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Article

Design and implementation of an intelligent waste classification device

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Abstract: This study presents a guideline for an intelligent waste classification device developed using a Raspberry Pi, a camera, and Google's Teachable Machine (TM) for image recognition. The device is designed to identify waste and classify it into recyclable and non-recyclable categories to improve recycling efficiency. The system is primarily controlled by the Raspberry Pi, with the camera capturing images, which are then processed by TM for image model training to facilitate waste classification. This paper describes the hardware and software components as well as their applications and verifies the effectiveness of the device in practical use. The device is cost-effective, offers good scalability, and is practical for waste classification in households, offices, and public spaces. This study provides valuable insights for the design and future applications of intelligent waste classification systems.

Keywords: intelligent waste classification; Raspberry Pi; teachable machine; image recognition; recycling; waste classification

1. Introduction

With over 2 billion tons of solid waste generated globally each year, and projections indicating an increase to 3.4 billion tons by 2050, the severity of waste management issues is becoming increasingly evident. The average recycling rate for global waste is only 13%, highlighting the significant potential for resource utilization that remains untapped. Furthermore, inadequate waste management contributes to environmental problems that result in approximately 7 million deaths annually from environmentally-related diseases and causes economic losses of up to $1.5 trillion, posing serious challenges to sustainable development. In light of the growing issues of global resource scarcity and environmental pollution, waste classification has emerged as a critical topic for sustainable development. Many countries and regions are promoting waste classification to enhance resource recovery rates [1–8]. However, traditional waste classification methods heavily rely on manual operations, which are time-consuming, labor-intensive, and often lack accuracy [9–11]. The emergence of intelligent waste classification devices offers technological solutions to these challenges. AI-based waste classification technologies can significantly improve efficiency and accuracy, making the process more automated and intelligent [12–18].

Digital technology innovations are important for waste classification because they can quickly and accurately identify waste types, making the classification process more efficient than manual methods. These systems can also collect and analyze waste data, helping organizations make better management decisions. Additionally, these digital devices can be easily updated and learn to recognize new types of waste over time. From an environmental perspective, digital technology can increase recycling rates, allowing more materials to be recycled and reducing the amount of waste sent to landfills. Using recycled materials also decreases the demand for new raw materials, helping to protect natural resources. Properly sorted waste reduces pollution from landfills and incineration, leading to improved environmental quality. These technologies also educate people about proper waste disposal practices, promoting recycling and responsible consumption habits. Ultimately, increased recycling efficiency can lower waste management costs and create job opportunities in the recycling sector.

This study developed an intelligent waste classification device utilizing Raspberry Pi [19–24] and Google's Teachable Machine (TM) [25]. The device employs a camera for image capture and uses deep learning techniques [26–29] to train a classification model. The image recognition model is trained with a large dataset of waste images, enabling it to accurately distinguish between recyclable and non-recyclable waste types. This machine learning-based approach substantially reduces the classification error rate commonly observed in traditional methods.

Numerous studies have investigated the application of various waste classification devices, demonstrating significant improvements in classification accuracy and efficiency. The integration of machine learning and deep learning algorithms into waste classification systems has yielded remarkable results [11–13,15,16,18]. The use of Raspberry Pi for automated waste classification systems has gained popularity due to its cost-effectiveness and simplicity, with many studies validating its feasibility [19–22,24]. Intelligent waste bins and smart waste management systems have enhanced recycling rates and classification efficiency in households and public spaces [4,6,23]. Various pilot programs have successfully implemented intelligent waste classification devices, showcasing strong market potential [1,3,10]. Overall, these studies indicate that waste classification devices have significant potential for technological advancement and practical application.

The system architecture consists of hardware and software components. The hardware incorporates Raspberry Pi as the primary controller, equipped with a high-resolution camera for real-time image capture. The software leverages TM for training and classifying waste images. The deep learning algorithms employed include Convolutional Neural Networks (CNN), which have demonstrated outstanding performance in image recognition tasks. Furthermore, the system integrates a simple touch interface, allowing users to view classification results and manually correct potential errors.

During the experimental phase, various types and sizes of waste images were tested. Results indicate that the system achieves a classification accuracy exceeding 90%, particularly excelling in the classification of metals, plastics, paper, and organic materials. The system's stability was further validated under different lighting conditions, demonstrating reliable performance even in low-light environments. Compared to other commercial waste classification devices, the developed system offers significant cost advantages. The low-cost components, such as Raspberry Pi and TM, make this device particularly suitable for deployment in households, offices, and public spaces, providing a feasible and economical solution for waste classification.

When evaluating the cost of the waste classification equipment, the design prioritizes affordability by utilizing widely accessible components such as Raspberry Pi and standard cameras. This approach ensures the equipment is feasible for households and small businesses. The initial investment can be recouped over time through reductions in waste disposal costs and increased revenue from recycling. Regarding technical difficulty, the development of this equipment necessitates a fundamental understanding of programming and hardware integration. However, platforms like Raspberry Pi offer user-friendly resources and community support, facilitating an easier adoption for both developers and users. The market potential is significant given the rising demand for efficient waste management solutions driven by heightened environmental awareness. The device's scalability makes it adaptable for various contexts, including residential, commercial, and public spaces, enhancing its market viability. Consequently, the combination of cost-effectiveness, manageable technical challenges, and strong market demand indicates that this waste classification equipment has favorable prospects for successful implementation.

2. Materials and methods

This study designs an intelligent waste classification system aimed at automatically identifying waste and classifying it based on its recyclability. The system is based on a Raspberry Pi as the main controller, combined with a camera and TM for image recognition. The schematic diagram of the device is shown in **Figure 1**. The following outlines the key design elements and steps of the system:

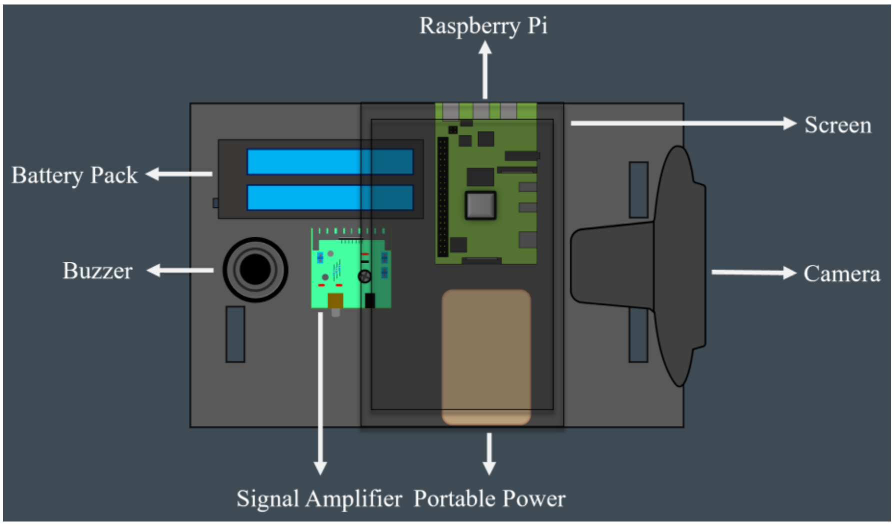

Figure 1. Schematic diagram of an intelligent waste classification device.

2.1. System architecture

The system architecture is divided into two main sections: The hardware part and the software part. In this study, all hardware components used are obtainable at very low cost, and the software part utilizes free open-source software. The details of these two sections are as follows:

2.1.1. Hardware components

1) Raspberry Pi: Serving as the core controller of the system, it is responsible for managing the image capture process through the camera and processing the image data. Raspberry Pi is characterized by low power consumption and high scalability, making it suitable for edge computing applications.
2) Camera: Mounted above the device, the camera captures real-time images of the waste. These images are transmitted to the Raspberry Pi for preprocessing and classification.

2.1.2. Software components

1) Image recognition model: The system uses transfer learning-based deep learning techniques for training and optimization. The initial image dataset, captured by the camera and labeled, is uploaded to TM for model training. After multiple iterations, the model with the highest accuracy is selected and deployed to the Raspberry Pi.
2) Image data processing: Before model training, image preprocessing and analysis are conducted, including cropping, adjusting lighting, and removing background noise. These preprocessing steps enhance the accuracy of image recognition.
3) Classification algorithm: The system utilizes Convolutional Neural Networks (CNN) for image classification. The model categorizes the identified waste into two classes: Recyclable and non-recyclable.

2.2. System workflow

The system workflow begins with a camera capturing images of the waste. These image data are then transmitted to the Raspberry Pi for classification. The system determines the waste category based on the classification results provided by the TM model. The relevant steps are described as follows:

1) Image capture: The camera captures images of the waste, and the image data is sent to the Raspberry Pi for preprocessing.
2) Image analysis: The preprocessed image data is uploaded to TM for image classification. Based on the model's classification results, the system determines the category of the waste.
3) Model optimization: Users continuously record the accuracy of the recognition results. If prediction errors are found, the incorrectly predicted images and similar new image data will be collected, and the model will be retrained to improve classification accuracy.

2.3. Model training and optimization

The process of model training and optimization encompasses several critical steps. Initially, images of various types of waste are captured using a camera and uploaded to Teachable Machine (TM) for training. These annotated images serve as the foundational data for training the model. Subsequently, based on the collected image dataset, multiple training and optimization iterations are conducted using Convolutional Neural Networks (CNN) on TM. After each training session, a new image recognition model is generated, and the best model is selected based on its accuracy and stability.

In this research, there are a total of 2186 images of recyclable items, of which 85% (1858 images) are used for model training, and the remaining 15% (328 images) are used for model testing. For non-recyclable items, there are a total of 2025 images, with 85% (1721 images) used for model training and the remaining 15% (304 images) used for model testing. In reality, the accuracy achieved through TM training is 91% for recyclable and 90% for non-recyclable, as shown in **Table 1** below.

Table 1. Training accuracy per class.

Class	Accuracy	Samples
Recyclable	91%	328
Non-recyclable	90%	304

Finally, the trained model is downloaded and deployed to the Raspberry Pi. The model's recognition performance is tested in real-world environments, parameters are adjusted, and updates are made to the model as necessary.

1) Data collection: Different types of waste are captured by the camera, and the images are uploaded to TM for annotation. These annotated images serve as the training dataset for the model.
2) Model training: Using the collected image dataset, CNN is trained multiple times on TM. After each training session, the system generates a new image recognition model and selects the best-performing model based on accuracy and stability.
3) Deployment and testing: The trained model is downloaded and deployed to the Raspberry Pi. It is then tested in a real-world environment, and relevant parameters are adjusted as needed. The model is updated based on the testing results.

3. Implementation

This intelligent waste classification device aims to improve the efficiency of waste classification by automatically categorizing waste into recyclable and non-recyclable types. The primary components include a Raspberry Pi, a camera, and a machine learning model trained using Google's TM. As shown in **Figure 2**, the software required for the Raspberry Pi in this intelligent waste classification device includes Keras, TensorFlow, OpenCV, Python, and TM, in addition to the Raspberry Pi OS (Raspbian). The following instructions detail the hardware components, software setup and verification procedures required to build this device.

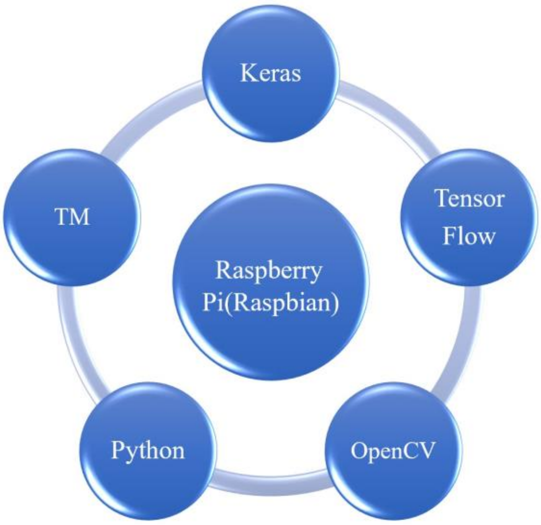

Figure 2. The relationship diagram between the Raspberry Pi and the software.

3.1. Hardware components

The main hardware components of the intelligent waste classification device include the Raspberry Pi, camera, power supply, and additional components. The descriptions of these hardware components are as follows:

1) Raspberry Pi:
   - Model: Raspberry Pi 4 or later.
2) Camera:
   - High-resolution camera compatible with Raspberry Pi;
   - Camera module.
3) Power supply:
   - Dedicated power supply for Raspberry Pi;
   - Portable power bank (optional for mobility).
4) Additional components:
   - Battery pack for backup power;
   - Signal amplifier;
   - Buzzer for audible alerts;
   - Screen for displaying classification results.

3.2. Software setup

This section primarily describes the software required to be installed on the intelligent waste classification device, along with the tools needed for training the model. The description of the software setup is as follows:

1) Operating system installation:
   - Install Raspberry Pi OS (Raspbian) on the Raspberry Pi.
2) Camera setup:
   - Enable the camera interface through the Raspberry Pi configuration settings;
   - Verifying the functionality of a camera module on a Raspberry Pi running Raspberry Pi OS using Python.
3) Install required libraries:

- Update the system and install Python 3.6;
- Install TensorFlow 2.4.3, Keras 2.4.3, and OpenCV 4.3 libraries on the Raspberry Pi.

4) Teachable Machine model:
   - Train an image recognition model using Google’s Teachable Machine;
   - Export the trained model and transfer it to the Raspberry Pi.
5) Python application:
   - Write a Python script to capture images from the camera and process them using TensorFlow, Keras, and OpenCV libraries for classification.

3.3. Verification procedures

Once the hardware is set up, the relevant software is installed, and the model is trained, the next step is to capture images of waste to verify the classification of recyclable waste and non-recyclable waste. The description of the verification procedures is as follows:

1) Recyclable waste:
   - Test the device with glass bottles, paper cups, waste paper, aluminum cans, and plastic bottles;
   - Verify that the device accurately classifies each type of recyclable waste.
2) Non-recyclable waste:
   - Test the device with face masks, polystyrene, plastic bags, food waste, and leaves;
   - Verify that the device accurately classifies each type of non-recyclable waste.
3) Performance metrics:
   - Record and analyze the classification accuracy;
   - Ensure the system consistently achieves 100% classification accuracy.

This build guide provides the necessary steps to create an intelligent waste classification device using readily available hardware and software components. By following these instructions, the intelligent waste classification device, as shown in **Figure 3**, can be developed. This device represents a cost-effective and scalable solution for improving waste management and recycling efficiency.

Figure 3. The implementation diagram of the intelligent waste classification device.

4. Validation process

Figure 4 illustrates the validation process of an automated waste classification device. Initially, waste is conveyed into the system, where a camera captures images of the incoming waste. These image data are transmitted to a Raspberry Pi for processing. The Raspberry Pi runs a pre-trained image recognition model developed using Teachable Machine. Teachable Machine is a user-friendly platform that allows users to quickly create and train machine learning models without requiring extensive technical expertise. The trained model is deployed on the Raspberry Pi, and a Python application is used to execute the model. Within the Raspberry Pi, the model operates based on TensorFlow and Keras, two robust machine learning frameworks. TensorFlow provides powerful numerical computation capabilities, while Keras, as a high-level API, simplifies and enhances the efficiency of model building and training. These frameworks work together to process the images captured by the camera and classify them using the model.

As the Raspberry Pi runs the model to analyze the images, the system determines the type of waste based on characteristics. Once these features are identified by the model, the waste is categorized as either recyclable or non-recyclable. Based on the model's classification, the system automatically classifies the waste into recyclable or non-recyclable categories. The entire system integrates efficient image capture technology with advanced machine learning models to achieve accurate waste classification.

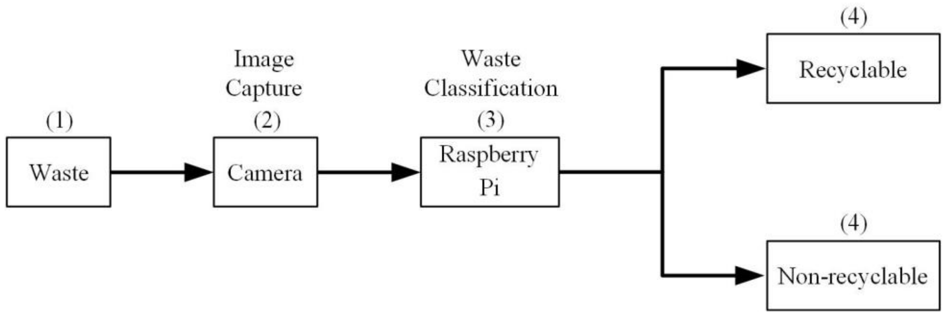

Figure 4. The validation flowchart of the intelligent waste classification device.

5. Results and discussion

This section describes the verification of the classification results of ten types of waste using the device developed in this study. The waste is categorized into recyclable and non-recyclable items. Recyclable waste includes glass bottles, paper cups, waste paper, aluminum cans, and plastic bottles. Non-recyclable waste includes face masks, polystyrene, plastic bags, food waste, and leaves.

Figures 5–9 show the classification results of recyclable waste. Each type of recyclable waste was subjected to the system, where high-precision cameras captured the images, and a pre-trained machine learning model, deployed on a Raspberry Pi, processed the image data. The model, trained using Teachable Machine, effectively identified and categorized the waste. The Python application running on the Raspberry Pi utilized TensorFlow and Keras frameworks to classify the waste based on features such as shape, color, and size. The classification results indicated that the system accurately identified and classified each type of recyclable waste with 100% accuracy.

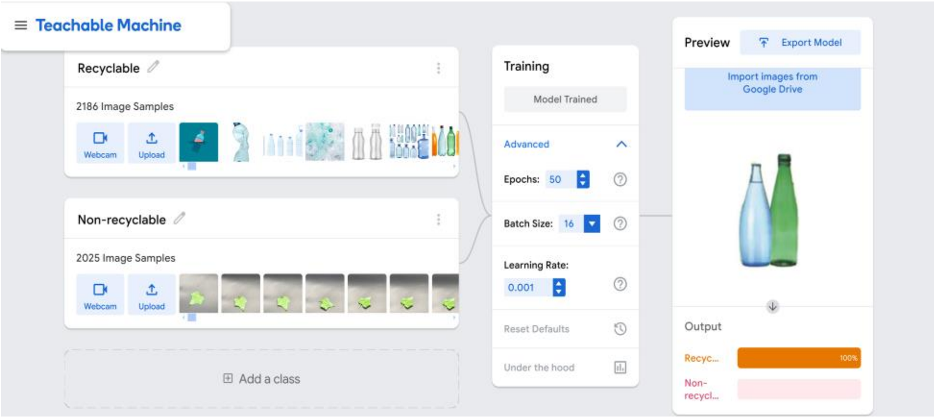

Figure 5. The classification results for glass bottles (recyclable).

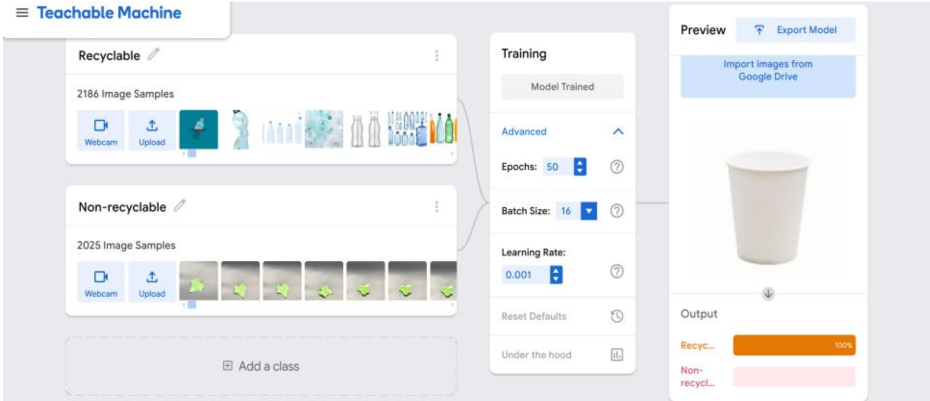

Figure 6. The classification results for paper cups (recyclable).

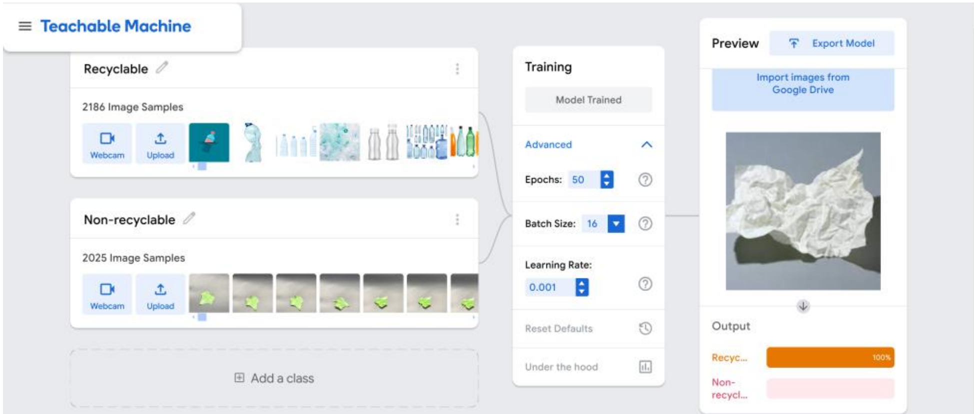

Figure 7. The classification results for waste paper (recyclable).

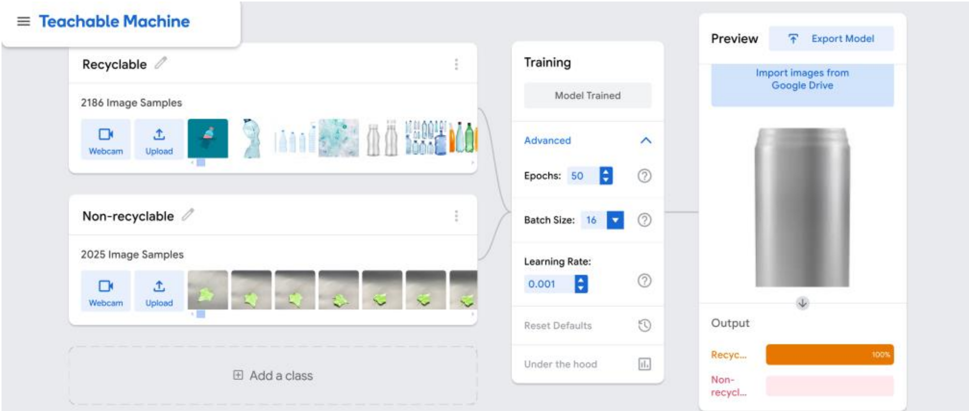

Figure 8. The classification results for aluminum cans (recyclable).

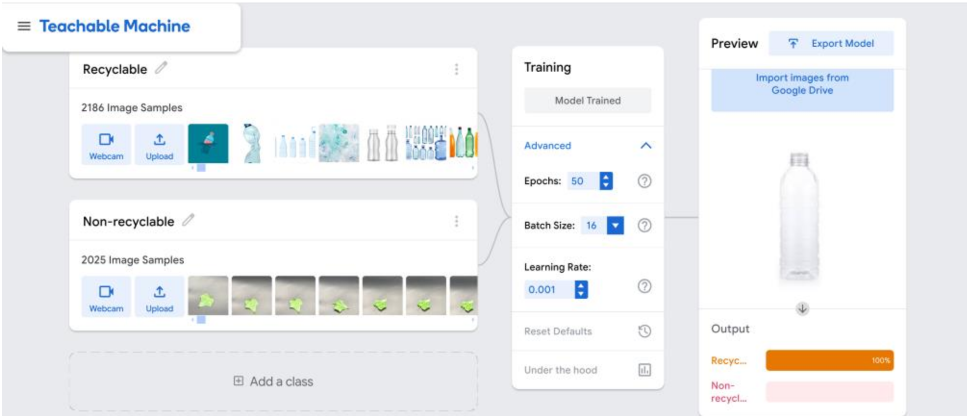

Figure 9. The classification results for plastic bottles (recyclable).

Similarly, **Figures 10–14** present the classification results of non-recyclable waste. The same high-precision image capture and machine learning processes were applied. The model accurately identified face masks, polystyrene, plastic bags, food waste, and leaves, demonstrating the system's capability to distinguish non-recyclable waste from recyclable waste with equal accuracy.

The classification results from the device developed in this study show that regardless of the type of waste input, the system can classify it with 100% accuracy. This level of accuracy demonstrates the effectiveness of integrating image capture technology with advanced machine learning models. The automated system not only enhances classification efficiency but also significantly reduces labor costs and environmental impact, exemplifying the potential of modern technology in waste management and environmental protection. This cost-effective solution integrates both hardware and software, providing a practical model for waste classification and resource recovery.

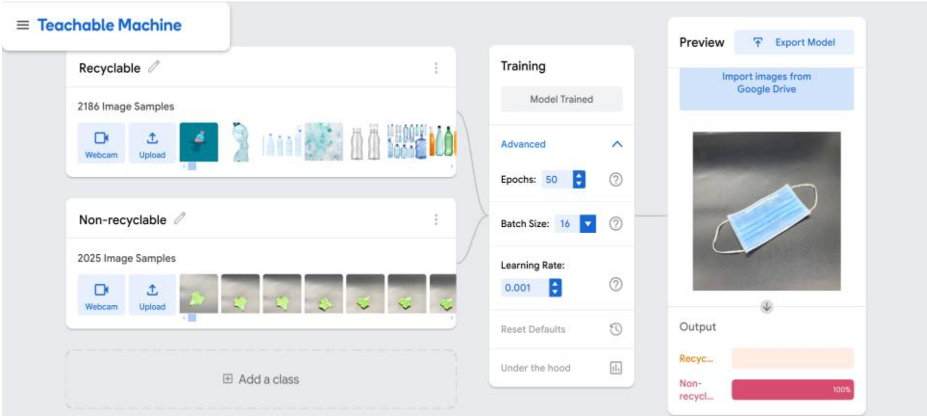

Figure 10. The classification results for face mask (non-recyclable).

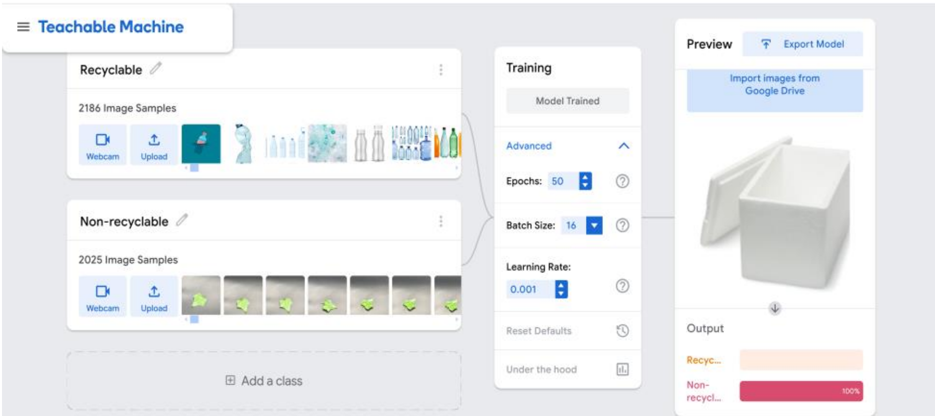

Figure 11. The classification results for polystyrene (non-recyclable).

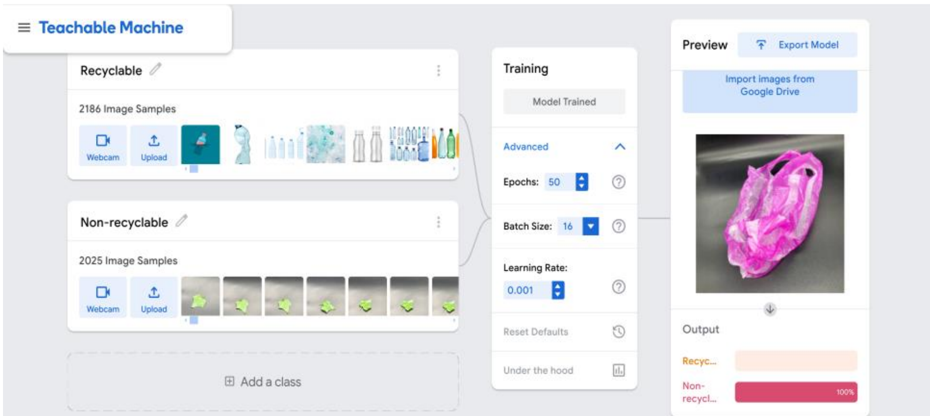

Figure 12. The classification results for plastic bag (non-recyclable).

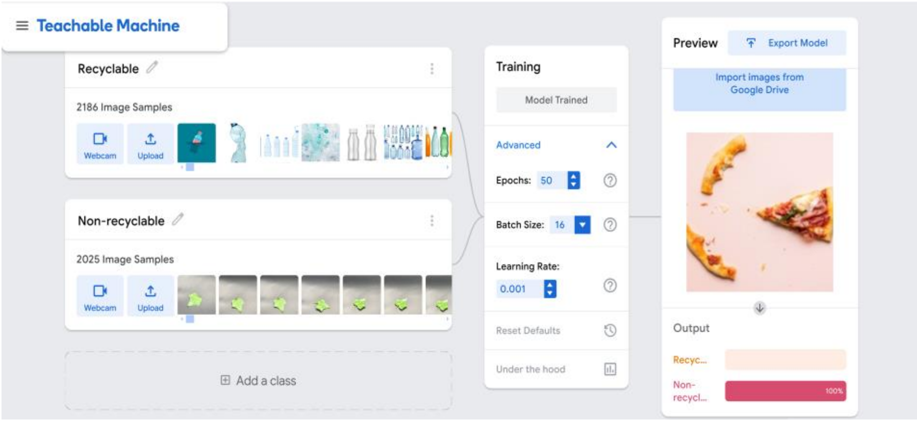

Figure 13. The classification results for food waste (non-recyclable).

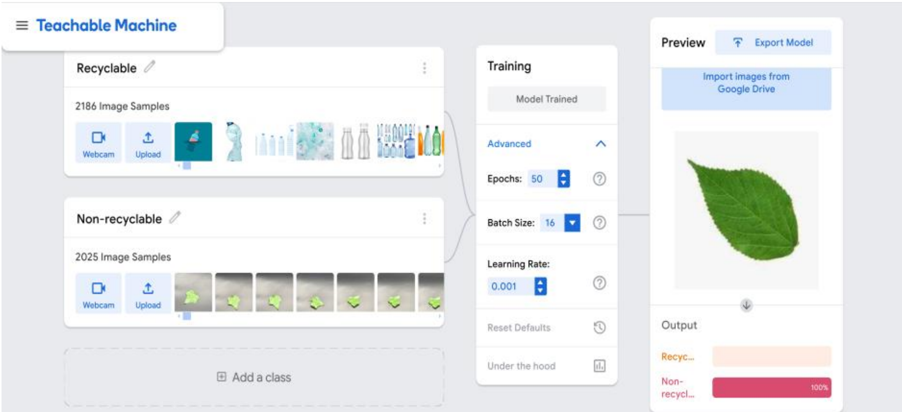

Figure 14. The classification results for leaves (non-recyclable).

In this research, obtaining usable training data is crucial, especially considering the impact of varying lighting conditions on the stability and accuracy of the model. The data used for training the image recognition model for waste classification is primarily collected through a camera. The camera captures images of waste items, which are then processed by Google's Teachable Machine (TM) to train a model capable of classifying items as recyclable or non-recyclable. The training process relies on having a sufficiently large and diverse dataset to ensure that the system can accurately identify and classify items in various environments. In the context of waste classification, the system not only needs to recognize the objects themselves but also handle appearance changes caused by lighting conditions. These images are preprocessed before being fed into TM for model learning. Based on the above, since the device needs to handle various types of waste, the quality and diversity of the dataset are crucial for the model's accuracy.

Regarding this issue, the following important points should be considered:

1) Data collection: The waste classification device relies on image data captured by the camera. This data needs to be diverse to ensure the model can generalize well.
2) Image preprocessing: Preprocessing techniques such as histogram equalization, contrast adjustment, and noise reduction can be applied to improve image quality, thereby reducing the impact of poor lighting conditions.

3) Model training: The success of the model depends on the quality and quantity of the training data, but potential issues include insufficient training data and overfitting. These issues can generally be addressed by balancing the training data, adding diverse training data, and adjusting hyperparameters.

The primary advantage of this system lies in its ability to implement a highly practical intelligent waste classification device using low-cost hardware components and free open-source software. The system advantages of this intelligent waste classification device are outlined as follows:

1) Low cost: The system is based on low-cost hardware such as Raspberry Pi and TM, making it significantly more affordable compared to traditional industrial-grade waste classification systems.
2) High accuracy: Using deep learning techniques for image recognition, the system can adapt to complex environmental changes, ensuring high classification accuracy.
3) Scalability: The system can be extended by adding more classification categories or optimizing the classification algorithm to suit different application scenarios.
4) Practicality: The system is suitable for households, offices, and public spaces, effectively reducing human involvement and enhancing the efficiency of waste classification.

6. Conclusion

This study successfully demonstrates the design and implementation of an intelligent waste classification device, leveraging a Raspberry Pi, a camera, and Google's Teachable Machine for image recognition. The device is meticulously engineered to enhance recycling efficiency by accurately identifying and categorizing waste into recyclable and non-recyclable types. The intelligent waste classification system operates primarily under the control of the Raspberry Pi, which processes images captured by the camera. These images are then fed into a model trained using Teachable Machine, enabling effective waste classification. The integration of TensorFlow and Keras within the Python programming environment has proven to be highly effective for real-time image processing and classification tasks.

The classification capabilities of the device were rigorously tested with various waste types, including glass bottles, paper cups, waste paper, aluminum cans, and plastic bottles as recyclable items; and face masks, polystyrene, plastic bags, food waste, and leaves as non-recyclable items. The results confirmed the system's ability to accurately classify all tested waste types with a 100% success rate. This highlights the robustness of the machine learning model and the overall efficiency of the system. This study provides essential insights into the design and application of intelligent waste classification systems, demonstrating the significant potential of combining hardware and advanced machine learning techniques. Future work could focus on refining the model for even more diverse waste types, enhancing the system's robustness, and exploring its integration with larger waste management infrastructures. The findings of this study underscore the importance of innovative technological solutions in addressing contemporary environmental challenges, paving the way for more sustainable and efficient waste management practices.

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