Trash Sorter using Object Detection

CSE 598 – Perception in Robotics

Portfolio Report

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***Abstract*—It is crucial to separate waste based on biodegradability since doing so will make the environment cleaner and consequently improve people's quality of life. As a result, automating the process would not only make it more effective, but also shield workers from the respiratory illnesses that are frequently linked to waste sorting. We use a conveyor belt—typically found in recycling facilities—a robot arm (Franka Research 3), a camera system (Intel RealSense D35 Camera), and an external system—in this case, the Raspberry-Pi (RPI) and laptop—to control all the sensors and actuators to solve this problem.**

Keywords—waste segregation, biodegradability, object detection, classification, automation, conveyor belt, Franka Research 3, robot arm, Intel RealSense D35 camera, image capture, Raspberry Pi, laptop, YOLO V8, TACO dataset.

I. Introduction

Waste segregation is an essential part of waste management that helps reduce pollution and promote sustainability. In recent years, there has been a growing interest in automating the waste segregation process to increase efficiency, reduce human error, and prevent respiratory diseases associated with manual trash sorting. The use of robotic vision for trash segregation has shown promising results and has been the focus of several research studies.

One of the most crucial components of an autonomous trash sorter is the camera system, which is responsible for detecting and classifying trash based on its biodegradability. Convolutional neural networks (CNNs) and other deep learning techniques have been used in numerous research to train camera systems to recognize and classify trash automatically [2][4]. These algorithms learn from the input photos and create predictions based on vast volumes of tagged data.to train the camera system to detect and classify trash automatically. These algorithms use large amounts of labeled data to learn and make predictions based on the input images.

Another important component of an autonomous trash sorter is the robot arm, which is responsible for moving the detected trash to the appropriate container. The robot arm must be precise, fast, and reliable to ensure accurate segregation and efficient waste management. Many studies have explored the use of various types of robot arms for trash segregation. YOLO models are optimized for automatic garbage detection and collection [5].

For Hardware based implementation, we have come across many approaches that use ultrasonic sonar sensors and camera modules attached to Raspberry Pi for object detection and classification. Hardware solutions for garbage segregation at the base level use deep learning architecture [1]. Real-time embedded systems are used for smart bin solutions [3].

Overall, an autonomous trash sorter that uses robotic vision to segregate trash has the potential to revolutionize waste management by increasing efficiency, reducing human error, and promoting sustainability. Ongoing research in this field is focused on improving the accuracy and speed of the trash segregation process, developing new hardware components, and exploring the use of alternative technologies, such as sensors and machine learning algorithms.

II. Problem Statement

To address this problem, we developed an autonomous trash sorter that uses robotic vision to segregate trash based on its biodegradability. The system consists of a conveyor belt, camera module (Intel RealSense D35 Camera), and robot arm (Franka Research 3).

A. System Design

Our system includes three main components: a conveyor belt, camera module, and robot arm. A motor controls the conveyor belt, which moves the trash along the system. The camera module captures an image of the object, and the classification model determines if the object is biodegradable.

B. System Operation

The system operates with a constant speed motor, which controls the conveyor belt. As the trash moves along the conveyor belt, the camera module captures an image of the object. The classification model is trained to determine if the object is biodegradable or not. If the object is biodegradable, it continues to move along the conveyor belt and is dropped into bin A. If the object is non-biodegradable, the conveyor belt stops, and the robot arm moves the object to bin B. The system continues to operate in this manner. The flow of the process is described in Figure 1.

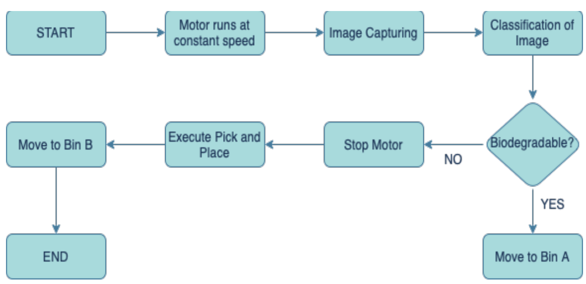

Figure 1: Flow of Process

C. Integration of Modules

Our system's success depends on the integration of three modules: conveyor belt assembly and motor control, classification model training, and robot arm pick and place operation. The conveyor belt was built from scratch and is controlled by a motor. The classification model was trained to determine the biodegradability of the object using loss and accuracy. In Figures 2 and 3, we can see the training and validation of loss and accuracy respectively. Finally, the robot arm was trained to execute the pick and place operation. If the object detected is non-biodegradable, the conveyor belt stops. This triggers the operation of the robot.

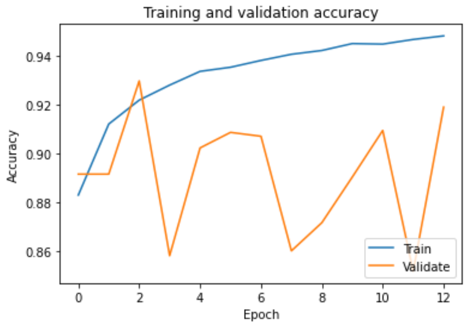

Figure 2: Training and Validation of loss

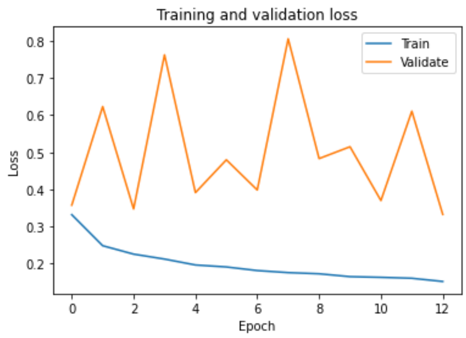

Figure 3: Training and Validation of Accuracy

III. Methodology

A. Conveyor Belt

Initially, we constructed the conveyor belt with wood as the base material as shown in Figure 4. We then installed a 24v DC motor onto the conveyor belt to move it. To control the speed and direction of the motor, we connected it to a motor driver (L298N) that is compatible with the Raspberry Pi. To manage the movement of the conveyor belt, we wrote Python code that runs a loop continuously in a specific direction. This code was integrated into a server using sockets to receive data from the laptop client, which is connected to the Intel Realsense D35 camera. The client performs detection and classification tasks. If the object is a non-biodegradable item, the client sends an interrupt to the server to stop the motor.


Figure 4: Conveyor belt

B. Franka Emika ARM

Our Pick and Place mechanism was completed using the Franka Emika Research 3 Arm, which is a 7-degree-of-freedom (7DOF) arm that requires real-time communication with a 1kHz sampling rate. It uses native ROS and libfranka and is wrapped in a ROS environment with frankaros. The gripper has two additional joints, and the MoveIt library is used to impose certain joint angles on the robot to replicate specific poses. We were able to plan the motion of the arm from its initial home position to a Pick position and a Place position, as well as simulate a grasping motion by adjusting the finger joint position of the Franka Emika arm. The pick and Place operation of the robot arm is shown in Figures 5 and 6.


Figure 5: Pick operation of the robot arm

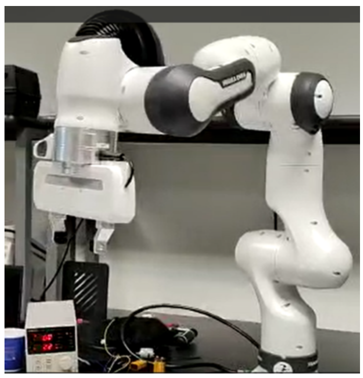
Figure 6: Place operation of the arm

C. Image Classification and Dataset

Our team improved our algorithm by upgrading to Yolo v8, which can perform both object detection and classification. This upgrade resulted in a faster real-time inference. We utilized Transfer Learning to enhance the accuracy of our algorithm. Our model was trained using Coco weights as a basis, with the parameters set to Epoch 100, learning rate = 10^{-4}, and SGD as the optimizing algorithm.

The TACO dataset (Trash Annotations in Context dataset) was utilized in our study, which comprises images of garbage found in natural environments. The dataset includes pictures of waste that are manually classified and segmented, and it covers a variety of settings. We classified the dataset into 18 distinct categories, such as "Aluminum foil," "Bottle cap," "Bottle," "Broken glass," "Can," "Carton," "Cigarette," "Cup," "Lid," "Other litter," "Other plastic," "Paper," "Plastic bag-wrapper," "Plastic container," "Pop tab," "Straw," "Styrofoam piece," and "Unlabeled litter." These labels were utilized to sort the trash according to its biodegradability. Examples of these, such as Plastic wrapper and Carton are shown in Figures 7 and 8 respectively.

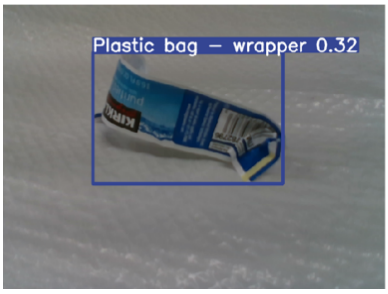

Figure 7: Non-biodegradable waste

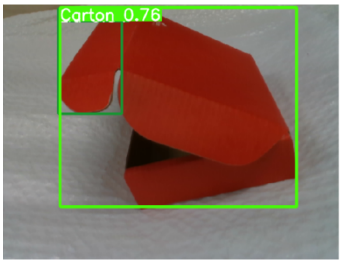

Figure 8: Biodegradable waste

IV. Results

Our Yolo v8 model, which underwent transfer learning on top of the Coco weights, achieved a mean Average Precision (mAP) of 0.448 at a threshold of 0.5 and a mAP of 0.36 between thresholds of 0.5 and 0.95. This indicates that the model was able to accurately detect and classify the different types of waste items in the images. Additionally, we were able to use the 18 labels from the TACO dataset to sort the waste items based on their biodegradability. While the categorization was not perfect, it provided a useful way to separate the waste items and allow for more efficient recycling or disposal. Overall, our system demonstrated promising results in automating the process of waste sorting, which has the potential to make a significant positive impact on the environment.

V. Individual Contribution

As part of the project team, my individual contribution was focused on several key areas. Firstly, I was responsible for the design and development of the conveyor belt system, we ensured that the conveyor would be capable of reliably transporting products from one point to another. I also played a key role in the design and programming of the robot arm, which was tasked with moving products onto and off the conveyor belt. In addition to these technical responsibilities, I was also responsible for conducting a thorough literature review of related work in the field, identifying best practices and potential areas for improvement. Finally, I contributed to the overall report by synthesizing our findings and recommendations, ensuring that our project was well-documented and presented in a clear and concise manner.

VI. Lessons Learnt

I have learned several concepts related to waste management, robotics, and automation from reading this paper. I gained knowledge about the importance of waste segregation in promoting sustainability and reducing pollution. I also learned about the potential of robotic vision for trash segregation and how it could revolutionize waste management. The role of camera systems and deep learning algorithms in detecting and classifying trash based on its biodegradability was also highlighted.

I have also learnt the concepts of deep learning algorithms like CNN, YOLO models, specifically the YOLO v8 model. I have learnt about the Franka Research ARM and the kind of libraries it uses to perform its operations.

I learnt the use of real-time communication and control systems to coordinate the operation of multiple components in an automated system. Finally, I gained insights into the potential benefits of automation in waste management, including increased efficiency, reduced human error, and improved worker safety.

VII. Team Members

- Anant Sah
- Yash Shah
- Pawan Kumar

Acknowledgment

I would like to take this opportunity to express my sincere gratitude to my professor, Dr. Nakul Gopalan and my teammates for their invaluable support and guidance throughout this project. My professor's knowledge and expertise in robotics and automation have been instrumental in shaping my understanding of the subject matter and provided me with the necessary direction and motivation to complete this project. Additionally, my team mates' hard work, dedication, and collaboration have made this project a success. Their contributions and constructive feedback have been crucial in refining our ideas and improving the quality of our work. I am fortunate to have had such a wonderful

team, and I extend my heartfelt thanks to each and every one of them.

References

[1] Siddhant Bansal, Seema Patel, Ishita Shah, Prof Patel, Prof Makwana, DR Thakker, et al. Agdc: Automatic garbage detection and collection. arXiv preprint arXiv:1908.05849, 2019.

[2] Tanya Gupta, Rakshit Joshi, Devarshi Mukhopadhyay, Kartik Sachdeva, Nikita Jain, Deepali Virmani, and Laura Garcia Hernandez. A deep learning approach based hardware solution to categorise garbage in environment. Complex & Intelligent Systems, pages 1–24, 2022.

[4] Shamima Hossain, Bidya Debnath, Adrita Anika, Md Junaed-Al-Hossain, Sabyasachi Biswas, and Celia Shahnaz. Autonomous trash collector based on object detection using deep neural network. In TENCON 2019-2019 IEEE Region 10 Conference (TENCON), pages 1406–1410. IEEE, 2019.

[5] Nur Athirah Zailan, Muhammad Mokhzaini Azizan, Khairunnisa Hasikin, Anis Salwa Mohd Khairuddin, and Uswah Khairuddin. An automated solid waste detection using the optimized yolo model for riverine management. Frontiers in Public Health, 10, 2022.