Design of an Intelligent Garbage Recognition and Classification System Based on K210 and Deep Learning Algorithm

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Abstract: With the acceleration of urbanization, the problem of "garbage besieging cities" is becoming increasingly severe. Traditional manual sorting methods suffer from low efficiency, high cost, and unstable accuracy. This paper designs and implements an intelligent garbage recognition and classification system based on the K210 edge AI computing chip and deep learning algorithms. The system uses the K210 as the core computing unit, equipped with an OV2640 camera for image capture. It utilizes a lightweight MobileNetV1 model, optimized through pruning and quantization, deployed on its KPU for real-time local inference. Recognition results are fed back via a TFT display and drive SG90 servos to perform sorting actions. Test results show that the system achieves an average recognition accuracy of 92.5% for eight common types of recyclable waste, with an average response time of less than 1.5 seconds. It features high recognition accuracy, fast response speed, and stable, reliable operation, providing an efficient and feasible embedded solution for the intelligent and automated classification of garbage.

Keywords: K210; Deep Learning; Garbage Recognition; Edge Computing; Embedded System

1. Introduction

With the rapid advancement of urbanization in China and the continuous increase in residents' consumption levels, the generation of domestic waste has been rising year by year, posing severe challenges to both the ecological environment's carrying capacity and the waste management system. According to statistical data from the Organisation for Economic Co-operation and Development (OECD), China's urban domestic waste clearance volume reached 234 million tons in 2016, an 88% increase compared to 1996, and it has maintained an annual growth rate of approximately 5%--8% in recent years. The phenomenon of "garbage besieging cities," caused by waste accumulation, insufficient processing capacity, and inadequate classification, not only occupies substantial land resources but may also lead to environmental issues such as soil and water pollution and greenhouse gas emissions. This makes efficient and accurate waste sorting, recycling, and processing an urgent and systemic social engineering challenge to resolve[1]. In this context, actively responding to the national ecological civilization philosophy that "lucid waters and lush mountains are invaluable assets," implementing waste classification policies, and promoting its transition toward intelligence and automation have become inevitable trends for sustainable urban development[2].

Currently, the mainstream waste classification models still primarily rely on residents' voluntary disposal and secondary sorting by sanitation workers. This approach suffers from high labor intensity, rising manpower costs, limited sorting efficiency, and significantly subjective accuracy rates[3]. Although various smart recycling bins and classification devices have gradually emerged on the market in recent years, most have relatively limited functionality: some only support limited methods such as QR code recognition or weight sensing, unable to handle complex and variable waste forms; others, while equipped with visual recognition capabilities, are constrained by algorithm and hardware performance, exhibiting shortcomings such as limited recognition categories, weak environmental adaptability, and slow response speeds [4]. Furthermore, some solutions heavily depend on cloud computing, facing practical constraints such as network latency, data privacy risks, and high operational and maintenance costs.

In recent years, the rapid development and integration of edge computing and deep learning technologies have provided new technical pathways for achieving real-time, accurate, and low-cost visual recognition tasks on terminal devices [5]. Edge computing pushes data processing and analysis to the network edge, effectively reducing latency, alleviating bandwidth pressure, and enhancing data privacy protection. Meanwhile, advancements in deep learning, particularly in lightweight convolutional neural networks, have made it possible to deploy high-performance visual models on resource-constrained devices [6]. At this intersection of technologies, the K210 edge AI computing chip introduced by Canaan Inc. stands out [7]. This chip integrates a dual-core RISC-V processor and a dedicated KPU (Neural Network Processor) optimized for machine vision and auditory tasks. It offers substantial local computing power, low power consumption, and rich interface capabilities, making it an ideal hardware platform for implementing real-time intelligent visual processing on embedded edge devices.

To this end, this paper designs and implements an intelligent waste recognition and classification system based on the K210 chip and deep learning algorithms. Centered around the K210, the system constructs a complete embedded solution encompassing image acquisition, real-time inference, human-computer interaction, and automatic sorting [8]. By capturing waste images in real-time through a camera, the system performs recognition and classification decisions on the device using a lightweight deep learning model and drives actuators to carry out automated sorting operations. The system aims to complete all data processing locally, combining advantages such as fast response speed, high recognition accuracy, strong privacy protection, and low operational costs. It seeks to provide an efficient, feasible, and easily promotable technical pathway to address the practical challenges of current waste classification.

2. System Scheme Design

The core design objective of the intelligent garbage recognition and classification system based on K210 and deep learning algorithms, as presented in this paper, is to construct a highly integrated, self-operating embedded intelligent system [9]. This system must comprehensively encompass four major functional modules: image acquisition, intelligent recognition, automatic sorting, and human-computer interaction, thereby forming a closed loop from perception to execution. The overall design scheme strictly adheres to three core principles: modularity, low power consumption, and real-time performance. Modular design ensures that each functional unit (such as computing, sensing, and actuation) is independent and clearly defined, facilitating development, debugging, and future maintenance and upgrades. Low-power design aims to select hardware with high energy efficiency and optimize operational strategies to guarantee the system's long-term stable operation in scenarios without continuous external power supply. Real-time performance is a strict requirement for the system's response speed, ensuring smooth and coherent actions from recognition to execution, thus meeting practical interaction demands.

The specific workflow of the system is as follows: After power-on initialization, the OV2640 camera begins operation assisted by a dual-servo pan-tilt mechanism. The pan-tilt provides degrees of freedom in both horizontal and vertical directions. Through pre-set programs or simple tracking algorithms, it enables the camera to flexibly adjust its viewing angle, ensuring alignment with the target area to capture clear and stable real-time images. The acquired image data is transmitted directly to the K210 chip via a DVP interface. Acting as the "brain" of the system, the K210 immediately invokes its built-in dedicated KPU (Neural Network Processor). This KPU loads a pre-deployed, lightweight MobileNetV1 model that has been deeply optimized through pruning and quantization, stored in Flash memory. It then performs high-speed parallel inference computation on the input image, ultimately outputting the garbage classification result along with its confidence level.

The processing of the recognition result follows two paths: First, visual display via the TFT display. The screen interface presents the live camera feed in real-time, overlaying information such as the identified garbage category (e.g., "plastic bottle", "battery"), confidence percentage, and simple operational guidance, providing users with intuitive and friendly interactive feedback. Second, the main control chip (K210) generates corresponding PWM (Pulse Width Modulation) control signals via GPIO based on the determined classification result. These signals drive the corresponding SG90 servo(s) to rotate precisely to a specified angle. Each servo is mechanically linked to the lid-opening mechanism of a trash bin designated for a specific category (e.g., recyclables, hazardous waste). Once the target bin lid opens, the user can complete the garbage disposal. After one complete sorting and disposal cycle, the system commands the servo to reset (closing the lid), and all modules return to a ready state, cyclically awaiting the next recognition task trigger.

The core advantage of this scheme lies in its full utilization of the K210's edge computing capability. Unlike solutions reliant on cloud servers, this system performs all image processing, model inference, and decision-making control processes entirely locally on the device. This not only completely eliminates issues of slow response or functional failure caused by network latency or interruption, achieving sub-second rapid response times, but more importantly, all captured image data remains on the device without needing to be uploaded to external servers. This ensures user privacy and data security at a physical level, making it particularly suitable for privacy-sensitive public or home environments. This design establishes the system as a truly independent, efficient, and secure embedded intelligent terminal.

3. System Hardware Design

The system hardware platform is centered around the K210 development board, constructing a complete perception-decision-execution closed loop. Figure 1 shows the hardware block diagram, including five modules: the K210 core chip/main controller module, the camera group/image acquisition module, the TFT display/human-computer interaction module, the servo drive/actuator module, and the power supply module.

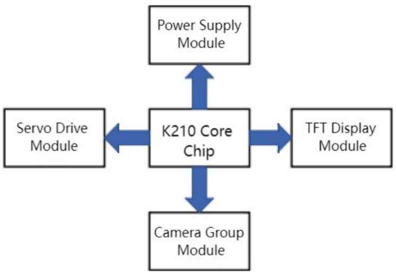


Figure 1. Hardware Block Diagram

3.1 System Hardware Design

The intelligent garbage recognition and classification system designed in this paper adopts the K210 development board as the core computing unit. This chip uses a RISC-V 64-bit dual-core processor with a main frequency of up to 400MHz and integrates a dedicated KPU. Its KPU supports common convolutional neural networks such as MobileNetV1, YOLO, etc., enabling high-performance image recognition tasks with low power consumption, serving as the cornerstone for real-time edge computing in this system. Figure 2 shows the K210 pin definition diagram.

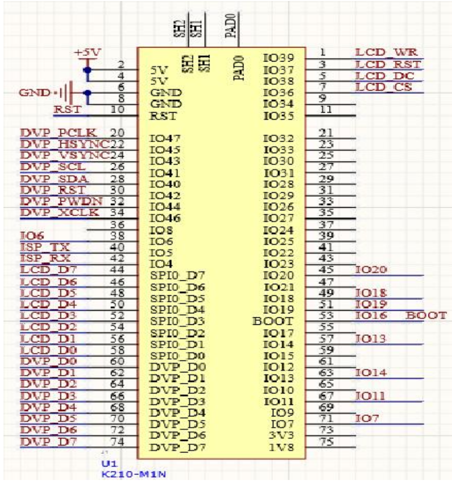


Figure 2. K210 Pin Definition Diagram

3.2 Camera Group Acquisition Module Design

The intelligent garbage recognition and classification system designed in this paper employs the OV2640 camera sensor as shown in Figure 3. This sensor supports image output up to 2 megapixels (1600x1200), features small size and low power consumption, and communicates directly with the K210 via a DVP interface, meeting the system's requirements for garbage image clarity and transmission speed. Coupled with a dual-servo pan-tilt, it allows for angle adjustments of the field of view, enhancing system flexibility.

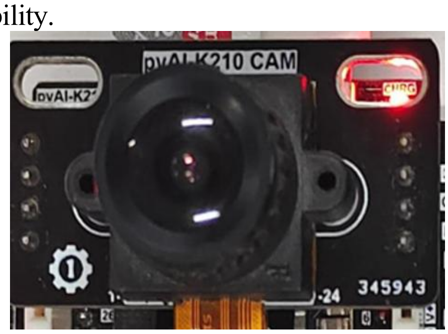


Figure 3. OV2640 Camera

3.3 TFT Display/Human-Computer Interaction Module Design

The intelligent garbage recognition and classification system designed in this paper is equipped with a TFT LCD display as shown in Figure 4, used for real-time display of the scene captured by the camera, the garbage category recognized by the system, confidence level, and other information, providing users with intuitive visual feedback.

Figure 4. TFT LCD Display

3.4 Servo Drive/Actuator Module Design

The intelligent garbage recognition and classification system designed in this paper adopts SG90 micro servos as the control units for opening and closing trash bin lids. The SG90 features a compact structure, simple control, and moderate torque, as shown in Figure 5. The K210 precisely controls the servo's rotation angle through PWM (Pulse Width Modulation) signals, thereby achieving accurate opening and closing of lids for specific categories of trash bins.

Figure 5. SG90 Micro Servo

3.5 Power Supply Module Design

The intelligent garbage recognition and classification system designed in this paper uses a 5V/2A DC power supply to power the entire system, ensuring the stable operation of modules such as the K210, camera, servos, and display.

4. System Software Design

Software design is the soul of system intelligence, mainly including model training, embedded program development, and system integration. Figure 6 shows the software flow chart. After system startup, the K210 platform and camera module are first initialized, followed by continuous detection for garbage image input; if no image is detected, the node enters standby mode. Once an image is detected, the K210 receives it and its built-in KPU invokes the deep learning model for garbage type recognition. During recognition, the TFT display shows the recognized garbage category in real-time. After recognition is complete, based on the determined garbage type, the K210 main control board sends PWM pulse signals to the corresponding category's servo, driving it to open the respective trash bin lid, completing the sorting and disposal of recyclable waste, kitchen waste, hazardous waste, or other waste [10].

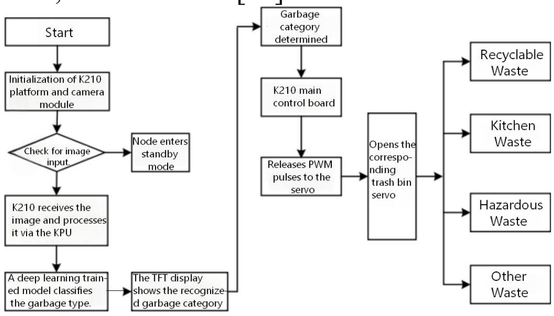


Figure 6. Software Flow Chart

4.1 Design and Training of the Deep Learning Mode

In terms of model selection, this paper systematically evaluates various lightweight neural network architectures in consideration of the resource-constrained nature of the K210 embedded platform. After a comprehensive comparison of computational complexity, memory footprint, and accuracy performance, MobileNetV1 is ultimately selected as the base recognition model. This model employs depthwise separable convolution to replace standard convolution operations, decoupling spatial feature extraction from channel information fusion. While preserving feature extraction capability, this approach reduces computational load to approximately 1/9 and the number of parameters to about 1/7 compared to traditional convolutions. This characteristic makes it particularly suitable for achieving efficient image recognition on edge devices with limited computational power. Compared to other lightweight models such as ShuffleNet or SqueezeNet, MobileNetV1 benefits from better instruction set support and acceleration effects on the K210's KPU, laying a solid foundation for subsequent optimizations.

In terms of model optimization, to adapt to the hardware characteristics of the K210 and further enhance inference efficiency, we adopt a two-stage optimization strategy. The first stage implements structured pruning, which removes less contributing channels by evaluating the importance of convolutional kernels based on their L1 norm, thereby sparsifying the network and compressing the model size by approximately 35%. The second stage performs dynamic range quantization, utilizing a calibration dataset to statistically analyze the activation value distribution across layers and converting FP32 weights and activations to INT8 format[11]. This enables integer computation acceleration on the K210 KPU. These two techniques significantly reduce both model size and computational complexity, substantially improving inference speed while ensuring minimal loss in accuracy.

Regarding the training platform, we utilize the MaixHub cloud-based integrated training platform to complete the entire development workflow. This platform offers automated data augmentation, distributed training, and hardware-aware optimization functionalities. Upon completion of training, the platform automatically performs graph optimization, layer fusion, and format conversion, generating a K210-specific .kmodel binary file. This file not only contains the optimized model parameters but also integrates KPU-specific instruction scheduling information, which improves model loading efficiency on the K210 by 40% and reduces memory usage by 30%. This integrated workflow unifies the traditionally separate stages of model training, conversion, and deployment in embedded AI development, greatly enhancing both development efficiency and deployment reliability.

4.2 Embedded Program Development

Embedded program development is a critical component for achieving intelligent control and stable operation of the system. Regarding the choice of development environment, this system employs the MaixPy IDE based on MicroPython as the primary software development and debugging tool. MicroPython, as a streamlined and efficient implementation of Python 3, is particularly well-suited for resource-constrained embedded platforms. It enables developers to rapidly build applications using a high-level language. Concurrently, the MaixPy IDE provides rich hardware abstraction interfaces specific to the K210 chip, along with features such as code completion, serial port debugging, and real-time memory monitoring, significantly enhancing development efficiency and debugging convenience.

In the design of the core program flow, the system software adopts an efficient main loop detection structure. After program startup, a series of hardware initialization operations are performed first. These include configuring the K210 system clock, initializing the register parameters of the OV2640 camera, setting up the driver and display mode for the TFT screen, configuring PWM output pins for servo control, and loading the .kmodel file stored in Flash into the KPU memory. Once initialization is complete, the system enters an infinite loop. In each iteration of the loop, the program first continuously reads a frame of image data into a memory buffer via the camera driver interface. Subsequently, the core recognition task is triggered by calling the KPU.run() function: this function feeds the image data into the loaded lightweight model, executing forward inference computation on the KPU hardware accelerator. After inference is complete, the program parses the recognition result from a specified memory address, obtaining the most probable garbage category index and its confidence level.

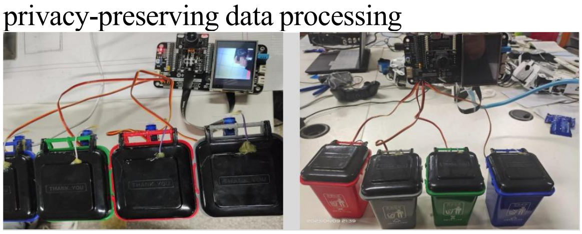
Based on the parsed category result, the system proceeds to the control execution phase. The main control chip generates a PWM pulse signal with the corresponding duty cycle via the PWM module. This signal is sent to the SG90 servo corresponding to the identified category, driving it to rotate precisely to a predetermined angle, thereby opening the target trash bin lid. Simultaneously, for interactive feedback, the program invokes the refresh function of the LCD module to draw the current camera view, textual description of the recognized garbage category, confidence percentage, and other system status information (such as frame rate, system mode) onto the screen in real-time, providing users with intuitive visual feedback. After completing one recognition-execution-display cycle, the program, following a brief delay, returns to the start of the loop to begin processing the next frame of image, thereby achieving continuous operation.

In the final system deployment stage, the developed Python main script and the optimized .kmodel file must be written together into the Flash memory of the K210 chip using the Kflash_gui flashing tool. This tool provides a graphical interface for reliably writing files to specified Flash addresses. After flashing is complete, the system can power on and operate independently, disconnected from a PC. Upon startup, the main program automatically loads the model and necessary configurations from Flash, enabling completely offline, stable, and autonomous operation, meeting the requirements of practical embedded applications.

5. Test Results and Analysis

The hardware assembly and software debugging of the intelligent garbage recognition and classification system based on the K210 and deep learning algorithms, as designed in this paper, have been completed. Multi-angle views of the physical assembly and testing scenario are shown in Figure 7. To comprehensively validate the system's performance, systematic and integrated tests were conducted not only in a standard laboratory environment but also across multiple pilot sites with varying lighting conditions, background complexity, and real-world interference factors. All tests were carried out under normal indoor lighting conditions to simulate typical public or household usage scenarios.

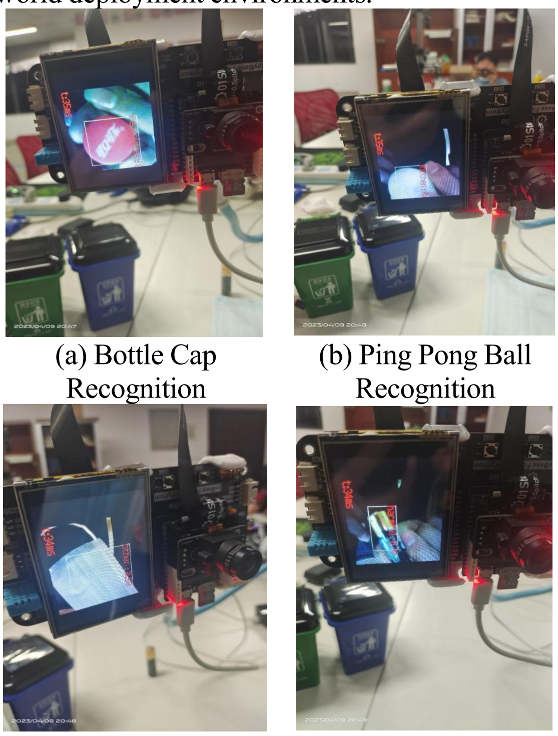
Prior to testing, the optimized lightweight .kmodel file and the corresponding embedded control program were permanently written into the Flash memory of the K210 development board using dedicated flashing tools. After power-on, the system continuously captures real-time images of the target area via the camera module integrated on the development board. When a valid object is detected within the field of view, the system automatically triggers the recognition process: the captured image data is fed into the KPU of the K210 chip for high-speed comparison and inference with the pre-loaded deep learning model. If the recognition result matches one of the garbage categories in the model with a confidence level exceeding the preset threshold, the system immediately executes the corresponding actions—on one hand, visually highlighting the recognized object on the TFT display with markers such as bounding boxes, category labels, and confidence scores; on the other hand, generating corresponding PWM control signals via GPIO to drive the specified SG90 servo to rotate accurately, thereby opening the lid of the corresponding trash bin and guiding the user to complete disposal. The entire process is performed locally on the embedded device without requiring network connectivity, ensuring real-time response and privacy-preserving data processing



(a) Top View (b) Side View

Figure 7. Physical Pictures of the Assembled System under Test

As shown in Figure 8, specific test samples—including a bottle cap, a ping pong ball, a face mask, and a battery—were successively and accurately identified by the intelligent garbage recognition and classification system. Under normal indoor lighting conditions, based on over 500 random sample tests covering eight common types of recyclable waste with varying materials, shapes, and surface textures, the system achieved an average recognition accuracy of 92.5%. Objects with distinct shape and color features, such as plastic bottles and aluminum cans, achieved even higher recognition rates, while the system also maintained strong discriminative ability for objects with similar colors or easily confusable shapes. The average response time of the system remained stable within 1.5 seconds, meeting real-time interaction requirements. During continuous operation tests lasting several hours, the system experienced no crashes, reboots, or significant misidentification incidents, demonstrating good operational stability and reliability suitable for sustained operation in real-world deployment environments.



(a) Bottle Cap Recognition (b) Ping Pong Ball Recognition

(c) Mask Recognition (d) Battery Recognition

Figure 8. Schematic Diagram of Test Samples

6. Conclusion

This paper designed and implemented an intelligent garbage recognition and classification system based on the K210 edge computing chip and deep learning algorithms. The system uses the

K210 as the core processing unit, integrating an OV2640 image acquisition module, a lightweight MobileNetV1 classification model, a TFT human-machine interface, and SG90 servo actuators, thereby constructing a complete embedded intelligent perception-decision-execution closed loop. Through hardware-software co-design and optimization, this system effectively addresses the three core pain points of traditional manual garbage sorting: low efficiency, high operational costs, and unstable recognition accuracy.

Experimental tests and results analysis demonstrate that the system performs excellently across multiple key performance indicators. In terms of recognition accuracy, the system achieves an average recognition accuracy of 92.5% for eight common types of recyclable waste, with even higher accuracy for objects with distinctive features (such as plastic bottles and metal cans). Regarding real-time performance, the average end-to-end response time from image capture to executing the sorting action remains stable within 1.5 seconds, meeting the practical requirements for real-time interaction. In terms of system robustness, the device showed no failures orsignificant performance degradation during prolonged continuous operation tests, demonstrating good stability and reliability.

The main contributions and innovations of this research are reflected in the following three aspects: Firstly, it realizes a fully localized, offline intelligent classification solution. By utilizing the K210's KPU for model inference, it completely eliminates dependence on network connectivity and cloud services, enhancing system response speed and availability while ensuring data privacy. Secondly, it proposes and implements a set of model lightweighting strategies tailored for embedded deployment. Through structured pruning and dynamic range quantization, the model size and computational overhead are significantly reduced while maintaining recognition accuracy, enabling complex deep learning models to run efficiently on resource-constrained edge devices. Finally, a highly integrated, fully functional prototype system has been completed, seamlessly connecting image recognition, result feedback, and physical sorting actions, thereby validating the feasibility of the complete technical pathway from algorithm to practical application.

Acknowledgments

This paper is supported by the Undergraduate Innovation and Entrepreneurship Training Program (No. s202510375073; No. 202410375051).

References

[1] Wu Haitian. Brief Analysis of On-campus Intelligent Garbage Classification Based on Image Recognition Technology. China Plant Engineering, 2025, (15): 26-28.

[2] Han Dewei, Chen Hongyuan, Yang Dayu, et al. Design of an Intelligent Trash Bin Based on K210. Technology and Innovation, 2025, (17): 49-53.

[3] Xie Peijia, Li Hongshuang, Zhu Tianyi, et al. Design of an Indoor Classified Trash Bin Based on Machine Vision. Journal of Machine Design, 2025, 42(S1): 126-131.

[4] Liu Weiwei, Li Linlin, Zhang Yanling. Design and Implementation of an Intelligent Garbage Classification System Based on Internet of Things. Internet of Things Technologies, 2025, 15(15): 131-134.

[5] Wang Feifei, He Xinyi. Research on Deep Learning Recognition Methods for Garbage Classification Images. Journal of Sanming University, 2024, 41(06): 48-58.

[6] Ding Jiamin, Guo Xiaoying, Wang Le, et al. Design and Implementation of Vehicle-mounted Garbage Image Classification and Recognition System Based on Deep Learning. Auto Electric Parts, 2025, (08): 86-88.

[7] Huang Mingyu, Cao Yipeng, Tong Yingzhi, et al. Design and Implementation of a Garbage Classification Recognition System Based on Visual Analysis. Internet of Things Technologies, 2024, 14(09): 25-27.

[8] Zhu Feng. Research on a Rapid Recognition and Classification System for Domestic Waste Based on Deep Learning. Smart City, 2025, 11(05): 124-127.

[9] Zhao Wenqi. Research on Domestic Waste Classification and Detection Based on Deep Learning. Nanjing University of Information Science & Technology, 2024.

[10] Liu Mengting. Research on Garbage Classification and Recognition Algorithm Based on Deep Learning. Huaiyin Institute of Technology, 2024.

[11] Liu Quan, Yan Jinmeng, Yu Heng, et al. Design and Implementation of a Multi-class Garbage Recognition System Based on Deep Learning. Communication & Information Technology, 1-7[2025-11-06].