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Automated Garbage Classification Using Deep Learning: Communication Presentation Report

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

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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, $\pm 40\%$ lighting

2. Approach 2 - Oversampling + Conservative Augmentation

- Same oversampling strategy
- Realistic transforms: 10° rotation, 1.1x zoom, $\pm 20\%$ 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 $\pm 40\%$ 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:** Less than 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)

Technical Recommendations

Future Enhancements:

❖ Augmentation Strategy:

- ❖ Develop hybrid augmentation: conservative for most classes, aggressive for metal
- ❖ Test class-specific augmentation parameters based on material properties
- ❖ Explore adaptive augmentation that adjusts based on prediction confidence

❖ Model Architecture:

- ❖ Test deeper architectures (ResNet50, EfficientNet)
- ❖ Explore ensemble methods combining multiple models

❖ Data Strategy:

- ❖ Expand dataset with facility-specific images
- ❖ Add data from different lighting conditions and seasons
- ❖ Include damaged/dirty items for robustness

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?

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