

# Material Stream Identification System

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## 1. Introduction

This project implements Material Stream Identification (MSI) system for post-consumer waste sorting. The system follows a classical machine learning pipeline consisting of data augmentation, feature extraction, classifier training, evaluation, and real-time deployment. The goal is to classify waste images into six material classes and reject uncertain inputs as Unknown.

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## 2. Dataset and Data Augmentation

The provided dataset contains images for six material classes: **glass, paper, cardboard, plastic, metal, and trash.**

To improve generalization and class balance, **data augmentation** was applied to increase the dataset size to **500 images** per class. Each original image generates additional samples using:

- Horizontal flipping: used to teach model to ignore the directionality of the objects.
- Rotation by  $\pm 15^\circ$  : used to teach model to ignore the rotation of the objects.

This results in a minimum dataset increase of over 200%, improving robustness against orientation and viewpoint variations.

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### **3. Feature Extraction**

Each image is converted into a fixed length **1D numerical feature vector**, as required.

#### **3.1 Preprocessing**

ensures that all images have the same size and format

- Images are resized to **128 × 64** pixels as a standard size.
- Color images are converted to grayscale for texture analysis.

#### **3.2 HOG Features**

Histogram of Oriented Gradients (HOG) is used to extract **shape and edge information**, which is effective for distinguishing structured objects such as bottles, cans, and cardboard. It focus on important object details while reducing noise.

#### **3.3 Color Features**

To capture color distribution and object parts (e.g., labels or caps), the image is vertically divided into three regions (top, middle, bottom). For each part, color histograms are extracted in the **HSV color space**. Only the **Hue and Saturation** channels are used because they are more stable under lighting changes. The histograms are **normalized** to make the features scale-independent.

#### **3.4 Final Feature Vector**

The final feature vector is created by combining:

- HOG features (shape and texture)
- HSV color histograms (color information)

This produces a representation suitable for classical classifiers.

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### **4. Models**

#### **4.1 Support Vector Machine (SVM)**

The Support Vector Machine (SVM) classifier is trained using the extracted features. Works well with high-dimensional feature vectors. Provides probability estimates for predictions. effective at finding clear boundaries between different material classes, And its accuracy according to the test data is nearly 87%.

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## 4.2 k-Nearest Neighbors (k-NN)

The k-Nearest Neighbors classifier is used as a comparison model.

Key properties:

- Uses  $k = 5$  nearest neighbors
- Applies distance-based weighting

k-NN is slower during prediction and performs worse with high-dimensional data, its accuracy is nearly 74%

so mostly the SVM model was better to use on the test data than the KNN one

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## 5. Handling the “Unknown” Class

The system detects inputs that do not belong to any known material class or are unclear.

This is done using **confidence-based rejection**:

- **SVM**: If the highest prediction probability is below a fixed threshold, the image is labeled as Unknown.
  - **k-NN**: If the average distance to the nearest neighbors is too large, the image is labeled as Unknown.
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## 6. Model Evaluation

The dataset is split into: 80% training data and 20% testing data. Accuracy is used to evaluate performance.

The SVM model achieves higher accuracy than k-NN and performs better on visually similar materials. Therefore, the SVM model is selected as the final system model.

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## 7. Real-Time System Deployment

The trained model is integrated into a **real-time camera application** using OpenCV.

Steps:

- Capture live video frames
- Crop the center region of the frame
- Extract features from the image

- Predict the material class
- Display the result and confidence on screen