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SMART WASTE SEGREGATION SYSTEM

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Abstract

Waste segregation is an important part of sustainable waste management, yet the process still depends heavily on users being able to identify different types of waste correctly. This study presents the development and preliminary evaluation of an offline Smart Waste Segregation System that uses a MobileNetV2-based Convolutional Neural Network (CNN) to support image-based waste classification. The model was developed using the TrashNet dataset, which contains 2,527 images across six categories: cardboard, glass, metal, paper, plastic, and trash. The trained model was subsequently integrated into a desktop application developed using Python, TensorFlow/Keras, Tkinter, and MySQL. Users can upload a waste image and receive a predicted category, confidence score, and disposal guidance without relying on continuous internet connectivity. Preliminary evaluation was based on eight classification records retained by the application and representative outputs captured during functional testing. Confidence scores in the retained records ranged from 50.51% to 99.88%, with a mean of 67.76%. Representative system outputs also showed predictions for glass, metal, paper, plastic, and trash. These preliminary results provide evidence that the trained model can be integrated successfully into an offline waste-classification application. However, the retained operational records do not contain corresponding ground-truth labels; therefore, accuracy, precision, recall, F1-score, and confusion-matrix analysis could not be reconstructed reliably. Further evaluation using a larger independently labelled real-world dataset is required before broader claims about classification performance can be made.

Keywords: Artificial Intelligence; Smart Waste Segregation; Convolutional Neural Network; Image Classification.

Introduction

Waste segregation plays an important role in sustainable waste management, yet effective sorting still depends largely on users correctly identifying different types of waste. Deep learning offers a practical way to support this process through automated image recognition. Recent studies have demonstrated the potential of CNN-based approaches for waste classification and recycling applications (Chhabra et al., 2024; Nahiduzzaman et al., 2025), while other work has explored mobile, embedded, and edge-based implementations (Fu et al., 2021; Narayan, 2021; White et al., 2020).

Despite these advances, waste recognition outside controlled datasets remains challenging because images can vary in lighting, background, orientation, and object appearance (Majchrowska et al., 2022). MobileNetV2 is relevant in this context because its inverted residual and linear bottleneck architecture was designed to provide efficient image representation with reduced computational complexity (Sandler et al., 2018). For waste classification, the TrashNet dataset introduced by Yang and Thung (2016) provides 2,527 images organised into six categories: cardboard, glass, metal, paper, plastic, and trash.

This study developed an offline Smart Waste Segregation System using MobileNetV2 and TrashNet. The prototype integrates waste-image classification, prediction confidence, and disposal guidance within a desktop application. Given the limited retained testing records, the study focuses on prototype development and preliminary functional evaluation rather than comprehensive classification benchmarking.

Methodology

The development of the Smart Waste Segregation System followed the Spiral Model, allowing the prototype to be refined iteratively as the classification model and user interface were developed. The main stages involved requirement identification, dataset preparation, model development, system integration, and functional testing.

The classification model was developed using the TrashNet dataset introduced by Yang and Thung (2016). The dataset contains 2,527 images distributed across six categories: cardboard, glass, metal, paper, plastic, and trash. Images were resized to 224 × 224 pixels to match the input requirements of MobileNetV2 and were

normalised before training. Data augmentation, including rotation, horizontal flipping, and contrast adjustment, was applied to introduce additional image variation during model development.

MobileNetV2 was used as the CNN backbone. The architecture employs inverted residual blocks and depthwise convolution, which were designed to reduce computational complexity while retaining useful image representations (Sandler et al., 2018). The implemented model consisted of a pretrained MobileNetV2 backbone followed by Global Average Pooling, a dense layer containing 128 neurons with ReLU activation, a dropout layer with a rate of 0.3, and a six-neuron Softmax output layer corresponding to the six waste categories. The model was trained using the Adam optimiser with categorical cross-entropy as the loss function. These model and preprocessing specifications are consistent with those documented in the original system implementation.

Following model development, the trained .keras model was integrated into a Tkinter-based desktop application. MySQL was used to support user authentication and system access. The application processes uploaded images locally and presents the predicted waste category together with a confidence score and disposal guidance. These functions were already part of the system described in the original manuscript. The overall process is illustrated in Figure 1, beginning with image selection and preprocessing before classification by the MobileNetV2 model and presentation of the prediction to the user. The interaction between users and the main system functions is further represented in Figure 2.

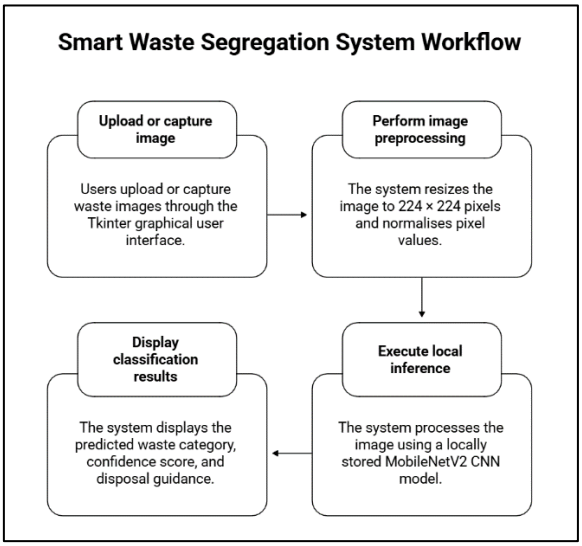


Figure 1. Smart Waste Segregation System Workflow

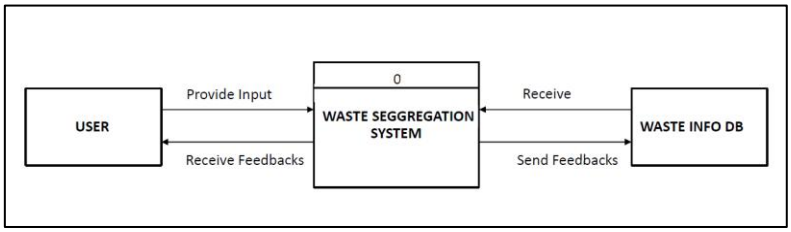


Figure 2. Context Diagram of the Smart Waste Segregation System

Results and Discussion

The completed prototype successfully combines image selection, waste prediction, confidence-score presentation, disposal guidance, and classification-history recording within a single desktop interface. The earlier version of the manuscript described these functional components, including image uploading, confidence-score display, disposal guidance, and local processing. The retained operational records now provide a small but verifiable quantitative basis for examining how the prototype behaved during use. Table 1 presents the eight classification events retained in the application's history.

Table 1. Preliminary classification records generated by the prototype

Predicted Class	No. of Records	Confidence Range (%)
Plastic	4	66.39–99.88
Paper	3	50.51–52.38
Glass	1	71.73
Overall	**8**	**50.51–99.88**

The recorded confidence scores in Table 1 ranged from 50.51% to 99.88%. Plastic predictions showed the widest variation, while the three paper predictions remained close to 50%. These values indicate differences in model certainty across the available samples, but they should not be interpreted as classification accuracy because the corresponding ground-truth labels were not retained in these initial operational logs.

To demonstrate system functionality across broader categories, Figure 3 presents five separate, representative graphical user interface (GUI) classification outputs obtained during standalone functional testing sessions. These screenshots represent a distinct evaluation trial from the batch logging in Table 1, selected specifically to demonstrate user interface responsiveness and model inference across diverse waste types: glass (99.15%), metal (97.85%), paper (71.69%), plastic (81.34%), and trash (72.33%)

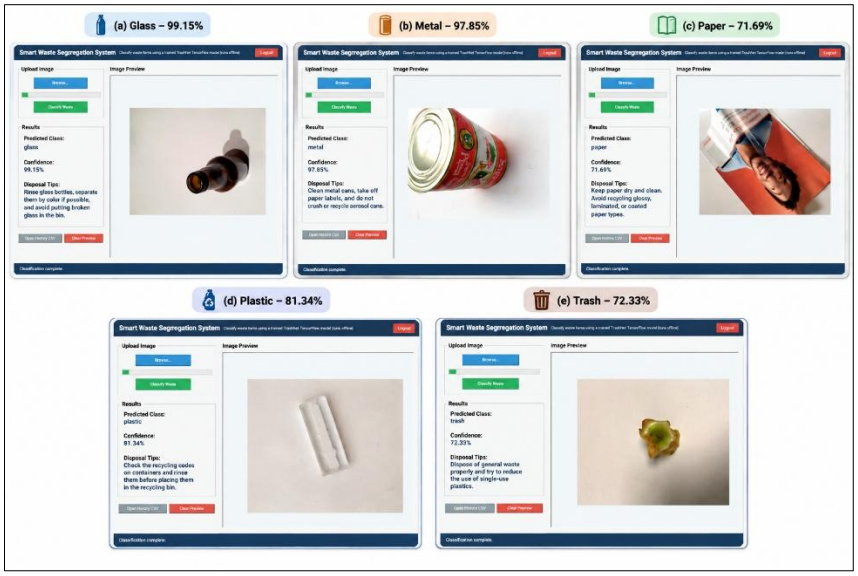


Figure 3. Representative outputs from the functional testing of the Smart Waste Segregation System: (a) glass, 99.15% confidence; (b) metal, 97.85%; (c) paper, 71.69%; (d) plastic, 81.34%; and (e) trash, 72.33%

The representative outputs confirm that the prototype can process distinct waste categories and return instant visual feedback alongside actionable disposal tips. Glass and metal produced relatively high confidence in these individual tests, while paper and trash produced more moderate values. Similar variations in waste recognition have been associated with differences in background complexity, lighting, and object deformation (Majchrowska et al., 2022). Consequently, these findings serve as a preliminary functional validation of the offline system rather than an exhaustive benchmark. A larger, independently labelled real-world dataset will be deployed in future work to comprehensively quantify accuracy, precision, recall, and confusion matrix characteristics.

Conclusion

The study developed an offline MobileNetV2-based Smart Waste Segregation System that integrates image classification, confidence-score presentation, and disposal guidance within a desktop application. Eight retained classification records produced confidence scores ranging from 50.51% to 99.88%, with a mean of 67.76%, while representative functional tests demonstrated predictions across five waste categories.

The current evidence supports the functional operation of the prototype, but not a comprehensive assessment of classification accuracy. Future testing should therefore use a larger labelled real-world dataset covering all six waste categories. Ground-truth labels should be retained to enable accuracy, precision, recall, F1-score, and confusion-matrix analysis. Inference time, model size, and hardware specifications should also be measured before making claims regarding real-time or computational performance.

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