BottleSort

Project Report

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Abstract

Increasing worldwide waste generation requires innovative and automated recycling techniques. This project describes the design and development of an automated system for sorting recyclable containers using an acoustic-based classification method. The system is designed to identify and separate plastic bottles, glass bottles, and metal cans by analyzing the unique acoustic signature generated upon impact. A microphone captures the sound, which is processed by a machine learning model developed on the Edge Impulse platform. Based on the classification result, a stepper motor activates a sorting mechanism to direct the item into the correct bin. The integrated system achieved a classification accuracy of 100% for plastic and around 95% for can during testing, and the final accuracy of 100% for both after fine-tuning, successfully demonstrating the viability of this audio-based method for automated waste segregation.

1 Introduction

According to the World Bank, 2.01 billion tonnes of waste is produced globally and this figure is projected to reach 3.40 billion tonnes by the year 2050. This substantial increase highlights the need for proper management of waste. While different types of waste are treated differently, (i.e composting for organic materials, land filling for residuals, etc.), recycling remains one of the most important ways of handling waste.

For effective recycling, waste separation is essential as Chen et al. points out [1]. However, due to the labor intensive nature of this task, many households tend to avoid manual separation [2]. Therefore, the goal of our project is to create an accurate waste separation system, that operates automatically or with minimal human intervention. This report details the design and prototyping of a system to achieve this goal, specifically for classifying and sorting common recyclable containers.

Among various household and commercial waste, bottles are one of the most common items that can be recycled. In this project, we focus on separating plastic bottles and metal cans.

Based on existing research, we considered several methods to identify the type of waste. After testing different sensors, we recognized some inconsistencies and constraints unique to each sensor type. Finally, we relied on an audio based approach combined with an AI model to classify the waste types. The sensing approaches we explored will be explained in the background section.

Different types of materials produce distinct sounds. This allows us to classify waste, in this case plastic and metal, by analyzing the impact sound of the bottle. To analyze the sound and identify the material, we use a machine learning platform, Edge Impulse. This platform was chosen for its ability to efficiently develop and deploy machine learning models to resource-constrained embedded devices.

On the subject of the physical structure, the build is made mainly of wood, as it is lightweight yet provide adequate stability. As we are sorting bottles, we use a cylindrical pipe to temporarily store the bottle until the AI model makes a decision and to dispose it into the correct bin. A stepper motor rotates this pipe about its axis. This design suits bottles and cans as it prevents the bottles from rolling and keeps them in place.

A rough outline of how our prototype works can be given as follows.

- Bottle travels down the PVC pipe and creates an impact sound
- The microphone on the wooden platform, captures this sound
- Edge Impulse ML model processes the sound
- Based on the output, the pipe rotates and drops the bottle into the correct bin (plastic or metal)

The next sections describe in detail, the designs, implementation and testing of the prototype. The scope of this prototype is limited to the sorting of single-item, empty containers based on their material composition.

2 Background

The most important decision in creating an automated sorting system is the choice of a suitable sensing approach. The following sub sections discusses typical methods reported in comparable projects, evaluates their limitation for this particular use, and explains the chosen audio-based machine learning method.

2.1 Sensor technologies

During our research, we considered several approaches to identify the type of waste. We found out that many similar projects were created using one or a combination of sensors such as infrared, ultrasonic, metal detecting etc. We wanted to combine traditional sensing approaches with artificial intelligence, to improve accuracy as well as learn more about the integration of machine learning models into real life cyber-physical projects.

At first we considered a vision based approach. We could capture the image of the waste with a camera and a photodetector, (in our case, an NIR sensor) and this way we could identify a wider range of materials using image classification. However this method requires good lighting conditions and also to deliver more accurate results, expensive cameras and components were essential.

Another method that was promising is the use of inductive proximity sensors to identify metal cans. This would provide accurate results for metal objects however can not distinguish between non conductive materials, in case we wanted to expand the range of waste materials we sort. Another challenge we faced was finding the correct placement for this sensor as the sensing range was very low, so the object should nearly touch the sensor for more accurate results.

2.2 Audio based approach

Issues with sensor placements and consistent environmental conditions led us to using an audio-based sensor, i.e a microphone. Since the impact sound is generated inside the pipe, the acoustics remains consistent. Also since the bottle is dropped into a vertical pipe, the height remains the same for all samples. These factors help provide more accurate results. Therefore we decided on using sound as the sensing modality and altered our physical structure to accommodate recording sound.

Even though using a microphone proved to be more straightforward compared to other sensors, the issue of background noise was still there, For this reason, we used a microphone which is super cardioid, which means it is more sensitive to sound directly in front of it. This reduces background noise and helps provide a more accurate outcome. To process and classify the recorded sounds we use Edge Impulse, which is a platform to train and develop machine learning models for edge devices. We will cover more on this topic in the methodology section.

2.3 Physical Structure Design

Since BottleSort trash can sorts bottles, one factor we considered when designing the structure was using a shape that accommodates the cylindrical shape of most bottles and cans. Using two conveyor belts at angle (inspired by "Pfandmachine"/ reverse vending machine) [3] was an option we explored, however due to the cost and the mechanical complexity of this design, we decided to opt for a different option. Also this design did not suit our sensing approach as we wanted to drop the bottle from a consistent height to achieve accurate results.

Another factor we had to consider was our sensing approach. Therefore we needed an enclosed structure to make the impact sound. Those two reasons led us to design a build with a pipe acting as a chute to direct the bottle to strike the wooden platform. This is also where the sound is recorded. The pipe is connected to the stepper motor that's responsible for rotating the pipe to the correct hole, and thus the correct bin. The microphone lies of the wooden platform, in front of the pipe to capture the audio.

This physical structure ensures that the bottles are dropped from a consistent height (height of the pipe, 50 cm) and the impact sound is made inside the pipe for consistent acoustics. In the next sections, we discuss how this design was achieved by using proper material and custom 3-D printed components.

3 Methodology

This section details the end-to-end implementation of the automated waste sorting system, encompassing the system design, data collection, machine learning model development, hardware construction, and the software workflow.

3.1 System Overview

The system operates through a sequential, automated pipeline:

1. A user drops a recyclable container into the intake pipe.
2. The item falls approximately 50 cm and strikes a fixed 10 mm MDF wood impact platform.
3. A Comica VM10 PRO super cardioid microphone, clipped onto the platform, captures the impact sound.
4. The audio data is processed by a machine learning model running on a Raspberry Pi 5.
5. The model classifies the material and sends the result to the motor control logic.
6. A stepper motor rotates the entire intake assembly to align an exit chute with the corresponding collection bin.

7. The item falls into the correct bin, and the system resets after a 1s delay.

3.2 Data Collection and Model Development

3.2.1 Data Acquisition

A dataset of impact sounds was created for the three target classes: *can*, *plastic*, and *noise*. Samples were collected by dropping each container from the top of the pipe onto the 10 mm MDF baseplate. The Comica VM10 PRO microphone, positioned on the platform, recorded the sound. In total, **34 samples** were used for training and **16 samples** for testing:

- **Training Set (68%): 14** plastic, **14** can, and **6** noise samples.
- **Testing Set (32%): 7** plastic, **5** can, and **4** noise samples.

Each sample was **1.0 second** long, recorded at **16 kHz**.

3.2.2 Impulse Design and Training

An *impulse* was designed in Edge Impulse to process the raw audio data. The processing block was configured to extract **Mel-filterbank energy (MFE)** features with a window size of **1000 ms** and an increase of **500 ms**. The specific MFE parameters were: a frame length of **0.025**, a frame stride of **0.01**, **41** filters, and an FFT length of **512**.

These features were fed into a **Convolutional Neural Network (CNN)** with the following architecture:

- Input Layer (4,018 features)
- Reshape Layer (41 columns)
- 2D Convolutional Layer (8 filters, 3x3 kernel)
- Dropout Layer (rate 0.25)
- 2D Convolutional Layer (16 filters, 3x3 kernel)
- Dropout Layer (rate 0.5)
- Flatten Layer
- Output Layer (3 neurons, one per class)

The model was trained for **300** epochs with a learning rate of **0.005**, a batch size of **128**, and a validation set size of **20%**. The final model achieved a perfect accuracy of **100%** on the validation set.

3.2.3 Deployment

The trained model was deployed as a library for the target device. The on-device performance showed an inferencing time of **1 ms**, making it suitable for real-time classification.

3.3 Hardware Implementation

3.3.1 Component Selection and List

The main components used in the system build are listed in Table 1.

Table 1: Bill of Materials

Component	Specification / Details
Processor	Raspberry Pi 5
Microcontroller	Arduino Mega 2560
Microphone	Comica VM10 PRO External Microphone
Stepper Motor	ViaGasaFamido 17Hs3401S (4-wire)
Stepper Motor Driver	QWORK TB6600 Driver (9-42V, 4.0A)
Power Supply (Motor)	24V DC DC Power Supply (within 9-42V range for TB6600 Driver)
Power Supply (MCU)	5V via USB for Raspberry Pi

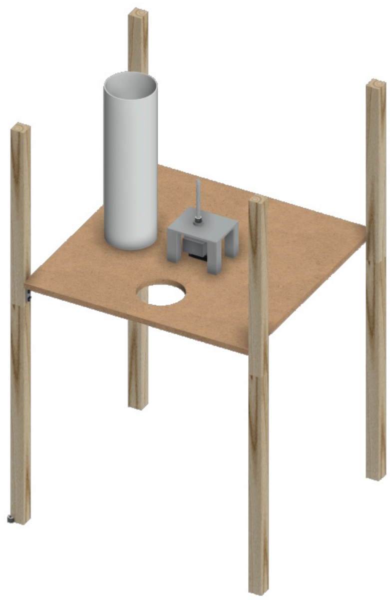

Figure 1: Photograph of the constructed prototype, showing the intake pipe, motor assembly, and collection bins.

PVC pipe	50cm length, 10cm diameter
10 mm MDF wood board	50cm x 50cm
8 wood pillars	35cm length
2 plastic bins	30cm depth

Table 2: Structural materials and dimensions

3.3.2 Structural material

A list of materials used to support the structure is given in Table 2

3.3.3 Circuit Assembly

The TB6600 stepper driver was connected to the Arduino for step and direction control. The 24 V power supply was connected to the driver's power input terminals. The Comica microphone was connected to the Raspberry Pi's USB port.

3.4 Software and Control Logic

The software integrates audio sampling, machine learning inference, and motor control.

3.4.1 Main Program Loop

The operational sequence is as follows:

1. **IDLE:** Monitor audio input for a threshold trigger.
2. **ACQUIRE:** Record a 1 second audio sample upon impact.
3. **PROCESS & CLASSIFY:** Run Edge Impulse inference on the sample.
4. **ACTUATE:** Map the result to a motor position and rotate the stepper motor to 0 degree or 180 degree position depending on the classification result.
5. **RESET:** Wait for 1000 milliseconds, then return to home position.

3.4.2 Key Software Libraries

The code utilizes the following key libraries:

- **Edge Impulse Inference Runtime** for Raspberry Pi.
- **Servo Library** for stepper motor control.

4 Implementation

This section describes the process of building the designed trash can, detailing how the hardware, software and actuating mechanisms were assembled.

4.1 Physical Structure

This prototype consists of a table-like structure, with the top level platform being made of 10 mm MDF wood. On this top level (50cm x 50cm), we have 3 cutouts, a rectangular hole of for the stepper motor and two circular holes of diameter (10cm) for the plastic pipe. The stepper motor fits in this rectangular cutout. A small table-like structure is mounted at the top level, which is connected to the stepper motor, for added stability.

A PVC pipe of diameter (10cm) and length (50cm) is connected to the stepper motor by a 3D printed arm vertically. This pipe rotates about its stepper motor's vertical axis, in a circular motion of diameter (40cm). This pipe rotates from 0 degrees to 180 degrees, and the two circular cutouts lie exactly opposite to each other.

Eight wooden pillars (35cm) were used to create the vertical frame to support these this horizontal platform.

When a bottle is dropped down the pipe, after it makes the impact sound and the material is recognized by the AI model, then the pipe will either rotate clockwise until it aligns with one circular cutout or counter clockwise until it aligns with the other circular cutout, depending on the waste classification.

The two bins, meant for plastic and metal, lie on the ground, directly under these two circular cutouts. They hold the discarded bottles and are not fixed to the structure. This makes the trash can easily portable.

5 Testing and Evaluation

This section shows the testing result of our Edge Impulse model and the analysis of this platform.

5.1 Test Results

We faced many issues with classification, but was able to fine tune the parameters to achieve 100% accuracy. First, we faced the problem with classifying cans. Plastic achieved 100% accuracy after very few data points, but cans were often misidentified as plastic or had a small probability of being plastic. Therefore, we had to change the parameters for can identification to improve the accuracy: we set mean FAR (False Alarm Rate) as 35.5%, mean FRR (False Rejection Rate) as 42.9%, averaging window duration as 4 ms, detection threshold as 0.38 and suppression period as 809 ms. We also wanted to include noise identification so that the machine does not activate by accident and by random sounds or noises. This led the data to be very random, and as such we learned the importance of targeting specific area when it comes to data sorting. In the end, we were able isolate the noise and achieve target areas for can and plastic.

Confusion matrix

	CAN	NOISE	PLASTIC	UNCERTAIN
CAN	100%	0%	0%	0%
NOISE	0%	100%	0%	0%
PLASTIC	0%	0%	100%	0%
F1 SCORE	1.00	1.00	1.00	

Figure 2: Confusion matrix on the same dataset as Figure 2

SAMPLE NAME	EXPECTED OUTCO...	LENGTH	ACCURACY	RESULT
testing.6314o...	noise	1s	100%	1 noise
z_openset.4b...	noise	1s	100%	1 noise
z_openset.4b...	noise	1s	100%	1 noise
plastic.6367n...	plastic	1s	100%	1 plastic
plastic.6367m...	plastic	1s	100%	1 plastic
plastic.6367m...	noise	1s	100%	1 noise
testing.6314p...	plastic	1s	100%	1 plastic
can.6312aoh4	can	1s	100%	1 can
can.63124boh	can	1s	100%	1 can
can.63122ri8	can	1s	100%	1 can
plastic.6311s...	plastic	1s	100%	1 plastic

Figure 3: Classification result - labels out of plastic, can and noise

5.2 Evaluation

We identified 2 main issues with our project which can be improved upon in the future. These issues can be mainly generalized as associated with materials and design.

In the initial design phase, we designed a structure with a metal frame. However, after budgeting and planning, we realized that metal is too inefficient and harder to work with so we ended up using wood. This was an oversight as we lacked the proper knowledge to build a strong frame and the foundation of the project ended up wobbly. Therefore, the importance of identifying the right materials are key to a successful embedded system project, in this case being wood for small scale cheap model and metal for strong stable machines.

The second key problem we faced was the lack of planning. Even in the design stage, we realized that the size may be a limiting factor, but we disregarded the this concern. However, it ended up backfiring as difficulties started to occur with moving the product and making it very complex. When we reduced the complexity to finish the project efficiently, it worked even better than what we originally planned. We learned the importance of scale and complexity when it comes to a prototype machine.

6 Conclusion

In this report, we have discussed the importance of sorting of most common types of household waste to achieve a successful recycling process. After researching several methods and available prototypes, we have designed, implemented and analyzed an automated trash can using an audio based approach.

This prototype classifies bottles into two categories: plastic and metal. By using a microphone to capture the impact sound the container makes when it is dropped, and comparing this to reference sounds from a custom Edge Impulse dataset, we can accurately determine the waste type. In this report we have listed the components and materials used, how they are integrated and the results acquired from testing and evaluating the final prototype.

Automating a tedious process such as separating a common type of waste leads to increased efficiency and more effective recycling. Further improvements can include,

- wider range of bottle types (including glass)
- wider range of materials (paper, cardboard, organic etc)
- an automatic lid with a proximity sensor
- a more aesthetically pleasing design for the physical structure

By integrating state of the art technology and more advanced machine learning models, the accuracy of sorting can be maximized, depending on the complexity of the prototype.

Overall, this project showcases one of the real life applications of cyber-physical systems, and how combining it with artificial intelligence can further increase the practical impact.

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References

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