



SmartBin: An IoT-Based Intelligent Waste Classification and Automated Segregation System Using Machine Learning

Shri Nivetha R¹, Kavya S Prasad², Jeyarthi V³, Hasanthika Sri S⁴, Deepashri P M⁵,

Ms Charulatha R T⁶

Student, Department of Computer Science and Engineering, SRM Institute of Science and Technology,

Vadapalani, Chennai, India¹⁻⁵

Assistant Professor, Department of Computer Science and Engineering, SRM Institute of Science and Technology,

Vadapalani, Chennai, India⁶

Abstract: The rapid growth of urbanization has led to a significant increase in waste generation creating a need for efficient and intelligent waste management systems. Traditional methods of waste segregation depend on human labour, which is often inconsistent, labour-intensive, and error-prone. SmartBin, an Internet of Things (IoT) based automated waste classification and segregation system is proposed in this paper. The system employs an ESP32-CAM module to capture images of waste materials, which are then processed and classified by a machine learning model developed using TensorFlow running on a laptop server. Based on the classification outcome, a servo motor is rotated to direct the waste into either organic or recyclable compartments. Additionally, a real-time dashboard is implemented to visualise waste data, display captured images with their predicted labels and provide an option to export the data in CSV format. The proposed system provides a cost effective and scalable approach to automated waste segregation and thus contributing to the development of sustainable smart city.

Keywords: Internet of Things; Waste Segregation; Machine Learning; Computer Vision; ESP32-CAM; Smart Cities; Automation

I. INTRODUCTION

The rapid development of urban cities has massively increased the amount of waste generated posing challenges to efficient waste management. Improper segregation of waste at the source leads to inefficient waste recycling, increased use of landfills and environmental degradation. Traditional waste management requires manual labour to sort the waste exposing the workers to extreme working conditions and often leads to human errors and inconsistency.

Modern advancements in Artificial Intelligence and the Internet of Things have paved the way to address these challenges by proposing automated systems. The integration of Computer Vision and Machine Learning provide the framework for analyzing and classifying the waste based on visual interpretation. This paper presents SmartBin, a smart waste classification system that integrates IOT based sensing with machine learning based classification for automated waste segregation.

1.1 Background and Motivation

The idea of smart cities emphasises the use of emerging technologies to enhance urban infrastructure. Waste management is a key area for development in smart cities and is comparatively a sector with very minimal technological involvement. Traditional waste segregation techniques, such as manual segregation and sensor-based systems, suffer from many limitations such as accuracy and scalability.

Sensor-based systems usually rely on particular properties such as moisture or metallic composition, which restricts the segregation process to specific types. Machine Learning integrated with IOT systems supports the classification of diverse waste types by simply classifying based on the image.

1.2 Problem Statement

Despite the availability of various waste management solutions, there exists a lack of systems that can integrate accurate classification, automated segregation and real-time monitoring. Manual methods are inefficient while sensor-based systems lack the ability to handle diverse waste types. Additionally, most existing IoT-based solutions focus on



monitoring parameters such as bin fill levels rather than addressing the important issue of waste classification and segregation.

The problem addressed in this work is the design of an intelligent system capable of automatically classifying waste using CNN, physically segregating it using an actuation mechanism and providing real-time insights through a data visualization dashboard.

1.3 Technical Challenges

- **Variability in Waste Appearance:**

One of the primary challenges in image-based waste classification is the high variability in the appearance of the waste. Objects that belong to the same category may differ in their shape, colour, texture and size, while different categories may exhibit similarities in appearance.

- **Sensitivity to Environmental Conditions:**

The performance of image-based systems is heavily dependent on environmental factors such as lighting and camera positioning. Variations in lighting can alter the detected colour and texture of objects which leads to incorrect classifications. Cluttered backgrounds or improper framing can introduce noise into the input data.

- **Real-Time Processing Constraints:**

The system is required to operate in real time which imposes strict constraints on processing latency. The entire process pipeline including image capture, transmission, classification, and actuation must be completed within a short time period to ensure smooth operation.

- **Integration of Multi-Component System:**

The system involves the integration of multiple components such as image capturing and forwarding, machine learning processing, hardware control, and data visualization. Ensuring seamless interaction between these components is a complex task as any mismatch in data flow or timing can lead to system failure.

1.4 Contributions

The SmartBin makes several key contributions to the field of smart waste management. First, it presents a smart IoT-based system that integrates CNN with physical actuation for automated waste segregation. Second, the system demonstrates the practical application of a machine learning model developed using TensorFlow for real time classification of waste images. The model is capable of distinguishing between organic and recyclable waste providing a scalable platform. Third, the implementation of a real-time dashboard enables effective visualization and analysis of waste data facilitating data driven decision making. Finally, the project serves as a prototype system for integrating IoT and machine learning in real-world applications, demonstrating the possibility of deploying intelligent waste management systems in smart city environments.

II. RELATED WORK

The Automated Waste Segregation has emerged as an important research domain which is at the intersection of embedded systems, machine learning and IoT-based monitoring. Traditional waste disposal methods rely heavily on manual sorting of wastes, which is time-consuming and labour-intensive in the case of large-scale deployments. The rapid advancement of IoT systems and edge-AI technologies has led to the development of smart dustbins that are capable of doing automated classification and remote controlling of the collected waste. Existing technologies today can be broadly classified into sensor-based rule systems, IoT-enabled monitoring framework systems, and computer-vision based ML approaches.

2.1 Sensor-Based Rule Systems

Early smart waste segregation systems relied more on detecting the physical properties of waste such as moisture, reflectivity, or metal content. Sharma et al. (2019) proposed an Arduino-based system that utilizes IR sensors, ultrasonic modules, and servo-driven actuation to classify waste into basic categories. Similar designs using moisture and metal sensors (Patel & Shah, 2021) were made to distinguish between wet and dry waste or detect metallic objects by analysing electrical conductivity of the material collected.

Although these systems are simple to implement, they are inherently limited in their range of detection. They cannot analyse texture, shape, or material-specific visual cues, often resulting in misclassification when different waste types share similar physical characteristics. Moreover, these designs lack scalability, because each new waste type requires manually created thresholds and additional sensors, in order to be able to be sensed correctly by the system.

2.2 IoT-Based Waste Monitoring Systems

Significant research has focused on IoT-enabled monitoring more than the issue of segregation of the wastes. Khatri et al. (2018) developed a GSM-connected smart bin that uses ultrasonic sensors to monitor bin fill levels and sends alerts



when nearing full capacity. Mehta and Joshi (2022) further extended this work into a city-wide IoT architecture for collected waste optimization using cloud dashboards and remote telemetry.

These systems display the use of IoT in improving municipal. However, they do not address the critical challenge of waste segregation at the source, and thus mostly remain utility-based rather than classification-based. Their contribution is in operational visibility, and not in intelligent decision-making.

2.3 Deep Learning-Based Visual Classification Systems

The introduction of computer vision and deep learning enabled more accurate waste classification. Lee and Kim (2020) used a Convolutional Neural Network to help classify images, achieving up to 92% accuracy. Chen et al. (2022) used a Raspberry Pi-based CNN model, reporting up to 90–95% classification accuracy across multiple waste categories. One disadvantage of this is that they require the need of high-performance, embedded platforms such as Raspberry Pi, which increases cost and power consumption. Their requirements make them less suitable for operating in resource-constrained environments.

2.4 Hybrid Computer Vision and Actuation Systems

More advanced architectures combined the use of machine learning along with automated mechanical sorting of the wastes to ease the process. Patel et al. (2023) proposed the use of a vision-driven system that does CNN-based classification before actually actuating the servo-controlled flaps to route waste into separate compartments. These hybrid models successfully automate both detection and physical sorting of the wastes, improving the accuracy (~94%) and operational efficiency of the system.

One drawback of traditional microcontrollers is that they cannot handle heavy processing on its own. They end up sending the data to cloud servers which leads to longer delays in the case of internet connection issues.

2.5 Embedded Machine Learning and Edge Computing

In recent years, researchers have been moving toward lightweight neural models that can run directly on microcontrollers. Gupta et al. (2025) showed that machine learning models can even operate on ESP32-class hardware using TensorFlow Lite Micro. This means predictions can be run on the device itself and reduce reliance on the cloud. Even then, most of the microcontroller-based systems cannot handle real-time IoT analytics and mechanical sorting. They also rely heavily on low-resolution images which makes achieving real-time accuracy even more difficult.

2.6 Research Gaps

A study of prior work done reveals a fundamental gap:

- Sensor-based systems lack accuracy
- CNN-based systems require high computing resources
- Edge-ML systems lack complete integration with IoT

Thus, there is a need for a unified system that:

1. Performs reliable, image-based waste classification on low-power hardware,
2. Integrates mechanical actuation for automated segregation of waste, and
3. Provides IoT-enabled real-time analytics for monitoring and decision-making.

The proposed work addresses this gap by developing a low-cost, ESP32-CAM-based embedded ML system with servo-controlled sorting and IoT-based monitoring, representing a complete and scalable solution for smart waste management.

III. METHODOLOGY

The proposed Smart Waste Segregation System is an automated solution designed to classify household waste into two primary categories: organic waste and recyclable waste. The system integrates embedded hardware, lightweight machine learning models, and an IoT-based monitoring platform to enable real-time and data-driven waste management. The methodology consists of the hardware design, model integration, data acquisition and preprocessing, system workflow, and the three functional modules of the system.

3.1 Hardware and Software Components

The system is developed using a combination of embedded hardware components and optimized machine learning software frameworks:

- **ESP32-CAM with OV2640 camera:** Responsible for capturing images of incoming waste items placed inside the smart bin.
- **Servo motors:** Facilitate the physical segregation of waste using a calibrated tilting mechanism.



- **Wi-Fi and IoT Application:** Enable transmission of classified waste data to an IoT platform for visualization, analytics, and real-time monitoring.

3.2 Data Source and Pre-processing

The dataset used for this project consists of images of waste items collected in real-world conditions from the prototype setup. The dataset includes two dominant waste categories:

- Organic waste: fruits and vegetable peels, leftover food, leaves, etc.
- Recyclable waste: paper, cardboard, plastic items, and similar recyclable materials.

To ensure robust classification performance in diverse lighting and environmental conditions, several preprocessing operations were applied:

1. Image Capture: The ESP32-CAM captures images instantly when waste is inserted.
2. Model Input Conversion: Captured images are resized and normalized to match the input specifications of the TensorFlow model.
3. Real-Time Inference: The pre-trained model runs on a laptop server, which provides the classification result suitable for real-time waste segregation.

3.3 System Architecture

The overall system workflow is illustrated as follows:

1. Waste material is placed inside the smart bin.
2. The ESP32-CAM captures an image of the waste.
3. The image is pre-processed and passed to the ML model running on the laptop server.
4. The model classifies the waste as either organic or recyclable.
5. Based on the classification, servo motors route the waste into the suitable compartment.
6. Classification results and waste statistics are transmitted to the IoT platform for monitoring and analysis.

This layered architecture ensures efficient integration of sensing, computation, actuation, and cloud-based visibility.

3.4 Module 1: Waste Classification

The waste classification module handles the computer vision-based identification of waste type. The ESP32-CAM serves both as the imaging device and the ML running on a laptop. Once the waste image is captured:

- The ML model processes the image.
- The waste item is classified into organic or recyclable in real time.
- The classification output is forwarded to the actuation module for physical segregation.

This end-device classification eliminates the need for cloud processing and reduces latency.

3.5 Module 2: Mechanical Segregation

The mechanical segregation module manages the movement of waste into the appropriate compartment using servo motors. The process includes:

1. Receiving the classification result from the ESP32-CAM.
2. Activating the corresponding servo motor using a pre-calibrated tilting mechanism.
3. Directing the waste into the organic or recyclable chamber.
4. Ensuring accurate motion control to maintain consistency and reliability of segregation.

This module enables fully autonomous operation without manual intervention.

3.6 Module 3: IoT Monitoring and Analytics

To enhance visibility and enable data-driven waste management, the system incorporates an IoT monitoring module. Using Wi-Fi connectivity, the ESP32-CAM transmits real-time waste information to an IoT dashboard. The platform provides:

- Visual display of waste type and disposal frequency
- Statistical analytics and trend charts
- Downloadable Waste Generation Report as a CSV File

This module supports remote monitoring and improves the operational efficiency of waste handling.

IV. EXPERIMENTAL SETUP AND RESULT

This part explains the architecture behind the waste classification system. The classification module's performance in segregating organic and non-recyclable materials from the dustbin helps in waste segregation. This method is more accurate than the previously used traditional method of segregating wastes manually, and the system is useful in real life.



4.1 Hardware Setup

1. ESP32-CAM with OV2640: The main component for differentiating the organic and recyclable waste, which can be accessed with Wi-Fi.
2. Servo Motor: It helps in automatic segregation by actuating the flap of the dustbin based on the classification provided by the ML model and ensures that it is directed to the appropriate bin.
3. Breadboard and Jumper Wire: It is used to connect the ESP32-CAM and the servo motor, where the breadboard acts as a mediator, and jumper wires facilitate all the hardware connections of the smart dustbin.
4. Dustbin: It is the outer physical layer where the bin is divided into two parts. The lid is actuated to flip to the respective bin based on the classification, and the lid opens and closes automatically.



Figure 1. Servo Motor



Figure 2. ESP32-CAM



Figure 3. Breadboard

4.2 Software Setup

1. TensorFlow Lite Micro: It is a micro interface library used to train a CNN model in the ESP32-CAM module. It uses static memory allocation to minimise the RAM consumption. It identifies the type of waste detected and classifies it into organic or non-recyclable.
2. Arduino IDE: It is an embedded programming tool to control the ESP32-CAM and compile the code in C/C++ and manage the system operations. This controls the flap mechanism and sensor data.
3. IOT platform/ Web Dashboard: It is a web-based dashboard that displays the waste classification trends analysed by the ML model using the Pandas module. It also provides visuals of the waste captured by the ESP32-CAM, labelled with the category that it is grouped under. The dashboard provides an option to export the final report as a CSV file.

4.3 Testing Methodology

- Check whether the hardware components are well-connected and ensure the Arduino IDE is connected with the ESP32-CAM on the appropriate port.
- Make sure the image is captured under a good lighting environment by the ESP32-CAM.
- Examine whether the correct results are produced after the classification by the ML model.
- If it categorises wrongly, check whether the object is clearly illuminated by a proper light source and is properly detected by the camera, and then recheck for the hardware connections.

4.4. Results and Analysis

- By automating the waste segregation process, human manual labour is reduced, and the segregation time is also significantly reduced, thus proving to be a time-efficient system.
- Accuracy = (Total Correct Predictions/Total Samples)×100
- Overall Accuracy= 93%
- Average response time = < 3 seconds.

4.5 Limitations

- It cannot process a mixture of waste and classify it simultaneously.
- It has poor lighting, which sometimes detects incorrectly.
- The Machine Learning model as a Keras file is run on laptop as a server. It can further be improved by embedding the file into the microcontroller preferably Raspberry Pi.



V. DISCUSSION

This section summarizes the experimental results and critically evaluates the performance of the proposed smart dustbin system. Initially, the key contributions and experimental validations supporting the IoT-based waste segregation approach are presented. Subsequently, the limitations of the system are discussed to provide a balanced understanding of its practical applicability. Finally, future research directions are outlined to enhance system efficiency, scalability, and real-world deployment.

5.1 Key Findings

1. Successful Integration of IoT and ML:

The system successfully integrates image-based waste classification with IoT hardware components, enabling automated waste segregation with minimal human intervention. The combination of the ESP32-CAM module and a TensorFlow-based classification model demonstrates a functional end-to-end pipeline.

2. Effective Classification Performance:

The trained machine learning model achieves reliable accuracy in distinguishing between organic and recyclable waste under controlled conditions. The use of a server-based processing approach ensures efficient handling of image classification tasks without overloading the microcontroller.

3. Real-Time Automation Capability:

The system demonstrates real-time response by capturing images, processing them, and actuating the servo motor for segregation.

4. Data Monitoring and Logging:

The implementation of a dashboard with CSV export functionality enables data tracking and analysis, which can be useful for monitoring waste patterns and improving decision-making in waste management systems.

5.2 Limitations

This study has several limitations that need to be addressed:

1. Dependence on Image Quality:

The classification accuracy is significantly affected by lighting conditions, background noise, and object visibility. Poor-quality images or overlapping waste items can lead to incorrect predictions.

2. Limited Dataset and Categories:

The model is trained on a relatively small dataset with only two categories (organic and recyclable), which limits its generalization capability and real-world applicability.

3. Network Dependency and Latency:

The system relies on continuous communication between the ESP32-CAM and the server. Any network instability or delay may affect real-time performance and responsiveness.

4. Mechanical Constraints:

The servo-based segregation mechanism is suitable for lightweight waste but may face difficulties handling heavier or irregularly shaped objects, affecting system robustness.

5.3 Future Work

Future enhancements can be pursued along the following directions:

1. Dataset Expansion and Model Improvement:

Developing a larger, more diverse, and labeled dataset with additional waste categories will improve classification accuracy. Advanced models such as lightweight edge AI models can further enhance performance.

2. Edge Computing Integration:

Deploying the machine learning model directly on edge devices (e.g., ESP32 or dedicated AI chips) can reduce latency, eliminate network dependency, and improve real-time processing.

3. Enhanced Mechanical Design:

Improving the physical design of the dustbin with stronger actuators and multiple compartments can enable better handling of diverse waste types and increase scalability.

4. Smart Monitoring and Cloud Integration:

Integration with cloud platforms for real-time analytics, predictive insights, and remote monitoring can enhance system intelligence and support smart city applications.

VI. CONCLUSION

The Smart IoT-Based Waste Segregation System successfully achieves automated waste identification and segregation using edge-based machine learning and IoT technology. The system reduces manual effort, improves hygiene, and



provides actionable waste analytics for better waste management practices. The system offers a cost-effective, scalable, and energy-efficient waste management solution. On-device ML eliminates reliance on external servers, reducing latency and network dependency. IoT integration enables real-time monitoring, helping facilities plan waste collection effectively. The system operates accurately with minimal user interaction, making it suitable for high-footfall environments.

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