

Waste Segregation System

ECE445 Design Document - Spring 2025

Team #55

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Table of Contents

Section 1: Introduction

1.1 Problem and Background.....	3
1.2 Solution	3
1.3 Visual Aid	5
1.4 High-Level Requirements.....	5

Section 2: Design

2.1 Block Diagram	7
2.2 Subsystem Descriptions	
2.2.1 Vision Subsystem	7
2.2.2 Power Subsystem	9
2.2.3 Processing Subsystem	11
2.2.4 Control Subsystem	12
2.2.5 Mechanical Subsystem	13
2.3 Tolerance Analysis	14

Section 3: Cost & Schedule

3.1 Cost Analysis.....	15
3.2 Schedule.....	16

Section 4: Ethics & Safety

4.1 Ethics	18
4.2 Safety	18

Section 5: Citations and References

19

1. Introduction

1.1 Problem and Background

Waste segregation is a pressing environmental issue that needs to be encouraged and normalized. It is a pillar of recycling and significantly reduces the waste of perfectly repurposable materials that could reduce the damage done by unsustainable disposal practices, overflowing landfills, and the subsequent environmental pollution that threatens both ecosystems and public health.

The Environmental Protection Agency (EPA) estimates that up to 75% of waste is recyclable, yet between 70% and 90% of recyclable materials still end up in landfills. This is evidenced by the 6.3 billion metric tons of plastic waste generated globally, the majority of which remains unprocessed in disposal sites. This inefficiency results in massive waste accumulation which can be easily avoided by promoting convenient waste segregation. Compared to countries like Sweden, which successfully diverts 99% of its waste from landfills, the U.S. faces an urgent need to improve waste segregation at the point of disposal.

Current waste sorting solutions fall into two main categories: large-scale automated sorting machines and basic multi-bin recycling systems. Industrial sorting machines, while effective, are expensive, require significant infrastructure, and are not feasible for small businesses or local implementation. On the other hand, multi-bin systems rely entirely on user discretion, lack verification mechanisms, and cannot ensure proper waste classification. This results in contamination of recyclable waste streams, reducing the efficiency of recycling facilities and increasing costs for waste management companies. Additionally, misclassification of waste contributes to environmental degradation, as improperly disposed materials release harmful pollutants into soil and water sources. Given the limitations of existing systems, there is a strong demand for an affordable, efficient, and automated waste segregation solution that can be deployed at the point of disposal to improve recycling accuracy and minimize landfill waste.

1.2 Solution

Our solution focuses on building an intelligent waste segregation system that automates the process of classifying and sorting waste using computer vision and mechanical automation. The main goal with this system is to take control out of human hands and use technology to accurately segregate waste. To the user, our bin will provide one opening that reduces the need for them to actively look for the correct bin and dispose of their trash. The system consists of a Raspberry Pi Camera that captures images of disposed waste items. These images are then processed by a TensorFlow Lite model running on a Raspberry Pi 4, which classifies the material into four categories: plastic, metal, perishables, and paper.

Once classified, the system initiates the sorting process using a mechanical arm. The arm slides the waste item toward a designated drop zone where it is deposited into one of the waste bins. Instead of using multiple stationary bins, our design features a rotating bin system mounted on a circular disc. This disc rotates to position the correct bin beneath the drop mechanism, allowing for an efficient, compact, and space-saving design. By using a single dropping mechanism with a rotating disc instead of multiple chutes, our system simplifies sorting while maintaining high accuracy.

Compared to existing large-scale industrial waste sorting machines, our system is cost-effective and compact. Unlike traditional multi-bin recycling systems, which rely on user knowledge, our solution provides real-time verification and automated classification, reducing errors in waste disposal. Additional features such as jam detection, emergency stop mechanisms, and status indicators ensure safe and reliable operation. By bridging the gap between expensive industrial systems and error-prone manual sorting, our automated waste segregation system introduces a smaller scale advancement towards enhancing recycling accuracy and accessibility at the point of disposal.

1.3 Visual Aid

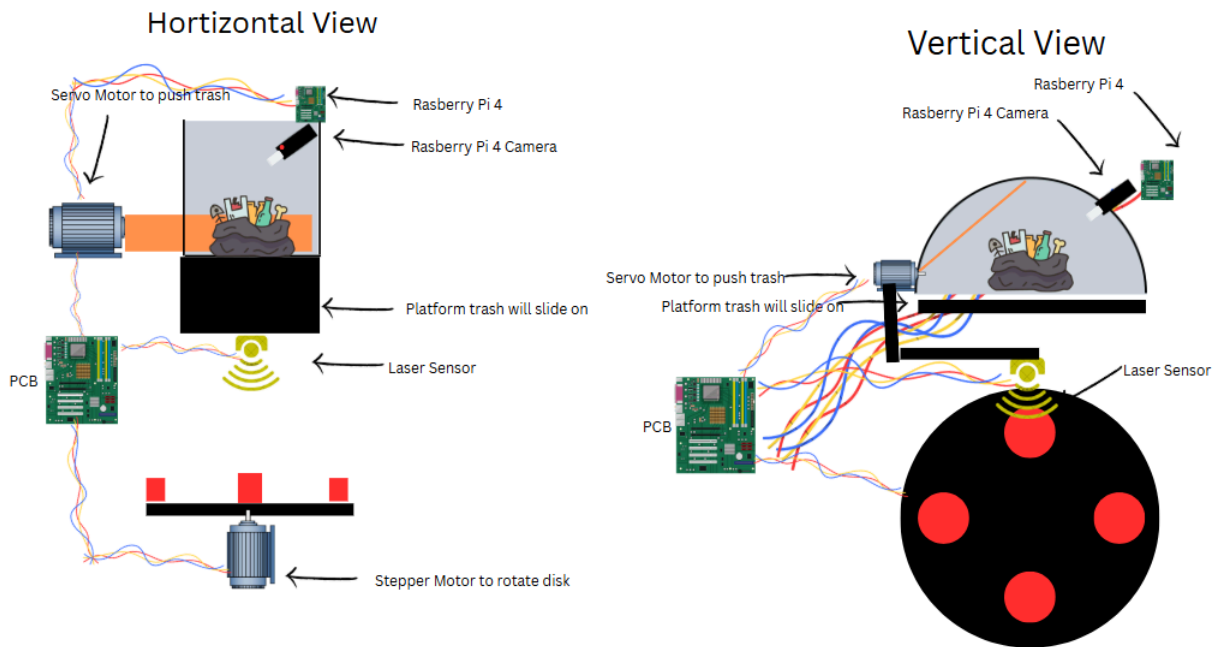


Image 1: A High Level Visual Aid of Our System

In image 1, we provide a visual representation of our waste segregation system as we have our camera detect the waste in a specialized compartment which is then sent to the TensorFlow Lite model to determine which of the four categories it belongs to and accordingly rotate the correct bin into position to dispose of the waste.

1.4 High Level Requirements:

To ensure the successful implementation of our intelligent waste segregation system, we have set the following key requirements that must be met. These requirements define the core functionalities that enable accurate classification, efficient sorting, and safe operation. Failure to meet these criteria would result in a system that is not an accurate model that could be directly commercialized for real-world use.

- **Accurate Waste Classification:** The machine learning model must classify waste materials into their **respective categories (plastic, metal, food, paper) with at least 85% accuracy** under standard indoor lighting conditions. This accuracy rate was carefully estimated based on the scope of this project and to account for the shards sized waste we will be testing.

- **Efficient Sorting Mechanism:** The mechanical arm and rotating bin system must successfully route classified items to their designated bins **within 5 seconds**, ensuring smooth and efficient operation. We estimate the classification process to take between 1 - 1.5s while the mechanical action would take 2-3 seconds, resulting in the 5 second estimate for the entire process.
- **Reliable Jam Detection and Error Handling:** The system must detect blockages or jams **within 2 seconds** and automatically halt operations while providing a visual alert to the user through our LEDs.
- **Safe and User-Friendly Operation:** The system must have physical barriers and emergency stop functionality to prevent user interaction with moving parts. The power system must operate within safe voltage and current limits, ensuring protection against electrical hazards. In the event of an emergency stop, the entire system must be stopped **within 2 seconds** to prevent harm.

2. Design

2.1 Block Diagram

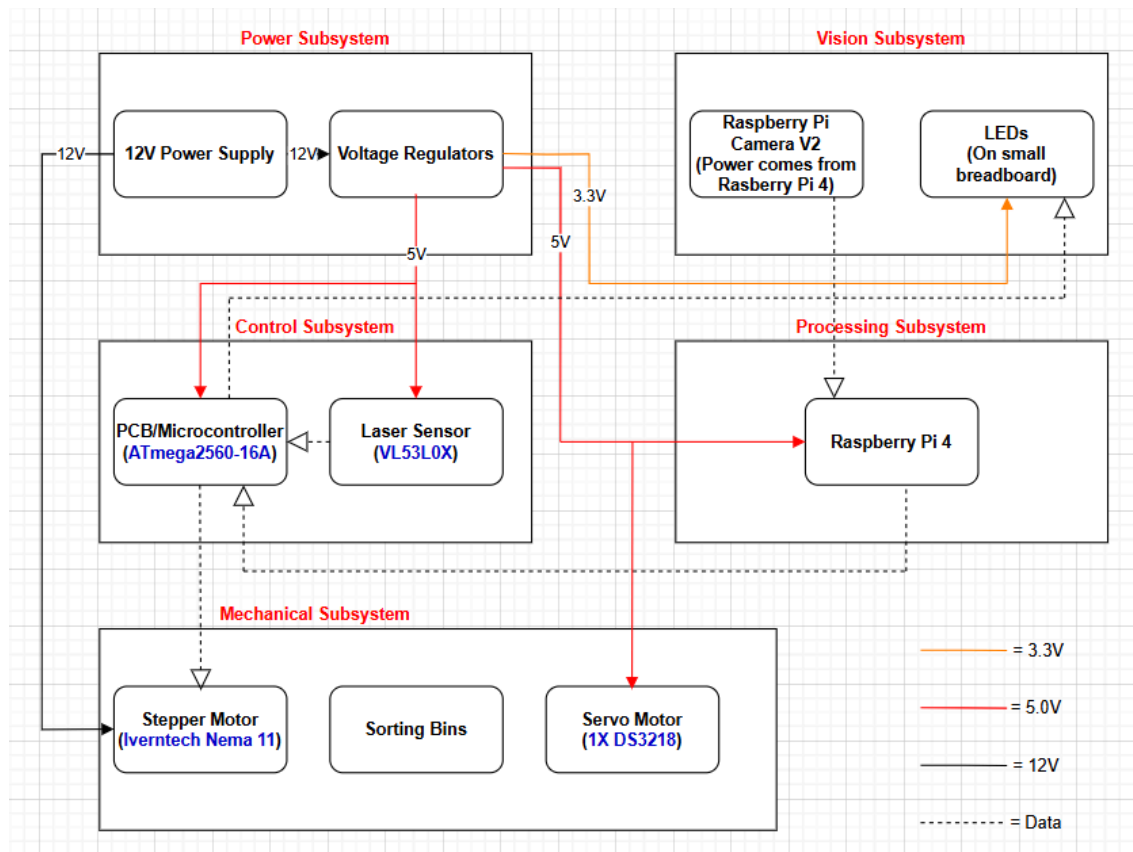


Image 2: A Block Diagram of all the Subsystems

2.2 Subsystem Descriptions

2.2.1 Vision Subsystem

The **Vision Subsystem** is responsible for capturing and analyzing images of waste items to classify them into predefined categories: plastic, metal, perishables, and paper. This subsystem integrates a **Raspberry Pi Camera**, a **TensorFlow Lite Model**, and **LED indicators** to facilitate real-time waste classification and system status updates.

1. Camera Module:

- The **Raspberry Pi Camera** captures **1280x720 resolution** images of waste items upon disposal.
- The camera is positioned above the waste entry point to ensure optimal image acquisition.

- The captured images are processed locally using **TensorFlow Lite** running on a **Raspberry Pi 4**.
2. **Camera Module:**
- The **Raspberry Pi Camera** captures **1280x720 resolution** images of waste items upon disposal.
 - The camera is positioned above the waste entry point to ensure optimal image acquisition.
 - The captured images are processed locally using **TensorFlow Lite** running on a **Raspberry Pi 4**.
3. **Machine Learning Model:**
- The TensorFlow Lite model classifies waste into **four categories** with a target accuracy of **at least 85%**.
 - The model is optimized for **real-time inference**, ensuring that classification completes within **1-1.5 seconds**.
 - Image preprocessing (grayscale conversion, noise reduction, and edge detection) is performed before classification to improve accuracy.
4. **LED Indicators:**
- **Status LEDs** provide real-time feedback on system operation:
 - **Green LED:** Funnel is clear and system is ready.
 - **Yellow LED:** Waste is being classified.
 - **Red LED:** A jam has been detected.
 - **Bin Capacity LEDs** indicate the fill level of the bins:
 - **Green LED:** Bin is not full.
 - **Red LED:** Bin is full and requires emptying.

<u>Requirements</u>	<u>Verification</u>
The camera must capture high-quality (1280x720) images with minimal distortion.	Perform test captures under different lighting conditions and verify image clarity.
The TensorFlow Lite model must classify waste items with at least 85% accuracy.	Conduct model testing on a dataset of at least 100 waste samples and record classification accuracy.
Classification must be completed within 1.5 seconds to ensure real-time operation.	Use timestamp logging to measure processing time per classification.
The system must correctly update status LEDs based on operational states.	Manually trigger each state and verify the corresponding LED response.
The bin capacity sensors must correctly	Fill a bin and verify LED response using a

trigger the red LED when full.	controlled test.
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2.2.2 Power Subsystem

This subsystem ensures reliable and regulated power distribution to all components, including the microcontroller (ATmega2560), Raspberry Pi 4, sensors, motors, and LEDs. It manages voltage conversion, motor power delivery, and system safety features.

Power Source and Regulation:

- The system is powered by a 12V DC input, supplied through a barrel jack connector.
- An LM7805 voltage regulator is used to step down 12V to 5V, providing power to the microcontroller, sensors, and LEDs.
- Multiple capacitors (470 μ F, 10 μ F, 0.1 μ F, and 22pF) are placed for voltage smoothing and noise reduction, ensuring power stability.

Microcontroller and Control Circuits:

- The ATmega2560 microcontroller operates at 5V and acts as the control hub, managing inputs from sensors and output signals to motors and indicators.
- The TXB0104 logic level converter ensures proper communication between the 3.3V Raspberry Pi 4 and the 5V microcontroller, preventing voltage mismatches.

Motor Power and Control:

- Stepper Motor Control:
 - The L298N motor driver regulates the 12V power supply to the stepper motor, enabling controlled movement for the circular platform to ensure bin rotation.
- Connected to the ATmega2560, the driver interprets microcontroller signals to manage motor speed and direction.

Servo Motor Control:

- The servo motor receives power from the 5V rail and is controlled via PWM signals from the microcontroller.
- A 0.1 μ F capacitor stabilizes voltage fluctuations at the servo input.

Status Indicators:

- LED Indicators provide real-time system status:
 - Jam LED (Red, Yellow, Green) – Detects and signals blockages in the system.
- Full Bin LED – Indicates when the waste bin is full and needs emptying.

Emergency Stop and Jam Detection:

- Sensors and interrupt signals detect mechanical jams and halt motor operation.
- The microcontroller monitors these events and can shut down power to motors if necessary.

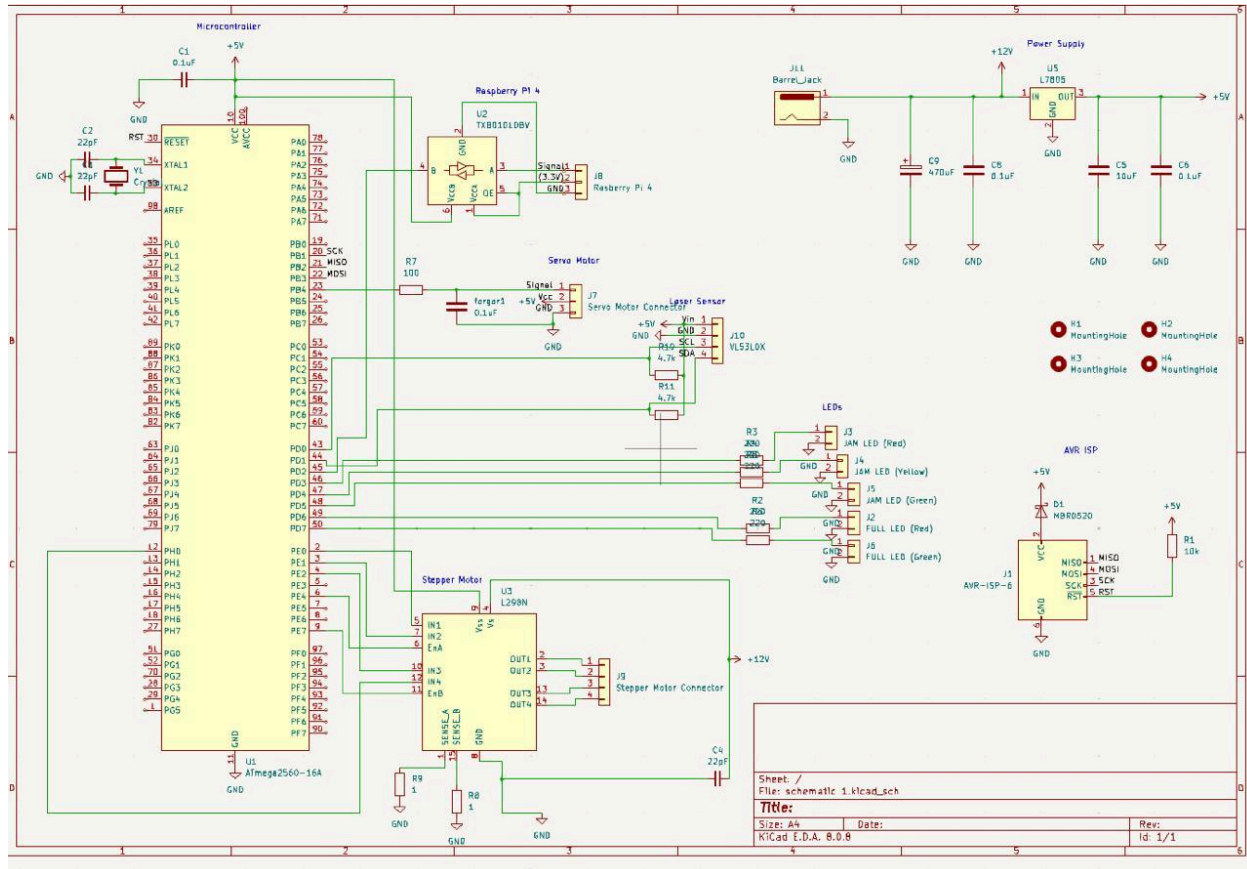


Image 3: Schematic of all the components used

The schematic diagram in image 3 provides a detailed view of all our components and their connections across the subsystems. This is a mockup of our PCB design as it serves to connect and communicate with the various subsystems in our project.

<u>Requirements</u>	<u>Verification</u>
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.	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.
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.	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.
The system’s emergency stop mechanism must cut power to motors (stepper/servo) within 2 seconds of activation.	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.

2.2.3 Processing Subsystem

The Processing Subsystem is responsible for receiving image data from the camera and performing the necessary object detection and classification on the Raspberry Pi 4 using the TensorFlow Lite Model. The goal of this subsystem is to identify and classify the nature of the item thrown to determine which of the Plastic, Metal, Paper, or Perishable categories the item belongs to. The model is a pre-trained model that will be adapted for this use case to ensure that we meet the requirements of classifying objects with a minimum of 85% accuracy.

The process starts with the Raspberry Pi 4 processing the images captured at 720p resolution (1280x720 pixels) by the camera, before using the TensorFlow Lite Model to determine the object category. The model inference is estimated to take less than 1.5 seconds. Once the object has been classified, the results are sent to the Control Subsystem for sorting.

1. Raspberry Pi 4

- Executes the TensorFlow Lite (TFLite) model to classify waste items.

- Handles image preprocessing (e.g., grayscale conversion, noise reduction, edge detection) to improve inference accuracy.
- Communicates classification results to the mechanical Control Subsystem for sorting.

2. TensorFlow Lite Model

- Optimized CNN architecture (e.g., MobileNet/EfficientNet) running locally.
- Target: $\geq 85\%$ classification accuracy on representative waste items.
- Latency: 1–1.5 seconds total from the moment the camera feed is acquired until a category label is produced.

<u>Requirements</u>	<u>Verification</u>
The classification process (capture + preprocessing + inference) shall complete in ≤ 1.5 seconds on average.	Log timestamps at the start of capture and end of inference. Calculate the average total time over 100 samples. Pass: Mean time ≤ 1.5 s, with no more than 2 samples exceeding 1.7s.
The CPU utilization on the Raspberry Pi 4 shall remain below 80% during inference to avoid performance bottlenecks.	Use a system monitor while running inference on 10 items. Record CPU usage during each inference. Compute average and peak usage. Pass: Average usage $\leq 80\%$, peak $\leq 90\%$.

2.2.4 Control Subsystem

The Control Subsystem is responsible for interpreting classification results from the Processing Subsystem and executing the necessary mechanical actions to sort objects into their designated waste bins. This subsystem operates using a custom PCB that integrates a microcontroller, a laser sensor, and motor control mechanisms.

Upon receiving a classification signal from the Processing Subsystem, the stepper motor rotates the sorting mechanism to align the appropriate bin for disposal. Once positioned, a servo motor is activated to push the object into the bin.

To ensure successful sorting, a laser sensor detects whether the bin's volume has increased, confirming that the object has been placed correctly. If the sensor does not detect a change, the system can trigger corrective actions. Additionally, the microcontroller interfaces with the LED

indicators from the Vision Subsystem to signal jams or other obstructions that may hinder the sorting process.

<u>Requirements</u>	<u>Verification</u>
The PCB must securely mount all components and withstand minor vibrations without disconnection.	Conduct a vibration test by placing the PCB in a moving environment (e.g., mechanical shaker) and ensuring stable operation.
The laser sensor must trigger an alert if no object is detected after disposal.	Simulate a failed disposal and verify that the system activates an LED alert or sends an error signal to the microcontroller.
The laser sensor must confirm object placement within 1 second after disposal (after trash slides down).	Trigger the disposal process and measure the time taken for the sensor to register the object using a high-speed timer.

2.2.5 Mechanical Subsystem

The Mechanical Subsystem performs the physical handling and sorting of waste items after classification. It consists of three primary components: a stepper motor for bin rotation, sorting bins to collect different waste categories, and a servo motor to push the waste into the appropriate bin.

We selected the Iverntech Nema 11 stepper motor to drive the rotation of our bin platform. This motor provides precise positional control with 200 steps per revolution (1.8° per step), enabling accurate alignment of bins with the waste chute. The Nema 11 offers an excellent balance of torque (holding torque of approximately 0.7 kg-cm) and compact size (28mm \times 28mm face), making it ideal for our application where space efficiency is essential.

The stepper motor receives control signals from the ATmega2560-16A microcontroller, which calculates the required rotation angle based on the waste classification result. The motor is positioned centrally beneath the rotating platform, with its shaft securely connected to ensure smooth and reliable movement. To minimize power consumption, the motor is only activated when bin repositioning is required.

After the appropriate bin is positioned beneath the waste chute, the 1XD DS3218 servo motor activates to push the classified waste item into the bin. This digital servo provides 20kg-cm of torque at 6V, ensuring reliable movement of various waste items up to 500g. The servo's 270° rotation range allows for a full extension and retraction cycle, with programmable speed control to optimize the pushing motion.

The servo is mounted adjacent to the waste detection area and is fitted with a custom paddle attachment designed to effectively guide items of various shapes and sizes into the waste chute. The paddle's movement path is carefully aligned with the chute to prevent jams while ensuring complete waste transfer.

<u>Requirements</u>	<u>Verification</u>
The servo motor must push the object into the bin within 3 seconds of receiving the signal.	Send a signal to the servo motor and measure the time taken for the object to be pushed. Conduct multiple trials to ensure consistency.
The stepper motor must complete rotation to the target bin within 3 seconds.	Send movement commands to the stepper motor and measure the time taken to reach the desired position. Conduct multiple trials for consistency.
The servo motor must apply enough force to move objects of up to 500g into the bin	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.

2.3 Tolerance Analysis

Our system uses a VL53L0X laser time-of-flight (ToF) sensor to verify that waste items have successfully fallen into the designated bin. This sensor must reliably detect small changes in distance when items are deposited, across various waste materials with different reflective properties. Failure to accurately detect waste placement would result in incorrect system feedback and potential jamming.

The VL53L0X sensor has the following relevant specifications:

Measurement range: Up to 2000 meters.

Accuracy: 2 - 3 mm fluctuation in the distance measurement in high accuracy mode

Field of View: 25 degrees

Wavelength: 940nm

Resolution: 1mm

In our application:

- Sensor mounting height above empty bin: 150mm
- Expected waste item height variation: 10-100mm
- Minimum detectable change: 10mm

Detection Reliability Calculation:

The sensor accuracy of 2-3 mm fluctuation in high accuracy mode means our potential measurement error is: Error range = $\pm 3\text{mm}$ (worst case). For our minimum detectable change of 10mm: Signal-to-noise ratio = $10\text{mm} \div 3\text{mm} = 3.33$. A signal-to-noise ratio of 3.33 indicates that we can reliably distinguish genuine waste detection events from measurement noise, with a comfortable margin of safety.

Surface Reflectivity Effects:

Different waste materials have varying infrared reflectivity properties: Paper/cardboard: ~80% reflectivity of plastics: ~60-70% reflectivity of food waste: ~40-60% reflectivity of metals: ~70-90% reflectivity. The VL53L0X sensor's sensitivity decreases with lower target reflectivity. Based on the manufacturer's data sheet, the detection reliability at our operating distance of 150mm remains above 95% for materials with reflectivity $>40\%$, covering all our waste categories.

3. Cost & Schedule

3.1 Cost Analysis:

Labor:

Let's assume a grad researcher at this position gets \$35/hour. 9 weeks left in the semester, assume we work 20 hours a week. $20 * 9 = 180$ hours of work left.

$$35 * 2.5 * 180 = \$15,750$$

Multiply by three for each member:

$$15750 * 3 = \$47,250$$

Parts:

Description	Manufacturer	Part #	Quantity	Cost
Servo motor	Dongguan Dsservo Technology	DS3218	1	\$ 13.66
Stepper motor	Inverntech	NEMA 17	1	\$ 9.99

Raspberry SC15184 Pi 4 Model B 2019 Quad Core 64 Bit WiFi Bluetooth (2GB)	Raspberry Pi	SC15184 Pi 4 Model B 2019	1	\$56.99
AC/DC Adapter	ALITOVE	12 V Power Supply	1	\$ 20.99
Raspberry Pi Camera Module V2-8 Megapixel,1080 p	Raspberry Pi	RPI 8MP CAMERA BOARD	1	\$14.49
Laser Sensor	HiLetgo	v15310x	1	\$ 6.79

Estimated Cost of Parts (Excluding Machine Shop Components) : \$122.91.

Overall Estimated Cost (Labor + Parts) : \$47,372.91.

3.2 Schedule:

Week	Task	Person
Feb 17 - Feb 24	Have the entire proposal in place, ensure to receive feedback from course staff about complexity and workability	Everyone
	Allocate different roles to team members, set up efficient communication methods	Syed
Feb 24 - March 3	Finalize macro-design of the systems with the Machine Shop, and get a green light from the professor and TA	Konark, Rutva
	Good progress on the PCB Design on KiCAD and	Syed

	coordinate with TA to ensure it meets all requirements	
March 3 - March 10	Finalize PCB Schematic for first round order	Syed, Rutva
	Coordinate with the Machine Shop & order parts	Konark
	Complete & submit design document	Everyone
March 10 - March 17	Build the circuit on the breadboard to demo to course staff	Everyone
	Coordinate status with Machine Shop for construction of mechanical components	Konark
	Coding tests to ensure basic functionality of ML model	Syed, Rutva
March 31 - April 14	Assembly of the physical components	Konark
	Advanced training of the ML model, testing it out with real-life objects to detect for segregation as simulation	Syed, Rutva
April 14 - April 21	Fix any bugs in the code or tweak for efficiency for faster processing and object identification times	Syed, Rutva
	Smooth operation and functionality of the mechanical and electrical subsystems	Konark
	Ensure that all systems coordinate synchronously with one another	Everyone
April 21 - April 28	Have everything finally set up, and ready to demonstrate	Everyone

	to course staff	
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4. Ethics & Safety

Our project promotes sustainability by improving waste segregation accuracy, aligning with ACM Code of Ethics Section 3.1, which prioritizes technology for public good. By automating waste classification, we encourage responsible disposal and reduce landfill waste. Unlike industrial-scale solutions, our system is cost-effective and an accessible model to be built upon, making automated waste sorting viable for small businesses and institutions.

A key ethical consideration is data privacy—our computer vision system does not store or process personal data, ensuring compliance with privacy standards. Additionally, we designed our system to be fair and inclusive, avoiding reliance on costly infrastructure.

Since our initial proposal, we have removed glass sorting from our system due to safety risks. Glass breakage during the sorting process posed hazards, including shattered fragments, injury risks, and maintenance challenges. Eliminating glass ensures a cleaner, safer disposal process.

Other key safety concerns and mitigation strategies include:

Concerns/Mitigation Strategies	Risk	Solution
Mechanical Hazards	Moving parts (mechanical arm, rotating bins) may cause pinching or jamming.	Jam detection sensors, and protective casing around moving parts.
Electrical Safety	Short circuits, overheating, and accidental electrical contact.	Insulated wiring, and low-voltage control circuits.
Material Contamination & Hygiene	Liquids, food residue, or bacterial growth.	Easy-access maintenance panels, and non-porous materials.
User Interaction Safety	Accidental misuse, exposure to moving parts.	LED indicators for system status, physical barriers, and enclosed design.

Battery and Power Management	Overcharging, overheating, fire hazards.	Battery protection circuits, regulated voltage control, and proper disposal guidelines.
Controlled environment testing	Unreliable operation of the system	Pre-demo functional safety checks

Section 5: Citations and References

Book Clean Go. “Recycling Statistics: The Truth About Recycling in the U.S.” *Book Clean Go*, <https://www.bookcleango.com/blog/recycling-statistics>.

Association for Computing Machinery (ACM). ACM Code of Ethics and Professional Conduct. 2018, [<https://www.acm.org/code-of-ethics>].