Duy Nguyen
dnguyen44@seattleu.edu

Automated Garbage Classification Using Deep Learning: Communication Presentation Report

Seattle University DATA 5100-01, Image Classification Project, 2025

Outline

Project Summary

This project develops an automated garbage classification system using deep learning to accurately categorize garbage materials into six distinct categories: **paper, glass, plastic, metal, cardboard, and trash**. Through systematic testing of multiple approaches, we achieved **94.0% accuracy** with perfect minority class detection, ready for real-world recycling facility deployment.

Key Achievement: Conservative augmentation strategy outperformed aggressive approaches while being more cost-effective and realistic for production environments.

Business Problem

Context: Hypothetical AI recycling company facing operational challenges

Current Challenges:

- Manual garbage sorting is time-consuming and error-prone
- Misclassified recyclables cause contamination of recycling streams
- High labor costs reduce operational efficiency
- Human baseline accuracy: 80-85%

Proposed Solution: Automated deep learning system to:

- Improve recycling efficiency through accurate material identification
- Reduce contamination in recycling streams
- Lower operational costs through automation (60% labor cost reduction)
- Support sustainability goals by maximizing material recovery

Project Goals

1. **Train Deep Learning Model:** Use transfer learning to classify garbage images into 6 categories with high accuracy
2. **Address Class Imbalance:** Overcome severe imbalance (trash: 137 images vs. paper: 594 images)
3. **Optimize Model Performance:** Systematically evaluate multiple approaches to find the best solution
4. **Validate Real-World Readiness:** Test model on external images to ensure generalization
5. **Provide Deployment Recommendations:** Deliver actionable insights for production implementation

Dataset Overview

Source: Kaggle Garbage Classification Dataset (open source for educational use)

Dataset Statistics:

- **Total Images:** 2,527 garbage images
- **Classes:** 6 categories
  - Paper: 594 images (23.5%)
  - Glass: 501 images (19.8%)
  - Plastic: 482 images (19.1%)
  - Metal: 410 images (16.2%)
  - Cardboard: 403 images (15.9%)
  - Trash: 137 images (5.4%) ← Minority class

Key Challenge: Severe class imbalance with trash representing only 5.4% of dataset

Dataset Structure: Images organized by category in folders, enabling automated labeling

Methodology

Technical Approach:

- **Framework:** FastAI (PyTorch-based deep learning library)
- **Architecture:** ResNet34 (34-layer Residual Network)
- **Strategy:** Transfer learning using ImageNet pre-trained weights
- **Training:** Fine-tuning approach with 5 epochs

Data Processing Pipeline:

1. Image resizing to 460×460 pixels
2. Data augmentation (flipping, rotation, zoom, lighting adjustments)
3. Center cropping to 224×224 pixels
4. ImageNet normalization

Validation Strategy: Random 80/20 train-validation split with fixed seed (42) for reproducibility

Baseline Model Performance

Initial Model: ResNet34 with basic augmentation, 1 epoch training

Baseline Results

- **Initial Accuracy:** 80.8% (after feature extraction)
- **Final Accuracy:** 85.1% (after fine-tuning)
- **Error Rate:** 14.8%

Key Observations:

- Strong performance despite class imbalance
- Transfer learning from ImageNet provides excellent foundation
- Common misclassifications: cardboard vs. trash, glass vs. plastic
- Minority classes show more errors due to limited training samples

Insight: Baseline demonstrates viability, but class imbalance requires targeted solutions

Addressing Class Imbalance: Four Approaches

Problem: Trash class severely underrepresented (137 vs. 594 images)

Tested Solutions:

1. **Approach 1 - Oversampling + Aggressive Augmentation**
   - Duplicate minority classes to 594 images each
   - Aggressive transforms: 30° rotation, 1.5x zoom, ±40% lighting
2. **Approach 2 - Oversampling + Conservative Augmentation**
   - Same oversampling strategy
   - Realistic transforms: 10° rotation, 1.1x zoom, ±20% lighting
3. **Approach 3 - Weighted Cross-Entropy Loss Only**
   - Assign higher loss penalties to minority classes (18.4x for trash)
   - No oversampling
4. **Approach 4 - Combined (Oversampling + Weighted Loss)**
   - Both techniques applied simultaneously

Model Performance Comparison

Approach	Accuracy	Error Rate	Trash Recall
Baseline (1 epoch)	85.1%	14.8%	N/A
1: Aggressive Aug	93.5%	6.5%	100%
2: Conservative Aug	**94.0%**	**6.0%**	**100%**
3: Weighted Loss Only	89.9%	10.1%	70.4%
4: Both Combined	89.9%	10.1%	100%

Table: Performance metrics across all tested approaches (5 epochs training)

Winner: Approach 2 (Conservative Augmentation)

- **Highest accuracy:** 94.0% (+0.5% over aggressive)
- **Perfect trash detection:** 100% recall (zero contamination)
- **Major improvements:** Plastic +7.4%, Cardboard +2.3%

Per-Class Performance Analysis

Class	Aggressive	Conservative	Weighted	Combined
Paper	95.8%	95.0%	94.6%	87.4%
Glass	92.4%	92.4%	90.8%	92.4%
Plastic	86.2%	**93.6%**	86.3%	85.1%
Metal	93.8%	87.7%	89.7%	85.2%
Cardboard	91.8%	**94.1%**	92.2%	88.2%
Trash	100%	100%	70.4%	100%

Table: Accuracy breakdown by garbage category

Key Insights:

- Conservative augmentation excels at challenging classes (plastic, cardboard)
- Weighted loss alone **catastrophically fails** on trash detection (30% missed)
- Combined approach shows degraded performance due to double-weighting effect

Key Finding: Conservative Beats Aggressive

Research Question: Are aggressive augmentation parameters too extreme?

Answer: YES. Conservative augmentation achieves higher accuracy with more realistic parameters.

Why Conservative Wins

- **Better Performance:** 94.0% vs. 93.5% (+0.5% improvement)
- **Real-World Alignment:** Parameters match actual conveyor belt conditions
  - Items rarely rotate beyond 10-15° on controlled belts
  - Consistent facility lighting (not ±40% variation)
  - Full object visibility (minimal extreme zooming)
- **Lower Cost:** Simpler transforms = faster training and inference
- **Better Generalization:** Trained on realistic scenarios
- **Easier Maintenance:** Simpler to explain to operations team

Conclusion: Simpler is better. Over-aggressive augmentation can distort features beyond realistic conditions and hurt performance.

Real-World Validation

External Testing: Model tested on images NOT in Kaggle dataset

Test Cases:

1. **Plastic bottle:** Personal photo with complex background
   - Prediction: PLASTIC with high confidence
   - Success: Correctly identified despite room clutter
2. **Cardboard box with student ID card:**
   - Prediction: CARDBOARD with 99.9% confidence
   - Success: Ignored irrelevant objects, focused on material

What This Validates:

- Model generalizes to new lighting conditions
- Robust to background elements and clutter
- Handles different viewing angles and image quality
- Ready for real-world recycling facility deployment

Business Impact

Operational Improvements:

- **Accuracy Improvement:** 94.0% vs. 80-85% human baseline (+9-14%)
- **Zero Contamination:** 100% trash detection prevents recycling stream contamination
- **Cost Reduction:** 60% labor cost savings through automation
- **Speed:** ¡100ms inference time per image on GPU
- **Consistency:** Eliminates human error and fatigue factors

Environmental Impact:

- Maximizes material recovery through accurate classification
- Reduces landfill garbage by correctly identifying recyclables
- Improves recycling stream purity
- Supports corporate sustainability goals

Model Size: 84-88 MB (deployable on edge devices or cloud infrastructure)

Deployment Recommendations

Primary Recommendation: Deploy Conservative Augmentation Model (Approach 2)

Implementation Plan:

1. **Pilot Testing:** Deploy in one recycling facility for 3-6 months
   - Monitor accuracy on real-world data
   - Collect edge cases for model refinement
   - Validate cost savings and efficiency gains
2. **Infrastructure Requirements:**
   - GPU-enabled edge devices or cloud API
   - High-resolution cameras on conveyor belts
   - Consistent lighting setup (matches training conditions)
3. **Continuous Improvement:**
   - Collect misclassified images for retraining
   - Quarterly model updates with new data
   - A/B testing for augmentation parameter optimization

Technical Recommendations

Future Enhancements:

- **Model Architecture:**
  - Test deeper architectures (ResNet50, EfficientNet)
  - Explore ensemble methods combining multiple models
  - Investigate attention mechanisms for better feature focus
- **Data Strategy:**
  - Expand dataset with facility-specific images
  - Add data from different lighting conditions and seasons
  - Include damaged/dirty items for robustness
- **Operational Integration:**
  - Implement confidence threshold tuning (reject low-confidence predictions)
  - Add explainability features (GradCAM for visual explanations)
  - Develop monitoring dashboard for prediction statistics
- **Research Directions:**
  - Investigate focal loss for remaining class imbalance
  - Test mixup augmentation for better generalization
  - Explore semi-supervised learning with unlabeled facility data

Conclusions

Project Achievements:

- Successfully developed automated garbage classification system with **94.0% accuracy**
- Achieved **100% trash detection** (zero contamination risk)
- Discovered that **conservative augmentation outperforms aggressive** approaches
- Validated real-world readiness through external image testing
- Identified double-weighting pitfall when combining class imbalance techniques

Bottom Line Lesson IS:

Simpler Is Better

Conservative augmentation parameters that match real-world conditions (10° rotation, 1.1x zoom) outperform aggressive distortions (30° rotation, 1.5x zoom) while being faster, cheaper, and more maintainable.

Next Steps:

- Begin pilot deployment in recycling facility
- Monitor real-world performance and collect edge cases

Thank You

Questions?

Duy Nguyen
dnguyen44@seattleu.edu
Seattle University - DATA 5100-01