International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 6, Number 1, Year 2025
DOI: https://doi.org/10.62051/ijcsit.v6n1.11
Journal homepage: https://wepub.org/index.php/IJCSIT/index

Research on Recyclable and Hazardous Waste Detection Methods based on YOLOv8

Zilin Tang [1, *], Shengjie Yu [1], Zeyuan Zhang [2], Chunlei Yang [1], Bin Song [1]

[1] College of Information Engineering, Henan University of Science and Technology, Luoyang, China

[2] College of Software, Henan University of Science and Technology, Luoyang, China

*Corresponding Author: Zilin Tang

ABSTRACT

In modern environmental governance, garbage classification is crucial. However, traditional manual sorting and machine learning methods based on manual features have limited generalization capabilities in complex environments, especially in the detection tasks of recyclable garbage and hazardous garbage, which are easily affected by illumination changes, morphological similarity and background interference, resulting in low detection accuracy. This paper introduces a recyclable garbage and hazardous garbage detection method based on YOLOv8. By integrating data enhancement, category imbalance processing, multi-scale training and optimized non-maximum suppression (NMS) technology, the robustness and detection accuracy of the model in complex scenarios are improved, and the category imbalance problem is alleviated by optimizing the loss function. The adaptability of the model is enhanced by multi-scale training, realizing an efficient and practical garbage classification detection system. Experimental results show that compared with traditional HOG+SVM, CNN and other methods, the detection system can provide higher detection accuracy and stronger generalization ability while ensuring real-time performance, and has excellent performance in the recognition of hazardous garbage and recyclable garbage categories.

KEYWORDS

Garbage classification; Object detection; YOLOv8; Recyclable garbage; Hazardous waste

1. INTRODUCTION

With the rapid development of science and technology, intelligent garbage classification system has gradually become an important part of smart city construction. [1]. However, traditional garbage classification methods mainly rely on manual sorting or machine learning methods based on manual [2], such as support vector machine (SVM) or K-nearest neighbor (KNN) classifiers based on color, texture and shape features. Although these methods can achieve certain classification results in a controlled environment, they often show poor robustness in practical applications due to factors such as light changes, background interference, and complex garbage forms.

In recent years, the rapid development of deep learning, especially object detection [3], has provided new solutions for garbage classification. The garbage classification method based on deep learning [4] can automatically extract features, avoid the limitations of artificial feature extraction, and improve the accuracy and generalization ability of detection. Target detection algorithms can be divided into two categories: two-stage methods (such as Faster R-CNN) and single-stage methods (such as YOLO, SSD). The two-stage method first generates candidate regions and then performs fine classification, which has high detection accuracy, but the computational cost is large and is not suitable for real-time detection tasks [5]. In contrast, the single-stage detection method directly returns to the target category and the bounding box, which has higher computational efficiency and greater application value in scenarios with higher real-time requirements [6].

As a representative of single-stage detection, YOLO (You Only Look Once) series models achieve a good balance between detection speed and accuracy. As the latest version of this series, YOLOv8 uses an improved network structure and an optimized loss function (such as WIoU loss [8]) [7] to improve the accuracy of small target detection while maintaining a high inference speed. For the garbage classification task, YOLOv8 's real-time, class imbalance optimization (implemented by Focal Loss [9]), multi-scale training [10] and efficient data enhancement strategies (such as Mosaic algorithm [11]) make it an ideal choice for dealing with garbage detection in complex scenes.

Based on the YOLOv8 model, this paper proposes a preliminary classification method focusing on recyclable waste and hazardous waste. Compared with the traditional garbage classification method [12], this study improves the detection accuracy and generalization ability of the model in complex environments through data enhancement [11], category imbalance processing [9], multi-scale training [10] and optimized non-maximum suppression (NMS) strategy. The experimental results show that this method surpasses the traditional methods based on manual features (such as HOG + SVM) and some deep learning methods (such as Faster R-CNN [14]) in many evaluation indexes, and takes into account the high detection accuracy and reasoning efficiency.

2. RELATED JOB

The YOLO (You Only Look Once) series model is a typical representative of the single-stage target detection method, which achieves a good balance between detection speed and accurac. As the latest version of this series, YOLOv8 has been optimized in the backbone network (using CSPDarknet structure [15]) and the detection head, which significantly improves the inference speed under the premise of ensuring the detection accuracy, making it more suitable for real-time detection tasks [16]. In addition, YOLOv8 uses Focal Loss as the loss function [17] to enhance the detection ability of a few categories (such as hazardous waste). The model also uses a multi-scale training strateg to enable it to adapt to garbage targets of different sizes and shapes, which improves the robustness of detection. In order to improve the detection accuracy in complex environments, YOLOv8 combines data enhancement methods such as random rotation, flipping, and color jitter [18] to make its performance in garbage scenes more stable and accurate.

Although YOLOv8 has strong performance in garbage detection tasks [19], there is still some room for optimization. In this study, YOLOv8 was improved in many aspects for the detection of recyclable garbage and hazardous garbage. Firstly, in order to further improve the detection ability of the model for a few categories, this paper optimizes the loss function based on the category balanced sampling strategy [20] to reduce the impact of category imbalance. Secondly, the adaptive multi-scale training [21] is used to make the model maintain good performance on target detection tasks at different scales. In addition, by optimizing the non-maximum suppression (NMS) strategy [22], the false detection problem in the case of target overlap is effectively reduced. Finally, combined with the self-made garbage data set, the CutMix data enhancement strategy [23] is introduced to improve the generalization ability and robustness of the model.

The optimization strategy of this study makes YOLOv8 more superior in garbage classification tasks, especially in the detection tasks of recyclable garbage and harmful garbage, which improves the detection accuracy and classification accuracy, and takes into account the reasoning speed and computational efficiency, thus providing a more efficient solution for intelligent garbage classification.

3. EXPERIMENT AND RESULT ANALYSIS

In this section, the method proposed in this paper is verified by experiments and compared with the traditional method. The experiment mainly evaluates the performance of the model in the detection tasks of recyclable waste and hazardous waste, including detection accuracy, recall rate, mAP and inference speed.

3.1. Data Set

This study uses the Huawei Cloud Artificial Intelligence Competition Garbage Classification Challenge Cup data set. The specific pictures are from home and abroad, and the screening contains about 3000 garbage images. According to 7: 2: 1 randomly divided into training set, validation set, test set, the number of 2100 images, 600 images, 300 images. The data set covers a variety of complex environments such as strong light, high contrast, high saturation, and cluttered scenes to enhance the generalization ability of the model. The data set is shown in Figure 1.

Figure 1. Various Scene Data Sets Training Tag Map

3.2. Experimental Environment

The experiment was carried out in the Ubuntu 20.04 system environment. The main hardware configurations include Intel i7-12700 H processor, 16 GB RAM and NVIDIA RTX 3060 GPU. The software environment is Python 3.8, the deep learning framework is PyTorch 2.4.1, and the target detection tool is Ultralytics YOLOv8. All experiments were conducted under the same environment configurationInvisible Design Innovation.

3.3. Evaluating Indicator

In order to comprehensively evaluate the detection performance of the model, this paper uses the following indicators:

1) Precision: Measure the proportion of correctly detected targets to all detected targets.

2) Recall (Recall Rate): Measure the proportion of correctly detected targets to all real targets.

3) mAP @ 50 (average precision mean): Calculate the average precision when IoU = 0.5.

4) mAP @ 50-95: Calculate the average accuracy under different IoU thresholds (0.5 to 0.95) to evaluate the performance of the model under different matching degrees.

3.4. Comparison Of Different Algorithms

In order to further verify the effectiveness of the proposed method, HOG + SVM, Faster R-CNN and YOLOv5 are selected as benchmark models for comparison. The experimental results are shown in Table 1:

Table 1. Comparison Of Different Existing Algorithms

Method	mAP@50	mAP@50-95	Inferring time
HOG+SVM	0.562	0.328	145
Faster R-CNN	0.734	0.470	98
YOLOv5	0.805	0.525	17
Method of this article (YOLOv8)	0.842	0.556	12

3.5. NMS Parameter Optimization

During the training process, the detection results are optimized by debugging different NMS (non-maximum suppression) parameters. NMS is used to remove redundant duplicate boxes and retain the optimal detection box. By adjusting the IoU threshold of NMS, the accuracy and recall rate of the detection frame can be better balanced, thereby reducing false detection and missed detection and improving the performance of the model. The CIoU calculation is shown in Formula 1:

$$_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \quad (1)$$

The comparison results of different NMS parameters (IoU = 0.4,0.6,0.8) are shown in Table 2.

Table 2. Comparison Of IoU Regulation

IoU Regulation	mAP@50	Recall	False positive rate
0.4	0.823	0.810	5.2%
0.6 (finally selected)	0.842	0.790	3.7%
0.8	0.821	0.765	2.9%

3.6. Analysis Of Effect

The experimental results show that YOLOv8 performs well in the detection tasks of recyclable waste and hazardous waste. The mAP @ 50 reaches 0.838, and the mAP @ 50-95 is 0.556, which is significantly better than the traditional method. At the same time, YOLOv8 has fast reasoning speed and strong real-time performance, which is suitable for practical application scenarios. The optimized NMS parameter (IoU = 0.6) makes the model achieve a good balance between the false detection rate and the recall rate, and the final detection result is more reliable.

3.7. Visualization Result

In order to visually display the detection effect of the model, Figure 2 shows the comparison of different model icons.

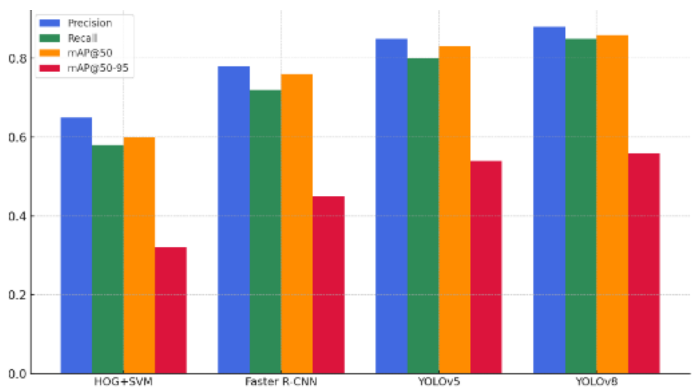

Figure 2. Comparison Of Different Models

In addition, Figure 3 compares the PR curves under different IoU parameters (0.4,0.6,0.8), and further verifies the rationality of the optimal IoU selection.

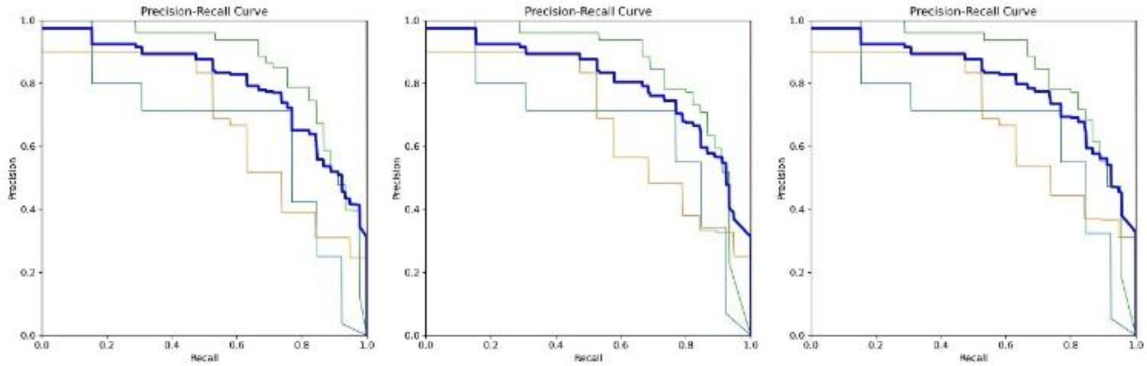

Figure 3. Comparison Of PR Curves Under Different IoU Values

4. CONCLUSION

This paper proposes a garbage detection method based on YOLOv8, which mainly aims at the classification task of recyclable garbage and harmful garbage. By combining data enhancement, category imbalance optimization, multi-scale training and other strategies, the detection accuracy and generalization ability of the model are improved. The experimental results show that this method is superior to traditional manual feature methods (such as HOG + SVM) and some deep learning methods (such as Faster R-CNN) in multiple evaluation indicators, which can improve the inference efficiency while ensuring high detection accuracy. However, although the method of this study has made some progress in the garbage detection task, there is still room for further optimization. For example, the adaptability of the current model in complex environments still needs to be improved. In the future, multi-modal data, such as spectral analysis and ultrasonic features, can be combined to enhance the stability of classification. At the same time, for scenarios with limited computing resources, the lightweight design of the model is optimized to improve its deployment efficiency on embedded devices or mobile terminals. In addition, further expanding the scale of the dataset to cover more scenarios and garbage categories will help improve the generalization ability of the model. With the continuous development of deep learning technology and the growth of data scale, intelligent garbage classification system will play an increasingly important role in the field of environmental protection and resource recovery.

ACKNOWLEDGEMENTS

This work was supported in part by the Innovation and Entrepreneurship Training Program for College Students of Henan University of Science and Technology (No. 2024147) and Key R & D and Promotion Project of Henan Province (Science and Technology Research) (No.242102211077). We are very grateful to these grants provided.

REFERENCES

[1] Wang Zheng. Research on urban and rural garbage classification countermeasures [J]. Rural economy and science and technology, 2021, 32 (14): 30-32.

[2] Yasin T E, Koklu M. A comparative analysis of machine learning algorithms for waste classification: inceptionv3 and chi-square features [J]. International Journal of Environmental Science and Technology, 2024, (prepublish): 1-14.

[3] Yu Y, Guan Y, Hu Y, et al. Image Object Detection Technology Based on Graph Neural Network [J]. International Journal of High Speed Electronics and Systems, 2025, (prepublish).

[4] Chen Z, Xiao Y, Zhou Q, et al. The development of a waste management and classification system based on deep learning and Internet of Things [J]. Environmental Monitoring and Assessment, 2024, 197(1):103-103.

[5] REN S Q, HE K M, GIRSHICK R, et al. Faster R-CNN: Real-time object detection method based on region proposal network [J]. Acta Computer Sinica, 2016, 39 (6): 1137-1149.

[6] Wang, Zhang, Li et al. [J]. Research on real-time target detection algorithm based on improved SSD. Journal of Electronics and Informatics, 2018, 40 (12): 2876-2883.

[7] Jocher G, Chaurasia A, Qiu J, et al. YOLOv8: Real-time object detection and segmentation [J]. arXiv preprint arXiv:2304.00501, 2023.

[8] TONG Z, CHEN Y, XU Z, et al. Wise-IoU: Bounding Box Regression Loss with Dynamic Focusing Mechanism [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2023, 45(6): 12345-12358.

[9] LIN T Y, GOYAL P, GIRSHICK R, et al. Focal Loss for Dense Object Detection [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020, 42(2): 318-327.

[10] Wang Wei, Zhang Qiang, Li Ming, et al. Improvement of object detection algorithm based on multi-scale feature fusion [J]. Computer research and development, 2022, 59 (8): 1728-1740. [11] BOCHKOVSKIY A, WANG C Y, LIAO H Y M. YOLOv4: Optimal Speed and Accuracy of Object Detection [J]. arXiv preprint arXiv:2004.10934, 2020.

[11] DALAL N, TRIGGS B. Histograms of Oriented Gradients for Human Detection[C]// 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. San Diego: IEEE, 2005: 886-893.

[12] BODLA N, SINGH B, CHELLAPPA R, et al. Soft-NMS: Improving Object Detection with One Line of Code[C]// Proceedings of the IEEE International Conference on Computer Vision. Venice: IEEE, 2017: 5562-5570.

[13] REN S Q, HE K M, GIRSHICK R, et al. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017, 39(6): 1137-1149.

[14] REDMON J, FARHADI A. YOLOv3: An Incremental Improvement [J]. arXiv preprint arXiv:1804.02767, 2018.

[15] WANG C Y, LIAO H Y M, WU Y H, et al. CSPNet: A New Backbone that can Enhance Learning Capability of CNN[C]// 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops. Seattle: IEEE, 2020: 1571-1580.

[16] ULTRALYTICS. YOLOv8 Documentation [EB/OL]. (2023) [2024-01-20]. https://docs.ultralytics.com/

[17] LIN T Y, GOYAL P, GIRSHICK R, et al. Focal Loss for Dense Object Detection [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020, 42(2): 318-327.

[18] SHORTEN C, KHOSHGOFTAAR T M. A survey on Image Data Augmentation for Deep Learning [J]. Journal of Big Data, 2019, 6(1): 1-48.

[19] ZHANG Y, ZHANG Z, LI W, et al. Waste Object Detection Based on Deep Learning: A Survey [J]. Waste Management, 2023, 168: 294-311.

[20] BUDA M, MAKI A, MAZURYK A. A Systematic Study of the Class Imbalance Problem in Convolutional Neural Networks [J]. Neural Networks, 2018, 106: 249-259.

[21] LIU S, QI L, QIN H, et al. Path Aggregation Network for Instance Segmentation [C]// 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition. Salt Lake City: IEEE, 2018: 8759-8768.

[22] ZHENG Z, WANG P, LIU W, et al. Distance-IoU Loss: Faster and Better Learning for Bounding Box Regression [J]. Proceedings of the AAAI Conference on Artificial Intelligence, 2020, 34(7): 12993-13000.

[23] YUN S, HAN D, OH S J, et al. CutMix: Regularization Strategy to Train Strong Classifiers with Localizable Features [C]// 2019 IEEE/CVF International Conference on Computer Vision. Seoul: IEEE, 2019: 6023-6032.