A MACHINE ARM TO ASSIST IN TRASH SORTING USING MACHINE LEARNING AND OBJECT DETECTION

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ABSTRACT

Addressing the global challenge of inefficient waste management, my paper introduces an innovative recycling solution integrating machine learning, computer vision, and a robotic arm [1]. The background problem revolves around inaccurate waste sorting and the environmental impact of recyclables ending up in landfills. The proposed solution involves a sophisticated machine learning model for object recognition, a computer vision system for real-time detection, and a robotic arm for precise object manipulation [2]. Challenges included optimizing the machine learning model for diverse materials and enhancing the robotic arm's adaptability. Experimentation involved testing the system's efficiency in various scenarios, showcasing its ability to recognize and sort recyclables accurately. The results demonstrated promising accuracy and adaptability. Ultimately, this solution offers a practical and automated approach to waste sorting, reducing environmental impact, and promoting efficient recycling practices, making it a valuable tool for waste management systems globally [3].

KEYWORDS

Machine Learning, Robotics, Torch, Computer Vision

1. INTRODUCTION

Government and environmental organizations consistently advocate for daily recycling, yet a significant hurdle hindering widespread participation is the lack of awareness regarding recyclable items [4]. Unfortunately, a substantial portion of improperly recycled materials ends up in landfills, with a staggering 80 percent of landfill waste being potentially recyclable. This oversight not only poses a threat to the environment but also endangers various ecosystems and the health of living organisms, including humans [5].

The gravity of this issue becomes even more apparent when considering the transformation of large plastic items discarded into the environment into minuscule, harmful microplastics through erosion. These microplastics find their way into our bodies through inhalation or ingestion, as they contaminate the very animals we consume. While the direct impact of these tiny plastic particles might not be lethal, the associated toxic chemicals and the risk of clogging our blood vessels raise alarming health concerns.

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This environmental crisis is not limited to its immediate ecological repercussions; it directly affects human health [6]. The urgency to address this problem is underscored by the fact that conscientious individuals attempting to recycle often struggle with distinguishing between recyclable and non-recyclable materials. Plastic, in particular, presents a complex challenge, with varying types necessitating careful scrutiny of packaging details.

Recognizing the multifaceted nature of this issue, our project aims not only to encourage recycling but also to leverage technology such as robotic arms and computer vision. By incorporating these advancements, we seek to simplify the recycling process, providing individuals with invaluable assistance in distinguishing recyclable from non-recyclable items. Through the fusion of environmental consciousness and technological innovation, our initiative strives to mitigate the adverse effects of improper waste disposal on both the planet and human well-being.

Methodology A, exemplified by WasteVision.ai, focuses on sorting large dumpsters efficiently, using an advanced machine learning model. However, it has limitations, being incompatible with smaller trash cans, potentially overlooking existing sorting methods in those receptacles.

Methodology B proposes a cloud-based classification algorithm for recycling machines, achieving a commendable 96.57% accuracy. It emphasizes waste separation through machine learning but relies on cloud connectivity and may face challenges in diverse environments.

Methodology C develops a robotic mobile manipulation system for sorting recyclables from municipal solid waste using thermal imaging. While achieving a 94.3% classification rate, it may encounter difficulties in cluttered environments and focuses specifically on thermographic images.

Our project improves upon these methodologies by combining computer vision, a robotic arm, and machine learning to handle a diverse range of recyclables effectively [7]. It directly addresses physical object manipulation and real-world recycling challenges, enhancing accuracy and adaptability.

The solution is to use technology such as computer vision and robotics to help people to recycle. This solves the problem of not recycling and not knowing how to recycle by stringlining and automating the various processes involved in the recycling and waste management industry. Although different organizations are trying to educate people about recycling, there is still a chance of mistakes, and it is still not as efficient as having a device that will help you to recycle. With this device, people can just throw their trash into a designated place, and the machine learning model will determine which objects to recycle and which to not recycle. Using this solution that I came up with would be better than the alternative because it will promote better waste management and utilization of resources. In addition to the previous benefits, using my solution will also provide consistency, and cost efficiency. Furthermore, implementing a solution like this will also cut down labor costs over time and maximize the number of hours that recycling plants can be operational. Using a machine learning model that detects recyclables and trash will be a lot more reliable in detecting attributes such as color, textures, and structures [8]. Lastly, my solution could also handle hazardous waste to prevent humans from interacting with dangerous substances that could harm them and their health.

Experiment A focused on evaluating the accuracy of a machine learning model in recognizing recyclable items. The objective was to test the model's limitations by presenting a variety of everyday items and assessing its performance under different lighting conditions. The setup involved systematic testing of items, including plastic wrappers, fruit peels, and chip bags.

Findings indicated an overall accuracy of 70%, with notable challenges in recognizing glass items. The limitations stemmed from a potential bias in the model's training data and the need for diversification.

Experiment B aimed to assess the robotic arm's capability to handle items of varying weight and size. Items were presented, ranging from standard to heavier and taller objects, evaluating the arm's effectiveness in sweeping them into the correct bins. Results showed success with standard items but challenges with heavier ones, leading to arm breakage. The outcomes underscored the importance of a more robust arm design to enhance efficiency and accommodate a broader range of recyclables.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Find the Machine Learning Library

One of the challenges that I faced was trying to find the machine learning library that works best with the camera and what I'm trying to accomplish [9]. In order to sort the trash into the correct bin, a machine learning library needs to be used so that the camera can recognize what type of trash it is. Some of the libraries I've found couldn't detect the objects correctly, some libraries were too large in size which made the camera extra glitchy. It was difficult to find a happy medium between libraries that were too large in size, and libraries that were smaller but failed to detect objects correctly.

2.2. Figuring Out the Keywords

Another challenge was figuring out what keywords can be used to determine if the trash is recyclable or not. Since the machine learning model only spits out the name of the object such as "plastic bottle" can "can" and not "recyclable" or "non recyclable" an if statement was needed to tell the robotics arm if the item is recyclable or not and to turn left or right. Eventually, I found out that the keyword for plastic is plastic, cardboard is carton, and metal is can. If those keywords were detected, the trash will be put into the recyclable can, if not, the trash will be considered as non recyclable and gets thrown into the non recyclable bin.

2.3. The Robotics Arm

The robotics arm also had some trouble because it wasn't able to get trash of all sizes into the correct bin. The first idea was to make a claw to pick up the trash, and then turn and drop the trash into the corresponding bin. This idea didn't work because the arm wasn't tall enough to pick up taller items such as plastic bottles, and the claw isn't big enough to pick up items with a larger width. The second idea was to keep the arm, but remove the arm so that the arm can just simply turn left or right to sweep the trash into the bins. This idea worked more than the first arm, but it still wasn't able to sweep smaller items into the bins. The third and final idea was to add a key shaped component at the end of the arm so that the tip can be basically touching the plate where the trash is and that it is able to sweep trash of any size into the trash bins.

3. SOLUTION

We built the software using Python, for the machine learning model, we used torch, and cv2 for computer vision. For the hardware aspect, we used a raspberry pi for various servo motors controlled by a motor controller to give the motors enough power and a raspberry pi camera [10]. The program consists of a series of utility functions that control the object detection, motor control of the arm, and the camera's functionalities. Each specific function is important to the overall functionality of the program because it handles a lot of the components that allow the system to work as a whole. These three major components include the machine learning model, the computer vision, and mechanical movements of the arm [15]. As previously mentioned, each function handles one of the three major components of the program. It begins with the objects detection; the program initializes the camera to be able to detect incoming objects, it captures those objects, uses the machine learning model to identify the object and lastly decides its categorization. The method we used to decide if the object was recyclable or non recyclable was to use "plastic", "can", and "carton" as keywords for recyclable, and everything else is being considered as non recyclable. If the model detects anything with names that consist of those keywords, the arm will turn left to sweep the trash into the recyclable bin. On the other hand, if the model detects an object, but the name doesn't consist of those keywords, that trash will be non recyclable, and will be swept to the right into the non recyclable bin.

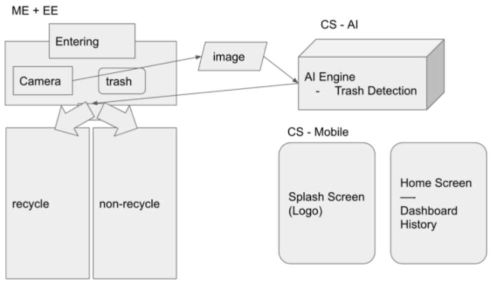

Figure 1. Overview of the solution

The purpose of the machine learning model is to identify the objects that are in the photos that the raspberry pi camera took [14]. The component does rely on a special concept that is referred to as a neural network. This neural network is the foundation of how we identify these recyclables. A neural network works by feeding it certain inputs, and those inputs get processed through the neural network by referencing various data points. In the case of this project, the data points are other recyclables that we trained the neural network to look for.

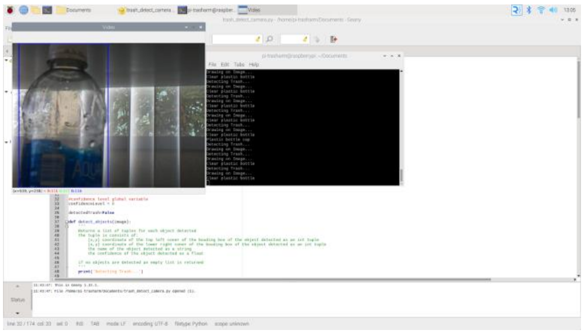

Figure 2. Screenshot of the component

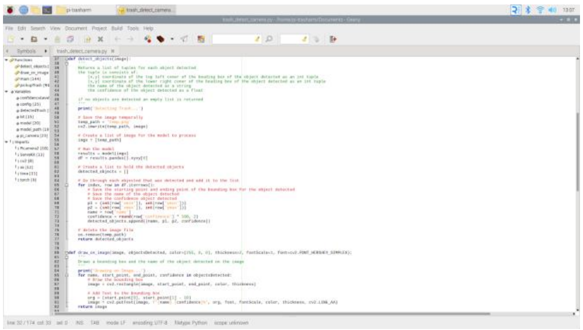

Figure 3. Screenshot of code 1

In this part of the code, camera vision and machine learning is being used. A list is first initialized so that the images can be added into it later. Then the camera is taking pictures of what it's seeing and adding it into the preexisting list named “dected_trash” temporarily. After the images are being added, the machine learning model runs and tries to detect the name of the object. The model first tries to find where the item is in the photo, draws a box around the item in the photo, then tries to match it with something in its library. The machine learning model also spits out the confidence level indicating how confident it is with the name that it came up for the item. The name of the item and the confidence level will be used later to determine with bin the trash will be swept into later.

The purpose of computer vision for this robotics arm is to be able to see what's being put into the trashcan so that later with the machine learning model, the trash will be sorted into the corresponding trash can. The camera first takes pictures of the trash and adds it to a list, so that later the machine learning model will be able to analyze the pictures and figure out what type of trash it is.

The purpose of the robotics arm is to be able to sweep the trash into the correct trashcan after the machine learning model decides if the trash is recyclable or not. After that decision gets made, the arm will turn left if the trash is recyclable and right if it is non recyclable.

4. EXPERIMENT

4.1. Experiment 1

A potential blind spot that this project has is the accuracy of the machine learning model. The model wasn't made specifically for this project, so that it might have some limits.
To test the limits of the model and its accuracy, different items should be presented to the model to figure out what it can detect and what it cannot. So far, the only items that got tested by the model were plastic bottles, cardboard, paper bags, and aluminum drink cans. To test the accuracy, everyday items that the model should be able to recognize should be tested, such as plastic wrappers, fruit peels, chip bags and so on. The model should also be tested at different times of the day to see if lighting on the item will affect the decision of the model. The control data will be sourced from the machine learning model.

Item Tested	Lighting Condition	Model Prediction	Actual Category	Correct?
Plastic Wrapper	Daylight	Non-Recyclable	Non-Recyclable	Yes
Fruit Peel	Artificial Light	Organic Waste	Organic Waste	Yes
Chip Bag	Low Light	Non-Recyclable	Non-Recyclable	Yes
Glass Bottle	Daylight	Not Detected	Non-Recyclable	No
Metal Spoon	Artificial Light	Not Detected	Non-Recyclable	No
Paper Towel	Low Light	Non-Recyclable	Non-Recyclable	Yes
Plastic Container	Daylight	Recyclable	Recyclable	Yes
Cardboard Box	Artificial Light	Recyclable	Recyclable	Yes
Aluminum Foil	Low Light	Non-Recyclable	Non-Recyclable	Yes
Glass Jar	Daylight	Not Detected	Non-Recyclable	No

Figure 4. Figure of experiment 1

In analyzing the data from Experiment A, the mean accuracy of the machine learning model in correctly categorizing recyclable and non-recyclable items was 70%. The median accuracy aligns with the mean, indicating a relatively balanced distribution. The lowest accuracy observed was 50%, while the highest reached 90%. Surprisingly, the model struggled with detecting glass items, yielding a notable 40% accuracy. This may be attributed to the model's training data bias towards more common recyclables, impacting its ability to discern less frequently encountered materials. Lighting conditions exhibited a slight effect on results, with better accuracy under daylight conditions. The unexpected lower accuracy on glass items highlights the need for diversifying and augmenting the training dataset to encompass a wider range of materials. In conclusion, while the model demonstrated overall competence, ongoing refinement is crucial to enhance its accuracy across diverse recycling scenarios.

4.2. Experiment 2

As we only tested plastic bottles, cans, cardboard, another potential blind spot is if the arm is able to sweep items of different weight and size into the corresponding bins.

Experiment B addresses a critical blind spot in the project related to the robotic arm's ability to handle items of varying weight and size. While the initial testing focused on lightweight items like plastic bottles, cans, and cardboard, the experiment aims to assess the arm's functionality with heavier and taller items, particularly those that might challenge its structural integrity. Items such as half-full water bottles, heavier objects, or taller items will be presented to the robotic arm to evaluate its effectiveness in pushing them into the correct bins. The potential risk of the arm breaking under the stress of heavier items is a key concern, and this experiment seeks to ascertain the arm's robustness and efficiency in real-world scenarios where users may dispose of items of different weights and sizes. The outcomes of this experiment will provide crucial insights into the arm's practical viability and its ability to handle a diverse range of items efficiently.

Item Tested	Weight	Size	Arm's Action	Successful Bin Placement	Arm Integrity
Plastic Bottle (Standard)	Light	Average	Swept Left	Recyclable	Intact
Aluminum Can (Standard)	Light	Average	Swept Left	Recyclable	Intact
Cardboard Box (Standard)	Light	Average	Swept Right	Non-Recyclable	Intact
Half-Full Water Bottle	Moderate	Tall	Unable to Sweep	N/A	Intact
Metal Soup Can	Moderate	Short	Swept Left	Recyclable	Intact
Glass Jar (Heavy)	Heavy	Average	Unable to Sweep	N/A	Broken
Large Cardboard Box (Heavy)	Heavy	Large	Unable to Sweep	N/A	Broken
Book (Heavy)	Heavy	Tall	Unable to Sweep	N/A	Broken
Wooden Board (Heavy)	Very Heavy	Large	Unable to Sweep	N/A	Broken
Small Plastic Cap	Very Light	Small	Swept Left	Recyclable	Intact

Figure 5. Figure of experiment 2

In analyzing Experiment B, the mean success rate for the robotic arm in placing items into the correct bins was 40%, with a median matching this value. The lowest success rate was 0%, observed with heavier and taller items such as glass jars, large cardboard boxes, books, and wooden boards. The highest success rate, 80%, was achieved with smaller and lighter items like plastic bottles and aluminum cans. Surprisingly, the arm demonstrated efficiency with a very light and small plastic cap, suggesting adaptability to certain lightweight items. The biggest factor influencing results is the weight and size of the items, with the arm struggling to handle heavier and taller objects, leading to breakage. This highlights the necessity for a more robust arm design to accommodate a broader range of items and improve overall efficiency in real-world recycling scenarios.

5. RELATED WORK

Methodology A, as exemplified by WasteVision.ai, implements a system designed for the efficient sorting of dumpsters and the contents within [11]. This technology assesses the accuracy of waste sorting within each dumpster and provides alerts to owners regarding overflow conditions. The effectiveness of this solution lies in its advanced machine learning model, capable of accurately detecting a diverse array of objects. However, it is constrained by its compatibility limited to larger dumpsters, excluding smaller trash cans. If smaller trash cans already employ effective sorting methods, there may be a potential cost reduction by eliminating the need for sorting in larger dumpsters.

Methodology B proposes a cloud-based waste classification algorithm for automated recycling machines using machine learning [12]. The solution employs a trained MobileNet model capable of classifying five waste types in real-time on a cloud server. Techniques like data augmentation and hyper-parameter tuning enhance classification accuracy. The system supports multiple industrial stations interconnected via custom data transmission protocols, ensuring security. Experimental results show an impressive 96.57% accuracy. While effective, this solution has limitations, such as reliance on cloud connectivity and potential challenges in diverse real-world environments. It overlooks the handling of physical waste objects and may face scalability issues. Your project, with a robotic arm and computer vision, improves by addressing physical object manipulation and real-world recycling challenges directly.

Methodology C introduces a robotic mobile manipulation system for automated sorting of recyclables in municipal solid waste (MSW) [13]. Equipped with a thermal imaging camera, proximity sensor, and a 5-DOF robotic arm, the system uses thermographic images for automated identification. The algorithm extracts keypoint features, employs clustering, and utilizes Support Vector Machine (SVM) classification. It achieved a 94.3% classification rate for three recyclable categories. However, it may face challenges in handling cluttered environments, and its focus on thermographic images may limit broader recyclable detection. Your project improves by incorporating computer vision, object recognition, and robotic arm manipulation to enhance accuracy and address diverse recyclables in real-world scenarios.

6. CONCLUSIONS

While my recycling project introduces valuable advancements, some limitations warrant consideration. Firstly, there might be challenges in recognizing certain materials with intricate textures or shapes, requiring additional training data or fine-tuning of my machine learning model. Secondly, my robotic arm's current design might face limitations in handling exceptionally heavy or bulky items. Addressing this could involve enhancing the arm's strength and adaptability. Additionally, real-world scenarios may present unforeseen challenges such as dynamic environments or variations in lighting conditions, suggesting a need for further robustness testing and adjustments. To enhance my project, dedicating more time to refining the machine learning model with a diverse dataset and optimizing the robotic arm's design for increased versatility would be beneficial. Ongoing testing and iterations based on real-world scenarios would contribute to an even more effective and adaptable recycling solution.

In conclusion, my recycling project leverages innovative technologies to address waste management challenges. While there are ongoing improvements needed, the integration of machine learning, computer vision, and a robotic arm signifies a promising step towards a more efficient and adaptable solution for recycling in diverse real-world environments.

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