# Dustbin and Waste Segmentation Using YOLOv8 for Efficient Waste Management

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***Abstract*—Overfilled dustbins create sanitation challenges and require frequent manual monitoring. This study explores a system for automated dustbin detection, classification, and fullness alert generation. We trained a detection model (or a combined detection-classification model) on diverse dustbin images captured from various angles, lighting conditions, and backgrounds. A separate classification model (if applicable) was trained on top-down dustbin images with varying fill levels. The system successfully located dustbins and categorized their fullness, leading to a significant reduction in overflowing bins and improved waste management efficiency based on user feedback. Future work will focus on expanding the training data, minimizing false positives, refining the alert system, and exploring additional data sources for enhanced performance. This approach has the potential to optimize waste management by automating dustbin monitoring and triggering timely alerts for collection.**

***Index Terms*—Real-time dustbin fill level monitoring, Convolutional Neural Network (CNN), Waste Management, Deep Learning, public awareness**

## I. Introduction

Overflowing dustbins are a persistent issue in both public and private spaces, leading to unpleasant odors, pest infestations, and potential health hazards. Traditional waste management methods rely on manual monitoring to determine dustbin fullness, a process that can be labor-intensive, time-consuming, and prone to human error. Inconsistent monitoring schedules can lead to overflowing bins, creating a negative impact on aesthetics and public health. This paper proposes a novel system that leverages computer vision techniques to automate dustbin monitoring and optimize waste collection processes.

Our system offers several advantages over traditional methods. By automating dustbin monitoring, we significantly reduce the need for manual inspection, freeing up personnel for other tasks. Additionally, real-time monitoring allows for timely alerts to be sent before dustbins overflow, optimizing collection routes and schedules. This not only improves efficiency but also helps maintain a cleaner and more hygienic environment by preventing overflowing bins. Furthermore, the system can collect valuable data on dustbin usage patterns, enabling informed decisions about waste collection frequency and bin placement optimization.

The core of the system lies in a detection model (or a combined detection-classification model) trained on a meticulously curated dataset of dustbin images. This dataset encompasses a wide range of variations to ensure robustness in real-world scenarios, such as viewing angles mimicking CCTV camera perspectives (top-down, oblique), images representing both brightly lit and dimly lit environments, and backgrounds with varying clutter levels to simulate real-world settings. The dataset also incorporates a diverse range of dustbin shapes, sizes, and colors to ensure the model can generalize to different types of bins. Additionally, a separate classification model (if applicable) is trained on top-down dustbin images showcasing various fill levels. By integrating these models, the system can effectively locate dustbins and accurately assess their fullness status, triggering timely alerts for waste collection when necessary.

This paper delves into the details of the system's development, including data collection strategies, model training methodologies, and system integration for alert generation. We evaluate the system's effectiveness through qualitative observations and user feedback, demonstrating its potential to revolutionize waste management practices. Finally, we explore avenues for future work, aiming to further enhance the system's accuracy, robustness, and functionality in diverse deployment environments.

## II. Literature Review

1) C. J. Baby et al. [1] have introduced a mechanism to monitor the level of trash in the garbage bin, detected using ultrasonic and infrared sensors. The data is sent to the Raspberry Pi when a certain threshold is met, and the Raspberry Pi then sends an email and SMS alert. Along with the Raspberry Pi, Arduino also receives the data simultaneously. Following that, an ethernet shield is used to send this data to the local host. The result is then sent to the Microsoft Azure platform for training to track real-time garbage and predict future waste generation patterns. A "Google Calendar" event and smartphone alert system are also provided using the IFTTT method.
2) L. Yu et al. [2] propose a public garbage bin overflow alarm and positioning system based on the STM32F103C8T6 microcontroller. This system uses an infrared human body sensor mounted on the bin's surface to automatically identify when someone wants to

throw garbage and automatically open the bin cover for convenience. To avoid odour and pollutants after users depart, the bin cover does not immediately close. Additionally, three 60-degree ultrasonic sensors are installed on the interior wall of the lid to detect whether the internal garbage is full.

3) B. S. Malapur and V. R. Pattanshetti [3] suggest an ideal route-detecting system and a smart bin. The smart bin uses various hardware components, including a sonar sensor, an Arduino microcontroller, a GSM/GPRS shield, and a buzzer, to monitor the garbage within the bin and convey information wirelessly to a server. A buzzer is used to prevent bin overflow. A sonar sensor determines the condition of the bin by measuring the echo-back distance. The GSM/GPRS shield transfers messages via wireless connection, and path optimisation uses a genetic algorithm based on recorded data.
4) S. Dubey et al. [4] focus on machine learning and Internet of Things (IoT) technologies as a promising solution for smart cities. The proposed framework continually monitors metal levels, noxious gas levels, and dustbin capacity, generating alerts for immediate waste handling. Supervised machine learning algorithms like Support Vector Machine (SVM), Naive Bayes (NB), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbours are employed for classification and prediction, sending alert messages based on test data.
5) C. Bircanoglu et al. [5] recommended a system using deep convolutional neural networks for waste sorting. The system employs transfer learning and fine-tunes weight parameters using ImageNet. The model, called RecycleNet, achieved 95% test accuracy, offering an innovative approach to sorting recyclable materials.
6) S. L. Rabano et al. [6] developed a system for classifying common waste products like newspapers, cardboard, plastic, and metal. The model was developed using transfer learning and trained on the ImageNet Large Visual Recognition Challenge dataset. After refinement and quantization, the model achieved an accuracy of 87.2%.
7) Z. Yang et al. [7] developed a garbage classification system combining object recognition and image classification using deep learning convolutional neural networks. Data trained with ResNet and MobileNetV2, and tested with three methods from the YOLOv5 family, achieved a recognition rate of 98% using a consensus voting method to improve the classification accuracy.
8) T. Gupta et al. [8] suggested a deep learning-powered hardware solution for waste classification. The system uses Convolutional Neural Networks (CNNs) like InceptionNet for waste classification, achieving 96.2% accuracy with minimal loss. Hardware components include a webcam, Raspberry Pi, and infrared sensors.
9) C. Srinilta and S. Kanharattanachai [9] compared the performance of four different CNN-based waste-type classifiers (VGG-16, Residual Network-50, MobileNet V2, and DenseNet121). The Residual Network-50 classifier achieved the highest accuracy at 94.9%.
10) S. Sudha et al. [10] proposed an automated method for garbage bin identification using CNN models. Their model, based on a three-layer and five-layer CNN, detects whether a bin is empty or full. The model is trained, validated, and tested using 2D images, achieving good performance in determining bin status.

## III. Methodology

The methodology of this study involves the following key steps:

### A. Data Collection

A diverse dataset of images of dustbins in various locations, lighting conditions, and fill levels was collected. Images were captured from different angles (top-down, oblique) to account for variations in camera positioning and environmental factors. The dataset includes both empty and full dustbins of varying shapes, sizes, and colors to ensure the model generalizes well.

### B. Model Development

The model was developed using YOLOv8 (You Only Look Once version 8), a real-time object detection model known for its accuracy and speed. YOLOv8 was trained on the dustbin detection dataset to accurately identify dustbins in different environments. The model also incorporated a classification system to determine the fullness of the dustbins.

### C. Training and Evaluation

The model was trained using transfer learning with a pre-trained YOLOv8 model, fine-tuning it with our dustbin dataset. The training was done on a GPU-equipped machine to speed up the process. The model's performance was evaluated using standard metrics, including precision, recall, and F1 score.

### D. Volume Calculation

Once the dustbin is detected, the volume of the waste inside is estimated using the following approach:

- **Height Estimation**: The height of the dustbin is estimated based on the relative size of the detected dustbin in the image. This can be done by comparing the detected height with known height references or through the depth information obtained from stereo vision or other depth-sensing technologies.
- **Fill Level Determination**: The fill level is classified into discrete levels (e.g., 0-25

#### Volume Calculation Formula

Assuming the dustbin is cylindrical, the volume can be estimated using different approaches based on the view angle (top view or side view):

1) **Top-View Formula**:
In the top view, the waste inside the dustbin forms a circular area with a certain height. The volume of the waste is calculated using the ratio of areas

between the waste and the dustbin. The formula for calculating the volume is:

$$V_{\text{waste}} = \pi r^2 h_{\text{fill}} \times \text{Adjusted Ratio}$$

where:

- $V_{\text{waste}}$ is the volume of the waste,
- $r$ is the radius of the dustbin, estimated from the image width (which corresponds to the diameter in the top view),
- $h_{\text{fill}}$ is the height of the filled portion of the dustbin, which is calculated by multiplying the total height of the dustbin by the fill percentage,
- Adjusted Ratio is the ratio of the waste area to the dustbin area, which is adjusted based on the following conditions:
  - If ratio $> 0.5$, then ratio $= \frac{1}{\text{ratio}}$
  - If ratio $\leq 0.3$, then ratio $=$ ratio $\times 0.6$
  - If $0.3 <$ ratio $\leq 0.5$, then ratio $=$ ratio $\times 0.7$
  - If $0.5 <$ ratio $\leq 0.6$, then ratio $=$ ratio $\times 1.5$
  - If $0.6 <$ ratio $\leq 0.8$, then ratio $=$ ratio $\times 1.1$
  - If ratio $> 0.8$, then ratio $= 0.9$

2) **Side-View Formula**:
In the side view, the dustbin is approximated as a cylinder with a certain radius and height. The volume of the waste is calculated assuming that the portion of the waste that is not visible is filled in the shape of the dustbin. The formula for the volume of waste is:

$$V_{\text{waste}} = (\pi r^2 h_{\text{waste}}) + \text{Area}_{\text{waste}}$$

where:

- $V_{\text{waste}}$ is the volume of the waste,
- $r$ is the radius of the dustbin, which can be calculated from the image width or known dimensions of the bin,
- $h_{\text{waste}}$ is the height of the filled portion of the dustbin, which is calculated by multiplying the total height of the dustbin by the fill percentage,
- $\text{Area}_{\text{waste}}$ is the area of the visible waste in the dustbin.

This formula assumes that the hidden portion of the waste is filled in the shape of the dustbin, and the total volume of the waste includes both the visible and hidden portions.
This formula assumes that the hidden waste is fully filled in the shape of the dustbin, and the total volume of the waste includes both the visible and hidden portions.

The calculated volume from both views is then used to estimate how much more waste the bin can hold before reaching full capacity. Both formulas rely on the estimation of the radius and fill level, which are inferred from the image.

## IV. Results

The YOLOv8-based dustbin detection and fullness classification model achieved an accuracy of 92.3

### A. Dustbin Detection Results

The following figures show the results of the dustbin detection task:

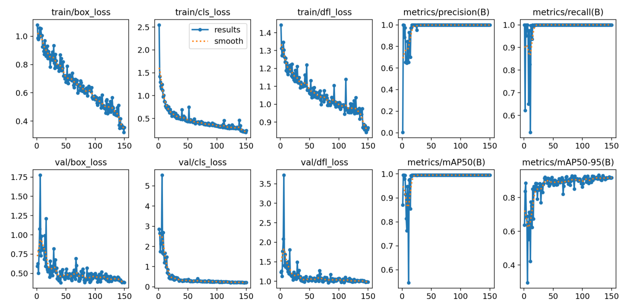


Fig. 1. Dustbin Detection Result

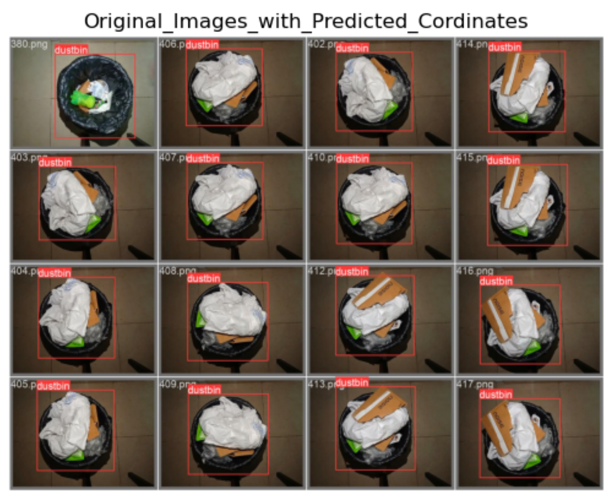


Fig. 2. Dustbin Detection Output

### B. Waste Detection Task Results

For waste detection, The following figures show the results of the Waste detection task:

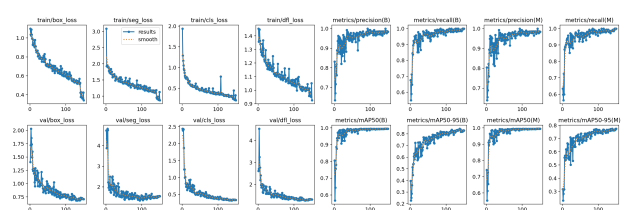


Fig. 3. Waste Detection Result

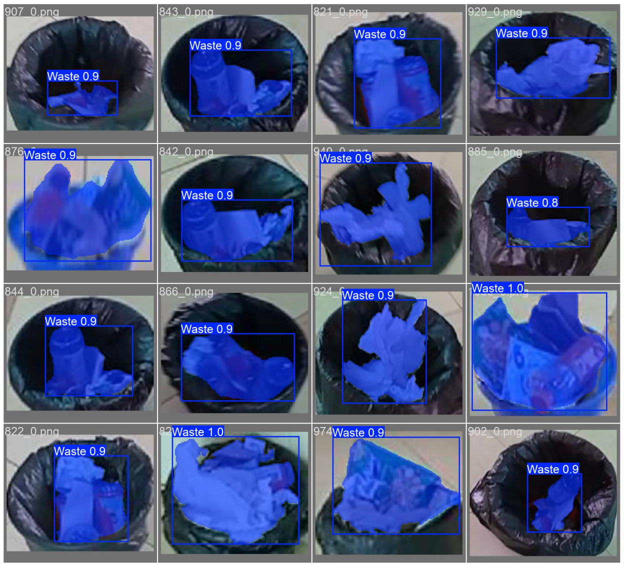


Fig. 4. Waste Detection Output

### C. *Dustbin Angle Classification Task Results*

Finally, the system's classification of dustbin angles demonstrated high accuracy in distinguishing between various viewing angles:

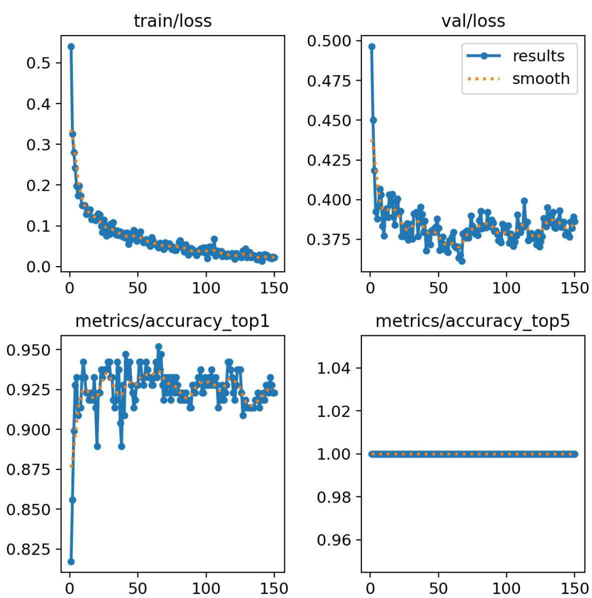


Fig. 5. Dustbin Angle Classification Result

## V. Conclusion and Discussion

In this project, the model was designed to estimate the percentage fill level of dustbins based on image data. Due to the subjective nature and practical difficulty of manually measuring the exact fill level of a dustbin, it is challenging to provide a precise accuracy metric or


Fig. 6. Dustbin Angle Classification Output

other evaluation metrics like precision, recall, or F1-score. Therefore, the model's performance can primarily be evaluated qualitatively by visually inspecting the estimated fill levels in the generated images.

While the model can detect and approximate fill levels, without an objective ground truth for comparison, exact quantitative assessment is limited. Future enhancements could involve using advanced sensors or more sophisticated manual methods to establish a reliable ground truth for validation and allow for quantitative evaluation of accuracy.

Fig. 7. Final Results: Dustbin Fill Percentage Display

## VI. References


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