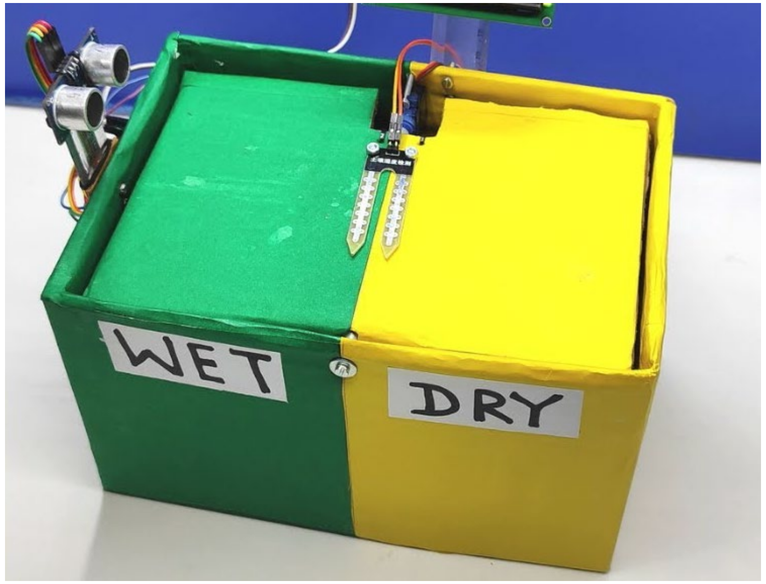
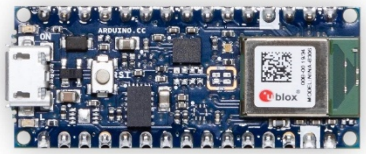
Smart Waste Segregation
using Arduino BLE
CP330 Project





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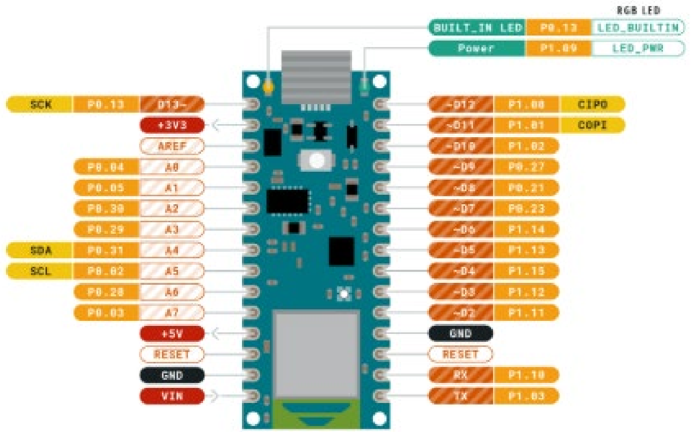
Edge AI

Introduction

Problem Statement

Waste separation is critical for improving recycling efficiency and reducing environmental impact. Traditional manual methods are slow, inconsistent, and labor-intensive.

Today, the world generates over 2 billion tons of solid waste annually. In many regions, waste is dumped into mixed bins, making it difficult to separate organic, recyclable, and non-recyclable materials. Manual segregation at landfills or recycling centers is labor-intensive, slow, expensive, and often inaccurate. As a result, huge amounts of potentially recyclable materials end up in landfills or incinerators, worsening environmental pollution and wasting valuable resources.



Importance of Segregation

- Increase recycling efficiency
- Reduce contamination in recycling streams
- Cut down landfill waste and greenhouse gas emissions
- Lower sorting costs and improve worker safety
- Support a circular economy, where materials stay in use longer

Motivation and Objectives

Motivation

We face a growing waste problem where most trash is mixed together, making recycling harder, more expensive, and less effective. Current waste systems often rely on manual sorting, which is slow and prone to mistakes. This project aims to use smart technology — like Edge AI and machine learning — to automatically identify and separate different types of waste. By doing this, we can improve recycling rates, cut down on landfill waste, and help create cleaner, more efficient waste management systems that can work at a large scale in cities and industries.

Objectives

- Develop an Edge AI system capable of accurately classifying and separating different types of waste.
- Integrate the system on that works offline and uses minimal power.
- Test and evaluate performance in terms of classification accuracy, speed, and energy efficiency.
- Create a scalable solution that can be implemented in smart bins, recycling stations, or small-scale facilities.
- Contribute to reducing landfill waste, improving recycling rates, and supporting global sustainability goals.

Long Term Vision

- Scale the Edge AI waste segregation system to municipal waste management systems across cities.
- Deploy smart, automated segregation units in households, offices, schools, and public spaces to enable source-level sorting.
- Expand the technology's application to industrial waste, hazardous waste, and e-waste segregation.

Impact Potential

- Increase recycling rates by improving the quality and purity of sorted waste streams.
- Reduce landfill overflow and the environmental damage caused by improper waste disposal.
- Cut operational costs for waste management companies by automating labor-intensive tasks.
- Lower carbon footprint by enhancing the efficiency of recycling and reducing virgin material extraction.

Methodology

Hardware Setup

We used an Arduino Nano 33 BLE Sense board, equipped with sensors and connected to an OV7675 camera module, to capture live waste images.

Data Collection & Annotation

Images of wet waste, cardboard, and plastic were collected directly from the device, then labeled to create a focused training dataset.

Model Development

Using Edge Impulse platform to preprocess the data and train a lightweight image classification model for the Arduino Nano's limited memory and processing power.

Model Deployment

The trained model was compiled and deployed onto the Nano 33 BLE Sense, enabling it to perform real-time inference without relying on cloud processing.

Real-time Classification & Output

When waste items were placed in front of the camera, the device classified them and provided classification results

Performance Evaluation

We tested the system's accuracy and response speed, identifying areas where lighting, image clarity, or more affected model performance, for further tuning

Data Collection

Target Waste Categories

We initially worked with **six categories**, including wet waste, cardboard, plastics, and others, collecting **~100 images per category**.

Image Capture Process

Phase 1: Collected images using a smartphone to quickly build the base dataset.
Phase 2: Captured images directly using the OV7675 camera module connected to the Arduino Nano 33 BLE Sense for real-world, device-specific data.

Data Preparation and Augmentation

Applied dimension reduction (resizing) and grayscaling to images to fit within the memory and processing limits of the Edge AI model.
Ensured balanced class distribution to avoid bias in training.

Final Dataset Use

Uploaded and labeled all data within Edge Impulse's platform.
Used the prepared dataset for training, validation, and deployment.

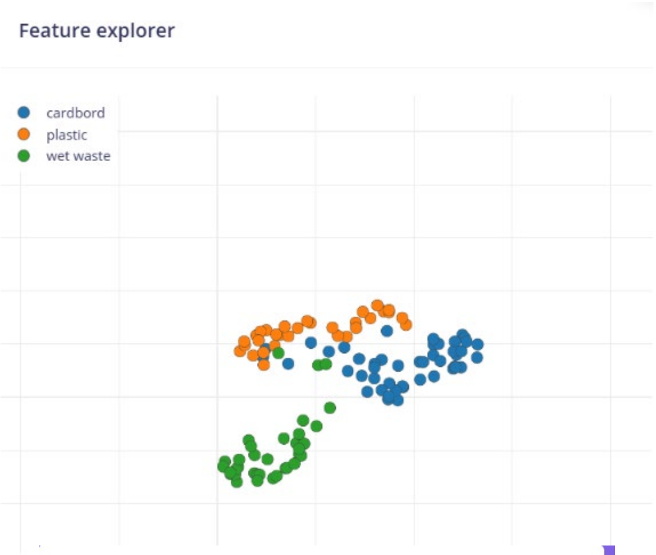




Model Development

- We developed and trained the image classification model using Edge Impulse, experimenting with different model architectures, including MobileNet and other lightweight CNNs, to find the best fit for our embedded system.
- We performed tuning on Edge Impulse, adjusting parameters like learning rate, number of epochs, and data augmentation strategies to improve model performance and avoid overfitting.
- After comparing models, we selected the quantized (int8) version, which provided excellent accuracy (92.86%) while reducing RAM usage by 18% and ROM by 15% compared to the unoptimized (float32) version, making it ideal for the Arduino Nano 33 BLE Sense.
- The final model achieved 100% accuracy on the validation set, with perfect precision, recall, and F1 scores across all categories (cardboard, plastic, wet waste), and operated efficiently with a total latency of ~570 ms using the EON compiler.

	IMAGE	TRANSFER LEARNI...	TOTAL
LATENCY	7 ms.	563 ms.	**570 ms.**
RAM	4.0K	213.1K	**213.1K**
FLASH	-	575.2K	-
ACCURACY			**92.86%**



Model — Model version: Quantized (int8)

Last training performance (validation set)

ACCURACY 100.0%

LOSS 0.04

Confusion matrix (validation set)

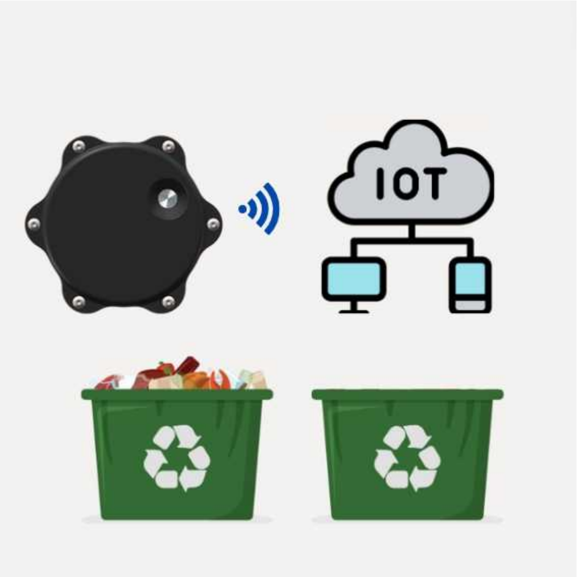
	CARDBORD	PLASTIC	WET WASTE
CARDBORD	100%	0%	0%
PLASTIC	0%	100%	0%
WET WASTE	0%	0%	100%
F1 SCORE	1.00	1.00	1.00

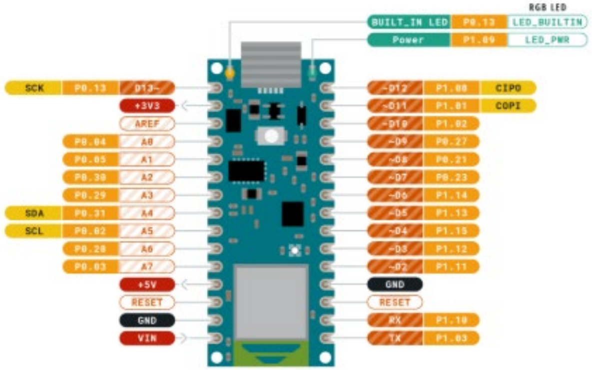
Metrics (validation set)

METRIC	VALUE
Area under ROC Curve	1.00
Weighted average Precision	1.00
Weighted average Recall	1.00
Weighted average F1 score	1.00

Future Developments

- **Expand Categories:** Increase the number of waste categories (e.g., metals, glass, textiles) to improve real-world sorting capabilities and broaden application scope.
- **Larger, More Diverse Dataset:** Collect and train on a larger, more varied dataset to improve model generalization across lighting, backgrounds, and object variations.
- **On-device Optimization:** Further optimize the model for even lower latency and power consumption, enabling continuous real-time sorting in energy-constrained environments.
- **Integration with Robotics:** Combine the model with robotic arms or *conveyor systems* to create automated waste sorting lines, increasing recycling efficiency and reducing manual labor.
- **Scalability & Impact:** Deploy at community recycling centers, urban waste facilities, or even home-level smart bins to significantly reduce landfill waste, improve recycling rates, and support circular economy goals.





Smart Waste Segregation
using Arduino BLE

Thanish Nasir (CST), Sathvik (CDS), Sindhura (CSA), and Pandarasamy Arjunan

Edge AI 2025

Background and Motivation

- We are increasingly facing challenges in managing and sorting waste efficiently, as improper waste segregation leads to environmental damage and lost recycling potential. Motivated by the need for smart, accessible solutions, we set out to develop a lightweight, AI-powered system using the Arduino Nano BLE Sense and Edge Impulse to automatically classify waste types. Our goal is to create a system that not only improves sorting accuracy but also supports sustainability efforts by making waste management smarter, faster, and more scalable.

Objectives

- To develop an AI-based waste classification system using Arduino Nano BLE Sense and Edge Impulse. Our aim is to improve waste segregation accuracy and support sustainable waste management practices.

Dataset / Data collection

- Collected ~100 images per category across six waste types (initially using phone, later OV7675 camera).
- Applied preprocessing like grayscale conversion and dimensionality reduction to fit model constraints.
- Built a balanced, augmented dataset optimized for training on lightweight embedded AI models.

Edge AI Model

- Model Compression: We used quantization (int8) to reduce model size without sacrificing accuracy
- Size Before and After Compression: Reduced from ~296 KB (float32) to ~80 KB (int8), saving ~70% memory.
- Performance: Maintained 100% validation accuracy with high precision, recall, and F1 scores across categories.
- Latency: Achieved an inference latency of ~570 ms per image using the EON compiler on the Nano BLE Sense.

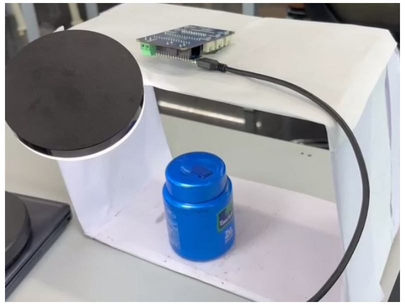
Hardware

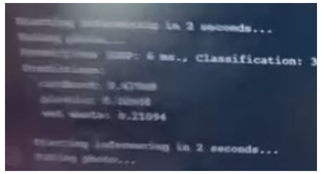
- Arduino Nano 33 BLE Sense (nRF52840, 64 MHz ARM Cortex-M4, 1 MB flash, 256 KB RAM)
- OV7675 Camera Module (low-cost, 640x480 resolution)
- Micro-USB connection for power and data transfer

Software

- Edge Impulse Studio (for data collection, model training, and deployment)
- Arduino IDE + Edge Impulse firmware (to run and test the model on device)

Prototype & demonstration





https://github.com/thanishnasir/SmartWasteSeginator