Edge-AI Waste Classification on OpenMV H7

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Abstract

This paper investigates the feasibility of real-time waste classification on microcontroller-class hardware by implementing an on-device computer vision model using the OpenMV H7 platform. The system classifies waste materials (glass, metal, paper, and plastic) directly from images, performing all computation locally. Using the TrashNet dataset and the Edge Impulse platform, we construct an end-to-end TinyML pipeline for preprocessing, model training, deployment, and evaluation. The quantized MobileNetV2 96×96 0.35 model achieves 72.1% validation accuracy and real-time inference at 36 ms per frame, with 215 KB RAM and 536 KB flash consumption. The results demonstrate that resource-constrained embedded vision systems can achieve practical accuracy and latency for sustainable waste management applications.

Index Terms

TinyML, Edge AI, Waste Classification, OpenMV, MobileNetV2, Edge Impulse, Embedded Vision

I. Introduction

Manual waste sorting is time-consuming and error-prone. Automated, vision-based classification can improve recycling efficiency and accessibility. Traditional solutions rely on cloud inference, incurring latency and privacy issues. Edge AI enables local inference, reducing cost, power, and dependency on connectivity. This work demonstrates an end-to-end waste classification system running entirely on the OpenMV H7.

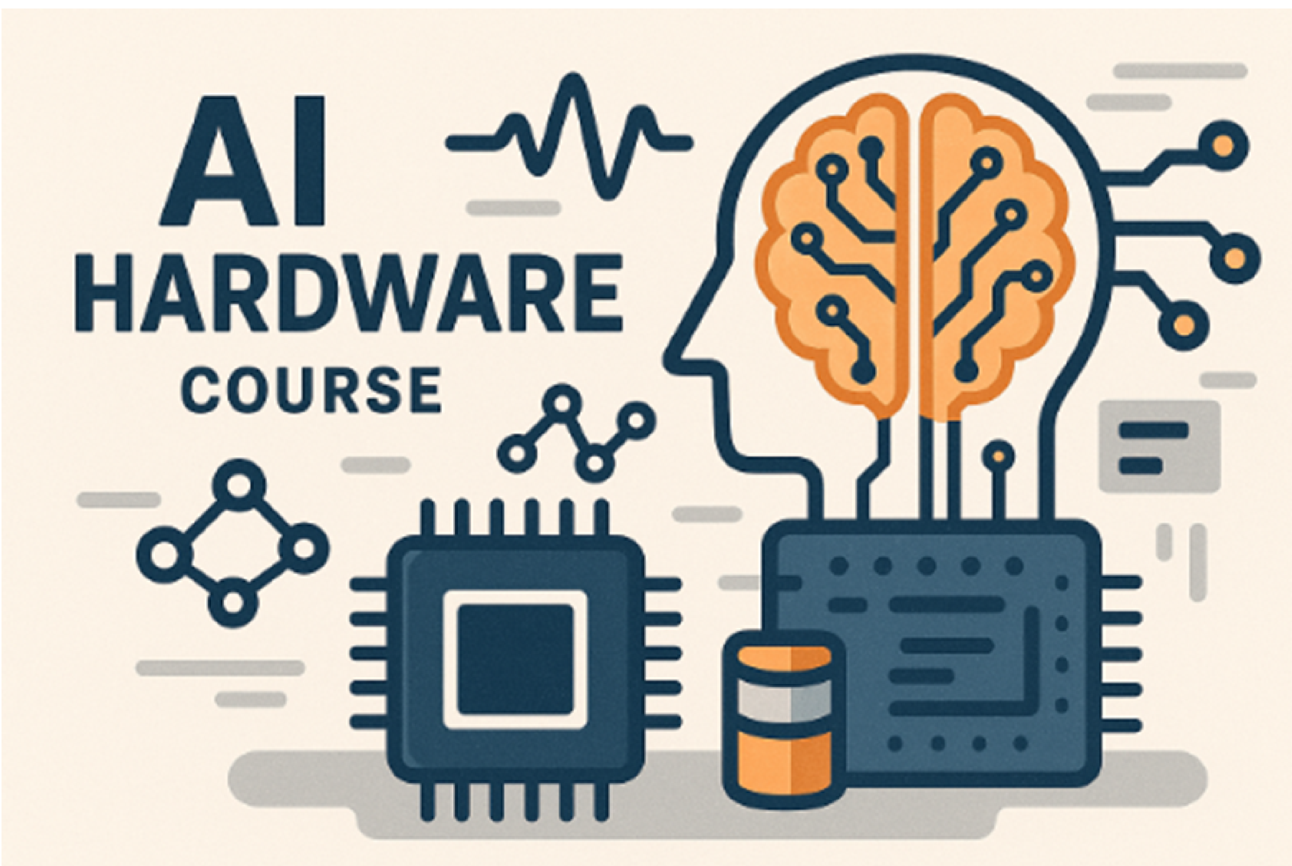

Fig. 1: Course/project banner image.

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II. Related Work

Waste classification is commonly modeled as image classification using convolutional neural networks (CNNs) trained on datasets like TrashNet. Larger CNNs such as ResNet or DenseNet provide high accuracy but require GPUs or cloud servers. TinyML offers a solution for deploying lightweight models to embedded devices. Edge Impulse facilitates this workflow by automating preprocessing, training, and MCU deployment. Previous open-source implementations are reported in [1]–[3].

III. Problem Definition

The objective is to classify one captured image from the OpenMV H7 camera into one of four waste material types: glass, metal, paper, or plastic. The model must meet strict real-time and memory constraints while maintaining acceptable accuracy. All computations are performed on-device, with predictions displayed in real time.

IV. Dataset and Preprocessing

The TrashNet dataset contains thousands of waste images across multiple classes. We filter it to four categories and resize to 96×96 pixels. Preprocessing includes grayscale conversion and normalization to fit memory limits. Within Edge Impulse, data augmentation enhances robustness to lighting and viewpoint variations.

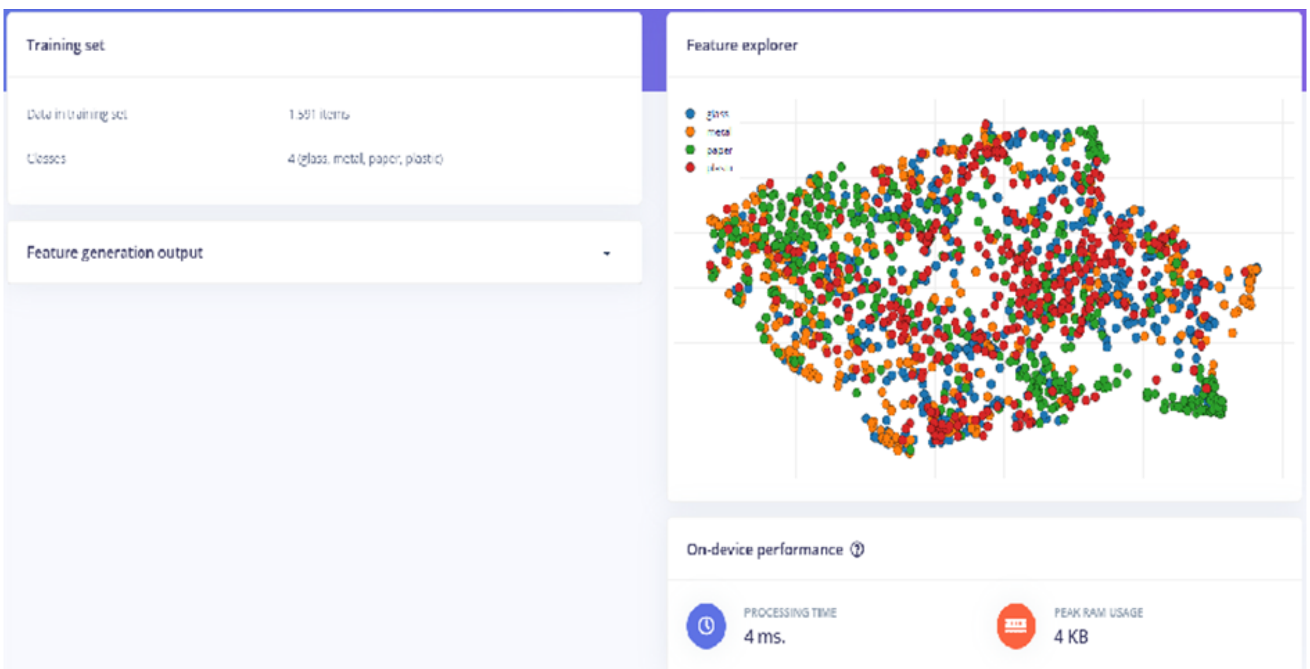


Fig. 2: Edge Impulse feature explorer / preprocessing view.

V. Model and Training

We adopt transfer learning with MobileNetV2 96×96 0.35 as the backbone. Training is performed for 45 epochs with a learning rate of 0.0005 and 20% validation split. Data augmentation (flip, rotation, brightness) improves generalization. The quantized model is exported as a TensorFlow Lite file and deployed to the OpenMV H7 for real-time inference.

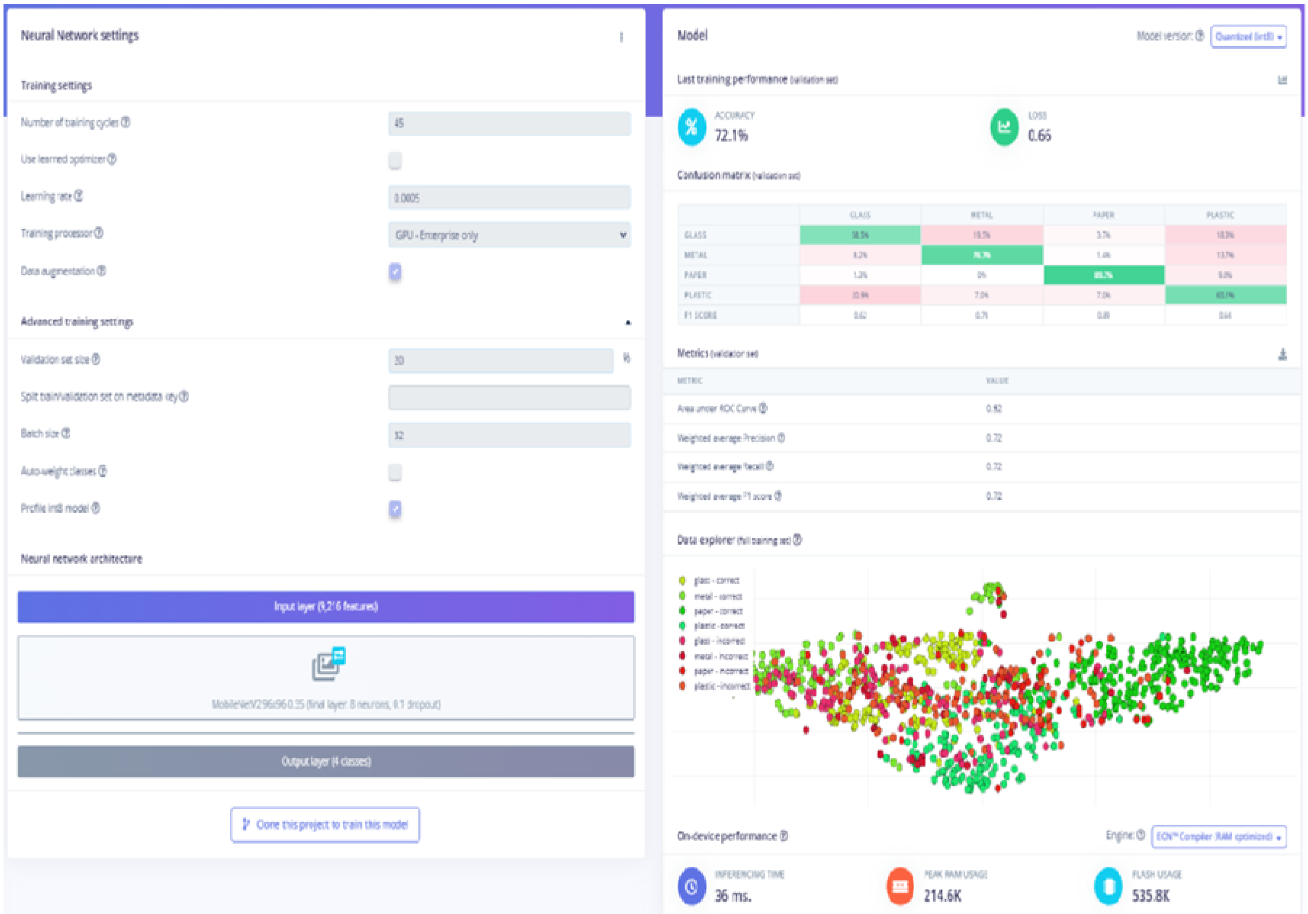


Fig. 3: Edge Impulse training configuration and model performance summary.

VI. Hardware Platform

The OpenMV Cam H7 Plus features an ARM Cortex-M7 processor at 480 MHz, with external RAM and flash sufficient for embedded vision tasks. It supports an OV5640 camera sensor and a MicroPython environment, suitable for low-latency, low-power computer vision applications.

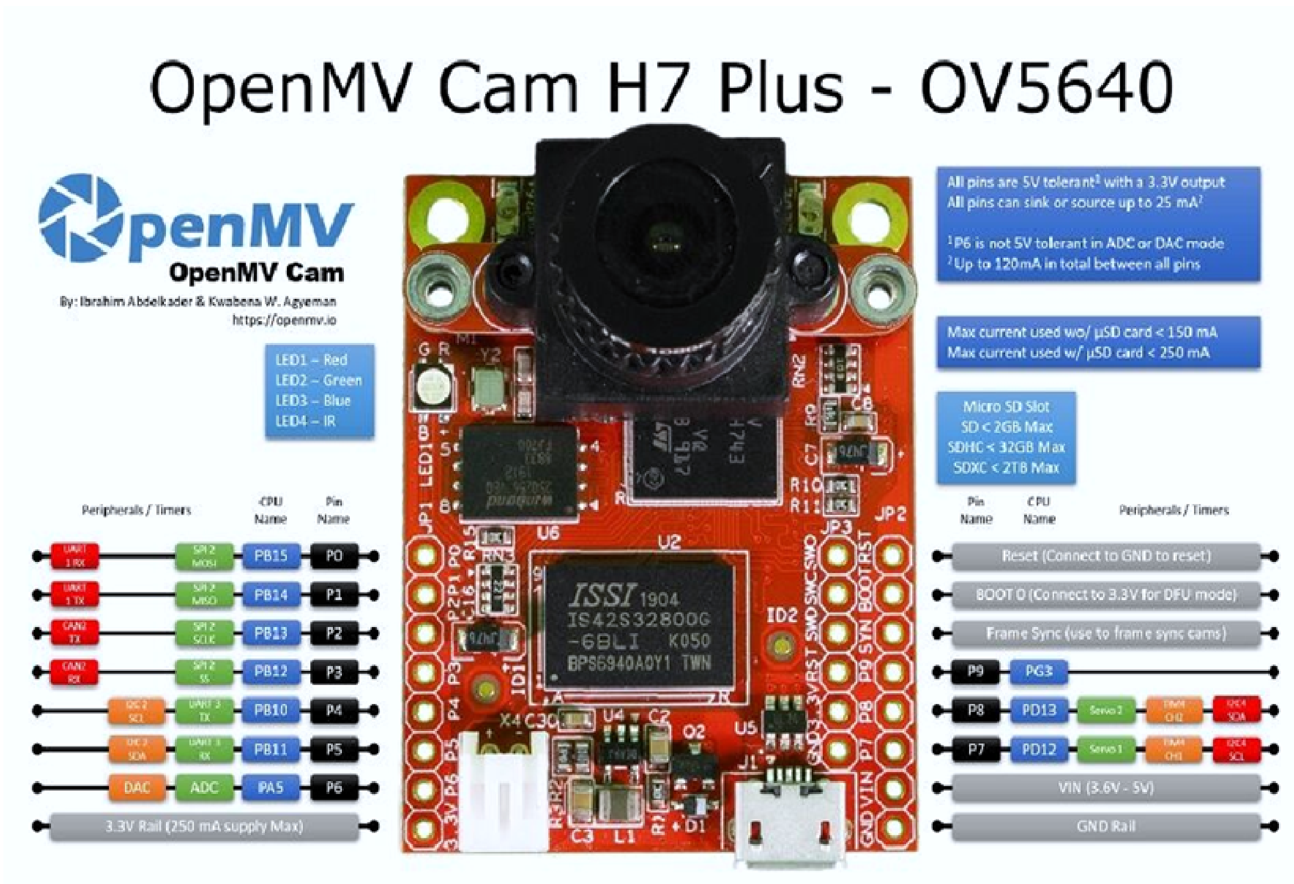


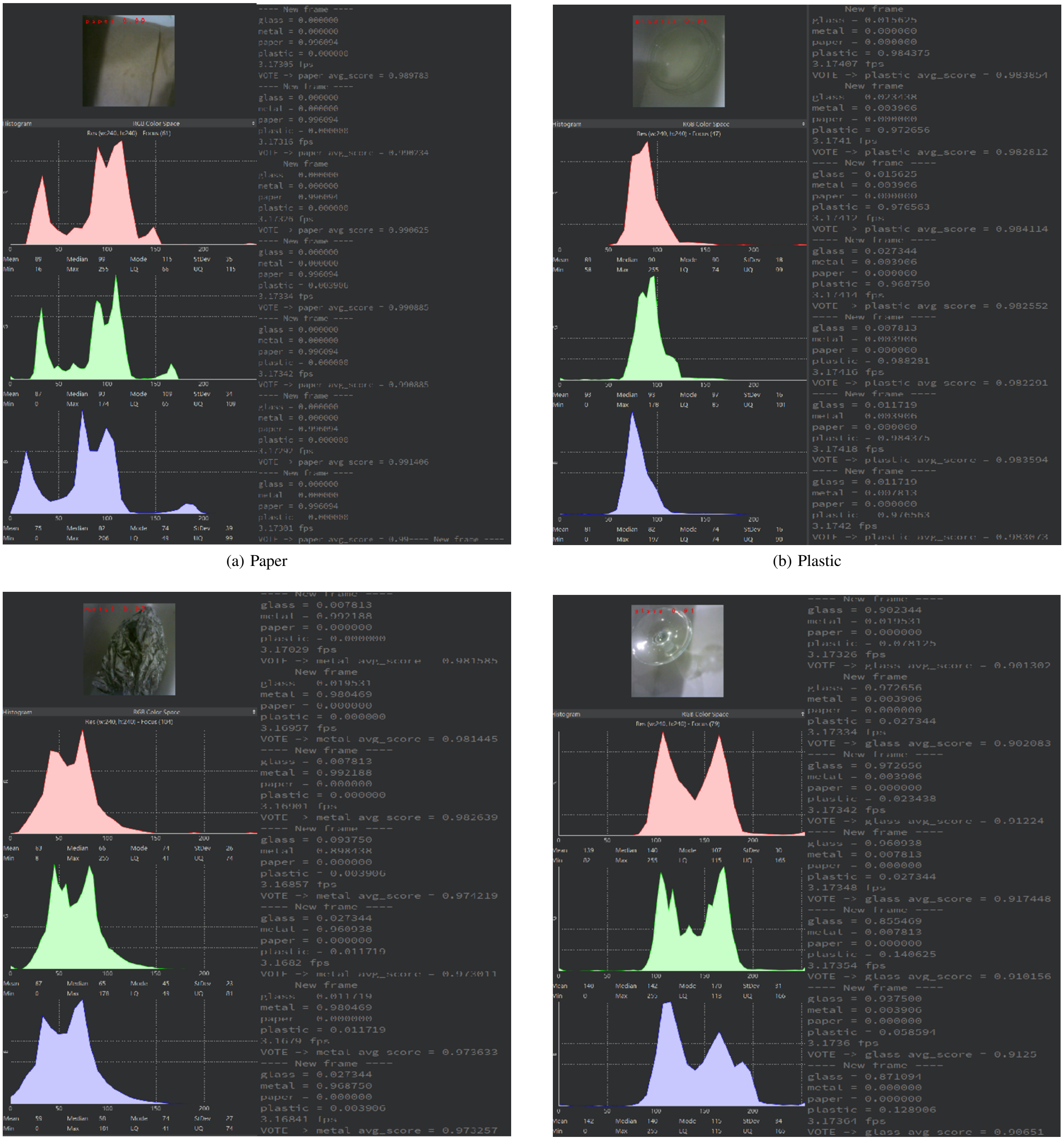
Fig. 4: OpenMV Cam H7 Plus hardware overview.

VII. Experimental Results

Validation accuracy reaches 72.1% with an AUC of 0.92. Paper achieves the highest recall, while glass and plastic are frequently confused. On-device inference runs at approximately 3.17 FPS (36 ms per frame), with stable predictions via majority voting across a short temporal window.

A. On-Device Qualitative Tests

We evaluate the deployed model on four representative household objects corresponding to paper, plastic, metal, and glass. The following screenshots illustrate the live camera view and serial output during testing.



(a) Paper (b) Plastic

(c) Metal (d) Glass

Fig. 5: On-device qualitative tests on OpenMV H7.

VIII. Discussion

The results validate that embedded MCUs can perform real-time visual classification. Accuracy is constrained by dataset mismatch and hardware limits. Reflective and transparent materials (metal, glass) reduce precision due to lighting sensitivity. The model balances trade-offs between speed, memory, and accuracy.

IX. Limitations and Future Work

The model generalizes moderately due to domain differences between TrashNet and live camera data. Future work will involve:

- Collecting OpenMV-native datasets under varied lighting and angles.
- Improving glass/metal robustness with targeted augmentation and sampling.
- Profiling the on-device pipeline to increase FPS (reduce logging/overlays).
- Exploring lighter backbones/quantization while maintaining accuracy.
- Expanding evaluation scenarios and improving UX feedback (LED/sound/icons).

X. Conclusion

We demonstrate an end-to-end TinyML waste classifier deployed entirely on the OpenMV H7 microcontroller. The system achieves $\sim$72% accuracy and real-time inference while fitting within tight RAM/flash constraints. This validates that embedded platforms can support meaningful, low-cost, and privacy-preserving computer-vision applications.

References

[1] V. Vohra, "Trashnet – deep learning based waste segregation project," https://github.com/vasantvohra/TrashNet, 2017.
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