Faculty of Computing

Garbage Classification System

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Team Members

Name	IT Number
Prameesha M.L.I	IT24101838
Puyumali M.C	IT24101884
Liyanage H.P.L.S.I	IT24101911
Paranahewa K.P	IT24103814
Tathsilu S.E.B	IT24101897
Abeysinghe A.A.S.D	IT24101823

Introduction

An AI/ML Garbage Classification System is an intelligent application that uses Artificial Intelligence (AI) and Machine Learning (ML) techniques to automatically classify waste into different categories such as plastic, paper, metal, glass, trash, and cardboard. The main goal is to promote smart waste management and environmental sustainability by enabling efficient recycling and disposal.

The system typically uses computer vision and deep learning models (like CNNs or transfer learning models such as MobileNet or ResNet) to analyze images of waste. When an image of garbage is input, the model processes visual features and predicts the correct category. This helps automate the sorting process, reduce human effort, and improve recycling accuracy.

The project involves several stages — data collection, image preprocessing (resizing, augmentation, normalization), model training, evaluation, and deployment. Such systems can be integrated with smart bins or waste management platforms to support real-time classification and reporting.

Project Objectives

- To develop an image classification model capable of classifying garbage.
- To build a user-friendly interface for image input and prediction

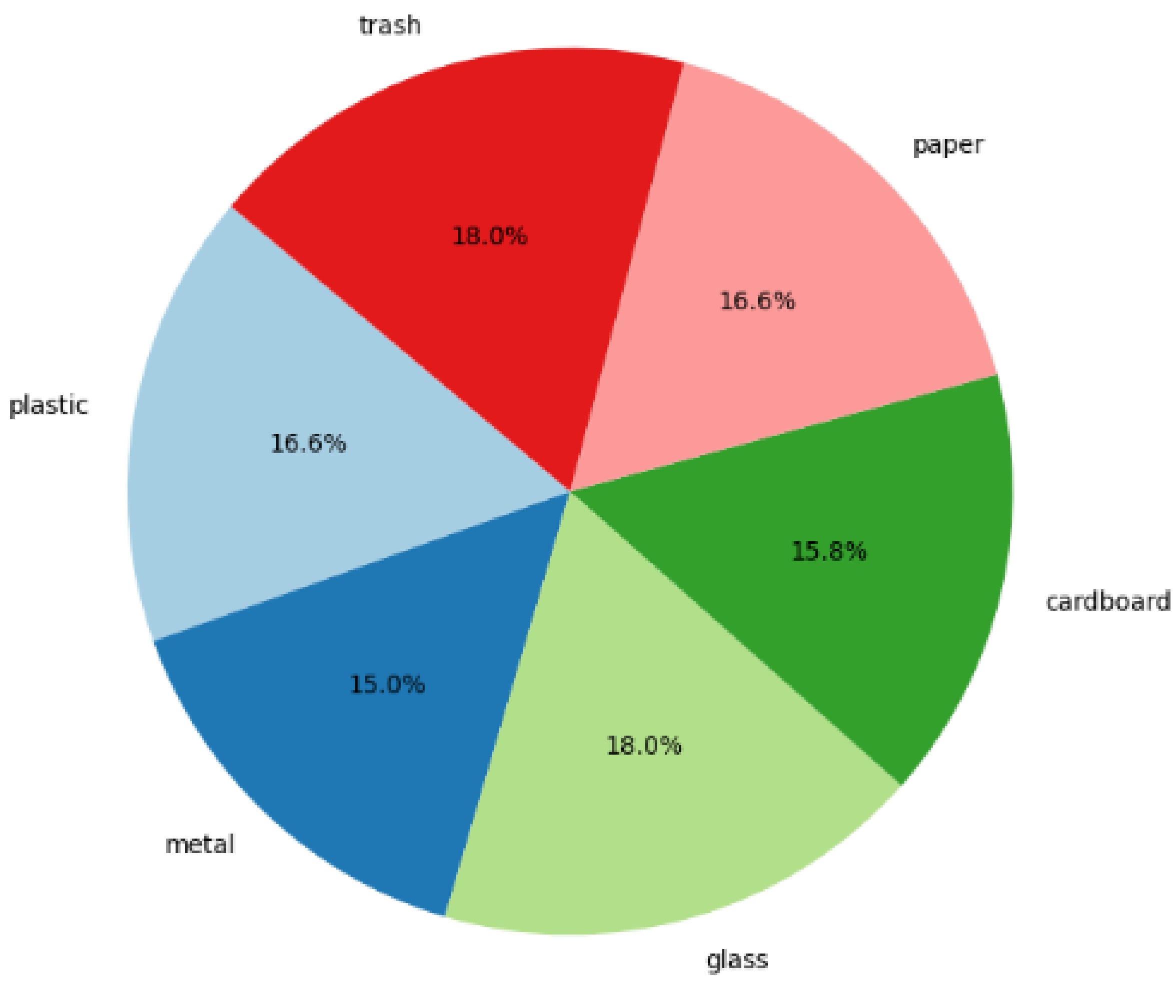
Dataset Description

- Dataset Source: Garbage Image Dataset
- Number of Images: 13900+ images • Classes: 6 classes
- Data Split:
  - Training data: 11121
  - Validation data: 2780

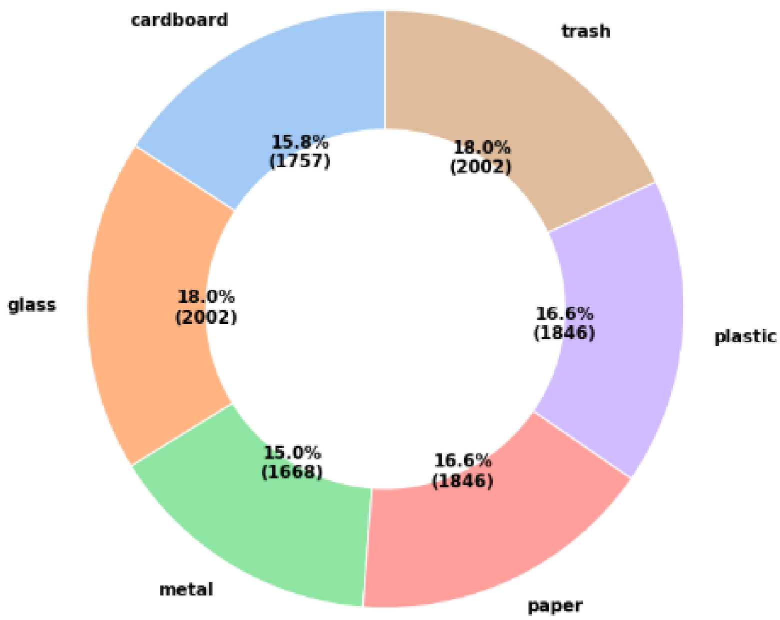
Image Preprocessing

- Resized all images to 224×224 pixels.
- Normalized pixel values to range [0,1].
- Applied data augmentation (rotation, flipping, zoom) to improve generalization.

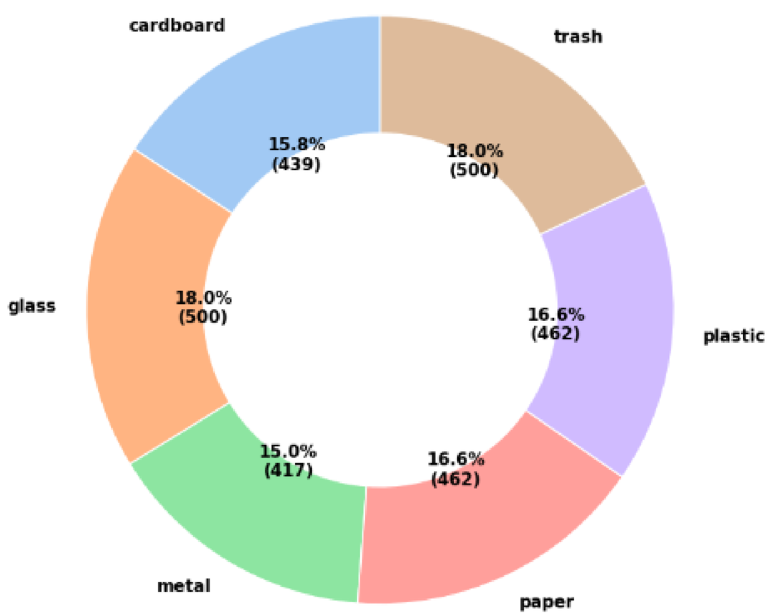
Dataset Analysis

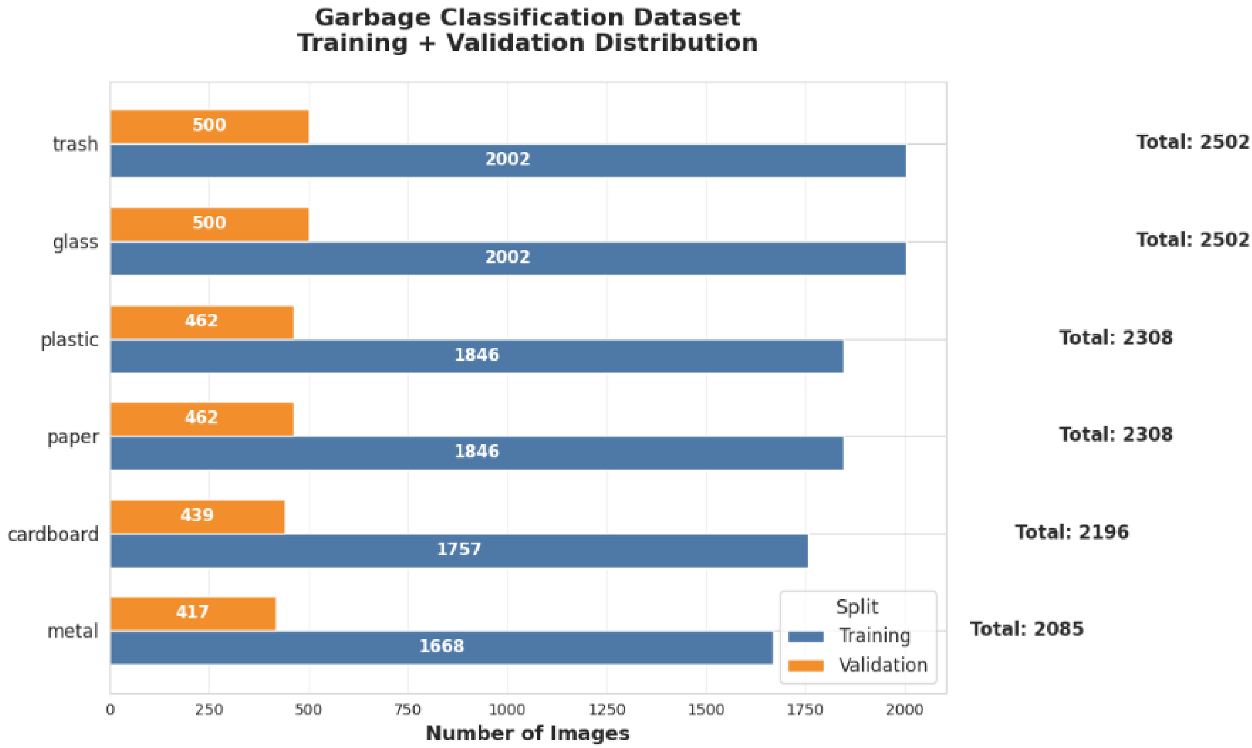


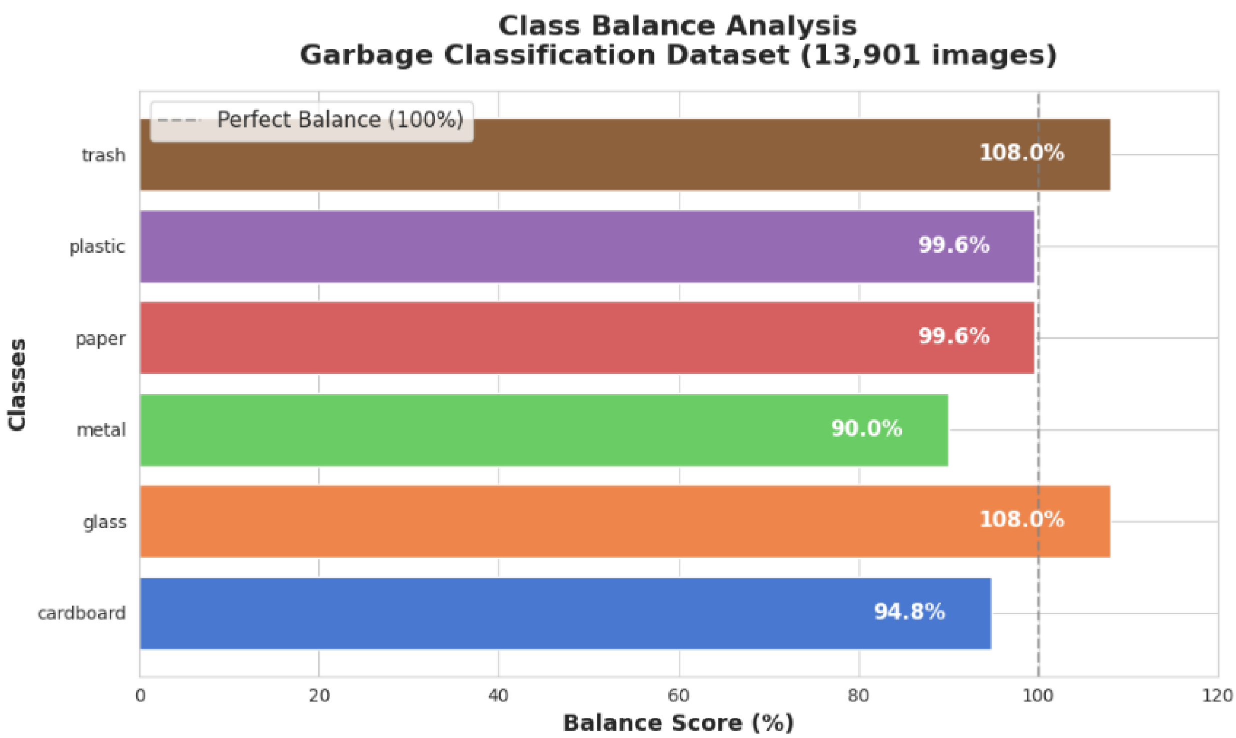
Training Set (11,121 images)



Validation Set (2,780 images)




Garbage Classification Dataset
Training + Validation Distribution
trash
glass
plastic
paper
cardboard
metal
500
2002
500
2002
462
1846
462
1846
439
1757
417
1668
Total: 2502
Total: 2502
Total: 2308
Total: 2308
Total: 2196
Total: 2085
Split
Training
Validation
0
250
500
750
1000
1250
1500
1750
2000
Number of Images


Class Balance Analysis
Garbage Classification Dataset (13,901 images)
Perfect Balance (100%)
Classes
trash
plastic
paper
metal
glass
cardboard
108.0%
99.6%
99.6%
90.0%
108.0%
94.8%
0
20
40
60
80
100
120
Balance Score (%)

Model Design and Implementation

This project implemented and compared six machine learning and deep learning models for garbage image classification: Convolutional Neural Network (CNN), MobileNetV2, ResNet50, Random Forest, Support Vector Machine (SVM), and Logistic Regression. Each model was trained using the same preprocessed dataset of labeled waste images resized to 224×224 pixels.

- Convolutional Neural Network (CNN)

A custom CNN architecture was built to serve as a baseline deep learning model.
It consisted of multiple convolutional layers with ReLU activation, MaxPooling2D for spatial reduction, and Dropout layers to prevent overfitting.
The network ended with a fully connected Dense layer using softmax activation for multi-class classification.
The model was compiled using the Adam optimizer, categorical cross-entropy loss, and trained for 15 epochs with a batch size of 32.

- MobileNetV2

Overall, MobileNetV2 leverages transfer learning to efficiently adapt a high-performance pre-trained model to a new domain — garbage image classification. Its combination of depthwise separable convolutions, inverted residuals, and linear bottlenecks allows for fast, memory-efficient training while maintaining competitive accuracy.

- ResNet50

ResNet50 is a deep convolutional neural network with 50 layers, known for introducing residual learning through skip connections that help mitigate the vanishing gradient problem in very deep networks.

In this project, a pre-trained ResNet50 model was used via transfer learning, initialized with ImageNet weights and include_top=False to remove the original classification head.

A new custom head was added with GlobalAveragePooling2D, Dropout(0.3), and a Dense softmax output layer corresponding to the number of garbage classes.

The model was compiled using the AdamW optimizer with a learning rate of 1e-4 and trained for 15 epochs.

ResNet50's deep architecture enabled the model to capture complex texture and shape features in garbage images, resulting in improved classification accuracy compared to shallower models.

- Random Forest Classifier

The Random Forest Classifier served as a traditional machine learning baseline for garbage classification.

Images were first converted from TensorFlow datasets into NumPy arrays, flattened into one-dimensional feature vectors, and normalized before model training.

A RandomForestClassifier with 100 estimators and a random state of 42 was trained on these image features using the scikit-learn library.

While Random Forests are effective for tabular data, their performance on high-dimensional image data is limited due to the absence of spatial feature extraction.

Nevertheless, the model provided useful comparative insights against deep learning methods and demonstrated the importance of feature representation in image-based tasks.

- Support Vector Machine (SVM)

The Support Vector Machine (SVM) model was implemented using scikit-learn's SVC with a Radial Basis Function (RBF) kernel to perform non-linear classification.

Input images were flattened into feature vectors and standardized using feature scaling techniques.

SVM works by finding an optimal hyperplane that maximizes the margin between different class boundaries, making it robust for smaller datasets and well-separated features.

Although computationally intensive for large-scale image data, SVM achieved reasonable accuracy and served as a strong baseline for evaluating the effectiveness of deep learning models in the project.

- Logistic Regression

Logistic Regression was applied as a simple, interpretable baseline model for multi-class garbage classification.

The flattened and standardized image pixel data were used as input features, and the model was trained using multinomial logistic regression with an L2 regularization penalty and the lbfgs solver.

This approach models the probability of each class using the softmax function and minimizes cross-entropy loss.

While Logistic Regression lacks the feature extraction capabilities of CNN-based models, it provided valuable insights into the linear separability of the dataset and established a fundamental performance benchmark for comparison.

Evaluation and Comparison

CNN (Convolutional Neural Network): Achieves 92.47% training accuracy but only 71.73% validation accuracy, with a high validation loss (1.2962) compared to training (0.2133). Indicates overfitting, likely due to insufficient regularization or limited validation data. Suitable for image tasks but needs dropout or augmentation to generalize better. Best for quick prototyping, not deployment. 🟡

MobileNetV2: Strong performer with 92.53% training and 86.96% validation accuracy. Low losses (0.2364 train, 0.3623 val) show good generalization. Lightweight, efficient for mobile devices, making it ideal for real-world deployment. Balances accuracy and computational cost effectively. Top CNN choice. ☑️

Random Forest: Claims 100% test accuracy on a small 223-sample set (cardboard only). Likely overfitted or unrepresentative test data. Lacks training/validation loss metrics. Use with caution until validated on a larger, diverse dataset. Questionable reliability for deployment. ❓

ResNet50: Solid 87.55% accuracy on both training and validation, with balanced losses (0.3645 train, 0.3594 val). Deep architecture handles complex features well but slightly underperforms MobileNetV2. Good for robust tasks but computationally heavier. Reliable choice for balanced performance. ☑️

SVM (Support Vector Machine): Poor performance with best kernel (RBF) at 39.83% accuracy. Linear (32.17%) and polynomial (20.50%) kernels fare worse. Unsuitable for this image classification task due to ineffective feature separation. Needs better feature engineering or alternative models. ❌

Logistic Regression: Excellent 90.15% test accuracy with consistent per-class metrics (F1-scores ~0.89–0.92). Robust across all classes, computationally efficient. Ideal for deployment where simplicity and high accuracy are key. Top overall performer for this dataset. ☑️

📊 Model Comparison Summary

Model	Training Accuracy	Validation/Test Accuracy	Training Loss	Validation/Test Loss	Notes 📝
CNN	92.47% ✅	71.73% ⚠️	0.2133 ✅	1.2962 ❌	Overfitting likely (high val loss)
MobileNetV2	92.53% ✅	86.96% ✅	0.2364 ✅	0.3623 ✅	Strong performance, balanced
Random Forest	N/A	100.00% ❓	N/A	N/A	Suspicious (small test set)
ResNet50	87.55% 🟡	87.55% ✅	0.3645 🟡	0.3594 ✅	Good but slightly underperforms
SVM (Best: RBF)	N/A	39.83% ❌	N/A	N/A	Poor performance
Logistic Regression	N/A	90.15% ✅	N/A	N/A	Excellent, robust results

Legend: ✅ Excellent (>85%), 🟡 Good (70-85%), ❌ Poor (<70%), ❓ Questionable

📈 Classification Report: Random Forest & Logistic Regression

Class	Model	Precision	Recall	F1-Score	Support
Cardboard	Random Forest	1.00 ✅	1.00 ✅	1.00 ✅	223
Cardboard	Logistic Reg.	0.88 ✅	0.90 ✅	0.89 ✅	443
Glass	Logistic Reg.	0.94 ✅	0.90 ✅	0.92 ✅	500
Metal	Logistic Reg.	0.88 ✅	0.91 ✅	0.90 ✅	417
Paper	Logistic Reg.	0.89 ✅	0.89 ✅	0.89 ✅	463
Plastic	Logistic Reg.	0.89 ✅	0.91 ✅	0.90 ✅	458
Trash	Logistic Reg.	0.93 ✅	0.90 ✅	0.91 ✅	500

Note: Random Forest only reported for cardboard (small test set). Logistic Regression shows robust metrics across all classes.

🏆 MODEL RANKING

Model	Accuracy	Rank	Status
Logistic Regression	90.200000	1	✅ EXCELLENT
MobileNetV2	87.000000	2	✅ BEST CNN
ResNet50	87.600000	3	✅ GOOD
CNN	71.700000	4	⚠️ OVERFIT
SVM (RBF)	39.800000	5	❌ POOR
Random Forest	100.000000	6	❓ DOUBT

Ethical Considerations and Bias Mitigation for Garbage Classification AI

1. Data Bias Analysis

- Class Distribution:
  - Cardboard: 15.8%, Glass: 18.0%, Metal: 15.0%, Paper: 16.6%, Plastic: 16.6%, Trash: 18.0%
  - Balance Score: 90–108% (ideal: 100%) → Fairly balanced, minor skew (Metal underrepresented, Glass/Trash overrepresented)
- Potential Bias:
  - Region: Unknown dataset origin (e.g., Kaggle); may reflect specific waste patterns (e.g., urban vs. rural).
  - Material: Overrepresentation of glass/trash may bias models toward those classes.
- Impact: CNN shows overfitting (71.7% val acc vs. 92.5% train); Logistic Regression (90.2%) and MobileNetV2 (87.0%) generalize better.

2. Environmental Impact

- Positive Impact:
  - Accurate classification (e.g., Logistic Regression: 90.2%, MobileNetV2: 87.0%) improves recycling sorting, reducing landfill waste.
  - Models like MobileNetV2 are lightweight, lowering energy use in deployment.
- Challenges:
  - Training deep models (e.g., ResNet50, CNN) consumes significant energy, contributing to carbon footprint.
  - Random Forest's 100% accuracy on small data (223 samples) may mislead real-world waste management if unvalidated.
- Solution: Optimize models (e.g., MobileNetV2) for low-power devices in recycling facilities.

3. Privacy and Data Usage Ethics

- Dataset Source: Kaggle (public domain), no personal data involved.
- Privacy Risks:
  - Potential for identifiable objects in images (e.g., labels, packaging with personal info).
  - SVM's poor performance (39.8% RBF) suggests ineffective feature extraction, risking misclassification in sensitive applications.
- Ethical Use:
  - Ensure anonymized datasets; no human data in training (confirmed for this project).
  - Transparent model deployment (e.g., Logistic Regression's clear metrics) to build trust in waste management systems.

4. Bias Mitigation Strategies

- Data Augmentation: Apply rotations, flips, and brightness adjustments to enhance dataset diversity (e.g., reduce CNN overfitting).
- Diverse Dataset: Collect images from varied regions/materials to balance classes (e.g., increase metal samples).
- Model Selection: Prefer robust models like Logistic Regression (90.2% acc, balanced F1-scores) over SVM (20.5–39.8%).
- Regularization: Add dropout to CNN/ResNet50 to improve validation accuracy (e.g., CNN: 71.7% val).
- Validation: Test Random Forest on larger, diverse sets to verify 100% claim.

5. Key Takeaways

- Balanced Dataset: Minor imbalances (90–108%); augment to balance metal/cardboard.
- Environmental Win: Logistic Regression and MobileNetV2 optimize recycling, reduce waste.
- Privacy Safe: No personal data; ensure anonymized inputs.

- Mitigation: Augmentation, diverse data, and robust models (Logistic Regression: 90.2%) ensure fairness.
- Next Steps: Deploy MobileNetV2 for efficiency; validate Random Forest; enhance CNN generalization. *Let's build ethical, sustainable AI!*

Reflections and Lessons Learned

• Technical Lessons: Preprocessing (e.g., augmentation) critical to reduce CNN overfitting (71.7% val acc). Hyperparameter tuning improved MobileNetV2 (87.0% val acc). Logistic Regression (90.2%) excelled with simple features.

• Teamwork: Clear task division and regular syncs boosted efficiency; Kaggle collaboration streamlined data handling.

• Limitations: Small test set skewed Random Forest (100% acc). Dataset (13,901 images) may lack regional diversity. SVM (39.8%) underperformed.

• Future Improvements: Deploy MobileNetV2 on smart bins; expand dataset with global waste types; optimize CNN for mobile apps.