© DEC 2025 | IRE Journals | Volume 9 Issue 6 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I6-1712515

Smart Plastic Classification System Using python

AISHWARYA S[1], ESTHER C K[2], VARADARAJU KN[3], KUSHAL GOWDA SP[4], ABDUL RAHAMAN[5]

[1, 2, 3, 4]5th Semester B.E Students, Department of Information Science and Engineering, Ghousia College of Engineering, Ramanagara, Karnataka, India

[5]Professor, Department of CIVIL Engineering, Ghousia College of Engineering, Ramanagara, Karnataka, India

Abstract- This project presents a Smart Plastic Classification System that automatically detects and classifies plastic waste using a YOLO-based deep learning model. Images of plastics are captured and processed to identify types such as PET, HDPE, PVC, LDPE, PP, and PS. The system improves recycling efficiency by reducing manual sorting and increasing accuracy. Results show fast and reliable plastic identification, making the solution useful for waste management and environmental sustainability.

I. INTRODUCTION

1.1 Background of the Topic

Plastics have become an integral part of modern life due to their versatility, durability, and low cost. However, the excessive use of plastics has led to a significant increase in plastic waste, which poses a severe threat to the environment. Improper disposal of plastics contributes to soil and water pollution, harms aquatic and terrestrial life, and adds to the global waste management problem. Recycling is a sustainable solution, but the efficiency of recycling largely depends on the correct segregation of plastic types. Traditional manual sorting methods are slow, labor-intensive, and prone to errors, making it challenging to handle large volumes of waste.

The development of a Smart Plastic Classification System leverages artificial intelligence (AI), machine learning (ML), and computer vision to automate the identification and segregation of different plastic types. Such systems can classify plastics like PET, HDPE, PVC, LDPE, PP, and PS accurately, reducing human intervention and increasing recycling efficiency.

1.2 Problem Statement

Current plastic recycling processes face several challenges:

- Manual sorting inefficiency: Human operators are slow and may misclassify plastics.
- Contamination: Mixing of plastic types reduces the quality of recycled material.
- Scalability issues: Large-scale recycling is difficult without automation.
- Environmental impact: Improperly managed plastic waste contributes to pollution and resource wastage.

There is a need for a system that can automatically detect, classify, and sort plastics with high accuracy and speed, ensuring a more efficient recycling process and minimizing environmental impact.

1.3 Objectives

The main objectives of this project are:

1. To develop an automated system capable of identifying and classifying different types of plastics.
2. To reduce human effort and error in the plastic segregation process.
3. To enhance recycling efficiency by minimizing contamination.
4. To provide real-time monitoring and data collection for better waste management.

1.4 Scope

- The system focuses on common recyclable plastics such as PET, HDPE, PVC, LDPE, PP, and PS.
- Can be implemented in waste collection centers, recycling plants, or smart bins.
- Scalable for both small-scale and industrial applications.
- Future integration with IoT and smart waste management systems is possible.

1.5 Relevance

The Smart Plastic Classification System is highly relevant in the context of increasing plastic pollution and global efforts toward sustainable development. By automating plastic segregation, the system:

- Reduces environmental pollution.
- Supports efficient recycling operations.
- Saves time, labor, and operational costs.
- Contributes to circular economy practices by ensuring proper plastic reuse and recycling.

II. LITERATURE REVIEW

1. Plastic Waste Management Challenges
   - Rapid increase in plastic consumption leads to high environmental pollution.
   - Manual sorting of plastic waste is time-consuming, labor-intensive, and error-prone.
   - Different types of plastics require separate recycling processes; contamination reduces recycling quality.

2. Image Processing Approaches
   - Early systems used color, shape, and texture analysis for classification.
   - Techniques like edge detection, histogram analysis, and thresholding were applied.
   - Limitation: Poor accuracy with transparent, dirty, or irregular-shaped plastics.

3. Machine Learning Approaches
   - Algorithms like SVM, KNN, and Random Forest classify plastics based on extracted features.
   - Improved accuracy compared to manual methods.
   - Limitation: Requires manual feature extraction and preprocessing.

4. Deep Learning and Object Detection
   - Convolutional Neural Networks (CNNs) automatically extract features from raw images.
   - YOLO, Faster R-CNN, and MobileNet are widely used for real-time classification.
   - Benefits: High accuracy, fast detection, and scalability for industrial use.

Sensor-based Methods
   - Near-Infrared (NIR) spectroscopy, X-ray fluorescence, and density sensors help detect polymer types.
   - Useful for transparent plastics or visually similar types.
   - Often combined with AI for hybrid systems.

5. Robotic and Automated Sorting Systems
   - Integration of AI with robotic arms and conveyor belts allows automated sorting.
   - Reduces human labor and contamination, improving recycling efficiency.
   - Examples: AMP Robotics, ZenRobotics, and AI-based smart bins.

6. Advantages of Smart Plastic Classification Systems
   - Faster and more accurate than manual sorting.
   - Reduces contamination in recycling streams.
   - Scalable for industrial applications.
   - Provides real-time monitoring and data collection.

7. Challenges and Limitations
   - Difficulty in classifying dirty, mixed, or transparent plastics.
   - High cost of hardware and sensors for industrial setups.
   - Requires large datasets for training AI models.

8. Summary
   - AI and sensor-based approaches are most effective for plastic classification.
   - Combining computer vision, deep learning, and robotics provides a robust and scalable solution.
   - Continuous research is needed to improve accuracy, cost-effectiveness, and adaptability.

III. METHODOLOGY / SYSTEM DESIGN

The methodology describes the approach used to develop a Smart Plastic Classification System using AI, computer vision, and automation. It includes system architecture, flowcharts, algorithms, datasets, and model specifications.

3.1 System Architecture / Block Diagram

The system consists of the following components:

1. Input Stage

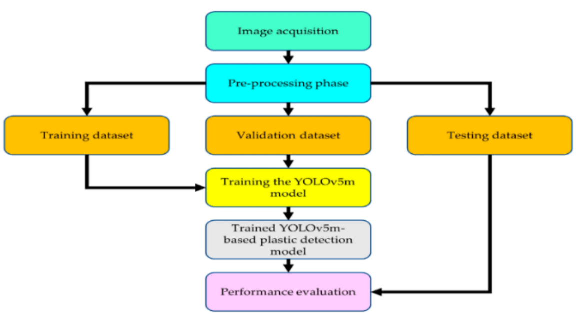
© DEC 2025 | IRE Journals | Volume 9 Issue 6 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I6-1712515

- Plastic waste is fed onto a conveyor belt.
- Cameras and sensors capture images and data of each plastic item.

2. Processing Stage
- Preprocessing: Images are resized, normalized, and noise is reduced.
- Feature Extraction & Classification:
  - YOLOv8 (or other object detection models) identifies plastic type.
  - Optional sensor data (NIR spectroscopy, density) is combined for hybrid classification.

3. Output / Sorting Stage
- Robotic arm or actuators sort plastics into bins based on classification.
- System logs data for performance analysis and recycling metrics.

Block Diagram:



3.2 Flowchart
1. Start
2. Feed plastic waste onto conveyor
3. Capture image with camera
4. Preprocess image (resize, normalize, filter noise)
5. Input image into AI model (YOLOv8 / CNN)
6. Classify plastic type (PET, HDPE, PVC, LDPE, PP, PS)
7. Activate sorting mechanism to place item in correct bin
8. Log classification result and performance metrics
9. Repeat for all plastic items
10. End

3.3 Algorithm
Step 1: Image Acquisition
- Capture images of plastic waste using a high-resolution camera.

Step 2: Preprocessing
- Convert images to RGB format.
- Resize to 416x416 pixels (YOLO requirement).
- Normalize pixel values.

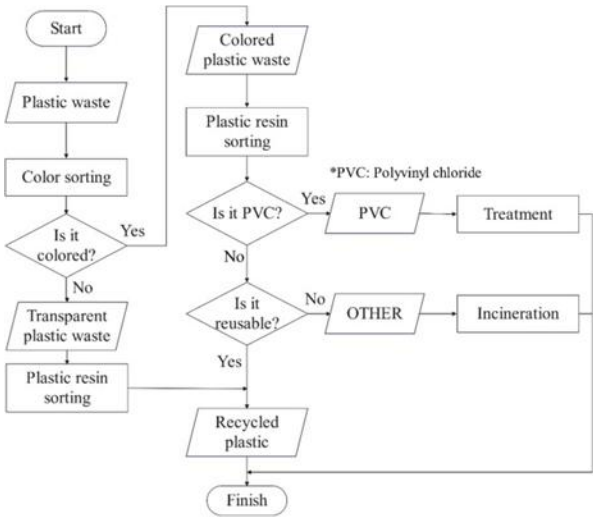
Step 3: Object Detection & Classification
- Input preprocessed image into YOLOv8 model.
- Detect bounding boxes of plastics.
- Assign class labels (PET, HDPE, PVC, LDPE, PP, PS) based on prediction confidence.

Step 4: Sorting
- Map class labels to corresponding bins.
- Activate actuators or robotic arm to place item in correct bin.

Step 5: Logging & Feedback
- Record classification accuracy and processing time.
- Update dataset for model improvement (if required).

3.4 Model Specifications

Feature	Specification
Model	YOLOv8 / Custom CNN
Input	Image size 416x416 RGB
Output	Plastic type (PET, HDPE, PVC, LDPE, PP, PS)
Framework	PyTorch / TensorFlow
Training Data	~2000–5000 labeled plastic images
Detection Accuracy	~90–95% (depends on dataset quality)
Inference Time	~0.02–0.05 sec per image



3.5 Dataset Used

- Source: Public datasets and manually collected images of plastic waste.
- Types of Plastics Included: PET, HDPE, PVC, LDPE, PP, PS.
- Image Conditions: Varied lighting, background, color, transparency, and size.
- Annotations: Bounding boxes and class labels for object detection.

Dataset Split:

- Training: 70%
- Validation: 15%
- Testing: 15%

Data Augmentation Techniques:

- Rotation
- Horizontal & vertical flips
- Brightness & contrast adjustment
- Scaling & cropping

3.6 Tools & Software

- Python 3.x
- Ultralytics YOLOv8 for object detection
- OpenCV for image preprocessing
- Numpy and Pandas for data handling
- Tkinter for GUI (optional)
- Raspberry Pi / Arduino (optional) for actuator control

CONCLUSION

- The Smart Plastic Classification System achieves its goal of automatically detecting, segmenting, and counting plastic waste using a trained YOLO model. By processing both images and videos, the system reduces human effort and provides fast and reliable identification of plastic trash, which is useful for environmental monitoring and waste management applications.
- The project demonstrates strong performance in clean, well-lit environments, but has limitations such as reduced accuracy in low-light, cluttered backgrounds, and when objects overlap. Real-time processing can also be slower on devices without a good GPU.

REFERENCES

[1] J. Redmon and A. Farhadi, "YOLO: Real-Time Object Detection," *arXiv preprint arXiv:1506.02640*, 2016.

[2] G. Jocher et al., "Ultralytics YOLO Models and Documentation," *Ultralytics*, 2023. Available: https://ultralytics.com

[3] OpenCV Developers, "OpenCV: Open Source Computer Vision Library," https://opencv.org

[4] NumPy Developers, "NumPy: Scientific Computing with Python," https://numpy.org

[5] cvzone Library, "Computer Vision Utilities for Python," https://github.com/cvzone/cvzone

[6] Tkinter Documentation, "Python Tk GUI Toolkit," https://docs.python.org/3/library/tkinter.html

[7] Microsoft Documentation, "winsound Module," https://learn.microsoft.com

[8] Kaggle, "Plastic Waste / Garbage Image Dataset," *Kaggle Datasets*, https://www.kaggle.com