Contribution

Jaekwang Shin: EDA, Data augmentation

Emily Zhang: Decision Tree, CNN

Victor Wang: CNN

Deep Learning Model for Automated Waste Classification

Emily Zhang, Victor Wang, Jaekwang Shin

DATASCI207

UC Berkeley School of Information

Agenda

1. Research Question
2. Data Exploration and Preprocessing
3. Baseline - Decision Tree
4. Performance - CNN
5. Results and Conclusion

Project Goal

Goal: Develop a deep learning model using the **RealWaste dataset** (4,700+ labeled images).

Motivation: Automated classification can reduce contamination, improve recycling rates, and support scalable waste management solutions.

Expected Outcomes:

- Improved sorting efficiency
- Reduction in manual labor and sorting errors

Research Questions

Leading Question: How effectively can CNNs classify real-world landfill waste images into correct material categories?

Sub-questions:

- What strategies (**data augmentation**, **advanced architectures**) can enhance accuracy over a baseline model?
- How significant are improvements over simple baseline approaches (e.g., Decision Trees, Majority Class Predictor)?

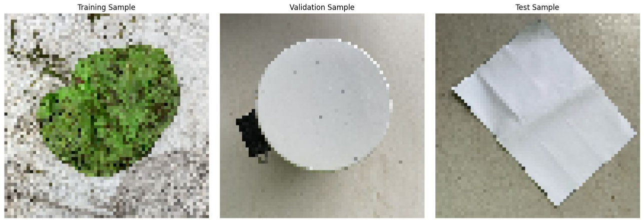
Objective: Identify the most effective modeling strategies to automate and optimize waste classification in real-world scenarios.

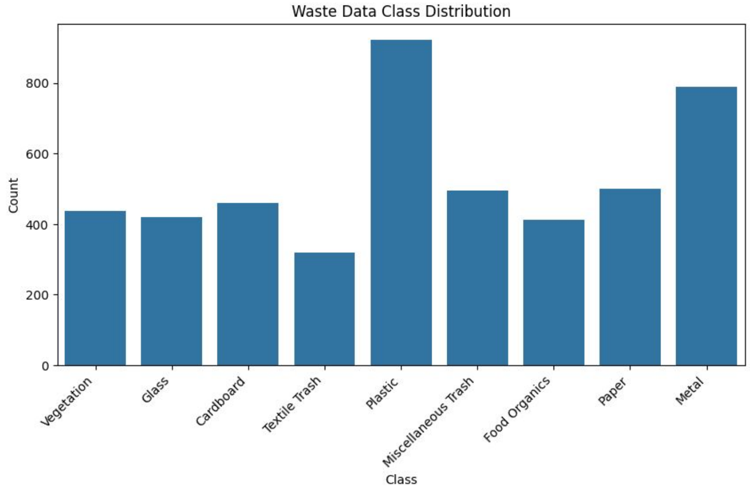
Data Exploration

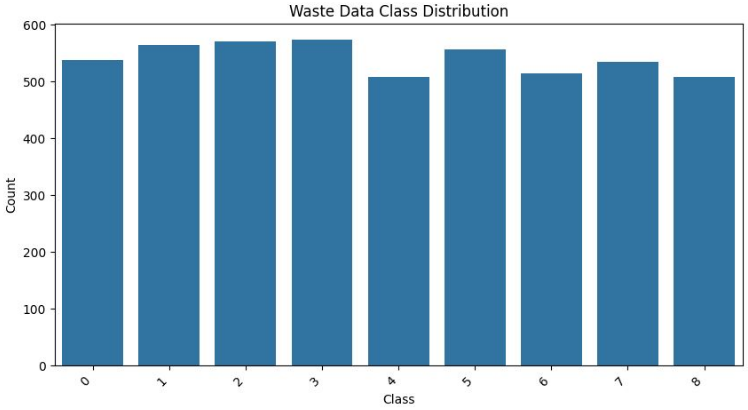
- ~4,700 labeled images
- 9 waste categories (e.g., plastic, glass, metal)
- Images taken in real-world conditions (different lighting, angles, backgrounds)

Data Preprocessing and Augmentation

- Normalization: Scaled pixel values
- Resizing: Made all images the same size
- Augmentation : rotation, flips, and brightness changes
- Uniform sampling







Why Decision Tree

- **Minimal Preprocessing Required**
  Can directly accept flattened image pixel data (64×64×3) without extensive preprocessing or feature extraction.

- **Interpretability and Transparency**
  Provides clear decision rules and pathways, making it easy to interpret initial results and troubleshoot.

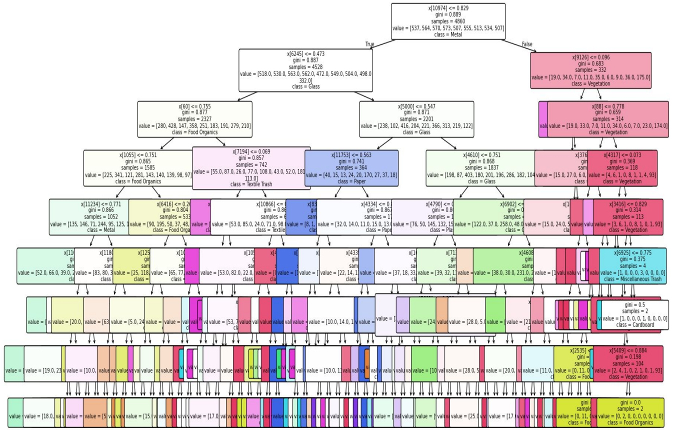
- **Quick Training and Evaluation**
  Enables fast baseline establishment and rapid feedback loops.

- **Effective Benchmarking Tool**
  Offers an accessible baseline to easily compare the relative improvement provided by more advanced models.

How is the Decision Tree Model Performance

- **Hyperparameters:**

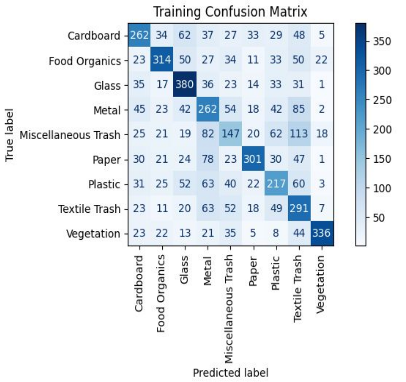
  max_depths = 8, min_samples_leaf = 2

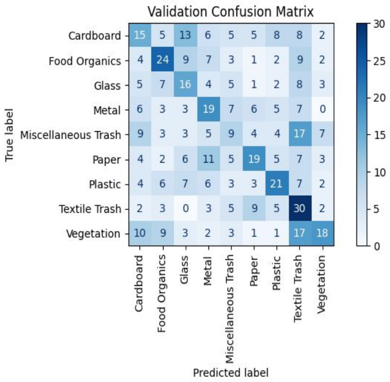


- **Performance**

Datasets\Metrics	Accuracy	Precision	Recall
Training Data	51.6%	53.5%	51.5%
Validation Data	31.7%	32.5%	31.9%

- **Confusion Matrix**





Limitation of Decision Tree Model

● **Poor Performance on Image Data**

Struggles to capture spatial relationships and visual patterns across pixels.

● **High Dimensionality Issues**

Flattened image inputs lead to sparse and noisy representations.

● **No Feature Hierarchy**

Lacks ability to learn layered visual abstractions (e.g., edges → shapes → objects).

● **Overfitting Risk**

Decision trees can easily overfit to pixel-level noise without regularization.

● **Limited Scalability**

Not well-suited for scaling to large or diverse image datasets like RealWaste.

Why CNN

- **Positional Invariance**

  CNNs can recognize patterns regardless of where they appear in the image.

- **Learns Visual Patterns**

  Automatically extracts low-level features (like edges, textures) and combines them into high-level concepts.

- **Robust to Real-World Variability**

  Handles variation in lighting, angles, and background noise present in the RealWaste dataset.

- **Improves Over Baseline Models**

  Outperforms decision trees by learning features directly from pixel data, without manual engineering.

- **Suited for Image-Based Classification Tasks**

  Designed for vision problems like waste categorization, where spatial structure matters.

Preliminary CNN Model Structure

Hyperparameters: ADAM optimizer with learning rate of 0.01. Trained for 2 epochs

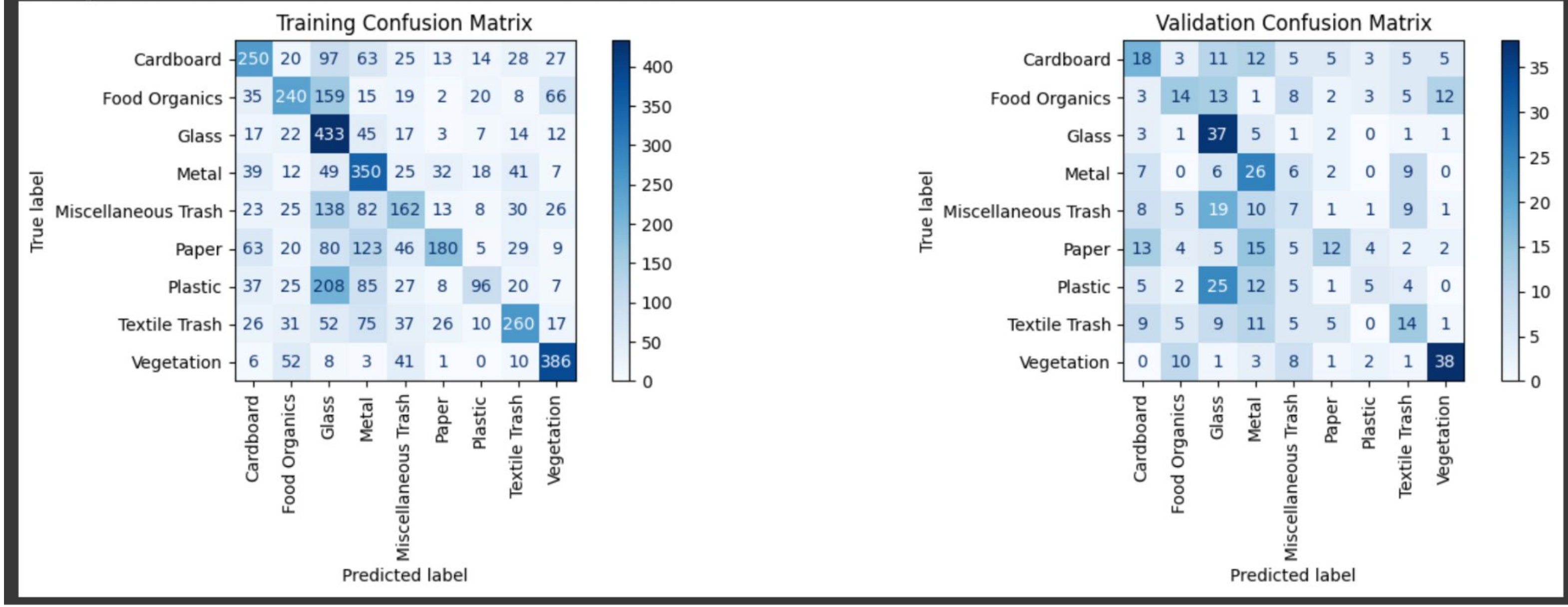
```
Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 64, 64, 24)	1,176
max_pooling2d_6 (MaxPooling2D)	(None, 32, 32, 24)	0
dropout (Dropout)	(None, 32, 32, 24)	0
flatten_2 (Flatten)	(None, 24576)	0
dense_3 (Dense)	(None, 9)	221,193

```
Total params: 222,369 (868.63 KB)
Trainable params: 222,369 (868.63 KB)
Non-trainable params: 0 (0.00 B)
```

Preliminary CNN Performance

```
152/152 ━━━━━━━━━━━━━━━━━━━━ 7s 48ms/step
17/17 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
Training Accuracy:  0.4849794238683128 Validation Accuracy:  0.31666666666666665
Training Precision:  0.5208449549628364 Validation Precision:  0.31960577559898445
Training Recall:  0.48230763259715065 Validation Recall:  0.323558578585098
```



- **Overfitting observed on validation set**
- **Common confusions:**

Paper ↔ Cardboard // Metal ↔ Glass // Plastic ↔ Misc Trash / Textile // Vegetation ↔ Cardboard //Plastic↔Glass

Limitation of Preliminary CNN Model

● **Shallow Architecture**

Limited number of convolutional layers restricted feature extraction capacity.

● **Low Input Resolution (64×64)**

Missed fine-grained visual details important for differentiating similar waste types.

● **No Regularization**

Lack of dropout or weight decay made the model prone to overfitting.

● **Static Learning Rate**

A fixed, high learning rate caused unstable convergence and poor generalization.

● **Underutilized Optimizer Settings**

Default optimizer configurations weren’t well-tuned for this task.

Final CNN Model Setup

Model Architecture

- Add more CNN layers - ~50%
- VGG16 Inspired- Too big
- ResNet - ~65%

Tried multiple Image Resolutions

- 64 * 64 - 65%
- 128 * 128 - 70%
- 256 * 256 - 70%

Learning Rate

- Static
  - 0.01 - Fast overfitting
  - 0.001 - 65%
  - 0.0001 - 70%
- Dynamic
  - 10x decrease in training rate - 75%

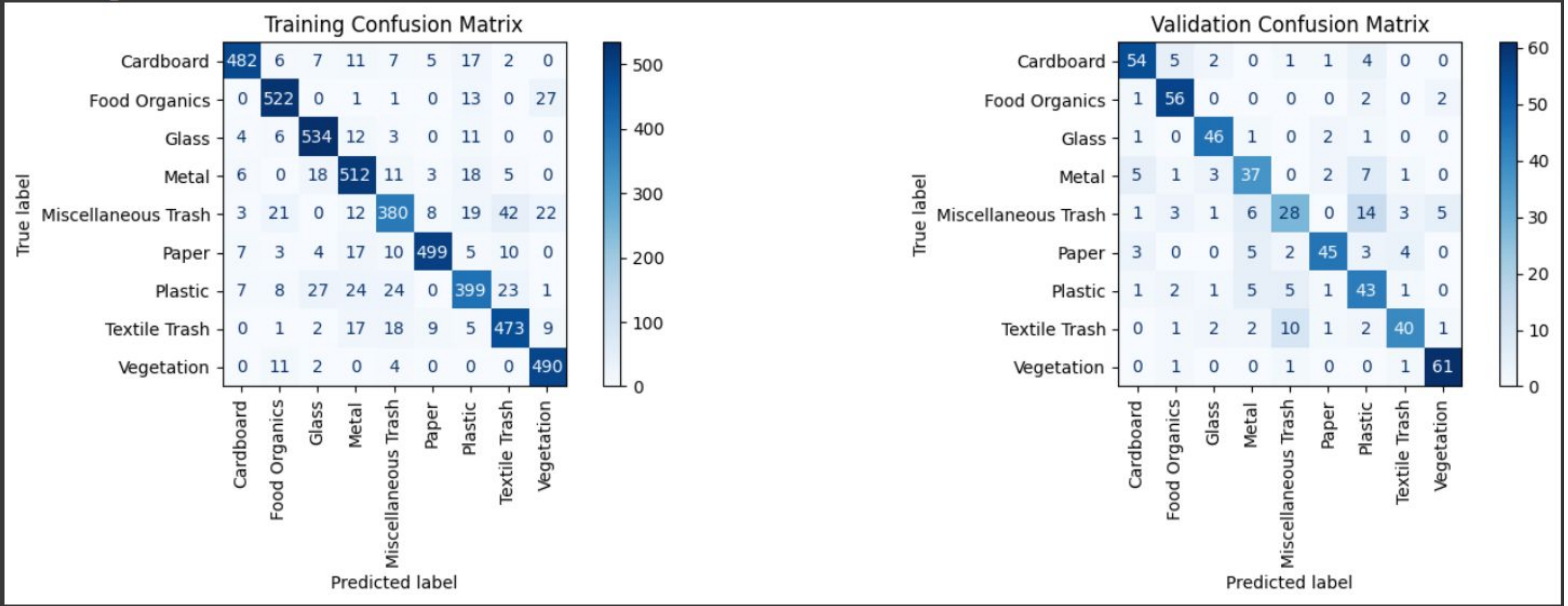
Optimizer

- Adam/AdamW/Nadam

Final CNN Model Performance

Depth = 20

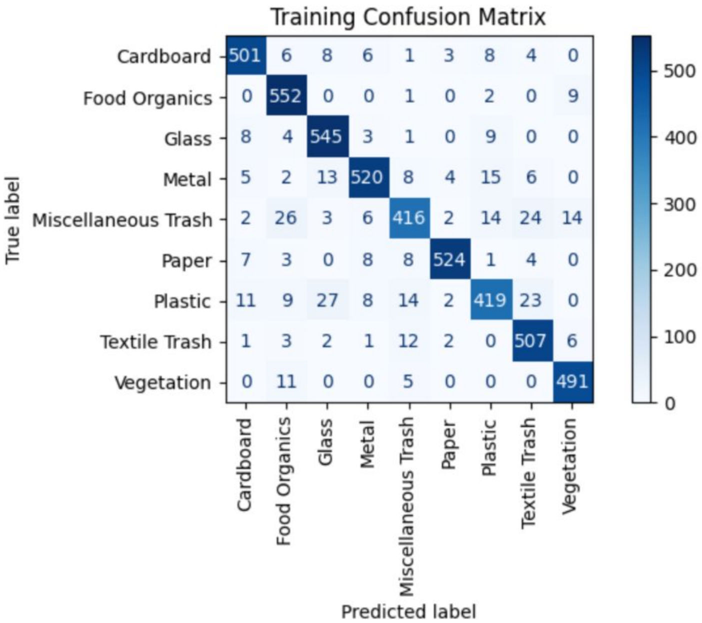
```
Training Accuracy:  0.8829218106995885 Validation Accuracy:  0.7592592592592593
Training Precision:  0.8822237515077148 Validation Precision:  0.7597589648991859
Training Recall:  0.8813463243847859 Validation Recall:  0.759045056915496
```

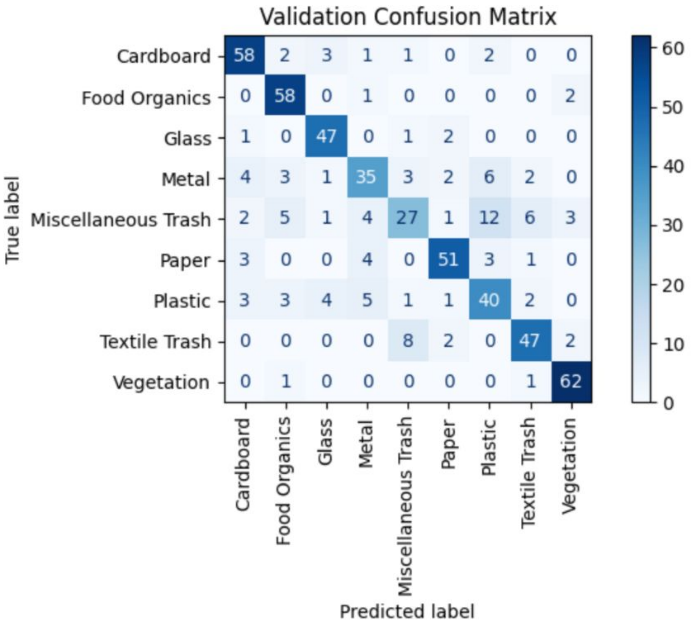


Final CNN Model Performance

Depth = 38

```
Training Accuracy:  0.9207818930041153 Validation Accuracy:  0.7870370370370371
Training Precision:  0.9207315068984274 Validation Precision:  0.7794186191520763
Training Recall:  0.9194033473380476 Validation Recall:  0.7857322009489529
```



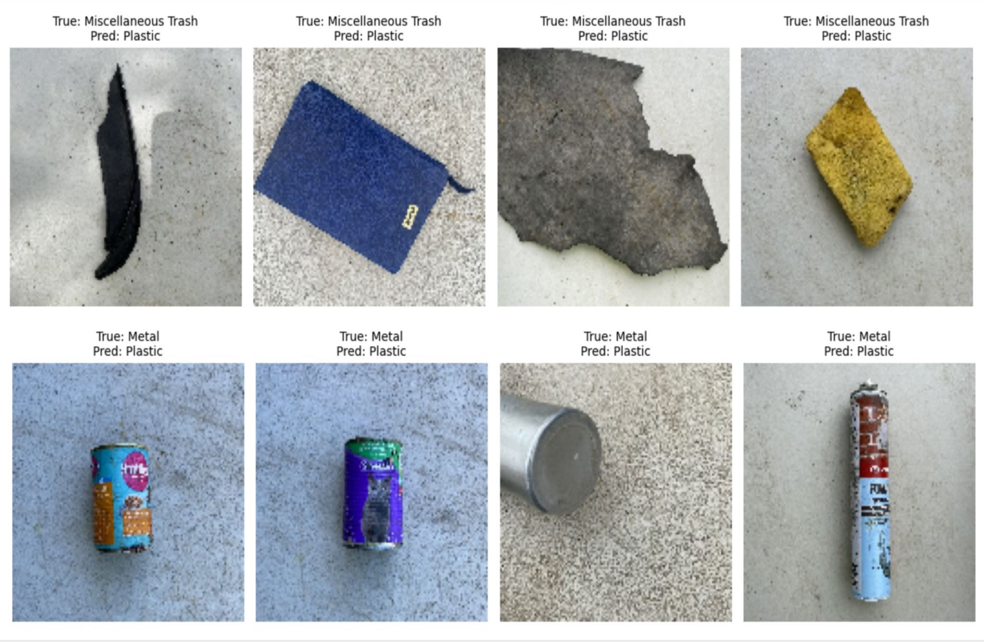


Final CNN Model Performance

- High accuracy & clean diagonals in training → model learned the patterns well
- Slight performance drop in validation → due to inter-class visual similarity, not overfitting
- Prediction accuracy varies among different classes

High Accuracy: Cardboard, Food Organics, and Vegetarian

Low Accuracy: Miscellaneous Trash vs Plastic, Metal vs Plastic. These categories share visual or material similarity



Summary and Future Improvements

Overall, the model is

- Well-regularized
- Strong across all major classes
- Especially strong in organic vs inorganic separation (e.g., Food Organics vs Plastic)
- Ready for deployment or fine-tuning

For Future, we could improve the prediction even better through:

- More Class-Specific Augmentation: E.g., rotate or distort plastic and glass samples differently, since they may appear similar from certain angles
- Multi-view or metadata if available: If available, use additional context like texture or edge features