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ISSN 2959-6157

Garbage Classification Based on ShuffleNet and Edge Detection Preprocessing

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Abstract:
With the rapid urbanization, the problem of municipal solid waste has become increasingly severe, and waste classification has become a key measure to achieve sustainable development. However, traditional manual sorting is inefficient and expensive, and the existing automatic identification methods based on deep learning have different limitations. In order to solve these problems, this paper proposes a waste classification scheme that combines Canny edge detection pretreatment with the lightweight ShuffleNet v2 network. First, denoise the image, and then use Canny edge detection to extract the waste profile to enhance the target characteristics and suppress background interference. Finally, enter the processed images into the ShuffleNet v2 network for classification. Experiments conducted on the kitchen garbage subset of Huawei's garbage classification data set show that the proposed method achieves superior overall performance than SSD, YOLOv3 and unprocessed ShuffleNet v2. While maintaining the advantages of lightweight architecture, the method significantly improves the identification accuracy, thus expanding the technical path of garbage classification and accelerating its intelligent development.

Keywords: Garbage classification, ShuffleNet, Edge detection, Image recognition.

1. Introduction

With the rapid urbanization, the global production of municipal solid waste has risen year by year, and the phenomenon of „garbage besieging cities“ has become a bottleneck restricting the sustainable development of cities. For example, in key areas such as national high-efficiency ecological economic zones, the garbage problem has caused serious social risks [1,2]. Garbage classification, as a key measure to meet this challenge, can not only improve the resource utilization rate of recyclables and reduce landfills, but also minimize the energy consumption and pollutant emissions of garbage disposal from the source [3]. However, the traditional manual sorting method is inefficient, the labor cost is high, and classification errors are frequent, which is difficult to meet the needs of large-scale and refined waste sorting [4].

Against this background, the intelligentization of garbage classification has become an inevitable trend. Automatic recognition technology based on deep learning and computer vision has become the core driving force for this intelligent transformation, but there are still some limitations. The high-precision model, represented by multi-scale convolutional neural networks, is characterized by a large number of parameters and high computational complexity, so it is not suitable for deployment on resource-limited edge devices, such as smart trash cans. For example, the improved Faster R-CNN model proposed by Ma Wen et al. is used for garbage detection. Its mAP@0.5 reaches 81.77%, and the processing time of each image is 4.103 seconds. However, the model has problems such as large model scale, insufficient accuracy and slow reasoning speed [5]. On the contrary, although lightweight networks have low energy consumption and fast reasoning speed, their accuracy tends to be low in scenarios dealing with small objects or multi-scale mixed garbage due to their limited feature extraction ability. For example, SSD algorithms are easy to miss small targets such as cartons and dry batteries, and may even misclassify small glass bottles as dry batteries [6]. In addition, garbage image acquisition in the real world is often affected by environmental interference such as light distortion and background noise, which further reduces the recognition performance. For example, although many types of junk data sets are large in scale, they may contain annotation errors, which will introduce noise, thus adversely affecting model training [7]. Therefore, there is an urgent need for a solution that can balance lightweight architecture, real-time performance and anti-interference ability.

In order to meet these challenges, this study proposes a garbage classification framework that combines the lightweight ShuffleNet network [8] with preprocessing based on edge detection. First, preprocess the garbage image to remove noise and extract the precise edge outline of the garbage object. Then, build the ShuffleNet model and use its architecture mechanism to enhance feature extraction while maintaining lightweight features. Finally, conduct comparative experiments to verify the performance of the proposed method.

This study explores the feature integration mechanism of lightweight network and edge detection preprocessing, and innovatively integrates edge detection preprocessing into the lightweight network process. Without increasing the computational burden, it effectively enhances the contour characteristics of small and complex garbage targets, and breaks through the accuracy bottleneck of lightweight model in complex garbage classification fields. Secondly, the framework proposed by the study achieves the optimal balance between model lightweighting and identification accuracy, and can adapt to resource-limited adge equipment, filling the technical gap between the high-precision garbage classification algorithm and the actual edge deployment needs. The study of the characteristic integration mechanism between lightweight network and edge detection pretreatment has enriched the technical means of waste classification and accelerated the development of intelligent waste management system.

2. Methods

2.1 Data Source and Description

In April 2019, China's Ministry of Housing and Urban-Rural Development and other relevant departments issued a notice, deciding to fully launch municipal solid waste classification work in all prefecture-level and above cities nationwide [9], making waste classification a prominent social issue. In response to this policy demand, Huawei Cloud organized the „Garbage Classification Challenge Cup“ open to the public, aiming to jointly explore artificial intelligence technologies for waste classification. The Huawei Garbage Classification Dataset was developed as a core supporting resource for the competition and subsequent related research. With the expanding influence of the event, the dataset has been opened to the public and has become a commonly used data resource in the field of intelligent waste classification research.

The Huawei Garbage Classification Dataset covers 4 major categories of common daily waste [10], including 40 subcategories such as power banks, cans, dry batteries, and fruit peels, with a total of 14,683 images. In this study, the kitchen waste category (one of the 4 major categories) was selected for experiments. This subset contains 3,367 images, covering 8 typical types of kitchen waste (e.g., leftover food, bones, fruit peels, etc.). To ensure experimental accuracy, 80% of the subset was used for model training and 20% for testing. The category distribution of the kitchen waste dataset is shown in Figure 1, and typical samples of the dataset are presented in Figure 2.

ISSN 2959-6157

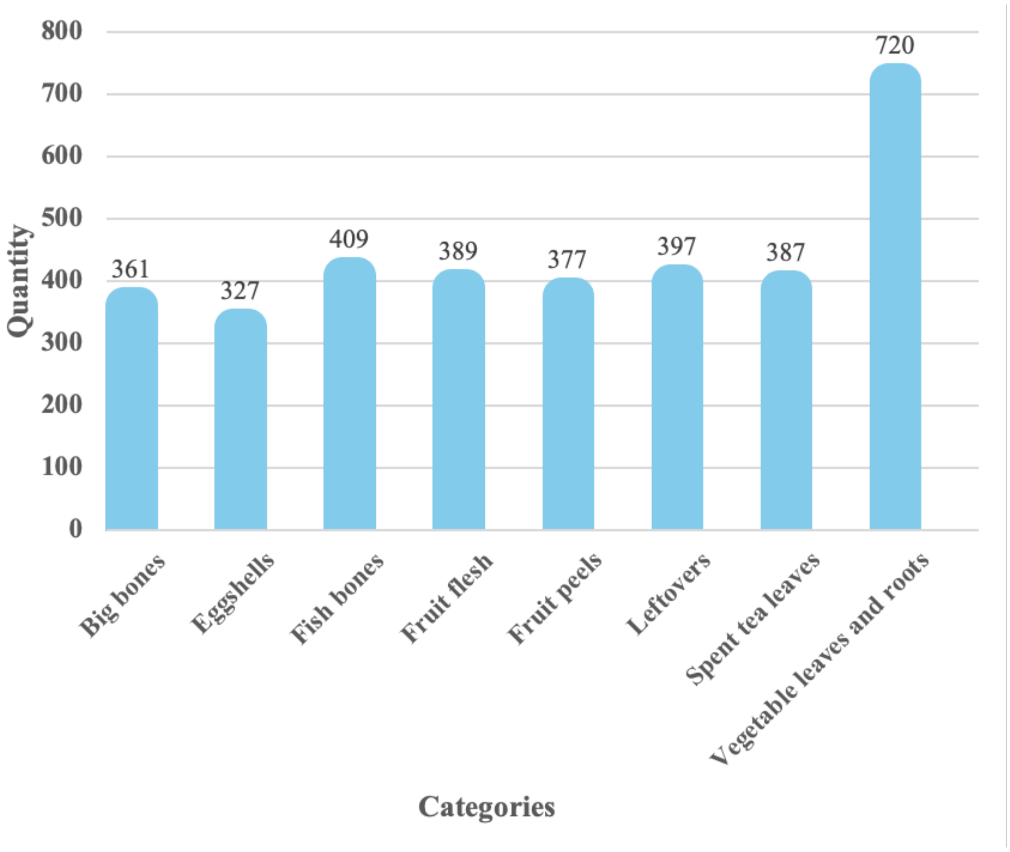

Fig. 1 Distribution of Categories in Kitchen Waste Dataset (Data from: Kitchen Waste Dataset)

Fig. 2 Typical Samples of Kitchen Waste Dataset (Data from: Kitchen Waste Dataset)

2.2 Method Description

The overall flow of garbage classification and recognition in this paper is illustrated in Figure 3. Firstly, the study employs a hybrid denoising method combining mean filtering and median filtering for image denoising. This method initially leverages the grayscale averaging characteristic of neighboring pixels in mean filtering to rapidly smooth Gaussian noise in images. Subsequently, it specifically suppresses salt-and-pepper noise through median filtering, preserving image edge details by virtue of sorting statistical properties and avoiding the problems of detail blurring or noise residue caused by a single filtering method. The effects before and after denoising are shown in Figure 4.

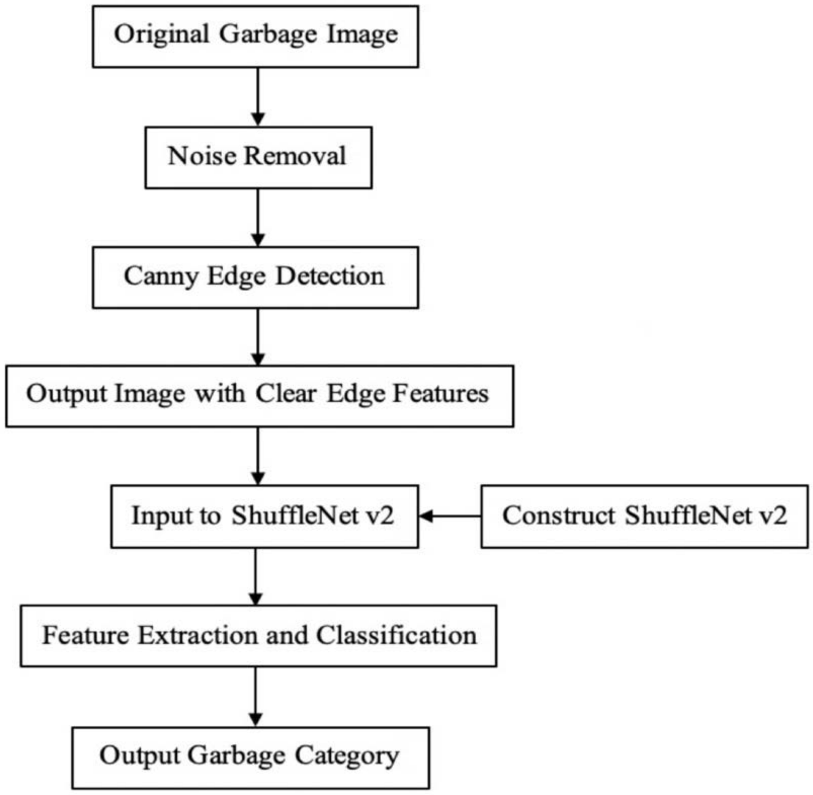

Fig. 3 Flow Chart (Picture credit: Original)

Fig. 4 Comparison Image before and after Denoising (Picture credit: Original)

After denoising, this paper adopts the Canny edge detection algorithm to extract the edge contour features of garbage images, with the comparison effects before and after processing presented in Figure 5. As a multi-stage edge detection algorithm, the Canny edge detection algorithm features a core process including Gaussian filtering for image smoothing, gradient magnitude and direction calculation, non-maximum suppression for edge thinning, and double-thresholding for true edge selection. Endowed with the key advantages of accurate edge localization, strong noise resistance, and efficient continuous edge capture, it can effectively weaken the interference of complex backgrounds on target recognition and highlight the shape and structural features of the garbage main body.

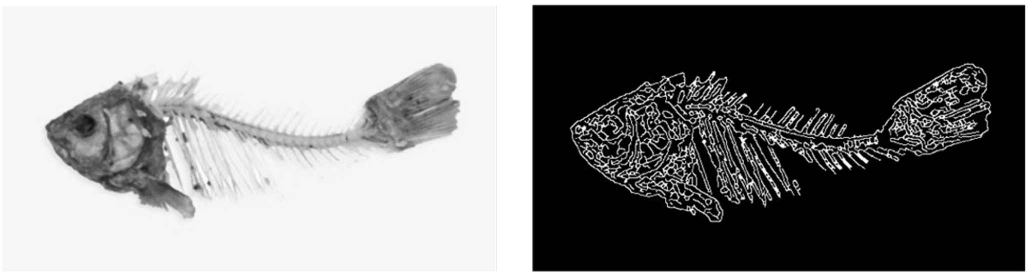

Fig. 5 Comparison Image before and after Processing (Picture credit: Original)

ISSN 2959-6157

Finally, the ShuffleNet v2 model is utilized for the classification and recognition of garbage images. As a lightweight convolutional neural network, ShuffleNet v2 significantly reduces the number of parameters and computational complexity by minimizing the computational overhead caused by grouping convolution and optimizing the ratio of channels between network layers, while ensuring the identification accuracy of the model. The structure it adopts can efficiently extract multi-scale image features, adapt to the identification needs of various garbage forms and complex features in garbage classification scenarios, and provide a lightweight solution for the deployment of edge equipment.

In order to comprehensively evaluate the performance of the model, especially its ability to accurately identify the type of garbage in the image, two core indicators are selected: mean Average Precision (mAP50) and inference speed.

3. Results and Discussion

3.1 Results

In order to verify the effectiveness of combining ShuffleNet with edge detection preprocessing, this study conducted a comparative experiment using a variety of target detection models, including SSD, YOLOv3 and ShuffleNet v2 without edge detection preprocessing. The results are shown in Table 1.

Table 1. Results of a Comparative Experiment on Different Models

Model	mAP50 (%)	FPS (frames/second)
SSD	68.3	18
YOLOv3	82.9	20
ShuffleNet v2(w/o preprocessing)	76.5	42
ShuffleNet v2 + Canny Edge Detection	84.7	36

As shown in Table 1, the model combining ShuffleNet v2 with Canny edge detection has achieved the highest mAP50 value in image recognition, reaching 84.7%, which indicates that the proposed method is feasible and effective. However, compared with the unpreprocessed ShuffleNet v2, the image processing speed of this model is slightly slower.

3.2 Discussion

The experimental results show that the combination of ShuffleNet v2 and Canny edge detection has achieved the best performance. This best performance is due to the fact that kitchen waste categories can usually be distinguished by edge and texture characteristics, and edge detection pretreatment effectively enhances these key information. Combined with lightweight networks, a good balance of accuracy and speed is achieved.

In contrast, SSD's mAP50 (68.3%) and FPS (18) are lower, mainly due to its limited ability to capture small target features and its difficulty in adapting to the scene of dense accumulation of kitchen waste. Although YOLOv3 has a higher accuracy rate (82.9%), its inference speed is slower (20FPS).

Despite the results, this study also has some limitations. Firstly, this experiment only compared three models and didn't include more advanced network architecture. Secondly, the experimental images were taken against a solid color background, without considering the complex situations in the real world, such as the messy environment and partial occlusion. Future research can further improve the performance of the algorithm by incorporating more images from the actual garbage classification site.

4. Conclusion

The current deep learning-based automatic garbage classification identification methods have respective shortcomings: the calculation of high-precision models is complex and the deployment cost is high, while the lightweight models have insufficient recognition accuracy in small target recognition and complex backgrounds. In order to solve this problem, this study proposes an identification scheme that integrates Canny edge detection preprocessing and ShuffleNet v2 network. Through the coordinated optimization of feature enhancement and lightweight design, an identification framework with both high precision and practicality has been built.

In the research process, first of all, the hybrid denoising method combining mean filtering and median filtering is adopted to remove the noise in the garbage image while retaining the edge details. Then the Canny edge detection algorithm is used to extract the contour features of the garbage subject to weaken the interference of complex backgrounds. Finally, take the lightweight ShuffleNet v2 network as the core model to achieve efficient identification of garbage images. And comparative verification experiments were carried out with SSD, YOLOv3 and ShuffleNet v2 without preprocessing.

The experimental results show that the mAP50 of the scheme proposed in this study reaches 84.7%, and its comprehensive performance is significantly better than that of the comparative models.

This study not only verifies the effectiveness and feasibility of combining edge detection pretreatment and lightweight networks in the field of garbage identification, but also provides a high-precision and low-cost technical solution for intelligent garbage classification in resource-limited environments. It enriches the technical system of garbage classification and recognition and has positive significance for promoting the intelligentization process of garbage classification. For future research, the dataset scale will be further expanded by incorporating more samples from real application scenarios, and the integration potential of newer generation lightweight networks will be explored to improve the generalization ability and practical application value of the model.

However, there are still certain limitations in this study, which need to be improved in future work. First, the degree of homogenization of garbage types and environmental scenes in the experimental dataset is relatively high, and the extreme weather environment that may be encountered in the real outdoor garbage classification scene cannot be fully simulated. Second, the proposed framework is mainly optimized for static garbage images, its performance in real-time dynamic garbage detection scenarios has not been fully verified. In addition, the existing model lacks the ability to adaptively adjust the detection parameters according to the density of different garbage accumulation, and the identification accuracy may decrease when dealing with densely stacked garbage.

Future research will further expand the sample under real application scenarios, expand the scale of dataset, and explore the integration potential of a new generation of lightweight networks to improve the generalization ability and practical application value of the model.

References

[1] Song Xiaona, Zhang Feng. Social Risk Assessment of „Garbage Siege“ in the National High-Efficiency Ecological Economic Strategic Zone[J]. Ecological Economy, 2022, 38(02), 190-196.

[2] Ma Mingyang. Study on temporal and spatial dynamics of municipal solid waste production and the influencing factors in China[D]. Beijing Forestry University, 2023.

[3] Li Lei, Yuan Guangjue. Present situation and prospects of municipal solid waste treatment in China[J]. World Environment, 2017, (06), 24-27.

[4] LI J Y, CHEN X L, ZHANG A H, et al.Survey of garbage classification methods based on deep learning[J]. Computer Engineering, 2022, 48(2), 1-9.

[5] MA W, YU J, WANG X, et al. Garbage detection and classification method based on improved faster R-CNN[J]. Computer Engineering, 2021, 47(8), 294-300.

[6] Dong Ziyuan. Design and Implementation of the Garbage Classification System Based on Deep Learning[D]. University of Chinese Academy of Sciences (Shenyang Institute of Computing Technology Chinese Academy of Sciences), 2020.

[7] Zhang Jianwei. Research on Algorithm of Garbage Classification Based on Deep Learning[D]. Fujian Agriculture and Forestry University, 2024.

[8] ZHANG X, ZHOU X, LIN M, et al. ShuffleNet: an extremely efficient convolutional neural network for mobile devices[C]// Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Piscataway: IEEE, 2017, 6848-6856.

[9] The Central People‘s Government of the People‘s Republic of China. Notice by the Ministry of Housing and Urban-Rural Development and Other Departments on Fully Implementing Household Waste Classification in All Prefecture-Level and Above Cities Nationwide [EB/OL].(2019-04-26)[2025-10-23].https://www.gov.cn/zhengce/zhengceku/2019-09/29/content_5434772.htm.

[10] Aliyun1856129113-17467, 2024, Garbage Classification Dataset, Retrieved from https://tianchi.aliyun.com/dataset/175980