KEC Conference 2026

ISSN: 3021-940X (Print)

DOI: 10.3126/injet.v3i2.95534

Vision-Based Smart Waste Segregator: An Embedded System

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Abstract

Improper waste disposal is a critical environmental challenge, particularly in urban areas where manual segregation remains inefficient, unsafe, and inconsistent. This paper presents a Vision-Based Smart Waste Segregator, an automated system that classifies and sorts waste into five categories: glass, metal, paper, plastic, and organic waste. The system employs a Raspberry Pi 4B as the central processing unit, which is triggered by a Time-of-Flight (ToF) sensor upon waste detection. A Pi Camera Module captures an image of the waste item, which is classified using a novel feature-fusion deep learning model combining EfficientNetB0 and DenseNet121. The fused feature vectors from both architectures are passed through fully connected layers with a Softmax output for five-class classification. Based on the results, a dual-motor mechanism, a stepper motor for bin alignment and a servo motor for waste release, directs the waste into the appropriate bin. Bin fill-level monitoring via a second ToF sensor transmits real-time status to a web-based interface through HTTP communication. The model achieved a validation accuracy of 94-95% and was optimized using TensorFlow Lite post-training quantization for efficient edge deployment.

Keywords: DenseNet, Dual-motor, EfficientNet, Feature Fusion, Raspberry Pi, Smart Waste Segregator, Time-of-Flight

1. Introduction

Waste management has become an urgent global concern, especially in developing countries where unplanned disposal methods pose serious risks to public health, the environment, and natural resources. Conventional manual waste segregation is labor-intensive, inconsistent, and increasingly inadequate given the scale of municipal solid waste generation. The rapid increase in municipal solid waste generation has made manual segregation increasingly inefficient and unsustainable, especially in urban areas [1]. There is an increasing demand for intelligent automated systems capable of real-time and accurate waste classification.

Recent advances in deep learning and embedded systems have enabled the deployment of sophisticated vision-based classification models on low-power hardware. Convolutional Neural Networks (CNNs), in particular, have demonstrated state-of-the-art performance in image recognition tasks. However, most existing automated waste segregation systems rely on single-model architectures, limiting their classification capability and accuracy. The primary objective of this research is to develop an intelligent vision-based smart waste segregation system capable of accurately classifying waste into five categories: glass, metal, paper, plastic, and organic waste using a feature fusion approach combining EfficientNetB0 and DenseNet121 and physically sorts it via a dual-motor mechanism. The study further aims to deploy the trained lightweight model on Raspberry Pi hardware for real-time automated waste sorting and monitoring.

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2. Literature Review

Chu and Li [2] proposed a multilayer hybrid system combining image-based CNN features from AlexNet with sensor data for urban waste classification, achieving over 90% accuracy. Their approach demonstrated the benefit of multimodal inputs in improving robustness for real-world waste scenarios.

Abdallah et al. [3] conducted a systematic review of 85 AI-based solid waste management studies (2004–2019). Their findings highlight the effectiveness of CNN models in waste classification and the potential of integrating AI with IoT for real-time monitoring. They also identify data scarcity and model interpretability as key challenges.

Mishra et al. [4] proposed a two-stage hybrid model combining DenseNet121 with an SVM classifier on the TrashNet dataset, reporting a classification accuracy of 99.84%. While impressive, this approach relies on offline classification without real-time embedded deployment.

Khadka et al. [5] developed a Raspberry Pi-based waste segregator using VGG-16 for three waste categories (metal, plastic, paper), demonstrating embedded deployment but constrained by limited categories and the high computational cost of VGG-16.

A significant research gap exists in feature-level fusion of multiple deep learning models for waste classification. Existing systems either use single architectures or combine deep features with classical classifiers. Moreover, existing embedded systems do not simultaneously classify five waste categories using a lightweight fused model optimized for edge deployment.

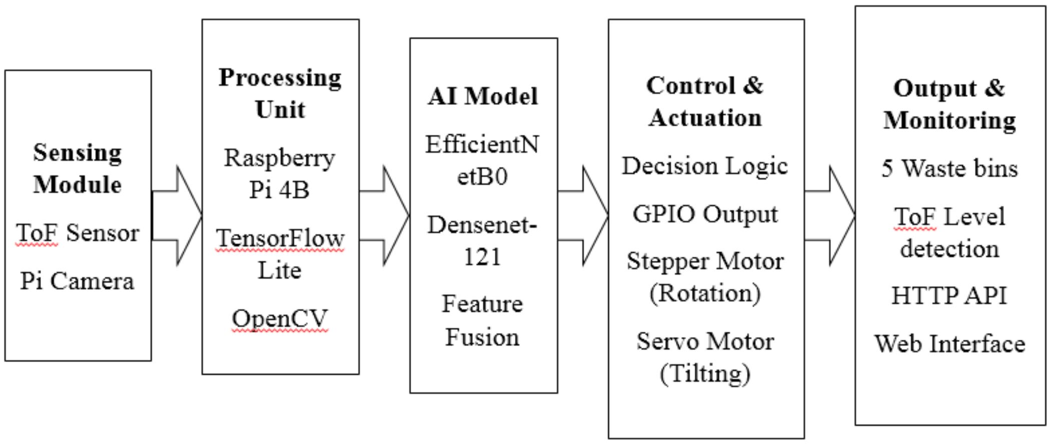
3. System Design and Methodology

3.1. System Architecture

The developed system is an integrated mechatronic platform in which hardware components and deep learning algorithms operate in a closed-loop configuration. The architecture consists of three distinct modules:

- Sensing Module: Pi Camera Module V2 for image acquisition and two Time-of-Flight (VL53L1X) sensors for waste detection and bin-level monitoring.
- Processing Module: Raspberry Pi 4B (8GB RAM) running Raspberry Pi OS, with TensorFlow Lite and OpenCV for inference and image preprocessing.
- Actuation Module: A stepper motor (28BYJ-48) for rotational bin alignment and a servo motor (SG90) for waste release via a flap-based inlet mechanism directing waste into five bins.

Upon system startup, the Raspberry Pi initializes GPIO pins, loads the TFLite model, and enters standby mode. When the inlet ToF sensor detects an object within 195 mm, the camera captures an image, the model classifies the waste, and the motors direct it to the correct bin. Bin fill level is monitored and status is transmitted to a web server via HTTP PATCH requests.



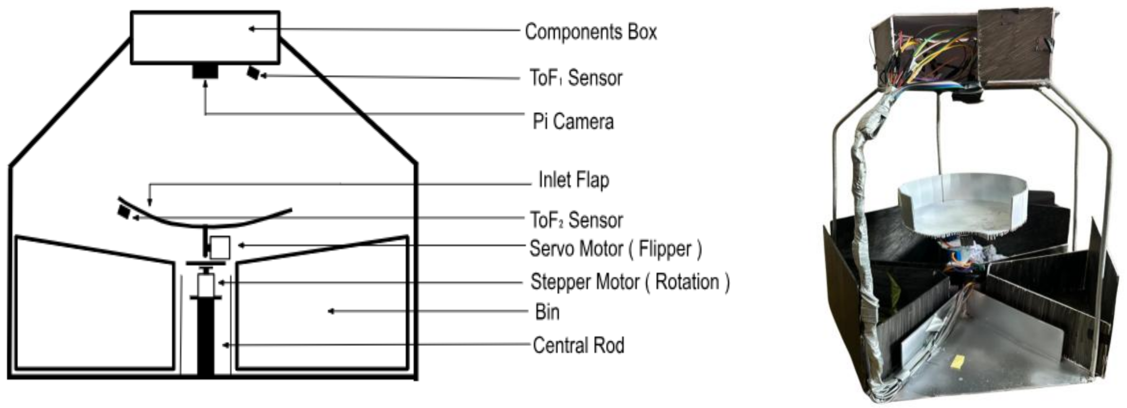


Figure 1. Mechanical Structure of the system

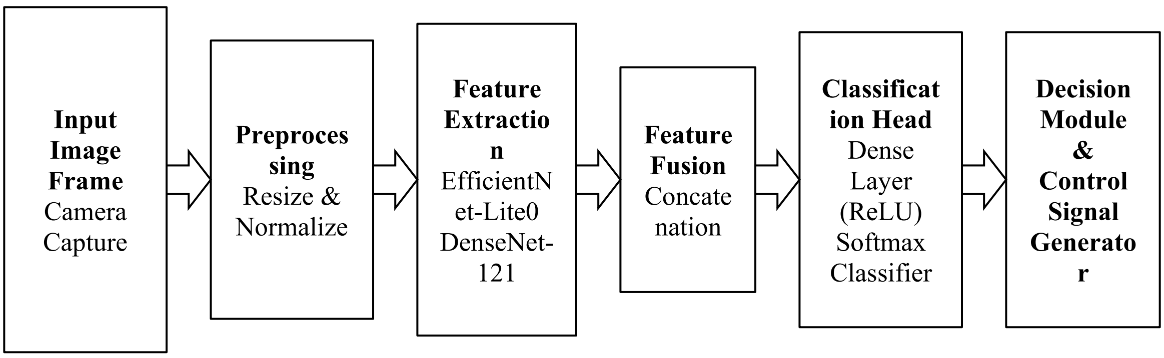
3.2. Deep Learning Model Architecture

The classification model employs feature-level fusion of two pre-trained CNN architectures: EfficientNetB0 and DenseNet121, both initialized with ImageNet weights and used as frozen feature extractors.

Each 224×224×3 RGB image is simultaneously provided as input to both models. The output feature maps from each network are passed through Global Average Pooling (GAP) layers to produce compact feature vectors F_eff (EfficientNetB0) and F_dense (DenseNet121). These are concatenated to form a fused representation:

$$F\_fused = concat(F\_eff, F\_dense) \in R^{n+m} \quad (1)$$

The fused vector is passed through two fully connected dense layers (256 neurons with ReLU, then 128 neurons with ReLU) and a final Softmax output layer with 5 neurons corresponding to the waste categories. EfficientNetB0 provides efficient compound-scaled global representations while DenseNet121 contributes dense feature reuse and fine-grained detail, yielding richer discriminative representations than either model alone.



3.3. Dataset and Training

The training dataset is sourced from the Garbage Classification V2 dataset [6], curated to approximately 1,013–1,016 images per class across five categories (glass, metal, organic, paper, plastic). A separate test set of ~200 images per class is drawn from the TrashNet dataset [7], for unbiased evaluation. The preprocessing stage includes normalization to the range [0,1], resizing to 224×224 pixels, and data augmentation techniques such as random rotation (up to 20°), zoom (up to 20%), and horizontal flipping. The Adam optimizer (lr = 0.0001) with categorical cross-entropy loss is used over 20 epochs, with an 80:20 training-validation split and class weighting to handle minor class imbalance. Training was performed on dual NVIDIA T4 GPUs (32GB combined VRAM) via Kaggle. The trained model is converted to TensorFlow Lite (.tflite) format with post-training quantization for efficient inference on the Raspberry Pi.

4. Results and Discussion

The model achieved rapid convergence, with training accuracy rising from below 60% to over 90% within the first three epochs. Validation accuracy stabilized between 94% and 95%, demonstrating strong generalization without significant overfitting. The minor dip observed around epoch 11 reflects a common stochastic fluctuation during Adam optimization, from which the model promptly recovered.

Table 1 summarizes the classification performance per category on the independent test set. Paper and metal achieved the highest precision values (0.912 and 0.730, respectively), while Organic waste achieved perfect precision with zero misclassifications as glass or plastic, critical for avoiding composting stream contamination. The primary misclassification occurred between glass and metal, as well as between plastic and metal, likely due to similarities in surface reflectivity and deformation characteristics. The observed lower F1-scores for Glass and Plastic can be attributed to domain shift between the training dataset and the independent test dataset. Differences in image background, resolution, illumination, and collection conditions affect the model's generalization performance, particularly for visually similar waste materials.

Table 1. Classification Performance per Waste Category

Waste Category	Precision	Recall	F1-Score	Class Weight
Glass	0.892	0.741	0.809	0.997
Metal	0.730	0.960	0.829	1.000
Organic	1.000	0.946	0.972	1.007
Plastic	0.902	0.735	0.810	0.998
Paper	0.912	0.985	0.947	0.997

The EfficientNet-DenseNet fusion model outperforms single-architecture approaches reported in the literature for five-category waste classification, while remaining deployable on resource-constrained hardware. The dual-motor actuation system reliably directed waste with stepper motor alignment in discrete step increments (0 steps for glass to 3,276 steps for plastic) at 0.002 s/step, and the servo motor executed flap tilts at 60° for waste release.

To evaluate the effectiveness of the proposed model, a comparative analysis was conducted with existing approaches reported in the literature. Table 2 summarizes the performance comparison of different models used for waste classification.

Table 2. Accuracy Comparison with other Model

Study	Model	Accuracy
Khadka et al.	VGG16	85%
Mishra et al.	DenseNet+SVM	99.84%
Developed System	EfficientNet+DenseNet	94-95%

As shown in Table 2, our system EfficientNet-DenseNet fusion model achieves competitive accuracy compared to existing approaches. Although Mishra et al. reported a higher accuracy of 99.84% using a DenseNet+SVM hybrid model, their approach is primarily designed for offline classification and does not consider real-time embedded deployment.

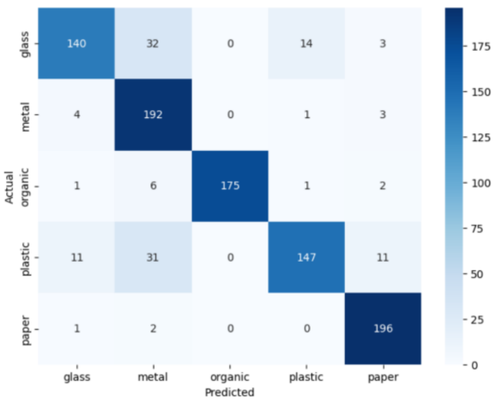
In contrast, the system is optimized for deployment on resource-constrained hardware (Raspberry Pi) using TensorFlow Lite, enabling real-time waste classification and physical segregation. This makes the proposed approach more suitable for practical, real-world applications despite a slightly lower accuracy. Furthermore, the system performs classification across five waste categories in an end-to-end automated system, whereas many existing approaches are limited in scope or lack integration with embedded hardware.

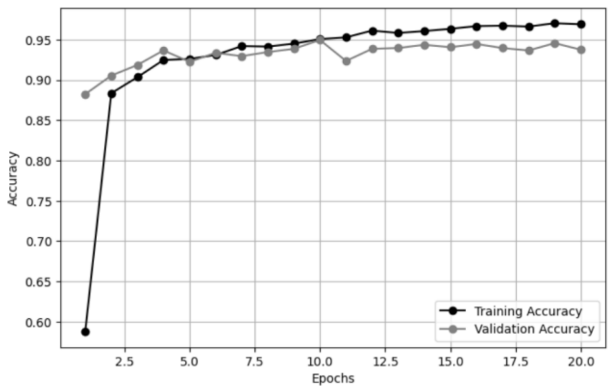
5. Limitation and Future Recommendation

Despite strong classification performance, the system has certain limitations. The model performance degrades under poor lighting conditions and domain shift caused by training and testing on different datasets. Inference speed on Raspberry Pi CPU is another limitation for real-time industrial-scale deployment. Future work will focus on improving dataset diversity, optimizing inference speed using Edge TPU acceleration, and extending classification to more waste categories.

6. Conclusion

This paper presents a vision-based smart waste segregator that integrates an EfficientNetB0–DenseNet121 feature fusion model with a Raspberry Pi-based embedded system for automated waste classification and sorting. The confusion matrix demonstrates strong multi-class classification performance across five waste material categories (glass, metal, organic, plastic, and paper), with the model achieving notably high correct predictions along the diagonal, particularly for metal (192), paper (196), and organic (175). The most prominent misclassification pattern occurs within the glass category, where 32 instances were incorrectly predicted as metal, suggesting visual or spectral feature overlap between these two material types.





The system achieved 94–95% validation accuracy with real-time operation on edge hardware, validated on an independent test set. Compared to existing systems limited to three categories and computationally heavy architectures, the proposed approach offers a broader classification scope, improved accuracy, and practical deployability.

Future work will focus on expanding the number of classifiable waste categories, integrating Edge TPU accelerators for faster inference, improving dataset diversity for better generalization across lighting conditions, and scaling the mechanical design for industrial deployment.

Acknowledgement

The authors sincerely thank Er. Sujin Gwachha, Senior Lecturer, Department of Computer and Electronics Engineering, Kantipur Engineering College, for his invaluable mentorship, technical guidance, and consistent support throughout this project. The authors also acknowledge the Kaggle platform for providing GPU resources for model training.

[1] H. I. Abdel-Shafy and M. S. Mansour, "Solid waste issue: Sources, composition, disposal, recycling, and valorization," Egyptian journal of petroleum, vol. 27, no. 4, pp. 1275-1290, 2018.

[2] Y. Chu and W. Li. (2018) Multilayer Hybrid Deep-Learning Method for Waste Classification and Recycling. [Online]. https://www.researchgate.net/publication/328692099

[3] M. Abu Talib, S. Fereoz, Q. Nasir, H. Abdalla, and B. Mahfood M. Abdallah, "Artificial intelligence application in solid waste management: A systematic research review," Waste Management , vol. 109, pp. 231-246, 2020.

[4] S. Mishra et al., "An integrated deep-learning model for smart waste classification," Environmental

Monitoring and Assessment, vol. 196, no. 3, p. 279, 2024.

[5] P. Joshi, N. K. Kanth, and S. Gwachha R. Khadka, "Waste segregation system," International Journal on Engineering Technology, vol. 2, no. 2, pp. 36-43, 2025.

[6] K. Suman. (2022) Garbage classification v2. [Online]. https://www.kaggle.com/datasets/sumn2u/garbage-classification -v2

[7] F.Ozkefe. (2020) Trashnet dataset. [Online]. https://www.kaggle.com/datasets/feyzazkef e/trashnet