Smart Waste Segregation using Arduino BLE and Edge AI

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***Abstract*—This paper presents a smart waste segregation system using OV7675 camera module and the Arduino Nano 33 BLE Sense. The system classifies waste images in real time to improve recycling efficiency and reduce environmental impact. The project uses TinyML techniques and Edge Impulse Studio to deploy a lightweight waste classification model on low-power embedded hardware. Despite the challenges posed by limited resources, such as low RAM, ROM, and camera resolution, the system demonstrates the potential for scalable waste management solutions.**

***Index Terms*—Smart Waste Segregation, Edge AI, TinyML, Arduino, Waste Classification, Image Processing, BLE, OV7675 Camera.**

I. Overview

Waste segregation plays a crucial role in improving recycling efficiency and reducing environmental impact. Traditional methods of waste sorting are labor-intensive, slow, and inefficient. With the global increase in waste generation, the need for automated, efficient waste segregation has become critical. This project aims to address the problem of manual waste sorting by developing an Edge AI system that automatically classifies and segregates waste materials. Using an Arduino nano BLE 33 sense lite device and the OV7675 camera, the system aims to improve recycling rates, reduce landfill waste, and promote sustainability.

II. Background and Motivation

The world's waste problem is escalating, with over 2 billion tons of solid waste generated annually. Most of this waste ends up in mixed bins, making recycling and waste management a challenge. The lack of an efficient system to automatically segregate waste has led to the reliance on manual sorting, which is costly, slow, and often inaccurate. This inefficiency results in recyclable materials being discarded, further contributing to environmental degradation. The motivation for this project is to leverage Edge AI and machine learning to develop an automatic waste segregation system that can classify and separate waste types such as cardboard, plastic, and wet waste, thereby enhancing recycling processes, reducing waste sent to landfills, and supporting a circular economy.

III. Challenges with BLE and OV7675 Camera

The Arduino Nano 33 BLE Sense lite, and the OV7675 camera, which provides a relatively low resolution, present several limitations when deploying an image classification model. These limitations impact both the model's performance and the practical deployment of the system.

A. Low Camera Resolution

The OV7675 camera, with a resolution of just 640x480 pixels, is relatively low when compared to other modern cameras with higher resolutions. This low resolution poses challenges in image classification, especially when dealing with objects that require fine-grained details for accurate classification. However, by using image preprocessing techniques and reducing the image size (down to 64x64 pixels), we were able to make the system work effectively for waste segregation tasks.

B. Limited RAM and ROM

The Arduino Nano 33 BLE Sense, despite being a capable low-power device,has 1 MB of flash memory and 256 kB of RAM. Deploying a complex image classification model such as ours, which involves deep learning techniques, poses significant challenges in terms of memory and storage. The model must be extremely optimized to fit within these constraints, requiring careful consideration of memory usage during model development and deployment.

In our case, the full six-class model was too large to fit within the available memory. Therefore, we reduced the number of classes from six to three—cardboard, plastic, and wet waste. This change allowed the model to fit within the limited ROM and RAM of the device without compromising too much on accuracy.

C. BLE's Limited Processing Power

Another challenge in using the Arduino BLE is its processing power. BLE devices are not designed for intensive computational tasks like real-time image classification. While the Arduino Nano 33 BLE Sense has a 32-bit ARM Cortex-M4 processor, it is still much slower compared to more powerful processors in standard computers or mobile phones. This limitation is particularly evident when trying to handle large images or complex models.

To address these constraints, we used the EON compiler to optimize the model for BLE devices, ensuring efficient inference with reduced latency and memory usage. The quantized (int8) version of the model was selected, which offered a good balance between accuracy and resource usage, with a reduction in RAM usage by 18% and ROM usage by 15%.

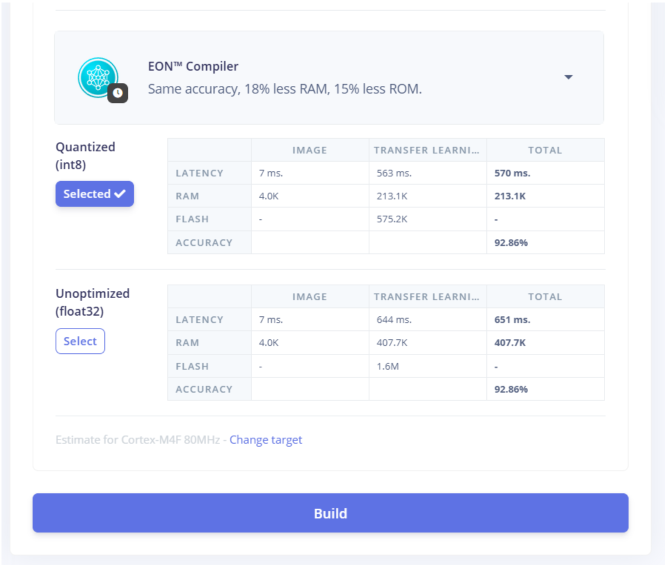

Fig. 1. EON compiler configuration for model quantization (int8).

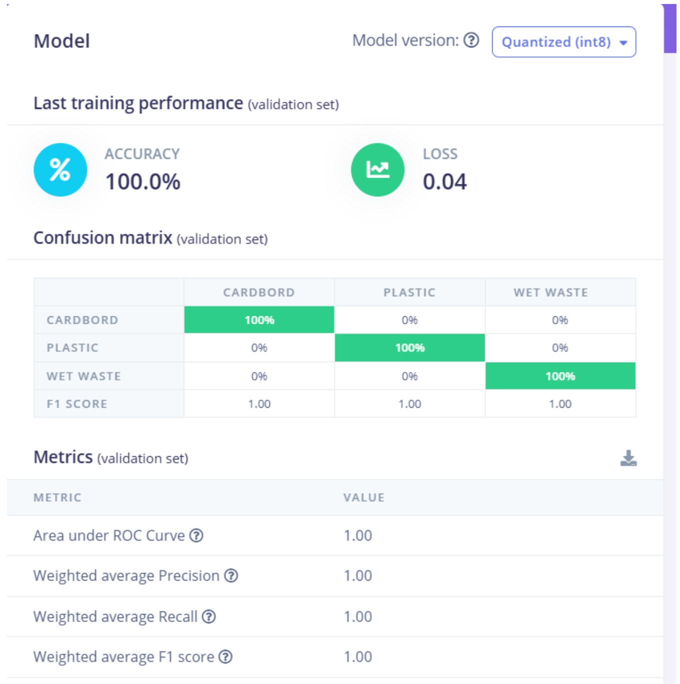

Fig. 2. Confusion Matrix of the model showing perfect classification accuracy (100% on the validation set) for all classes. The matrix highlights the model's performance across cardboard, plastic, and wet waste categories.

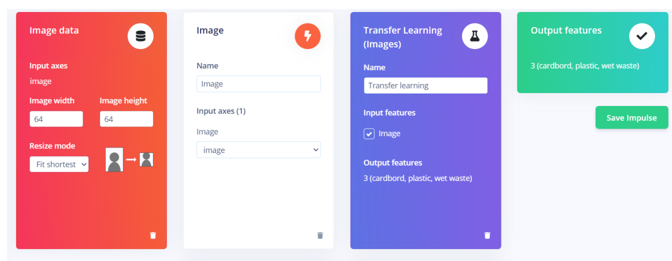

Fig. 3. Edge Impulse Studio showing the transfer learning configuration with output features for waste categories.

IV. Methodology

A. List of Hardware Required and Their Specifications

- **Arduino Nano 33 BLE Sense:** A low-power microcontroller , suitable for Edge AI applications. Specifications: 32-bit ARM Cortex-M4, 1 MB of flash memory and 256 kB of RAM.
- **OV7675 Camera Module:** A low-resolution camera used for capturing waste images for classification. Specifications: 640x480 resolution, suitable for low-cost solutions but limited for detailed image recognition tasks.

B. List of Software Used

- **Edge Impulse Studio:** For model development and training on the embedded system.
- **Arduino IDE:** To program the Arduino Nano 33 BLE Sense.
- **Python:** For pre-processing data.

C. Data Collection

Initially, we collected a dataset of 691 images across six classes using a phone camera setup above an A4 sheet. These images were manually labeled and organized into class-specific folders. To maintain a balanced training and testing process, we performed an 80-20 train-test split and uploaded the dataset to Edge Impulse through its image data uploader.

D. Model Development and Compression

We trained the model with data augmentation enabled and achieved 100% accuracy on both training and validation, and 92% accuracy during model testing. The model was quantized (int8) with the EON compiler enabled for efficient inference. We then deployed the model as an Arduino library, flashed it onto the Nano 33 BLE Sense, and successfully ran live inference using the `edge-impulse-run-impulse` command.

V. Prototype and Demo

A prototype of the smart waste segregation system was developed, which integrates the Edge AI model with the Arduino BLE Sense. The system is designed to operate autonomously, capturing images of waste materials and classifying them into categories such as cardboard, plastic, and wet waste. A demo of the system showed successful waste segregation, with the ability to classify waste types in real-time with high accuracy.

VI. Project Resources

The following resources are available for this project:

- **Github link:** https://github.com/thanishnasir/SmartWasteSeginator

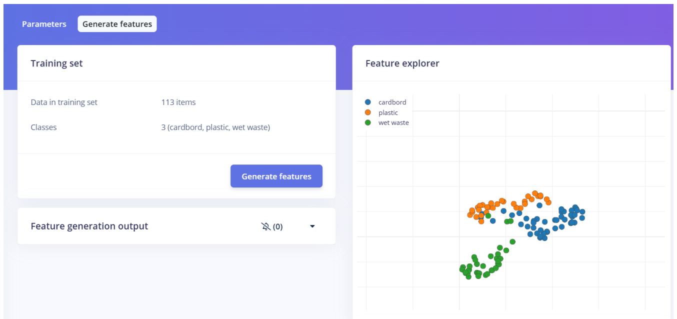

Fig. 4. Feature generation output for waste classification. Each class (cardboard, plastic, wet waste) is represented by distinct clusters.

VII. Challenges and Workarounds

Several challenges were encountered during the project:

- **Data Variability:** Variations in lighting and background conditions affected the model's performance.
  Solution: Data augmentation techniques were applied during training to improve model robustness.
- **Memory Constraints:** The Arduino Nano 33 BLE Sense has limited memory, which posed a challenge when deploying large models.
  Solution: The model was quantized to reduce memory usage, allowing it to run on the device with minimal resource consumption.
- **Low Camera Resolution:** The OV7675 camera's resolution was a limiting factor in classification accuracy.
  Solution: Image resizing and preprocessing techniques were employed to optimize the images for classification.

Interesting Learnings: This project provided valuable insights into the challenges of deploying machine learning models on embedded systems, especially regarding memory, computational constraints, and the limitations of low-cost camera modules like the OV7675. It also emphasized the importance of model optimization and the impact of Edge AI in real-world applications.

VIII. References

References

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