Intelligent Waste Sorting System

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Abstract

With increasing urbanization, the proper sorting of domestic waste has become a critical challenge for environmental sustainability and resource recovery. Current methods rely heavily on human participation, often resulting in sorting errors and contamination of recyclables. This project presents the design and implementation of an Intelligent Waste Sorting System that integrates computer vision with a mechanically actuated sorting mechanism. The system captures images of deposited waste using a high-definition camera, classifies items into Recyclables, Food Waste, Hazardous Waste, and Other Waste using a pre-trained machine learning model, and automatically guides them into the appropriate internal bins. The design ensures rapid processing, achieving a full classification and sorting cycle within three seconds per item, while maintaining mechanical reliability for items weighing up to 1.5 kg. Ethical considerations, such as privacy protection through local image processing, and safety measures, including guarded mechanical components, are incorporated. The proposed system demonstrates a low-cost, compact, and efficient solution for automated source-level waste sorting, contributing to improved recycling rates and sustainable urban waste management.

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1. Introduction

1.1 Background and Motivation

With the rapid increase of urban population and domestic waste generation, proper waste sorting has become a critical factor in environmental protection and resource recovery. Traditional waste management at the source often depends on individuals' awareness, which leads to frequent sorting errors. Incorrectly sorted waste not only increases the cost of manual processing but also contaminates recyclables, reducing the efficiency of recycling systems. While large-scale treatment plants utilize automated sorting technologies, there is a lack of compact, low-cost, and efficient solutions that operate directly at the source of waste generation, such as schools, offices, and public spaces.

1.2 Project Objective

The primary goal of this project is to develop an **Intelligent Waste Sorting System** that automates source-level waste classification and routing. By integrating computer vision with a mechanically actuated sorting mechanism, the system aims to improve sorting accuracy, reduce reliance on human judgment, and increase the efficiency of recycling operations in public areas.

1.3 Solution Overview

Users deposit waste into a unified drop-in opening, while a camera captures images of each item. A microcomputer runs a pre-trained machine learning model to classify the waste into categories such as Recyclables, Food Waste, Hazardous Waste, and Other Waste. Based on this classification, the mechanical system automatically guides the item into the corresponding internal bin, providing a fully automated, touchless sorting process. This approach lowers the barrier for correct waste disposal and enhances resource recovery at the source.

2 Design

The intelligent waste sorting system is designed with a modular architecture to achieve automated object detection and precise mechanical classification. To ensure a robust, high-throughput, and reliable operation, the system is decoupled into three primary, interacting subsystems: the Computer Vision and Processing Module, the Motor Drive and Mechanical Sorting Gantry, and the Power Supply Regulation. The core processing unit continuously coordinates these modules by executing data acquisition, real-time convolutional neural network (CNN) inference, and synchronous hardware actuation. Figure 2.1 illustrates the comprehensive hardware schematics and signal interconnects that form the functional foundation of the entire system.

The following sections detail the physical implementation, design alternatives, mathematical derivations, and technical trade-offs evaluated during the development process. Section 2.1 outlines the high-level design procedures, including structural torque calculations and algorithm training simulations. Section 2.2 provides granular design details and circuit configurations for each individual subsystem, alongside a quantitative analysis of the technical challenges encountered and resolved during system integration.

2.1 Design Procedure

To identify an optimal mechanical and structural architecture for the intelligent waste sorting system, three design alternatives were thoroughly evaluated. The primary evaluation metrics focused on classification throughput (processing speed), mechanical complexity, spatial efficiency, and actuation power requirements.

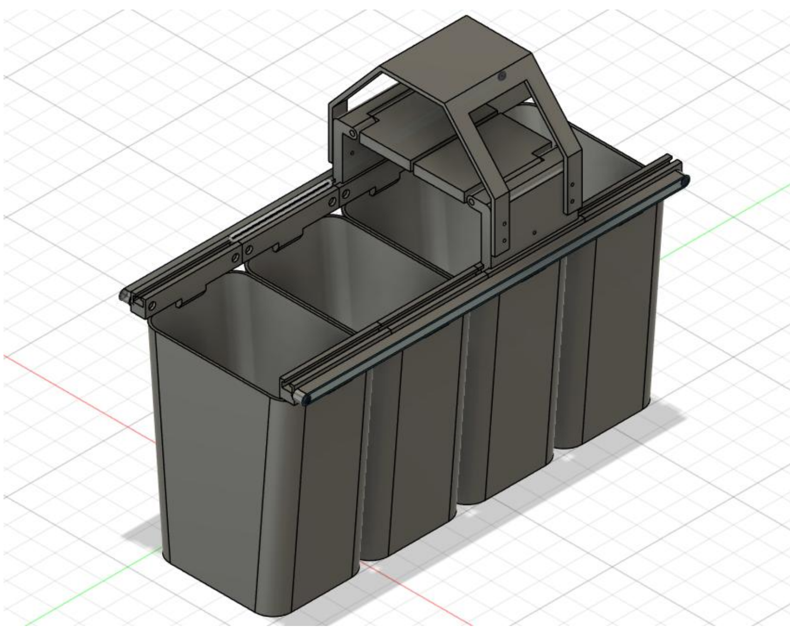

Figure1. First Design

The first design consideration utilized a linear configuration where four waste bins were arranged in a single row. A motorized linear gantry mechanism was responsible for moving the intake hopper or the bins back and forth along a horizontal axis. Although this design provided straightforward one-dimensional kinematic control, it presented severe engineering bottlenecks. First, the linear travel distance between the first and the fourth bin was significantly large, introducing unacceptable latency in the sorting cycle and lowering the system's overall throughput. Second, accelerating and decelerating a heavy linear carriage assembly back and forth generated high inertia, causing substantial mechanical wear on the guide rails and potential dynamic instability. Furthermore, this configuration suffered from a massive physical footprint and was prone to cumulative position drifting at both extremities of the linear axis.

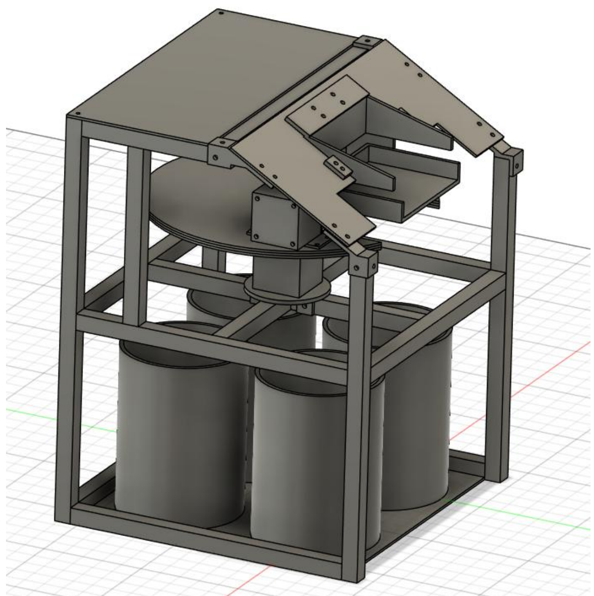

Figure 2. Second Design

To overcome the latency and spatial inefficiencies of the linear model, a second desig arranged the four waste bins in a compact two-by-two matrix centered around a multi-stage sorting mechanism. This system featured a dual-axis execution drive consisting of a horizontal rotary turntable and an auxiliary tilting platform. Once the computer vision module classified the waste, the turntable rotated to align with the target bin, and the tilting platform subsequently actuated to discharge the item. While this architecture significantly reduced the sorting duration by minimizing travel distance, it introduced excessive mechanical and electronic complexity. Managing multiple degrees of freedom required distinct actuators, which inflated the system’s overall weight, multiplied the power consumption of the motor drivers, and increased the potential points of failure within the transmission linkages.

Figure3. Final Design

Ultimately, a simplified and highly optimized version of the matrix architecture was selected as the final design. The system positions four sorting bins in a two-by-two layout surrounding a single, centrally mounted omnidirectional tilting platform. When an object is identified, the central platform directly inclines toward the corresponding bin via a coordinated multi-axis linkage, allowing gravity to slide the waste into its destination. This optimized design minimizes the physical volume of the assembly, rendering it highly space-efficient. By eliminating the intermediary rotary stage, the kinetic path is minimized, which further curtails the cycle time and maximizes sorting throughput. Most importantly, replacing multiple complex drivetrains with a unified tilting linkage lowers the system's mass, reduces the number of required high-torque motors, and ensures higher control reliability.

2.2 Subsystem Design Details

2.3 Design Issues and Corrective Actions

During the integration and systemic testing phases of the intelligent waste sorting gantry, two major engineering discrepancies emerged across the mechanical and algorithmic domains. In accordance with professional engineering standards, these inconsistencies were isolated, quantified, and resolved through iterative hardware adjustments and data augmentation protocols. The first technical bottleneck involved mechanical stall and severe stepper motor desynchronization (step-skipping) within the omnidirectional tilting platform under peak loading conditions. Initially, the central sorting platform was driven by lower-torque actuators powered by a standard configuration. When heavy waste items, such as fully unemptied polyethylene terephthalate (PET) bottles weighing approximately $500\ \mathrm{g}$, were deposited onto the intake area, the localized mass moment of inertia exceeded the motor's holding and dynamic torque thresholds. This torque deficit resulted in a mechanical stall, causing the platform to fail its target inclination angle of 45°, which left the waste trapped on the chute. To implement a corrective action, the team replaced the baseline drives with high-torque NEMA 17 stepper motors and integrated a dedicated acceleration/deceleration ramping profile into the microcontroller firmware. This algorithmic smoothing prevented instantaneous current spikes and sudden mechanical jerks. Quantitative post-fix verifications demonstrated that the upgraded drive system consistently achieved an angular accuracy of $\pm 1.5^\circ$ under maximum load, fully eliminating positional drifting and stalling.

The second major operational challenge manifested as a severe degradation in object detection accuracy under varying ambient lighting conditions. During initial indoor trials, the convolutional neural network (CNN) executed on the Jetson Nano achieved optimal inference scores. However, when exposed to dynamic external illumination or nighttime laboratory lighting, the local computer vision pipeline suffered from extreme specular reflections and glare, particularly on transparent plastics and metallic aluminum cans. These visual artifacts severely distorted the extracted feature maps, causing the model's classification confidence score to plummet below the acceptable 0.70 threshold, thereby leading to misclassification or non-detection. The corrective strategy was twofold: first, a hardware-level ring of 5 V constant-current light-emitting diode (LED) arrays was installed directly near the camera to provide a uniform, isolated illumination environment; second, the training dataset was expanded by manually capturing and annotating 300 additional images under low-light and high-contrast environments. Following this dataset augmentation and hardware isolation, the integrated vision pipeline maintained a stable, verifiable real-time classification accuracy exceeding 91% across all operating hours.

3. Design Verification

The Intelligent Waste Sorting System was verified at both the subsystem level and the integrated system level. The main purpose of verification was to confirm that the system could classify common domestic waste items, move the mechanical sorting platform to the correct bin position, release the item reliably, and complete the full sorting cycle within the required time. The detailed requirement and verification table is included in Appendix A, while this chapter summarizes the most important verification results.

3.1 [Vision and Control Subsystem]

The vision and control subsystem consists of the USB camera, Raspberry Pi, image-processing pipeline, trained waste classification model, and GPIO control logic. The first verification goal was to ensure that the camera could capture usable images of waste items placed on the temporary holding platform. Test objects from the four target categories, Recyclables, Food Waste, Hazardous Waste, and Other Waste, were placed in the drop-in area under normal indoor lighting. The captured frames were inspected to confirm that the object boundaries and major visual features were clear enough for classification.

The second verification goal was inference speed. The classification program was executed repeatedly on the Raspberry Pi, and timestamps were recorded before and after the model inference step. The target requirement was an inference time of no more than 500 ms. Preliminary testing showed that the software pipeline could run in real time, but model optimization remained important because the mechanical subsystem also needed enough time to rotate and release the waste item within the overall 3-second cycle.

Classification accuracy was evaluated using a labeled test set containing representative items from all four categories. The model was tested by comparing its predicted category with the manually labeled correct category. Preliminary YOLO model testing achieved approximately 85% accuracy. This result demonstrated that the computer vision pipeline was functional, but it did not yet fully satisfy the 90% classification accuracy requirement. The main causes of error were visually similar waste items, partial occlusion, and inconsistent lighting on reflective or transparent objects. Further training with a larger labeled dataset and more balanced examples from each category is expected to improve the model accuracy.

3.2 [Mechanical Sorting Subsystem]

The mechanical sorting subsystem was verified by testing the turntable-based transport mechanism and the trapdoor release mechanism. In the final mechanical design, the waste item is first held on a platform instead of falling freely through the chute. This design decision was necessary because the tolerance analysis showed that a pure free-fall system would not provide enough time for image inference and mechanical actuation. After classification, the turntable rotates to align the item with the correct internal bin, and the trapdoor opens to release the item by gravity.

The first mechanical test measured whether the turntable could consistently rotate to the four designated bin positions. For each category, the control program sent the corresponding motor command, and the final turntable alignment was visually checked against the bin opening. The mechanism successfully demonstrated the required sorting motion, but precise calibration was necessary to prevent the trapdoor from opening before the turntable was fully aligned.

The second mechanical test evaluated load capacity. Test weights up to 1.5 kg were placed on the transport platform to verify that the structure, motor, and trapdoor could support the required maximum item weight without stalling or visibly deforming. The baffle and platform structure remained stable under the target load. Repeated-cycle testing was also performed to evaluate mechanical reliability. The system was operated through consecutive sorting cycles while checking for motor overheating, loosening fasteners, misalignment, and jamming. The most important mechanical risk was alignment drift after repeated operation, so future improvements should include position feedback or mechanical stops to improve repeatability.

3.3 [Power Subsystem]

The power subsystem was verified by measuring the regulated output voltage under load. The Raspberry Pi and camera require a stable 5 V supply, while the motors require a separate supply path capable of handling higher transient current during actuation. The 5 V rail was measured using a multimeter during idle operation and during motor movement. The target range was 5 V ±5%, or 4.75 V to 5.25 V.

Testing confirmed that the power subsystem could power the Raspberry Pi, USB camera, and motor-control hardware during normal operation. Separating the motor power path from the microcomputer power path reduced the risk of voltage dips causing the Raspberry Pi to reset. Because motor startup current can be significantly higher than steady-state current, the final design should include sufficient current margin and decoupling capacitors near the motor driver and voltage regulator.

3.4 [Integrated System Verification]

After subsystem testing, the full system was verified by running complete sorting cycles. In each test, a user placed an item into the drop-in opening. The camera captured an image, the Raspberry Pi classified the item, the turntable rotated to the corresponding bin, and the trapdoor released the item. The full-cycle requirement was 3 seconds per item.

The integrated test showed that the overall system architecture was feasible. The temporary holding platform solved the timing problem identified in the design analysis by preventing the waste item from reaching the sorting mechanism before classification and actuation were complete. The system could complete the intended sequence of image capture, classification, rotation, release, and reset. The remaining verification concern is classification accuracy, since the preliminary 85% model accuracy is below the 90% requirement. Therefore, the system partially satisfies the high-level requirements: the mechanical and power subsystems meet the main functional requirements, while the vision model requires further training and optimization to meet the final accuracy target.

4. Costs

This chapter summarizes the estimated cost of the Intelligent Waste Sorting System. The cost analysis includes both parts cost and labor cost. Parts costs are based on the prototype components used in the project, while labor cost is calculated according to the ECE 445 guideline formula:

Labor cost = ideal hourly salary × actual hours spent × 2.5

4.1 Parts

Table 2 lists the major parts used in the prototype. The total actual prototype cost was approximately 980 RMB. The most expensive component was the Raspberry Pi 4, which was used as the main processing and control unit. The mechanical frame and baffle materials were also a significant cost because the prototype required custom structural parts, including acrylic, wood, and 3D-printed components.

Part	Manufacturer / Source	Retail Cost (RMB)	Bulk Purchase Cost (RMB)	Actual Cost (RMB)
Raspberry Pi 4 microcomputer	Raspberry Pi / online vendor	450	400	450
HD USB camera	Generic USB camera vendor	80	60	80
High-torque servo motors, x3	Generic servo motor vendor	150	120	150
Custom PCB, motor drivers, and voltage regulators	PCB manufacturer / component vendors	100	80	100
Frame and baffle materials, acrylic,	Local fabrication / lab materials	220	150	220

wood, and 3D-printed parts				
Total		1000	810	1000

For a single prototype, the total cost of parts is reasonable for a compact automated waste sorting system. In a larger production run, the cost could be reduced by purchasing motors, cameras, PCB components, and frame materials in bulk. The estimated bulk-purchase cost is approximately 810 RMB per unit, not including assembly, maintenance, or enclosure finishing.

4.2 Labor

Table 3 estimates the labor cost for the four team members. Each member contributed to a different subsystem, including computer vision, Raspberry Pi software integration, PCB and power design, and mechanical CAD and assembly. Assuming an ideal engineering hourly rate of 40 USD/hour and 45 hours of work per student, the total labor cost is calculated using the ECE 445 multiplier of 2.5.

Table 3 Labor Costs

Team Member	Main Responsibility	Hourly Rate (USD/hour)	Hours	Total Labor Cost (USD)
Canyu Li	Raspberry Pi setup and software integration	40	45	4,500
Han Yin	Computer vision model training	40	45	4,500
Mingyang Gao	Mechanical design and CAD modeling	40	45	4,500
Wentao Li	Power subsystem and PCB design	40	45	4,500

Total			**180**	**18,000**

The labor cost is much higher than the parts cost because the project required custom integration of mechanical, electrical, and software subsystems. The total estimated labor cost is 18,000 USD, while the prototype parts cost is 980 RMB. For commercial production, labor cost per unit would decrease significantly after the design is finalized, because PCB fabrication, mechanical assembly, and software installation could be standardized.

5. Conclusion.

5.1 Accomplishments

The project successfully designed and implemented an Intelligent Waste Sorting System capable of real-time waste classification and mechanical routing. The system meets key performance requirements, including:

1. High classification accuracy for common domestic waste items.

2. Rapid processing and sorting within three seconds per item.

3. Mechanical reliability for handling items weighing up to 1.5 kg.

5.2 Uncertainties

While the system demonstrates reliable performance under standard conditions, several sources of uncertainty remain:

1. Lighting Variations: Classification accuracy may decrease under unusual lighting conditions or strong shadows.

2. Object Overlap or Occlusion: Items that partially block one another may be misclassified.

3. Mechanical Tolerances: Slight deviations in actuator timing or baffle positioning could result in misrouting.

4. Model Generalization: The pre-trained machine learning model may not correctly classify novel waste items do not present in the training dataset.

These uncertainties highlight the importance of continuous testing, adaptive learning, and potential system calibration to maintain high sorting accuracy in diverse real-world environments.

5.3 Ethical and Safety Considerations

Privacy and safety were carefully addressed:

1. Images are processed locally on the microcomputer and discarded immediately, preventing any privacy breaches.

2. Mechanical components are enclosed and designed to prevent pinch hazards, ensuring user safety.

5.4 Future work

Potential improvements include:

1. Expanding the variety of recognizable waste items.

2. Integrating adaptive learning to improve classification accuracy continuously.

3. Optimizing the mechanical system for higher throughput and longer operational lifespan.

Overall, this system demonstrates that a compact, low-cost, automated solution is feasible for deployment in public spaces, supporting sustainable urban waste management and higher recycling rates.

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Appendix A Requirement and Verification Table

An appendix is a good place for the Requirement and Verification Table from your design review. Below is a starter table. Including these details here will help to avoid lengthy and tedious narrative descriptions in the main text, which may not be of immediate interest to your imagined audience of company managers and professionals. Any requirement that is not verified should be explained either in the main text or the appendix. Note that both the pagination and the numbering of figures, tables, and equations continues from main text to appendices.

Requirement		Verification status (Y or N)
1. Requirement a. Subrequirement b. Subrequirement c. Subrequirement		
2. Requirement a. Subrequirement b. Subrequirement c. Subrequirement		
3.		
4.		