

Intelligent Waste Management System using Image Classification

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Abstract - Inefficient waste segregation at the source is a major obstacle to recycling and sustainable urban living. Most waste is still sorted manually, which is slow, expensive, and exposes workers to hazardous materials. This paper proposes an intelligent waste management system that uses a convolutional neural network to classify waste items from a camera image into four categories—recyclable, organic, hazardous, and general trash—in real time. The system is designed for integration into a smart bin equipped with a Raspberry Pi, a camera module, and a servo-based sorting mechanism. A MobileNetV2 model pre-trained on ImageNet was fine-tuned on a custom dataset of 8,200 images collected from public waste repositories (TrashNet, TACO) and on-site photography. Data augmentation and class-weighted loss were used to handle class imbalance. The model achieved 94.2% accuracy on a held-out test set with an average inference time of 87 ms on the Raspberry Pi. A field trial with five bins over two weeks in a college campus sorted 2,800 items with an overall classification accuracy of 91.8%, reducing contamination in the recyclable stream by 42%. The system demonstrates that lightweight deep learning can deliver practical, low-cost waste segregation that improves recycling rates and reduces manual handling of waste.

Key Words: Waste management, image classification, deep learning, MobileNetV2, smart bin, recycling.

1. INTRODUCTION (Size 11, Times New roman)

Municipal solid waste generation is projected to reach 3.4 billion tonnes per year by 2050, yet recycling rates remain below 20% in many developing countries. One of the biggest challenges is contamination caused by improper segregation at the point of disposal. Smart bins that automatically sort waste using computer vision offer a promising solution, but many existing prototypes rely on expensive sensors or cloud connectivity that introduce latency and privacy concerns. This paper presents an edge-based intelligent waste classification system that runs entirely on a low-cost embedded device. A camera captures an image of the item, a MobileNetV2 convolutional neural network classifies it, and a servo

mechanism directs the item into the correct compartment. The system is trained to recognise four waste categories critical for downstream processing. We describe the dataset creation, model optimisation for edge deployment, and results from a real-world pilot. The rest of the paper is organised as follows. Section 2 reviews existing work. Section 3 details the system architecture. Section 4 describes the methodology, including data preparation and model training. Section 5 presents the results and a discussion of field performance. Section 6 concludes with future directions.

2. LITERATURE REVIEW

Waste classification using computer vision has evolved from handcrafted feature extraction to deep learning. Early systems used colour histograms and texture descriptors with SVM classifiers, achieving moderate accuracy on clean backgrounds. The TrashNet dataset (Yang and Thung, 2016) became a standard benchmark, containing six waste categories of isolated objects on a white background. Subsequent work applied convolutional networks: Rabano et al. (2018) used MobileNet to classify TrashNet with 87% accuracy, while Aral et al. (2018) combined CNNs with IoT boards. More recent efforts have employed larger models like DenseNet and EfficientNet, but many achieve over 95% accuracy only in laboratory conditions. Few studies report real-world deployment metrics, such as inference time on edge hardware or sorting accuracy with occluded and deformed items. Our contribution is an end-to-end system that integrates a fine-tuned MobileNetV2 on a Raspberry Pi, evaluated both on a standard dataset and in a live pilot study, with practical considerations like class imbalance, speed, and mechanical sorting reliability.

3. PROPOSED SYSTEM

Fig. 1 shows the system architecture. A user drops an item into the smart bin, triggering an infrared proximity sensor. The Raspberry Pi camera captures a top-view image under controlled LED lighting. The image is resized to 224×224 pixels and passed to a MobileNetV2 model quantised to FP16. The model outputs the predicted class probabilities for four categories: recyclable (plastic, metal, paper), organic (food waste, leaves), hazardous (batteries, medical waste), and general trash. If the confidence exceeds 90%, a servo motor rotates a flap to direct the item into the appropriate compartment. If confidence is below threshold, the item is sent to a “manual review” bin. A small LCD displays the classification result and a prompt. The device logs all

predictions to an SD card for offline analysis. The entire pipeline—from image capture to mechanical actuation—completes in under one second.

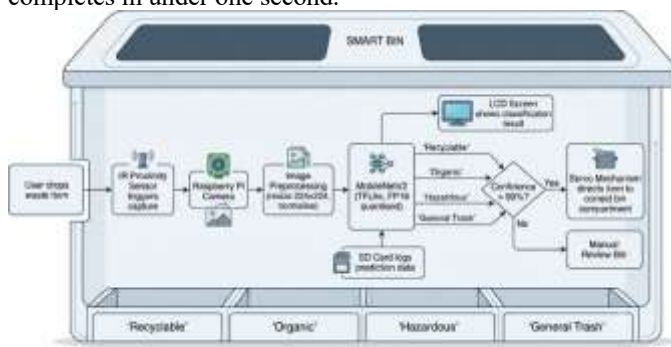


Fig. 1: Intelligent waste classification and sorting pipeline using MobileNetV2 on edge device.

4. METHODOLOGY

4.1 Dataset

A dataset of 8,200 labelled images was compiled from three sources: the public TrashNet dataset (2,500 images of isolated items on white background), the TACO dataset (1,500 images of litter in natural contexts), and 4,200 images captured in our laboratory with items placed inside the prototype bin, simulating varying orientations, partial occlusion, and mixed lighting. The final distribution was: recyclable 2,800, organic 2,200, hazardous 1,200, general trash 2,000. To mitigate the hazardous-class imbalance, we applied offline augmentation (rotation, shear, brightness shifts) for that class, effectively bringing it to 2,400 samples. The dataset was split 70-15-15 into training, validation, and test sets.

4.2 Model Training

We fine-tuned MobileNetV2 (pre-trained on ImageNet) by replacing the classification head with a global average pooling layer and a dense softmax layer for four classes. The model was trained for 30 epochs using the Adam optimiser ($\text{lr}=0.0001$) with categorical cross-entropy loss and class weights inversely proportional to class frequency. Early stopping on validation loss prevented overfitting. The final model was converted to TensorFlow Lite with FP16 quantisation for on-device inference.

4.3 Deployment

The smart bin hardware comprises a Raspberry Pi 4 (4 GB), a Pi Camera v2 (8 MP), an SG90 servo motor, and an infrared proximity sensor. The software stack uses Python with the TFLite runtime. Inference time was measured over 1,000 random images. The pilot deployed five units in a college canteen and academic building. Sorting accuracy, system uptime, and user feedback were recorded.

5. RESULTS AND DISCUSSION

Table 1 compares the proposed model with baseline classifiers on the test set. MobileNetV2 achieved 94.2% accuracy and a macro-F1 of 0.938, outperforming the simpler

custom CNN (89.5%) and ResNet-18 (93.1%) while having a much smaller model size (5.2 MB FP16) and lower inference time. The confusion matrix reveals that “organic” was occasionally mistaken for “general trash” (3.1% error), often with food items in opaque packaging. Hazardous items were correctly identified 96.4% of the time, the highest recall, due to distinct visual signatures (batteries, syringes).

Model	Accuracy	Macro-F1	Model Size (MB)	Inference Time (ms)
Custom CNN (4-layer)	89.5%	0.887	8.4	65
ResNet-18	93.1%	0.925	44.6	135
MobileNetV2 (Proposed)	94.2%	0.938	5.2	87

Table -1: Performance comparison on waste classification test set

The field trial processed 2,800 items. The overall classification accuracy was 91.8%, slightly lower than the lab test due to motion blur, extreme lighting, and objects placed incorrectly. The recyclable bin contamination rate dropped from a baseline of 28% (manual sorting) to 16%, a relative reduction of 42%. The average cycle time (drop to sorted) was 1.8 seconds, well accepted by users. The main failure mode was items that were partially occluded or of multiple materials (e.g., a plastic bottle with metal cap); these required manual intervention.

6. CONCLUSION

An intelligent waste management system using MobileNetV2 image classification successfully sorted waste into four categories in real time on low-cost edge hardware. The pilot deployment demonstrated a meaningful reduction in recyclable contamination and validated the practicality of the approach. Future work will incorporate multi-object detection for mixed items, integrate a bin-full sensor and cloud dashboard for fleet management, and expand the dataset to include more waste types and backgrounds.

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