DWaste: Greener AI for Waste Sorting using Mobile and Edge Devices

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Introduction

The growth of convenience packaging has increased waste generation [1], underscoring the need for efficient sorting. DWaste is an AI-powered waste sorting and data collection platform that runs directly on smartphones and edge devices, reducing reliance on cloud computing and internet connectivity.

Methods

- **Data:** Images collected from internet, DWaste platform, and community submissions were annotated into seven categories (biological, cardboard, glass, metal, paper, plastic, trash) using Annotate Lab.
- **Models:** Classification (EfficientNetV2S/M, MobileNet, ResNet50/101) and detection (YOLOv8n, YOLOv11n) models trained using transfer learning.
- **Evaluation:** Metrics included accuracy, precision, recall, F1-score, and mAP. We also compared VRAM usage, carbon emissions, and model size (before and after quantization).

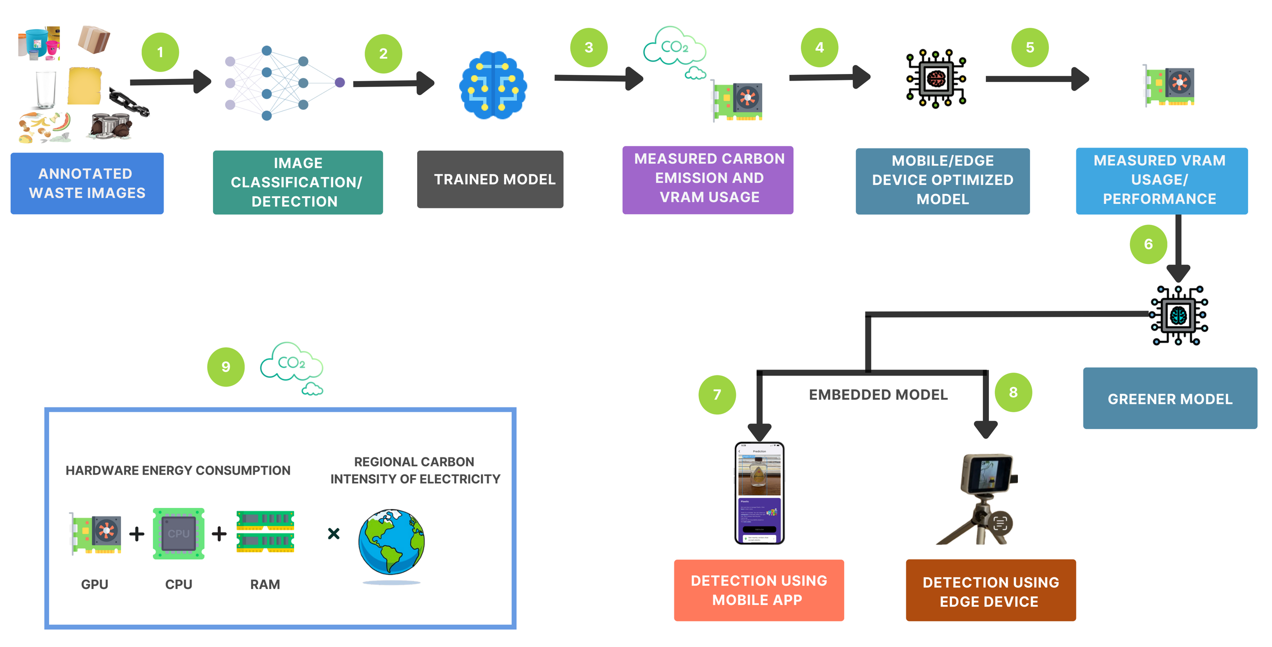

Figure 1: Process flow diagram

Results

- **EfficientNetV2M/S:** High accuracy (∼95%–96%) but large size and higher training/deployment emissions.
- **MobileNet:** Lowest size (14.7 MB → 3.5 MB quantized), minimal energy usage, but lower accuracy (∼67%).
- **ResNet50/101:** High accuracy (91-92%), large size and high emissions.
- **YOLOv8n / YOLOv11n:** Balanced performance (75–77% accuracy) with small model sizes (∼3 MB quantized), making them ideal for low-carbon, real-time use.

Table 1: Experimental results (best in bold).

Model	A	P	R	F1	mAP	Size (MB)	Q-Size (MB)
MobileNet	67.5	0.67	0.68	0.67	–	14.7	3.5
EffNetV2M	94.7	0.94	0.95	0.95	–	216.0	56.4
EffNetV2S	**96.0**	**0.96**	**0.96**	**0.96**	–	84.3	22.1
ResNet101	92.1	0.91	0.93	0.92	–	174.6	43.6
ResNet50	91.4	0.90	0.92	0.91	–	97.9	24.2
YOLOv8n*	75.5	0.78	0.65	0.75	0.76	6.5	3.1
YOLOv11n*	77.1	0.77	0.69	0.77	**0.77**	**5.4**	**2.8**

Note: **A** = Accuracy, **P** = Precision, **R** = Recall, **F1** = F1 Score, **mAP** = mean Average Precision, **Q-Size** = Quantized Size.
* Indicates object detection model.

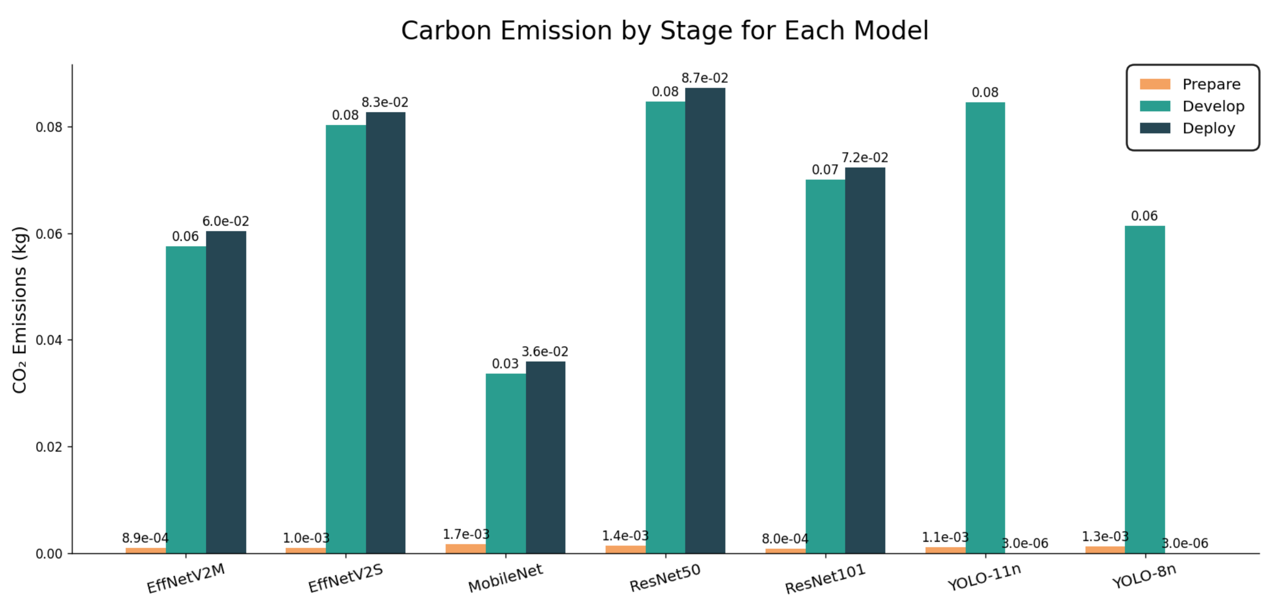

Figure 2: Carbon emission by stage for each model

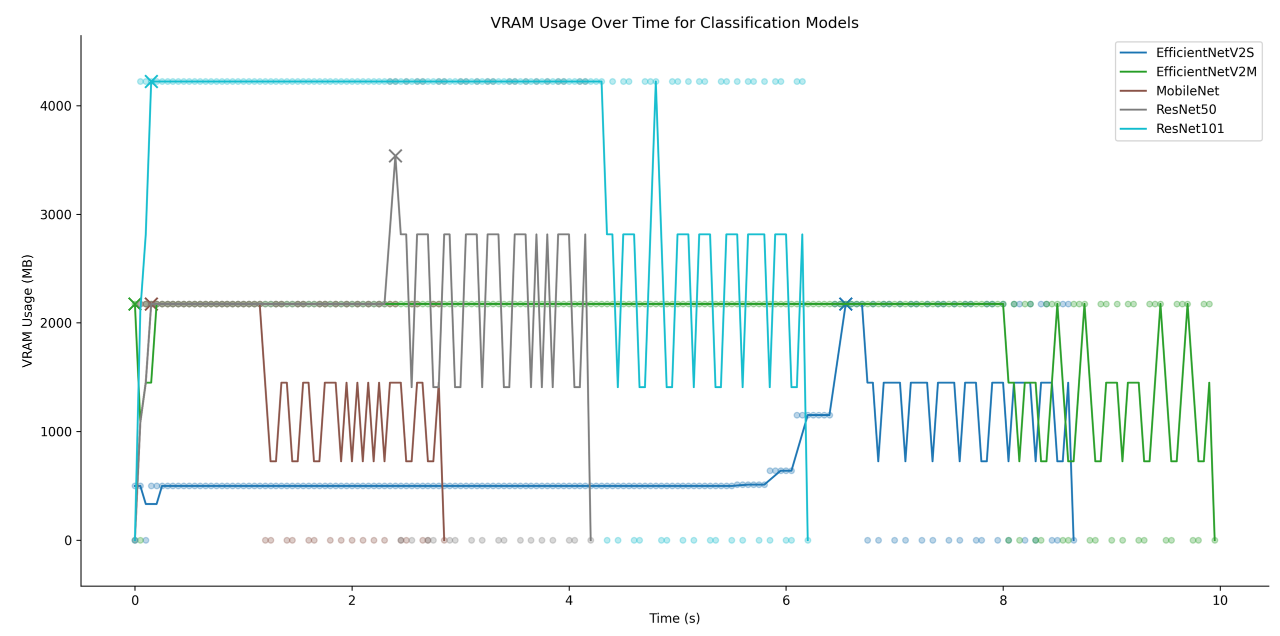

Figure 3: VRAM usage of classification models under inference

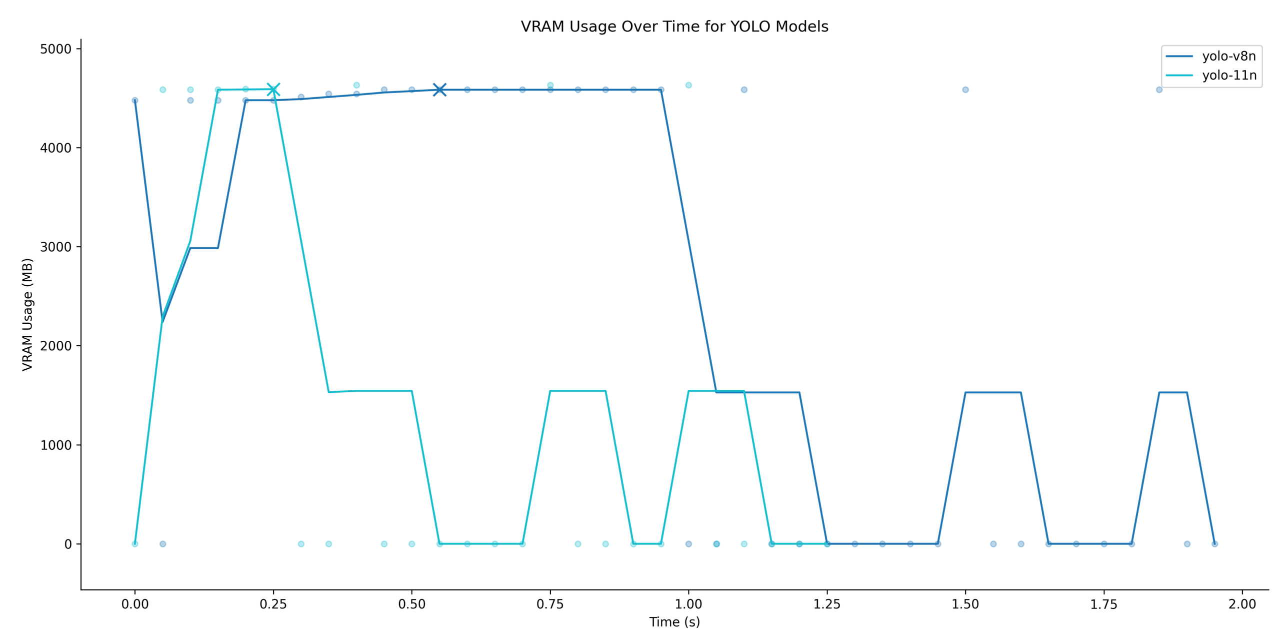

Figure 4: VRAM usage of YOLO models under inference

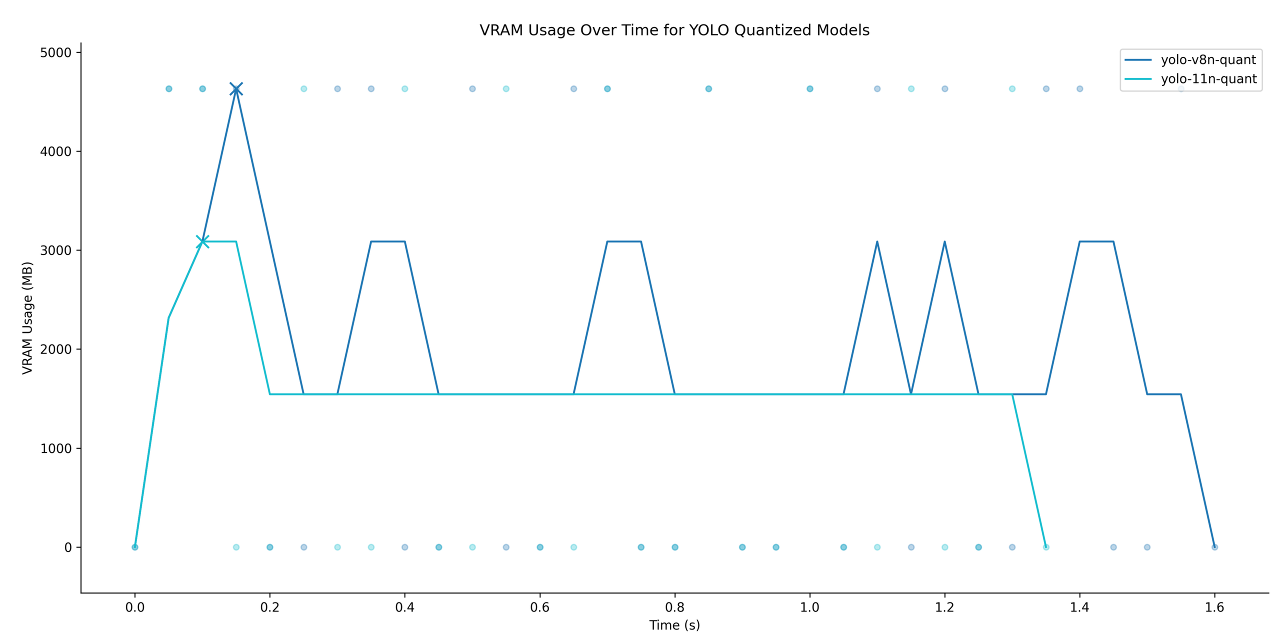

Figure 5: VRAM usage of quantized YOLO models under inference

Dynamic quantization achieves up to 95% reduction in the number of parameters and model size [2], lowering energy use, while local deployment avoids energy-intensive data centers.

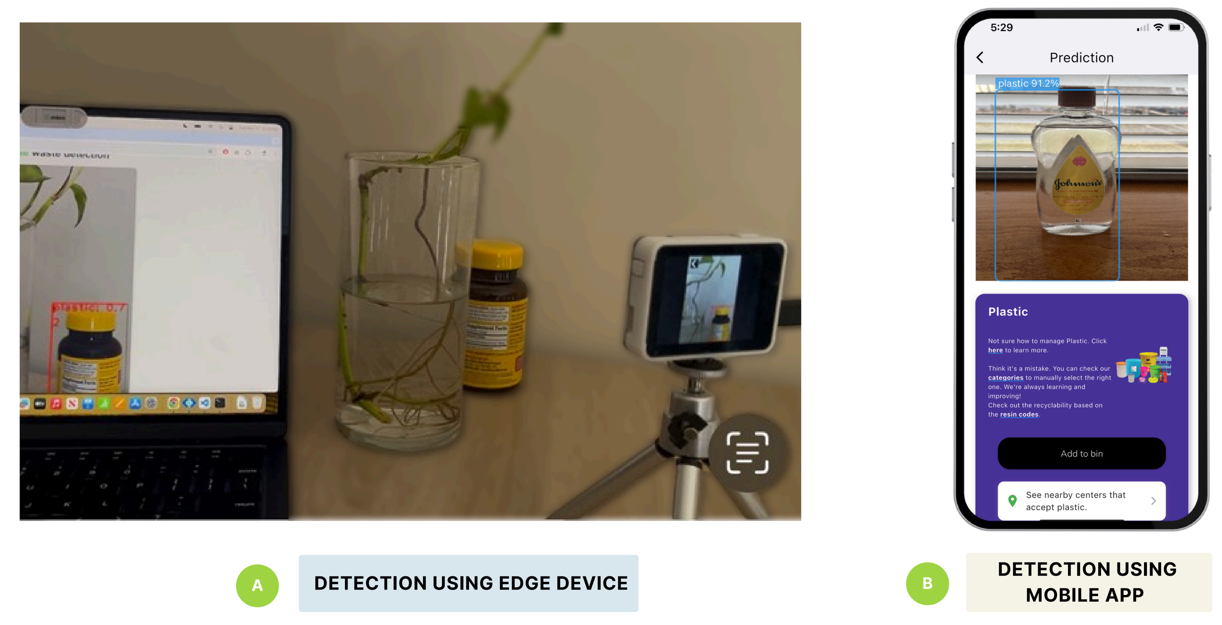

Figure 6: Real-World Detection on Edge and Mobile Devices

Conclusion

- **Trade-off:** Larger models (EfficientNetV2, ResNet) achieve higher accuracy but demand more energy.
- **Greener & Minimalist Options:** YOLOv11n balances accuracy, low VRAM, and emissions; MobileNet is ultra-lightweight but less accurate.
- **Impact:** DWaste enables sustainable, on-device waste sorting without cloud dependence.
- **Future Work:** Expand datasets, refine lightweight models, and scale deployment in schools and communities.

References

[1] Juan Pinos, John N. Hahladakis, and Hong Chen. Why is the generation of packaging waste from express deliveries a major problem? Science of The Total Environment, 830:154759, 2022.

[2] Samer Francy and Raghubir Singh. Edge ai: Evaluation of model compression techniques for convolutional neural networks, 2024.

Affiliations

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