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Article

Design and implementation of a cleaning robot

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Abstract: This study focuses on the development of a cleaning robot, covering the three main aspects of mechanical design, circuit design, and software design. First, in the area of mechanical design, we created a structure capable of agile movement and efficient cleaning to ensure the robot can operate smoothly in various environments. Second, for circuit design, we developed a microcontroller-based control system to coordinate the operation of various components, including drive motors, sensors, and image recognition modules. Furthermore, in the software design aspect, we utilized YOLO (You Only Look Once) and OpenCV technologies to enable the robot to accurately identify and classify waste during the automatic cleaning process. Finally, we conducted practical cleaning experiments to verify the robot's ability to recognize waste and the accuracy of waste classification. The experimental results show that the cleaning robot not only possesses the ability to recognize waste but also accurately classify it, demonstrating its potential for practical applications.

Keywords: cleaning robot; mechanical design; circuit design; software design; image recognition; waste classification; YOLO

1. Introduction

With the rapid advancement of artificial intelligence technology and the widespread adoption of smart environment concepts, cleaning robots have become essential tools in modern environments as technology evolves quickly, the demand for efficient and intelligent cleaning solutions continues to grow. Traditional cleaning methods are increasingly unable to meet the high-intensity and complex cleaning requirements of various environments. In recent years, cleaning robots that incorporate machine learning and computer vision have become essential solutions to modern cleaning challenges, as they not only perform cleaning tasks efficiently but also adapt to diverse application scenarios [1–5].

Advancements in robot navigation and sensing technologies have driven the evolution of cleaning robots. Today's cleaning robots must possess accurate environmental perception and motion planning capabilities to cope with the diverse and dynamic indoor and outdoor environments. From a design perspective, enhancing the flexibility and stability of the motion mechanism is critical for improving the robot's cleaning efficiency [6]. Additionally, the application of multi-sensor fusion technology, integrating various data to achieve more accurate environmental modeling and localization, has become a key challenge in modern cleaning robot technology. This study focuses on optimizing the mobile mechanism to improve its stability and work efficiency in different operational environments [7–9].

In terms of hardware design, microcontroller-based circuit architecture can effectively reduce costs and improve control precision. A microcontroller is a small computing system that integrates a processor, memory, and input/output interfaces, typically used to control electronic devices or systems. Research shows that coordinating drive motors, sensors, and image processing modules using microcontrollers is a major approach in implementing the control systems of cleaning robots [10,11]. Regarding the technical demands of garbage identification and classification, image processing has gradually been integrated into the design of cleaning robots. For example, the integration of technologies such as YOLO and OpenCV enables cleaning robots to more accurately identify garbage features, thereby improving classification accuracy [12,13].

Although current cleaning robots can achieve a certain level of automation, there is still room for improvement in the accuracy of garbage recognition and classification. Studies show that image processing using deep learning models can significantly improve classification accuracy, but it also increases the demand for computational resources. Therefore, this study optimizes the image recognition algorithms in the software design to balance recognition accuracy with system computational load, enhancing response efficiency [14–17].

The development of this cleaning robot covers three main aspects: motion mechanism design, electronic circuit design, and software development. In terms of motion mechanism design, our goal is to create a stable mobility system that meets the demands of diverse scenarios, while optimizing the garbage collection system to enhance cleaning efficiency. In electronic circuit design, we employ a microcontroller-based architecture that integrates various sensors and control modules to precisely coordinate the robot's movements. The software development section uses YOLO and OpenCV for image recognition and garbage classification, which not only improves classification accuracy but also reduces the risk of misclassification. Finally, a series of application scenario experiments are conducted to verify the garbage identification and classification performance of the robot. See the end of the document for further details on references [18–20].

2. Design of a cleaning robot

This section focuses on the design of the cleaning robot from three perspectives [21,22]: mechanical, circuit, and software design. The mechanical design section covers material selection and structural engineering for building the robot. The circuit design section explains the control and drive mechanisms. Lastly, the software design section details the use of deep learning models and programming to enable garbage classification, image detection, and recognition.

2.1. Mechanical design

This section focuses on the material selection and structural design of the cleaning robot's power module. The primary structural material is 6061 aluminum alloy. Initial design sketches are created in SOLIDWORKS, followed by computer numerical control (CNC) machining to fabricate the individual components. CNC machining is the use of computer numerical control technology to precisely control machine tools to shape and size materials with high accuracy. The cleaning robot's mechanism is divided into four main parts: chassis, transmission, cleaning, and conveying. The chassis support plate is secured with high-strength bolts for enhanced stability, while precision components support the transmission, cleaning, and conveying systems to ensure operational accuracy and reliability.

2.1.1. Material selection

In this study, aluminum alloy 6061, as shown in **Figure 1**, is chosen as the primary structural material for the power module chassis, with the parts processed through CNC machining. The advantages of using 6061 aluminum alloy are as follows:

- Higher Strength and Hardness: After heat treatment (T6), 6061 aluminum alloy offers enhanced strength and hardness, making it more durable than aluminum extrusions and suitable for bearing heavy loads.
- Suitability for Complex Structures and Non-Standard Shapes: 6061 can be processed using CNC machining to create parts with complex shapes, allowing for customization according to specific requirements.
- Better Precision: CNC machining of 6061 aluminum alloy ensures high precision and smooth surface finishes.
- Good Fatigue Resistance: 6061 exhibits excellent fatigue resistance, especially after heat treatment, making it ideal for long-term loading applications.
- Corrosion Resistance: With its strong corrosion resistance, 6061 is well-suited for use in the humid environment of Taiwan.

Figure 1. Cleaning robot materials of aluminum alloy plate.

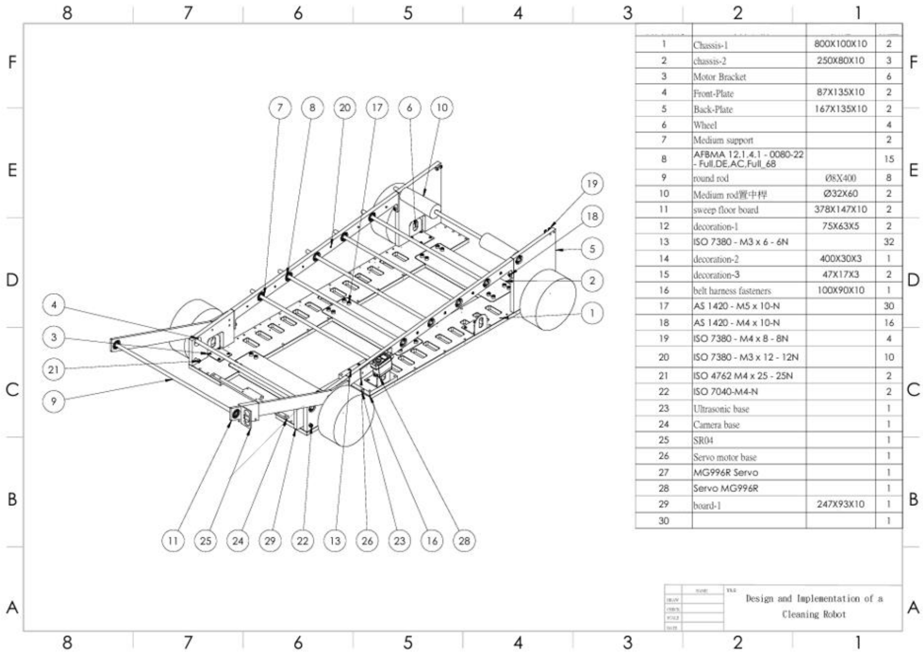
2.1.2. Structural design

In designing the chassis structure, we used SOLIDWORKS for modeling and analysis. SOLIDWORKS is a powerful 3D design software that provides precise drawing and modeling tools, effectively supporting the design of complex chassis structures. First, we created an initial design model based on requirements, considering chassis strength, rigidity, and weight to meet application needs. At the same time, we ensured that manufacturability and ease of assembly were considered, resulting in a simple and efficient structure that is easy to produce.

During the chassis manufacturing phase, a CNC milling machine was used to produce the chassis parts, ensuring machining accuracy and stability. The CNC milling machine offers high precision and cutting capability, making it ideal for producing parts to the exact dimensions and shapes designed in SOLIDWORKS. This not only ensures structural consistency but also eliminates errors that may arise from manual processes.

To guarantee assembly accuracy and structural stability, precision-matched connections were used between the plates, and high-strength bolts secured the components. This design and manufacturing process enhance the chassis durability and load resistance, ensuring stable performance under various loading conditions.

The cleaning robot's mechanism is planned as a comprehensive system divided into four main parts: the chassis structure, transmission structure, garbage cleaning structure, and conveyor belt structure. Based on this, we created the cleaning robot assembly diagram and parts list, as shown in **Figure 2**, with detailed descriptions provided below.



1	Chassis-1	800X100X10	2
2	chassis-2	250X80X10	3
3	Motor Bracket		6
4	Front-Plate	87X135X10	2
5	Back-Plate	167X135X10	2
6	Wheel		4
7	Medium support		2
8	AFBMA 12.1.4.1 - 0080-22 - Full,DE,AC,Full_68		15
9	round rod	Ø8X400	8
10	Medium rod置中桿	Ø32X60	2
11	sweep floor board	378X147X10	2
12	decoration-1	75X63X5	2
13	ISO 7380 - M3 x 6 - 6N		32
14	decoration-2	400X30X3	1
15	decoration-3	47X17X3	2
16	belt harness fasteners	100X90X10	1
17	AS 1420 - M5 x 10-N		30
18	AS 1420 - M4 x 10-N		16
19	ISO 7380 - M4 x 8 - 8N		4
20	ISO 7380 - M3 x 12 - 12N		10
21	ISO 4762 M4 x 25 - 25N		2
22	ISO 7040-M4-N		2
23	Ultrasonic base		1
24	Camera base		1
25	SR04		1
26	Servo motor base		1
27	MG996R Servo		1
28	Servo MG996R		1
29	board-1	247X93X10	1
30			1

Figure 2. Cleaning robot structural parts diagram.

a) Chassis structure:

- Chassis-1 and Chassis-2: Chassis-1 serves as the two main support plates of the overall chassis structure, providing the foundation for the robot's main body. Chassis-2 acts as the connecting piece between the two main support plates, ensuring the stability and strength of the entire structure. The specific shapes and designs of Chassis-1 and Chassis-2 are shown in **Figure 3**.

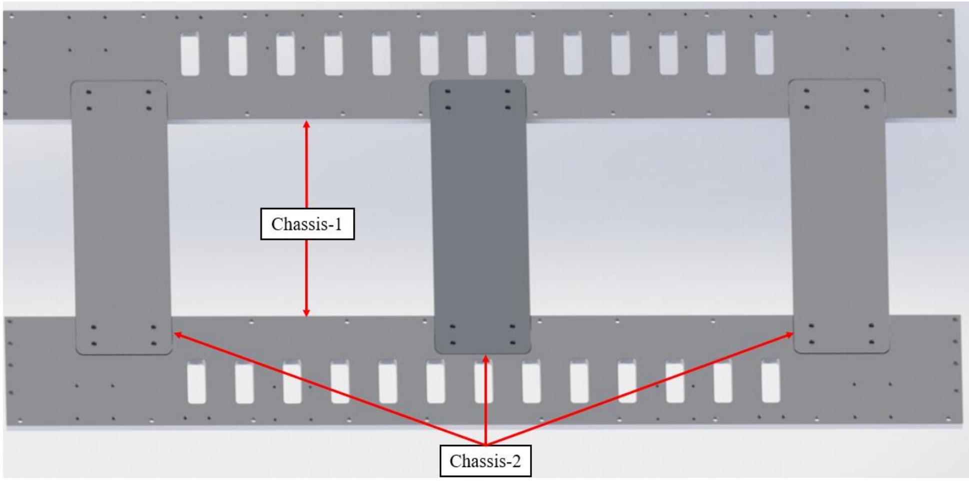


Figure 3. Chassis structure of cleaning robot.

- Front Side Plate and Rear: Side Plate: The front side plate primarily supports the conveyor belt's transmission structure by providing bearing support for the front roller, while also serving as the lower support for the garbage cleaning structure. The rear side plate serves as the rear bearing support for the conveyor belt's roller, ensuring the stability of the conveyor belt. The structures of the front and rear side plates are shown in **Figure 4**.

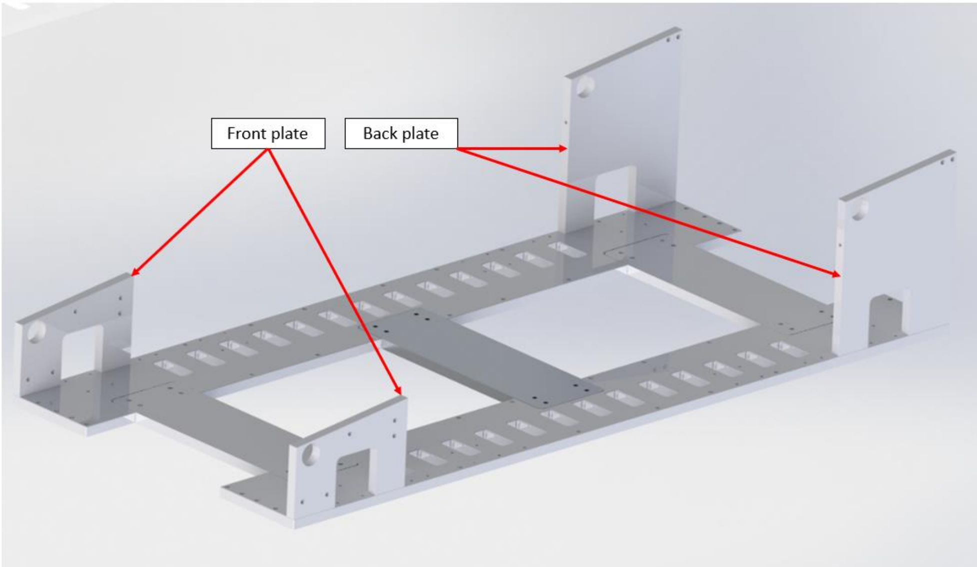


Figure 4. Chassis side panel structure of cleaning robot structure.

b) Garbage removal structure:

As shown in **Figure 5**, this component serves as the upper support frame of the cleaning structure. It has the dual functions of structural support and bearing positioning to ensure the stability and accuracy of the cleaning action.

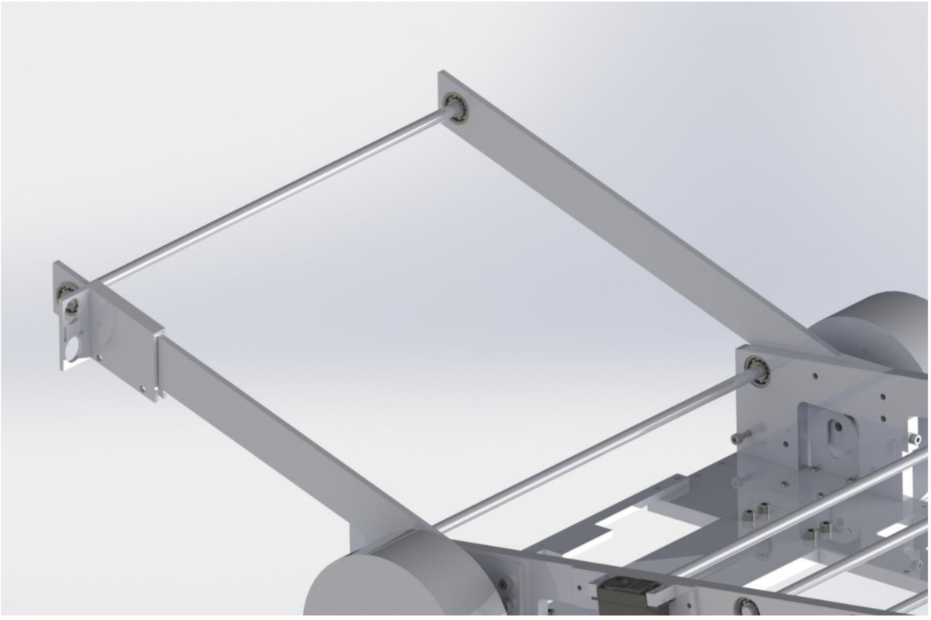


Figure 5. Garbage removal agency of cleaning robot.

c) Garbage conveying structure:

The core objective of the garbage conveyor structure design is to ensure that the cleaning robot can stably and efficiently transport collected waste to the storage area. This structure comprises bearings, rollers, support frames, and the conveyor belt's transmission system, with all components working cohesively to achieve optimal performance. Below is a detailed explanation of each component and the method for calculating the belt length.

Key Components and Design Features:

- Bearings and Rollers as Main Transmission Components:

The bearings and rollers are critical for stable and efficient garbage transport. Custom bearings tailored for the rollers were produced using 3D printing technology, ensuring precise fitting. This approach minimizes errors associated with traditional machining, resulting in a stable and reliable transmission system after assembly. The precision integration prevents looseness or misalignment during operation, maintaining high efficiency in waste transport.

- Middle Support for Structural Stability:

The middle support, which anchors the bearings, serves as a robust structural frame. Designed through rigorous mechanical calculations and careful material selection, the middle support possesses sufficient strength to bear the system's load and withstand the pressures of prolonged operation. This design prevents wobbling or deformation during transmission, ensuring smooth conveyor belt operation. The structural layout of the middle support is illustrated in **Figure 6**. This meticulous design not only extends the system's lifespan but also enhances overall operational efficiency.

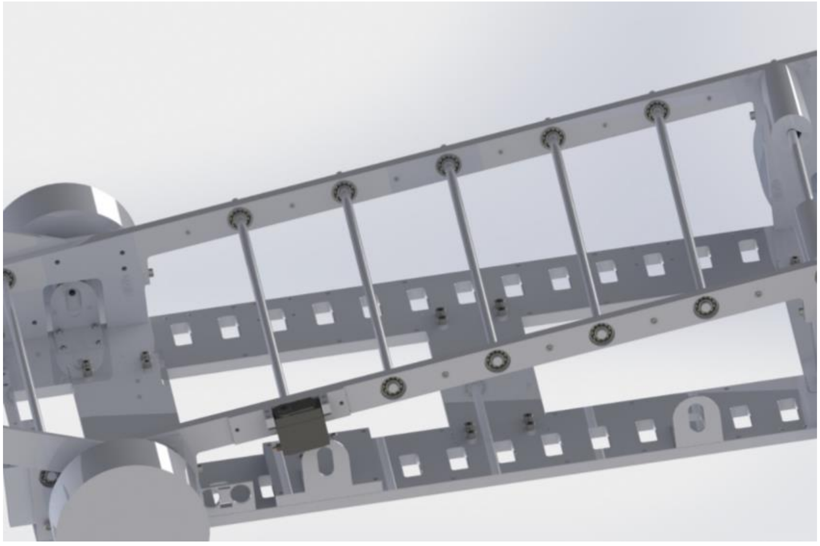


Figure 6. Waste hauling agency of cleaning robot.

To ensure smooth operation of the transmission structure, accurately calculating the belt length is crucial. Based on the geometric parameters of the pulleys and the structural requirements, the belt length can be calculated using the following equation:

$$\mathrm{L} = \frac{\pi}{2}(D + d) + 2C + \frac{(D - d)^2}{4C} \tag{1}$$

The total belt length (L) is a critical parameter in belt drive systems, influenced by several geometric factors. It is determined by three key variables: the center distance (C) between the two pulleys, the diameter of the larger pulley (D), and the diameter of the smaller pulley (d). These geometric variables collectively define the configuration and operational performance of the belt system, ensuring adequate tension and optimal power transmission efficiency. Accurate calculation and optimization of these parameters are crucial for achieving the desired mechanical efficiency and ensuring the longevity of the belt system.

2.2. Circuit design

Figure 7 illustrates the basic circuit design concept of the cleaning robot, while **Figure 8** depicts the wiring layout. To ensure stable motor control during operation, the L298N motor driver module is utilized. This module not only regulates current output but also stabilizes motor operation, enabling the cleaning robot to move reliably across various terrains and under changing loads. The system incorporates three L298N driver modules: two control the front and rear pairs of motors for smooth forward, backward, and turning motions, while the third manages peripheral devices.

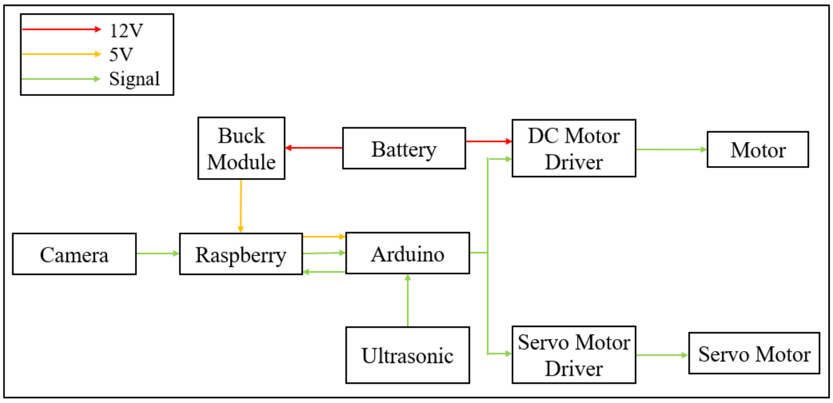


Figure 7. Electronic components integration diagram.

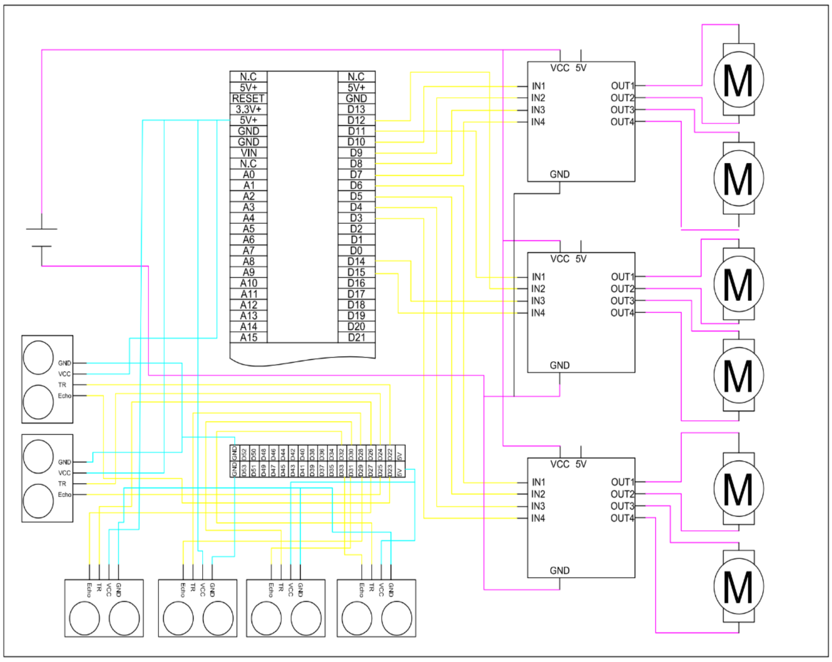


Figure 8. Wiring diagram of clean robot.

The trash sorting function is achieved using two servo motors, which transport waste into designated bins for recyclable and non-recyclable materials. The control system is centered around an Arduino Mega, which receives high-level commands from a Raspberry Pi. These commands regulate the L298N modules to drive the motors, ensuring precise control of movement direction and speed. This coordination enables the cleaning robot to navigate accurately to desired locations.

To support environmental sensing, the robot is equipped with multiple ultrasonic sensors, such as the SR04, for real-time monitoring of the surroundings. These sensors are strategically installed to measure distances between the robot and nearby obstacles, providing spatial data essential for collision avoidance during cleaning operations. The collected data is transmitted from the Arduino Mega to the Raspberry Pi via serial communication for further processing.

2.3. Software design

This section will explain in detail the software architecture design of the deep learning model training and garbage classification image detection and recognition used in YOLOv5 in the cleaning robot.

Deep learning model training

To enhance the accuracy of the waste classification system, a deep learning model was trained. A large dataset of waste images was first collected and annotated using the LabelImg tool, as shown in **Figure 9**. Features of waste objects in each image were precisely labeled. Following the annotation process, the labeled data was used to train the YOLOv5 model. Through iterative backpropagation, the model parameters were continuously adjusted during the training and validation phases to improve classification accuracy.

Figure 9. LabelImg tool feature circle selection.

Once the training process was completed, the optimized model was integrated into the system for real-time waste classification. This implementation ensures that the autonomous vehicle achieves reliable classification and tracking capabilities. The detailed workflow of the image training process is illustrated in **Figure 10**.

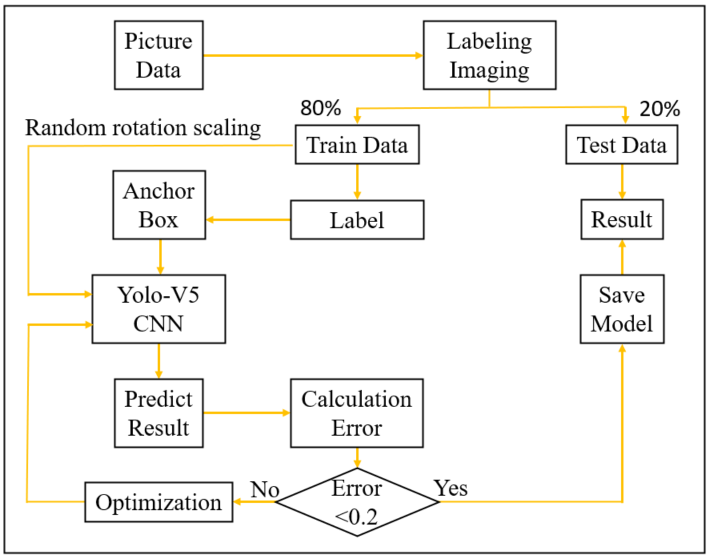


Figure 10. Garbage classification model training flow chart.

3. Implementation

This section discusses the development and experimental process of the cleaning robot, emphasizing the integration of autonomous vehicle control with image recognition for waste classification. The widely adopted YOLO algorithm is employed to ensure the efficient and precise detection and classification of objects, as illustrated in **Figure 11**.

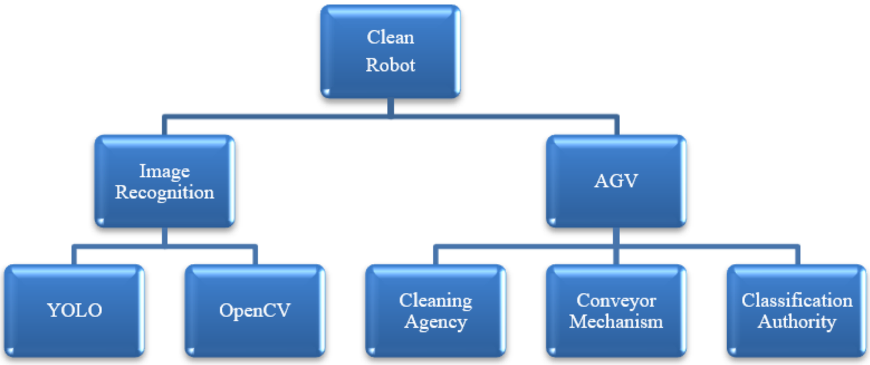


Figure 11. Cleaning robot research architecture diagram.

3.1. The autonomous vehicle system of a cleaning robot

The autonomous vehicle system of the cleaning robot is divided into three main mechanisms: the cleaning mechanism, the conveyor mechanism, and the sorting mechanism. Upon receiving commands from the Raspberry Pi, the instructions are parsed by the Arduino and sent to the respective mechanisms to execute the required actions and complete the task.

In the Raspberry Pi, Python is used to output control commands and collect distance data from the ultrasonic sensors, enhancing the robot's waste classification capabilities. The Raspberry Pi is also connected to a camera module, which captures image data of the cleaning area. Using image processing and deep learning algorithms, the robot identifies object features, determines whether the object is waste, and classifies it (e.g., aluminum foil, plastic bags, PET bottles, etc.). Based on the classification result, the Raspberry Pi sends control signals back to the Arduino to manage the subsequent actions.

This cleaning robot employs mecanum wheels, enabling six different movement modes: forward, backward, left and right translation, and left and right rotation. These movement modes facilitate the efficient navigation of the cleaning area, ensuring the effective removal of waste, as shown in **Figure 12**.

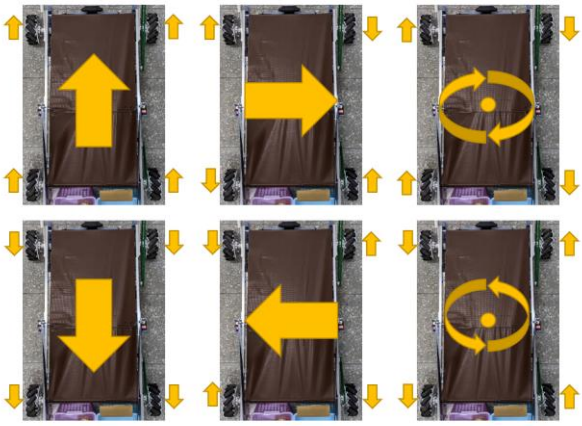


Figure 12. Sport mode of clean robot.

In the cleaning mechanism, in order to prevent the mechanism from blocking the camera's line of sight, this study uses a set of limit switches to position the cleaning mechanism so that it does not block the line of sight, as shown in **Figure 13**. When image recognition and tracking of objects are in progress, the cleaning mechanism will be positioned at a higher position without affecting the camera's recognition of the object to be tracked.

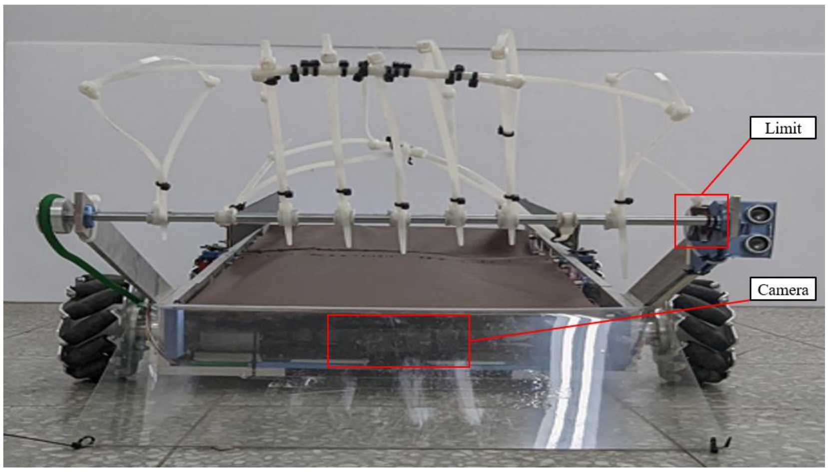


Figure 13. Use limit of clean robot.

In the cleaning robot, the conveyor belt and cleaning mechanism transmit power through the belt. As shown in **Figure 14**, the driving wheel is used to drive the belt and the driven wheel is rotated to drive the conveyor belt or cleaning mechanism to rotate, and the combination of the driving wheel and the driven wheel has a deceleration effect. This combination can optimize the speed of the conveyor belt and cleaning mechanism.

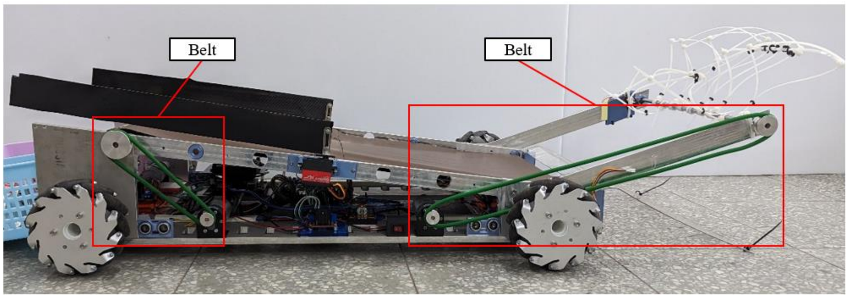


Figure 14. Cleaning robot belt drive mechanism.

After detecting the waste, this study designs two panels for sorting purposes. Upon identifying recyclable and non-recyclable waste, the system receives commands from the Arduino to activate two sets of servos, which perform the corresponding sorting actions. The waste is then directed by the panels into the appropriate collection bins, as shown in **Figure 15**.

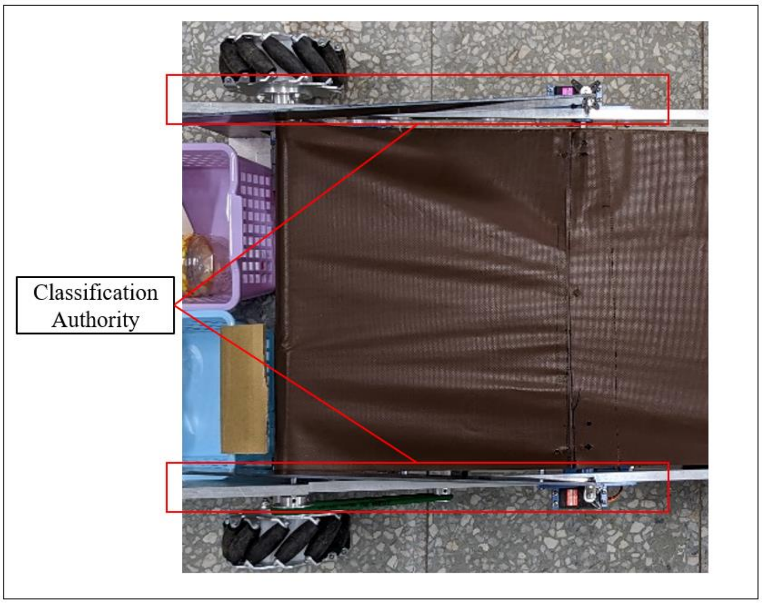


Figure 15. Cleaning robot classification mechanism.

3.2. Image recognition of cleaning robots

In the image recognition system, we use technologies such as YOLOv5 and Channel and Spatial Reliability Tracking (CSRT). With limited hardware resources, we use the advantages of software technology to achieve high efficiency and high-precision recognition purposes.

Among these two technologies, YOLOv5 combined with CSRT has the following advantages when applied to embedded equipment:

a) Efficient object detection and tracking:
- YOLOv5 is responsible for object detection with high accuracy.
- CSRT is responsible for target tracking, which has certain stability and reliability even if the target is blocked.

b) Resource optimization:
- Combined with the CSRT function, computing requirements are reduced.

- Since CSRT does not rely on the GPU during tracking, it effectively reduces resource requirements and improves recognition speed.

c) Good ability to adapt to scenes:
- YOLOv5 can quickly identify objects in the first scene and is suitable for a variety of scenes.
- CSRT has been tested on YOLOv5 and can provide stable single object tracking.

d) Open source and ease of use:
- YOLOv5 has quite a lot of open-source materials that can be used for reference.
- CSRT does not rely on additional special equipment and is easy to use on limited equipment.

The garbage classification image detection module plays a core role in the self-cleaning vehicle system, identifying and locating garbage objects through real-time image analysis and tracking. The overall system process is shown in **Figure 16**.

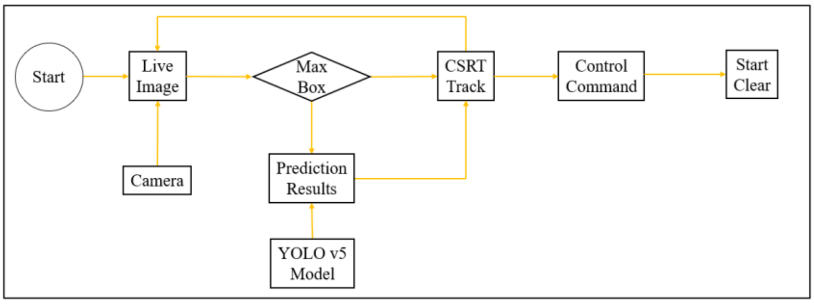


Figure 16. Garbage classification image detection and recognition.

a) Capture real-time images: When the system is turned on, the camera starts first and continues to capture real-time images of the scene for subsequent image identification and tracking. The real-time image capture function ensures that the system can update the image in real time, allowing subsequent model calculations to perform garbage detection based on the latest visual information.

b) Import YOLOv5 for prediction: Each captured image frame is imported into the YOLOv5 deep learning model for object prediction. YOLOv5 has high-performance real-time object detection capabilities, which can quickly locate various objects in images and predict their classification. This model has been trained on a large number of garbage images, so it can accurately identify the type of garbage.

c) Confidence level screening: In the prediction results of YOLOv5, the system gives a confidence level for the prediction of each object. If the confidence level is higher than 0.8, the system determines that the object is garbage. Setting this confidence level threshold is intended to improve the reliability of detection and reduce the occurrence of misjudgments, thereby preventing self-propelled vehicles from tracking irrelevant objects and improving classification accuracy.

d) Switch to CSRT tracking: For objects judged to be garbage, the system will enable the CSRT tracking method. CSRT is an efficient and accurate object tracking algorithm that can stably track objects in captured images. CSRT is particularly good at tracking fast-moving or partially obscured objects, and has good anti-noise capabilities, making it suitable for garbage tracking in dynamic scenes when autonomous vehicles are running. CSRT's tracking framework uses spatial and channel reliability to ensure that the target object is continuously positioned accurately, even if the target is slightly deformed or occluded. Therefore, when YOLO detects the maximum confidence level w, h of an object, the parameters are imported into CSRT to track the position of the object in the image.

e) Control the Arduino self-propelled vehicle module: The system determines the relative position of the garbage based on the CSRT tracking results, and generates corresponding control signals to send to the Arduino self-propelled vehicle module. The self-propelled vehicle module then automatically adjusts the direction, steering angle and moving speed based on the image position of the target object in order to accurately approach and locate the area where the garbage is located. When the self-propelled vehicle completes its positioning, it starts the cleaning function and transfers the garbage to the garbage collection module.

In the test samples, as shown in **Figure 17**, YOLOv5 successfully identified multiple types of objects, accurately drawing bounding boxes around each one, while also labeling each object with its class name and predicted confidence score. The model effectively handles objects of different shapes, sizes, and colors. Even in cases of partial occlusion or complex backgrounds, it maintained a high level of recognition accuracy.

Figure 17. YOLOv5 target detection results display.

4. Experiment

This section presents the hardware configuration and experimental results of the cleaning robot. The experiment utilized a camera, ultrasonic sensors, motors, Arduino Mega 2560, and Raspberry Pi 4. The results demonstrate that the robot successfully employed YOLOv5 for waste detection and integrated CSRT for object tracking and classification.

4.1. Hardware configuration

The specifications of the hardware equipment used in this experiment are shown in **Table 1**, and the cleaning robot result is shown in **Figure 18**.

Table 1. cleaning robot hardware specifications.

Material Component	Specification	Quantity
Camera	Logitech C922 pro	1
Ultrasound	HC-SR04	2
Motor	DC12 V 110 rpm	6
Battery	12 V LiPo	1
Buck Module	DC to DC 75 W (12 V to 5 V)	1
Arduino Mega 2560	Microcontroller: ATmega2560 Working voltage: 5 V Input voltage: 6–20 V	1
Raspberry Pi 4	CPU: Broadcom BCM2711 Cortex-A72 1.5 GHz RAM: 4G GPU: VideoCore VI	1
L298N	Driving voltage: 5 V~35 V Drive current: 2 A Max power: 25 W	3

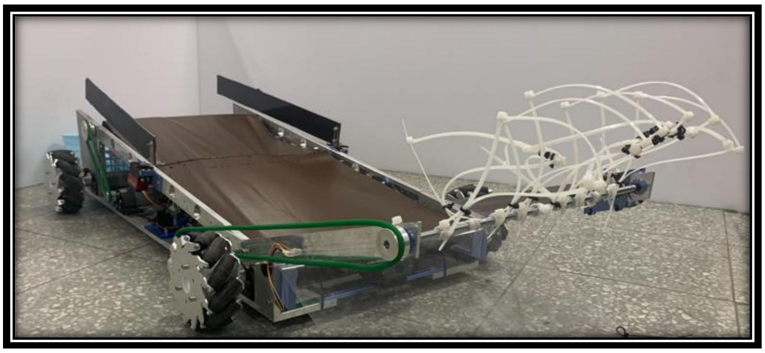


Figure 18. Cleaning robot results.

4.2. Experimental results

The experimental results of the cleaning robot are primarily analyzed from three aspects: waste detection, waste classification, and cleaning efficiency. First, in waste detection, the cleaning robot uses the YOLOv5 model to identify waste objects. In the tests, the detection showed high accuracy for objects with clear shapes and distinct features (such as plastic bottles and metal cans). However, for irregularly shaped or deformed waste (such as crumpled packaging paper), the detection accuracy slightly decreased. **Figure 19** presents the results of the waste detection, with green boxes clearly indicating the successfully detected and identified waste objects.

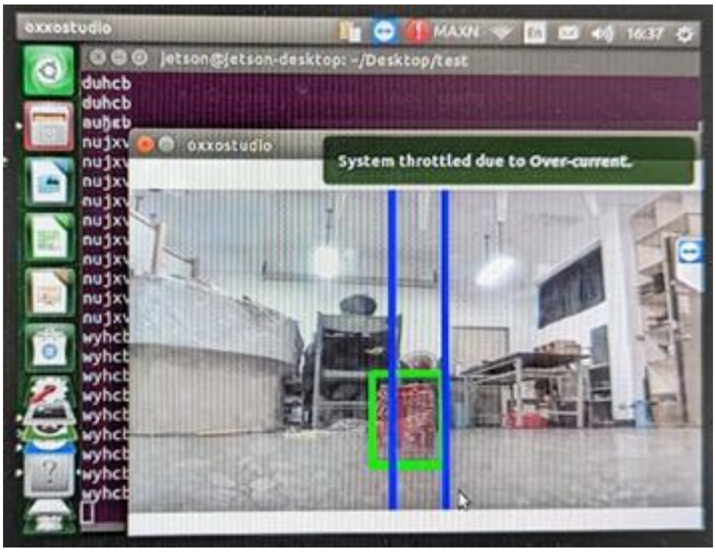


Figure 19. The cleaning robot uses YOLOv5 for object detection (green box).

To enhance cleaning efficiency, the system employs the CSRT function for efficient object tracking after waste detection. Once the YOLOv5 model completes the detection, the detection box data is fed into the CSRT algorithm for real-time tracking. **Figure 20** shows the tracking results, with yellow boxes representing stable tracking of the target objects using CSRT, demonstrating the system's ability to handle dynamic scenarios effectively.

Figure 20. Schematic diagram of cleaning robot tracking using CSRT (yellow box).

In terms of waste classification and handling, the cleaning robot accurately classifies the waste and places it into the corresponding recycling bins based on the recognition results from the YOLOv5 model, as shown in **Figure 21**. The entire cleaning and classification process not only verifies the accuracy and efficiency of the robot system but also highlights its potential for practical applications.

Figure 21. Schematic diagram of a cleaning robot recycling garbage.

The following summarizes the accuracy and efficiency of the experiment in practical applications based on waste detection accuracy, cleaning efficiency, and waste classification and handling results.

Waste detection accuracy:

- For objects with clear shapes and distinct features, the detection accuracy was 95%.
- For irregularly shaped or deformed waste, the detection accuracy was 85%.

Cleaning efficiency:

- The number of waste objects that can be detected and tracked per hour is 50.
- The real-time tracking success rate of the CSRT algorithm was 92%.

Waste classification and handling:

- Based on the recognition results from the YOLOv5 model, the waste classification accuracy reached 90%.
- The accuracy of placing the classified waste into the corresponding recycling bins was 88%.

Although the detection accuracy for irregular or deformed waste is 85%, possible solutions include integrating additional sensors, such as depth cameras, to improve the detection of irregularly shaped waste. Additionally, enhancing the image recognition model by using more diverse training data can increase the system's ability to identify non-standard items. In terms of adaptability to various environments, besides the robot's mechanical design allowing agile movement in different settings, robust control can be introduced to the robot's control system to enhance its adaptability in various environments. Finally, for the robot's energy usage, the future consideration of using both batteries and solar power can improve the use of sustainable energy.

5. Conclusion

This study successfully designed and implemented a cleaning robot that integrates mechanical, electronic, and AI software systems, achieving automated waste detection and classification. The mechanical structure is constructed from CNC machined 6061 aluminum alloy, providing the necessary strength, precision, and durability for stable operation in diverse environments. The circuit system, centered around the Arduino Mega microcontroller and the L298N motor driver module, ensures reliable coordination between the drive motors, sensors, and actuators.

The AI software system utilizes YOLOv5 for object detection, combined with CSRT for real-time tracking, demonstrating excellent performance in waste recognition and classification. Experimental results show that the robot achieves high accuracy in detecting various types of waste and exhibits stable classification capabilities. Additionally, the use of mecanum wheels enables multiple movement modes, further enhancing the robot’s operational flexibility.

In conclusion, the cleaning robot developed in this study holds significant potential for waste management applications, offering a scalable and efficient automated solution for both cleaning and sorting. Future research will focus on optimizing the system’s computational efficiency, expanding its application to more complex environments, and integrating sustainable energy sources to maximize its environmental benefits.

Author contributions: Conceptualization, YHC and SYP; methodology, YHC and SYP; software, SYP; validation, YHC and SYP; formal analysis, YHC and SYP; investigation, YHC and SYP; resources, YHC; data curation, YHC and SYP; writing—original draft preparation, YHC and SYP; writing—review and editing, YHC; visualization, YHC and SYP; supervision, YHC; project administration, YHC and SYP; funding acquisition, YHC. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

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