Intelligent Waste Sorting System

By

Canyu Li

Han Yin

Mingyang Gao

Wentao Li

Final Report for ECE 445, Senior Design, Spring 2026

TA: Hengjia Ran

15 May2026

Project No. 37

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.

Contents

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.

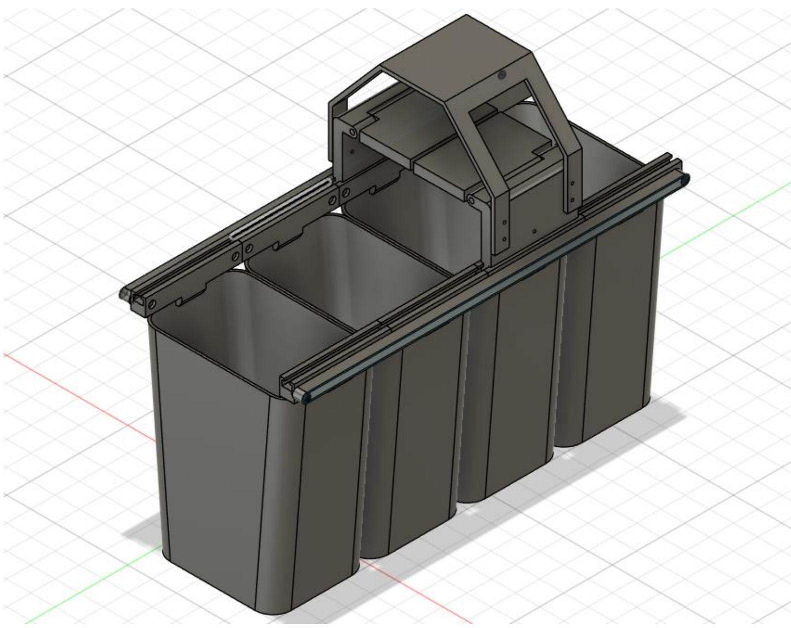


Figure1. First Design

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.

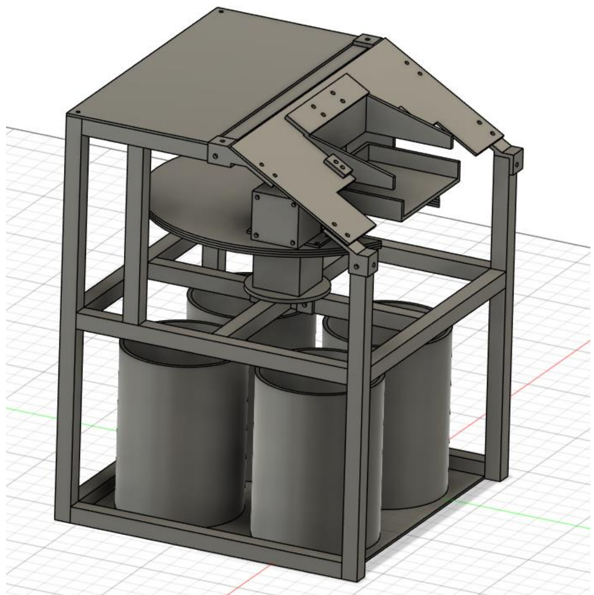


Figure 2. Second Design

To overcome the latency and spatial inefficiencies of the linear model, a second design 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.

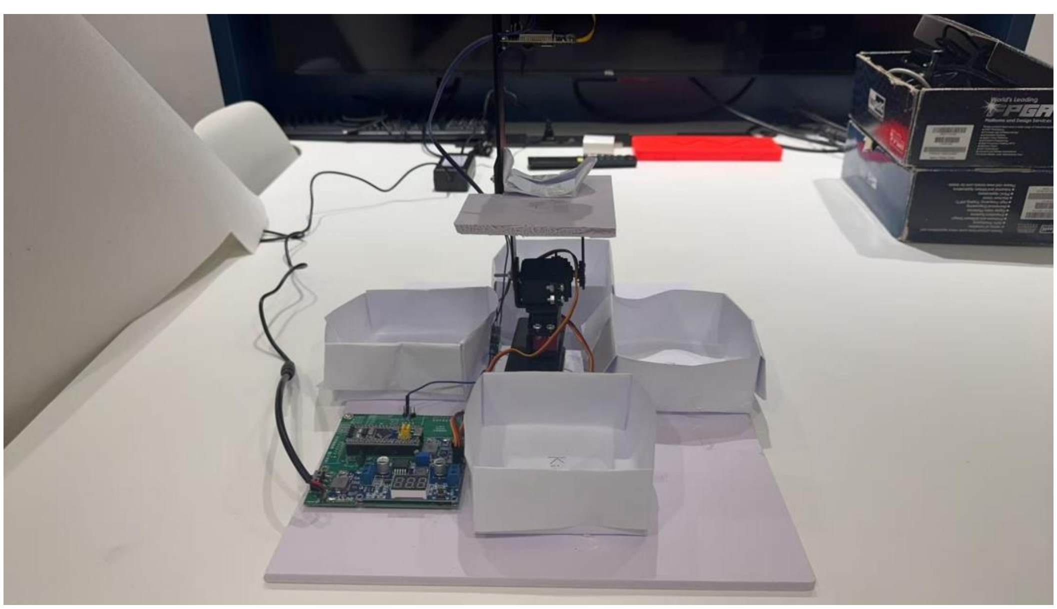
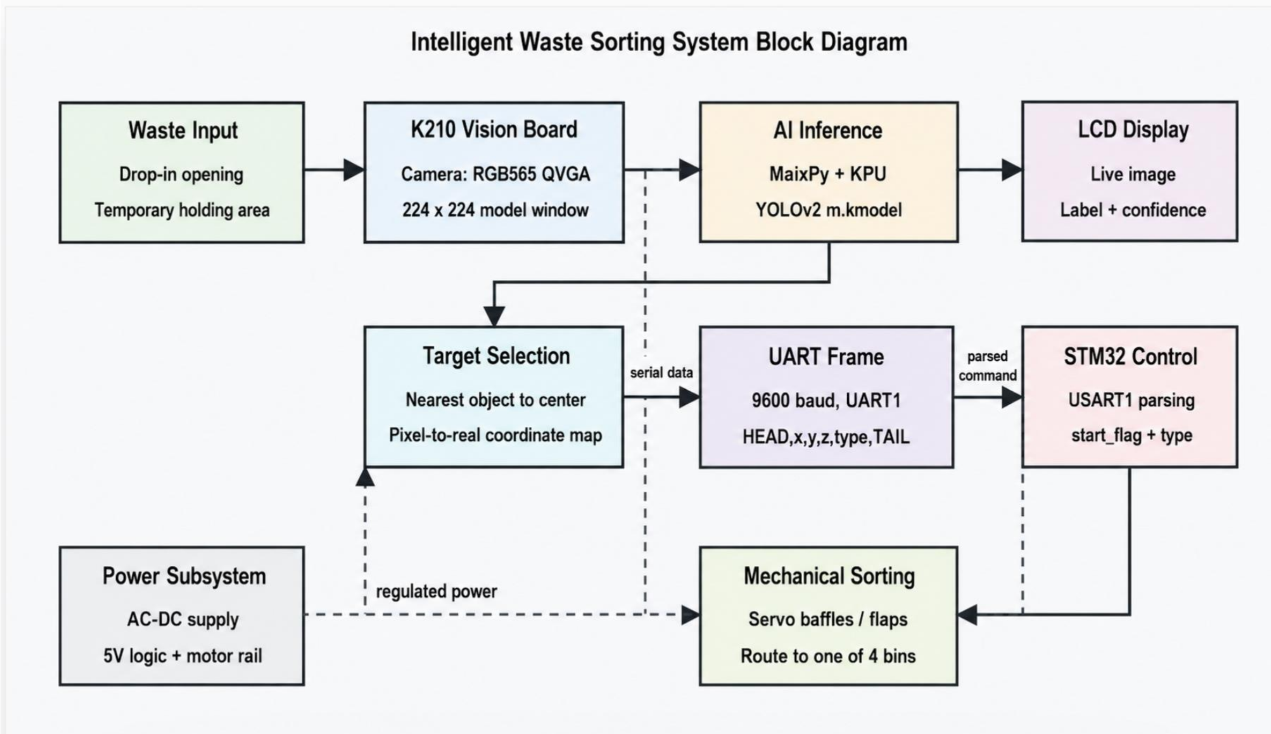


Figure3. Final Design

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. The following figure is the block diagram of our final design.



2.2 Subsystem Design Details

2.2.1 Vision and Control Subsystem

The vision subsystem consists of the K210 board (figure 5), camera module, LCD debug display, SD card, YOLOv2/KPU model file, and labels file. The camera captures RGB565 QVGA frames and crops a 224 x 224 input window. The model uses a confidence threshold of 0.5 and an NMS threshold of 0.3. The board displays the label, bounding box, confidence, and timing information during debugging.

2.2.2 Mechanical Sorting Subsystem

The mechanical subsystem uses a temporary holding platform and servo-actuated routing baffles. The holding platform prevents the item from falling past the sorter before image capture and inference finish.

After receiving a validated category, the STM32 commands the corresponding baffle position, releases the item, and resets the mechanism for the next cycle.

2.2.3 Power Subsystem

The power subsystem separates the logic rail from the actuator supply path. The K210, camera, LCD, and STM32 use a regulated 5 V logic rail, while the servo motors are supplied through a separate actuator path. A common ground is maintained for control signals. This separation reduces voltage dips and processor resets during motor startup current transients.

2.2.4 Communication and Control Logic

The K210 sends classification information to the STM32 through UART1 at 9600 baud. Each message uses the frame format HEAD,x,y,z,type,TAIL, where x, y, and z are coordinate fields and type is an integer category from 1 to 4. The STM32 accepts a command only after both HEAD and TAIL delimiters are found, reducing the chance of acting on partial or misaligned data. After parsing the category, the STM32 state machine generates the corresponding PWM command for the baffle and trapdoor sequence.

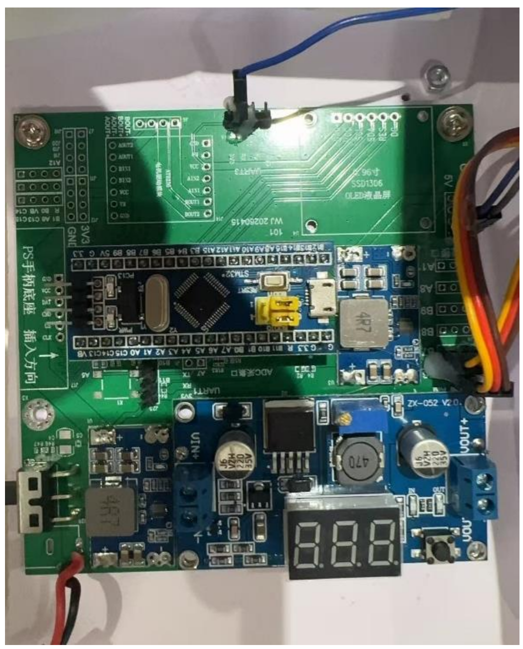


Figure 4. STM32 Microcontroller Board with Voltage Control Part

Figure 5. K210 Board (Visual part)

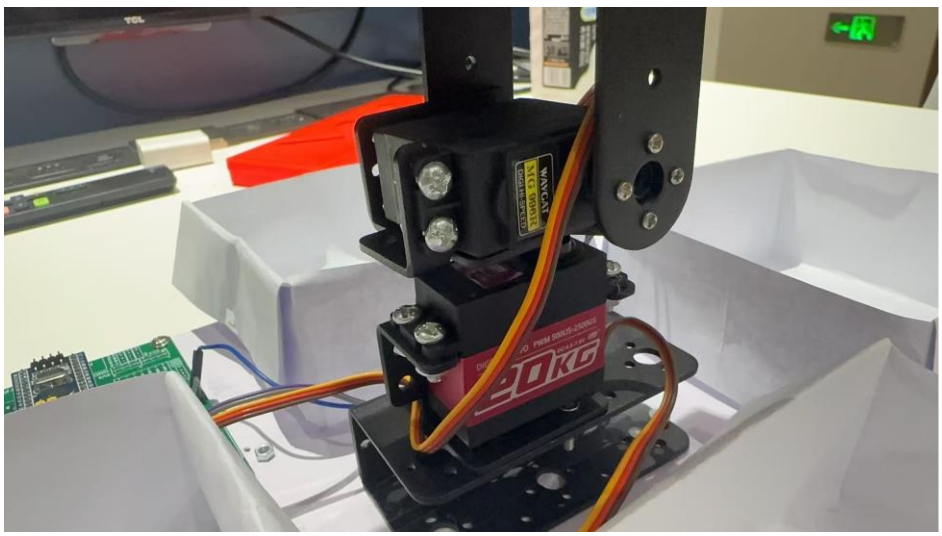


Figure 6. Mechanical Structure

2.3 Design Issues and Corrective Actions

The most important timing risk is that an item may fall through the chute before classification and actuator motion are complete. If the drop height is h and the item is approximated as free-falling, the fall time is: $t = \mathrm{sqrt}(2h/g)$. For $h = 0.30$ m and $g = 9.81$ m/s^2, the fall time is approximately 0.247 s. This is shorter than the measured vision-processing time and also shorter than the combined classification and actuation time. Therefore, a pure free-fall chute cannot satisfy the sorting requirement.

The cycle-time budget is $t\_cycle = t\_capture + t\_inference + t\_uart + t\_actuation + t\_release + t\_reset$. The measured average full-cycle time was 2.31 s, which is below the 3 s requirement. For load capacity, the worst-case gravitational force for a 1.5 kg item is $F = mg = 14.7$ N. Assuming a representative 0.10 m lever arm from the hinge/servo axis to the load center, the required holding torque is $tau = F r = 1.47$ N*m before safety factor. With a design safety factor of 2, the actuator path should provide at least 2.94 N*m equivalent torque at the baffle/holding platform. The prototype verification was visual and functional rather than encoder-based, so future work should replace this with measured torque margin and angular error.

2.4 Design Issues and Corrective Actions

The first major issue was timing: a free-fall chute did not leave enough time for image inference and actuator movement. The corrective action was to add a temporary holding platform. The second issue was lighting sensitivity. The model was sensitive to pose, reflections, and indoor lighting variation because the training/demo set was limited. The third issue was UART robustness; explicit HEAD/TAIL framing was added so the STM32 could reject incomplete frames.

3. Design Verification

Verification was performed at the subsystem and integrated-system levels. The test environment was indoor laboratory lighting of approximately 300 lux and room temperature of about 25 C. Test objects ranged from approximately 0.1 kg to 1.5 kg.

Table 1 Final Demo Verification Summary

ID	Test	Pass Criterion	Method	Result	Status
V1	Vision classification accuracy	At least 90% correct on representative four-category test set	40 items, 10 per category, indoor lighting about 300 lux; compare predicted label to manual ground truth	37/40 correct = 92.5%	Pass for demo set
V2	Vision processing time	Average vision pipeline time <= 1.0 s	Record K210 timing during repeated detection trials	0.82 s average vision pipeline time	Pass
V3	Full sorting cycle time	Complete capture, classification, actuation, release, and reset within 3 s	Time complete sorting cycles with representative items	2.31 s average full cycle	Pass
V4	UART communication	Valid frames parsed without missing HEAD/TAIL fields	Send HEAD,x,y,z,type,TAIL frames at 9600 baud and inspect STM32 parsing	100% valid frames in observed test	Pass
V5	Mechanical short-cycle reliability	No jam or failure during repeated short-cycle demo testing	Run 20 consecutive sorting cycles and inspect reset, baffle motion, and jams	20 cycles, 0 failures	Pass for short-cycle test; 500-cycle target not completed
V6	Load capacity	Mechanism handles items up to 1.5 kg	Place/drop representative loads up to 1.5 kg on holding and sorting path	No visible yielding or stall in prototype test	Pass

		without yielding or stalling			
V7	Power stability	5 V logic rail remains in 4.75-5.25 V range and controllers do not reset	Measure rail under inference and actuator motion; observe K210/STM32 resets	No processor reset observed; regulator path separated from actuator rail	Pass qualitatively; more logged voltage samples recommended

3.1 Vision and Control Subsystem

The vision subsystem was tested with 40 representative items, 10 per category. The model correctly classified 37 items, giving an observed accuracy of 92.5%. The most common failure causes were reflective surfaces, unusual viewing angles, and visually similar waste items. The average measured vision pipeline time was 0.82 s, satisfying the 1 s project target.

3.2 Mechanical Sorting Subsystem

The mechanical subsystem was tested by sending known category commands and checking whether the baffles moved to the correct sorting position. A short-cycle reliability test of 20 consecutive cycles produced no jams or failures. The prototype handled items up to 1.5 kg without visible deformation or actuator stall. However, the original 500-cycle reliability target was not completed before submission, so long-term reliability remains a limitation.

3.3 Power Subsystem

UART messages were checked using the HEAD,x,y,z,type,TAIL frame format at 9600 baud. Observed test frames were parsed correctly by the STM32. The logic and motor supplies were separated to reduce reset risk; no K210 or STM32 reset was observed during normal actuator motion. Future testing should log voltage samples under worst-case motor startup current.

3.4 Uncertainty and Limitations

The reported 92.5% accuracy is based on a limited 40-item demonstration set, so it should not be interpreted as full real-world generalization. Lighting, object pose, dirty or damaged waste, occlusion, and unseen object types may reduce accuracy. Mechanical reliability was demonstrated for 20 short cycles, but not for the original 500-cycle long-term target.

3.5 Teammates Provided Verification Count

Table 2: Teammate-Provided Verification Counts

Team Member	Subsystem / Responsibility	Data Provided	Use in Final Report
Canyu Li	Raspberry Pi / K210 setup and software integration	Average vision processing time of 0.82 s; average full sorting cycle time of 2.31 s	Used to verify the visual processing time requirement and the complete 3-second sorting cycle requirement
Han Yin	Computer vision model training and testing	40 demo test items, 10 per category; 37/40 correct classifications; approximately 92.5% accuracy	Used to verify the final classification accuracy requirement of at least 90%
Mingyang Gao	Mechanical design, CAD modeling, and sorting mechanism testing	20 short-cycle sorting tests with 0 observed failures; load condition up to 1.5 kg	Used to verify demo-level mechanical reliability and the maximum item weight requirement
Wentao Li	Power subsystem, PCB, STM32 control, and UART verification	Valid K210-to-STM32 UART frame parsing during the demo test; stable control operation during actuation	Used to verify communication reliability and system control during integrated sorting

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, wood, and 3D-printed parts	Local fabrication / lab materials	220	150	220
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.

4.3 Schedule

To ensure the structured and timely execution of the Intelligent Waste Sorting System project, a comprehensive 10-week development timeline was strictly followed. Tasks were systematically distributed among the team members based on their technical specializations to maintain engineering efficiency. Mechanical architecture conceptualization, CAD modeling, and physical frame fabrication were led by Mingyang Gao. The deployment of the K210/YOLO computer vision pipeline and dataset curation were managed by Han Yin. Firmware control logic and UART communication protocols were developed by Canyu Li, while the power distribution subsystem and servo actuation electronics were engineered by Wentao Li. Collaborative integration, modular debugging, and system-level performance evaluations were conducted jointly in the final weeks to ensure seamless hardware-software synchronization and to fulfill all high-level engineering requirements.

Week	Main Work / Task Description	Team Member(s)
Week 1	Defined the project goal, four waste categories, timing requirement, and 1.5 kg maximum load requirement.	All members
Week 2	Researched existing waste sorting solutions and generated the initial linear-belt mechanical concept.	Mingyang Gao, Wentao Li
Week 3	Compared the first linear design with the carousel-based design and identified timing and space limitations.	All members

Week 4	Selected the simplified final sorting structure and began mechanical CAD and subsystem planning.	Mingyang Gao
Week 5	Built the vision pipeline and prepared the waste image dataset for K210/YOLO model testing.	Han Yin
Week 6	Implemented STM32 control logic, UART communication format, and initial actuator control.	Canyu Li, Wentao Li
Week 7	Fabricated and assembled the mechanical frame, baffles, flaps, and holding platform.	Mingyang Gao
Week 8	Integrated the K210 vision module, STM32 controller, servo actuation, and power subsystem.	All members
Week 9	Performed subsystem tests, including vision accuracy, UART parsing, mechanical motion, and load testing.	All members
Week 10	Conducted final demo testing with 40 representative items, timing measurements, and 20 short-cycle mechanical tests.	All members

Weekly Project Schedule Summary

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.

References

[1] United Nations Environment Programme, *Global Waste Management Outlook 2024: Beyond an Age of Waste*. Nairobi, Kenya: UNEP, 2024. Available: https://www.unep.org/resources/global-waste-management-outlook-2024.

[2] S. Kaza, L. Yao, P. Bhada-Tata, and F. Van Woerden, *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*. Washington, DC, USA: World Bank, 2018. Available: https://openknowledge.worldbank.org/entities/publication/d3f9d45e-115f-559b-b14f-28552410e90a.

[3] M. Yang and G. Thung, "Classification of trash for recyclability status," CS229 Project Report, Stanford University, Stanford, CA, USA, 2016. Available: https://cs229.stanford.edu/proj2016/report/ThungYang-ClassificationOfTrashForRecyclabilityStatus-report.pdf.

[4] P. F. Proença and P. Simões, "TACO: Trash Annotations in Context for litter detection," *arXiv preprint arXiv:2003.06975*, 2020. Available: https://arxiv.org/abs/2003.06975.

[5] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," *arXiv preprint arXiv:1804.02767*, 2018. Available: https://arxiv.org/abs/1804.02767.

[6] M. Hussain, "YOLOv5, YOLOv8 and YOLOv10: The go-to detectors for real-time vision," *arXiv preprint arXiv:2407.02988*, 2024. Available: https://arxiv.org/abs/2407.02988.

[7] Raspberry Pi Ltd., "Raspberry Pi 4 Model B specifications," Raspberry Pi, 2026. Available: https://www.raspberrypi.com/products/raspberry-pi-4-model-b/specifications/.

[8] Analog Devices, *TMC2209 Datasheet*, Rev. 1.09. Available: https://www.analog.com/media/en/technical-documentation/data-sheets/tmc2209_datasheet_rev1.09.pdf.

Appendix A Requirement and Verification Table

Table A.1 summarizes the major requirements and verification results for the Intelligent Waste Sorting System. The requirements are organized according to the four main verification categories discussed in Section 3: the vision and control subsystem, the mechanical sorting subsystem, the power subsystem, and the integrated system. Requirements that were not fully verified are marked as “N” and discussed in the main text.

Table A.1 Requirement and Verification Table

Requirement	Verification Method	Verification status (Y or N)
1. Vision and Control Subsystem a. The camera shall capture clear images of waste items placed on the temporary holding platform. b. The image-processing pipeline shall classify waste into four categories: Recyclables, Food Waste, Hazardous Waste, and Other Waste. c. The inference time shall be no more than 1 s per item. d. The classification accuracy shall be at least 90% on a labeled test set.	a. Place representative waste items from all four categories under normal indoor lighting and inspect whether the captured frames contain clear object boundaries and major visual features. b. Run the trained classification model on a labeled test set and compare the predicted category with the manually labeled ground-truth category. c. Record timestamps before and after the model inference step and calculate the average inference time. d. Compute classification accuracy as the number of correct predictions divided by the total number of test samples.	Y
2. Mechanical Sorting Subsystem a. The sorting mechanism shall move the waste item to the correct bin position according to the predicted category. b. The transport platform and trapdoor shall support waste items up to 1.5 kg without visible deformation or motor stalling. c. The trapdoor shall release the item by gravity after the turntable is aligned with the target bin. d. The mechanism shall complete repeated sorting cycles without severe jamming, overheating, or loosening.	a. Send motor commands corresponding to each of the four waste categories and visually check whether the final turntable position aligns with the correct bin opening. b. Place test weights up to 1.5 kg on the platform and observe whether the structure remains stable and the motor can still actuate the system. c. Run sorting tests with sample items and verify that the trapdoor opens only after the turntable reaches the target position. d. Operate the system through repeated sorting cycles and inspect the motor, fasteners, platform, and baffle for	Y

	overheating, misalignment, loosening, and jamming.	
3. Power Subsystem a. The Raspberry Pi and USB camera shall receive a regulated 5 V supply. b. The 5 V rail shall remain within ±5% of the nominal value, corresponding to 4.75 V to 5.25 V. c. The motor power path shall be separated from the microcomputer power path to reduce voltage dips during actuation. d. The Raspberry Pi shall not reset during motor movement.	a. Measure the regulated output voltage using a multimeter during idle operation and motor actuation. b. Compare the measured voltage with the acceptable 4.75 V to 5.25 V range. c. Verify that the motor driver and Raspberry Pi are powered through separate supply paths. d. Run motor actuation tests while observing whether the Raspberry Pi remains powered and the control program continues running.	Y
4. Integrated System Verification a. The system shall complete a full sorting cycle consisting of image capture, classification, motor movement, item release, and reset. b. The full sorting cycle shall be completed within 3 seconds per item. c. The system shall route the item to the bin corresponding to the classification result. d. The overall system shall satisfy the target classification accuracy of at least 90%.	a. Place representative waste items into the drop-in opening and observe whether the system completes the full sequence automatically. b. Measure the elapsed time from item placement to completion of the reset step. c. Compare the final bin location with the category predicted by the vision model. d. Evaluate the integrated system on labeled samples and compare the measured accuracy with the 90% requirement.	Y