Recycled Materials Classification System - Project Documentation

1. CHOSEN FIELD AND MOTIVATION

The field chosen for this project is computer vision for recycled materials classification. In an era of increasing environmental awareness, effective waste sorting and recycling have become critical challenges. Automated classification of recyclable materials can significantly improve waste management systems, reduce contamination in recycling streams, and increase recycling rates. The motivation behind this project is to develop a computer vision-based system that can accurately identify different types of recyclable materials (boxes, metal, and plastic) to aid in automated sorting systems or assist individuals in proper waste disposal.

2. DATASET AND SELECTION RATIONALE

Dataset: "Recyclable and Household Waste Classification"

Source: https://www.kaggle.com/datasets/alistairking/recyclable-and-household-waste-classification

This dataset was selected for several key reasons:

- It contains images of common recyclable materials divided into clear categories (Boxes, Metal, Plastic)
- The images feature realistic variations in lighting, angles, and backgrounds, mimicking real-world scenarios
- The dataset size (1050 training images and 225 test images) is substantial enough for meaningful model training while remaining manageable for computational resources
- The images capture various states of recyclable materials (clean, partially crushed, etc.) which is essential for building a robust classification system
- The dataset is well-organized with pre-divided training and testing sets, facilitating model development and evaluation

3. PIPELINE ARCHITECTURE AND IMPLEMENTATION DETAILS

The complete pipeline consists of eight major components:

3.1 DATA LOADING AND PREPROCESSING

Images are loaded from the dataset directory using file paths specified in txt files. Each image undergoes a comprehensive preprocessing workflow:

- Conversion from BGR to RGB color space
- Resizing to 128x128 pixels for computational efficiency
- Noise reduction using Non-Local Means denoising
- Contrast enhancement using CLAHE (Contrast Limited Adaptive Histogram Equalization)
- Normalization of pixel values to the range [0, 1]

INPUT: Raw image files (.jpg, .png)

OUTPUT: Preprocessed image arrays (128×128×3, float32, normalized)

3.2 SEGMENTATION (FROM SCRATCH)

Multiple segmentation techniques are implemented and combined to extract objects of interest:

- Otsu thresholding for automatic binarization
- Edge-based segmentation using Canny edge detection
- Region growing segmentation with multiple seed points
- K-means clustering for color-based segmentation

These methods are weighted and combined to create a final segmentation mask, which is then applied to the original image to isolate the objects of interest.

INPUT: Preprocessed images

OUTPUT: Segmented images and binary masks

3.3 FEATURE EXTRACTION

A comprehensive set of features is extracted from each image:

- Color histograms in RGB space (16 bins per channel)
- HSV color space features (10 bins per channel)
- Texture features including statistical measures
- Gabor filter responses for texture pattern analysis
- Edge histograms for structural information
- Shape features including area, perimeter, circularity, aspect ratio, and extent

INPUT: Preprocessed and segmented images

OUTPUT: Feature vectors (104-dimensional)

3.4 CLASSIFICATION MODEL

A neural network classifier is implemented from scratch with the following architecture:

- Input layer matching the feature vector dimension
- Two hidden layers (256 and 128 neurons) with ReLU activation
- Output layer with 3 neurons (one per class) and softmax activation
- Dropout (0.3) for regularization
- Training with mini-batch gradient descent and early stopping

INPUT: Feature vectors from training data

OUTPUT: Trained classifier model

3.5 MODEL EVALUATION

The classifier is evaluated using standard metrics:

- Accuracy: 0.7600

- Precision: 0.7613
- Recall: 0.7600
- F1-score: 0.7580
- Confusion matrix visualization

INPUT: Feature vectors from test data

OUTPUT: Performance metrics and visual analysis

3.6 SPECIALIZED DETECTION IN GUI

For the graphical interface, specialized detection methods were implemented for each material type:

- Boxes: Edge detection and polygon approximation to identify rectangular shapes
- Metal: Brightness-based detection and silver/gray color detection
- Plastic: Multi-range color detection for different plastic types
- Generic fallback detection when needed

INPUT: User-selected image

OUTPUT: Classification result with bounding boxes

4. TECHNIQUE SELECTION JUSTIFICATION

4.1 PREPROCESSING TECHNIQUES

- Non-Local Means denoising: Preserves edges and details better than simpler methods like Gaussian blur
- CLAHE: Enhances local contrast without over-amplifying noise, improving feature visibility
- Resizing to 128×128: Balances computational efficiency with retention of important visual details

4.2 SEGMENTATION APPROACHES

- Multiple segmentation methods: Different materials have varying visual characteristics requiring diverse approaches

- Weighted combination: Leverages strengths of each method while minimizing individual weaknesses

- Contour extraction: Provides shape information critical for distinguishing material types

4.3 FEATURE EXTRACTION STRATEGY

- Comprehensive feature set: Materials differ in color, texture, and shape, necessitating multi-aspect feature extraction

- Color histograms: Capture color distribution critical for differentiating materials (e.g., metal vs. plastic)

- Texture features: Capture surface patterns that distinguish different materials

- Shape features: Capture geometric properties helping distinguish structural differences

4.4 CLASSIFICATION APPROACH

- Neural network from scratch: Provides flexibility and educational value while maintaining strong performance

- Two hidden layers: Balances model complexity with generalization ability

- Dropout regularization: Prevents overfitting on the limited dataset

- Early stopping: Prevents overfitting while reducing unnecessary training time

4.5 GUI IMPLEMENTATION

- Material-specific detection algorithms: Different recyclables have distinct visual properties

- Professional bounding box visualization: Enhances user experience with clear visual feedback

- Error handling: Ensures robustness in real-world application

5. EVALUATION METRICS DISCUSSION

The model achieved solid performance across all metrics:

- Accuracy (0.7600): Indicates the model correctly classifies about 76% of all materials
- Precision (0.7613): Indicates low false positive rate; when the model predicts a class, it's correct about 76% of the time
- Recall (0.7600): Indicates the model successfully identifies about 76% of instances of each class
- F1-score (0.7580): The harmonic mean of precision and recall, confirming balanced performance

These metrics suggest the model performs consistently across different classes without significant bias toward any particular material type. The similar values across metrics indicate balanced performance rather than excelling in one area at the expense of another.

6. LIMITATIONS AND CHALLENGES

Despite the promising results, several limitations and challenges were encountered:

6.1 DATASET LIMITATIONS

- Limited diversity in object orientation and lighting conditions
- Some images contain multiple objects, complicating segmentation
- Background variations sometimes caused segmentation errors

6.2 TECHNICAL CHALLENGES

- GLCM texture feature extraction produced numerical instability requiring simplification
- Feature dimensionality matching between training and inference
- Finding appropriate segmentation parameters that work across all material types
- Balancing model complexity with computational efficiency

6.3 IMPLEMENTATION CONSTRAINTS

- Implementing neural networks from scratch limited advanced optimization techniques
- GUI performance depends on computational resources
- Bounding box accuracy varies significantly between material types

7. FUTURE IMPROVEMENTS

Several potential improvements could enhance the system:

- Deep learning approaches like CNNs could potentially improve accuracy
- More sophisticated segmentation using semantic segmentation networks
- Data augmentation to increase training set diversity
- Ensemble methods combining multiple classifiers
- Extension to more material types beyond the current three classes

8. CONCLUSION

The implemented recycled materials classification system demonstrates the effectiveness of classical computer vision techniques combined with machine learning for waste sorting applications. With an accuracy of 76%, the system provides a solid foundation for automated recycling sorting assistance. The from-scratch implementation provides valuable insights into each component of the computer vision pipeline while achieving respectable performance. The custom GUI with specialized detection algorithms for each material type enhances usability for real-world applications.

9. REFERENCES

- Dataset source: https://www.kaggle.com/datasets/alistairking/recyclable-and-household-waste-classification