

Literature Review: Garbage Classification by Robotic Arm Based on Image Recognition

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ABSTRACT

To address the problems of low efficiency and high cost of traditional manual garbage classification and promote the intelligent transformation of garbage classification, robotic arm garbage classification technology based on image recognition has become a research hotspot, which is of great significance for improving sorting efficiency and facilitating resource recycling. Adopting the literature research method and case analysis method, this paper systematically combs the core system, domestic and foreign research progress and application status of this technology, aiming to clarify the current technical bottlenecks and propose future development directions. The research finds that image recognition algorithms (such as YOLO series and Faster R-CNN) and robotic arm control technologies (such as PID control and visual servo control) have been partially applied in garbage sorting. Foreign countries take the lead in multi-sensor fusion and reinforcement learning, while domestic research focuses on the technical optimization adapted to local classification standards. However, there are still key challenges including insufficient recognition accuracy of small targets, high confusion rate of similar garbage categories, poor adaptability to grabbing irregular garbage, and low system collaboration efficiency. Future research should focus on breakthroughs in multi-modal fusion recognition, flexible robotic arm grasping and intelligent operation and maintenance, so as to promote the low-cost and large-scale application of this technology.

Keywords: Garbage Classification; Image Recognition; Robotic Arm; Intelligent Sorting; Environmental Protection

1. INTRODUCTION

With the acceleration of global urbanization and the transformation of consumption patterns, the output of domestic garbage continues to rise, bringing enormous pressure to environmental governance and resource recycling. As a key link to realize resource recycling and the “dual carbon” goal, the intelligent transformation of garbage classification has become an inevitable trend. Traditional manual sorting is plagued by low efficiency, unstable accuracy and high cost, making it difficult to meet the needs of large-scale urban garbage treatment. Intelligent sorting systems integrating computer vision and robot technology have emerged as the times require. The image recognition-based robotic arm classification technology can realize full-process automation including automatic identification, positioning, grabbing and classification, improve sorting efficiency and accuracy, and promote the intelligent and refined development of the environmental protection industry, with important application value and academic significance.

Research in this field follows an evolutionary path from single technology exploration and system integration to scenario optimization. Early studies focused on garbage image recognition algorithms. The deep transfer learning strategy solves the problem of limited dataset scale and improves the generalization ability of models^[1]. The lightweight network LWCNet designed for household scenarios meets real-time requirements, greatly reducing computational complexity while ensuring accuracy^[2]. The low-power embedded YOLOv8-NANO system adapts to the computing power constraints of edge devices through algorithm pruning and optimization, realizing rapid sorting^[3], providing core support for the “eyes” of the system. Research on the execution end has advanced synchronously. The campus sorting mobile robot based on ARM platform combines a mobile chassis with a robotic arm, expanding application scenarios^[4]. The special sorting system for medical garbage reflects the professional application trend of the technology^[5], laying a practical foundation for the “hands” and “feet” of the system.

Current research is evolving toward multi-modal fusion and collaborative optimization. Integrating multi-sensor information such as vision, weight and touch can effectively improve system robustness^[6]. International research has also improved the accuracy and efficiency of sorting in complex backgrounds through innovative network structures and algorithm optimization^[7,8]. The Realwaste dataset close to real scenarios provides reliable support for algorithm training

[9]. Application scenarios are constantly expanding. UAV aerial photography can realize the identification and evaluation of construction garbage on a large scale [10]. Fixed sorting devices have formed a complete technical closed loop from image collection to sorting execution [11,12], and balance-controlled sorting robots present a more autonomous form. International research also emphasizes the core role of deep learning in sustainable garbage management [14].

Existing research methods are diverse with prominent engineering characteristics. Theoretical research adopts the literature analysis method to sort out research contexts; algorithm research carries out experimental verification based on public or self-built datasets [9]; system integration verifies feasibility through case construction [5]. The development of open-source frameworks, mature robot operating systems and edge computing technologies provides a complete tool chain for technology implementation [3,6].

Currently, the technology presents four major development trends: first, algorithm lightweighting and edge deployment to seek an optimal balance among accuracy, speed and power consumption; second, multi-modal perception fusion to break through the bottleneck of single RGB images in coping with complex scenarios such as occlusion and stains; third, urgent breakthroughs in flexible adaptive grabbing technology to improve the sorting success rate of irregular and soft garbage; fourth, systems need to adapt to different scenario requirements such as China's four-category garbage classification standard to solve the problems of large-scale implementation [12].

The image recognition-based robotic arm garbage classification technology is in a critical stage of transitioning from technological breakthroughs to large-scale applications. Future research should focus on the research and development of lightweight and high-precision recognition algorithms, multi-modal flexible grabbing strategies, and low-cost and high-reliability systems adapted to domestic working conditions. Through interdisciplinary innovation and industry-university-research cooperation, it will provide support for smart city construction and circular economy development.

2. GARBAGE IMAGE RECOGNITION AND CLASSIFICATION METHODS

Accurate recognition of garbage images serves as the "eye" of the entire sorting system, whose core task is to locate and identify different types of garbage from complex backgrounds. The research methods in this field have evolved from traditional image processing technologies relying on manual features to deep learning technologies capable of automatically extracting deep-level features.

2.1 Traditional Detection Methods

Before the popularization of deep learning, automatic garbage classification based on image recognition mainly relied on traditional machine vision technologies. Such methods generally include image preprocessing, feature extraction and selection, and classifier design. Researchers describe garbage objects by designing manual features such as color (RGB and HSV histograms), texture (Local Binary Pattern, LBP; Gabor filter) and shape (contour, geometric moment). For example, early automatic garbage sorting devices realized preliminary identification and sorting functions based on these basic features [11]. Subsequently, machine learning models such as Support Vector Machine (SVM), AdaBoost and shallow neural networks were adopted as classifiers. However, traditional methods are highly dependent on the quality of feature engineering. Garbage features are diverse in form with complex backgrounds, occlusion and contamination, making it difficult for manual features to robustly describe all garbage categories. Such methods can achieve certain effects in small-scale and specific scenarios, but have obvious bottlenecks in generalization ability and recognition accuracy when facing diverse garbage forms in real-world scenarios. It is worth noting that traditional vision tasks usually separate classification (judging the garbage categories in images) and positioning (determining the position of objects in images) or only achieve coarse-grained category discrimination. In robot sorting systems, only knowing the category without the position cannot guide the robotic arm to grab objects. Therefore, target detection that outputs both category labels and bounding box coordinates is essential. Limited by the expression ability of manual features, traditional methods often fail to balance classification and positioning, which promotes the rapid development of subsequent deep learning-based target detection technologies.

2.2 Deep Learning-Based Target Detection

The rise of deep learning, especially the application of Convolutional Neural Networks (CNN), has revolutionized the machine vision field and garbage classification. Different from traditional methods relying on manual features, deep learning models can automatically learn hierarchical feature representations from massive data, significantly improving the ability to recognize and locate targets in complex scenarios. In the context of robot sorting, the vision task is clearly defined as target detection: the model outputs a bounding box (providing pixel coordinates of the grabbing center) and its

corresponding category (determining the delivery destination) for each garbage instance. The output quality directly determines the “visual perception” and “decision-making” capability of the robotic arm. Average Precision Mean (mAP), Intersection over Union (IoU) and Frames Per Second (FPS) are core indicators adopted to evaluate the performance of detection models.

2.2.1 Two-Stage Detection Algorithms

Represented by Faster R-CNN, such algorithms first generate candidate regions through a Region Proposal Network (RPN), and then classify and refine the position of these regions. In garbage classification tasks, Faster R-CNN is applied to scenarios requiring high accuracy by virtue of its high precision advantage. Researchers adopt the deep transfer learning strategy to migrate pre-trained models (such as ResNet and VGG) trained on large-scale datasets to small-sample garbage classification tasks, effectively solving the problem of limited garbage image dataset scale and improving the generalization ability of models [1].

2.2.2 One-Stage Detection Algorithms

Represented by the YOLO (You Only Look Once) series algorithms, the core idea is to transform the target detection task into a regression problem, directly predicting the category and bounding box of targets in images to realize end-to-end real-time detection. Due to the high real-time requirement of garbage sorting tasks, YOLO series algorithms have become a research hotspot. In particular, lightweight YOLO versions such as YOLOv8-NANO simplify the network structure through model pruning, quantization and other technologies, balancing high recognition accuracy and low computational complexity, enabling deployment on low-power embedded devices and realizing real-time rapid garbage sorting [3]. For instance, the EcoSweep system included in IEEE Xplore in 2025 is an automatic garbage sorting robot integrating YOLO real-time image recognition and a robotic arm, which can accurately classify garbage into four categories: paper, plastic, glass and metal, with the robotic arm realizing autonomous picking and classified delivery. In addition, lightweight networks such as LWCNet designed for household scenarios also seek the optimal balance among model accuracy, computation volume and inference speed [2].

2.2.3 Other Models and Optimization Strategies

In addition to mainstream algorithms above, researchers are constantly exploring innovative network structures and optimization strategies. For example, ECCDN-Net is structurally optimized specifically for organic and recyclable garbage classification, achieving efficient recognition [7]. Some studies combine deep learning with intelligent optimization algorithms (such as the multi-objective beluga whale optimization algorithm) to automatically search and optimize hyperparameters of network models, further improving the performance and stability of models in complex garbage classification tasks [8].

2.3 Dataset Status

Data is the core driver for improving the performance of deep learning models. Early research mostly adopted small-scale self-built laboratory datasets, which were convenient for algorithm verification but had a large gap with real application scenarios, leading to poor model generalization ability. To promote technology implementation, constructing high-quality large-scale datasets close to real scenarios has become an inevitable trend. The Realwaste dataset fills this gap. Collected from real landfills, it contains garbage images under challenging conditions such as complex illumination, occlusion and overlap, providing a solid foundation for training and evaluating robust deep learning models [9]. In addition, datasets for different segmented scenarios are constantly enriched, including UAV aerial datasets for construction garbage [10] and special datasets for medical garbage recognition [5]. High-quality, diversified and finely annotated real-scene datasets are important cornerstones for continuous breakthroughs in algorithms in the future.

3. ROBOTIC ARM CONTROL TECHNOLOGY

After the image recognition module completes the positioning and classification of garbage, the robotic arm, as the “executor” of the system, is responsible for accurate grabbing and delivery operations. The performance of robotic arm control technology directly determines the sorting success rate and overall system efficiency, mainly covering grabbing pose planning and motion control.

3.1 Grabbing Pose Planning

The goal of grabbing pose planning is to calculate the optimal grabbing position, direction and pose for the end-effector of the robotic arm (such as pneumatic suction cups, two-finger or three-finger grippers) to ensure stable and damage-free grabbing of target objects. Garbage classification tasks pose special challenges: garbage objects are highly irregular in shape (plastic bottles, broken glass, soft packages, etc.), diverse in material (rigid, flexible, fragile and perishable), and may be stacked or deformed.

Extensive explorations have been carried out in existing research. For example, during the launching ceremony of the 4th National Urban Domestic Garbage Classification Publicity Week on May 25, an intelligent “robot dog” equipped with a multi-functional robotic arm was applied to patrol and pick up garbage autonomously. For fragile medical garbage or kitchen waste, special flexible grippers or pneumatic suction cups are designed with gentle grabbing poses planned [5]. Some studies have introduced learning-based grabbing pose detection methods, combining point cloud information to directly generate candidate grabbing points through deep neural networks (such as GraspNet), improving the adaptability to objects with unknown shapes. However, adaptive and damage-free grabbing pose planning for garbage with uneven mass distribution and soft texture (such as wet garbage bags) remains a major technical difficulty, with common problems such as low grabbing success rate, slipping and object damage.

3.2 Motion Planning and Control

Motion planning and control focuses on solving the motion mode of the robotic arm, including path/trajectory planning and underlying control strategies.

3.2.1 Motion Planning

Motion planning consists of path planning and trajectory planning. Traditional algorithms such as RRT and A* can meet the requirements of simple desktop sorting scenarios. For complex environments (such as mobile robots combined with mobile platforms [4]), the planning algorithm needs to handle higher degrees of freedom and coordinate the motion of the robotic arm and mobile chassis to avoid collisions with the surrounding environment.

3.2.2 Control Strategies

The traditional Proportional-Integral-Derivative (PID) control is widely used in basic position control due to its simple structure and easy implementation. However, the target position in garbage classification scenarios is not completely fixed, which makes visual servo control a research hotspot. Visual servo control integrates real-time visual feedback (such as the dynamic position of targets in images) into the robotic arm control closed loop, effectively compensating for positioning errors and dynamic interference. It shows superior robustness when sorting moving objects or correcting calibration errors between vision systems and robotic arms. For example, the high-speed sorting robot put into trial operation at the Xinke Garbage Compression Station in Baiyun District, Guangzhou, can accurately identify 8 types of recyclables including lunch boxes, cans, paper and metal, with a sorting speed of 5,400 times per hour. Currently, the core bottleneck restricting high-frequency sorting efficiency is the system collaboration delay, including target locking by image recognition, grabbing pose solution, motion planning and delivery execution.

4. CONCLUSION

With the acceleration of global urbanization and the advancement of China’s dual carbon goals, garbage classification has become a core measure for resource recycling and environmental load reduction. Traditional manual sorting, featuring low efficiency, high cost and high health risks for workers, can no longer meet the needs of large-scale urban garbage treatment, making intelligent transformation imperative. Integrating computer vision and robot control technologies, the image recognition-based robotic arm garbage classification technology realizes full-process automation of garbage identification, positioning, grabbing and classification. It solves the core pain points of manual sorting, with important application value and academic significance.

Domestic and foreign research has gone through three stages: the early stage of traditional machine vision-based hardware framework construction, the deep learning stage of algorithm accuracy improvement, and the recent stage of edge deployment and scenario adaptation. Domestic research is closely aligned with national garbage classification standards: in the early stage, it completed the prototype development of machine vision sorting devices, built the core framework of image recognition and robotic arm control, and verified the feasibility of full-process operation. In the deep learning stage, it optimized lightweight algorithms (LWCNet for household scenarios, low-power YOLOv8-NANO) and developed multi-

scenario hardware equipment (ARM-based campus sorting robots, medical garbage sorting systems, UAV-based construction garbage identification devices). Foreign research started earlier, with outstanding achievements in algorithm innovation (ECCDN-Net for organic and recyclable garbage classification), dataset construction (Realwaste dataset for real landfill scenarios) and model optimization (multi-objective beluga whale optimization combined with deep learning), promoting the commercialization of relevant technologies.

Three mainstream research methods have been formed: first, deep learning optimization, which adopts transfer learning to solve data scarcity problems and lightweight algorithms to adapt to edge device deployment; second, hardware integration, with mature robotic arm motion planning and grabbing control technologies and verified feasibility of multi-scenario prototypes; third, multi-modal fusion, which solves misjudgment problems caused by single image recognition and adapts to edge computing equipment. The core technical system is mature with great potential for practical implementation.

Current existing problems include: algorithm level, low recognition accuracy of small targets and similar garbage categories and poor model generalization; control level, insufficient adaptive grabbing capability for irregular garbage and high system collaboration delay; application level, high equipment cost and poor scenario adaptability. Future development trends focus on algorithm lightweighting and edge deployment, multi-modal perception fusion, construction of real-scene datasets, and customized solutions for segmented application scenarios.

The technology has attracted extensive research attention and yielded fruitful achievements, but it still faces deficiencies in recognition accuracy, grabbing adaptability, scenario matching and cost control, falling short of large-scale industrial application. In the future, it is necessary to adapt to China's classification standards and actual application scenarios, focus on system collaborative optimization, break through key technical bottlenecks, develop lightweight and multi-modal intelligent sorting technologies, reduce application costs, improve real-scene datasets, promote large-scale and standardized implementation of the technology, and provide strong support for the development of green low-carbon economy and smart city construction.

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