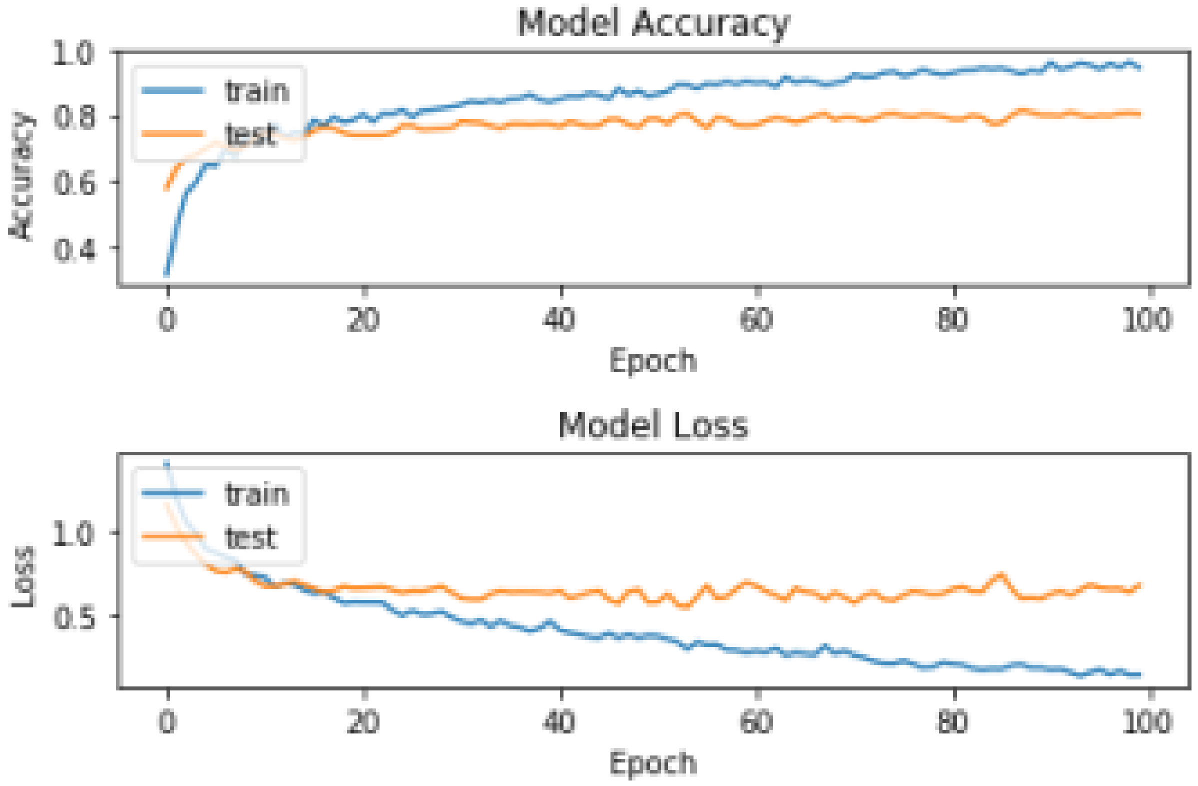
```
Metal: 205 images
Network predictions given an image of Metal:
        Glass: 32.2%
        Paper: 9.27%
        Cardboard: 6.34%
        Plastic: 7.32%
        Metal: 42.44%
        Trash: 2.44%
```

Metal: 42%

```
Trash: 69 images
Network predictions given an image of Trash:
        Glass: 34.78%
        Paper: 4.35%
        Cardboard: 7.25%
        Plastic: 8.7%
        Metal: 5.8%
        Trash: 39.13%
```

Trash: 39%

Results - Dataset 2



- 80% testing accuracy
- Dataset:
  - Specific items for each category

Results - Dataset 2

```
Breakdown of network predictions for testing set:
-------------------------
Glass: 178 images
Network predictions given an image of Glass:
        Glass: 78.09%
        Plastic: 2.81%
        Cardboard: 8.43%
        Can: 10.67%


Plastic: 136 images
Network predictions given an image of Plastic:
        Glass: 26.47%
        Plastic: 48.53%
        Cardboard: 2.21%
        Can: 22.79%
```

Glass: 78%

Plastic: 48%

```
Cardboard: 175 images
Network predictions given an image of Cardboard:
        Glass: 1.14%
        Plastic: 0.0%
        Cardboard: 98.86%
        Can: 0.0%


Can: 179 images
Network predictions given an image of Can:
        Glass: 6.7%
        Plastic: 1.12%
        Cardboard: 3.35%
        Can: 88.83%
```

Cardboard: 99%

Cans: 89%

Conclusion

- A convolutional neural network might be used to categorize recyclables if
  - The dataset contains images for categories for specific items
  - Additional methods and layers are used to optimize performance and accuracy
  - Prevention for overfitting is used
  - Images of the items have different rotations and features

Demo