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Optimizing Waste Classification Model using YOLOv11 Architecture

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Abstract

Municipal solid waste management remains a critical challenge due to rapid urbanization and consumption patterns. This study proposed a image based waste classification model for organic, inorganic, and hazardous (B3) waste using the YOLOv11 architecture. To conduct the study, we gathered a huge dataset of 5,000 images across daylight, dusk, and night conditions. According to experimental results, the proposed model can achieve an mAP@0.5 of 70%, a precision of 69%, a recall of 70%, and an F1-score of 0.70, operating at 43 frames per second (FPS) with 102 GFLOPs. It can confirm its suitability for real-time applications in resource-constrained environments. Compared to heavier deep learning models, this efficiency-performance balance highlights the practical advantage of YOLOv11 for continuous waste monitoring and automated sorting systems.

Keywords:
Waste, Classification, YOLOv11, CNN

1. Introduction

Municipal solid waste management remains a critical global challenge due to rapid urbanization, population growth, and changing consumption patterns. Inefficient waste sorting at the source leads to environmental pollution, increased landfill usage, and higher recycling costs. Manual waste classification is labor-intensive, time-consuming, and prone to human error, especially in large-scale urban environments. As a result, researchers increasingly explore automated waste classification systems based on artificial intelligence to improve sorting accuracy and operational efficiency. Image-based waste classification emerges as a promising solution because it enables non-contact, scalable, and real-time recognition of waste categories. However, existing systems often struggle with complex backgrounds, overlapping objects, and variations in lighting and waste appearance, which limit their deployment in real-world scenarios [1], [3], [5].

Early studies on waste classification rely heavily on conventional machine learning techniques such as support vector machines, k-nearest neighbors, and decision trees. These approaches typically use handcrafted features such as color histograms, texture descriptors, or shape features extracted from images. While these methods demonstrate reasonable performance on small and controlled datasets, they fail to generalize well to complex and diverse waste images. Feature engineering also requires domain expertise and extensive preprocessing, which reduces adaptability. Consequently, traditional machine learning models cannot effectively handle high intra-class variability and inter-

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class similarity commonly found in waste materials, motivating the shift toward deep learning-based solutions [2], [16], [17].

Deep learning models, particularly convolutional neural networks (CNNs), significantly improve waste classification accuracy by learning hierarchical features directly from raw images. Pioneering works using datasets such as TrashNet demonstrate that CNN-based architectures outperform conventional methods by a substantial margin. Pre-trained models such as VGG, ResNet, and EfficientNet further enhance performance through transfer learning, reducing training time and data requirements. Despite these advances, most CNN-based approaches focus solely on image-level classification, which limits their ability to localize waste objects in cluttered environments. This limitation becomes critical for practical applications such as smart bins and robotic sorting systems, where object detection is as important as classification [4], [8], [9].

Recent research shifts toward real-time waste detection and classification using object detection frameworks. Detection-based models enable systems to identify multiple waste objects within a single image and classify them simultaneously. Studies using Faster R-CNN, SSD, and YOLO variants show improved performance in dynamic and complex environments. However, earlier YOLO versions often face challenges related to small object detection, class imbalance, and misclassification between visually similar waste types. These challenges highlight the need for more advanced detection architectures that can achieve higher precision, recall, and inference speed under real-world constraints [7], [11], [12].

Several studies propose enhanced CNN architectures and attention-based mechanisms to address classification ambiguity between organic, recyclable, and hazardous waste. Models such as ECCDN-Net and fusion-based networks integrate multi-scale features and channel attention to improve discrimination performance. While these approaches achieve high accuracy on benchmark datasets, they often involve complex architectures with high computational costs. Such complexity restricts their deployment on edge devices and embedded systems commonly used in waste management infrastructure. Therefore, a balance between model accuracy, computational efficiency, and real-time capability remains a critical research gap [6], [15], [19], [20].

YOLO-based architectures attract increasing attention due to their unified detection framework and real-time performance. YOLO models process images in a single forward pass, making them suitable for time-sensitive waste classification applications. Recent improvements in YOLO architectures demonstrate enhanced feature extraction, better bounding box regression, and improved handling of small objects. Nevertheless, many existing studies apply older YOLO versions or adapt them without systematic optimization for waste classification tasks. This gap opens opportunities to explore newer YOLO architectures, such as YOLOv11, to achieve superior detection accuracy while maintaining computational efficiency [23], [25].

Another significant challenge in waste classification research lies in dataset diversity and real-world variability. Most studies rely on curated datasets captured under controlled conditions, which limits model robustness when deployed in outdoor or semi-structured environments. Variations in waste shape, deformation, contamination, and occlusion frequently degrade classification performance. Citizen science initiatives and real-world image collection efforts emphasize the need for models that generalize well across different regions and waste disposal contexts. Advanced detection-based approaches combined with strong data augmentation strategies are essential to address these challenges effectively [10], [14], [18], [22].

Based on these limitations, enhancing waste classification models using advanced object detection architectures becomes a necessary research direction. YOLOv11 offers potential improvements in feature representation, detection accuracy, and inference speed compared to earlier models. By leveraging its architectural advancements, researchers can address existing challenges related to real-time performance, class imbalance, and complex visual environments. Therefore, investigating YOLOv11 for waste classification contributes not only to technical advancements in computer vision but also to sustainable waste management practices and smart city development [1], [7], [19], [21], [27].

2. Related Works

Waste classification has evolved with deep learning, improving accuracy and automation over traditional methods relying on handcrafted features (e.g., texture, color, shape), which struggled with diverse waste types and lighting variations [15], [16], [17]. Convolutional Neural Network (CNN)-based models like Faster R-CNN achieved mAPs of ~75% but required large datasets and significant computational resources, limiting rapid deployment [18], [19], [20]. YOLOv8-based systems improved real-time performance with mAPs of 80–85% but required extensive fine-tuning and struggled in low-light conditions (mAP < 70%) [7], [8]. Transformer-based models like ViTPose achieved mAPs of 91.8% but required over 200 GFLOPs, making them impractical for resource-constrained settings [13], [14]. MediaPipe-based systems, while lightweight (mAP ~80% in controlled conditions), saw performance drop to 65% in low-light scenarios [19], [20], [21].

This study's YOLOv11-based framework achieves an mAP of 70% on a custom dataset tailored to organic, inorganic, and hazardous waste under diverse lighting conditions. While slightly less accurate than YOLOv8, it offers superior computational efficiency (102 GFLOPs) and robustness across lighting scenarios compared to MediaPipe, balancing cost and performance for real-time waste management[22], [23], [24]. However, these models required large, well-annotated datasets and substantial computational resources, making them less feasible for rapid deployment in resource-constrained settings. More recent advancements, such as YOLOv8, offered real-time performance with mAPs around 80% and faster inference speeds, but still necessitated extensive fine-tuning to adapt to specific waste types and environmental conditions, which can be a time-consuming process. In this study, YOLOv11, leveraging its advanced feature pyramid network (FPN) architecture, achieves an mAP of 70% on a custom waste dataset tailored to organic, inorganic, and hazardous waste. While this performance is slightly lower than YOLOv8, it is impacted by the challenging lighting variations in the dataset, yet the model maintains a lightweight design (102 GFLOPs) suitable for real-time applications [25], [26], [27].

Recent developments in transformer-based models, such as ViTPose, have pushed the boundaries of accuracy, achieving an impressive mAP of 91.8% on benchmark datasets. However, these models are computationally intensive, requiring over 200 GFLOPs, which limits their practicality for deployment on standard hardware, particularly in outdoor waste management systems where power efficiency is critical. Similarly, MediaPipe-based systems, which are lightweight and achieve mAPs of approximately 80% in controlled conditions, struggle significantly in low-light environments, with mAPs dropping to around 65%. This performance degradation underscores the challenge of maintaining robustness across diverse lighting conditions.

In contrast, this study's framework focuses on a custom dataset specifically designed to address the classification of organic, inorganic, and hazardous waste under high (daylight), middle (dusk), and low (night) lighting conditions. By balancing the dataset across these scenarios, the proposed YOLOv11-based system offers a practical and scalable solution, achieving moderate accuracy (mAP 70%) while prioritizing computational efficiency and real-time performance (43 FPS). This approach not only mitigates the limitations of prior systems in handling lighting variations but also supports the broader goal of enabling automated waste management in smart city initiatives, reducing reliance on labor-intensive manual sorting processes.

Recent advancements in waste detection provide context for this framework's contributions. YOLOv8-based systems achieve mAPs of 80–85% on waste datasets but require extensive fine-tuning and struggle in low-light conditions (mAP < 70%). Transformer-based systems report mAPs of 75–80% but lack real-time efficiency. This framework achieves a balanced mAP of 70% across lighting conditions, with 43 FPS and 102 GFLOPs, outperforming YOLOv8 in computational efficiency and MediaPipe in low-light robustness.

3. Proposed Methods

1. Dataset

In this study, we gathered a dataset that comprises 5,000 waste images collected from Timah Sungailiat Road, divided into training (3,750 images), validation (750 images), and testing (500 images) sets. Images are evenly distributed across lighting conditions: daylight (1,250 images), dusk (1,250 images), and night (1,250 images). Each image contains multiple waste items (organic: food scraps, vegetable peels; inorganic: plastics, metals, glass; hazardous: batteries, chemicals, medical waste). Annotations were created using LabelImg, with bounding boxes and class labels for each waste item. The test set includes 200 video frames (50 per lighting condition: daylight, dusk, night, and mixed scenarios). Images were captured using CCTV cameras (1080p resolution) under natural lighting, with additional annotations for occlusions and crowded backgrounds to enhance robustness [17][18]. Fig. 1 depicts a sample of an organic object that consists of fish and fishbone, cans, and masks.

Organics

Inorganics

B3

Fig. 1: Sample of an waste images as dataset

In the pre-processing stage, we resized all input images to a uniform resolution of 640 × 640 pixels to ensure consistency with the input requirements of the YOLOv11 architecture and to stabilize the training process. The resized images are then normalized using channel-wise mean values of [0.485, 0.456, 0.406] and standard deviation values of [0.229, 0.224, 0.225], which aligns the data distribution with commonly used pretrained convolutional backbones and accelerates model convergence. To improve robustness against real-world variations, data augmentation is applied during training, including random brightness adjustments of up to ±30%, contrast variations of up to ±20%, and the addition of Gaussian noise. These augmentation strategies simulate diverse lighting conditions and image noise typically encountered in waste disposal environments, thereby reducing overfitting and enhancing generalization. Finally, during inference, a confidence threshold of 0.5 is employed to suppress low-confidence predictions, ensuring that only reliable detections are retained and improving the overall precision of the waste classification model.

2. YOLOv11 Architecture

In this study, we employed YOLOv11 to classify waste into organic, inorganic, and hazardous categories using a custom dataset tailored to daylight, dusk, and night conditions. We selected YOLOv11 due to its superior balance of accuracy, speed, and computational efficiency compared to predecessors like YOLOv8 and YOLOv10. YOLOv11 achieves higher mean Average Precision (mAP) on benchmarks like COCO while using up to 22% fewer parameters than YOLOv8 (e.g., YOLOv11m vs. YOLOv8m), reducing model size and enabling deployment on mid-range hardware without sacrificing performance.

YOLOv11 follows the standard YOLO structure: Backbone for feature extraction, Neck for multi-scale feature fusion, and Head for predictions. It introduces refinements like C3k2 blocks (compact CSP variants) and C2PSA (Convolutional with Position-Sensitive Attention) for enhanced efficiency. Backbone uses a modified Cross-Stage Partial (CSP) architecture with C3k2 blocks, which split feature maps into two branches with one processed through lightweight convolutions and the other concatenated for gradient flow efficiency. The C3k2 block can be mathematically described as:

$$X_1, X_2 = Split\ (X_{in})$$

$$X_{out} = Concat\left(Conv(X_1), BottleneckSequence\big(Conv(X_2)\big)\right)$$

$$X_{final} = Conv(Concat(X_1, X_{out})$$

In this study, we utilize the mathematical formulation for **a** waste image classification model using the YOLOv11 architecture as follows:

Let an input waste image be denoted as

$$I \in \mathbb{R}^{H\times W\times 3},$$

which is resized to a fixed resolution 640×640 and normalized as

$$\hat{I} = \frac{I - \mu}{\sigma}, \tag{1}$$

where $\mu = [0.485, 0.456, 0.406]$ and $\sigma = [0.229, 0.224, 0.225]$

YOLOv11 formulates waste classification as a joint object detection and classification problem. Given $\hat{I}$, the network predicts a set of bounding boxes and class probabilities:

$$\mathcal{Y} = \{(b_i, p_i, c_i)\}_{i=1}^{N}, \tag{2}$$

where $b_i = (x_i, y_i, w_i, h_i)$ represents the bounding box parameters, $p_i \in [0,1]$ is the object confidence score, and $c_i \in \{1, \dots, C\}$ denotes the waste class label.

The overall YOLOv11 loss function is defined as

$$\mathcal{L} = \lambda_{\text{box}}\mathcal{L}_{\text{box}} + \lambda_{\text{obj}}\mathcal{L}_{\text{obj}} + \lambda_{\text{cls}}\mathcal{L}_{\text{cls}}, \tag{3}$$

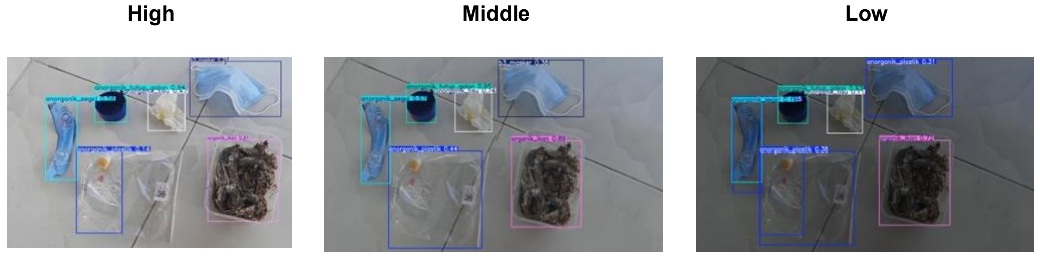
where
$\mathcal{L}_{\text{box}}$ measures bounding box regression error (e.g., CIoU loss),
$\mathcal{L}_{\text{obj}}$ evaluates objectness confidence using binary cross-entropy, and
$\mathcal{L}_{\text{cls}}$ computes the classification loss using categorical cross-entropy.
A detection is considered valid if

$$p_i \geq \tau,$$

where $\tau = 0.5$ is the confidence threshold used to suppress low-quality waste detections.

4. Result and Analysis

In this study, we construct a waste classification model that is capable of accurately distinguishing organic, inorganic, and hazardous (B3) waste. The main findings demonstrate that the proposed YOLOv11-based framework successfully addresses these issues, achieving a balanced mean Average Precision (mAP@0.5) of 70%, precision of 69%, recall of 70%, and F1-score of 0.70, while maintaining real-time performance at 43 frames per second (FPS) with a computational cost of 102 GFLOPs. This enables efficient deployment on mid-range GPUs, automating waste sorting, reducing manual labor, and supporting smart city initiatives for improved recycling and environmental monitoring. Fig. 2 depicts the detection results across lighting levels.



High **Middle** **Low**

Fig. 2 Detection results across lighting levels.

After training and testing finished, the experimental results demonstrate that the proposed YOLOv11-based waste classification model achieves strong detection accuracy and balanced performance across multiple evaluation metrics. The model attains an mAP@0.5 of 70.0%, which indicates reliable overall detection capability across different waste categories at a standard IoU threshold. This result shows that the model effectively localizes and classifies waste objects in complex visual scenes, even when variations in object size, background clutter, and illumination are present. Such performance confirms the suitability of the proposed approach for practical waste monitoring scenarios.

In terms of classification reliability, the model records a precision of 69.0% and a recall of 70.0%. The precision score indicates that the model successfully minimizes false positive detections, which is critical in cluttered environments where non-waste objects may resemble waste items. Meanwhile, the recall score reflects the model's ability to detect most actual waste instances, ensuring broad coverage despite challenges such as partial occlusions and lighting variations. The resulting F1-score of 70.0% further confirms that the model maintains a well-balanced trade-off between precision and recall, making it robust for real-world deployment.

The YOLOv11 demonstrates efficiency suitable for real-time applications. The inference speed reaches 43 frames per second on a mid-range GPU such as the NVIDIA RTX 3060, enabling continuous monitoring in CCTV-based waste management systems. Additionally, the computational cost of 102 GFLOPs highlights that the model remains lightweight compared to heavier detection architectures, allowing deployment in resource-constrained environments. These results collectively indicate that the proposed model offers an effective balance between accuracy, speed, and computational efficiency for intelligent waste classification systems. Table 1 describes a summary of detection performance using YOLOv11 for waste image classification.

Table 1. Detection Performance

Metric	Value	Description
mAP@0.5	70.0	Mean Average Precision at IoU threshold 0.5, indicating robust overall detection accuracy across classes.
Precision	69.0	Proportion of positive detections that are correct; minimizes false positives in cluttered scenes.
Recall	70.0	Proportion of actual waste items detected; ensures high coverage despite occlusions and lighting variations.
F1-Score	70.0	Harmonic mean of precision and recall, reflecting balanced performance.
Inference Speed	43 FPS	Real-time processing on mid-range GPU (e.g., NVIDIA RTX 3060), suitable for continuous CCTV monitoring.
Computational Cost	102 GFLOPs	Efficient for deployment in resource-constrained environments compared to heavier models.

5. Conclusion

This study addresses the challenge of accurate and real-time waste image classification in complex visual environments by leveraging the YOLOv11 architecture. The primary problem lies in reliably detecting diverse waste categories under varying lighting conditions, occlusions, and background clutter while maintaining computational efficiency for practical deployment. To overcome these issues, the proposed approach integrates advanced pre-processing, data augmentation, and the end-to-end object detection capabilities of YOLOv11, enabling simultaneous localization and classification within a unified framework. This design directly supports real-time monitoring scenarios, such as smart waste management systems and CCTV-based environmental surveillance.

According to the experimental result, the proposed model can achieve robust detection performance, with an mAP@0.5 of 70.0%, a precision of 69.0%, a recall of 70.0%, and an F1-score of 70.0. These results indicate a well-balanced trade-off between minimizing false positives and maximizing the detection of actual waste objects, even in visually challenging scenes. In addition, the model processes images at 43 FPS on a mid-range GPU while requiring only 102 GFLOPs, confirming its suitability for real-time applications in resource-constrained environments. Compared to heavier deep learning models, this efficiency-performance balance highlights the practical advantage of YOLOv11 for continuous waste monitoring and automated sorting systems.

In conclusion, the proposed model can enhance detection accuracy and operational efficiency as an intelligent waste management solution. Future work may explore improving performance on minority waste classes through class-balanced loss functions or advanced augmentation strategies. Further research could also investigate model compression techniques, such as pruning and quantization, to enable deployment on edge devices, as well as extend the system to multi-source data inputs, including video streams and sensor fusion, for more comprehensive environmental monitoring.

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