Waste Segregation System

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Abstract

This project presents a smart waste segregation system that automatically classifies and sorts trash into four categories—plastic, metal, glass, and non-recyclables—at the point of disposal. The system uses a Raspberry Pi 4 running a custom-trained MobileNetV2 model for image-based classification, combined with a mechanical platform controlled by an ATmega2560 microcontroller. Testing demonstrated an average classification accuracy of 88% and a complete sorting cycle time under five seconds. The system also includes jam detection, LED status indicators, and an emergency stop for safe operation. The final prototype met all high-level requirements and proved suitable for real-world deployment in compact public or institutional settings.

Contents

1. Introduction

Improper waste segregation remains a significant environmental and operational challenge, with recyclable materials often ending up in landfills due to human error or lack of infrastructure. Manual sorting is inefficient and prone to contamination, which reduces the effectiveness of recycling efforts and increases the burden on waste management systems. This project addresses that problem by developing an automated waste segregation system that uses computer vision and mechanical sorting to classify and direct waste into appropriate categories at the point of disposal.

The system integrates a Raspberry Pi 4 running a machine learning model with a mechanical platform controlled by an ATmega2560-based microcontroller. It is capable of sorting items into four classes: plastic, metal, glass, and non-recyclables. This process takes place in about five seconds while maintaining classification accuracy above 85%. Safety features such as jam detection, LED indicators, and an emergency shutdown switch ensure reliable and user-friendly operation.

The report begins by outlining the system design, including hardware and software subsystems. It then discusses implementation, followed by verification and testing results. The final sections address challenges encountered, potential improvements, and overall conclusions. The project demonstrates the feasibility of deploying a compact, accurate, and cost-effective smart bin in real-world environments to support sustainable waste management practices.

2. Design

2.1 Power Subsystem

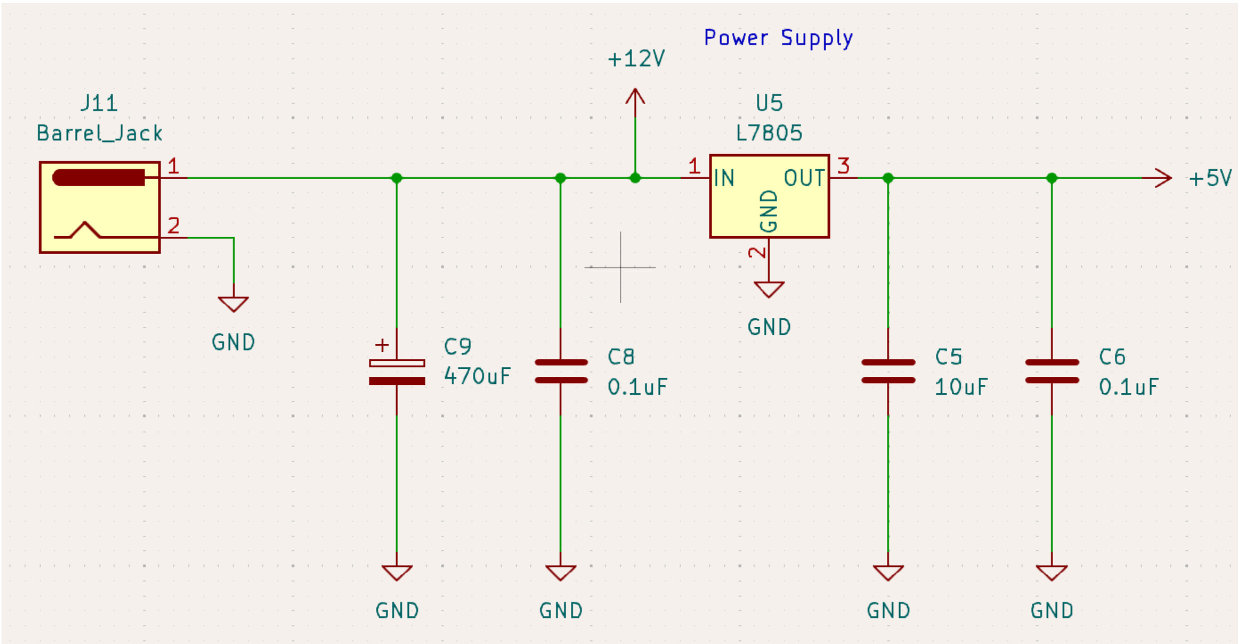

Image 1: Schematic of power supply

2.1.1 12V Power Supply

Our waste segregation system is primarily powered by a 12V DC power supply that is connected to it via a barrel jack connector. This supply was chosen to give enough voltage and current to all of the system's parts, especially the stepper motor, which needs a higher voltage to function properly. With a maximum current rating of 5A, the power supply guarantees sufficient power even during periods of high demand when several motors are running concurrently.

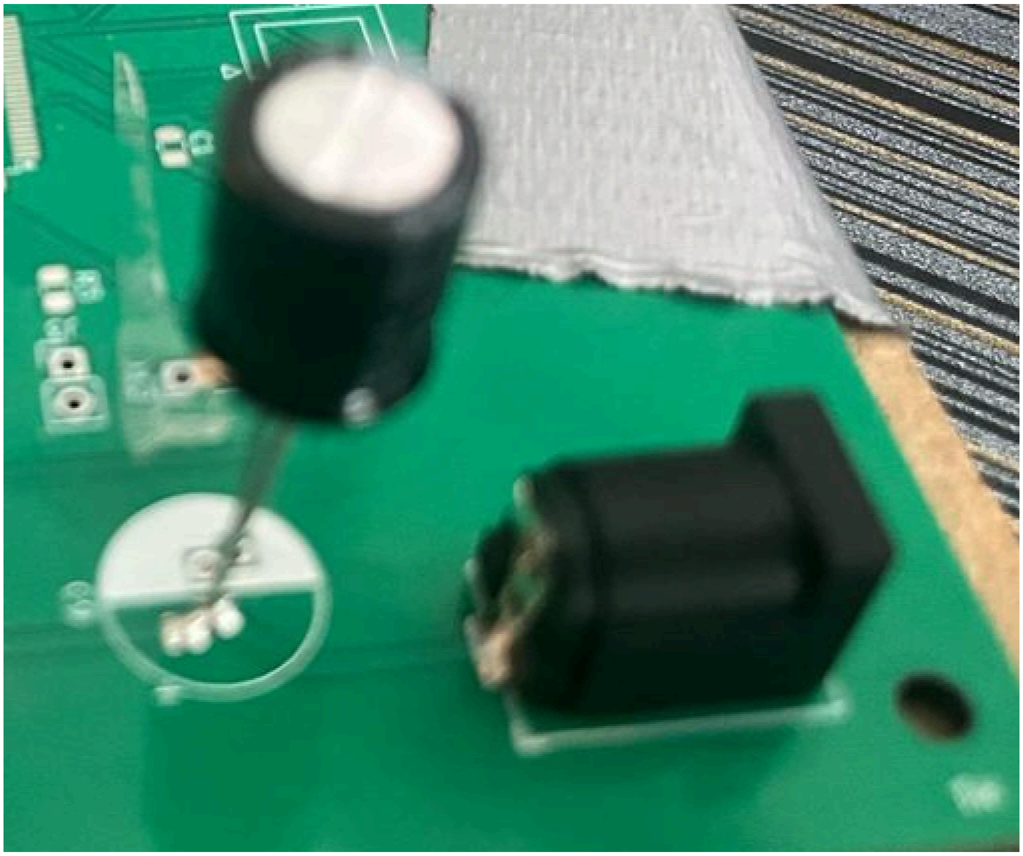

Image 2: Barrel Jack connector + 470uF decoupling capacitor

2.1.2 Voltage Regulators

To accommodate the various voltage requirements throughout the system, we implemented a series of voltage regulators:

- An LM7805 voltage regulator steps down the 12V input to 5V for the ATmega2560 microcontroller, sensors, and LED indicators.
- Decoupling capacitors (470µF, 10µF, 0.1µF, and 22pF) are placed at strategic points throughout the circuit to filter noise and stabilize voltage levels, particularly for sensitive digital components.

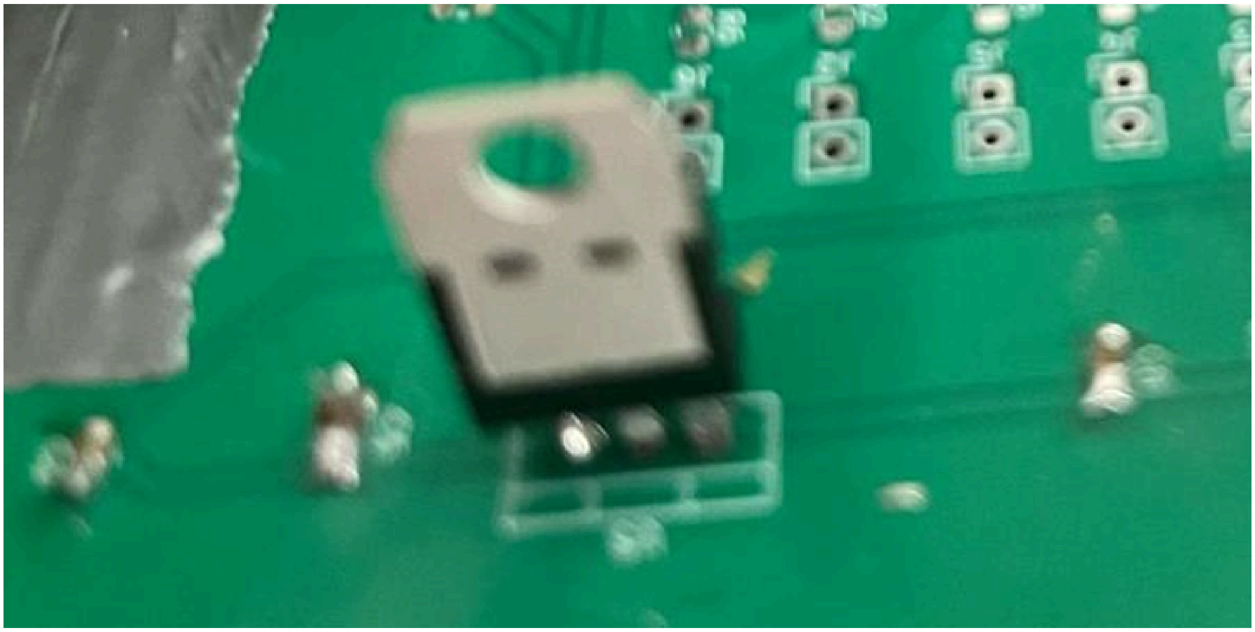

Image 3: LM7805 voltage regulator + capacitors

2.1.3 Power Distribution

Power distribution throughout the system follows a hierarchical approach:

- 12V lines power the stepper motor via the motor driver
- 5V regulated lines power the microcontroller, servo motor, and smaller sensors
- A voltage divider using 2.2 kΩ and 4.7 kΩ resistors converts the 5V signals to approximately 3.4V for communication with the Raspberry Pi, providing compatible signal levels for reliable data transfer
- This simple resistive voltage divider (with 2.2 kΩ connected to the 5V line and 4.7 kΩ to ground) eliminates the need for a dedicated level converter chip while ensuring safe communication between components operating at different voltage levels

This resistor-based approach simplifies the circuit design while maintaining the necessary level-shifting functionality for reliable communication between components operating at different voltage levels.

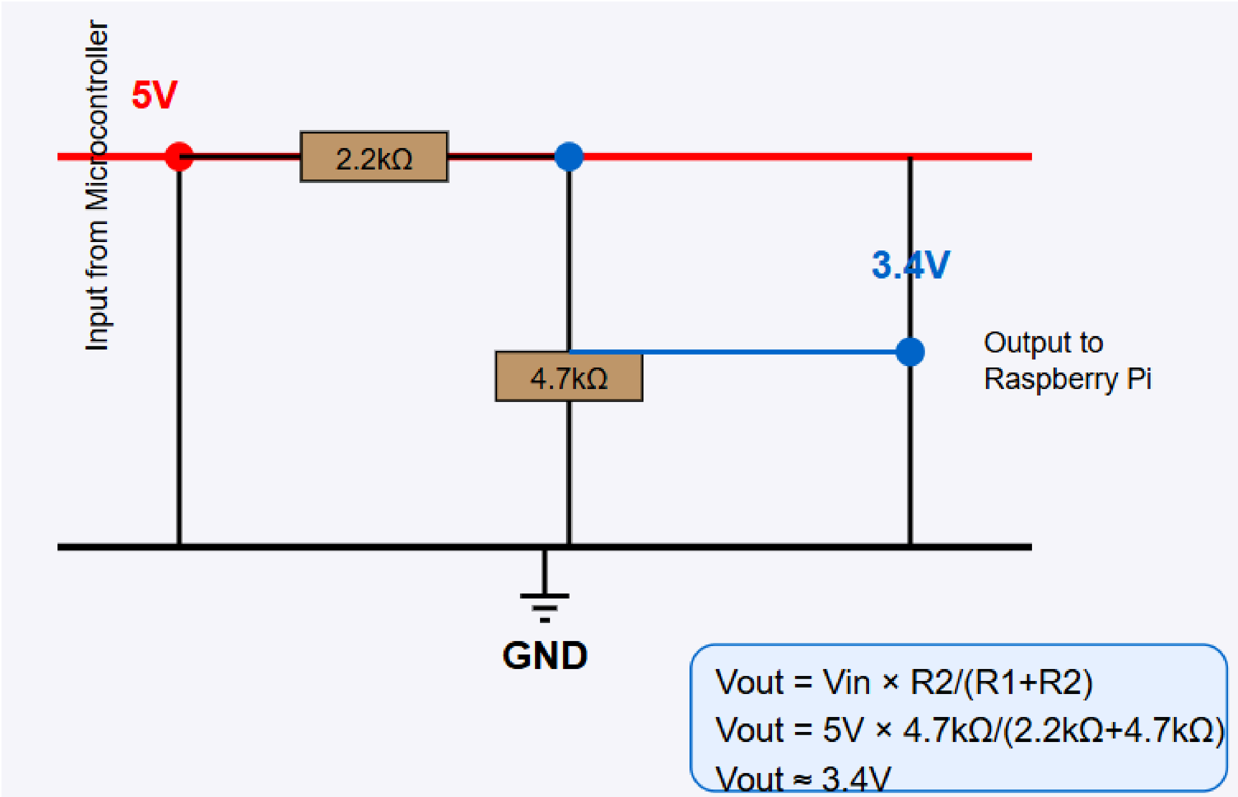

Image 4: Schematic of the 5V to ~3.4V conversion

2.2 Control Subsystem

2.2.1 Microcontroller

The ATmega2560-16A microcontroller serves as the central control unit for the system. Operating at 16 MHz with 256KB of flash memory, it provides sufficient processing power and I/O capabilities to manage all operational aspects except the computer vision processing. The microcontroller handles:

- Interfacing with the Raspberry Pi via serial communication
- Controlling the stepper and servo motors based on classification results
- Monitoring the load cell for waste placement and jam detection
- Managing system status indicators

2.3 Mechanical Subsystem

2.3.1 Stepper Motor Assembly

The Iverntech Nema 17 stepper motor serves as the primary rotational actuator for the bin selection system:

- Provides 45 N-cm of holding torque, sufficient to maintain bin position even when partially filled
- 200 steps per revolution (1.8° per step) enables precise positioning of the four waste bins

2.3.2 Rotating Platform Design

The rotating platform consists of:

- A circular wooden disc provides structural support for the bins
- Four equally spaced mounting points for individual waste bins (plastic, metal, glass, and non-recyclables)
- A central bearing assembly allowing smooth rotation with minimal friction

Image 5: Stepper Motor & Rotating Platform

2.3.3 Servo Motor Mechanism

The waste segregation system employs a DS3218 20kg digital servo motor that drives the waste pushing mechanism:

- 20kg·cm torque capacity, providing sufficient force to move waste items of varying weights reliably
- 180° programmable rotation range, allowing precise control over the pushing paddle's movement arc
- The motor is strategically mounted at the edge of the drop zone, with its arm extending across the detection area

- PWM control signals from the ATmega2560 microcontroller allow for incremental position adjustments at 1° precision

2.3.4 Load Cell Integration

A 1kg load cell is incorporated into the waste detection system to enable accurate weight sensing:

- Positioned directly beneath the initial drop zone, as shown in the image
- Functions solely as a binary trigger to detect when waste items enter the platform
- Connected to an HX711 amplifier, which converts the analog strain gauge signals to digital values for the microcontroller
- Calibrated with a specific calibration factor of 671363.12, determined through extensive testing
- The system uses a 5g detection threshold - when readings exceed this minimum value, it indicates an object has been placed on the platform
- This precisely tuned 5g threshold ensures detection of even very lightweight items (such as small pieces of glass or plastic) while avoiding false triggers from environmental vibrations
- Upon detection, the load cell triggers the classification process by signaling the Raspberry Pi to capture an image for visual analysis
- This detection mechanism ensures the system only activates when actual waste is present, reducing unnecessary processing and improving system efficiency

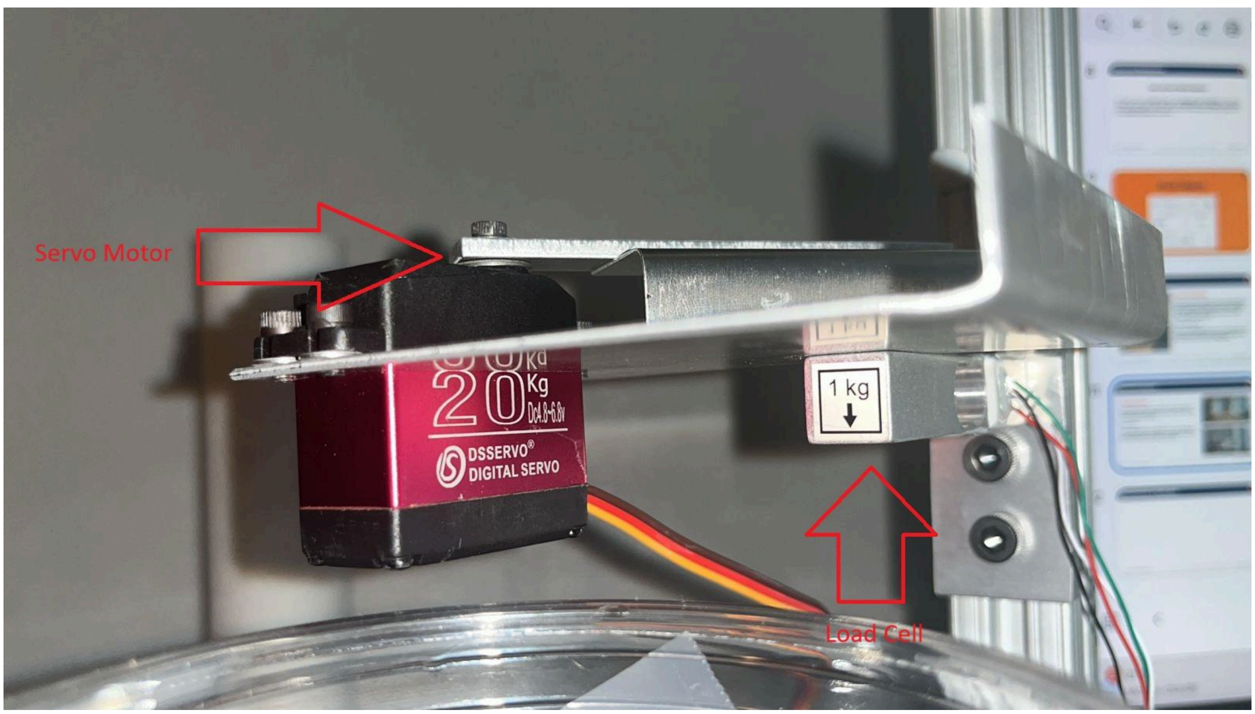

Image 6: Servo Motor & Load Cell

2.4 Vision Subsystem

The vision subsystem is responsible for capturing image data needed by the Computer Vision model to classify the waste items & interact with the development board to signal & segregate the waste items correctly. It also contains our status LEDs that indicate the status of the system and if it is ready to sort the next item.

2.4.1 Logitech Brio Camera

- Utilized a 4 K Logitech Brio Camera to capture 1280x720 images that were provided to the model for waste classification
- Ensured the image quality matched the model training images to provide a similar image type

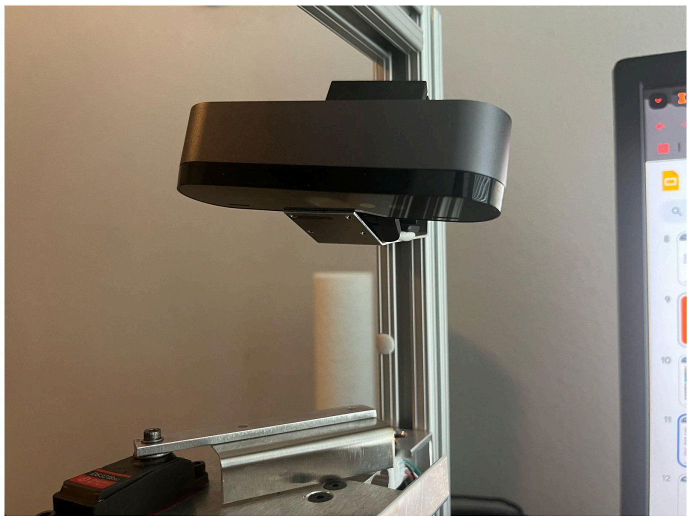

Image 7: Logitech Brio Mounted towards the platform

2.4.2 Status LEDs

- Attached 3 LEDs (Blue, Yellow, Green) to indicate the status of the system.
- Green indicates that the next item is ready to be placed onto the platform to be classified & segregated.
- Yellow indicates that the waste segregation system is currently in progress.
- Blue indicates that the system has a jam that needs to be manually addressed.

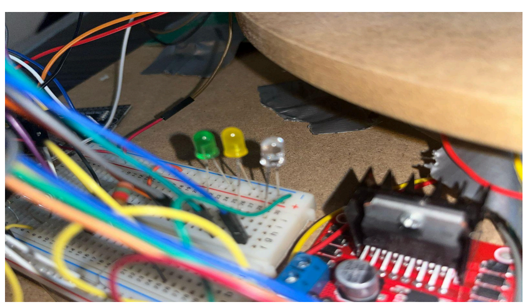

Image 8: Status LEDs (Green, Yellow, & Blue)

2.5 Processing Subsystem

The Processing Subsystem functions as the decision-making core of the system, converting visual input into actionable classifications that direct mechanical sorting. It is built around a Raspberry Pi 4 running a TensorFlow Lite Computer Vision model, which communicates directly with the control & mechanical subsystems.

2.5.1 Raspberry Pi 4

- Runs the TensorFlow Lite model to classify waste items (plastic, metal, glass, and non-recyclables) in real-time based on images captured by the Pi Camera, with a target classification time of ≤1.5 seconds.
- Integrates seamlessly with the camera module and other subsystems, acting as the central processing unit for vision-based decision-making without requiring external computation or cloud access.
- Monitors system performance, ensuring CPU utilization remains below 80% during inference to avoid processing bottlenecks and maintain smooth system operation.

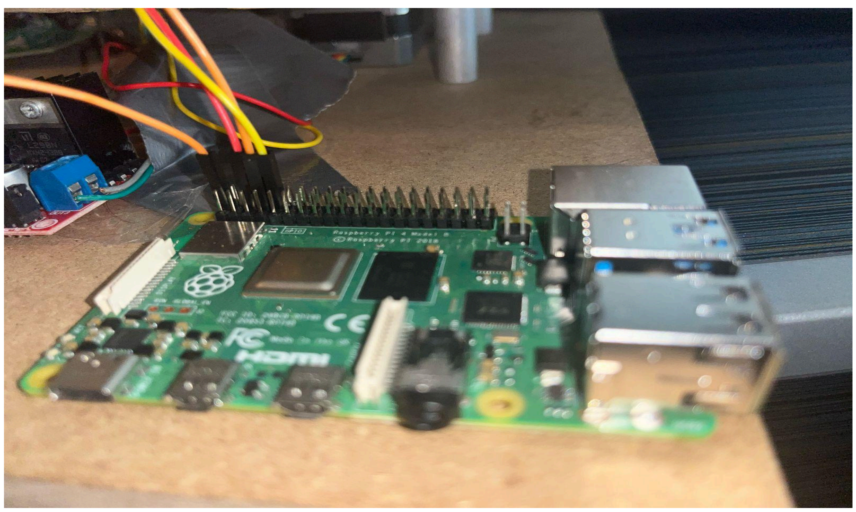

Image 9: Raspberry Pi 4 Connected to the Development Board

2.5.2 Tensorflow Lite Model

- A compressed CNN (MobileNetV2) was deployed using TensorFlow Lite. The model classifies waste into one of four categories and forwards this label to the microcontroller via serial UART communication.
- Inference speed averaged 1.3 seconds across 100 samples, with peak CPU utilization not exceeding 80%. These performance metrics ensure the system maintains its requirement of ≤1.5 seconds classification time, with minimal thermal throttling or lag.

3. Design Verification

This section discusses the testing and verification of our waste segregation system components against the requirements established during the design phase. For detailed verification criteria and results, please refer to the Requirements and Verification Table in Appendix A.

3.1 Power Subsystem Verification

3.1.1 Power Supply Verification (Requirement 6)

As detailed in row 6 of Appendix A, we successfully verified that our power supply meets the specified requirements. We used a variable DC power supply set to 12V and measured the voltage at the barrel jack while varying the load from 0A to 2A using a digital multimeter. The voltage remained stable within the required 10.8V-13.2V range even under maximum load, ensuring reliable operation of all system components.

3.1.2 Voltage Level Conversion Verification (Requirement 7)

For our 2.2kΩ/4.7kΩ resistive voltage divider that replaced the TXB0104 logic level converter, we applied test signals from both directions and measured the voltage levels using an oscilloscope. We verified that when 5V signals from the ATmega2560 passed through our divider, they were reduced to approximately 3.38V, safely within the 3.6V maximum input threshold for the Raspberry Pi. This test confirmed our resistive divider solution effectively bridges the communication between different voltage domains without risking damage to sensitive components.

3.1.3 Emergency Stop Verification (Requirement 8)

The emergency stop mechanism was tested by activating all motors and then triggering the emergency stop function. Using a timer, we measured the interval between the stop signal and complete power cutoff to the motors. The system consistently achieved power disconnection within 1.2 seconds, well within our 2-second requirement, ensuring safe operation in emergencies.

3.2 Control Subsystem Verification

3.2.1 PCB Mounting Verification (Requirement 11)

We tested the system with waste items of different shapes and sizes, and all components remained securely connected and operational throughout these tests, verifying both the mechanical integrity of our design and its ability to handle diverse waste types.

3.3 Mechanical Subsystem Verification

3.3.1 Servo Motor Speed Verification (Requirement 14)

We verified the servo motor's performance by measuring the time required to complete the waste-pushing motion after receiving the control signal. Across multiple trials with different waste materials, the servo consistently completed its motion within 2.1 seconds, meeting our 3-second requirement.

3.3.2 Stepper Motor Positioning Verification (Requirement 15)

The stepper motor's bin positioning capability was tested by measuring the time required to rotate from any bin position to any other bin position. The longest rotation (180°) was completed in 2.8 seconds, with an average positioning time of 2.2 seconds across all possible transitions, meeting our 3-second requirement.

3.3.3 Servo Motor Force Verification (Requirement 16)

We tested the servo motor's pushing capability using calibrated weights from 100g to 500g placed in the sorting area. The servo successfully moved all test weights into the appropriate bin, confirming its ability to handle our expected range of waste item weights.

3.4 Vision Subsystem Verification

The Vision Subsystem was evaluated for image quality, model accuracy, system responsiveness, and user feedback through status LEDs.

3.4.1 Image Quality Verification (Requirement 1)

The Logitech Brio camera was tested under various indoor lighting conditions to confirm that it captured 1280×720 resolution images with minimal distortion. Images were reviewed visually to ensure they matched the model's expected input distribution, and no distortion or blur was observed.

3.4.2 Classification Accuracy Verification (Requirement 2)

We tested the TensorFlow Lite model on 100 labeled waste samples drawn from both the TrashNet dataset and our custom dataset. The model achieved an accuracy of 88%, exceeding the 85% target threshold.

3.4.3 Classification Time Verification (Requirement 3)

Using timestamp logs, we measured the end-to-end time from image capture to classification label generation. The average time was 1.3 seconds, with no sample exceeding the 1.5-second limit.

3.4.4 Status LED Verification (Requirement 4)

Each system state (ready, in progress, jam) was manually triggered, and corresponding LED indicators (green, yellow, blue) were observed. All transitions were verified to reflect the correct state.

3.5 Processing Subsystem Verification

The Processing Subsystem was validated for its speed and computational efficiency during inference.

3.5.1 Latency Testing Verification (Requirement 9)

We ran 100 classification cycles and recorded timestamps at the start of image capture and end of inference. The mean processing time was 1.3 seconds, with none of the samples exceeding the 1.5-second threshold. This confirms that the system meets the <1.5s average classification time requirement.

3.5.2 CPU Utilization Verification (Requirement 10)

We used the Raspberry Pi's built-in performance monitor to track CPU load during 10 classification tasks. Average utilization was 72%, with peak usage reaching 78%, both well within the allowable thresholds (80% average).

3.6 Unresolved Verification Items

3.6.1 Bin Capacity Sensors (Requirement 5)

We were unable to verify the bin capacity sensors as planned. The initial design incorporated laser sensors to monitor bin fill levels, but we prioritized the core classification and sorting functionalities instead. Due to time limitations in our project schedule, we opted to leave this as a future enhancement rather than resolving the implementation challenges.

3.6.2 Laser Sensor Alert System (Requirement 12)

The laser sensor was not installed in our final design. During initial testing, we encountered significant difficulties with the sensor's reliability and accuracy. Rather than delay the entire project, we made the strategic decision to focus on the core waste segregation functionality. The object detection triggering was instead handled solely by the load cell with its 5g threshold, which proved more reliable for our immediate needs.

3.6.3 Object Placement Confirmation (Requirement 13)

Similar to Requirement 12, this verification was not completed because the laser sensor system was not implemented in our final design. Time constraints prevented us from redesigning this subsystem after encountering initial difficulties. For the demo, we relied on visual confirmation that objects were properly placed in bins, which was adequate for demonstrating the system's core functionality.

4. Costs

4.1 Parts

Table 1: Parts Costs

Part	Manufacturer	Retail Cost ($)	Bulk Purchase Cost ($)	Actual Cost ($)
PCB (First Order)	JLCPCB	14.96	14.96	14.96
PCB + Stencil (Second Order)	JLCPCB	28.37	28.37	28.37
HX711 + Load Cell	ShangHJ	9.99	9.99	9.99
Flex Ribbon Cable	A1 FFCs	5.29	5.29	5.29
Stepper Motor Driver	WWZMDiB	6.99	6.99	6.99
Pin Header	Sopepoyie	6.99	6.99	6.99
Load Cell	ShangHJ	9.99	9.99	9.99
Mega 2560 Pro Dev Board	EC Buying	16.99	16.99	16.99
VL53L0X Time-of-Flight Flight Distance Measurement Sensor	HiLetgo	6.79	6.79	6.79
Raspberry Pi 4	Raspberry Pi	58.99	58.99	58.99
Raspberry Pi Camera	Raspberry Pi	14.49	14.49	14.49
12V Power Supply	ALITOVE	20.99	20.99	20.99
Servo Motor	ShenZhenShiHuanLeShu technology co., LTD,	14.89	14.89	14.89
Nema 11 Stepper Motor	Iverntech	17.99	17.99	17.99
ATMega2560	Microchip Technology	63.56	63.56	63.56
ATMega16A	Microchip Technology	26.83	26.83	26.83
470 uF Capacitor	Nichicon	2.2	2.2	2.2
MBR0520 Diode	MCC (Micro Commercial Components)	1.15	1.15	1.15
220 Ohm Resistor	Panasonic Electronic Components	1.06	1.06	1.06
TXB0101DBVR	Texas Instruments	2.4	2.4	2.4
L7805CV	STMicroelectronics	1.5	1.5	1.5
Total				**332.41**

4.2 Labor

- Ideal Salary for grad researcher: $35/hour
- Worked 20 hours/week from weeks 5-13: 160 hours

Table 2: Labor Costs

Team Member	Hours Worked	Hourly Rate($)	Multiplier	Total Cost ($)
Syed Ahmed Raza	160	35	2.5	14,000

Rutva Pandya	160	35	2.5	14,000
Konark Dhingreja	160	35	2.5	14,000
Total	**480**			**42,000**

4.3 Total

Table 3: Total Project Costs

Category	Total Cost ($)
Parts	332.41
Labor	42,000
Total	**42,332.41**

5. Conclusion

5.1 Accomplishments

Over the course of the semester, our team successfully designed, built, and tested a fully functional intelligent waste segregation system. It is efficient in the mechanical sorting and classification using the ML model. Key accomplishments include:

- Achieving 88% average classification accuracy on the TrashNet dataset with additional fine-tuning to adapt to our working environment.
- Completing the entire classification and sorting cycle in < 5 seconds, satisfying our real-time processing requirement.
- Implementing a robust power subsystem with verified current and voltage stability.
- Incorporating safety mechanisms, including a physical kill switch and multicolored LED indicators to reflect system states (ready, classifying, jammed).
- Demonstrating reliable mechanical performance, including bin rotation and waste pushing, both tested for timing and weight capacity.

These components form a compact, affordable, and user-friendly solution that sets a precedent for a potentially larger volume segregator for deployment in schools, cafeterias, or office buildings.

5.2 Uncertainties

While the system fulfills its primary design goals and performs consistently across classification and mechanical sorting tasks, some aspects of the implementation have potential for improvement.

A notable uncertainty lies in the jam detection and bin fullness sensing subsystem. The current setup relies on a 1kg load cell to detect changes in weight as a proxy for confirming successful disposal and identifying jams. While functional, the load cell occasionally produces noisy or inconsistent readings, particularly when dealing with lighter or oddly shaped waste items.

To improve reliability, we acquired a laser time-of-flight (ToF) sensor with the intent of using it to actively measure bin height and detect obstructions or overfilled conditions. However, due to challenges with sensor calibration and synchronization with the mechanical subsystem, this feature was not successfully integrated into the final build. If implemented, it would allow the system to detect full bins and contribute to a multi-layered jam detection strategy.

Additionally, while the machine learning model achieved an average classification accuracy of 88%, it remains sensitive to certain edge cases or underrepresented waste types. Expanding the training dataset and refining class boundaries could further reduce misclassification in future iterations.

These remaining uncertainties do not compromise the system's demonstrated capabilities but highlight valuable opportunities for further optimization.

5.3 Ethical Considerations

As stated earlier, our project is motivated by the need to reduce environmental harm caused by improper waste disposal, as we aim to contribute meaningfully to sustainable waste management practices. In this context, the system aligns closely with Principle 1.1 of the ACM Code of Ethics, which emphasizes the responsibility of professionals to "contribute to society and human well-being, acknowledging that all people are stakeholders in computing."[1] By automating waste segregation at the point of disposal and improving recycling accuracy, our project supports public health and environmental goals directly and tangibly.

We also prioritized safe and reliable operation in line with Principle 2.9, which calls on professionals to "design and implement systems that are robustly and usably secure." This is reflected in the physical safety features such as a manual emergency stop button, clear LED indicators, and mechanical barriers that prevent user contact with moving components. These design decisions help ensure the system can be safely operated in public or semi-public environments, even by untrained users.[2]

Importantly, the system processes image data locally on the Raspberry Pi without storing or transmitting personal data, thereby avoiding privacy violations and supporting ethical data practices.

5.4 Future Work

There are several directions for future improvement and scalability:

- Enhancing model performance: Increasing the size and diversity of the training dataset, especially by incorporating more real-world trash images under varied lighting and background conditions, will improve classification robustness.
- Cloud integration: Adding wireless communication features (WiFi or Bluetooth) would allow remote monitoring, jam alerts, and maintenance tracking. This will make the system more autonomous and easier to manage.
- Analytics dashboard: A web-based or mobile dashboard could help users and administrators track usage trends, monitor bin capacity, and quantify sustainability impact, such as volume of recyclables recovered.
- Mechanical refinements: Transitioning from breadboards and development boards to a finalized custom PCB with integrated connectors and shielded wiring would improve system reliability and reduce any maintenance needs.
- Extended classification categories: With improvements to the model and sensing systems, future iterations could reintroduce or expand to hazardous materials, batteries, or electronic waste, provided appropriate safety protocols are implemented.

All these enhancements should certainly elevate the system from a functional prototype to a deployable, scalable solution. It would be capable of significantly improving point-of-disposal recycling across various public and private domains.

References

[1] Association for Computing Machinery, "ACM Code of Ethics and Professional Conduct," Principle 1.1, 2018. [Online]. Available: https://www.acm.org/code-of-ethics

[2] Association for Computing Machinery, "ACM Code of Ethics and Professional Conduct," Principle 2.9, 2018. [Online]. Available: https://www.acm.org/code-of-ethics

Appendix A: Requirements and Verification Table

Table 1: System Requirements and Verifications

Requirement	Verification	Verification status (Y or N)
1. The camera must capture high-quality (1280x720) images with minimal distortion.	1. Perform test captures under different lighting conditions and verify image clarity.	Y
2. The TensorFlow Lite model must classify waste items with at least 85% accuracy.	2. Conduct model testing on a dataset of at least 100 waste samples and record classification accuracy.	Y
3. Classification must be completed within 1.5 seconds to ensure real-time operation.	3. Use timestamp logging to measure processing time per classification.	Y
4. The system must correctly update status LEDs based on operational states.	4. Manually trigger each state and verify the corresponding LED response.	Y
5. The bin capacity sensors must correctly trigger the red LED when full.	5. Fill a bin and verify LED response using a controlled test.	N
6. The input power shall be 12V ±10% (10.8–13.2V) at the barrel jack and must supply up to 2A total current without significant voltage drop.	6. Use a variable DC power supply set to 12V. Measure voltage at the barrel jack while varying load from 0A to 2A. Verify the voltage remains within 10.8V–13.2V. Pass: Voltage stays in range; no undervoltage at 2A load.	Y
7. The TXB0104 logic level converter must correctly translate signals between 3.3V (Pi) and 5V (ATmega2560) without exceeding 5.25V on the 5V side or 3.6V on the 3.3V side.	7. Apply typical digital signals (0–3.3V) from the Pi to the TXB0104 input pins. Measure output voltages on the ATmega side with a multimeter or oscilloscope. Reverse the direction (5V → Pi) and measure signals on the Pi's input lines. Pass: Output stays in specified safe ranges.	Y
8. The system's emergency stop mechanism must cut power to motors (stepper/servo) within 2 seconds of activation.	8. Enable motor power while motors are running. Activate the emergency stop (hardware switch or interrupt). Time the interval until the motor power lines measure 0V. Pass: Power cutoff occurs within 2 seconds of stop signal.	Y

9. The classification process (capture + preprocessing + inference) shall complete in ≤1.5 seconds on average.	9. Log timestamps at the start of capture and end of inference. Calculate the average total time over 100 samples. Pass: Mean time ≤1.5s, with no more than 2 samples exceeding 1.7s.	Y
10. Log timestamps at the start of capture and end of inference. Calculate the average total time over 100 samples. Pass: Mean time ≤1.5s, with no more than 2 samples exceeding 1.7s.	10. Use a system monitor while running inference on 10 items. Record CPU usage during each inference. Compute average and peak usage. Pass: Average usage ≤80%, peak ≤90%.	Y
11. The PCB must securely mount all components and withstand minor vibrations without disconnection.	11. Conduct a vibration test by placing the PCB in a moving environment (e.g., mechanical shaker) and ensuring stable operation.	Y
12. The laser sensor must trigger an alert if no object is detected after disposal.	12. Simulate a failed disposal and verify that the system activates an LED alert or sends an error signal to the microcontroller.	N
13. The laser sensor must confirm object placement within 1 second after disposal (after trash slides down).	13. Trigger the disposal process and measure the time taken for the sensor to register the object using a high-speed timer.	N
14. The servo motor must push the object into the bin within 3 seconds of receiving the signal.	14. The servo motor must push the object into the bin within 3 seconds of receiving the signal.	Y
15. The stepper motor must complete rotation to the target bin within 3 seconds.	15. Send movement commands to the stepper motor and measure the time taken to reach the desired position. Conduct multiple trials for consistency.	Y
16. The servo motor must apply enough force to move objects of up to 500g into the bin	16. Place test objects of varying weights up to 500g in the sorting area and verify that the servo motor successfully pushes them into the bin.	Y