



# Smart Waste Segregation System Using Image Processing

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**Abstract:** Effective waste management is crucial for environmental sustainability and public health. This research presents the development of a Smart Waste Segregation System using image processing and deep learning to automate the classification and sorting of waste. The system classifies waste into five categories: paper, glass, metal, plastic, and organic waste. It integrates both hardware and software components to enhance the accuracy and efficiency of waste segregation. The hardware consists of an ESP32-CAM module to capture waste images and an ESP32 development board to control the mechanical sorting system. Captured images are processed on a laptop using the MobileNetV2 deep learning model for real-time classification. Upon identification, the waste is sorted into the appropriate bin using a conveyor belt and servo motors. To ensure optimal performance, the system was tested using five deep learning models: MobileNetV2, VGG16, ResNet50, InceptionV3, and Xception. Experimental analysis revealed that MobileNetV2 offers the best balance of accuracy and computational efficiency, making it ideal for real-time waste classification. Key features of the system include automated image-based waste identification, real-time sorting, and LED indicators to display the detected waste category. This automated approach reduces human intervention, improves sorting accuracy, and increases operational efficiency. The proposed system is scalable, cost-effective, and suitable for applications in smart cities and industrial waste management, offering a sustainable and efficient solution for modern waste handling challenges.

**keywords:** Smart Waste Segregation, Image Processing, Deep Learning, Automated Waste Classification, MobileNetV2, VGG16, ResNet50, InceptionV3, Xception, ESP32-CAM, Waste Management, Real-Time Sorting, Environmental Sustainability, Mechanical Automation, Smart Cities.

## 1. INTRODUCTION

With the rapid increase in urbanization and industrialization, waste generation has become a significant environmental concern. Inefficient waste segregation leads to pollution, increased landfill overflow, and reduced recycling efficiency. Proper waste classification and management are essential to minimize environmental degradation and promote sustainable living. Traditional waste segregation methods rely on manual labour, which is not only time-consuming but also prone to errors and inefficiency. As a solution to these challenges, automated waste segregation systems using image processing and deep learning offer a more efficient, accurate, and scalable approach to handling waste.

This research focuses on developing a Smart Waste Segregation System that automates the identification and sorting of waste into five categories: paper, glass, metal, plastic, and organic waste. The system integrates hardware and software components to enhance the accuracy and efficiency of the segregation process. The hardware includes an ESP32-CAM module for image capture, an ESP32 development board for controlling mechanical components, and a conveyor belt with servo motors to direct waste to the appropriate bins. The software employs the MobileNetV2 deep learning model to classify waste in real time. Once the waste is identified, the system activates the mechanical components to sort the waste accordingly.

To ensure the best performance, the system was tested using five different deep learning models: MobileNetV2, VGG16, ResNet50, InceptionV3, and Xception. After a comparative analysis, MobileNetV2 was found to provide the best balance between computational efficiency and classification accuracy, making it the optimal model for real-time applications. The system also includes LED indicators to display the identified waste category, improving user interaction and monitoring.

The proposed system addresses the limitations of manual waste segregation by reducing human intervention, improving classification accuracy, and increasing sorting efficiency.



This research contributes to the field by offering a scalable, cost-effective, and automated solution suitable for modern smart cities and industrial waste management applications. By integrating image processing with mechanical automation, the Smart Waste Segregation System provides a practical and sustainable approach to improving waste management practices and promoting environmental sustainability.

## II. RELATED WORK

Kumar et al<sup>[1]</sup>. (2021) introduced a novel waste segregation system using the YOLOv3 deep learning algorithm for smart waste management. The study demonstrated significant improvements in classification accuracy across diverse waste categories through real-time object detection. By integrating Convolutional Neural Networks (CNNs), the system efficiently identifies recyclable and non-recyclable materials. The researchers highlighted the potential of automated waste segregation to minimize human intervention and operational costs. Their findings suggest that deep-learning-based models can enhance the efficiency and scalability of modern waste management. This research contributes to the development of intelligent waste disposal systems for smart cities.

Shahab and Anjum<sup>[2]</sup> (2022) explored the solid waste management scenario in India and proposed using AI-driven deep learning for detecting illegal waste dumps. The study employed image recognition techniques to identify unauthorized waste disposal sites from satellite imagery. Their approach aimed to improve municipal surveillance and enforce waste management regulations more effectively. The research emphasized the importance of sustainable waste practices and the role of artificial intelligence in enhancing large-scale monitoring systems. The findings indicated that integrating AI with geospatial data improves detection accuracy and response time. This method provides a scalable and automated solution for waste policy enforcement.

Debrah et al<sup>[3]</sup>. (2022) analysed the barriers to adopting circular economy models in sub-Saharan Africa's waste management system. The study identified major challenges such as limited infrastructure, inadequate policies, and low public awareness. Their research emphasized the need for policy reforms and technological innovations to improve waste collection and recycling processes. The authors proposed a circular economy framework that promotes resource recovery and sustainable practices. Their findings suggest that successful implementation requires cross-sector collaboration and public engagement. The study provides strategic recommendations to improve waste management and promote environmental sustainability.

Bernat<sup>[4]</sup> (2023) focused on the post-consumer plastic waste management process, from collection to mechanical recycling. The research highlighted advancements in machine learning for improving plastic sorting efficiency. The study emphasized the economic and environmental benefits of using automated systems for plastic recycling. By optimizing the waste sorting process, the study aims to reduce landfill waste and increase the efficiency of recycling operations. Bernat also examined the challenges in handling mixed plastic materials and proposed innovative solutions to enhance material recovery. The research underscores the importance of technological advancements in addressing plastic pollution.

Gunaseelan et al<sup>[5]</sup>. (2023) proposed an innovative deep-learning algorithm to enhance garbage segregation accuracy. Their system performs real-time classification of waste into multiple categories using advanced image processing. The study integrated IoT frameworks to enable real-time data collection and improve operational efficiency. The research demonstrated improved precision and reduced error rates in waste identification. The authors emphasized the scalability of the system, which can be deployed in smart waste management infrastructures. Their findings suggest that deep learning can significantly improve waste identification accuracy and streamline the sorting process.

## III. METHODOLOGY

The methodology of the Smart Waste Segregation System is structured into a sequence of well-defined steps, integrating both hardware and software to achieve automated waste classification and sorting. The following steps outline the complete working process:

1. **Image Acquisition:**
  - The ESP32-CAM module captures images of waste materials placed on the conveyor belt.
  - Each image is transmitted to the connected laptop via a Wi-Fi communication protocol.
2. **Image Processing and Classification:**
  - The captured images are processed using the MobileNetV2 model on the laptop.
  - The model identifies and classifies the waste into one of five categories: paper, glass, metal, plastic, or organic waste.



- To improve performance, the system uses data augmentation techniques during training, such as rotation and scaling, enhancing the model's ability to recognize waste under varying conditions.
  - The classification decision is based on the highest probability output from the model, ensuring precise categorization.
3. **Data Transmission:**
- Once classified, the waste category is sent back to the ESP32 Dev Board.
  - This information is used to control mechanical operations for accurate sorting.
  - The communication between the devices is secured using encrypted data packets to prevent transmission errors.
4. **Mechanical Actuation:**
- The conveyor belt is activated to move the waste along the system.
  - Based on the classification, servo motors guide the waste to the appropriate bin.
  - The system is programmed to calibrate servo angles dynamically, ensuring accurate bin positioning and minimizing sorting errors.
5. **User Feedback:**
- An LED indicator provides real-time visual feedback on the detected waste category.
  - This ensures transparency and allows for manual intervention if necessary.
  - Additional logs are maintained to track classification outcomes and mechanical actions for performance analysis and debugging.
6. **System Optimization:**
- The system is designed for real-time operation with minimal latency.
  - Future improvements can include additional waste categories and optimization of the machine learning model.
  - The system can be scaled by integrating multiple ESP32-CAM units for parallel image processing, increasing throughput.
  - Ongoing model retraining with new waste samples ensures the system remains accurate as waste types evolve.

#### IV. EXPERIMENTAL RESULTS & DISCUSSION

The Smart Waste Segregation System was thoroughly tested to evaluate its performance across five waste categories: paper, glass, metal, plastic, and organic waste. The system's efficiency was assessed by analysing the accuracy of waste classification, processing speed, and the overall functionality of the mechanical sorting mechanism. The experimental process involved capturing waste images, classifying those using deep learning models, and executing physical sorting through the conveyor belt and servo motors.

##### 1. Model Performance Comparison:

The system was tested using five pre-trained deep learning models MobileNetV2, VGG16, ResNet50, InceptionV3, and Xception to identify the most accurate and efficient model for real-time waste classification. Each model was evaluated based on the following performance metrics:

- **Accuracy:** The percentage of correctly classified waste samples.
- **Processing Time:** Time taken by the model to process and classify each waste image.
- **Model Efficiency:** The balance between classification accuracy and computational speed for real-time execution.

Results indicate that MobileNetV2 achieved the highest efficiency due to its lightweight architecture and fast inference time while maintaining high classification accuracy. The comparative analysis of the models is summarized below:

Model	Accuracy (%)	Processing Time (ms)	Efficiency
MobileNetV2	94.2	120	High
VGG16	92.8	230	Moderate
ResNet50	93.5	250	Moderate
InceptionV3	91.7	310	Low
Xception	90.3	350	Low

**Conclusion:** MobileNetV2 was selected as the final model for implementation due to its superior accuracy and faster processing time, making it ideal for real-time waste segregation.



## 2. Waste Category Classification Accuracy:

The system was tested using multiple waste samples for each category. The classification accuracy was calculated by comparing the model's output with the actual waste type. The system achieved high classification accuracy for paper, plastic, and metal, while glass and organic waste posed minor challenges due to visual similarities and irregular shapes.

Waste Category	Classification Accuracy (%)
Paper	95.6
Glass	91.2
Metal	94.0
Plastic	96.3
Organic	89.5

**Observation:** The system performs best with well-defined objects such as plastic and paper. Minor misclassifications occurred with organic and glass waste due to overlapping textures.

## 3. Mechanical Sorting Accuracy

The mechanical system, including the conveyor belt and servo motors, was tested for reliability in waste placement. The accuracy of mechanical sorting was measured based on whether the waste was successfully deposited in the correct bin.

- **Sorting Accuracy:** 93.8%
- **Failure Rate:** 6.2% (Due to misalignment or overlapping waste pieces)

**Enhancements:** Improving servo motor precision and optimizing conveyor speed can further increase mechanical sorting efficiency.

## 4. System Efficiency and Scalability

The Smart Waste Segregation System demonstrated consistent performance across multiple test cycles. The real-time classification and mechanical sorting process were completed within an average time of 3.5 seconds per waste item, making the system suitable for large-scale deployment. The system is scalable to include additional categories by retraining the model with a broader dataset.

## 5. Summary of Experimental Analysis

- **Best Performing Model:** MobileNetV2 (94.2% accuracy, 120 ms processing time)
- **Overall Classification Accuracy:** 93.3% across five waste categories
- **Mechanical Sorting Accuracy:** 93.8%
- **System Response Time:** 3.5 seconds per waste item
- **Key Strengths:** High classification accuracy, efficient real-time sorting, and scalable architecture.

The experimental results confirm that the Smart Waste Segregation System is an accurate, efficient, and cost-effective solution for automating waste classification and sorting. Further improvements in image pre-processing and mechanical alignment can enhance the system's overall performance.



Fig.1: Hardware Setup



```

1 import cv2
2 import requests
3 import numpy as np
4 import tensorflow.lite as tflite
5 import time
6
7 # ESP32-CAM & ESP32 Sorting Device URLs
8 ESP32_CAM_BASE_URL = "http://192.168.4.249/" # Change to your ESP32-CAM IP
9 ESP32_DEV_URL = "http://192.168.4.122" # Change to your ESP32 sorting system IP
10
11 # Possible endpoints for capturing images
12 CAMERA_ENDPOINTS = ["/capture", "/stream"]
13
14 # Load TensorFlow Lite Model
15 MODEL_PATH = "waste_model_quantized.tflite"
16
17 try:
18     interpreter = tflite.Interpreter(model_path=MODEL_PATH)
19     interpreter.allocate_tensors()
20
21     # Low confidence (0.54), ignoring detection.
22     # Image received from http://192.168.4.249/capture
23     # Low confidence (0.41), ignoring detection.
24     # Image received from http://192.168.4.249/capture
25     # Detected: Plastic (Confidence: 0.89)
26     # ESP32 Response: OK
27
28     # Waiting for object removal...
29     # Image received from http://192.168.4.249/capture
30     # Image received from http://192.168.4.249/capture
31     # Detected: Paper (Confidence: 0.88)
32     # Error sending classification result to ESP32: HTTPConnectionPool(host='192.168.4.122', port=80): Read timed out. (read timeout=5)
33     # Waiting for object removal...

```

Fig.2: Waste Classification using TensorFlow Lite

```

1 #include "esp_camera.h"
2 #include <WiFi.h>
3 #include "esp_http_server.h"
4
5 // Wi-Fi Credentials
6 const char* ssid = "Kp";
7 const char* password = "12345678kp";
8
9 // Flash LED Pin (AI Thinker ESP32-CAM)
10 #define FLASH_LED_PIN 4
11
12 // Camera Pin Configuration
13 #define PWDN_GPIO_NUM 32
14 #define RESET_GPIO_NUM -1
15 #define XCLK_GPIO_NUM 0
16 #define SIOD_GPIO_NUM 25
17 #define SIOC_GPIO_NUM 27
18 #define Y9_GPIO_NUM 35
19 #define Y8_GPIO_NUM 34

```

```

20:59:28.429 -> [X] Wi-Fi Connected!
20:59:28.429 -> [X] ESP32-CAM IP Address: 192.168.102.249
20:59:28.627 -> [X] Camera Server Started Successfully!
20:59:28.660 -> [X] Camera Ready! Access:
20:59:28.660 -> [X] Stream: http://192.168.102.249/stream
20:59:28.660 -> [X] Capture: http://192.168.102.249/capture
20:59:31.546 -> [X] Image captured and sent.
20:59:41.584 -> [X] Image captured and sent.
20:59:44.634 -> [X] Image captured and sent.

```

Fig.3: Image Capture using ESP32-CAM

#### IV. CONCLUSION

The Smart Waste Segregation System using image processing successfully automates the waste classification and sorting process, enhancing efficiency and accuracy in waste management. By integrating the MobileNetV2 model with ESP32-CAM and ESP32 Dev Board, the system achieves real-time waste identification across five key categories: paper, glass, metal, plastic, and organic waste. The combination of advanced image classification algorithms and precise mechanical actuation ensures accurate waste segregation with minimal human intervention.

The modular architecture of the system supports easy scalability and future enhancements. The use of a secure Wi-Fi communication protocol between the ESP32 devices and the laptop ensures reliable data exchange and control. Additionally, real-time visual feedback through LED indicators enhances user interaction and monitoring capabilities. The experimental results demonstrate high accuracy in waste classification and efficient mechanical sorting. Regular calibration and system optimization techniques further improve performance and reliability. This system provides a robust and adaptable solution for automated waste management, reducing manual labour and promoting environmental sustainability.





Future enhancements may include expanding waste categories, improving model performance through continuous retraining, and integrating IOT-based monitoring systems for remote supervision. Overall, the Smart Waste Segregation System presents an innovative approach to addressing waste management challenges through advanced technology and automation.

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