Garbage Sorting in Waste Management

Alfiya Sheikh[1], Bhavika Makode[2], Vanshika Makode[3] Zoya Khan[4], Dr.Dhananjay Dumbere[5]

[1,2,3,4] *student, Department of Computer Science and Engineering*

[5] *Assistant professor. Department of Computer Science and Engineering*

Rajiv Gandhi College of Engineering Research and Technology, Chandrapur, Maharashtra, India

Abstract: Using an ESP32 camera, the device captures multiple images of objects placed against a clear background, generating a dataset categorized into three classes: empty, metal, and plastic. These images are then processed and labeled using the Edge Impulse platform.The model employs a three-layer object detection framework with two output labels—plastic bottle and metal can—and undergoes 60 iterations of training. The code leverages Edge Impulse's FOMO (Faster Objects, More Objects) model for lightweight and real-time object detection on the ESP32 platform.Additional hardware includes LEDs and a servo motor for physical object sorting. The servo motor, controlled via the ESP32, enables mechanical separation based on the detected object type. This integrated system provides an efficient and low-cost solution for automated garbage sorting.

I. INTRODUCTION

Waste management is a critical challenge in modern society, with significant environmental and economic implications. Effective recycling and separation of waste materials, particularly plastics and metals, are essential for reducing landfill use and promoting sustainable resource use. However, manual sorting processes are labor-intensive and prone to inefficiencies, underscoring the need for automated solutions. This project introduces a smart garbage sorting device designed to automate the separation of metal and plastic waste. Leveraging advancements in machine learning and embedded systems, the device uses an ESP32 camera to capture images of waste items and classify them using a lightweight object detection model. The system integrates Edge Impulse's FOMO (Faster Objects, More Objects) framework for efficient real-time detection, enabling it to distinguish between plastic bottles and metal cans.The device is equipped with a servo motor to physically sort items into designated bins based on classification results. LED indicators provide visual feedback, while the entire process is controlled by an Arduino-based program tailored to the ESP32 hardware. This solution demonstrates a practical approach to integrating AI and IoT technologies for improving waste management efficiency and accuracy.

II. LITERATURE REVIEW

A. Waste Sorting Technologies: Automated waste sorting is a growing field that integrates image processing, machine learning, and robotics to address waste management challenges. The reviewed garbage sorting device employs cutting-edge object detection and classification techniques to distinguish between plastic and metal, contributing to efficient recycling practices.

B. Dataset Creation and Labeling : Dataset creation and labeling are fundamental steps in the sorting device's development. The process includes uploading images to platforms like Edge Impulse for feature generation and training outputs. Specifically, labeling the images for "plastic bottles" and "metal cans" provides the necessary groundwork for accurate classification.

C. Machine Learning for Classification: The sorting device employs a three-layer object detection model trained with 60 iterations. This emphasizes the importance of iterative training to improve model accuracy in distinguishing between different waste types.

D. Hardware Utilization: An ESP32 camera module is used for image capture, which provides high-quality images essential for machine learning models. The integration of the ESP32 camera with Edge Impulse demonstrates the application of low-cost hardware in real-world waste management.

E. Implementation of Actuation Systems: The inclusion of servo motors and LEDs in the device supports the physical sorting process and feedback mechanisms. Servo motors position the waste items, while the LEDs provide status indicators, enhancing the system's usability.

F. Technological Integration: Using libraries like EdgeImpulse_FOMO and esp32cam, the device bridges TinyML (Tiny Machine Learning) with embedded systems. This integration allows the execution of complex machine learning models directly on constrained hardware.

III. RELATED WORK

1.Dataset Creation

> Object Placement: Objects (e.g., plastic bottles and metal cans) are placed in front of a camera with a clear background to ensure accurate detection.

> Image Capture: Multiple images of each object are captured to form a dataset. This helps create a diverse and robust dataset for training.

Dataset Categories: The dataset is categorized into three classes:

1.Empty: Background or no object.
2.Metal: Metal cans.
3.Plastic: Plastic bottles.

2. Data Processing and Training

> Edge Impulse: The dataset is uploaded to the Edge Impulse platform for machine learning tasks.

>Labeling: Images in the dataset are labeled according to their respective categories. This step is critical for supervised learning.

>Model Training: A three-layer object detection model is trained:

1.It uses two labels (metal and plastic).

2.The training involves 60 iterations for the FOMO (Faster Objects, More Objects) detection framework.

3.FOMO enables efficient object detection, even on resource-constrained devices like the ESP32 camera.

3. Hardware Components

>ESP32 Camera: Functions as the primary imaging device. Configured for high-quality image capture (VGA resolution and high saturation).
>Servo Motor: A servo is attached to a pin on the ESP32 to handle the physical sorting mechanism.

Based on the detection result, the servo moves to separate metal from plastic.

>LED Indicators: The device is equipped with red, green, and blue LEDs for signaling purposes.

>Torch Pin: Used for additional lighting, if needed, during image capturing

4. Code Overview

>The code initializes and configures the ESP32 camera for image capturing. It integrates Edge Impulse's FOMO model for object detection.

>Key processes include:

1.Capturing images from the camera.

>Running the FOMO model to detect objects (plastic bottles or metal cans).

>Sorting based on detection results.

Error-handling mechanisms are embedded for situations like failed image capture or model execution.

5.Sorting Process

>Detection Output: If the detected object is a plastic bottle, the servo moves to place it in a specific bin. Similarly, metal cans are directed to another bin.

>If no object is detected, no action is taken.

>LED Feedback: LEDs may provide visual feedback on detection results or device status.

4. Detected objects or text are passed to the TTS engine for conversion to audio.
5. The user hears an audio description of the environment, helping them navigate or understand the scene.

IV. KEY FEATURES

A. Hardware Features

Camera-Based System: Utilizes an ESP32 camera with VGA resolution and enhanced saturation to capture images for object detection. Servo Motor Integration: A servo motor is used to physically sort detected objects into categories like metal and plastic. LED Indicators: Red, green, and blue LEDs are included to provide visual feedback during operation.

B. Image Dataset

Multiple Image Captures: Objects are placed against a clear background for multiple image captures to create a robust dataset.

Three Dataset Categories: The datasets are divided into:

Empty

Metal

Plastic

C. Machine Learning Integration

1.Edge Impulse Platform:

2.Images are uploaded for preprocessing and labeling.

3.Labels include specific object types such as plastic bottles and metal cans.

4.Training Model: A three-layer object detection model with two labels trained for 60 iterations.

5.FOMO (Feature Optimized Object Detection): Used for lightweight and efficient object detection on the ESP32.

D. Code Functionality

1.Error Handling: The program checks for errors during camera initialization and model execution, ensuring robust operation.

2.Real-Time Object Detection: The system uses the FOMO model to classify objects in real-time.

3.Control System: Outputs are connected to servo motors for sorting and LEDs for feedback.

E. Work flow

1.Image Capture: Captures and processes images using the ESP32 camera.

2.Object Detection: Runs the trained FOMO model to classify objects.

3.Actuation: Activates the servo motor to sort the object based on its classification.

4.Feedback: LEDs provide status updates or indicate results.

V. EVALUATION

A. Strengths

Utilizes low-cost hardware (ESP32 camera) and accessible tools (Edge Impulse). The integration of FOMO ensures fast and efficient object detection.

The multi-layer model provides flexibility in detection accuracy and efficiency.

B. Limitations

The system currently supports only two labels (Plastic and Metal), which limits its sorting capability. Training iterations (60) may be insufficient for higher accuracy or complex datasets. The setup relies on clear backgrounds, which may reduce performance in real-world, cluttered environments.

C. Recommendations for Improvement

Increase the number of training iterations and expand the dataset to include more object types and varied conditions. Enhance background handling to improve robustness in diverse environments. Optimize servo movements for faster sorting and add mechanical improvements for reliability

VI. FUTURE WORK

In the future, we plan to enhance the Model with the following features:

Expanded Dataset and Training:

Increase Object Categories: Extend the model to detect additional types of waste, such as glass, paper, and organic materials, making the device suitable for broader recycling applications.

Diverse Backgrounds: Include images with varied and cluttered backgrounds to improve real-world performance.

Larger Dataset: Collect and label a significantly larger dataset to improve the model's accuracy and generalizability.

Improved Hardware Integration

High-Resolution Cameras: Upgrade the ESP32 camera to a higher-resolution module for better image clarity and detection accuracy.

Enhanced Sorting Mechanism: Design a more robust and faster mechanical sorting system with conveyors or robotic arms.

Power Efficiency: Optimize the device for lower power consumption to make it more energy-efficient and suitable for deployment in remote locations.

Advanced Machine Learning Models

Model Optimization: Experiment with more advanced machine learning algorithms for higher accuracy, such as CNNs or lightweight transformers.

Edge AI Enhancements: Incorporate more advanced Edge Impulse features or other TinyML frameworks to improve real-time performance.

Dynamic Learning: Implement online learning for the device to adapt to new objects and environments dynamically.

IoT and Cloud Integration

Cloud Data Storage: Upload sorting data to the cloud for analytics, reporting, and tracking waste statistics.

Remote Monitoring: Allow remote monitoring and updates through IoT platforms, enabling centralized control of multiple devices.

User Feedback: Develop a user interface or mobile app to provide feedback, alerts, and performance insights to users.

VII. CONCLUSION

This mini project demonstrates a practical and efficient solution for separating metal and plastic using AI. By integrating machine learning algorithms with sensors, the project achieves accurate and automated sorting, significantly reducing human effort and errors. This innovation not only enhances the efficiency of recycling processes but also supports environmental sustainability by facilitating better waste management. With further improvements and scalability, this AI-powered sorting system has the potential to become an essential tool in modern recycling facilities, contributing to a cleaner, more sustainable future.

VIII. REFERENCES

YouTube Tutorials on Object Detection with AI

Search for beginner tutorials on "object detection with AI" or "machine learning for image classification." These tutorials often use libraries like TensorFlow or OpenCV, which are helpful for building a model to recognize metal and plastic.

Google Scholar

Search for papers on "AI in recycling" or "AI for material sorting." Look for articles that explain the basics of using AI for waste management. Even just reading the abstract and conclusions can give you useful ideas.

TensorFlow and PyTorch Documentation

These popular AI libraries have beginner-friendly tutorials on image classification and object detection. You can use these tutorials to train a model to detect and classify materials.

Arduino and Raspberry Pi Resources

If you plan to add sensors for metal detection, check Arduino or Raspberry Pi guides. These platforms provide tutorials on connecting sensors, which could be used to detect metal versus non-metal objects.

Articles on AI in Recycling

Websites like Medium or Towards Data Science have articles explaining how AI is transforming recycling. Search for terms like "AI for recycling industry" or "machine learning in waste sorting."

OpenAI's Introductory Guides

OpenAI's blog and documentation offer simple explanations of AI concepts, which can help in understanding the fundamentals of machine learning and how it can apply to sorting materials.