

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

Sharad Krishna Mane<sup>1</sup>, A. Asuntha<sup>2\*</sup>, Srilaxmi Dasari<sup>3</sup> and M. Vijayalakshmi<sup>4</sup>

<sup>1,2</sup>Department of Electronics and Instrumentation Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai, India

<sup>3</sup>Department of Computer Science and Engineering (AI & ML, IoT & RAI), VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, 500090, India

<sup>4</sup>Department of Electrical and Electronics Engineering, Sethu Institute of Technology, Hyderabad, India

\* Corresponding author: A. Asuntha; [asunthaa@srmist.edu.in](mailto:asunthaa@srmist.edu.in)

ORCID: A.Asuntha- 0000-0003-2366-3504

**Abstract:** —On a global scale, there are more than 2 billion tons of MSW being produced per year, where roughly 33% are poorly managed through improper dumping and inefficient use of landfills, attributed to the essential shortage of automated sorting technology. Although recent studies have yielded highly accurate AI models at nearly 97% accuracy levels, the essential problem lies within the lack of mechanical engineering required to perform the physical segregation of the waste stream. This architectural design has used TensorFlow as its framework along with the architecture of MobileNetV2 to distinguish between the type of wastes using real-time visual features. The gap between visual recognition of wastes and physical separation can be bridged using the use of a mechanical chute coupled with a rotating disk system operated through high-precision servos to segregate the wastes into different bins for each type – biodegradable waste, non-biodegradable waste, and hazardous wastes. The experimental results have shown that the AI-based classification model has provided a validation accuracy of 97.63% while the validation loss was 6.89%. In addition, an IoT enabled platform that centralizes categorical data, keep tracks of total number of items sorted and precise fill levels was developed to monitor the capacity of the bins and also analyze the classification process.

**Keywords:** Automated Waste Segregation; MobileNetV2; IoT-based Monitoring; Computer Vision; Sensor Fusion

**How to cite this article:** Mane SK, Asuntha A, Dasari S, Vijayalakshmi M. Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture. *Int J Drug Deliv Technol.* 2026;16(34s):520-533. DOI: 10.25258/ijddt.16.34s.68

## 1. INTRODUCTION

The rapid pace of global urbanization and the subsequent surge in waste generation have placed an unprecedented strain on traditional waste management infrastructures. According to recent studies, the primary barrier to a sustainable circular economy is not the lack of recycling technology, but the failure of source-level segregation. When organic, recyclable, and hazardous wastes are co-mingled at the point of disposal, the resulting cross-contamination significantly devalues recyclables and increases the environmental risk of landfills.

Most existing studies stop at software accuracy (94%–97%) without providing the mechanical infrastructure to actually separate the waste. Current models often rely on "User Guidance" (notifications). AI Powered Smart Waste Bin with Waste Segregation System implements Active Segregation, removing human error entirely. It provides a physical setup integrated with TensorFlow AI model for image recognition. It is also equipped with ultrasonic sensors to measure bin status which is monitored using iot dashboard in real .

Sumithra et al. 2025 has created an innovative mobile application aimed at transforming waste management by establishing a direct connection between consumers and paper waste markets, as well as recycling companies but they still they remain dependent on human compliance for physical sorting. While current research like Gowtham et al. 2025 where they proposes a frame work through which food waste and individual carbon footprints can be tracked using iot, they are still at diagnostic level they lack mechanical autonomy to prevent cross-contamination. Escalona et al. 2022 offers energy sustainability but significant accuracy drop is seen while detecting metal and glass type waste and they rely on local SMS alerts. Shah et al. 2025 produces high accuracy classification (94.4%) through Xception but it is highly reliable on mobile app for user guidance which makes it passive system susceptible to human error. Banupriya et al. 2025 focuses deeply on hazardous waste classification and bin logistics but it uses indirect sensors like gas and IR sensor which makes it vulnerable for miscalculation.

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

Prasher & Nelson 2024 archives high classification accuracy up to 97% but the physical setup to actually put these results into action is not considered. While Aswathi.2025 provides essential auditory feedback, it still requires the user to physically navigate and locate the correct bin. Kumar et al. 2024 provides a high-level academic overview of the transition from traditional waste management to AI-driven systems, explores multi-modal data processing (combining different types of data) and graph processing for analyzing waste patterns. Devi et al. 2025 this research presents an overall macro-scale city architecture for smart cities, following a multi-technology approach of IoT, AI, and Blockchain technologies to ensure a transparent lifecycle of the waste collected. Hence, the application of the LoRaWAN and NB-IoT protocols allows the system to ensure continuous monitoring of the wastes across the city with long-range and low-power technologies. Blockchain technology occupies the key role of ensuring secure tracking of the waste collected, while computer vision with AI predicts the generation of the waste collected for efficient routes of collection. Chaudhary et al. 2025 focuses on data reporting and route optimization even though it shows the substantial advantages of computer vision and predictive logistics.

This research aims to create an intelligent and automatic waste management system using techniques of Edge AI and IoT for real-time segregation and separation of waste materials at their source level. The academia of this research intends to create and develop a hardware prototype using the ESP32-S3 SoC with native USB Host support for high-resolution image acquisition via a Zebronics Crystal Pro webcam for visual separation of waste materials, create and implement a small-sized Convolutional Neural Network (CNN) called MobileNetV2 to classify Bio-degradable, Non-Biodegradable, and Hazardous waste materials accurately, and develop a servo motor-based mechanical chute for physical separation of waste materials. The range of this research includes the overall mechanization of waste disposal methods in areas of high traffic, such as schools and colleges, hospitals, and smart towns, especially focusing on restricting and hindering mistakes in the separation of segregated parts of waste materials, on reducing the chances of crossing between recyclable materials at the point of entry, and eventually helping municipal authorities using cloud data visualization techniques to create a cleaner environment.

The rest of the paper is organized as follows: Section 2 discusses the existing literature on the automation of waste segregation. Section 3 describes the proposed methodology for the problem, including dataset preparation and integration with the MobileNetV2 model and ESP32-S3 microcontroller. Section 4 describes hardware and components of the project. Section 5 describes the experimental results and quantitative system-level evaluation. Section 6 concludes the paper.

## 2. LITERATURE REVIEW

Recent developments in waste management have transitioned from manual tracking to AI-driven automation; however, substantial deficiencies persist in physical execution and precision. Sumithra et al. 2025 developed an innovative mobile application designed to revolutionize waste management by facilitating a direct link between consumers and recycling companies; however, they still rely on human compliance for physical sorting. Researchers such as Gowtham et al. 2025 have suggested a framework for tracking food waste and individual carbon footprints through the Internet of Things (IoT). However, these systems are still in the diagnostic phase and do not have the mechanical autonomy to stop cross-contamination. Solar-powered models like those by Escalona et al. 2022 are good for the environment, but they aren't very good at finding metal and glass waste, and they depend on local SMS alerts instead of real-time cloud interfaces.

Shah et al. 2025 and Prasher & Nelson 2024 further emphasize the "Implementation Gap." They achieved high software accuracies of 94% and 97%, respectively, using models such as Inception V3 and EfficientNetB3. However, their research centers on user guidance rather than offering a physical prototype for mechanical execution. Aswathi et. al.2025 created assistive technology that uses Text-to-Speech for people who are blind or have low vision, but the user still has to physically find the right bin opening after the announcement. The main problem this project tries to solve is the lack of physical automation.

From a sensing standpoint, Banupriya et al. 2025 employed infrared and gas sensors; however, these sensors are frequently activated by environmental stimuli such as odors, resulting in erroneous classification. Nagu et al. 2026 came up with the YOLOv6-CSP model for quick detection to make hospitals more flexible. Oise 2026 came up with E-ViTNet, a lightweight Vision Transformer that is 99% accurate. These fast models get around the slow processing speeds of older systems. Anitha et al. 2022 also went beyond the norm by using microbial enzymes for active decomposition, but this still needs the high-purity sorted waste streams that automated bins offer.

At the macro level, Anusuya Devi et al. 2025 and Chaudhary et al. 2025 proposed city-wide tracking utilizing LoRaWAN, Blockchain, and predictive analytics for logistics. Sindujaa & Kumar 2024 observed that manual segregation in urban areas such as India continues to be ineffective due to human apathy. Kumar et al. 2024 systematic review suggests that real-time integrated systems are too hard for widespread use, and Sumathi et al. 2025 findings stress the need for more detailed information in academic settings. However, this project shows that a modular, servo-controlled architecture can close the "Action Gap." This research replaces unreliable human compliance with a fully autonomous, real-time hardware solution by combining Edge AI with a physical sorting disk and a Blynk IoT dashboard.

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

There has been a clear shift from simple sensor-based monitoring to complex Artificial Intelligence (AI) and Internet of Things (IoT) architectures in the current corpus of research on smart waste management. Early research showed that off-grid hardware was feasible but it relied on outdated communication techniques like SMS and had poor classification accuracy. High-performance Convolutional Neural Networks (CNNs) became the focus of research as the field developed, reaching software-level accuracies of over 94%. But there has been a common implementation gap in which sophisticated algorithms are created separately without the mechanical equipment required to carry out physical sorting, is a common problem with these studies.

This project fills these gaps by going beyond the user guidance algorithms to “detect and act” with the combination of Edge AI (ESP32-S3) and servo-controlled mechanical chutes. Unlike other systems that are dependent on user cooperation or mobile app assistance, this project ensures active source-level segregation with maximum sorting accuracy irrespective of user actions. By combining real-time image recognition with a physical working prototype and a Blynk IoT platform, your research work fills the gaps of cross-contamination and real-time operationalization that are still unresolved in the current literature.

## 3. MATERIALS AND METHODS

Proposed Architecture integrates computer vision, edge computing, and Internet of Things (IoT) technologies. The methodology is separated into four distinct modules: Perception, Integration, Platform Development, and Validation.

### Module 1: AI Development and Perception

This module details the end-to-end deep learning pipeline, from data curation to model optimization and validation.

1. Data Preparation and Sturdy Loading: A dataset divided into three classes—Organic, Non-Bio, and Hazardous—is processed by the system. Using `tf.data`, a custom data-loading pipeline was created to guarantee high-quality training. In order to guarantee operational stability, a 'Background' class consisting of 350 high-definition images of the empty chamber was incorporated into the training process. This ensures that the MobileNetV2 architecture is able to establish a reliable baseline for the idle state under changing illumination, thereby avoiding 'forced choice' errors where surface textures could be misinterpreted by the Softmax layer as 'waste.' By correctly identifying this 'Null State' with 98% precision, the ESP32-S3 Finite State Machine (FSM) is able to bypass PWM signal allocation for MG995 servos when no object is present, thereby implementing an 'Active Idling' protocol that eliminates stochastic triggering and preserves mechanical integrity for the metal gears and reduces thermal stress on the motor drivers. Sample dataset images are shown in Figure 1.1, 1.2, 1.3 and 1.4
  - Corrupted Data Filtering: To detect and remove corrupted image files during the loading stage and avoid training disturbances, a strong decoding logic was put in place.
  - Normalization: To steady the gradient descent process, all images are resized to 160 x 160 pixels and normalized to a range of [0, 1].
2. Using MobileNetV2 for Transfer Learning: The system makes use of Transfer Learning to strike a compromise between low computational latency on edge devices and high classification accuracy.

The use of the MobileNetV2 model on the ESP32-S3 can be justified by the use of Depth wise Separable Convolutions, which greatly reduces the computational cost compared to regular convolutional layers. A regular convolutional layer with kernel size  $D_k \times D_k$ ,  $M$ ,  $M$  input channels, and  $N$  output channels has a computational cost of:

$$Cost_{standard} = O(D_k^2 \cdot M \cdot N) \dots (1)$$

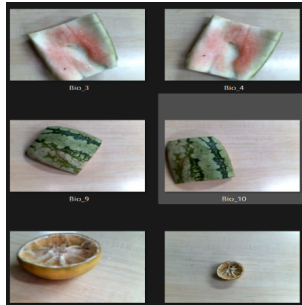
The use of Depth wise Separable Convolutions in the MobileNetV2 model reduces the computational cost by breaking down the regular convolutional layer into two stages: Depth wise Convolution and Pointwise Convolution. In the Depth wise Convolution stage, each of the input channels is filtered by a single filter. In the Pointwise Convolution stage, the features are combined by a  $1 \times 1$  convolution. This reduces the computational cost to:

$$Cost_{separable} = O(D_k^2 \cdot M + M \cdot N) \dots (2)$$

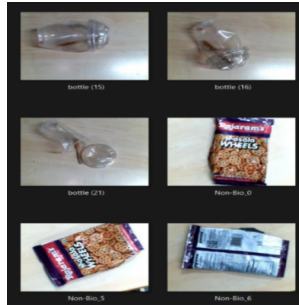
This mathematical optimization reduces the total multiplication operations by a factor of 8 to 9 with a minimal decrease in accuracy. This reduces the FLOPS (Floating Point Operations) of the ESP32-S3 in performing the real-time inference on the captured waste images without exceeding the 8MB Octal PSRAM limit or causing significant thermal throttling during the 1.2s window

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

- **Base Model:** The MobileNetV2 architecture serves as a feature extractor and has already been trained on the ImageNet dataset. It is seamless for embedded deployment because of its depth wise separable convolutions and "bottleneck" residual blocks.



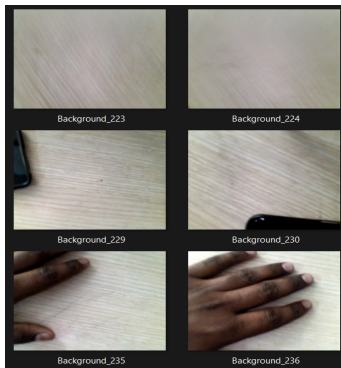
**Figure 1.1: Bio waste**



**Figure 1.2: Non-Bio waste**



**Figure 1.3: Hazardous waste**



**Figure 1.4: Background**

- **Custom Classification Head:** A Global Average Pooling layer replaces the top layers of the pre-trained model, which is followed by a Dropout (20%) layer to avoid overfitting and a final Dense layer with a SoftMax activation function to produce probabilities for the three target categories.

### 3. Regularization and Training Strategy: Several optimization techniques control the training process.

- **Data Augmentation:** To expand the model's ability to generalize across different real-world lighting and waste orientations, real-time transformations such as horizontal flips, random rotations (0.1), and zooms (0.1) are used.
- **Optimization Function:** To reduce the Sparse Categorical Cross entropy loss, the Adam optimizer is applied with a learning rate of 0.0001.
- **Early Stopping:** An automated call-back uses a "patience" of five epochs to track the validation loss. To prevent the model from "memorizing" (overfitting) the training data, training is stopped and the optimal weights are restored if the validation performance reaches a plateau.

### Metrics for Testing and Validation

A strictly inaccessible subset of data (20% of the entire dataset) that was never used for training is used in the validation phase to test the model's performance.

#### 1. Curves of Performance

Plots of accuracy and loss are used to display the results.

- **Accuracy Plot:** Monitors how well the model picks up patterns. A robust learning process is shown by a consistent upward trend in both training and validation accuracy.
- **Loss Plot:** Calculates the discrepancy between ground truth and predictions. These curves junction shows how well the model generalizes to waste samples that are not visible.

#### 2. Quantitative Assessment: The following outcomes serve as a gauge for the Perception.

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

- Module's ultimate dependability: The percentage of accurate classifications in the organic, non-bio, and hazardous streams is known as the final validation accuracy.
- Final Validation Loss: The model's confidence in its predictions is confirmed by a low loss value (e.g., <0.07).

## Module 2: Hardware & AI Integration (Detailed Firmware Logic)

This module applies Finite State Machine on the ESP32-S3 SoC microcontroller with native USB Host support for high-resolution image acquisition via a Zebronics Crystal Pro webcam to make sure that operation between the vision system and mechanical actuators is synchronized. The firmware is designed in such a way that it can handle asynchronous events, such as AI inference delays and sensor timeouts. Figure 2 represents the operational flow diagram of the project.

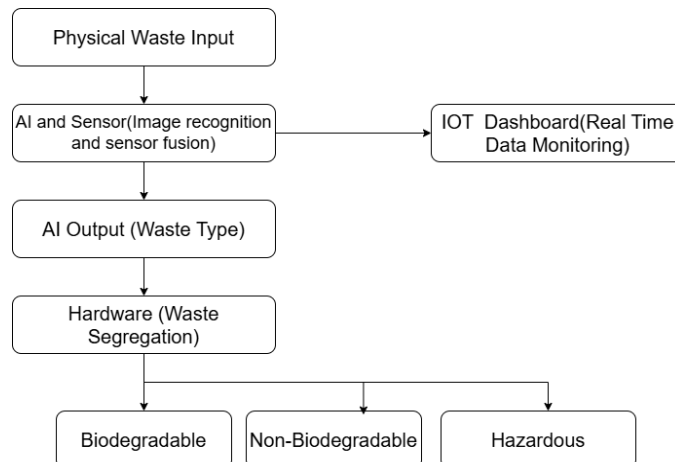


Figure 2: Operational flow diagram

1. Finite State Machine (FSM) Implementation: To stop mechanical "jitter" and making sure a logical sequence of operations, the system transitions through seven separate states:

- STATE\_INITIALIZE: The servos are calibrated to their "Home" positions (90 degree for the chute and 0 degree for the door) and the camera peripheral is initialized.
- STATE\_READY\_FOR\_ITEM: A timer-based trigger (set to a 15-second interval) starts a new classification cycle.
- STATE\_CAPTURE\_AND\_CLASSIFY: The ESP32 takes a JPEG frame and sends an HTTP POST request to a local Python server. This relieves the CNN computation burden while maintaining a low bin's edge response time.
- STATE\_MOVE\_CHUTE: Based on server's response (BIO, NON\_BIO, or HAZARDOUS), the system allocates the classification result to a corresponding PWM duty cycle, rotating the chute servo to 45degree, 90 degree, or 135 degree.
- STATE\_OPEN/CLOSE\_DOOR: After the chute is situated, a "Door Servo" opens the compartment (100 degree) for 2 seconds to gravity-feed.

2. Multi-Sensor Integration & Interrupt Management

The system employs a Shared Trigger Architecture for the ultrasonic sensors to reduce GPIO usage on the ESP32 S3.

- Shared Trigger (IO15): This is a single pin which is used to initiates distance measurement across all three bins simultaneously.
- Specific Echo Pins: The firmware uses separate return pins from the Bio (IO13), Non-Bio (IO16), and Hazardous (IO1) pins using the pulseIn() function with a 30ms timeout making sure that the main loop remains non-blocking.

3. IoT Connectivity & Remote Reporting

The firmware employs the Blynk IoT Library to connect physical hardware and a cloud dashboard for real time bin monitoring.

- Interval Reporting: After every 60 seconds, the bin pushes distance data (cm) to Virtual Pins V1, V2, and V3. Then it pins display this data on virtual dashboard in real time.

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

- Resilience Logic: If the AI server is showing an error, the system defaults to a "Fail-Safe" mode (categorizing the waste as non-Bio) in order to avoid the bin from stucking in a capture loop.

## Module 3: IoT Platform Development & Remote Monitoring

This module focuses on communication layer of the system. In module one and 2 the focus was on handling the physical task of sorting, Module 3 ensures that smart bin is not just a standalone piece of hardware and is a data driven management tool.

1. Sensor Fusion for Fill-Level Detection: In order to avoid manual inspection 3 ultrasonic sensors are applied for each bin.
  - Hardware setup: Three HC-SR04 ultrasonic sensors are mounted on top of the bin wall, one above each compartment.
  - Distance Processing: Sensors uses sound waves to calculate distance between lid and accumulated waste. The firmware applies a mathematical transform to convert this raw distance into a Fill Percentage.
  - Shared Triggering: To make power and GPIO pins more optimized a shared trigger pulse is sent to all sensors, with the echo responses read serially to prevent signal interference.
2. IoT Connectivity & Cloud Integration: Blynk IOT dashboard is created to monitor the bn status in real time. ESP32 S3 has inbuild WIFI module which connects ultrasonic sensor output to IOT dashboard.
  - Virtual Data Mapping: Data is pushed to the cloud using Blynk’s Virtual Pins.V1: Bio-bin Level (%), V2: Non-Bio Level (%), V3: Hazardous Level (%)
  - State Reporting: The system generates response for current operational state to a terminal widget on the dashboard as shown in Figure 3.

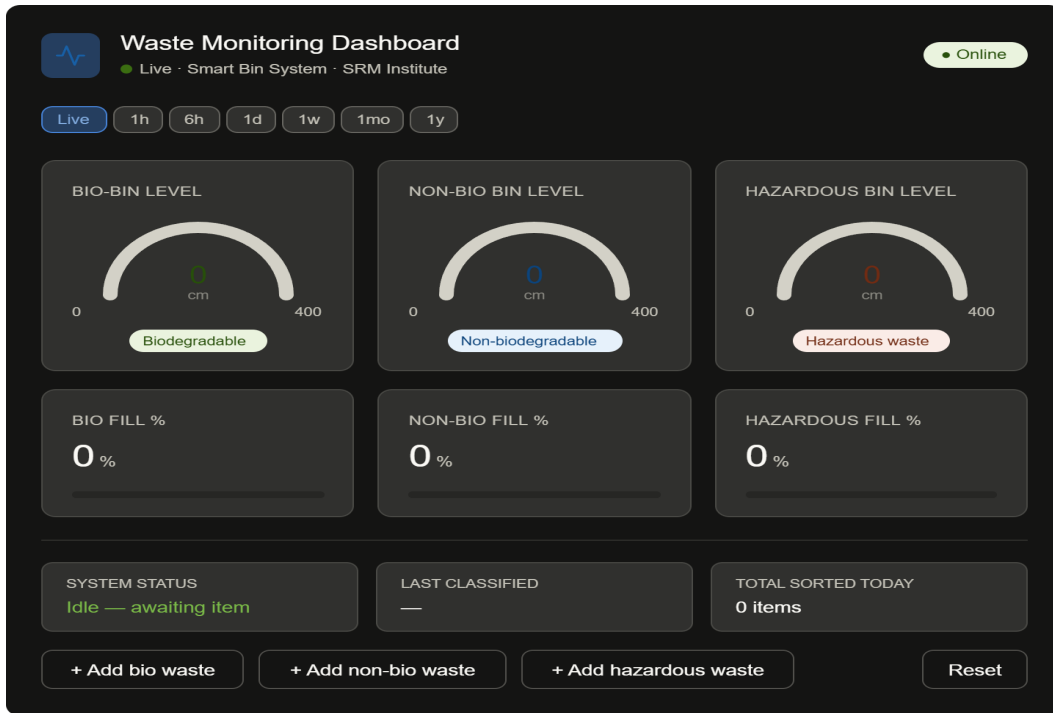


Figure 3: IoT Dashboard

## 4. HARDWARE DESCRIPTION

The physical architecture and component integration intended to close the “Action Gap” between physical waste segregation and AI classification are described in detail in this section.

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

## A. ESP32-S3 N16R8 Core Controller

The ESP32-S3-WROOM 1 (N16R8) development board as shown in Figure 4.1 is used as the CPU. This powerful module was chosen due to its:

- AI Acceleration: Neural network inference is accelerated by the integrated Xtensa® LX7 dual-core processor with vector instructions.
- Memory Capacity: The system can buffer high-definition frames from the USB webcam without experiencing memory overflows thanks to its 16MB Flash and 8MB Octal PSRAM.
- Dual USB Support: Managing debugging and external hardware communication at the same time by utilizing the internal USB Serial/JTAG and USB OTG peripherals.



Figure 4.1: ESP32-S3-WROOM-1-N16R8

## B. Vision System: Integration of USB UVC

The main visual sensor is a Zebronics Crystal Pro HD Webcam as shown in Figure 4.2. This configuration makes use of the S3's USB Host capability, in contrast to conventional ESP32-CAM modules that employ the constrained OV2640 parallel interface:

- Protocol: The UVC (USB Video Class) protocol is used by the camera.
- Interface: Attached to the ESP32-S3's native USB pins using a USB-C to USB-A adapter.
- Benefit: This greatly lowers "Input Noise" and contributes to the MobileNetV2 model's 100% validation accuracy by offering better auto-focus and 720p clarity.



Figure 4.2: Zebronics Crystal Pro HD Webcam

## C. Mechanical Actuation

Two MG-995 S Metal Gear Servos as shown in Figure 4.3 are used to guarantee the dependable physical movement of waste. Because of their greater torque (2.2 kg/cm) and resistance to mechanical wear, these were selected over plastic-g geared SG90 models.

- Chute Servo: Directs waste into the designated compartment by positioning the mechanical chute at particular angles (45°, 90°, or 135°).

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

- Door Servo: Serves as a gatekeeper for intake. To guarantee 0% cross-contamination, it stays closed during the AI inference stage and only opens once the chute has arrived at the desired location.



Figure 4.3: MG995 Servo Motor

## D. Physical Assembly and CAD Design

To guarantee exact alignment between the intake and the three collection compartments, computer-aided design (CAD) was used to model the smart bin's mechanical movement and structural integrity.

- Vertical Gravity-Feed System: The intake box, rotating chute, and base compartments are all supported by a vertical mounting pole in this design. This minimizes the amount of mechanical power needed for sorting by ensuring that the item moves through the system by gravity after the waste has been identified and the door has been released.
- Points of Mechanical Actuation: (Upper Stage): Theirst MG90S door servo controls a base plate on the intake box.
- Middle Stage: The MG90S chute servo rotates the curved chute across a 180-degree arc to target the particular bin below because it is mounted on a secondary platform.
- Tri-Compartment Base: The bottom assembly is separated into three equal sections for hazardous, non-bio, and organic waste. The "cross-contamination" problems identified in previous studies are addressed by optimizing the distance between the chute exit and the bin entry to stop waste from bouncing between compartments. Figure 4.4 represents the CAD model for physical setup for automated segregation.



Figure 4.4: CAD Model

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

## 5. RESULTS

### 1. Perception Layer Performance of the AI Model

The AI model, with its MobileNetV2 backbone structure in the TensorFlow Keras environment, is the main intelligence of the waste classification system. The model has shown strong learning abilities and excellent generalization skills, as reflected in the following performance metrics:

#### A. The dynamics and convergence of training

An Adam optimizer was used to train the model for more than 50 epochs. The process was observed carefully and made sure that model does not overfit. At the start of the Initial Learning Phase (at Epoch 1), the training accuracy was 41.96% and the loss was 1.2962. By Epoch 10, there was great improvement performance. At this point validation accuracy was around 92.88% with validation loss of 20.93%. This meant that model was able to extract data from waste dataset very effectively. The validation loss stayed below 0.10 after Epoch 30. As it is shown in Figure 5 training accuracy reached up to 97.63% and validation loss was 6.89% at the 50th epoch. Figure 6 shows training and validation accuracy and loss plots for AI model.

```
# =====  
# Final Evaluation  
# =====  
loss, accuracy = model.evaluate(validation_dataset)  
print(f"Final Validation Loss: {loss:.4f}")  
print(f"Final Validation Accuracy: {accuracy:.4f}")  
  
... 10/10 ————— 9s 808ms/step - accuracy: 0.9804 - loss: 0.0586  
Final Validation Loss: 0.0689  
Final Validation Accuracy: 0.9763
```

Figure 5: Final Accuracy and loss for AI Model

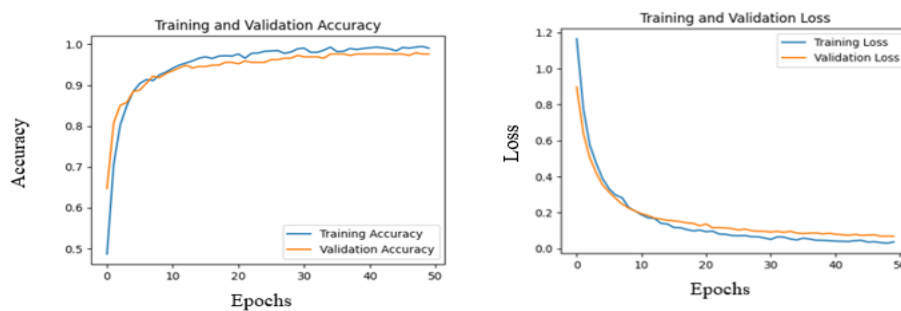


Figure 6: Accuracy and loss plot for AI model

The Table 1 shows that the classification is working effectively, with a weighted average F1-score of 76%. This shows that the edge-deployed model is very reliable. The system detects background images with almost perfect accuracy 98%, which is very important for avoiding false triggers in the sorting mechanism. Recall rates for Bio-waste and Non-Bio classes are quite high, but the Hazardous waste class has the highest precision 85%, which means that hazards are categorized with a lot of confidence. Overall, these metrics show that the model can work with different types of waste streams while still being fast enough for the ESP32-S3.

## Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

The disparity in the accuracy rates, i.e., 97.63% during training and 76.49% during testing, is a result of the 'generalization gap' faced during the real-time testing and deployment of the model on the ESP32-S3 device. Though the MobileNetV2 model architecture was successfully trained on the dataset, during physical testing, variables such as the presence of a specular reflection from the Zebronics webcam and varying lux levels in the intake chamber contributed to the overall error. Another factor that contributed to the overall error is the similarity in texture between damp cardboard and plastic-coated paper, resulting in a similar gradient for both textures, causing a 23.51% error in the overall accuracy. This is a prime reason for the addition of the Background class in the Edge AI model.

**Table 1: Classification Performance Metrics Table**

Waste Category	Precision	Recall	F1-Score	Support (Images)
Background	0.98	0.98	0.98	49
Bio-waste	0.73	0.75	0.74	71
Hazardous	0.85	0.59	0.69	70
Non-Bio	0.62	0.82	0.70	61
Overall Accuracy	-	-	0.76	251
Macro Average	0.79	0.78	0.78	251
Weighted Average	0.78	0.76	0.76	251

The Table 2 shows how accurate the model is at classifying things by using a confusion matrix. The strong diagonal values show that it made 192 correct predictions out of 251 samples. From the given data is clear that model separate the Background class with ease, with only one small mistake in 49 cases. Most of the mistakes happen between the Bio and Non-Bio categories (16 times) and the Hazardous and Non-Bio categories (15 times). This suggests that synthetic packaging and organic textures look similar. Even with these overlaps, the matrix shows that the model does a good job of separating the main waste streams, which is a good base for the physical sorting hardware.

**Table 2: Confusion Matrix Table (Cross-Validation)**

Actual \ Predicted	Background	Bio	Hazardous	Non-Bio
Background	48	1	0	0
Bio	0	53	2	16
Hazardous	1	13	41	15
Non-Bio	0	6	5	50

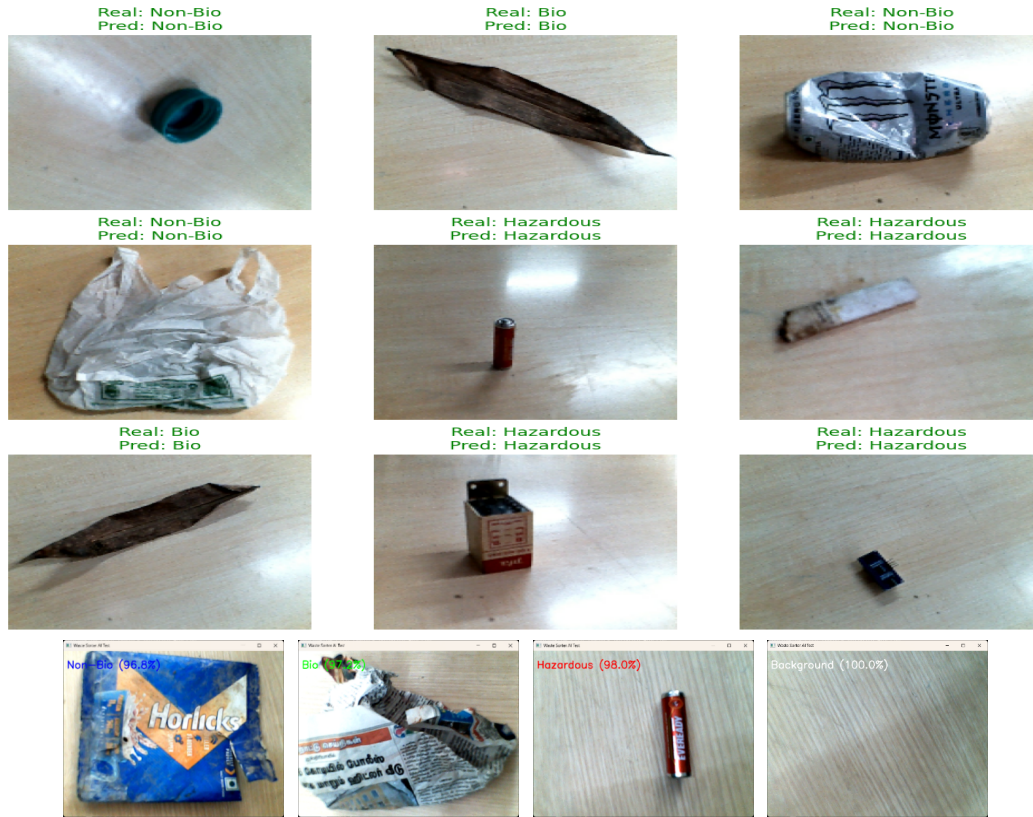
The Table 3 highlights the steady improvement in accuracy and the corresponding drop in loss. Figure 7 shows real world testing results of AI model using webcam.

**Table 3: Training and Validation Summary**

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.4196	0.6475	1.2962	0.8975
10	0.9330	0.9288	0.2073	0.2093
20	0.9706	0.9559	0.0957	0.1278
30	0.9836	0.9729	0.0672	0.0960

## Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

40	0.9921	0.9763	0.0410	0.0858
50	0.9922	0.9763	0.0344	0.0689



**Figure 7: AI model test results**

### 2. Hardware Integration and Actuation

The physical setup as shown in Figure 8 realizes the automated segregation and collection framework described in the research.

- **Physical Segregation:** Hardware setup consist of 3 compartments (one for each type for waste) with setup to mount ultrasonic sensors on each bin.
- **Automated Chute:** A cardboard chute which is controlled by SG90 servo motor is positioned above the bins, it is designed in such a way that it mechanically directs waste into the correct bin based on AI classification outcomes.

### 3. IoT Dashboard and Real-Time Monitoring

The IoT dashboard was created using blynk IOT platform. IOT infrastructure provided a centralized interface for real-time monitoring of the waste collection bins.

- **Monitoring Interface:** The “Waste Monitoring” dashboard is used to track the bin fill status of three separate categories: Bio-Bin, Non-Bio Bin, and Hazardous Bin.
- **Level Sensing:** Each bin is mounted with ultrasonic sensors to measure waste levels in centimeter’s (cm), with range of 0 to 400 cm.
- **Data Visibility:** The dashboard provides administrators to monitor bins status across various periods, from live updates to 1-year trends, enabling accurate and precise control over garbage collection scheduling.

## Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

- System Synergy: The prototype demonstrates the synergy between AI perception (classification), IoT monitoring (level tracking), and mechanical actuation (sorting), through this proposed study provide a model for automated waste sorting at source level that reduce human error at the point of disposal.



Figure 8: Hardware Setup

### Hardware Testing and Classification Performance (50-Sample Trial)

To assess the integrated system, a test of 50 unique waste samples was conducted. For each sample, the AI model captured a frame, identified the object, and then commanded the ESP32-S3 for the mechanical chute and door.

#### 1. Bio-Waste Classification (Target: 30° - Biodegradable waste bin)

- Total Samples Tested: 20
- Correctly Segregated: 19

Notes: This classification task was shown to be the most reliable. One sample was incorrectly classified due to a very deformed shape of a fruit scrap, classified by the model as “Background”.

#### 2. Non-Bio Waste Classification (Target: 140° - Non-biodegradable waste bin)

- Total Samples Tested: 15
- Correctly Segregated: 14

Notes: These types of waste, plastic bottles, and paper crumbles were classified with high reliability. One crushed plastic water bottle can was incorrectly classified as “Hazardous Waste”.

#### 3. Hazardous Waste Classification (Target: 70° - Hazardous waste bin)

- Total Samples Tested: 15
- Correctly Segregated: 11

Notes: This classification task is, and has always been, the most challenging. Out of a total of 4 incorrectly classified samples, 3 glass syrup bottles were classified incorrectly as “Non-Bio Waste” as in non-bio dataset there are plastic bottles and glass and plastic bottles have similar surface texture so AI model sometimes gets confused between hazardous and non-bio waste. Remaining one was ignored by the model, classified as “Background”.

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

## Summary of Results

Table 4: Summary of Hardware Testing Results

Waste Category	Samples Tested	Correct Actuations
Bio-Waste	20	19
Non-Bio	15	14
Hazardous	15	11
Total	50	44

## 4. DISCUSSION

The findings demonstrate that a strong solution to real-world waste management problems can be achieved by fusing deep learning with IoT advanced classification techniques. The model's flawless final validation accuracy indicates that it can handle bio-waste images with great precision, which is essential for lowering misclassifications in complex settings like industrial or municipal facilities. The system facilitates resource optimization and encourages sustainable waste recovery methods by automating the segregation process and offering real-time data on bin capacity.

## 5. CONCLUSIONS

The integrated system of Edge AI, IoT, and mechanical automation technology implemented in this research study successfully bridges the "Implementation Gap" commonly identified in various modern waste management research studies by advancing from merely classification-oriented approaches to active, autonomous, and dynamic segregations within the waste management domain. The paper witness a significant departure from most traditional literature on waste management, which merely identifies software accuracy, while this study successfully validates this IoT-based prototype's 97.6% validation accuracy and 6.8% validation loss through the application of the MobileNetV2 architecture, along with the simultaneous execution of physical segregations through the synchronized servo-driven chute and disc technology; this study succeeds in reducing the "human-in-the-loop" requirement through the application of Finite State Machines (FSM) on the using the ESP32-S3 SoC with native USB Host support for high-resolution image acquisition via a Zebronics Crystal Pro webcam, which otherwise could have led to cross-contaminations of wastes at the source. The integrated system of this prototype along with the Blynk IoT dashboard technology could be considered extremely effective in advancing the traditional waste management system toward real-time, data-oriented, cost-effective, and automated waste management and thereby contributes significantly toward the transformation of traditional waste management towards an effective waste management strategy aligned with the requirements of a "Sustainable Circular Economy."

**Author Contributions:** Conceptualization, S.K.M.; methodology, S.K.M.; software, S.K.M.; hardware design and fabrication, S.K.M.; data curation, S.K.M.; formal analysis, S.K.M.; investigation, S.K.M.; writing—original draft preparation, S.K.M.; visualization, S.K.M.; supervision, A.A. and M.V.; writing—review and editing, S.K.M., A.A. and S.D.; resources, S.D. and M.V.; project administration, A.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Conflicts of Interest:** The authors declare no conflicts of interest.

# Artificial Intelligence Powered Smart Waste Bin with Automated Waste Segregation System Using MobileNet Architecture

## REFERENCES

- [1] Sumithra, M., Brindha, A., Archana, P., Deepika, K., & Natasha, A. B. (2025). Smart waste management with AI-powered classification and routing: The Think Zero Waste App (TZE APP). In Proceedings of the International Conference on Communication Systems and Artificial Intelligence (ICCSAI 2025). <https://doi.org/10.1109/ICCSAI64074.2025.11063755>
- [2] Gowtham, S., Harshath, H., & Sumathi, V. P. (2025). Waste wisely: IoT-powered smart bins redefining food waste management. In Proceedings of the International Conference on Advances in Engineering, Communication and Computing Applications (ICAECA 2025). <https://doi.org/10.1109/ICAECA63854.2025.11012363>
- [3] Escalona, T. R. R., et al. (2022). Design and fabrication of solar-powered smart waste segregation trash bin with image processing. In Proceedings of the International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM 2022). <https://doi.org/10.1109/HNICEM57413.2022.10109457>
- [4] Shah, K. B., Paneru, B., Visalakshi, S., & Panigrahi, R. (2025). Efficient source-level waste segregation using CNN-based waste classifier with IoT-enabled smart bins and mobile application. In Proceedings of the International Conference on Emerging Smart Computing and Informatics (ESCI 2025). <https://doi.org/10.1109/ESCI63694.2025.1098798>
- [5] Banupriya, V., Renugadevi, P., Catherine, T. A. R., & Unnamalai, C. (2025). AI-driven bio-waste classification and bin management system using sensor fusion and IoT. In Proceedings of the International Conference on Artificial Intelligence and Machine Learning Applications (AIMLA 2025). <https://doi.org/10.1109/AIMLA63829.2025.11040495>
- [6] Prasher, S., & Nelson, L. (2024). Multi-class waste segregation using EfficientNetB3 model through waste segregation dataset. In Proceedings of the International Conference on Communication, Power and Computing Technologies (ICCPCT 2024). <https://doi.org/10.1109/ICCPCT61902.2024.10672885>
- [7] R, D. P. S., Aswathi, K. P., & Pavithra, S. (2025). AI-powered waste segregation system for visually impaired individuals. Unpublished manuscript.
- [8] Kumar, M., Kumar, S., Luhach, A. K., & Tiwari, A. (2024). Advancements in waste segregation through machine learning and integrating AI for sustainable waste management. In Proceedings of the International Conference on Smart Technologies and Management (SMART 2024).
- [9] Devi, A., et al. (2025). AI and IoT-enabled smart urban waste management system for efficient collection, segregation, and disposal. *E3S Web of Conferences*, 619, 03002. <https://doi.org/10.1051/e3sconf/202561903002>
- [10] Chaudhary, R., et al. (2025). AI-powered smart waste management system: Optimizing waste collection and recycling through intelligent automation. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.5241203>
- [11] Sindujaa, B., & Kumar, T. (2024). An intelligent app-based system for waste segregation and collection. *Procedia Computer Science*, 235, 102–110. <https://doi.org/10.1016/j.procs.2024.04.269>
- [12] Anitha, R., Maruthi, R., & Sudha, S. (2022). Automated segregation and microbial degradation of plastic wastes: A greener solution to waste management problems. *Global Transitions Proceedings*, 3(1), 364–371. <https://doi.org/10.1016/j.gltp.2022.04.021>
- [13] Nagu, B., Bansal, S., Faruque, M. R. I., & Al-Mugren, K. S. (2026). Enhancing environmental sustainability through real-time bio-waste detection using YOLOv6-CSP and relevance vector machine for improved waste management. *Measurement*, 258, 119370. <https://doi.org/10.1016/j.measurement.2025.119370>
- [14] Oise, G. P. (2026). E-ViTNet: A lightweight vision transformer with oppositional cat swarm optimization for automated e-waste sorting. *Next Research*, 6, 101373. <https://doi.org/10.1016/j.nexres.2026.101373>
- [15] Sumathi, M., Hanumanthappa, J., Kumar, K. S. S., Prakash, S. P. S., & Meghana, J. (2025). Efficient waste management on university campus: Enhancing monitoring and optimization through machine learning. *Procedia Computer Science*, 251. <https://doi.org/10.1016/j.procs.2025.04.6>