Autonomous Camera Based Recycling

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Problem Description and Statement

Humans are competent, active creatures. This is precisely why humans are inefficient at tackling a menial but crucial job in Canadian society, waste sorting. Waste management jobs are undesirable and are bleeding employees. Waste Management is among the largest companies within the waste management field. They operate in the USA, Canada and India and annually report employee turnover of 21-25% from 2021 to 2023 [1]. To replace their 49,317 employees, they hired 9,904, leading to a total employee loss of over 1,400. [1]

In 2020, Canadian waste management plants diverted 27.5% of the received 36 Million tonnes of solid waste to recycling and compost plants, the remaining 72.5% was sent to landfills. [2] Of the 27.5% reclaimed, 68.2% are materials such as paper, metals, plastic, and glass; thus less than 19% of these materials are properly recycled. The dwindling amount of workers does not bode well for reaching recycling goals, both for total removal and contamination. Since 2018, China, one of the world's largest recycling reclaimers, brought on legislation to only accept 0.5% level of contamination of recycling bundles received from exporters [3], a figure Canada has issues facing due to high-density cities like Toronto and Edmonton having 26% and 24% waste contamination from residential sources. [4] Contamination rates must decrease for the Canadian system to move beyond landfills for handling its waste.

The recycling industry needs an improved method of recycling to meet the demands of the population and reclaimers.

We propose an autonomous camera-based recycler, which utilizes convolutional neural networks (CNNS) to classify recyclables and a robotic vacuum arm system that grabs and dispels waste in its proper bin. Ideally, this autonomous recycling waste sorter is able to retrieve and dispel common objects, can classify and track waste as it moves across a conveyor belt, and can be operated with minimal human intervention and maintenance during use.

Through this contraption, the tedious job of recycling sorting and the rigorous demands of the processors can be aided by an autonomous system.

Related Works

Victor Dewulf laid the groundwork in his master's paper that would become the company 'Recycleye' which combines CNNs with robotic arms to grab waste from a conveyor belt. [5] The paper discusses the architecture and performance of the custom-made Recycleye CNN. The images fed into the model are classified as cardboard, glass, metal, paper, or plastic with 93% accuracy on the Flickr Materials Dataset, which was used for its diversity of images for each material.

An interview with the technical sales director of Recycleye states that the company can classify even specific types of plastics based on the colour and the backlog of materials based on the shape and brand of the waste. [6] The robotic arm they use is multi-jointed, allowing for simultaneous repositioning across multiple axes. They use an air jet vacuum which is strong enough to launch the retrieved item to the correct bin.

Koskinopoulou et al cover the an autonomous waste sorter similar to this project with an

ABB IRB360 delta robot with a blower vacuum system. [7] They used a Mask Regional Convolutional Neural Network (MASK R-CNN) with a ResNet50 to perform instance segmentation on its classifications. For training, they used public datasets TrashNet and Taco to get single instances of waste - namely aluminium, paper, plastic bottles, and nylon -, applied geometric transformations, and then put those instances over coloured backgrounds with others. This paper outlines the general approach my team and I will employ, with the addition of making a robotic arm system based on 2 axes and a model drawing bounding boxes as opposed to segmenting objects.

Kshirsagar et al used a UR5 robotic arm and tested both a suction-based and a gripper-based approach to handling objects. [8] They employed a LeNet CNN to classify glass and plastic with 86.75% accuracy in their testing set. Their findings affirm that suction is a more dynamic approach to object handling as the gripper fails to grasp flat and thin pieces of plastic with over 70% success. They do not specify their robotic arm system beyond the gripper. My project will expand on the number of classifications to fit the Ontarian recycling system.

Technical Requirements

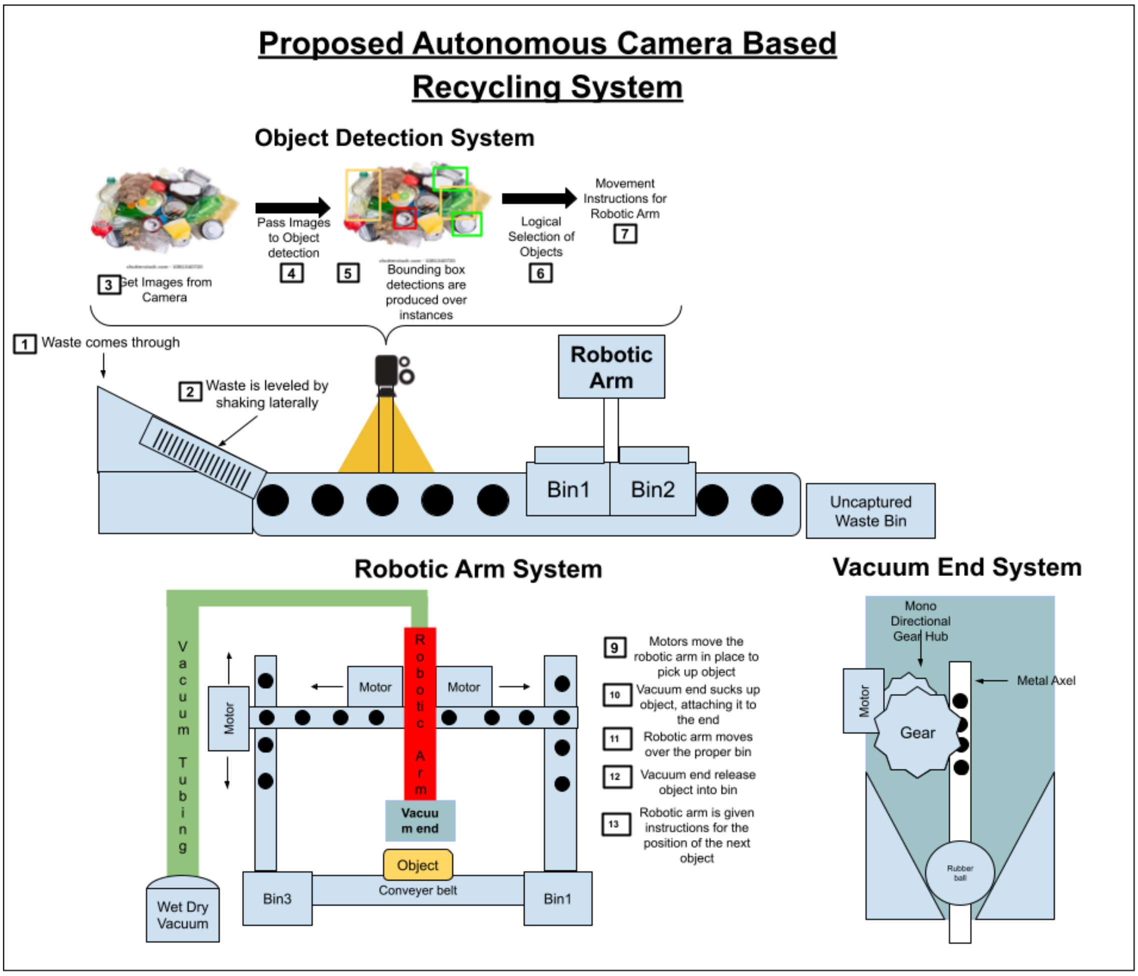
Baseline Requirements:

- Object detection
    - A pre-trained YOLOV5/8/10 for bounding box detections and object id'ing
    - Minimum 4 classes:
        - Cardboard
        - Metal
        - Glass
        - Plastic
    - Phone camera / webcam
- Robotic Arm
    - Wet and Dry Vacuum
        - <80 decibels
        - >2 horsepower
    - Vacuum end (as defined in the Architecture section)
    - Chasse:
        - Plastic/wood construction
        - Rails and linear actuators/gears to move the robotic arm in the YZ directions
        - Large enough to encompass the conveyor belt + the bins
- Conveyer belt:
    - Waste moves < ½ m/s across the belt
    - Shaker to decluster waste

Nice to haves:

- Object detection:
    - Advanced classification, based on specific material types such as different types of plastics and metals
    - Optimal surface detection
        - Alignment based on the flattest part of the object, will require a LiDAR based approach or with sterovision which can be achieved with 2 non parallel cameras
- Robotic arm:
    - Malleable-cylinder approach for a vacuum gripper, where the gripper's end conforms to the object, minimising wasted horsepower from the shop vac
    - Fast and seamless 2 axle movement
    - Multiple robotic arms across the conveyor belt, operating in unison at handling objects missed by the previous arm

Architecture



To go over the Vacuum End System:

The idea of this vacuum end is to allow for a near instantaneous response rate for a vacuum to be constantly on without applying a force to the items on the conveyor belt until the vacuum end is pressing against the object. The housing is a tube that slopes down to an open-ended point. That is where a rubber ball with a metal axel lies. The end of the metal axel is connected to the dispel system, which consists of an electric motor, a mono-directional gear hub, and a gear with which the axel makes contact.

To pick up the item, the object will push up against the axle, breaking the seal of the rubber ball and applying a suction force to the object. The mono-directional gear hub allows for the axel to move freely from this action without a complicated conformation system.

To dispel the item, the motor will turn which applies torque to the gear hub, in turn turning the larger gear, moving the axle downwards. This will simultaneously reestablish the seal and eject the item from the end of the casing.

In terms of mechanical design, I elect a 2 axis approach akin to a 3D printer to the movement of the robotic arm. The implementations discussed in the Related Works section use multi-joint robotic arms that allow for simultaneous movement across 3 axes. I believe that 2 axes can produce better results given a restricted budget and in real-life scenarios, as

1. A single 2-axis robotic system requires less space across the conveyor belt than one with 3 axes, allowing more robotic arms across the same area
2. To make use of 3 axes, the robotic arm must operate quickly to effectively sort all objects moving across the belt. A slower, 2-axis system has less strict requirements as it can be expected to have multiple robotic arms to pick up objects the previous one missed
3. Each robotic arm can be fit with different grasping methods, such as universal grippers, which can grab objects the vacuum cannot (such as deformed cans with poor suction points)

The current design of the vacuum end requires tight tolerances for the rubber ball to not move before the object presses against the axel. Further development such as a force lever on the end of the axle should be explored if the system requires a reinforced method for object collection confirmation.

Implementation

Waste datasets will be aggregated and modified for our desired use case (such examples are available here: https://github.com/AgaMiko/waste-datasets-review). The annotations of these datasets vary from classification, image segmentation, and bounding boxes. Regardless of the annotations, tools such as OpenCV can be used to subtract the instances of an object from the images, find the midpoint of detections, and draw individual boxes that encompass the item within the photos. Similar to Koskinopoulou et al, I plan on compiling different object instances and applying image augmentations to increase the diversity of the dataset.

The team can also explore generative adversarial networks (GANS) to generate artificial images of items to enlarge the dataset further.

As a final testing set, the team should evaluate the performance of the bounding box model on the images of assorted waste on the conveyor belt.

I propose a YOLO model for bounding box inferencing and tracking. I elected YOLO because of its fast inferencing, community support, and pre-implemented solutions to unique object tracking, which is the main factor I focused on to eliminate other object detection models such as Detectron2, Faster R-CNN, and Single Shot MultiBox Detector (SSD).

Although YOLO has instance segmentation capabilities, I believe bounding boxes are suffice for this application because:

1. The midpoint of the object is, for most common objects (ie. coffee cups, cans, plastic bottles, paper, etc.), a reasonably optimal place to apply suction to
2. Calculating the midpoint of the image can be tedious, particularly for objects that do not necessarily have an ideal midpoint, such as cups with rips in the middle.
3. Annotation of images from image segmentation formats can be reasonably converted into bounding box format, the same can not be true vice versa
4. Easier to annotate by hand, which will be particularly helpful for the final testing set

To finetune, the head of the model can be frozen to train only the classification and the pre-trained weights of YOLO can be used to get a baseline understanding of a variety of classes.

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