



Comparative Evaluation of Deep Learning Models for Real-Time Waste Classification

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Abstract

Waste management has become a pressing global challenge due to rapid urbanization and population growth, leading to increased environmental pollution and resource depletion. Automating waste segregation using deep learning can significantly improve recycling efficiency and reduce manual labor. In this study, five deep learning models: YOLOv8, YOLOv5, MobileNetV2, Single Shot Multibox Detector (SSD), and Google's pre-trained EfficientNet, were evaluated for real-time waste detection and classification. A dataset consisting of 15,150 images across 12 waste categories was used for training and testing, representing common household waste materials and evaluated using real-world objects such as water bottles, glass bottles, cans, and used face masks. Testing was conducted on both a high-performance workstation and a Raspberry Pi 4 edge device to assess detection accuracy, inference speed, and practical deployment feasibility. The results indicate that YOLOv8 achieved the highest average accuracy of 83% with reliable performance across diverse object types, whereas EfficientNet achieved moderate accuracy of approximately 60% with higher inference latency. Lightweight models such as MobileNetV2 and SSD were computationally efficient but exhibited lower accuracy, at 42% and 41%, respectively, particularly when handling irregular or overlapping objects. These findings demonstrate that YOLOv8 provides the most effective balance between accuracy and real-time performance, making it well suited for intelligent waste sorting systems.

Keywords: deep learning; EfficientNet; MobileNetV2; Raspberry Pi; single shot multibox detector (SSD); waste management; YOLOv8

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1. Introduction

The rapid increase in municipal solid waste has intensified environmental concerns, making efficient waste segregation an essential component of sustainable waste management practices. Global reports and recent studies highlight that improper waste handling contributes significantly to environmental pollution, greenhouse gas emissions, and public health risks, particularly in densely populated urban areas [1], [2]. Existing waste sorting processes continue to depend largely on manual inspection, resulting in limited scalability, inconsistent classification, and considerable labor requirements. As a result, automated and

intelligent waste classification systems have gained increasing attention.

Early research demonstrated that visual information extracted from waste images can be utilized to automate waste classification, reducing reliance on manual sorting processes [3]. These studies established that waste materials exhibit distinguishable visual characteristics that can be captured using computer vision techniques. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the dominant paradigm for waste classification, significantly outperforming traditional image processing pipelines, particularly for recyclable materials such as plastic, metal, and glass [4]. CNN

architectures automatically capture multi-level visual representations from raw images, allowing them to perform reliably under diverse imaging conditions [2].

To support deployment in practical environments, especially on embedded and edge devices, lightweight CNN architectures have been widely explored. MobileNetV2 has demonstrated competitive performance in waste recognition tasks by providing an effective compromise between prediction accuracy and computational complexity [5]. In addition, studies have shown that architectural optimization, preprocessing strategies, and training refinements can further enhance CNN performance on multi-class waste datasets [6], [7]. Beyond local image classification, deep learning techniques have also been extended to large-scale waste monitoring scenarios, including the use of aerial and satellite imagery for regional-scale environmental assessment [8]. However, the limited availability of labeled waste datasets remains a challenge, motivating the adoption of transfer learning using scalable pre-trained models such as EfficientNet to improve accuracy while reducing training time and data requirements [9].

In parallel with classification-based approaches, real-time object detection models have become increasingly important for automated waste segregation systems that require both localization and classification. One-stage detectors are particularly attractive for real-time deployment due to their computational efficiency. The Single Shot Multibox Detector (SSD) is a foundational one-stage detection framework that performs localization and classification in a single forward pass, making it a common baseline for real-time detection on

resource-constrained platforms [10]. Building upon this framework, SSD-based variants have been proposed specifically for garbage detection, incorporating feature fusion and multi-scale representations to improve detection accuracy while maintaining lightweight computation [11-13]. Recent developments have shown that the YOLO-based of object detectors offers excellent real-time detection capability while maintaining high computational efficiency in smart-bin and embedded environments [14-16], with newer versions such as YOLOv5 and YOLOv8 offering improved speed-accuracy trade-offs compared to earlier detection architectures [17], [18].

Several studies have further focused on electronic waste and intelligent waste segregation systems, which introduce additional challenges due to complex object shapes, small components, and heterogeneous material compositions. Deep learning-based approaches have been shown to significantly improve the identification and separation of e-waste components compared to conventional methods [19-21]. System-level implementations, including automated segregation machines, smart waste bins, and real-time monitoring systems, demonstrate the practical feasibility of deploying deep learning models in real-world environments [22-25]. Cloud-based deep learning frameworks have also been proposed to support scalable and integrated waste management solutions [26]. The architectural characteristics and performance considerations of the evaluated deep learning models are summarized in Table 1.

Table 1. Architectural characteristics of evaluated deep learning models

Model	Architecture Type	Detection/Classification	Key Strength	Limitation	Edge Deployment Suitability
YOLOv8	One-stage object detector (anchor-free)	Detection	High accuracy; strong multi-scale; robust localization.	Higher computational cost than lightweight models.	High
YOLOv5	One-stage object detector with CSP backbone (anchor-based)	Detection	Fast inference; stable performance; good speed-accuracy balance	Slightly lower accuracy than YOLOv8.	High
Google's pre-trained EfficientNet	Compound-scaled convolutional neural network (CNN)	Classification	Strong feature extraction; effective transfer learning (e.g., ImageNet)	Not designed for object localization.	Medium
MobileNetV2	Lightweight CNN with depthwise separable convolutions	Classification	Low computational cost; optimized for mobile/edge devices	Less robust in cluttered or occluded scenes.	Very High
SSD (Single Shot MultiBox Detector)	One-stage object detector (anchor-based)	Detection	Fast detection; simple architecture.	Lower accuracy for small or irregular objects.	Medium

Despite significant progress in deep learning-based waste classification, existing studies still exhibit several important limitations. Most previous works focus only on single-model evaluation, classification-only frameworks, or controlled laboratory conditions that do

not accurately represent real-world deployment scenarios. Furthermore, limited research has conducted comprehensive comparisons between lightweight classification models and real-time object detection models under identical testing conditions, particularly

on resource-constrained edge devices such as the Raspberry Pi 4. Existing studies also often prioritize benchmark accuracy while providing limited discussion on practical deployment feasibility, inference efficiency, and robustness under varying environmental conditions such as lighting changes, background clutter, and object occlusion. Therefore, a practical comparative evaluation integrating accuracy, real-time performance, and edge-device deployment remains necessary.

Building upon these prior works, this study presents a comparative evaluation of YOLOv8, YOLOv5, MobileNetV2, SSD, and Google's pre-trained EfficientNet for automated waste classification. This study addresses the identified research gap by comparing both detection and classification-based models. We focus on detection accuracy, inference speed, and suitability for real-time deployment on edge devices, particularly the Raspberry Pi 4. The results aim to provide practical insights for selecting efficient and scalable deep learning models for automated waste sorting systems in urban environments.

2. Methods

This study follows a structured research methodology, as illustrated in Figure 1, consisting of five main steps: data collection, data preprocessing, model training, testing, and evaluation.

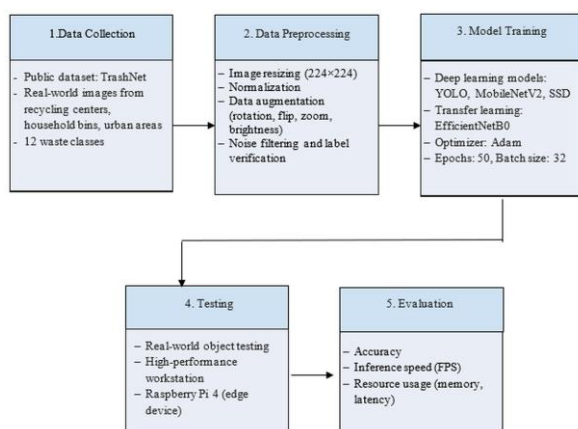


Figure 1. Research methodology

2.1 Data Collection

The dataset used in this study was sourced from both publicly available repositories and real-world image collections to ensure diversity and representativeness. Public datasets, including the well-known TrashNet dataset [27], which contains 2,527 images across six waste categories glass, paper, cardboard, plastic, metal, and mixed trash were used as a foundation for labeled waste categories. To enhance realism, an additional 12,623 images were collected from recycling centers, household waste bins, and urban disposal areas, capturing variations in lighting conditions, backgrounds, and clutter levels typically encountered in real-world environments. Sample images from the additional dataset are illustrated in Figure 2.

Although the TrashNet dataset originally consists of six broad categories, this study adopts a finer-grained class definition to better reflect real-world waste segregation requirements. In particular, the glass category was subdivided into green glass, brown glass, and white glass due to differences in material composition and recycling processes. Furthermore, additional classes such as clothes, shoes, batteries, and biological waste were introduced based on waste items frequently observed during real-world data collection.

In total, 15,150 images covering 12 distinct classes of household waste were utilized for training and evaluation. These classes include paper, cardboard, biological waste, metal, plastic, green glass, brown glass, white glass, clothes, shoes, batteries, and mixed trash. This combination of curated and naturally captured data ensures a balanced and comprehensive dataset, enabling deep learning models to better generalize to practical waste classification scenarios. During real-world testing, specific waste items such as face masks, plastic spoons, and plastic bags were evaluated as representative objects and were categorized under the corresponding dataset classes, primarily 'mixed trash' or 'plastic', depending on their material characteristics.

The complete dataset was divided into training, validation, and testing sets using a ratio of 70%, 15%, and 15%, respectively. The split was performed randomly while ensuring a balanced distribution of samples across all waste classes. The validation set was used for model tuning and early stopping, whereas the testing set was reserved exclusively for final performance evaluation.



Figure 2. Sample images from the dataset, representing various waste categories, (a) plastic bottle, (b) paper, (c) metal, (d) white glass, (e) mixed trash, (f) biological waste, (g) batteries, (h) brown glass, (i) cardboard, (j) clothes, (k) green glass, (l) shoes

2.2 Data pre-processing

Prior to model training, several preprocessing activities were applied to the dataset to improve its suitability for model learning, including:

The preprocessing stage included image resizing to 224×224 pixels, normalization of pixel values to the [0,1] range, data augmentation through random rotation, horizontal flipping, zooming, and brightness adjustment, and filtering of low-quality or mislabeled images. These preprocessing steps collectively ensured a clean, diverse, and well-structured dataset, enabling the deep learning models to achieve better generalization and improved robustness when deployed in real-world waste classification scenarios.

2.3 Training

The training process was conducted using a high-performance computing environment capable of supporting deep learning workloads efficiently. Most of the models used in this study, including YOLO, MobileNetV2, and SSD, were trained from scratch using the collected waste classification dataset. This approach enabled fine control over model architecture and training dynamics, allowing optimization specifically for waste detection tasks.

In contrast, Google's pre-trained models, such as EfficientNetB0, were fine-tuned using transfer learning. By leveraging weights pre-trained on large-scale datasets (e.g., ImageNet), these models benefited from improved generalization and faster convergence when adapted to the waste classification domain.

Key training parameters were as follows:

The models were trained using the Adam optimizer with a learning rate of 0.001, batch size of 32, and 50 training epochs. Cross-entropy loss was used for classification tasks, while IoU-based loss functions were used for object detection tasks.

During training, early stopping was applied to prevent overfitting by monitoring validation loss. The models were trained using GPU acceleration on a high-performance workstation equipped with CUDA-enabled hardware. For YOLO-based models, default augmentation and anchor optimization strategies provided by the Ultralytics framework were utilized. The classification models employed softmax activation in the output layer for multi-class prediction across the 12 waste categories.

Model training was implemented using both TensorFlow and PyTorch frameworks, chosen based on the compatibility and flexibility required for each model. This combination allowed efficient experimentation while ensuring reproducibility across different architectures.

2.4. Testing

For real-time testing, inference was performed using live camera input with single-object and multi-object

waste scenarios. Each model was evaluated under identical environmental conditions to ensure fair comparison. Average detection accuracy was computed from repeated testing trials conducted across multiple object orientations and lighting conditions.

To evaluate the effectiveness of each model in practical scenarios, testing was conducted using real-time waste classification with actual physical objects such as plastic bottles, glass bottles, metal cans, paper, and other household waste items. The models were deployed in a setting that mimicked real-world conditions, including variable lighting, background clutter, and different object orientations, to assess their robustness beyond controlled datasets, as shown in Figures 3–5.

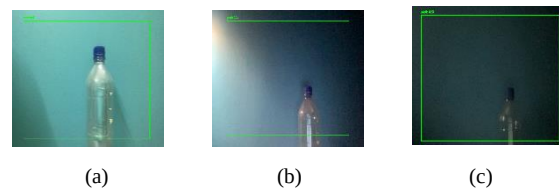


Figure 3. Effect of lighting conditions on waste object detection: a) bright lighting, b) dim lighting, and c) uneven lighting.

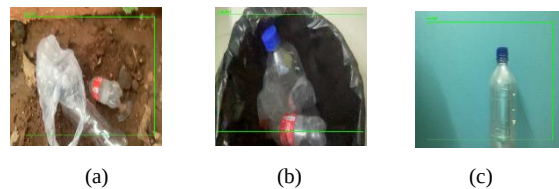


Figure 4. Impact of different background conditions on waste object detection: a) ground surface, b) inside a dustbin, and c) plain background.

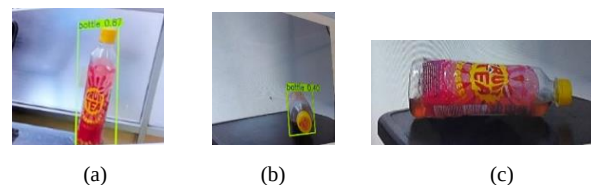


Figure 5. Examples of object positions: (a) upright, (b) frontal view, and (c) tilted orientation.

In addition to testing on a high-performance workstation, the models were also deployed on a Raspberry Pi 4 Model B (4 GB RAM) to evaluate their suitability for low-cost, edge-based implementations such as IoT-enabled smart bins, as shown in Figure 5. The test on the Raspberry Pi focused on assessing inference speed (frames per second), memory consumption, and overall responsiveness, which are critical for real-time embedded applications.

Performance metrics including detection accuracy, inference latency, and resource utilization were evaluated on both a high-performance workstation and a Raspberry Pi 4 edge device to assess real-time deployment feasibility. This dual evaluation ensured that the models not only achieved high detection accuracy in a standard computing environment but also maintained acceptable performance and efficiency when deployed on resource-constrained edge devices.

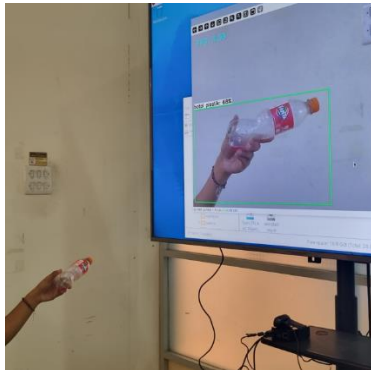


Figure 5. Real-world testing setup using Raspberry Pi and camera

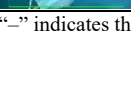
3. Results and Discussions

The performance of each model was evaluated using various real-world waste objects, including water bottles, cups, pop bottles, plastic bags, plastic spoons, cans, glass bottles, and face masks. Five deep learning models, YOLOv8, YOLOv5, Google's pre-trained EfficientNet, MobileNetV2, and SSD, were evaluated

under real-world conditions. While YOLOv5 demonstrated fast inference and stable detection for rigid objects such as cups and pop bottles, its overall average accuracy was lower than that of YOLOv8, particularly for small or flexible objects. Table 2 presents the test results obtained from these real-world objects, highlighting clear variations in detection accuracy across different models and object types. The reported results are based on object-level testing, where individual waste items were mapped to their corresponding dataset classes.

YOLOv8 consistently achieved the highest detection accuracy across most categories. For instance, it detected water bottles with 98% accuracy, glass bottles with 96% accuracy, and cans with 89% accuracy. Even for more challenging items like face masks and plastic spoons, YOLOv8 maintained reasonably high detection performance at 79% and 86%, respectively. Its superior results demonstrate the strength of YOLOv8 in both precision and generalization for diverse waste objects.

Table 2. Object-level detection accuracy under real-world testing

Object	Picture	Models				
		YOLOv8	Google Pre-trained Model (EfficientNet)	YOLOv5	MobileNetV2	SSD
Water bottle		98%	79%	83%	81%	56%
Cup		74%	81%	86%	36%	61%
Pop Bottle		91%	52%	88%	62%	56%
Plastic Bag		86%	-	-	83%	-
Plastic Spoon		86%	-	34%	-	-
Cans		89%	58%	35%	-	56%
Glass bottle		96%	61%	85%	63%	54%
Face Mask		79%	-	-	86%	-

Note: The symbol “-” indicates that the corresponding model did not produce a valid detection for the object under the tested conditions.

Table 3. Dataset-level performance comparison of the evaluated models

Rank	Model	Average Accuracy	Speed & Precision	Device Performance
1	YOLOv8	83%	High speed; high precision; effective for real-time sorting.	Runs smoothly on workstation; ~3-4 times slower but usable on Raspberry Pi 4
2	Google-Pre-trained (EfficientNet)	60%	Slightly lower; consistent under varied conditions.	Moderate latency on workstation; slower but functional on Raspberry Pi 4.
3	YOLOv5	42.33%	Fast; stable; lower accuracy than YOLOv8	Real-time on workstation; borderline responsive on Raspberry Pi 4
4	MobileNetV2	42%	Efficient; suitable for low-power devices; limited in complex scenes.	Well-suited for Raspberry Pi 4; low resource usage.
5	SSD	41%	Very fast; less reliable in real-world scenarios.	Fast on both devices; lower accuracy.

Tables 2 and 3 represent different evaluation perspectives. Table 2 reports object-level detection accuracy obtained from real-world testing using a limited set of representative waste items to demonstrate practical model behavior. In contrast, Table 3 presents the average classification accuracy computed over the entire test dataset across all 12 waste classes. As a result, the average values reported in Table 3 are not derived by averaging the object-level accuracies shown in Table 2. For example, the 83% average accuracy reported for YOLOv8 reflects its performance across all test samples and classes, whereas the higher value obtained by manually averaging Table 2 results corresponds only to a subset of tested objects and does not represent overall dataset-level performance.

Object	Picture	Models				
		YOLOv8	Google Pre-trained Model (EfficientNet)	YOLOv5	MobileNetV2	SSD
Water bottle		98%	79%	83%	81%	56%
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Pop Bottle		91%	52%	88%	62%	56%
Plastic Bag		86%	-	-	83%	-
Plastic Spoon		86%	-	34%	-	-
Cans		89%	58%	35%	-	56%
Glass bottle		96%	61%	85%	63%	54%
Face Mask		79%	-	-	86%	-

Due to the real-time and application-oriented focus of this study, performance evaluation emphasizes detection accuracy and inference efficiency rather than benchmark-oriented metrics such as mAP. In addition, the evaluation is conducted using real-world testing scenarios and edge-device deployment, which prioritize practical performance over standardized benchmark comparisons.

Google pre-trained EfficientNet model showed mixed performance. It achieved 79% accuracy for water bottles and 81% for cups but struggled with more irregular or flexible objects such as plastic bags and face masks, which it failed to identify. Similarly, YOLOv5 produced moderately high accuracy for some objects

like cups (86%) and pop bottles (88%), but its performance dropped significantly for smaller or ambiguous items, e.g., cans (35%) and face masks (unidentified).

MobileNetV2, while lightweight and efficient, showed a trade-off in accuracy. It performed well for face masks (86%) and water bottles (81%), but its detection was inconsistent for more complex objects like plastic spoons or cans, where it failed to recognize them entirely. SSD achieved the lowest overall performance, with relatively lower detection accuracy (e.g., 56% for water bottles and cans, and 54% for glass bottles) and failed to classify several smaller or less distinct items.

When analyzing object-specific performance, rigid and well-defined objects like water bottles, cups, and glass bottles were classified more reliably by most models. However, flexible and less structured objects such as plastic bags, spoons, and face masks posed challenges, leading to reduced accuracy or unidentified classifications in lightweight models like MobileNetV2 and SSD.

Overall, the experimental findings indicate that YOLOv8 offers the most reliable solution for practical real-time waste detection applications. Although pre-trained models like EfficientNet and lighter architectures such as MobileNetV2 are beneficial for low-resource devices, they exhibit reduced robustness in detecting irregular or occluded objects. The findings obtained in this work are consistent with recent studies highlighting the effectiveness of YOLO-based architecture for automated waste recognition. Midgudla et al. [17] reported that YOLOv8 achieved superior detection accuracy compared to EfficientDet and Detectron2 in waste segregation tasks, particularly under complex environmental conditions. Similarly, Abo-Zahhad and Abo-Zahhad [18] highlighted the strong real-time monitoring capability of YOLOv8 and YOLOv5 for intelligent waste management systems. Compared to these studies, the present work further extends evaluation by incorporating both lightweight classification models and edge-device deployment analysis using Raspberry Pi 4. The results also confirm that lightweight models such as MobileNetV2 provide computational efficiency but exhibit reduced robustness for irregular and partially occluded objects, which aligns with observations reported in [5] and [7].

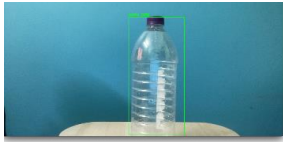
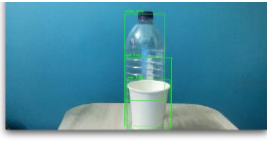
Table 3 summarizes the average performance of the five tested models, highlighting their accuracy, speed, and suitability for different deployment scenarios. YOLOv8 ranked first, achieving the highest average accuracy of 83%, with high speed and precision that make it highly effective for real-time waste sorting. It runs smoothly on a high-performance workstation and, while approximately 3-4 times slower on a Raspberry Pi 4, remains usable for edge deployment. Google pre-trained EfficientNet model ranked second, with an average accuracy of 60%. Although slightly less responsive than YOLO-based models, it maintained consistent performance under varied lighting and

background conditions. However, it showed moderate latency on a workstation and slower inference on Raspberry Pi 4, though it remained functional. YOLOv5 achieved 42.33% average accuracy, ranking third. It offered fast and stable detection on a workstation but exhibited noticeably lower accuracy compared to YOLOv8. On Raspberry Pi 4, its responsiveness was borderline for real-time applications. MobileNetV2, ranking fourth with 42% average accuracy, was the most resource-efficient model, making it suitable for low-power devices like the Raspberry Pi 4. However, it showed limitations in handling complex environments and was less reliable for detecting irregular or overlapping waste objects. Finally, SSD ranked last with 41% average accuracy. While it delivered very fast detection speeds on both workstation and Raspberry Pi 4, its reliability and precision were significantly lower, making it less suitable for accurate waste classification.

Overall, these results indicate that YOLOv8 offers the best balance of accuracy and speed for practical waste

classification, whereas lighter models such as MobileNetV2 and SSD are preferable only when computational efficiency and low-power deployment are prioritized over detection precision. To further evaluate model robustness, an additional experiment was conducted under partial occlusion conditions, where approximately 20–40% of the object was intentionally obstructed, simulating common real-world waste sorting scenarios. As shown in Table 4, detection-based models such as YOLOv8 and YOLOv5 were still able to correctly detect the object and maintain relatively stable bounding box localization despite the obstruction. This robustness is attributed to their spatial localization and multi-scale feature extraction mechanisms. In contrast, classification-based models such as EfficientNetB0 (Google-pretrained) and MobileNetV2 showed reduced performance when distinctive object features were partially hidden. These findings indicate that detection-based models are more robust to occlusion, making them more suitable for practical waste sorting systems operating in dynamic and cluttered environments.

Table 4. Comparison of detection results for original and partially occluded images.

Models	Original Images	Result	Occluded Images	Result
YOLOv8		Bottle: 89%		Bottle: 87% Cup: 60%
YOLOv5		Bottle: 79%		Bottle: 73% Cup: 87%
MobileNetV2		Bottle: 58.22%		Bottle: 76.35% Cup: Unknown
SSD		Bottle: 54%		Bottle: 58% Cup: 68%
Google Pre-trained Model (EfficientNet)		Bottle: 60%		Bottle: 63% Cup: 53%

4. Conclusions

This work presented a comparative assessment of five representation deep learning architectures to determine their suitability for real-time waste classification under practical deployment scenarios: YOLOv8, YOLOv5, MobileNetV2, SSD, and Google's pre-trained

EfficientNet. A dataset of 15,150 images across 12 waste categories was used to train and test the models on both a high-performance workstation and a Raspberry Pi 4 edge device. The results demonstrated that YOLOv8 consistently outperformed the other models, achieving the highest average accuracy of 83% and reliably detecting both rigid objects (e.g., bottles

and cans) and more challenging flexible items such as face masks and plastic spoons.

In comparison, EfficientNet achieved moderate accuracy (60%), offering the advantage of transfer learning but exhibiting higher latency on embedded devices. YOLOv5 showed relatively fast inference but lower accuracy (42.33%) compared to YOLOv8. MobileNetV2 and SSD, while highly resource-efficient and faster on low-power devices, recorded the lowest accuracy (42% and 41% respectively), making them less reliable for precise waste detection.

Overall, YOLOv8 proved to be the most effective model for practical waste sorting systems, balancing speed, accuracy, and deployment feasibility on both high-performance and edge computing environments. Lightweight models remain beneficial in scenarios where computational efficiency is prioritized over high detection precision.

Despite these promising results, this study has several limitations. First, the models showed reduced performance when detecting irregular, flexible, or partially occluded objects, which are common in real-world waste scenarios. Second, deployment on low-power edge devices such as the Raspberry Pi 4 introduces constraints in terms of inference speed and computational efficiency. Third, although the dataset includes diverse waste categories, it may not fully represent all real-world variations, particularly in highly cluttered or complex environments.

Future investigations may emphasize expanding dataset diversity by incorporating a larger variety of waste categories and images captured in more realistic and cluttered environments to improve model generalization. Additionally, model optimization techniques such as quantization and pruning should be explored to reduce computational load, enabling faster and more efficient inference on edge devices like the Raspberry Pi 4 or NVIDIA Jetson Nano. Future work should also include repeated experimental trials and statistical significance testing to further validate the comparative performance of the evaluated models. Finally, integrating the optimized models into IoT-enabled smart waste systems could enhance automation, allowing real-time waste sorting combined with cloud-based monitoring and analytics for large-scale deployment in urban waste management.

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