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Automated Recycling Sorter

ENPH 454 – Engineering Design Project

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Executive Summary

With the increasing production of consumables and disposable items, efforts to improve waste management systems have become an increasingly popular topic for governments around the world. Many municipalities have adopted sustainable recycling methods that facilitate the recycling process for citizens and support more environmentally conscience practices. However, these changes can lead to a higher rate of inaccurate sorting of recycling which ultimately causes a significant portion of recyclable items to be incorrectly distributed to landfills. As a result, this project aims to improve this efficiency by developing a proof-of-concept automated recycling sorter.

The proposed automated recycling sorter receives clean individual recyclable items as an input and guides the objects to one of three categories of recycling: paper, plastic or metal. The sorter transports items via a conveyor belt system and labels each item via a computer vision apparatus. Once labeled, an arm sorting system separates the items into one of the three categories. The overall structure was composed of wooden beams and controlled via an Arduino and computer system.

With regards to the success criteria, five items were chosen to determine whether the project were a success. The criteria required that the sorter be able to redirect and sort items with a size of at least 210 mm × 210 mm × 297 mm and a mass of 0.5 kg. Furthermore, the structure was required to support a total mass of 1.5 kg and process items at a rate of 1 item per minute. Lastly, the computer vision model was required to sort items with an accuracy of 90%.

The chosen design achieved and exceeded the spatial and weight requirements. The rate of sorting was determined to be approximately 2.37 ± 0.02. The computer vision model was able to achieve an accuracy of 93.5 % on a test set but ranged from 60-70 % when implemented in a real-world setting. It is suspected that this may be due to the lack diversity in the training dataset and variation of environmental conditions of the implementation which inhibited the applicability of the model in the final design.

Future efforts would primarily strive to reduce the difference in accuracy between the simulated predictions and the implemented test cases. This would include developing a more isolated imaging apparatus with consistent lighting and limited variation between image positions. Furthermore, integration of delays and a more sophisticated coding structure could allow for a faster rate of item sorting.

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Introduction

Over the past century, pollution has risen to become a significant environmental issue affecting communities around the world. As a result, government and industry stakeholders are beginning to prioritize making processes more efficient, sustainable and environmentally conscious [1]. One specific example of this prioritization can be observed in the evolving recycling industry.

A common trend in many municipalities has included the adoption of a “one-bin” system where recycling is sorted after collection, facilitating the process of community citizens and consumers being able to recycle their waste [2]. This greatly increased participation of recycling in these locations, though greater improvements to the efficiency of sorting systems is still evident [3].

However, while this policy change has increased the number of items recycled, efficient methods are required to categorize recycling items and distribute them to the correct facilities. In the past, these recycling sorting systems utilized a combination of mechanical systems, pneumatics, magnets, and human labour [4]. However, these methods can be costly and prone to error [5]. The recovery rate of recycling programs ranges from 70-90% with some municipalities as low as 40%. This means that 10-30% of items placed in recycling bins end up in the landfill due to limitations of current systems [3]. This presents a potential opportunity for artificial intelligence, which has shown significant potential in this application, to contribute to environmental sustainability efforts through improving this process [6].

A promising candidate for automated recycling sorting that has gained popularity originates from the increased use of computer vision for classification tasks [7]. In comparison to traditional pneumatic sorting systems or labour-intensive sorting, computer vision has been shown to achieve promising results when classifying recycling items while also remaining cheap in terms of operating costs [8]. These characteristics make computer vision a strong candidate for an automated recycling sorting apparatus that can be used by various sizes of municipalities. Thus, the approach utilized in this project aimed to leverage machine learning to sort the recycling.

Motivation

The goal of this project is to design and build a physical proof-of-concept apparatus that accurately and efficiently sorts recycling into various bins. The proof-of-concept will utilize mechanical components to orchestrate the transportation and distribution of the recycling items. Furthermore, a computer vision program was implemented to sort and distinguish the individual items. Overall, this project aims to support municipal recycling facilities in their efforts to sort recycling efficiently and reliably. Ultimately, this will reduce waste sent to landfills while also prevent pollution, conserve energy, and protect natural resources [9].

Project Scope

The minimum viable product required the development of a proof-of-concept computer vision system to accurately sort recycling items and distribute them into their respective bins. The desired outcome was to produce a small-scale recycling sorter with an integrated sorting and transportation system that reacted to signals from the computer vision model. The objectives of the project included assembling a functional conveyor belt, constructing rotating sorting arms that operated with the computer vision software, and sorting between at least three distinct types of recycling. A total budget of $1000.00 CAD was allocated to complete the project.

It should be recognized that multiple tests were conducted distinguishing between different sets of outputs. Specifically, a different computer vision model was established that sorted items between garbage, paper and blue box items. However, the three main types of recycling materials used for the testing and analysis of the proof-of-concept system were plastic, carboard, and metals. This was due to their lower variation of physical characteristics and availability which made them easier to acquire and distinguish between.

With regards to constraints, the project was confined by various parameters. The time and space constraints required the design to be constructed at a smaller scale then the real-world implementation. Furthermore, it was required that the overall design fit into the lab space and on the work bench which was approximately 6 ft by 2.5 ft. Furthermore, the time constraint required any product built to be made within 12 weeks which limited the scale and complexity of the design.

For the computer vision model, the design of the final product required several sequential steps. As a result, the proof-of-concept was simplified to ensure that it remained feasible within the given time frame. Specifically, the recycling used for training was required to be common items found in households and cleaned to allow for proper recycling. Furthermore, the models were made with minimal complexity to ensure they were adaptable to design changes.

Stakeholders

The primary stakeholder for this project were municipal governments. However, additional stakeholders are outline in Table 1.

*Table 1: The main stakeholders of the project and their associated objectives. The considerations required to accommodate each of the stakeholders' needs are also stated. *** indicates the primary stakeholder.*

Stakeholder	*Objectives*	*Considerations Required*
*Local Municipalities****	To sort recycling accurately for their respective citizens.	Success Criteria
Recycling Facility Workers	To sort the recycling in a safe and practical manner.	Safety Considerations, Relevant Technical Standards
Environment	To support sustainability practices and improve current environmental efforts.	Environmental Considerations
Citizens of the Municipalities	To meet the guidelines of the municipality and remove waste from private buildings.	Equity and Societal Considerations

Success Criteria

The design was evaluated based on five parameters for success shown in Table 2.

Table 2: The proposed success criteria for the project which addresses the sorter's accuracy, intake parameters and sorting rate.

Criteria	*Requirement*
Accuracy	Sorting accuracy of 90% between three categories
Weight	Supports three items of 0.5 kg
Size	Supports items up to 210mm x 210mm x 297mm
Distribution Strength	Can shift items of 0.5 kg into each output destination
Sorting Rate	Processes items at one item per minute

The chosen sorting accuracy of 90% was chosen based on similar projects that have been conducted in an industry setting [10] [11]. While these projects consisted of more robust imaging and modeling techniques, the simplification of items in this project's setup were assumed to balance out this lack of input data in the proof-of-concept. As a result, the accuracy appeared feasible given the scope and constraints of the project.

The criteria for the minimum weight, size of the items, and belt speed that the system must be able to support was chosen based on the allocated budget and the spatial constraints of the lab. An A4 piece of paper was compared to several recycled items and was demonstrated to be an ideal minimum size that represented most input items. Thus, the input was required to take in a size of 210 mm x 210 mm x 297 mm. Using this size and the maximum average weight of target recycled items (50 lbs/yd^3), the maximum weight of an item was determined to be 0.5 kg with an approximate safety factor of 20% [12]. These criteria were verified with experimental comparisons to several recycling items.

The sorting rate requirement was approximated using the frame rate of the camera, the estimated distance of the camera's field of view and what the team decided would be feasible for the project. The total weight that the system was required to suspend was determined by assessing how far individual items would be spaced on system and what their combined weight would yield. As a result, the team hypothesized three items could be processed at once given the space and thus, the total weight suspended was required to be 1.5 kg.

Design Decisions

Design decisions were separated into one of three categories: the conveyor belt subsystem, the computer vision model and the sorting apparatus.

Conveyor Belt Subsystem

To transport the target objects through the computer vision setup and sorting mechanism, a transportation system was required. The general flow requires the recyclables to be transported to the computer vision system that would computationally label the object and sort it into a specific category. The system would also be required to move objects from the computer vision setup to the mechanical sorting system. As a result, several solutions were considered such as conveyors, ramps, and pneumatics. The primary functional requirement was the ability to move objects at a constant speed and control the speed. This was to accommodate the frame rate of the camera for the AI system. The team deliberated the options by assessing the build complexity, functionality and cost of the various options. These were all evaluated in a weighted evaluation matrix shown in Table 3.

Table 3: A weighted evaluation matrix for three different object transportation methods that would transport items throughout the automated recycling sorter.

Criteria	*Weight*	*Conveyors*	*Ramps*	*Pneumatics*
Build Complexity	1	3	5	1
Functionality	2	5	1	3
Cost	1	3	5	1
Total		**16**	**12**	**8**

The pneumatics system was too complex given the project's time constraints and would not meet the functional requirements with the same ease as a conveyor belt. A ramp system was the easiest and cheapest option. However, it would not be able to keep the object moving at a consistent rate as items would have different masses and accelerate at different rates. The ramp would also not allow for the stopping of the object for the computer vision system if the item movement speed was too fast. This led the team to conclude that a conveyor belt was the most appropriate option.

When considering the acquisition of the conveyor belt, two options were presented. Firstly, prebuilt conveyor belts could be purchased in various sizes from online commercial websites such as Amazon or McMaster-Carr. However, considering the nature of the computer vision project, integration into the rest of the system would have been more difficult as purchased conveyor belts would limit the customizability of the overall structure. This was essential in the decision, as the conveyor belt was made to fit the required sizes of the success criteria with a safety margin. Furthermore, a customized conveyor belt allowed for a simple integration with the electrical components and allowed for control from an Arduino. This allowed for the stopping and starting of the belt to be controlled from the same controller as the remaining subsystems.

Computer Vision Model

From previous research, various projects have used computer vision to accomplish similar tasks using a variety of models. One common model architecture used for computer vision are convolutional neural networks. Convolutional neural networks are composed of three components: convolutional layers, pooling filters and fully connected layers [13]. The convolutional layers provide feature extraction using the encoded pixel values of the image. The data is then down sampled using pooling layers where the dimensionality is reduced for further processing in the fully connected layers [14]. The fully connected layer consists of an artificial neural network as described in [15]. A diagram showing a high-level overview of the convolutional neural network architecture can be seen in Figure 1.

With regards to applications of convolutional neural networks, Zhang et al. were able to use a convolutional neural network to sort garbage [8]. Similarly, Funch et al. utilize a similar model to identify glass and metal in trash bags [16]. As a result, this project aimed to translate similar technology to support the classification of common household recycling and garbage items. Thus, the project strived to use a convolutional neural network to label and sort the items.

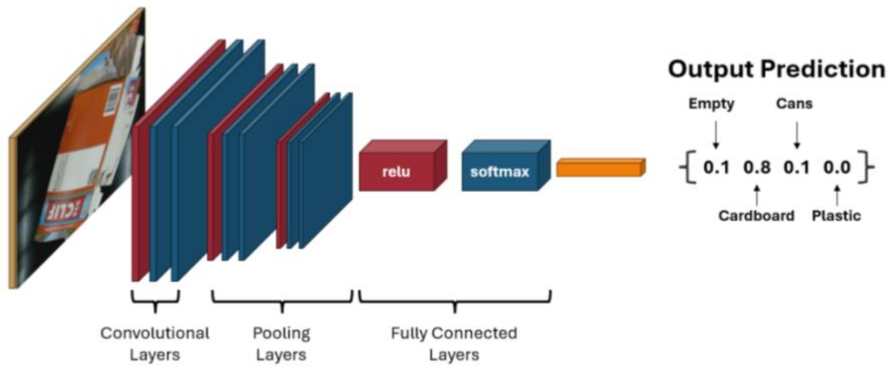

Figure 1: A diagram showcasing the fundamental components of a convolutional neural network. The model receives an input image, passes parameters through various layers and outputs a confidence score for each of the categories. The confidence scores are used to determine the final prediction of the model.

While other architectures exist, the design choice of using a custom made convolutional neural network results from the customizability of the model and the ability to readily change features when encountering issues. Specifically, the use of transformers for imaging tasks have shown promise in capturing long-range dependencies. However, these models have significant complexity [17]. This makes them more computationally intense, less adaptable to changes and more difficult to apply them in real-time applications [18]. Another architecture, U-Net, that integrates features of convolutional neural networks presents similar challenges to transformers when being used for recycling sorting applications [19]. Thus, the convolutional neural network provided the most suitable features that fit within the constraints of the project.

Lastly, although pretrained models may have provided a simpler implementation into the model, creating a custom model would allow for the model to be focused on the specific environment of the project. Thus, this decision would allow for the model to achieve increased accuracies and be more time efficient despite being slightly more difficult to implement.

Sorting Apparatus

There were multiple potential ways to physically organize the material once classified by the computer vision model. The team discussed three potential designs:

1. A chute mechanism that translated allowing items to exit at different position as shown in Figure 2.
2. A turntable that could rotate bins under where objects would fall off the belt as shown in Figure 3.
3. Mechanical arms to redirect moving objects off the belt in specified locations as shown by Figure 4.

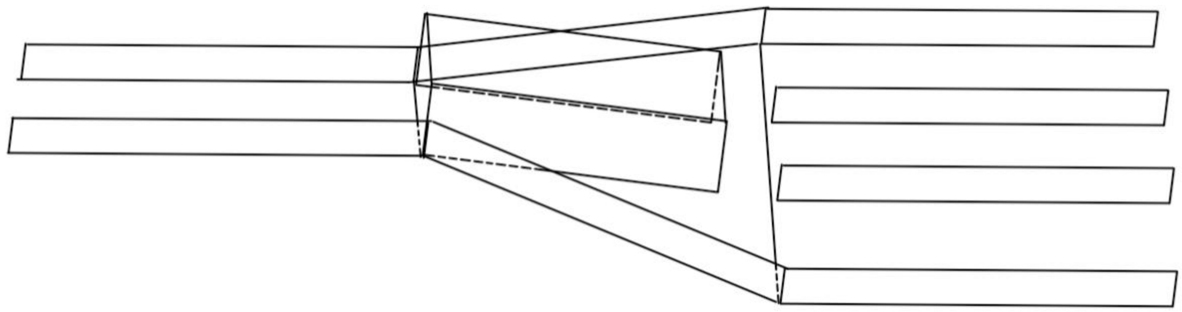

Figure 2: A preliminary sketch of a chute design to sort recycled items. The center piece would rotate to guide the items into various categories.

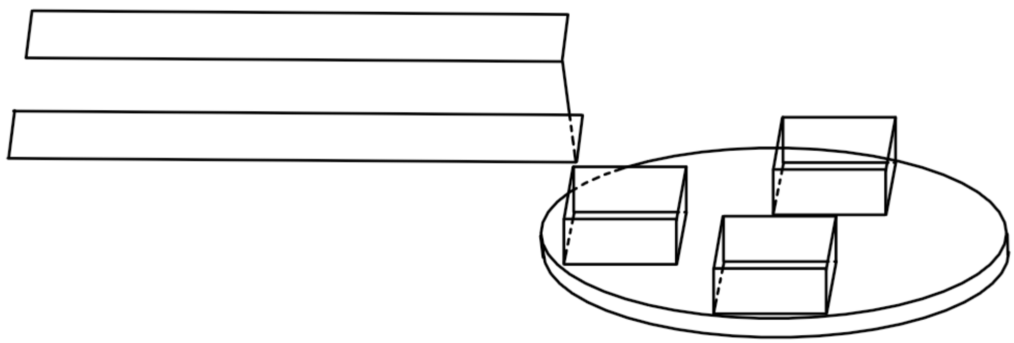

Figure 3: A preliminary sketch of a turntable design to sort recycled items. The three recycling bins are rotated on the turntable to change the bin that items fall into.

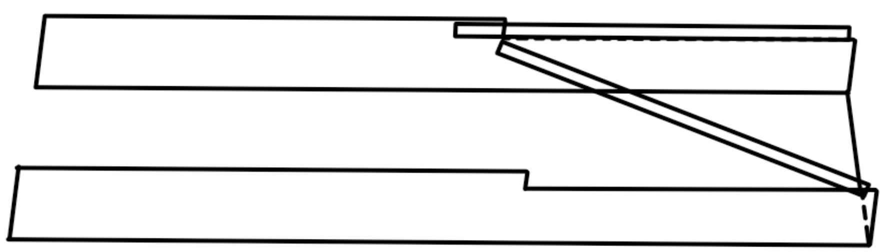

Figure 4: A preliminary sketch of the robotic arm design to sort recycled items. Robotic arms direct the items into one of three categories and can push the items if required.

A process of elimination methodology was used on these potential solutions to determine which design would be most appropriate to meet the objectives of the project. Bins on a rotating turntable would involve only a few parts but would be difficult to turn if the bins accumulated substantial weight. A chute mechanism would have required more moving parts and would be more prone to mechanical errors. Thus, it would require more troubleshooting which made it less suitable for the provided time frame. By eliminating these options, the two-arm mechanical design provided the most appropriate solution as it only required a few parts, could be integrated into the rest of the apparatus, and did not require and excessively strong motor.

Relevant Technical Standards

To ensure the appropriate use of all electrical and mechanical equipment, relevant technical standards were reviewed and used to make more defined components of the overall setup.

Specifically, the RS-232 standard was used for communications to ensure compatibility between a host and the peripheral systems [20]. In the project, this applied to the computer and the Arduino to the motor and the computer controller. This standard specifies the common voltage and signal levels, common pin-writing configurations, and the minimal amount of control information between the host and the peripheral systems. As a result, the projects voltage values are approximately +5 and +12 volts which abides by the recommended +3 to +15 volts. Furthermore, communications between devices followed the signals dictated by the standard.

IEC-60204 applies to the electrical, electronic and programmable electronic equipment and systems not portable by hand while working [21]. This applies to nominal supply voltages not exceeding 1500 volts for direct current (DC) voltages, 1000 volts for AC voltages and supply frequencies not exceeding 200 Hz. This is directly applicable to the electronic components used throughout this project, in which the safety guidelines were strictly followed to ensure safe working environments. To comply with this standard, external casing was installed around electrical components and an emergency stop button was implemented.

Lastly, ISO-21183 directly involves the principal characteristics and its applications of light conveyer belts [22]. It should be recognized that most guidelines do not apply due to the dimensions and the purpose of the system. However, guards and casings were implemented to limit the risk of hazards and comply with the standard.

Additional Considerations

Considerations were made in project decisions and added to the final design to support objectives of the stakeholders as indicated in the Stakeholders section.

Safety Considerations

The required mechanical and electrical setup introduced safety hazards that needed to be considered when completing the design. The setup included many moving parts, electrical components, and a wooden frame which required steps to mitigate risks and reduce negative consequences.

To minimize the risk of the moving parts causing injuries, protocol was implemented around the sorter which required physical distance from the apparatus while in motion and verbal communication before program commencements. The items were placed on the opposite side of the belt from the sorting arms, and on separate surfaces to prevent the jamming or rapid redirection of items. Furthermore, the motors and the small belt controlling the rotating pipes were covered to prevent potential injuries or obstructions of the belt. This can be seen in a) of Figure 5.

While the electrical system showcased minimal risk due to low voltages and currents, safety precautions were integrated into the design to avoid damaging components or causing injuries. To prevent problems with the electrical system all components were properly isolated and contained on one side of the apparatus as shown in b) of Figure 5. Wires were also cut down to the minimal length to reduce disorganization. Lastly, a single shutoff was incorporated by using a DC-to-DC converter along with a relay. Thus, the complete system can be shut off from one button on the power supply or Arduino.

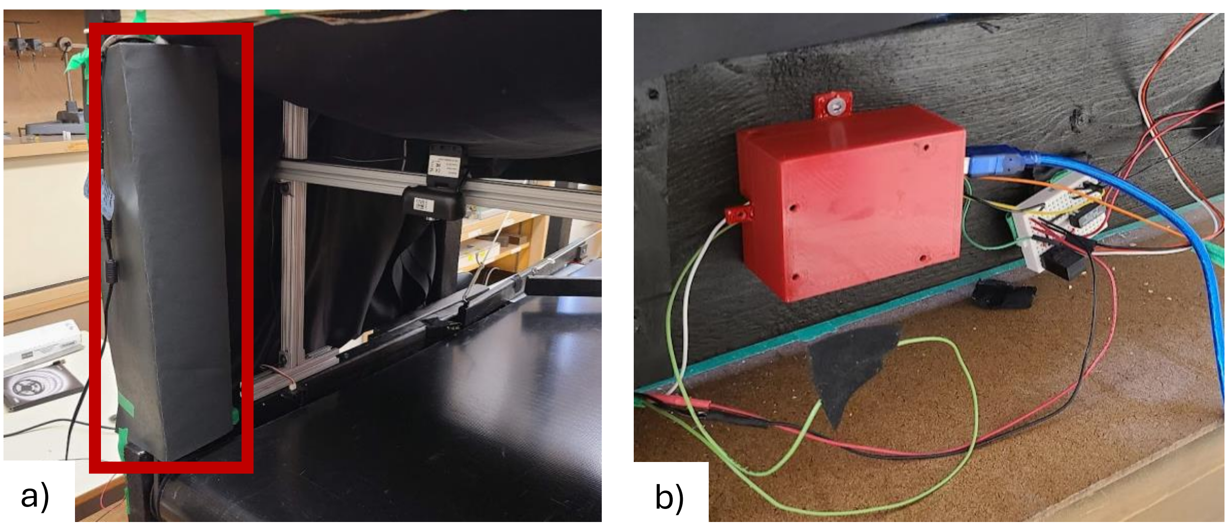

Figure 5: a) A motor system enclosure for the small timing belt and DC motor. b) An electrical safety box enclosing the Arduino and protecting wiring connections.

To prevent injury from sharp objects on the frame all the wooden beams were properly sanded and painted over with black water-based paint. Furthermore, metal sharp pieces were rounded or folded to mitigate the risk of injury.

Equity and Societal Considerations

When considering equity in the design, the proof of concept is constrained to only a few items of recycling that the computer vision can be trained on due to limited time and resources. When implementing the design in a real-world context, training data would consist of a wide range of recycling items including thousands of items able to be recognized and processed for a diverse range of communities.

In terms of promoting accessibility, the controls and user interface for the device will all be positioned in one place, in an easy to access location and with user-friendly methods of activation and troubleshooting for staff and users with various accommodations. Furthermore, the emergency shutoff is also accessible from the singular control location.

Environmental Considerations

When training the computer vision model, it was a priority for the team to achieve the highest possible accuracy while optimizing the efficiency of the proof-of-concept. This was accomplished by optimizing the parameters of the machine learning model and using only one power supply for all automated components. By improving the recycling capabilities and the accuracy of recycling sorting, power usage of the model was reduced, and recycling capabilities were improved to keep recycling from being disposed of improperly. This is important in an environmental context as contaminated or improperly sorted recycling can lead to items being incorrectly sent to landfills.

Construction Methodology

To design the overall structure, the methodology was broken down into six main components: Frame Construction, Conveyor Belt, Computer Vision, Sorting Apparatus, Electrical Design, and Computer Integration.

Frame Construction

The architecture of the recycling sorter system includes a few key components: the adjustable wooden frame siding, vertical supporting wooden beams and a metal sheet baseplate.

The wooden frame was constructed using the displayed dimensions in Figure 7. The length and width of the frame were set according to the size of the table to abide by the spatial constraints of the project. Furthermore, the belt width was set using the minimum size offered for purchase that exceeded the size constraint set in Table 2.

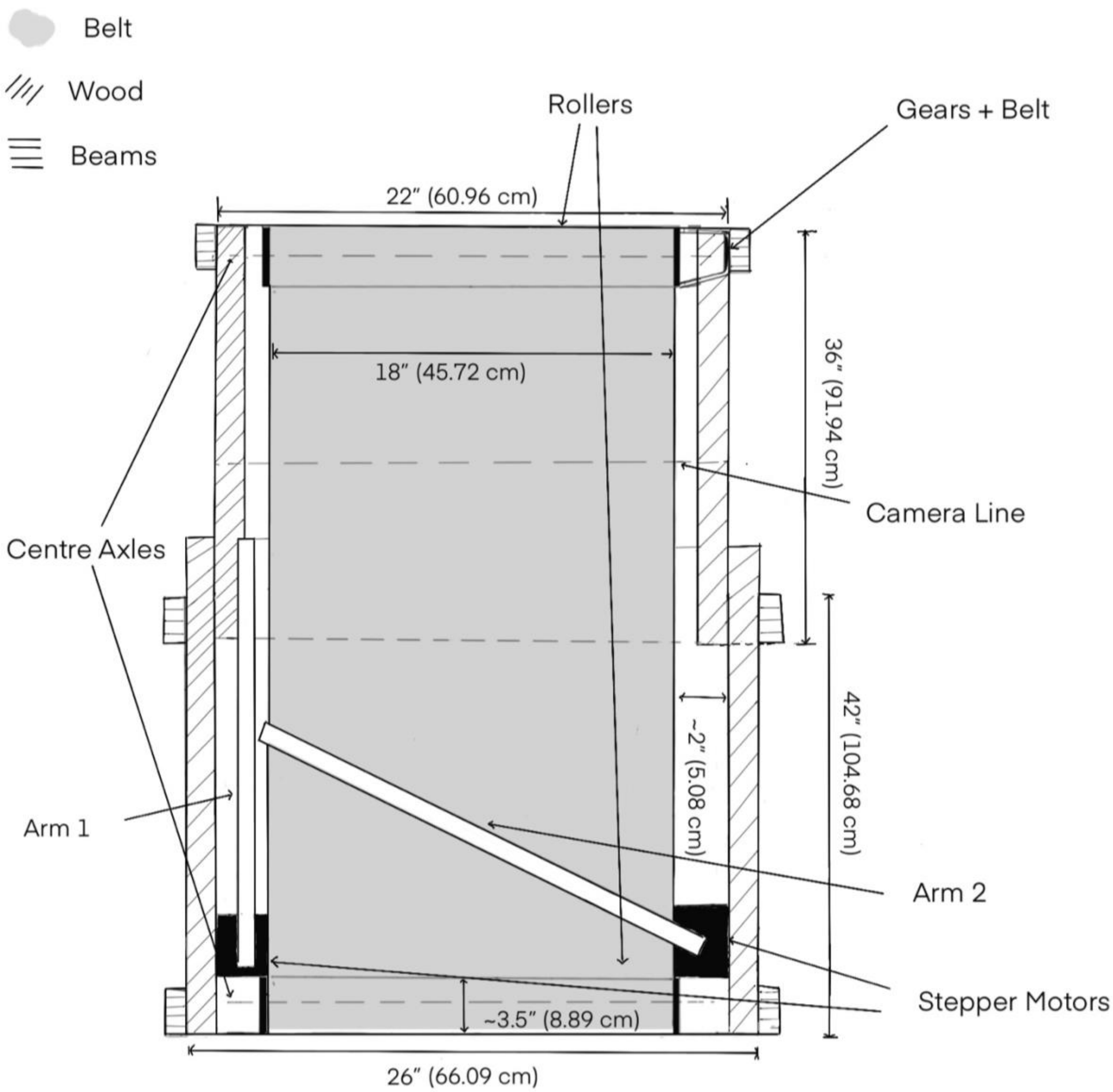

Figure 6: An engineering drawing of the physical apparatus from a top-down view. Key components are labeled and the respective dimensions of each of the physical components are stated.

To ensure that adequate tension was applied to the belt, the frame siding was created to vary the distance between the two rollers of the belt. This was constructed using two wooden 2 in. by 6 in. wooden planks which were cut to 2.5 ft. and 3 ft. lengths. The two wooden beams used bolts fixed into a slot and hole mechanism to allow for each siding's length to be adjusted independently. Once optimal locations were identified a supporting barrier was added to fix the pieces in place with the screws. The preliminary setup of the base can be seen in Figure 7.

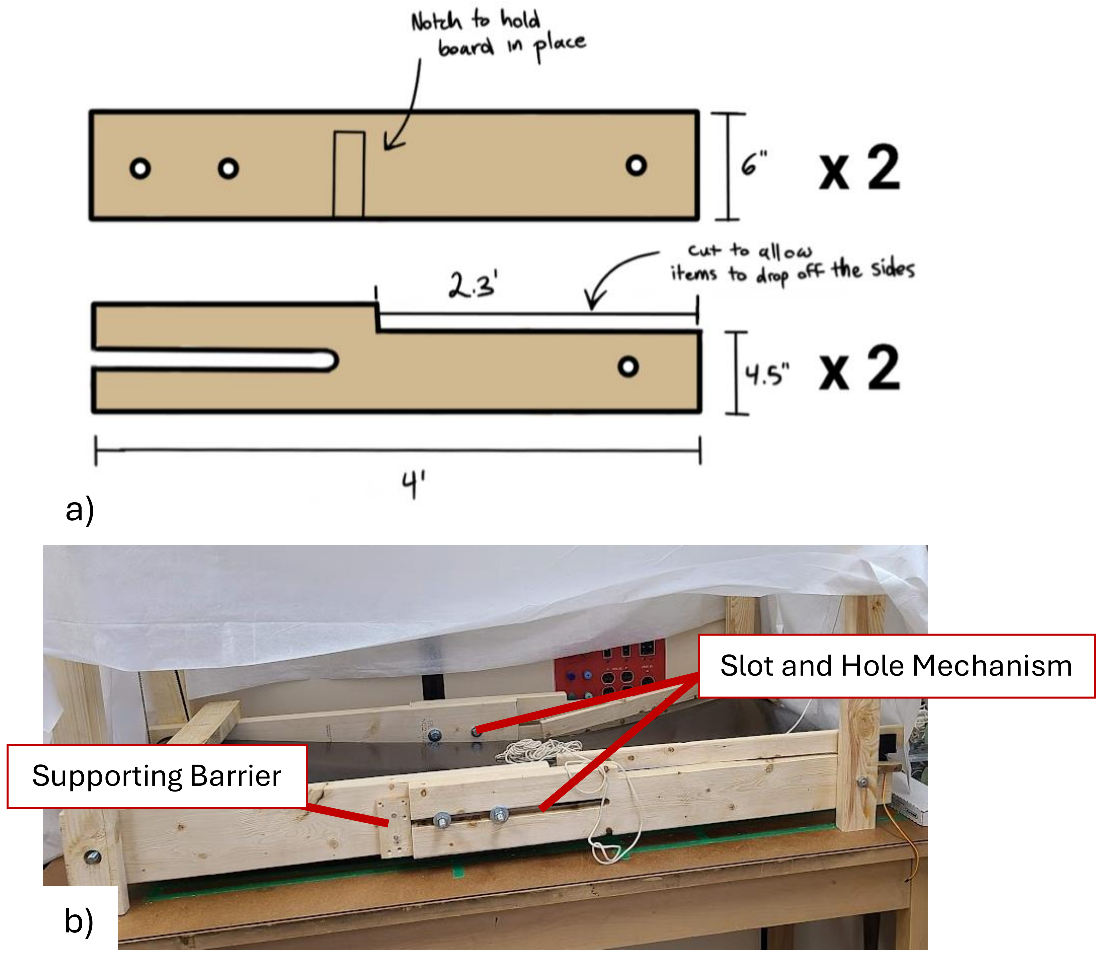

Figure 7: a) A layout drawing of the adjustable wooden frames and their respective dimensions. There exist two sets of the items to adjust each individual side. b) The implementation of the adjustable wooden frame with the supporting barrier and slot and hole mechanism labeled.

The entire apparatus was designed to be 5 ft. long when fully constructed to allow time for the camera to take pictures of the recycling items moving through the device and for the sorting arms to adjust according to the item classification by computer vision. Calculations for the time and size can be seen in the Arm Strength and Size Calculations section of the report. The end of the conveyor belt also included a metal plate underneath to prevent items from falling in-between the wooden frame and conveyor when being pushed off the side. A figure highlighting the features can be seen in Figure 8.

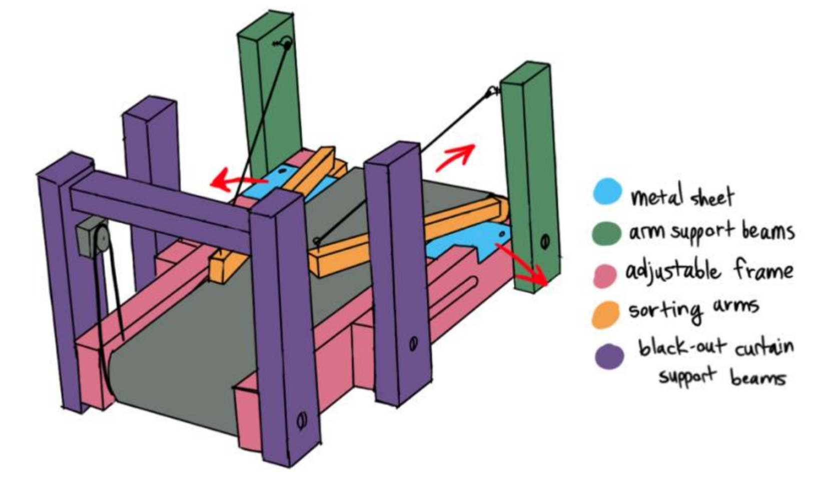

Figure 8: A structural diagram of the apparatus underneath the blackout curtain. Red arrows indicate distribution locations for recycling. Structural components are highlighted and referred to in the legend provided.

It should be noted that all bolts and threaded rods used a ½ in. diameter. An exception is the bolts used to connect the wooden frame to the DC motor mount which used a ¾ in. diameter.

Conveyor Belt

To avoid unnecessary cost, the only purchased parts included the belt and the belt clips that connect the ends of the belt together. The rollers were constructed from 3 in. diameter ABS tubing with 80-grit sandpaper glued around the outside to increase the friction between the rollers and the belt. The diameter of the belt including the edges was 3.5 in.. The diameter was selected as it exceeded the minimum size required by the technical specifications of the purchased belt and fit the spatial requirements of the design [23]. To connect the tubing to the axles, 3D printed caps were designed with custom inserts for ½ in. press-fit bearings. The caps and sandpaper were attached to the ABS tubing. A roller and the main roller cap can be seen in Figure 9 and Figure 10, respectively.

Figure 9: An image of the completed belt roller. The blue outer surface consisted of sandpaper and the caps were attached to the rollers via epoxy. The left side contains a specialized cap with a gear to turn the roller.

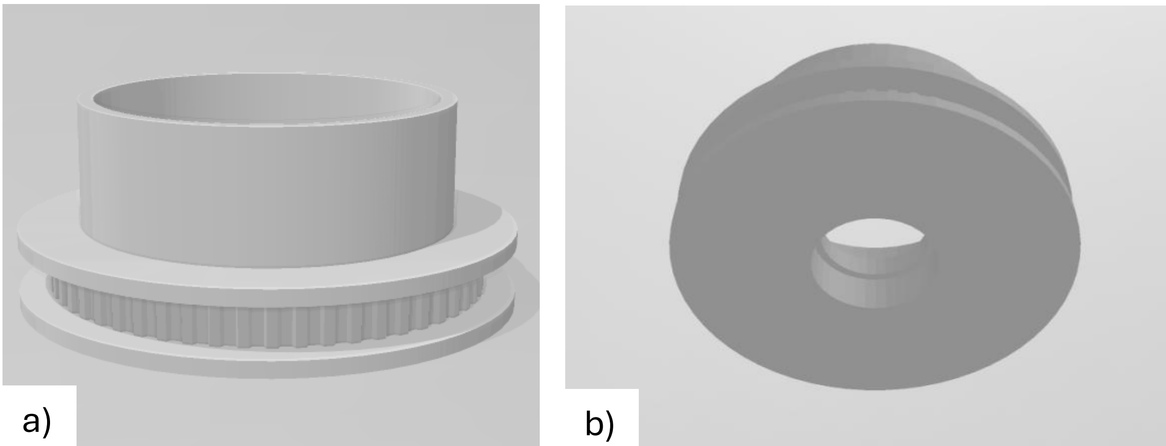

Figure 10: The computer aided design of the cap used to connect the DC motor timin belt to the roller. Similar caps were used on each end of the rollers but did not include the gear attachment. a) A side view of the primary cap used to turn the conveyor belt. b) The bottom view of the cap indicating the bearing location.

The axles were made of 1/2” threaded rod for easy fastening of the axle to the rollers and the frame. Furthermore, the threaded rod allowed for adjustability of the rollers in the horizontal directions to help centre the conveyor belt.

The movement of the conveyor belt system was set via a DC motor. The motor was chosen based on the high torque requirements shown in Equation 1 in the Conveyor Belt Torque Calculations. As a result, the motor purchased was a 12V 30 RPM DC motor with 58 kg·cm of torque. The DC motor was connected to the front roller via a 480XL037 timing belt. The 3D printed gears were attached onto the axle with a metal bracket to prevent the motor heat from melting the gear. The DC motor was fastened to the front of the conveyor belt via a 3D printed bracket. The bracket used a slot and hole mechanism to allow for adjustable tension on the timing belt. The setup of the DC motor can be seen in Figure 11.

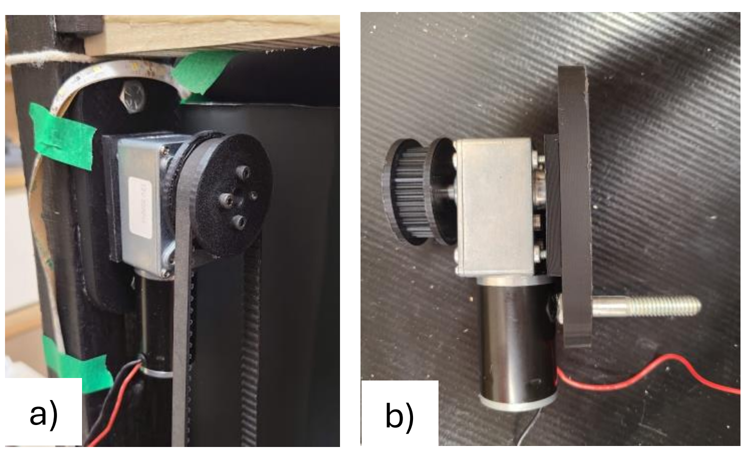

Figure 11: a) The DC motor mount design in the final design of the automated recycling sorter. b) An isolated view of the DC motor, the mounted gear and the associated mounting bracket.

To determine the size of the conveyor belt, the success criteria was used to set a minimum threshold of 297 mm in width. By incorporating a safety factor and purchasing an available size, the belt width was chosen to be 18 in. (457.2 mm) with a length of 5 ft.. A belt of thickness 0.135 in. was also chosen to increase the tensile strength of the belt when under significant tension from the two rollers.

Computer Vision

To train the machine learning model, an experimental apparatus was setup in a dark room to simulate the imaging environment. Using this apparatus, images were taken to generate a preliminary dataset that was used to determine the model parameters and architecture. Images were captured every 3 seconds while a user would manually rotate or exchange an object to capture the data.

The preliminary apparatus consisted of a 110-degree wide angle, 1080p camera on top of an aluminum frame structure. A black Styrofoam piece was utilized to mimic the conveyor belt that would be used in the final design. The camera was raised to include the entire field of view between the two supporting beams to ensure no items escaped the camera's view. The preliminary apparatus included light emitting diodes (LEDs) directly in the aluminum frame to illuminate objects in the target area. The apparatus can be seen in Figure 12.

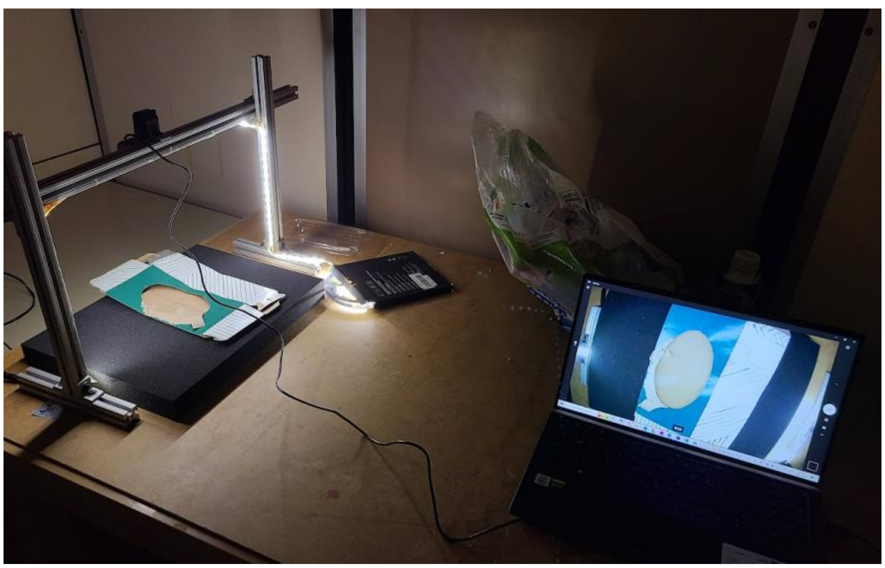

Figure 12: The preliminary apparatus design used for training purposes prior to the complete design of the conveyor belt. The setup was used in a dark room with LED lights on the camera mounting frame.

The full setup required the translation of the experimental setup to the wooden frame outline in Figure 7. The aluminum strut was cut to size and fixed into place to prevent horizontal movement. The height of the camera was set to 30 cm and then adjusted to encompass the entire belt width in the field of view. Additional length was used to support the curtain and prevent it from dropping into the field of view. The LEDs were moved to the roof of the structure to reduce glare and create a uniform backdrop that could be rotated in the training of the computer vision model. Furthermore, the exposure was fixed and calibrated before image acquisitions and testing the overall setup. An infrared (IR) sensor was used to detect if objects were present under the camera. The final implementation of the camera apparatus is shown in Figure 13.

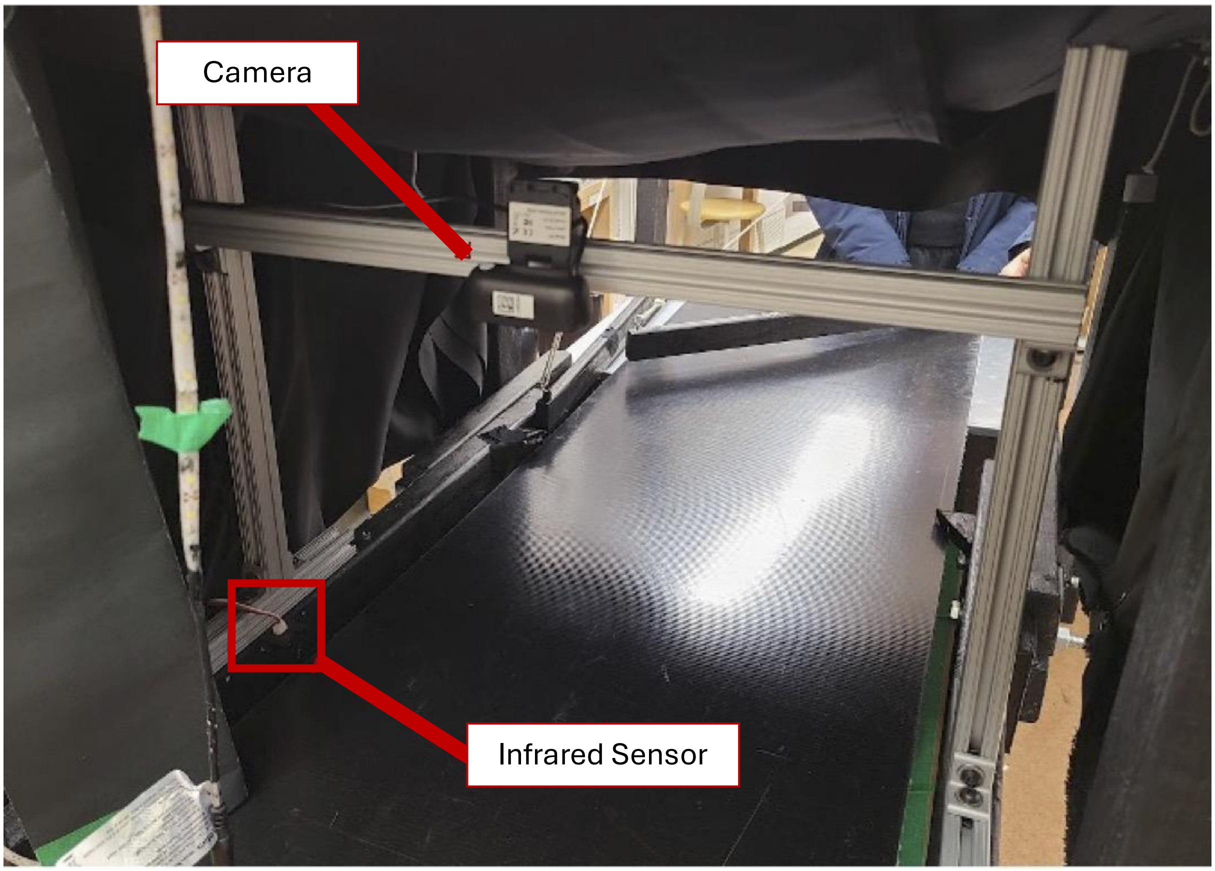

Figure 13: The final design of the imaging apparatus from a front facing direction. The apparatus was fixed by two screws on each side to the wooden frame to minimize horizontal motion along the belt.

Additionally, further datasets were generated using the full apparatus with the moving conveyor belt. To capture large quantities of images, images were captured every 0.05 seconds and objects were rotated using a black wire which blended in with the background conveyor belt. Various objects were used throughout the data sets. Furthermore, images were captured with the belt connection point in each dataset to ensure that the model would not distinguish the belt connection as a determining feature for classification.

The chosen model for the computer vision architecture was a convolutional neural network due to its ability to reduce dimensionality of large datasets and extrapolate relevant information. The architecture design is detailed in the Convolutional Neural Network Architecture section of the report.

Sorting Apparatus

To sort items into three distinguishable categories, the sorting apparatus was designed and constructed. The general design included two wooden arms that could rotate and shift items into three separate directions using servo motors.

The servo motors used were 70KG brushless servo motors (BLS-HV70MG) due to their high torque capabilities which could help shift items off the back plate if required as demonstrated in Equation 9 in Arm Strength and Size Calculations. Specifically, the torque was rated at 58 Kg·cm with at a voltage of 4.8 V to 71 Kg·cm at 8.4V.

The motors were placed on either side of the belt and the wooden beams were suspended using rope connected to the top of the back wooden vertical beams. The horizontal beams were chosen to be 70 cm as shown in Figure 15. The arm length was calculated using Equation 2 and is based on the other length requirements of the system. The beams were supported by a custom bracket on the servo motor and the other siding to reinforce the arms when bracing against incoming items. The overall setup can be seen in Figure 14.

Figure 14: An image of the complete arm sorting system with the supporting strings connected to the rear vertical beams.

The three positions of the arms can be seen in Figure 15.

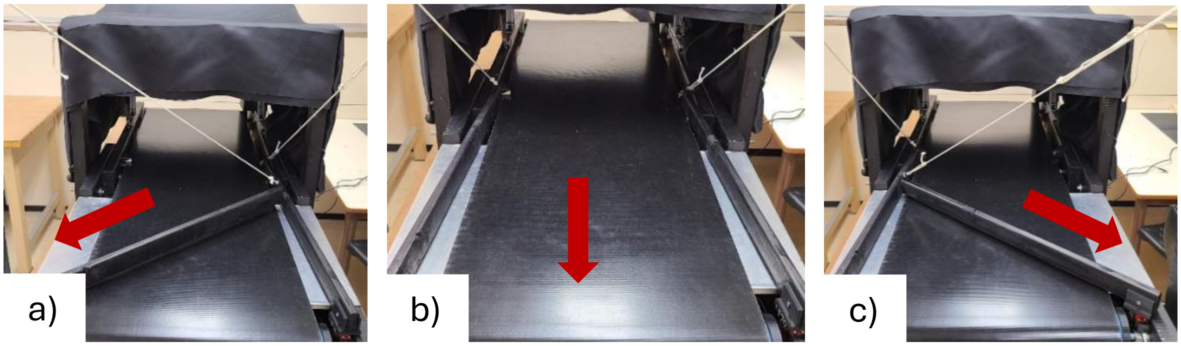

Figure 15: The three positions of the arm sorting system to distribute the items into the three separate categories. a) The left bin orientation that was used for metals. b) The middle bin orientation that was used for cardboard items. c) The right bin orientation that was used for plastic items.

Electrical Design

The electrical circuit provided power and controlled all electrical components from a singular power supply separated from the Arduino. This allowed for one button to shut down the entire system and acted as an emergency stop. Furthermore, all components were controlled via the Arduino.

The circuit was split into a 12 V section and a 5 V section to enable different components to receive their specified voltages. Thus, a 12 V KD3005D Digital-Control DC power supply was used and split via a DC-DC converter. To complete the circuit, all grounds between the power supply, Arduino, and other components were connected.

The 12 V component of the circuit is connected to the DC motor that rotates the belt. The 12 V supply was cut off using a relay to allow the circuit to be controllable from the Arduino.

The second section of the circuit involved a Sharp (GPY0A02) IR sensor and two Stemedu 70KG brushless servo motors requiring around 5 V to operate. The servo motors were controlled by sending a pulse-width modulation signal to the signal input where the width of the pulse corresponded to the angle of the motor, a 500ms pulse width correlated to the 0° angle, and 2500ms with 180°.

To programmatically shut off power to the entire circuit, a JWD-107-1 reed relay was added to the circuit and acting as a NO (normally open) switch on the main positive terminal of the 12 V supply. This was controlled via the Arduino by connecting a digital out pin to the 2-pin of the relay as seen in Figure 16 to supply 5 V. This closed the switch allowing for 12 V to pass from the 14-pin to 8-pin in Figure 16. The overall circuit design and implemented circuit can be seen in Figure 17 and Figure 18, respectively.

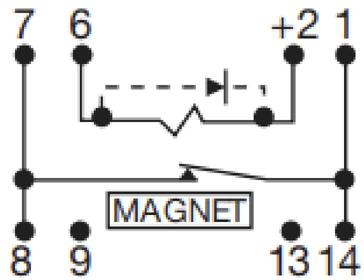

Figure 16: A visual diagram for the JWD-107-1 relay that showcases the use of each of the terminals.

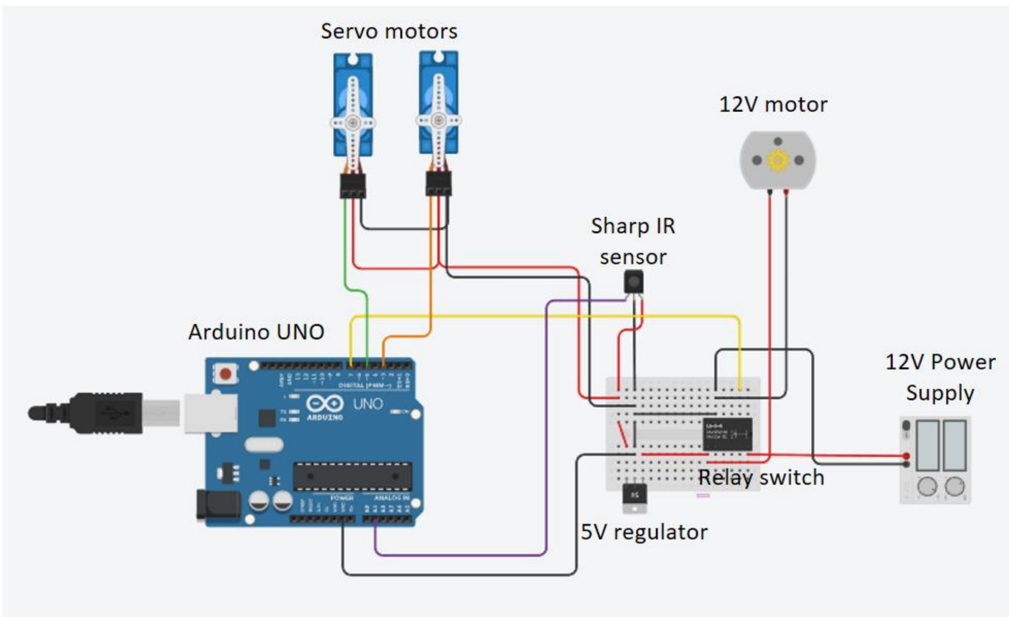

Figure 17: An overall design of the circuit including the Arduino, servo motors, DC motors, IR sensor, power supply and associated electrical components. Created in TinkerCad.

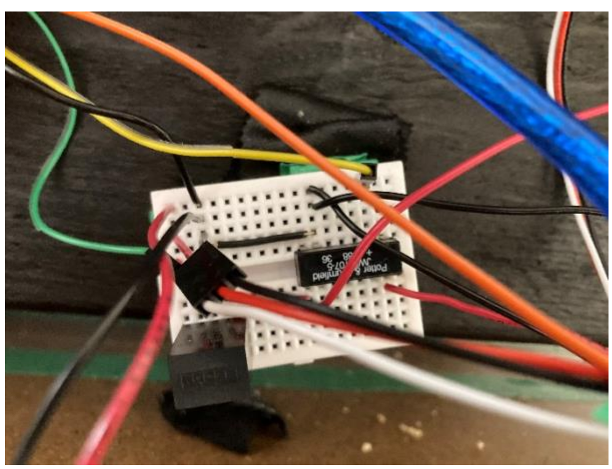

Figure 18: The integrated circuit design as determined by the overall circuit design. Wires were shortened and colour coded to follow safety protocol and facilitate design iterations.

Computer Integration

To control the overall setup of the recycling sorter apparatus, a single computer controlled the Arduino and camera. Specifically, the computer was able to connect the system with the 12 V power supply using the Arduino to power it on and off. The Arduino would send signals to the computer from the IR sensor. Additional commands could be sent to the Arduino to change the arm positions. These specific commands are detailed in Arduino Commands section.

The process of the design required a combination of all subsystems and was integrated via python. The process flow diagram of the main program is illustrated in Figure 19. It should be recognized that additional programs were created that utilized different components and delays to achieve different results such as an increased item processing rate. However, the stated program below was used for all tests and results stated in this report. The python code and additional programs can be found in the GitHub repository in the Code and Data Availability section.

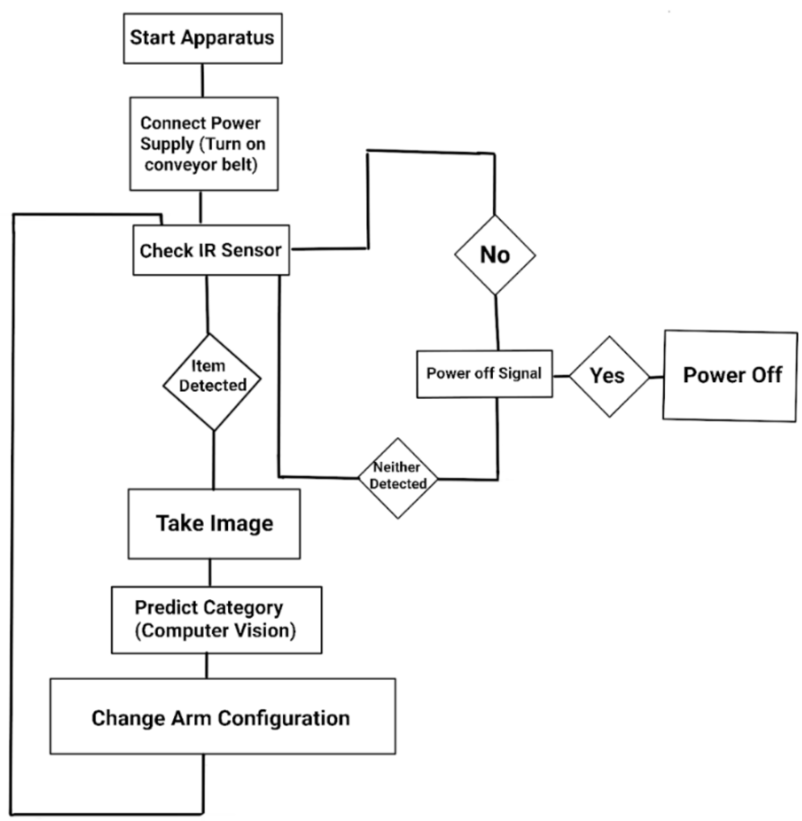

Figure 19: The process flow diagram of the overall coding implementation.

Results

Three analyses were conducted to determine the success of the project. The Physical Criteria Analysis assessed the proof-of-concepts ability to meet the spatial and structural success criteria. The Computer Vision Analysis evaluated the accuracy of the computer vision model and the Economic Analysis determined whether the project remained within the financial constraints.

Physical Criteria Analysis

The four physical criteria the project strived to achieve consisted of a processing time of 1 minute, transporting a mass of 0.5 kg, supporting a weight of 1.5 kg, and a dimension size of 210mm x 210mm x 297mm. The model was able to meet these requirements and exceed them.

The processing time was determined based on the speed of the belt, where an object was found to clear the length of the belt in 25.3 ± 0.2 seconds. Overall, the apparatus was able to sort an object at approximately 2.37 ± 0.02 items per minute which was faster than the required rate. Additional programs where objects were hit off the belt at fixed intervals demonstrated a potential avenue for exceeding this requirement further.

The ability of the apparatus to support a minimum weight of 1.5 kg was tested by placing a mass of 1.5 kg to one end allowing the conveyor belt to transport it across the apparatus. The belt exhibited minimal change and deflection, thereby meeting the required criteria outlined above.

The ability to sort an object of 0.5 kg was tested by adding a weight of 0.5 kg into one of the objects being sorted, in which the arms were able to redirect into all three categories as expected. Lastly, the dimensions of the physical apparatus which would determine if an object of the required dimensions is able to fit in the machine. The test weight can be seen in Figure 20.

Figure 20: An image of the experimental object used to verify if the arms could distribute the required weight of 0.5 kg as required by the Success Criteria.

Computer Vision Analysis

After performing simulations on the preliminary training data, the optimal features of the number of layers and nodes per layer were identified. As illustrated by Figure 21, the optimal number of layers was determined to be five with a size of 128 nodes per layer. These values achieved near the maximal accuracies of greater than 95% while also faster training times and reduced complexity in comparison to the larger sizes. The model training parameters and results can be found in the Convolutional Neural Network Architecture.

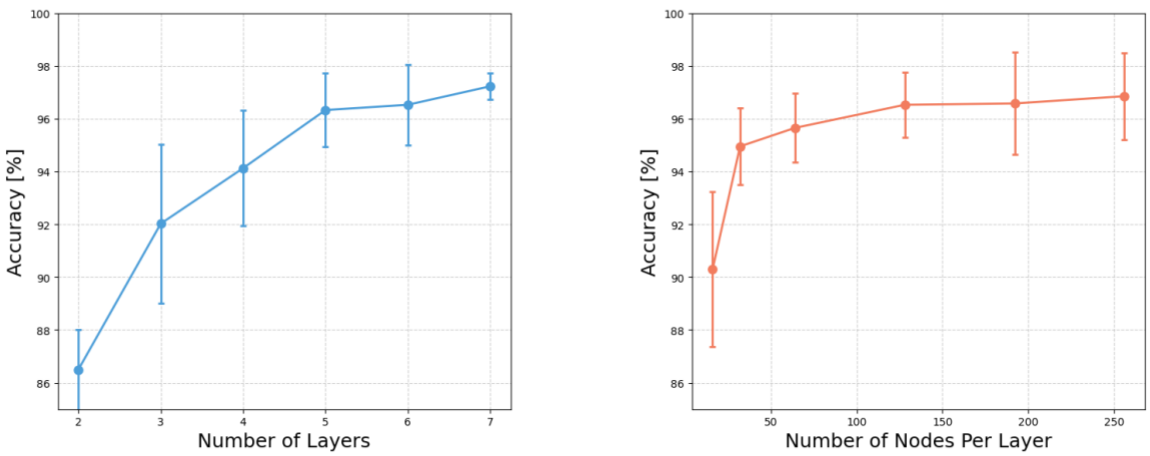

Figure 21: The results of a 5-fold cross validation tests on by varying the number of layers and nodes per layer. The models were assumed to have fully converged when accuracies reached above 95 %.

For evaluating the computer vision model, four metrics were used. The model training and testing accuracies were obtained and compare to test if the model architecture was overfitting or performing as anticipated. The model was then implemented into the overall apparatus and tested to determine if the model preformed similarly in a practical setting. Two tests were conducted using the overall apparatus, one with previously used items and one with a new set of items unseen by the model.

As a result, the simulated tests achieved similar performance and exceeded the required threshold. However, the implementation tests achieved lower accuracies. Further, the model scored lower when viewing new previously unseen items. These results can be seen in Table 4 and are displayed in Figure 22.

Table 4: The accuracy scores for each of the different types of testing data with their corresponding number of datapoints in each of the datasets.

Accuracy Type	*Accuracy Score*	*Number of Items/Images*
Training	91.8 %	8928
Testing	93.5 %	2232
Previously Seen Items	70 %	20
New Items	60 %	10

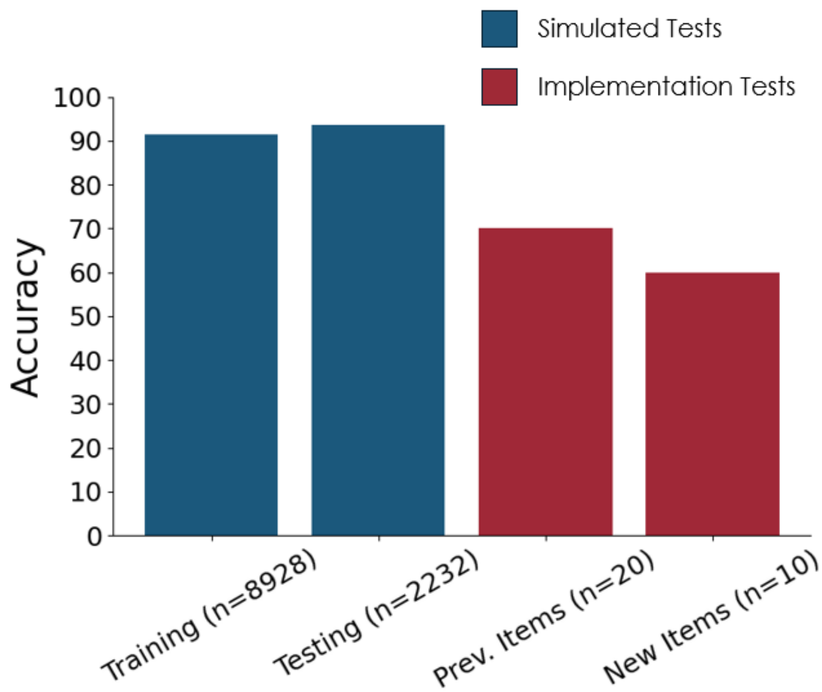

Figure 22: A graphical representation of the accuracy results for each of the different types of testing data.

The test set accuracies were further categorized by each individual class that was used for the test set. The specific accuracies are tabulated in Table 5.

Table 5: A breakdown of the accuracies for each of the chosen recycling categories in the simulated test set.

Image Class	*Accuracy*
Empty	99.2 %
Cardboard	94.2 %
Plastics	90.6 %
Metals	90.1 %

Economic Analysis

The total cost of the project was $613.55 CAD which was within the provided budget of $1000.00 CAD. These results do not include items obtained internally through existing supplies at Queen's University. Table 6 below shows all the components that were purchased.

Table 6: Complete list of all the items that were purchased for the project along with the cost. This table does not include items that were acquired internally and did not contribute to the stated budget.

Item	Quantity	Price (CAD)
Conveyor Belt	1	$123.36
Wooden Beams	1	$25.92
Threaded Rod	1	$19.15
Ball Bearing	1	$18.95
Paint	2	$29.98
Gear Motor	1	$36.46
Conveyor Belt Stitching	1	$88.12
3D Printing	1	$58.00
Computer Vision		
T-strut frame	1	$33.25
Sorting Apparatus		
Motors	4	$159.18
Wood beam for arms	1	$3.58
DC to DC converter	1	$17.54
Total		$613.55

It should be recognized that two extra sorting motors were purchased due to a malfunctioning servo motor. The safety factor of the torque was increased with this purchase to accommodate the possibility of the arms needing to apply force to move the items off the conveyor belt as opposed to guiding items off the belt. Furthermore, additional items were obtained, or 3D printed in house and are not reflected in Table 6.

Discussion

In this project, the evaluation criteria discussed in Table 2 were met for all physical constraints. For the minimum size, mass and weight, the thresholds were exceeded. A maximum for each of these quantities was not found due to the possibility of damaging equipment while testing. However, due to the minimal deflections of equipment and informal testing conducted with the overall setup, these thresholds were all considered met and exceeded with significant margins.

For the rate of processing items, the rate was calculated to be 2.37 ± 0.02 items per minute which surpassed the required rate of 1 item per minute. However, further efficiency of the program and using the arms to push items off the conveyor belt could increase the rate significantly by allowing items to be more closely spaced. For this system, the limiting factor would be the requirement that items be placed an equal distance apart to ensure two items are not in the camera's field of view simultaneously. Preliminary code was made for this program and can be found in the GitHub in the Code and Data Availability section.

While the other criteria were met and exceeded, the accuracy of the computer vision model did not achieve the required threshold for the proof-of-concept implementation results. However, the model did achieve a greater than 90% accuracy in the simulated test set indicating that the model was not overfitting to the training data. This further indicates that the inaccuracy likely originates from a difference between the simulated data and the images taken in real-time.

One candidate for this discrepancy originates from the varying lighting of the environment. Specifically, due to difficulties purchasing a custom blackout curtain, a less adequate curtain which did not extend the required length was used. Therefore, light was able to enter the environment from a nearby external source that varied by the time of day. This caused significant altercations to the exposure of captured images and a calibration of the camera before each trial was required to achieve an accuracy greater than 50%.

Additionally, by optimizing the process of acquiring training data, the position of items in the training data may not have accurately represented the item positions in images from the final setup. This may be due to the IR sensor capturing images in one unique location of the camera's field of view, whereas the training data was taken with objects in various sections of the camera's field of view.

Lastly, it is possible that the limited amount of items may not have been enough to train the convolutional neural network. Specifically, it is possible that the model may have overfit to specific features of the items that are not highly correlated with the items category. This could include brand labels, reflections off surfaces or packaging colours. Therefore, it is recommended the dataset be expanded in future design iterations.

For the computer vision, lower accuracies in the plastic and metal sections indicate the convolutional neural network was less accurate at distinguishing these two categories. It was hypothesized that this may be due to the glare of both objects and the lack of variation in the training items.

With regards to the financial budget, the cost of the project was $613.55 CAD. However, it should be noted that the total cost would be increased if the proof-of-concept were to be constructed in an industry setting. Specifically, wires, 3D printed custom parts, and some building materials were acquired internally and did not appear on the budget. Furthermore, the cost of the Arduino and graphics processing resources used in the model were not included in the stated budget.

Conclusion

Overall, the project does provide significant support for using computer vision in a mechanical and electrical apparatus to sort recycling items. This can be justified by the final product and simulated accuracies meeting the success criteria of the project. The project also remained within the required budget and spatial constraints dictated at the beginning of the project.

However, future work should be conducted to improve the real-world implementation accuracy of the sorting items and improve the rate of item sorting. Additional directions could also include sorting multiple items of the same class in one. Further testing can also be conducted to better interpret the computer visions decision making process and identify potential errors in the system. These directions will provide substantial support to bring computer vision systems to real applications.

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Appendix

The Appendix contains materials to support the justification of design decisions and include data to support the reproducibility of the project.

Conveyor Belt Torque Calculations

To calculate the torque required by the DC motor, the calculation from [24] was used as shown in Equation 1.

$$T = \frac{1}{2} D(F + \mu W g) \tag{1}$$

Where D is the diameter of the roller, F is the applied force of the conveyor belt, μ is the coefficient of static friction of the belt, W is the mass of the load on the belt and g is the gravitational acceleration. The diameter of the roller is 3.5 in. (0.0889 m) and the coefficient of static friction of the belt was experimentally determined to be 0.6. An applied force of 50 N was assumed for the system which included a significant safety factor to ensure the design met the requirements. The weight of 1.5 kg was used from the criteria and gravitation acceleration was assumed to be 9.8 m/s^2.

$$T = \frac{1}{2}(0.0889\ m)(50\ N + (0.6)(1.5\ kg)(9.8\ m/s^2))$$

$$T = 2.61\ N \cdot m = 26.1\ kg \cdot cm$$

Using a safety factor of 100%, the total torque required was determined to be 52.2 kg·cm.

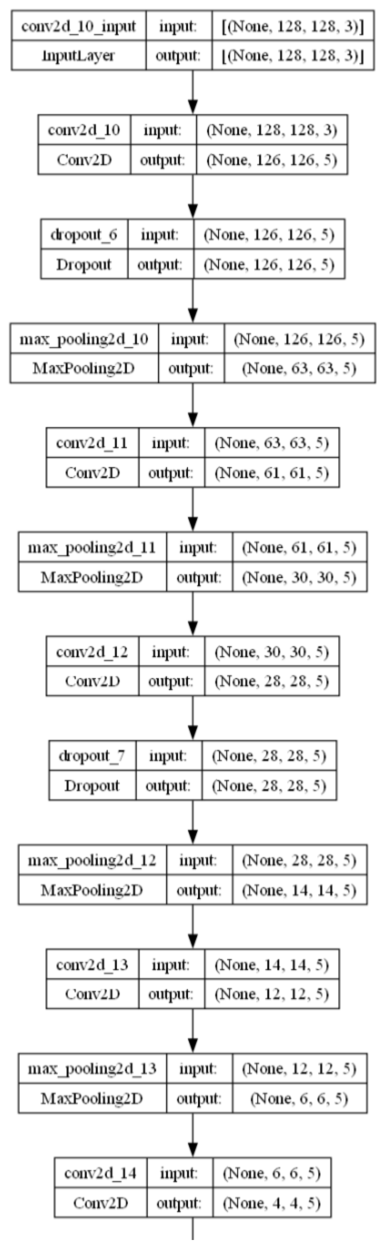
Convolutional Neural Network Architecture

To determine the optimal parameters of the model, simulations were conducted using various parameters in a 5-fold cross validation step. First, the number of layers were determined with a fixed layer size. Using these results, the optimal layer size was then determined by varying they layer size and analyzing retrieved accuracy scores. Optimal parameters were retrieved by selecting the lowest parameters that still reached a high accuracy threshold. Parameters were constricted to common intervals that are either products of two or multiples of powers of two to improve computational efficiency.

A filter size of dimension size 3 was used due to its frequency of use in computer vision projects [25]. The model then used a rectified linear activation function followed by a sigmoid activation function to provide a final output. The model incorporated a categorical cross entropy loss function for training. This model design has shown significant promise in computer vision tasks [26].

To preprocess data for the computer vision model, images were reduced to 128 by 128 pixels to improve computational efficiency while maintaining essential features. The training images were also augmented to increase the robustness of the model. First images were flipped in the horizontal and vertical directions randomly and rotated in intervals of 90 degrees. The images were also scaled to a random range within 80% and 120% times their original size. Lastly, the contrast and brightness of the models were varied by 10% and 20% respectively. To prevent overfitting, a dropout rate of 25% was used on every other layer.

The overall architecture can be seen in Figure 23.



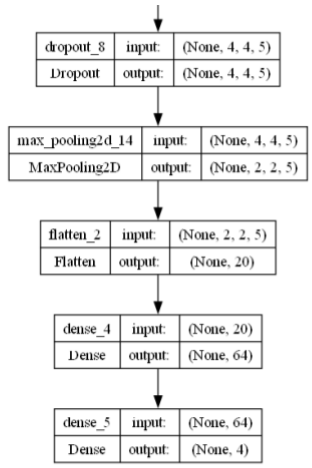


Figure 23: The complete Tensorflow architecture for the convolutional neural network that was used for the primary classification model of the project.

Arm Strength and Size Calculations

Assumptions:

- The coefficient of static friction for any object will be less than 1: $\mu_s = 1$
- Objects will be reaching the arms where forces/torques are at a maximum. (L/2)
- Each arm will not be rubbing against the belt.
- The arms will be just long enough to cover the side exits with minimal excess to minimize weight.

The distance between the sides of the belt was around 50cm, this sets the minimum length of the arm at 50 cm however, to accommodate the objects sliding down the arms to either side, they will be at an angle of 45°.

$$\cos(\theta) = \frac{adj}{hyp} \tag{2}$$

$$hyp = \frac{50}{\cos(45)} \cong 70.7\ cm$$

From this, the length of the arm was chosen to be 70cm.

The proposed material was a 19x45x700 mm piece of pine wood, and the following calculations were done to determine if this was a suitable material.

Based on the MVP, the maximum weight one arm would have to resist would be 0.5 kg and in the fixed position for either side.

A 0.5 kg object pushed by the conveyor belt would exert a force of:

$$F_f = F_n * \mu_s \tag{3}$$

$$F_f = 0.5 * 9.8 * 1$$

$$F_f = 4.9N$$

To determine the dimensions of the arm piece, the allowable deformation must be calculated as:

$$\delta = \frac{L}{160} \tag{4}$$

Where L is the length of the beam (70 cm) however assuming this is at the center of the arm, the expected deflection would be half the value:

$$\therefore \delta \cong 0.21\ cm$$

Deflection under load can be calculated using the following formula:

$$\delta = \frac{FL^3}{3EI} \tag{5}$$

Where F is Force, L is the length, E is Youngs modulus, and I is the moment of inertia.

Taking the perpendicular force to the arm:

$$F = F_f \cos(45^o) = 3.464\ N \tag{6}$$

Again, assuming the force is halfway down the arm:

$$L = 35cm$$

Youngs modulus for pine wood is ~7000 MPa, and the moment of inertia for the beam is ~0.0271.

$$\delta = \frac{3.464 * 0.35^3}{3 * 7 * 10^9 * 0.0271} \ll 0.21cm$$

This proves the arms chosen were more than strong enough to resist the force of the heaviest objects.

Due to the design of the arm system, it is assumed that there would be no force preventing the arms from moving into position. The only requirement then for the motors is having a torque able to move the arms in enough time to meet the MVP metric of one item per minute. For this, the time available for the arms to move into position after classification would be ~30 seconds. Each arm would have to move separately to avoid colliding with each other so the time per arm to move 45° is a maximum of 15s (assuming starting from rest).

$$\theta = \frac{1}{2}\alpha t^2 \tag{7}$$

$$\alpha = \theta * \frac{2}{t^2} = \frac{\pi}{4} * \frac{2}{15^2} = 0.007\frac{rads}{s^2} = 0.4\frac{degrees}{s^2}$$

The required torque on the motor is then calculated:

$$\tau = I\alpha \tag{8}$$

$$\tau = 0.0271 * 0.007 = 0.00019Nm$$

As this value is so small, it was reasonable to alter the design and get stronger motors that could push objects off the belt once they are further down the arm. The minimum torque required to push the objects can be calculated as follows.

$$\tau = F * D \tag{9}$$

$$\tau = 4.9N * 0.7m = \ 3.43Nm$$

The above equation shows that the arms could move an object anywhere on the belt if the torque is greater than 3.43Nm.

Arduino Commands

In Table 7 are the commands setup via the Arduino code into easy-to-use inputs from the computer. The command number can be sent over serial bus to the Arduino to run the specified actions.

Table 7: The Arduino commands that determined how the overall system would function.

Command Number	*Action*
0	Shuts off all equipment.
1	Turns on all equipment (starts conveyor belt).
2	Moves servos into position for objects directed into the bin left of the belt.
3	Moves servos into position for objects directed into the bin right of the belt.
4	Moves servos into position for objects directed into the bin at the end of the belt.
5	Sends a signal when an object was in front of the IR sensor.

Convolutional Neural Network Training

The models were trained on 40 epochs with a learning rate of 0.0005 and a clip rate of 1.0 to prevent an exploding gradient. Furthermore, most models and all models used in the results for this report utilized a uniform loss weight for all the classes. The results of the model training can be seen in Figure 24.

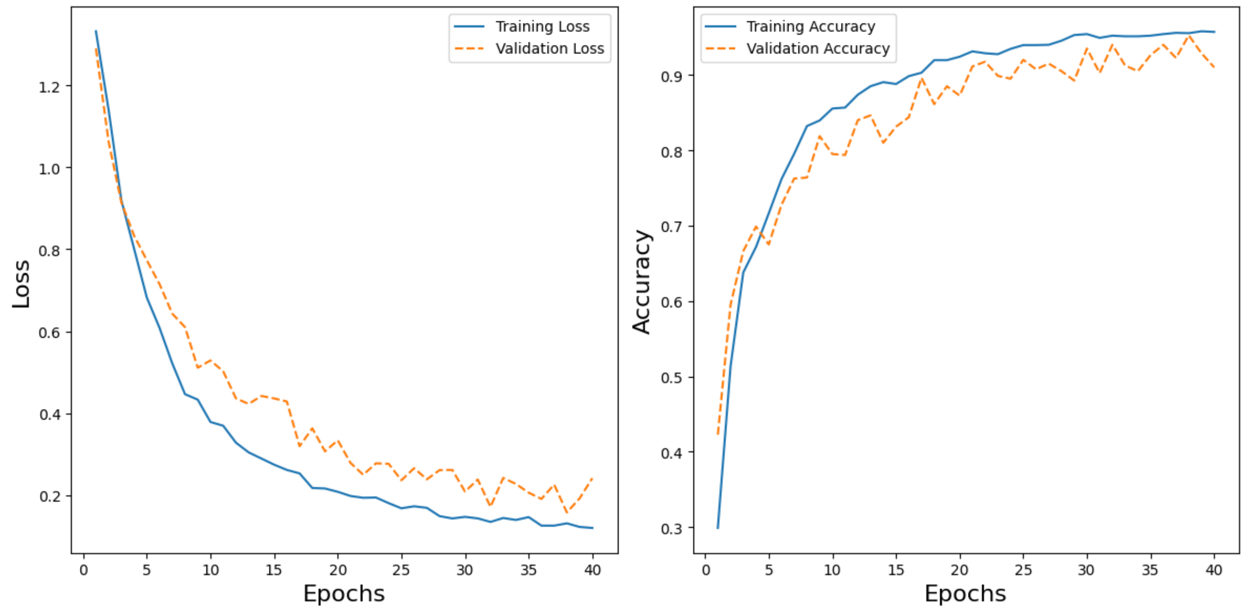


Figure 24: Illustrating the results from training the model. Comparing the loss and accuracy of the training and the validation sets

Code and Data Availability

The code utilized for this project can be found at: https://github.com/ciaranbylesho/enph454-recycling-sorter.git.

The electrical components were all controlled via the Arduino code in the GitHub repository. The Arduino is set to continuously check if the main computer has sent any instructions based on the python classification script and follows those instructions then returning a character to indicate successful completion of the task.