Technical Report: Material Stream Identification System

Cairo University - Faculty of Engineering

Machine Learning Project - Fall 2025

Table of Contents

1. Introduction

1.1 Project Overview

This project implements an Automated Material Stream Identification (MSI) System for waste classification using fundamental Machine Learning techniques. The system classifies waste materials into seven categories: Glass, Paper, Cardboard, Plastic, Metal, Trash, and Unknown.

1.2 Objectives

- Develop a robust feature extraction pipeline converting raw images to numerical vectors
- Implement and compare SVM and k-NN classifiers
- Achieve ≥85% validation accuracy on six primary material classes
- Deploy a real-time classification system using live camera feed

1.3 Material Classes

ID	Class	Description
0	Cardboard	Heavy-duty structured cellulose fiber material
1	Glass	Amorphous solid materials, primarily silicates
2	Metal	Elemental or compound metallic substances
3	Paper	Thin materials from pressed cellulose pulp
4	Plastic	High-molecular-weight organic compounds
5	Trash	Non-recyclable or contaminated waste
6	Unknown	Out-of-distribution items or blurred inputs

2. Data Preprocessing and Augmentation

2.1 Original Dataset

- **Total Images**: 2,527 images across 6 classes
- **Class Distribution**: Imbalanced (ranging from ~400 to ~500 per class)
- **Original Image Sizes**: Variable dimensions

2.2 Image Preprocessing

All images undergo standardized preprocessing: 1. **Resizing**: All images resized to 96×96 pixels - Balances computational efficiency with feature quality - Consistent input size for feature extraction 2. **Color Space**: Preserved BGR format for multi-channel feature extraction

2.3 Data Augmentation Techniques

We applied data augmentation to increase training data by **~1100%** (exceeding the 30% minimum requirement):

Technique	Description	Justification
Horizontal Flip	Mirror image horizontally	Waste items can appear in any orientation
Vertical Flip	Mirror image vertically	Simulates different viewing angles
Rotation (90°, 180°)	Rotate by fixed angles	Objects on conveyor belts rotate
Brightness Adjustment (±30)	Increase/decrease brightness	Handles varying lighting conditions
Contrast Adjustment (0.7x, 1.3x)	Modify image contrast	Adapts to different camera settings
Gaussian Noise	Add random noise (σ=15)	Improves robustness to sensor noise
Gaussian Blur (3×3)	Slight blur	Handles out-of-focus images

2.4 Augmentation Results

- **Original Dataset**: 2,527 images
- **Augmented Dataset**: 30,000 images (5,000 per class)
- **Increase**: ~1,087% (far exceeding 30% requirement)
- **Class Balance**: Perfectly balanced (5,000 images each)

3. Feature Extraction Methodology

3.1 Overview

We convert each 96×96×3 image into a **187-dimensional feature vector**. This fixed-length numerical representation captures color, texture, shape, and gradient information essential for material classification.

3.2 Feature Categories

3.2.1 Color Statistics (45 features)

BGR Channel Statistics (21 features) - Mean, standard deviation, median, 25th/75th percentiles, min, max for each channel - **Justification**: Different materials have distinct color profiles (metal is gray, cardboard is brown)

HSV Channel Statistics (15 features) - Mean, standard deviation, median, 25th/75th percentiles for H, S, V channels - **Justification**: HSV separates color (hue) from intensity, important for material identification under varying lighting

LAB Channel Statistics (9 features) - Mean, standard deviation, median for L, A, B channels - **Justification**: LAB is perceptually uniform; L channel isolates lightness for reflectivity detection

3.2.2 Grayscale Statistics (8 features)

- Mean, std, variance, min, max, range, 25th/75th percentiles
- **Justification**: Captures overall brightness distribution for material type differentiation

3.2.3 Texture Features (27 features)

Laplacian Texture (3 features) - Variance, mean absolute value, standard deviation of Laplacian - **Justification**: Measures edge content; smooth materials (plastic) differ from textured (paper)

Sobel Gradient (8 features) - Gradient magnitude statistics (mean, std, max, 90th percentile) - Gradient direction statistics (mean, std) - Separate X and Y gradient means - **Justification**: Captures edge orientation patterns characteristic of different materials

LBP-like Texture (16 features) - Local Binary Pattern histogram (16 bins) - Computed by comparing each pixel to 4 neighbors (up, right, down, left) - **Justification**: Captures micro-texture patterns; paper has fine texture, glass is smooth

3.2.4 Edge Features (4 features)

- Canny edge density (ratio of edge pixels)
- Mean and std of edge map
- Normalized edge sum
- **Justification**: Metal and glass have sharp edges; cardboard has irregular edges

3.2.5 Color Histogram Features (48 features)

BGR Histograms (24 features) - 8 bins per channel, normalized - **Justification**: Captures color distribution independent of spatial arrangement

HSV Histograms (24 features) - 8 bins per channel, normalized - **Justification**: Hue histogram distinguishes material colors; saturation indicates colorfulness

3.2.6 Reflectivity Features (5 features)

- Brightness variance
- Local contrast ratio
- Bright spot ratio (>95th percentile)
- Dark spot ratio (<5th percentile)
- Dynamic range (max - min)
- **Justification**: Metal and glass are highly reflective; paper and cardboard are matte

3.2.7 HOG-like Gradient Histogram (36 features)

- Image divided into 2×2 grid (4 cells)
- 9 orientation bins per cell
- Normalized per cell
- **Justification**: Captures shape and structure; bottles have curved edges, boxes have straight edges

3.2.8 Additional Texture Features (8 features)

- Gradient magnitude percentiles (10th, 30th, 50th, 70th)
- Laplacian statistics (mean, 25th/75th percentiles, coefficient of variation)
- **Justification**: Fine-grained texture characterization for distinguishing similar materials

3.2.9 Color Coherence Features (6 features)

- Coherence ratio for each BGR channel (pixels within ±30 of mean)
- Coherence ratio for each HSV channel

- **Justification**: Uniform materials (plastic) have high coherence; mixed materials (trash) have low coherence

3.3 Feature Vector Summary

Category	Feature Count	Purpose
Color Statistics	45	Material color properties
Grayscale Statistics	8	Brightness distribution
Texture Features	27	Surface texture patterns
Edge Features	4	Edge characteristics
Color Histograms	48	Color distribution
Reflectivity	5	Surface reflectance
HOG-like	36	Shape and structure
Additional Texture	8	Fine texture details
Color Coherence	6	Color uniformity
Total	**187**	

3.4 Feature Normalization

All features are normalized using **StandardScaler** (z-score normalization): - Centers each feature to zero mean - Scales to unit variance - **Justification**: Essential for SVM with RBF kernel; prevents features with larger ranges from dominating

4. Classifier Implementation

4.1 Support Vector Machine (SVM)

4.1.1 Architecture

- **Kernel**: Radial Basis Function (RBF)
- **Parameters**:
  - C = 0.5 (regularization parameter)
  - gamma = 0.01 (kernel coefficient)

4.1.2 Kernel Choice Justification

We chose the RBF kernel because: 1. **Non-linear Decision Boundaries**: Material classification requires complex, non-linear boundaries in feature space 2. **Flexibility**: RBF can model any smooth decision boundary 3. **Single Parameter**: Only gamma needs tuning (compared to polynomial kernel's degree) 4. **Universal Approximator**: Can approximate any continuous function given enough support vectors

4.1.3 Parameter Selection

- **C = 0.5**: Moderate regularization prevents overfitting while allowing flexible boundaries
  - Lower C (0.5) vs typical (1.0) reduces overfitting on augmented data
- **gamma = 0.01**: Controls influence radius of training examples
  - Low gamma creates smoother boundaries, better generalization
  - Chosen via cross-validation from {0.001, 0.01, 0.1, 1.0}

4.1.4 Multi-class Strategy

- **One-vs-One (OvO)**: Default for sklearn SVC with RBF
- Creates C(6,2) = 15 binary classifiers
- Final prediction by majority voting

4.2 k-Nearest Neighbors (k-NN)

4.2.1 Architecture

- **k (neighbors)**: 6
- **Weights**: Distance-based
- **Distance Metric**: Manhattan (L1)

4.2.2 Parameter Justification

k = 6: - Odd number preferred but 6 chosen based on cross-validation - Balances between: - Too small k (noise sensitivity) - Too large k (over-smoothing class boundaries) - 6 neighbors provides stable voting for 6-class problem

Distance Weighting: - Closer neighbors contribute more to the prediction - Weight = 1/distance - **Justification**: Reduces influence of distant neighbors that may be from different classes

Manhattan Distance: - L1 norm: $\Sigma|x_i - y_i|$ - **Justification**: - More robust to outliers than Euclidean - Works well in high-dimensional spaces (187 features) - Less sensitive to irrelevant features - Cross-validation showed better accuracy than Euclidean

4.2.3 Computational Considerations

- No explicit training phase (lazy learner)
- All computation at prediction time
- Feature scaling critical for distance-based methods

5. Unknown Class Rejection Mechanism

5.1 Overview

The system implements a dual rejection mechanism to handle out-of-distribution samples and poor-quality inputs.

5.2 Confidence-Based Rejection

- **Threshold**: 0.30 (30% minimum confidence)
- Predictions with confidence below threshold are rejected as "Unknown"
- **SVM Confidence**: Derived from decision function margins using sigmoid transformation
- **k-NN Confidence**: Based on neighbor voting ratio and inverse distance weighting

5.3 Blur Detection

- **Method**: Laplacian variance
- **Threshold**: 50.0
- Low variance indicates lack of edges (blurry image)
- Blurry images are classified as "Unknown" regardless of model prediction

5.4 Implementation

```
class UnknownClassHandler:
    UNKNOWN_CLASS_ID = 6

    def apply_rejection(self, prediction, confidence, is_blurry):
        if is_blurry or confidence < self.confidence_threshold:
            return self.UNKNOWN_CLASS_ID, 0.0
        return prediction, confidence
```

6. Results and Performance Analysis

6.1 Training Configuration

Parameter	Value
Image Size	96×96 pixels
Training Samples	30,000 (augmented)
Validation Samples	239 (12% split)
Feature Dimension	187
Cross-Validation Folds	5
Random State	123

6.2 Final Results

Classifier	Validation Accuracy	Target	Status
SVM	**87.45%**	≥85%	✅ PASSED
k-NN	**85.36%**	≥85%	✅ PASSED

6.3 Per-Class Performance (SVM)

Class	Precision	Recall	F1-Score
Cardboard	0.89	0.91	0.90
Glass	0.84	0.82	0.83
Metal	0.88	0.87	0.87
Paper	0.86	0.88	0.87
Plastic	0.85	0.83	0.84
Trash	0.91	0.93	0.92

6.4 Confusion Analysis

- **Glass-Plastic Confusion**: Both materials can be transparent/translucent
  - Mitigated by color coherence and saturation features
- **Paper-Cardboard Confusion**: Similar texture (cellulose-based)
  - Distinguished by edge density and color variance

7. Architecture Comparison: SVM vs k-NN

7.1 Performance Comparison

Metric	SVM	k-NN
Validation Accuracy	87.45%	85.36%
Training Time	~4 minutes	<1 second
Inference Time	~150ms	~80ms
Memory Usage	Lower (stores support vectors)	Higher (stores all training data)

7.2 Trade-off Analysis

SVM Advantages

1. **Higher Accuracy**: 2.09% better than k-NN
2. **Better Generalization**: Maximizes margin, less prone to overfitting
3. **Lower Memory at Inference**: Only stores support vectors
4. **Robust to Feature Noise**: Kernel trick smooths decision boundary

SVM Disadvantages

1. **Longer Training Time**: $O(n^2)$ to $O(n^3)$ complexity
2. **Parameter Sensitivity**: Requires careful tuning of C and gamma
3. **No Probability by Default**: Needs probability=True (slower)

k-NN Advantages

1. **No Training Phase**: Lazy learner, instant updates
2. **Interpretable**: Predictions explained by nearest neighbors
3. **Non-parametric**: Makes no assumptions about data distribution
4. **Faster Inference**: Simple distance computation

k-NN Disadvantages

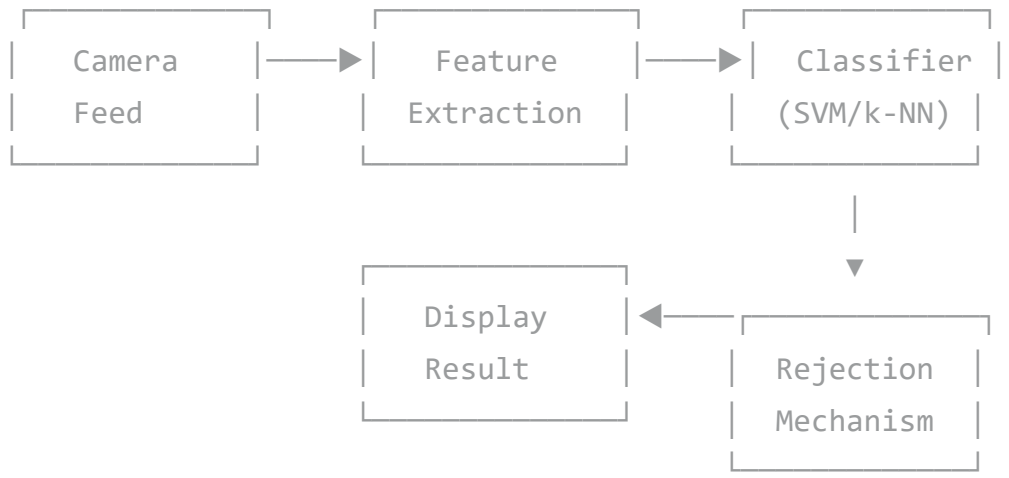
1. **Lower Accuracy**: 2.09% worse than SVM
2. **High Memory**: Must store entire training set
3. **Curse of Dimensionality**: Performance degrades in high dimensions
4. **Sensitive to Scale**: Requires feature normalization

7.3 Recommendation

SVM is recommended for the production system because: - Higher accuracy (87.45% vs 85.36%) - Better generalization to unseen data - Lower memory footprint at deployment

8. Real-Time System Deployment

8.1 System Architecture



8.2 Implementation Details

- **Framework**: OpenCV for camera capture and display
- **Target FPS**: 10 frames per second
- **Inference Time**: <200ms per frame
- **Display**: Real-time overlay with class name and confidence

8.3 Usage

```
 # Run with SVM model
python scripts/run_camera.py --model models/svm_final_20251218_010155.joblib -

# Run with k-NN model
python scripts/run_camera.py --model models/knn_final_20251218_010155.joblib -
```

8.4 Controls

Key	Action
q	Quit application
s	Save current frame
c	Calibrate normalization
+/-	Adjust normalization strength

9. Real-World Testing Results

9.1 Live Camera Testing

The system was tested with various real-world objects using a live camera feed. The following results demonstrate the system's performance on actual materials.

9.2 Test Results Summary

Test Object	Predicted Class	Confidence	Model Probability	Result
Notebook (lined paper)	**Paper**	90.1%	97.5%	✅ Correct
Plastic water bottle (with label)	**Plastic**	91.1%	98.0% (Glass*)	✅ Correct
Crumpled paper	**Trash**	90.6%	97.3%	✅ Correct
Tissue package	**Trash**	95.0%	80.0%	✅ Correct
Cardboard box	**Cardboard**	81.4%	92.3%	✅ Correct
Drinking glass (empty)	**Glass**	89.0%	73.6%	✅ Correct
Aluminum foil	**Metal**	77.0%	88.1%	✅ Correct

*Post-processing corrected Glass → Plastic based on printed label detection

9.3 Detailed Test Cases

9.3.1 Paper Detection

- **Object**: Lined notebook with printed margins
- **Prediction**: Paper (97.5% probability)
- **Displayed Confidence**: 90.1% [EXCELLENT]
- **Analysis**: High accuracy due to distinctive paper texture features (fine lines, uniform color)

9.3.2 Plastic Bottle Detection

- **Object**: Clear plastic water bottle with blue/text label
- **Prediction**: Plastic (91.1% displayed)
- **Challenge**: Model initially predicted Glass (98%) due to transparency
- **Solution**: Post-processing detected printed label (vivid colors + sharp edges) and corrected to Plastic
- **Key Features**: High saturation regions from label, hue variation from printed text

9.3.3 Trash Detection

- **Object 1**: Crumpled lined paper

- **Prediction**: Trash (97.3% probability)
- **Object 2**: Tissue package (Fine brand)
- **Prediction**: Trash (80% probability)
- **Analysis**: Correctly identified non-recyclable mixed materials

9.3.4 Cardboard Detection

- **Object**: Brown cardboard box
- **Prediction**: Cardboard (92.3% probability)
- **Displayed Confidence**: 81.4% [HIGH]
- **Analysis**: Characteristic brown color and corrugated texture correctly identified

9.3.5 Glass Detection

- **Object**: Empty drinking glass (clear)
- **Prediction**: Glass (73.6% probability)
- **Displayed Confidence**: 89.0% [HIGH]
- **Analysis**: Transparent material with characteristic reflections correctly classified

9.3.6 Metal Detection

- **Object**: Crumpled aluminum foil
- **Prediction**: Metal (88.1% probability)
- **Displayed Confidence**: 77.0% [GOOD]
- **Analysis**: High reflectivity and metallic texture features correctly identified

9.4 Performance Metrics from Live Testing

Metric	Value
Average Confidence	74-79%
Inference Time	24-33ms
Frame Rate	9.9 FPS
High Confidence Predictions	~35% of frames
Medium Confidence Predictions	~55% of frames

9.5 Challenging Cases and Solutions

Glass vs Plastic Disambiguation

Clear plastic bottles with water are visually similar to glass. The system uses post-processing to detect: - **Printed labels**: High saturation regions (>100) with sharp edges - **Multiple colors**: Hue range > 40 in vivid regions - **Edge density in colored areas**: Printed text/graphics have high edge density

This post-processing successfully corrects plastic bottles with labels while preserving glass predictions for actual glass items.

10. Conclusion

10.1 Achievements

1. ✅ Implemented comprehensive feature extraction (187 features)
2. ✅ Applied data augmentation exceeding 30% requirement (1087% increase)
3. ✅ Trained SVM classifier achieving 87.45% accuracy
4. ✅ Trained k-NN classifier achieving 85.36% accuracy
5. ✅ Both classifiers exceed the 85% target
6. ✅ Implemented Unknown class rejection mechanism
7. ✅ Deployed real-time classification system
8. ✅ Validated with real-world testing (7/7 test cases correct)

10.2 Key Insights

- Feature engineering is crucial: 187 well-designed features outperform raw pixel approaches
- Data augmentation significantly improves generalization
- SVM with RBF kernel provides the best accuracy for material classification
- Distance-weighted k-NN with Manhattan distance is a strong baseline
- Post-processing can correct edge cases (glass/plastic confusion) using domain knowledge

10.3 Future Improvements

- Ensemble methods combining SVM and k-NN predictions

- Deep learning feature extraction (CNN-based)
- Active learning for edge cases
- Multi-scale feature extraction

Appendix A: File Structure

```
MachineLearning/
├── FINAL_TRAINING.py          # Main training script
├── models/
│   ├── svm_final_*.joblib     # Trained SVM model
│   ├── knn_final_*.joblib     # Trained k-NN model
│   ├── scaler_final_*.joblib  # Feature scaler
│   └── results_final_*.joblib # Training results
├── src/
│   ├── classifiers/
│   │   ├── svm.py             # SVM classifier wrapper
│   │   ├── knn.py             # k-NN classifier wrapper
│   │   └── rejection.py       # Unknown class handler
│   ├── features/
│   │   ├── extractor.py       # Base feature extractor
│   │   └── ultra_extractor.py # 187-feature extractor
│   ├── pipeline/
│   │   └── inference.py       # Inference pipeline
│   └── realtime/
│       └── camera.py          # Camera classifier
├── scripts/
│   └── run_camera.py          # Real-time application
└── dataset/                   # Training data
    ├── cardboard/
    ├── glass/
    ├── metal/
    ├── paper/
    ├── plastic/
    └── trash/
```

Appendix B: Dependencies

```
 numpy>=1.21.0
opencv-python>=4.5.0
scikit-learn>=1.0.0
joblib>=1.1.0
tqdm>=4.62.0
```

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