RESEARCH

# WHAT A WASTE: Recovering Trash from Philippine Landfills with Object Detection

Rex Gregor Laylo*, Alyannah Bianca Saringan, Ana Dominique Vasquez and James Daniel Zabala

*Correspondence:
RLaylo.MSDS2024@aim.edu
Aboitiz School of Innovation and Entrepreneurship, Paseo De Roxas, Legazpi Village, 1229 Makati, Philippines
Full list of author information is available at the end of the article

**Abstract**

The Philippines grapples with a critical waste management challenge, largely driven by its "sachet economy." This economic model relies heavily on single-use plastic packaging, leading to an alarming accumulation of non-biodegradable waste. Overflowing landfills and inadequate waste segregation further exacerbate the problem. While manual sorting in Materials Recovery Facilities (MRFs) remains common, scalability is a major hurdle. Automating MRFs presents an opportunity to leverage object detection models. This study aimed to develop a YOLOv8-based model using publicly available image datasets. However, initial performance on a Philippine waste test set yielded a disappointing mean Average Precision (mAP@50) of 23%. Analysis revealed a significant data discrepancy between training and test data and to address this, we implemented web scraping to augment the training data with Philippine-specific waste images. This data augmentation strategy significantly improved model performance, achieving an mAP@50 of 71% on the test set.

**Keywords:** object detection; waste segregation; YOLOv8; Philippines

## HIGHLIGHTS

- Training object detection models on available datasets in the internet might perform poorly during local implementation.
- Augmenting Philippine-specific images of garbage greatly improved test performance from 23% to 71%
- YOLOv8's real-time video inferencing for Philippine-specific is feasible and deployable.

## 1 Introduction

On the 10th of July 2000, the Payatas Landslide occurred in the Payatas Dumpsite, a massive landfill in Quezon City Philippines. The incident involved a large pile of garbage collapsing and catching fire which resulted in the destruction of about 100 squatters' houses, and claiming 218 lives according to official data. This tragic event serves as a poignant reminder of the persistent problem of waste management in the Philippines.[1]

The Philippines faces significant challenges in managing the waste generated by its rapidly growing population and urbanization. The country produces approximately 61,000 tons of solid waste daily, with Metro Manila, the capital region, contributing a substantial portion. Projections indicate that by 2025, the daily waste production could reach 65,000 tons. This rapid increase in waste generation places immense pressure on the existing waste management infrastructure and systems, underscoring the urgent need for effective solutions.[2]

The problem is further exacerbated by the Philippines being what is referred to as a *"Sachet Economy"*. Majority of Filipinos, specially in the lower income bracket rely heavily on products sold by sachets. Sachets are convenient, affordable, and accessible, but they are also notorious for dominating majority of the Philippines' residual waste. Filipinos on average use a staggering 164 million sachet packets per day, contributing to 52% of the total residual plastic waste.[3]

One potential solution to this imminent garbage problem is the practice of garbage segregation. Implementing garbage segregation at various stages of waste management can effectively contribute to the reduction of waste that is ultimately disposed of in landfills. The act of categorizing waste into recyclable, biodegradable, and residual waste yields numerous advantages. Recyclable materials can be gathered and repurposed, while biodegradable materials can be utilized for composting. The residual waste, which serves no further purpose, will then be disposed of in a secure location. In addition to reducing landfill waste, removing biodegradable waste from landfills mitigates the associated health and environmental hazards.

Trash segregation is a longstanding concept in the Philippines, anchored in Republic Act 9003, also known as the Ecological Solid Waste Management Act of 2000, which outlines the separation of waste. However, the challenge lies in how responsibilities are often shifted between different entities. Existing laws allocate responsibilities to LGUs, agencies, boards, and others, but a recurring sentiment from the government is that waste management is a collaborative effort involving the government, private sector, and the public. The main issue with implementation lies in the practical execution of RA 9003. Often, households diligently segregate their trash, only to find it combined during garbage collection, or local ordinances on segregation are not adhered to by citizens. Failure to implement segregation effectively at the initial stages of waste management complicates efforts to enforce segregation practices later in the process. In waste management, Materials Recovery Facilities (MRFs) serve as the last line of defense for segregation. MRFs in the Philippines often contend with mixed heaps of trash that haven't undergone sufficient pre-separation. This requires human intervention to manually sort through and pick out reusable materials. Technological advances have introduced automated processes such as rotating drum separation, magnetic separation for metallic waste, vibratory separation techniques, and more. These processes rely on the physical and chemical properties of the garbage. However, they are not foolproof, and their effectiveness often depends on the incoming garbage being well-separated beforehand.

## 2 Related Works

Object detection is a fundamental computer vision task that aims to identify and localize objects within an image or video. It plays a crucial role in various applications, including self-driving cars, medical image analysis, and robotics. In recent years, deep learning approaches have revolutionized object detection, achieving high accuracy and robustness. This section will provide a brief overview of common object detection techniques, followed by a discussion of how deep learning is leveraged for waste management tasks, specifically focusing on garbage detection.

Compared to image classification, object detection presents a more intricate challenge. While image classification focuses on assigning a single label to an entire image, object detection tackles two crucial tasks simultaneously: identifying the presence of specific objects or instances and precisely locating them within the image. Furthermore, object detection must handle scenarios with multiple objects of different classes within a single image. This is in contrast to image classification, which assumes only one dominant category per image.

A recent review by Amjoud & Amrouch (2023) explored the diverse landscape of deep learning techniques for object detection. This includes established methods like Convolutional Neural Networks (CNNs) and emerging architectures such as Vision Transformers (ViTs). Object detection models themselves come in various forms, each with its own strengths and weaknesses:

- **Anchor-based detectors:** These methods rely on predefined shapes (anchors) to propose potential object locations. They can be further categorized as two-stage (Faster R-CNN) or one-stage (YOLO) approaches.

- **Anchor-free detectors:** Unlike anchor-based methods, these models bypass the use of anchors, focusing on directly learning from the extracted features.

- **Transformer-based detectors:** This is a cutting-edge approach that leverages transformer architectures, traditionally used in natural language processing, for object detection tasks. While ViTs show promise, they are still under development in this domain.

While various object detection architectures, like anchor-based and anchor-free detectors, can achieve high accuracy (around 70% mAP@50 on the MS-COCO dataset), real-world applications often require a balance between accuracy and speed. This is particularly crucial for live video streams, where object detection needs to happen in real-time.

The speed at which a model performs inference, measured in frames per second (fps), is critical for real-time applications. In our case, with garbage detection on a conveyor belt in an MRF (Material Recovery Facility), a fast inference speed is essential. The model needs to detect objects quickly and send signals to actuators for sorting mechanisms within a short time window. Since objects on the conveyor belt are constantly moving, a slow inference speed would lead to unactionable detections and consequently potential sorting errors. Based on the results of the review Yolo architectures were observed to achieve a good balance between performance and inference speed, this makes it an ideal candidate model for our application.

Several studies have explored applying object detection techniques to garbage classification tasks. For instance, Majchrowska et al. (2021) achieved a mAP@50 of 16.2% on the extended TACo dataset. Their model classified objects into seven different waste categories. However, when they focused solely on object detection for a single class ("litter") on the same dataset, the mAP@50 significantly improved to 56.8%. This highlights the challenges of multi-class waste detection compared to single-class object detection.

## 3 Data and Methods

### 3.1 Data Source

Two datasets were used in this study: the Trash Annotations in Context (TACO) dataset and the Trashnet dataset. TACO provides 1,500 high-resolution annotated images of waste found in real-world settings, categorized into 28 top-level and 60 sub-categories (Figure 1). This rich data serves as a foundation for training the object detection model[4].Trashnet contains 2,527 images of waste photographed over a clear background, originally under six categories[5]. Trashnet will mainly be used to augment TACO for cases when the category distribution is under-represented based on actual statistics for types of Philippine waste[6].

### 3.2 Data Preparation and Augmentation

Images from the combined TACO-Trashnet dataset were annotated based on the three main categories of waste in the Philippines: biodegradable, recyclable, and residual.

A total of 700 annotated images was used as the initial training and validation data to set the baseline, with a category mix of 14% biodegradable waste, 29% recyclables, and 57% residuals. The training and validation data was then segregated with a 75-25 split.

A secondary set of training-validation data was prepared by augmenting the original dataset with Philippine-specific waste such as Filipino-branded items and sachet products. In total, 300 additional images were web scraped from Pinterest while retaining the same percentage distribution of biodegradable, recyclable and residual waste. Similarly, the set was segregated with a 75-25 split. Figure 2 shows examples of images that were part of the augmentation.

Lastly, the holdout dataset was prepared in the same manner as the augmented Philippine-specific waste, through the process of web scraping images of litter. Of the 250 images collected, 150 were residuals, 50 were biodegradable waste, and the remaining 50 were recyclables.

### 3.3 Model

For this project, we opted for YOLOv8, a state-of-the-art object detection model known for its exceptional balance between performance and inference speed. This

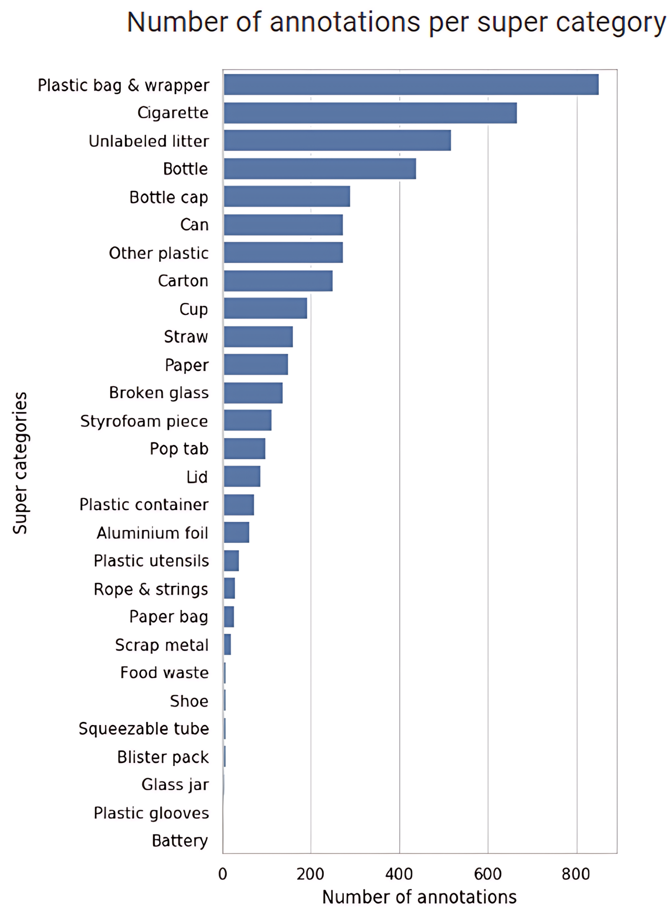


**Figure 1** Bar Graph showing the Number of annotations per super category (TACO dataset)

single-stage detection system, building upon the You Only Look Once (YOLO) architecture, predicts bounding boxes and class probabilities directly from an image in one pass. YOLOv8's efficiency stems from its custom CSPDarknet53 backbone network, which utilizes cross-stage partial connections for improved information flow during training. Additionally, a novel feature extractor neck combines features from various resolutions, enabling the model to detect objects at different scales. Finally, the detection heads predict bounding boxes and class probabilities for the identified objects within the image. While newer YOLO versions (v9 and v10) exist, we chose YOLOv8 due to its relative maturity and stability, offering a well-tested and reliable foundation for our real-time garbage detection application. The final model had the following properties:

- Layers : 168
- Parameters: 11,126,745
- n-estimators: 200

Using Google Colab Pro with T4 Hardware Accelerator and High-Ram option (51


**Figure 2** Example of images added as localized trash augmentation

GB System RAM and 15GB GPU RAM), an inference speed of 12.4 milliseconds was achieved, this includes pre and post processing.

## 4 Results and Discussion

The model was initially trained on the TACO dataset plus portion of Trashnet, and tested on manually scraped images of the local trash scene. The training dataset is then augmented with local images of trash, in the hopes of improving the performance on test.

### 4.1 Base Model

The YOLOv8 based model was able to achieve an admirable performance on the validation set at 76% mAP@50, near the performance of other attempts on the TACO dataset. However, it did not perform so well on the test set, achieveing a measly 22.9% mAP@50.

| Classifier | Validation Score | Test Data |
|---|---|---|
| All | 79.0% | 22.9% |
| Biodegradable | 75.5% | 32.3% |
| Recyclable | 82.0% | 22.4% |
| Residual | 79.4% | 14.0% |

**Table 1.** Base Model Performance (mAP@50) on Original Dataset

### 4.2 Data Localized Model

The model that was trained on the set of images which was augmented with images of Philippine-specific trash performed well on the test data, in contrast with the unaugmented base model. Table 2 shows the different scores for each class, and it is also worth noting that the

| Classifier | Validation Score | Test Data |
|---|---|---|
| All | 76.0% | 71.5% |
| Biodegradable | 71.0% | 73.6% |
| Recyclable | 79.0% | 67.1% |
| Residual | 77.9% | 73.9% |

**Table 2.** Data Augmented Model Performance (mAP@50) on Original Dataset

Given the desirable performance of the data augmented model, the model can now be used for predictions, and as seen in Figure 3 it is able to detect and classify garbage to a certain extent.

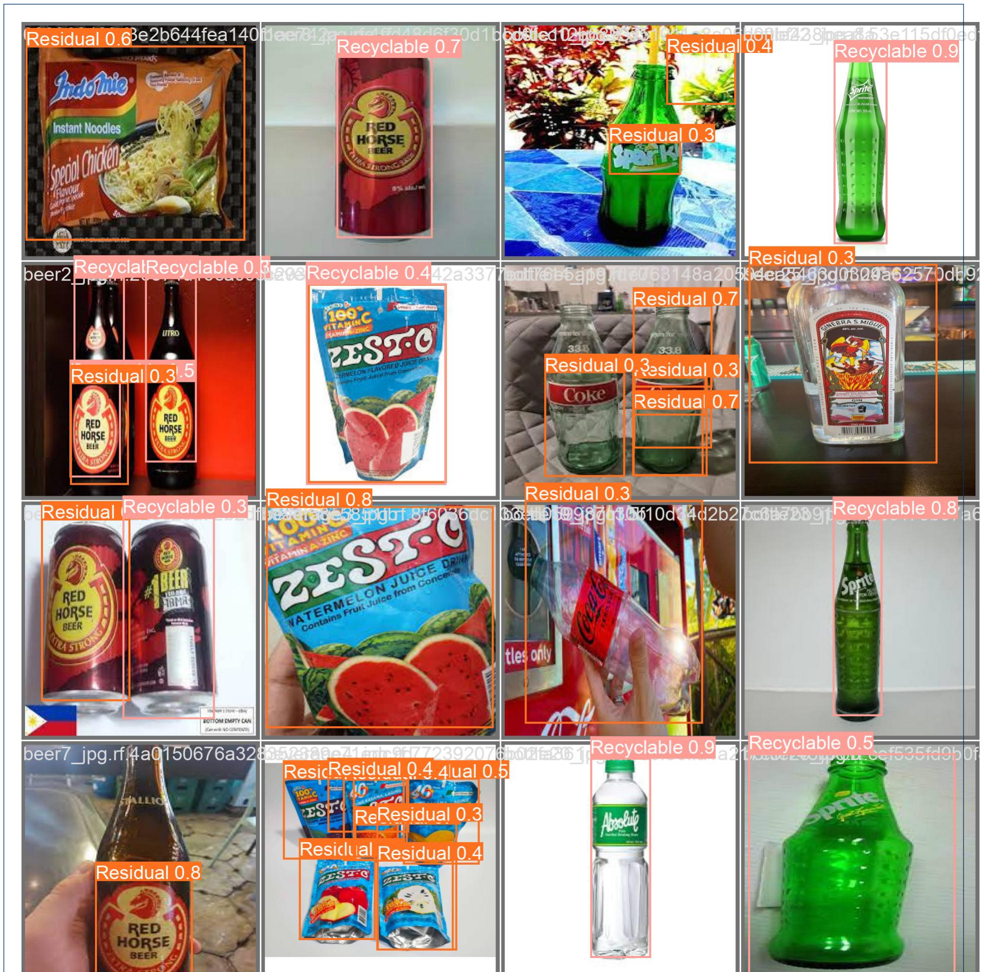


**Figure 3** A sample batch prediction using the data augmented model

## 5 Conclusion

This study successfully developed a robust object detection model for garbage classification, leveraging the pre-trained YOLOv8 convolutional neural network architecture. The model's performance on the test data exhibited a significant improvement, primarily attributable to the implementation of data augmentation techniques. This finding underscores the critical role of data in object detection tasks. Training models on datasets that closely mirror real-world deployment scenarios is paramount for achieving optimal performance. Reliance on generic internet datasets, while readily available, often leads to models that struggle with the inherent variability of real-world environments. These variations can include diverse lighting conditions, background clutter, and object poses not adequately represented in generic datasets.

Consequently, such models exhibit performance degradation when deployed in real-world applications.

This project emphasizes the importance of tailoring training data to the specific application domain. By augmenting the data using a localized set of images, we were able to artificially expand the training dataset, introducing variations that better reflect the anticipated deployment environment for the garbage classification model. This approach significantly improved the model's ability to generalize to unseen data and perform effectively in a real-world setting.

The success of this project highlights the potential of object detection models for real-world waste management applications. Future research could explore the integration of this model into automated sorting systems for improved efficiency and waste diversion. Additionally, investigating the effectiveness of transfer learning, where a pre-trained model is fine-tuned on a domain-specific dataset, could further enhance the model's performance and adaptability to various waste management scenarios.

## 6 Recommendation

Our group considered potential steps for further exploration as extensions of this project:

- **Data Augmentation**: Models trained on images greatly benefit from data augmentation. For this application data augmentation techniques such as rotation, cropping, cutouts can greatly help the robustness of object detection because in actual implementation the garbage would most likely be a dense heap, where pieces of garbage would most likely be overlapping with each other.
- **Generate your Custom Dataset**: As demonstrated, training a model on a set of images that does not represent the conditions where it is going to be implemented in. If a model like this is going to be implemented on segregation facilities where it would perform object detection.
- **Play around IoU values**: Depending on the sorting mechanism, the degree of detection might not be as important. Playing around with Intersection over Union (IoU) values might improve detection rate specially for cases when it is much more important to detect and classify rather than to get the exact boundaries of the object itself.

Our group is convinced that implementing these recommendations will significantly enhance the effectiveness of garbage detection.

**Competing interests**

The authors declare that they have no competing interests.

**Acknowledgements**
We would like to express our sincere gratitude to our professors and mentors who have provided invaluable guidance and support throughout the development of this research project. Firstly, we would like to thank our professor, **Dr. Christopher Monterola**, for introducing us to the subject matter and providing us with a strong foundation in the field. We appreciate his clear explanations, insightful discussions, and encouragement throughout the semester. His constructive criticisms and suggestions are the main reason that we were able to change our approach to our problem. We are especially grateful to **Prof. Leodegario U. Lorenzo I** for his constant support and mentorship throughout the entire project. His willingness to answer our questions, provide feedback on our work, and offer valuable suggestions significantly contributed to the successful completion of this research. We would also like to acknowledge **Prof. Kristine Ann M. Carandang** for her role as a mentor during the academic term. We appreciate her presence and guidance, which greatly contributed to our overall learning experience. We are truly grateful for the knowledge, guidance, and support we received from our mentors throughout this project. Their expertise and dedication have significantly enriched our learning experience and helped us achieve this accomplishment.

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