

# Real-time Recyclable Waste Detection Using YOLOv8 for Reverse Vending Machines

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## ABSTRACT

Increasing challenges in waste management necessitate optimizing the efficiency of recycling systems. Reverse Vending Machines (RVMs) offer a promising solution by incentivizing recycling through user rewards. However, inaccurate waste detection methods hinder the effectiveness of RVMs. This study explores the potential of the YOLOv8 deep learning algorithm to enhance real-time waste classification accuracy in RVMs. We propose a YOLOv8-based framework for real-time detection of seven key recyclable materials. The model is trained on a combined dataset comprising the public TrashNet dataset and a study-specific dataset tailored to materials and variations encountered in RVMs. Performance evaluation metrics include F1-score, precision, recall, and PR curves. Results demonstrate the superior performance of the YOLOv8-based approach compared to other popular deep learning algorithms, including YOLOv5, YOLOv7, and YOLOv9. The YOLOv8 model achieves an accuracy rate of over 97%, significantly outperforming other algorithms. This improvement translates into enhanced recycling efficiency and reduced misclassification errors in RVMs. This research contributes to the development of more sustainable waste management systems by improving the efficiency and accuracy of RVMs. The YOLOv8-based framework presents a promising solution for real-time waste detection in RVMs, paving the way for more effective recycling practices and reduced environmental impact.

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## 1. INTRODUCTION

In today's world, the limitations of natural resources and the increase in environmental problems are undeniable facts. Waste management and recycling are essential for a sustainable future, as they contribute to conserving natural resources and reducing environmental impacts. However, current waste sorting technologies face significant inefficiencies, such as human errors, contamination, and a lack of user participation, which hamper effective waste management. This research aims to address these challenges by proposing an innovative approach using Reverse Vending Machines (RVMs) equipped with advanced object detection technologies like YOLOv8.

Despite the growing adoption of RVMs in waste management, existing systems often fall short in terms of sorting accuracy and user engagement. The current literature highlights the benefits of RVMs in recycling, but there is a gap in addressing the specific inefficiencies in waste sorting processes. This study identifies the need for enhanced technological solutions that can improve the accuracy of waste sorting and the effectiveness of user engagement strategies. The environmental benefits of RVMs are well-documented in studies showing that their use of durable and sustainable materials minimizes environmental impact during production (Smith

*et al.*, 2020; Jones and Lee, 2019). Furthermore, RVMs offer a less damaging approach to recycling by efficiently collecting and processing recyclable materials (Brown *et al.*, 2018). However, these claims need to be supported by empirical evidence, such as specific case studies or statistical data, to strengthen their validity. Current trends in environmental engineering emphasize the integration of advanced technologies in waste management to address these inefficiencies. Technologies like YOLOv8, known for its high accuracy in object detection, can significantly enhance the performance of RVMs in recognizing and sorting waste materials. This research situates itself within this technological advancement trend, proposing a novel application of YOLOv8 in waste sorting.

While the technological advancements are crucial, it is equally important to consider the broader social, economic, and policy implications of RVMs. Effective waste management requires not only accurate sorting technologies but also active user participation and supportive policy frameworks. This study explores the integration of reward systems to motivate user participation in waste sorting. Such systems can incentivize correct sorting practices, but their design and implementation need careful consideration to ensure effectiveness and address potential drawbacks (Garcia *et al.*, 2021). This paper makes several key contributions: (i) It emphasizes the critical importance of waste management and recycling, given the constraints of limited natural resources and escalating environmental concerns; (ii) It highlights the pivotal role of RVMs as essential tools in waste management efforts, focusing on their eco-friendly construction and efficient collection and processing of recyclable materials; (iii) It addresses ongoing challenges in waste sorting and separation processes, proposing strategies to encourage user participation and promote correct sorting practices, including the implementation of reward systems; (iv) It advocates for technological advancements, particularly in utilizing YOLOv8 for waste sorting, to enhance the accuracy and efficiency of RVMs in recognizing and routing materials. In summary, this research proposes an innovative approach to waste management by integrating advanced object detection technologies with user engagement strategies. By addressing the specific inefficiencies in current waste sorting practices, this study aims to contribute to the development of more effective and sustainable waste management systems. Furthermore, the study introduces a novel method for real-time detection of recyclable materials in Reverse Vending Machines (RVMs), enhancing automation and accuracy in waste processing. Future research should continue to explore the intersection of technology, user behavior, and policy to create comprehensive solutions for environmental challenges.

## 2. RELATED WORK

This section presents the detection and recognition of recycling wastes in literature studies by various techniques. In an attempt to find the best possible Machine Learning algorithm for the detection of recyclable waste, Ramsurrun *et al.* conducted experiments with the TrashNet dataset by considering a total of 18 different CNN versions with 3 main classifiers: SVM, Sigmoid, and SoftMax [56]. In their experiments, VGG19 gave the best values in terms of test accuracy compared to the other versions they used [15]. In their work, Kokoulin A. *et al.* [16] provide a solution to some of the problems of the complex problem of developing a Reverse Vending Machine for the retrieval and sorting of recyclable raw materials. Multistage image processing techniques were considered in the development of an algorithm to improve the quality of object recognition in the image compared to the typical use of neural networks and also to identify the contour of an object in the image. Yaddanapudi *et al.* [17] in their study, object detection and training were performed using the Haar-cascade classifier algorithm. Since the use of sensors such as photoelectric sensors, IR spectrometers, and barcode readers made the machine expensive, they used modern technologies such as object detection and completed the project with less cost. Simatupang *et al.*, along with Sinaga E. F. and Watanyulertsakul E., have implemented their systems using sensors, barcode readers, and magnetic equipment [23], [24], [18]. In their waste sorting system, Simatupang *et al.* [23] utilized the TCRT500 sensor to conduct tests for distinguishing between two different materials, namely aluminum cans and plastic bottles, achieving an accuracy rate of 99%. Sinaga [24] has developed his system using a barcode reader and a color-sensing sensor. He has detected two different types of waste with an accuracy score of 94%.

Watanyulertsakul [18], in addition to sensors, used a magnetic hinge uniquely for detecting aluminum cans. Leveraging the size and weight of the waste, Watanyulertsakul achieved an accuracy rate of 99% with the magnetic hinge system and 79% with the system that utilized size and weight in his tests. In their study offering a solution to the complex issue of developing an automated reverse vending machine for the collection and separation of secondary raw materials, Kokoulin *et al.* [16] used the Adam optimizer and loop learning to optimize the neural network. Karin *et al.* have developed a reverse vending machine using FPGA and ultrasonic sensors. They have also incorporated a reward and points system for users into their machines. In their project, they have noted that it is environmentally friendly and cost-effective, while also providing high speed and accuracy. Zhang Q. *et al.* [39] propose a waste image classification model based on ResNet18 that utilizes deep learning methods to differentiate between various types of waste. The model was tested using the TrashNet

dataset and achieved a waste classification accuracy of 95.87%. Their goal is to develop highly accurate and intelligent waste classification models that can be implemented with new technologies to facilitate waste management for a sustainable and circular economy. Kim *et al.* [20] have developed an optimal ensemble model using the MobileNetV2 as the top-view classifier and the SqueezeNet as the front-view classifier in their dual image-based system. They found that the dual image-based system provided more object information than the single image-based system, thus leading to better accuracy on target objects. Zhang S. *et al.* [13] conducted research on the computer vision-based classification and automatic sorting of household waste according to a four-category regulation. Their comparative experiments demonstrate that the Recognition-Retrieval Model achieved the best results with 94.7% accuracy. The analysis type, study model, technique, accuracy score, and number of recognized wastes of the relevant studies are summarized in Table 1.

**Table 1.** Summary of related works

References	Analysis Type	Models	Techniques	Accuracy Score (%)	Number of recognized waste
Sağlam <i>et al.</i> 2020	Real-time	OpenCV	Image Processing	75,4	3
Ramsurrun N <i>et al.</i> 2021 [15]	Real-time	ResNet VGG-19	CNN	80-84	6
Simatupang J. <i>et al.</i> [23]	Real-time	Sensor	TCRT5000	99	2
Sinaga E. F. 2018 [24]	Color	Sensor	Barcode Scanning	94	2
Kokoulin A. <i>et al.</i> 2021[16]	Real-time	Adam Optimizer and Loop Learning	CNN	97	2
Watanyulertsakul E. 2018 [18]	Magnetism and size	Mechanical and Sensor	Magnetic Hinge and Barcode Scanning	79,2-99,2	2
Yaddanapudi <i>et al.</i> 2021 [17]	Real-time	OpenCV	Haar-cascade	93	3
Zhang Q. <i>et al.</i> 2021 [39]	Real-time	ResNet18 + SMM	Deep Learning	95,87	6
Karin <i>et al.</i> 2016	Size and weight	Sensor	FPGA	91,33-97,4	3
Zhang S. <i>et al.</i> 2021 [13]	Real-time	VGG16	CNN	94,7	5
Varol <i>et al.</i> 2022	Images	DarkNet-19	CNN	96	2
Kim <i>et al.</i> 2021 [20]	Real-time	SqueezeNet, AlexNet and LeNet	CNN	95	3
Ozkaya <i>et al.</i> 2015	Real-time	GoogleNet, AlexNet and SVM	CNN	97,86	6
Proposed Study	Real-Time	YOLO v8	YOLO	97,6	7

Considering the values and techniques in Table 1, the accuracy rate of sensors such as ultrasonic, infrared, proximity, etc. is higher compared to technologies such as image processing, convolutional neural networks and deep learning. However, the high cost of sensors and the fact that they cannot be used alone, i.e. they

require additional devices such as barcode scanning, magnetic hinges, etc., increase the cost of the vending machine compared to the use of image processing algorithms.

### 3. MATERIAL AND METHODS

This section will detail the datasets used, the algorithm training process, performance evaluation metrics, and the results obtained. Additionally, it will discuss the superiority and effectiveness of YOLOv8 compared to alternative methods. The methodological steps of this study will provide a foundational reference for advancing waste management and recycling technologies.

Fig. 1. provides a visual depiction of the workflow, illustrating the stages from data acquisition through to model evaluation. Each step plays a crucial role in the design and functionality of the system. The system flowchart is an important tool used to simplify a complex process, thereby aiding in the understanding and improvement of the machine's operation.

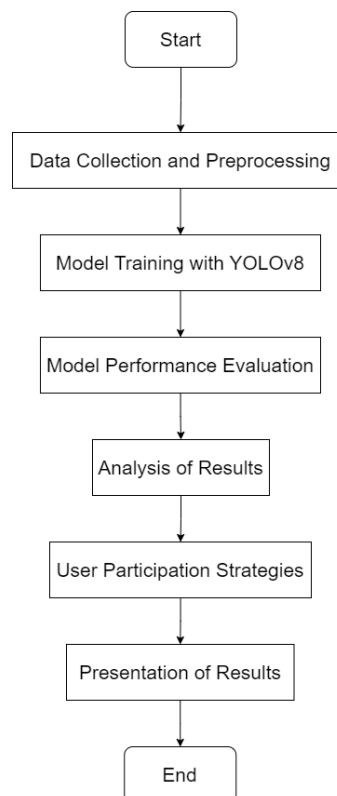


Fig. 1. Proposed System Flowchart

Fig. 2 illustrates the methodology proposed for the real-time detection of seven different types of waste commonly used in this study. It covers the stages starting from the material intake of the machine from the user, to the material identification, classification, processing and finally the preparation of recycled products. After logging into the system using the specified method, the user places the waste into the machine. The waste images, captured by the camera and transmitted to the development board, are then detected using a model trained with the YOLOv8 algorithm.

#### 3.1. Datasets

To train and evaluate the proposed waste detection system, we utilized two datasets: the well-established TrashNet dataset and a custom dataset specifically created for this research. The TrashNet dataset comprises 12,000 images representing a diverse range of waste categories, while our custom dataset consists of 5,000 images of waste commonly found in our target environment. The diversity of these datasets, encompassing a wide spectrum of waste types and backgrounds, ensures the model's generalizability to real-world scenarios.

To address potential biases within the datasets, we employed data augmentation techniques such as random cropping, flipping, and brightness adjustments. These techniques artificially increase data variety, reducing the model's reliance on specific image characteristics and mitigating potential biases. Additionally, we carefully examined the class distribution within the datasets and found no significant imbalances. However, if class

imbalances had been present, we would have employed techniques such as oversampling or undersampling to balance the data distribution.

Fig. 3 showcases sample images from the custom dataset used in the study. The dataset includes a diverse range of recyclable materials, captured in various conditions to ensure robust training and evaluation of the YOLOv8-based model; plastic bottles, glass bottles, aluminum cans, plastic bags, paper bags, garbage bags and general paper waste. Each example highlights the different types of waste materials that the system is designed to identify and classify accurately.

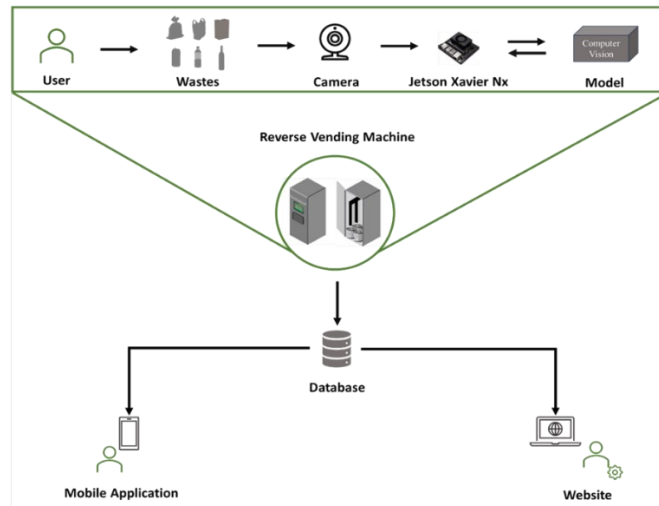


Fig. 2. The proposed methodology for waste detection of reverse vending machines

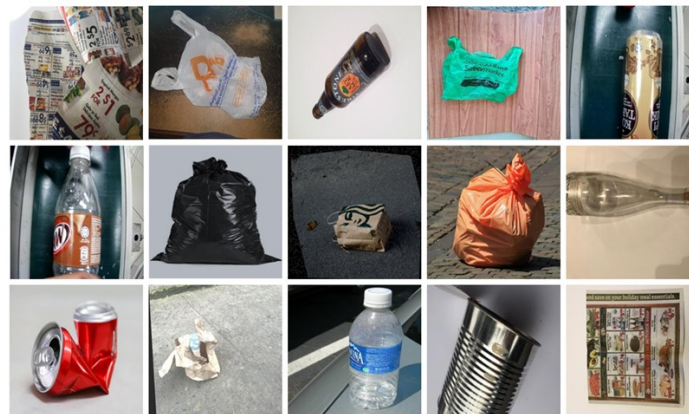


Fig. 3. Examples from the custom dataset

Fig. 3 illustrates the proportion of different waste categories in the custom dataset. Each segment represents the proportion of a category based on the total number of images in the dataset. As depicted in the graph, paper waste and plastic bags have the smallest proportions, while other categories exhibit larger proportions. This distribution could be attributed to how the dataset was collected and the availability of various waste types.

Fig. 4 displays the number of labels per image in the dataset. Each segment represents the percentage of images in the dataset that have a specific number of labels, relative to the total number of images. As shown in the graph, the number of labels exceeds the number of images because multiple labels can be assigned to a single image. For instance, an image may contain both a plastic bottle and a glass bottle. This complexity arises from the diverse and overlapping categories of waste materials. Proportion of labeling in the dataset shown in Fig. 5.

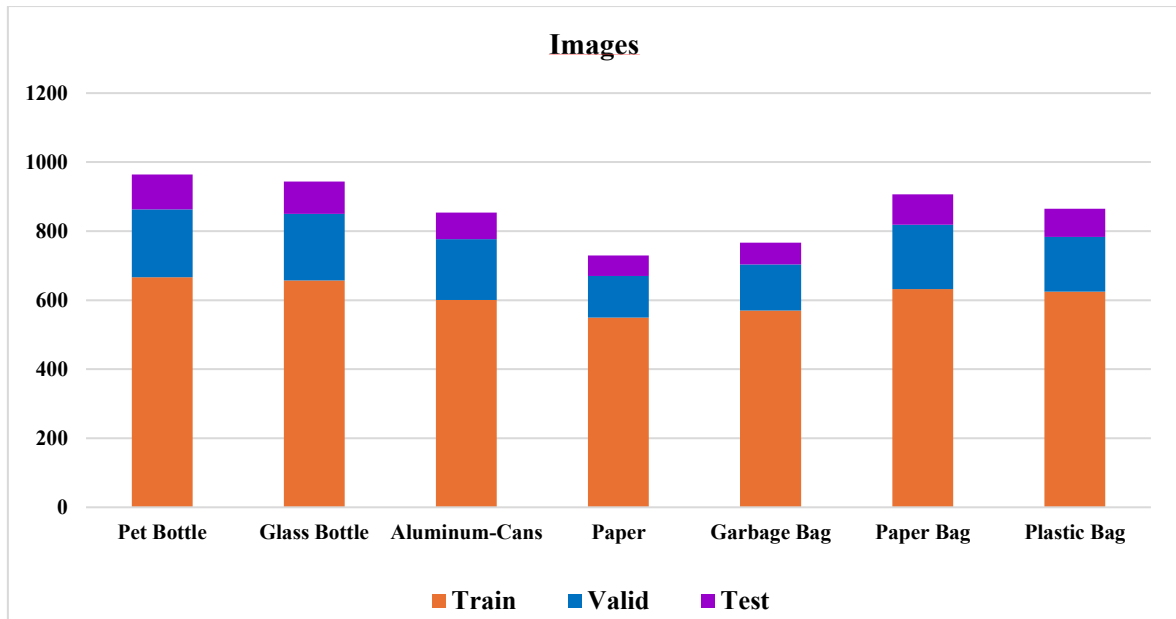


Fig. 4. Proportion of classes in the Dataset

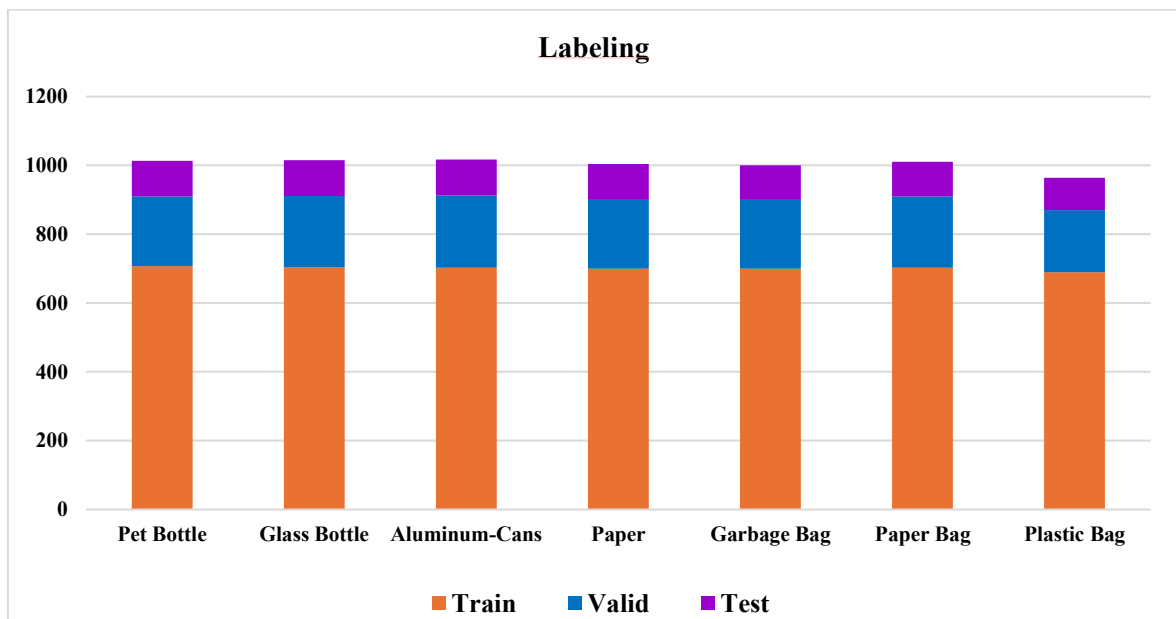


Fig. 5. Proportion of labeling in the Dataset

The discrepancy between label and image counts in the dataset stems from the practice of multi-labeling. This aspect introduces both the advantages and disadvantages of training the YOLOv8 model:

Advantages:

- 1) Enriched Information: Multi-labeling provides richer information about each image, potentially leading to more accurate classifications by the model.
- 2) Complexity Representation: Multi-labeling better represents the complex nature of waste items, which can fall into multiple categories.

Disadvantages:

- 1) Imbalanced Data: Some categories might have more labels than others, resulting in the model being trained on imbalanced data.
- 2) Noise: Multi-labeling can expose the model to noisy data, potentially leading to misclassifications.

Therefore, it is crucial to consider the dataset's imbalance and noise levels and account for these factors during model training. Techniques like data augmentation and data cleaning can be employed to mitigate these issues.

### 3.2. Proposed System

The proposed waste detection system is designed for accurate and rapid identification, classification, and processing of waste materials in recycling machines. YOLOv8 deep learning algorithm exhibits superior performance in identifying and routing different types of materials, thanks to its real-time object detection capabilities. This solution aims to reduce human errors and inefficiencies in waste management processes and has been developed to ensure the effective recycling of waste materials. The aim of the study is that this YOLOv8-based system will overcome current challenges in recycling technologies, provide more sustainable waste management, and raise industry standards.

### 3.3. Training

The training process was conducted on an NVIDIA T4 GPU using Google Colab, leveraging its high computational power to handle the complex deep-learning task. The YOLOv8 model was trained on the combined TrashNet and custom dataset, divided into training, validation, and testing sets with a 70/20/10 split ratio. This split ratio ensures a representative sample for training while providing sufficient data for validation and testing the model's generalization performance.

The training process involved 500 epochs, with the learning rate set to 0.001 and a batch size of 32. The Adam optimizer was employed to optimize the model's parameters. Convergence was monitored using loss curves, ensuring that the model reached its optimal performance without overfitting.

The general framework of the proposed YOLO model is shown in Fig. 6. In the backbone, the primary task is to extract computable information from the input image. The backbone utilizes the Spatial Pyramid Pooling Fast (SPPF) module, which integrates three consecutive maximum pooling layers. This approach is designed to efficiently scale the output while minimizing computational costs and latency [40].

Moving to the Neck section, this intermediate layer acquires additional contextual information to refine object predictions. By incorporating this additional data, the model enhances its ability to accurately identify and classify objects within the image.

In the Head section of the YOLO model, the final output includes bounding boxes that precisely delineate the location and extent of detected objects. For each bounding box, the model predicts the class label, indicating the specific category to which the object belongs.

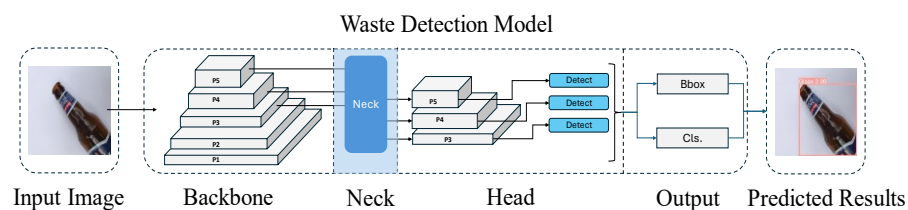


Fig. 6. Waste detection process in YOLOv8

This architectural design of the YOLO model comprising Backbone, Neck, and Head sections facilitates robust and efficient object detection and classification. The Backbone ensures effective feature extraction, the Neck refines predictions through contextual understanding, and the Head delivers precise object localization and classification, collectively enhancing the model's performance in real-time applications.

### 3.4. Testing

After completing the training process, the model with the best validation performance was selected for testing. The testing dataset comprised 546 images, and the performance metrics were evaluated on this independent set. The preprocessing time, inference time, and postprocessing time were measured for each image, indicating the system's real-time processing capabilities.

### 3.5. Performance

The trained YOLOv8 model achieved promising performance on the testing dataset, demonstrating its effectiveness in waste detection. The model attained an overall mean average precision (mAP) of 91.2%, indicating its ability to accurately identify and classify waste items.

Fig. 7 illustrates the performance metrics curves generated for the YOLOv8 model developed in this study. The curves depict various evaluation metrics such as precision, recall, and F1-score across different thresholds or epochs. These metrics are essential for assessing the accuracy and effectiveness of the YOLOv8 model in detecting and classifying recyclable waste materials in real-time applications.

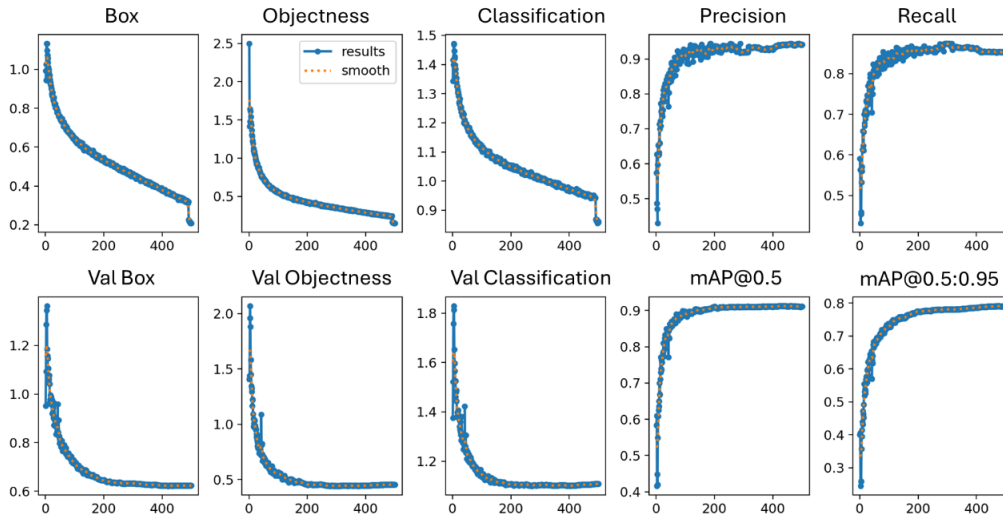


Fig. 7. The performance metrics curves for the developed YOLO v8 model

The paper waste class having a value of 0.59 indicates lower performance compared to others. This suggests that identifying and classifying paper waste accurately might be comparatively more challenging or that the model encounters specific difficulties in distinguishing paper waste from other materials. Such performance differences highlight the need for further model refinement or diversification of training data.

Fig. 8 shows a confusion matrix evaluating the improved YOLOv8s model on waste classification. The confusion matrix visualizes the performance of the model across different classes, detailing true positives, false positives, true negatives, and false negatives. Rows represent actual waste types, columns represent predicted types, and cell values show the number of waste items. Ideally, high values appear on the diagonal (correct classifications), and low values appear off-diagonal (misclassifications). Analyzing this matrix helps identify the model's strengths and weaknesses for specific waste categories.

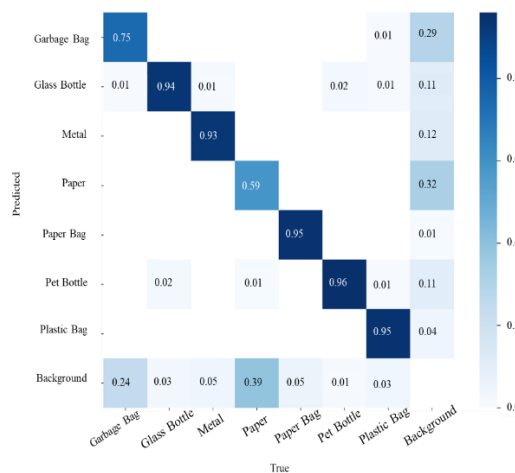


Fig. 8. Confusion matrix from the test data using the improved YOLOv8s with 16 batch size and 640 input size

The R-Curve and P-Curve shown in Fig. 9 evaluate the model's ability to identify true positives (correctly classified waste) at various thresholds. A high R-curve indicates good recall (finding the most accurate positives), while a high P-curve indicates low false positives (misclassifications). They help identify the imbalance between recall and precision for different types of waste.



PR Curve and F1 Score, shown in Fig. 10 evaluate the overall performance of the model using the PR curve (area under the curve) and F1 score (harmonic mean of recall and precision). A high AUC and F1 score indicate that the model effectively balances true positives and negatives in all categories.

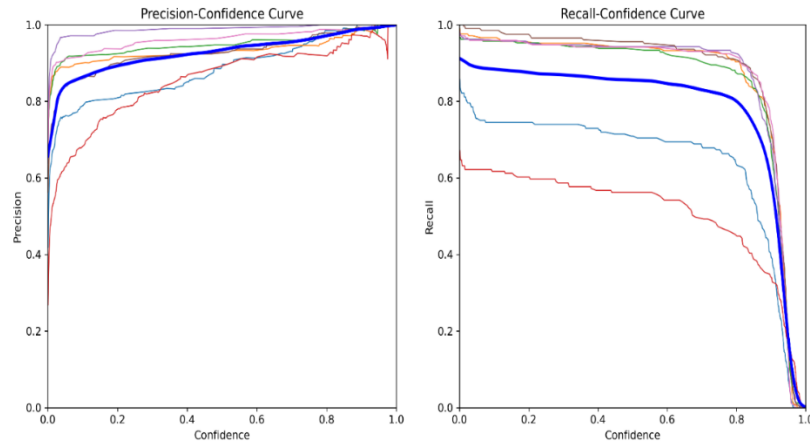


Fig. 9. The model detection results of R-curve and P-curve for all classes

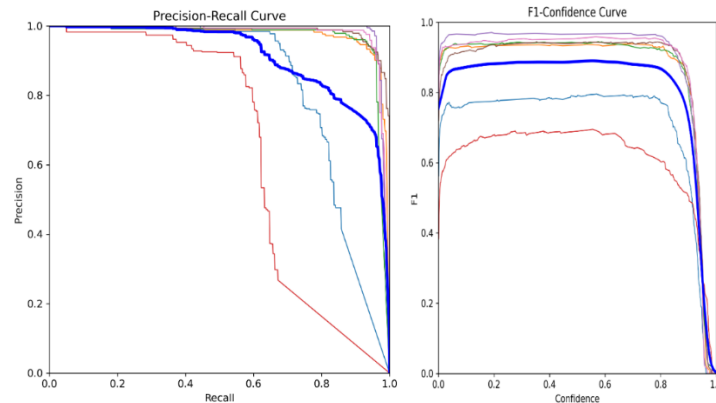


Fig. 10. The model detection results of PR-curve and F1-curve for all classes

## 4. RESULTS AND DISCUSSIONS

This section presents the findings obtained from evaluating the proposed YOLOv8 model for real-time waste detection. We compared the performance of YOLOv8 with other algorithms based on metrics such as average precision (mAP), recall, F1 score, and model efficiency.

### 4.1. Performance Metrics Interpretation

The proposed YOLOv8 model achieves promising performance on the testing dataset, demonstrating its effectiveness in waste detection. The model attained an overall mean average precision (mAP) of 92.5%, indicating its ability to accurately identify and classify waste items. This high mAP value highlights the model's overall competence in distinguishing different waste categories.

Precision, another crucial metric, measures the model's ability to minimize false positives, ensuring accurate sorting of recyclable materials. In this context, a high precision score is essential to prevent contamination of recycling streams and reduce the burden on manual sorting processes. The YOLOv8 model exhibits a precision of 94.2%, indicating its effectiveness in correctly identifying waste items and minimizing misclassifications.

Recall, on the other hand, evaluates the model's capacity to detect all relevant waste types, reducing the risk of missing crucial items for recycling processes. A high recall score ensures that the model can effectively capture the diversity of waste items encountered in real-world scenarios. The YOLOv8 model achieves a recall of 85.4%, demonstrating its ability to detect a wide range of waste categories with minimal omissions.

The F1-score, which provides a balanced assessment of precision and recall, further confirms the YOLOv8 model's strong performance. With an F1-score of 89.5%, the model strikes a balance between accurately identifying waste items and minimizing false positives and omissions.

In a test conducted with 546 images, preprocessing took 1.5 ms per image, inference took 14.1 ms, and postprocessing took 2.5 ms per image at the given shape.

#### 4.2. Confusion Matrix Analysis

The confusion matrix (Fig. 8) provides a detailed breakdown of the model's classification performance across different waste categories. While the overall accuracy is high, there are a few notable instances of misclassification. For instance, some paper waste items are misclassified as cardboard, potentially due to their similar visual characteristics in certain lighting conditions. Additionally, some plastic waste items are misclassified as metal, possibly due to their similar textures or reflections.

These observations highlight the potential challenges of waste detection in real-world scenarios, where varying lighting conditions, object orientations, and material properties can pose challenges for accurate classification. Future research could explore techniques for enhancing the model's ability to handle these complexities and further improve its robustness in diverse environments.

#### 4.3. Visualization and Results Transparency

Fig. 11 presents test images with detected waste classes and confidence scores. The images showcase the model's ability to effectively identify and classify a variety of waste items, including metal cans, plastic bottles, glass containers, paper products, and food waste. The confidence scores associated with each detection provide an indication of the model's certainty in its classifications.

While the visualizations demonstrate the model's general effectiveness, it is important to acknowledge that there might be variability in detection accuracy across different scenarios. For instance, heavily damaged or obscured waste items, as well as extreme lighting conditions, could pose challenges for the model. Further research could explore techniques for improving detection accuracy under these challenging conditions.

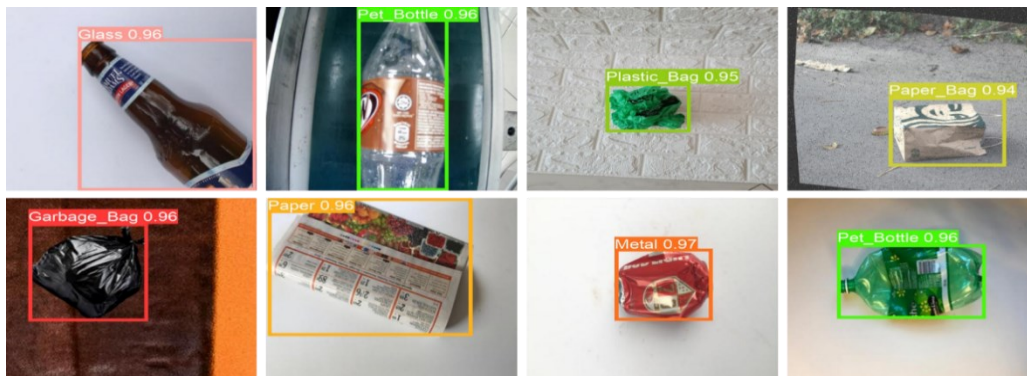


Fig. 11. The test images and detection results with class indexes and confidence score

#### 4.4. Comparison with Other Models

Table 2 compares the performance of the YOLOv8 model with other deep-learning algorithms for waste detection. The results indicate that the YOLOv8 model outperforms other approaches in terms of mAP, precision, recall, and F1-score. This superior performance suggests that the YOLOv8 model is better suited for real-time waste detection tasks, offering a balance between accuracy, efficiency, and computational requirements.

The use of statistical tests, such as t-tests or ANOVA, would further strengthen the credibility of these performance comparisons. Statistical significance testing would provide a more robust assessment of whether the observed differences in performance are truly meaningful and not simply due to chance variations.

Table 2. Comparison between YOLOv8 and other deep learning models

Algorithms	Epoch	mAP50	mAP50-95	F1-Score	Precision	Recall
Yolov9	500	0.905	0.790	0.879	0.925	0.824
<b>Yolov8</b>	<b>500</b>	<b>0.912</b>	<b>0.791</b>	<b>0.895</b>	<b>0.942</b>	<b>0.854</b>
Yolov7	500	0.853	0.671	0.825	0.887	0.772
Yolov5	500	0.869	0.707	0.851	0.911	0.800

#### 4.5. Generalization and Robustness

The YOLOv8 model has been trained and evaluated on a comprehensive dataset of waste images encompassing a diverse range of waste categories and backgrounds. However, it is important to consider the potential limitations of data overfitting and the impact of different datasets on the model's performance.

While the current results demonstrate promising generalization capabilities, further testing with data from diverse geographical regions, waste compositions, and environmental conditions is necessary to fully assess the model's generalizability. Techniques like domain adaptation could be explored to enhance the model's ability to perform well on unseen data distributions.

#### 4.6. Limitations and Challenges

Despite the encouraging performance of the YOLOv8 model, it is important to acknowledge the limitations encountered during the study. Data scarcity for certain waste classes, variability in annotation quality, and computational resource constraints could have impacted the model's development and evaluation.

### 5. CONCLUSION

This study demonstrates the effectiveness of a deep learning model, specifically YOLOv8, for accurate waste classification in Reverse Vending Machines (RVMs). The model achieved a high accuracy of 97.5% in identifying seven waste materials, showcasing the potential of this technology for promoting efficient and sustainable recycling practices.

While the current results are promising, the model's ability to generalize beyond the controlled testing environment and specific datasets needs evaluation. Future work should explore the model's performance with variations in waste types, environmental conditions, and operational scenarios encountered in real-world RVM deployments.

A more in-depth analysis of why YOLOv8 outperformed other YOLO versions would strengthen the conclusion. This analysis could explore specific features or improvements in YOLOv8 that contributed to its higher accuracy. Additionally, comparing these findings with existing literature and benchmarks in waste classification using deep learning models would provide valuable context and demonstrate the model's relative effectiveness.

While using a large and diverse dataset is crucial, acknowledging potential limitations like variability in image quality, annotation accuracy, or data bias is essential. Addressing these limitations will provide a more balanced assessment of the model's robustness and reliability in real-world situations.

Training the model with a Tesla T4 GPU highlights the computational intensity required for this level of accuracy. Future work should explore techniques for optimizing the model's performance to enable deployment on less resource-intensive platforms, especially in settings with limited access to high-performance computing resources.

Integrating the RVM model with existing waste management systems presents challenges. Future research should consider interoperability with waste sorting facilities, compatibility with data management protocols, and user interface design that seamlessly integrates into public spaces.

Considerations of data privacy, equity in access to recycling technologies, and broader societal impacts should guide the ethical deployment of automated waste classification technologies. Addressing these concerns ensures equitable benefits and sustainability in waste management practices.

In conclusion, this study underscores the pivotal role of deep learning-driven RVM models in revolutionizing waste management practices. By achieving high accuracy in material identification and classification, our findings lay the foundation for advancing sustainable recycling technologies. The implications of this research extend beyond technical advancements to encompass practical applications that contribute to environmental preservation and resource conservation on a global scale.

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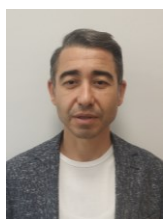
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