# AI-Powered Garbage Classification: A Deep Learning Approach for Smart Waste Management

**Sakshi Chandrakant Shinde**
P.D.E.A.'s Prof. Ramkrishna More Arts, Commerce and Science College (Autonomous), Akurdi Pradhikaran, Pune-411044
E-mail: sakshishinde152004@gmail.com

**Prof. Ankush Dhamal**
P.D.E.A.'s Prof. Ramkrishna More Arts, Commerce and Science College (Autonomous), Akurdi Pradhikaran, Pune-411044
E-mail: ankushdhamal01@gmail.com

**Abstract**

The escalating volume of municipal solid waste (MSW) due to rapid urbanization and population growth poses severe challenges to sustainable waste management. Manual sorting is labor-intensive, inconsistent, and hazardous. This paper proposes an automated garbage classification system using deep learning with transfer learning on the ResNet-50 architecture. The model is trained on the RealWaste dataset (4,752 real-world images across nine categories: Cardboard, Food Organics, Glass, Metal, Miscellaneous Trash, Paper, Plastic, Textile Trash, Vegetation) and achieves a test accuracy of **96.36%**. A simple Tkinter-based graphical user interface (GUI) demonstrates real-time classification capability. Results show superior performance compared to baseline CNNs (~72%) and traditional methods (60–70%), offering a practical solution for smart bins, conveyor systems, and municipal frameworks. This work supports enhanced recycling efficiency, reduced environmental impact, and alignment with Sustainable Development Goals 11 and 12.

**Keywords**: Waste classification, deep learning, convolutional neural networks, transfer learning, smart waste management, ResNet-50, RealWaste dataset

## 1. Introduction

Rapid urbanization and population growth have significantly increased municipal solid waste (MSW) generation worldwide. According to the latest estimates, MSW generation reached approximately 2.3 billion tonnes in 2023 and is projected to rise to 3.8 billion tonnes by 2050 if no urgent action is taken [1], [2]. Effective source segregation is essential for recycling, composting, resource recovery, and reducing landfill dependency, yet traditional manual sorting remains inefficient, error-prone, and unsafe [3], [4].

Advances in computer vision and deep learning, particularly convolutional neural networks (CNNs), have enabled accurate image-based waste classification into categories such as organic, recyclable (plastic, metal, paper, glass), and hazardous [5]–[7]. Integrating these models into smart waste systems can improve efficiency, lower costs, and support circular economy goals.

This paper presents a deep learning-based garbage classification system using transfer learning on ResNet-50, trained on the RealWaste dataset. The model achieves 96.36% test accuracy and includes a GUI for real-time demonstration, addressing key gaps in generalization and practical deployment.

### 1.1 Background of the Study

Urban waste management faces challenges including low source segregation rates, health hazards for workers, high operational costs, inconsistent human sorting accuracy, and environmental impacts such as methane emissions from landfills [8], [9]. Automatic image-based classification using deep learning offers a scalable solution, with CNNs (e.g., ResNet, EfficientNet) excelling at feature extraction even under varied conditions [10].

Transfer learning, fine-tuning pre-trained models on specific datasets, is effective for limited waste image data. Automated systems provide higher accuracy, scalability, reduced human exposure to hazards, data-driven insights, and integration into smart infrastructure. This aligns with UN Sustainable Development Goals 11 (Sustainable Cities and Communities) and 12 (Responsible Consumption and Production).

### 1.2 Problem Statement

Existing waste classification models often suffer from limited dataset diversity, poor generalization in real-world conditions (e.g., varying lighting, backgrounds), and lack of practical deployment demonstrations. This hinders adoption in municipal settings.

This study addresses these by developing a ResNet-50-based model using transfer learning on the RealWaste dataset (4,752 real-world images across nine categories), achieving 96.36% test accuracy and demonstrating real-time usability via a GUI.

### 1.3 Research Objectives

The objective of this study is to design, develop, and evaluate a transfer learning-based ResNet-50 model for accurate classification of real-world garbage images from the RealWaste dataset, including a graphical user interface (GUI) for real-time demonstration in smart waste management systems.

### 1.4 Scope of the Study

The research is limited to image-based classification using the RealWaste dataset (4,752 images across nine categories: Cardboard, Food Organics, Glass, Metal, Miscellaneous Trash, Paper, Plastic, Textile Trash, Vegetation). It employs ResNet-50 with transfer learning, standard preprocessing, and augmentation. Evaluation occurs in a software environment (Python, PyTorch); hardware deployment is beyond scope.

### 1.5 Significance of the Study

This work provides a high-accuracy, practical AI solution for waste segregation, enhancing recycling efficiency, reducing costs and environmental impact, and improving worker safety. By achieving strong performance on real-world data and demonstrating usability, it bridges research and real-world application, supporting smart city initiatives and sustainable waste management.

## 2. Literature Review

### 2.1 Introduction to Literature Review

Automated waste classification has gained significant attention with the integration of deep learning and computer vision techniques. This section reviews key theoretical foundations, widely used datasets, prominent model architectures, and major studies in the field. It critically examines existing approaches and highlights persistent limitations to position the present work.

### 2.2 Theoretical Framework

Convolutional Neural Networks (CNNs) remain the dominant architecture for image classification tasks, extracting hierarchical features through alternating convolutional and pooling layers [11]. Transfer learning, which reuses models pre-trained on large datasets such as ImageNet and fine-tunes them on a smaller target dataset, is particularly valuable when annotated data is scarce, as is common in waste classification [12].

Widely adopted architectures include VGG [13], ResNet [14], EfficientNet [15], MobileNet [16] and, more recently, Vision Transformers (ViT) [17]. Standard data augmentation techniques (rotation, flipping, brightness/contrast adjustment) and preprocessing steps (resizing, normalization) are routinely applied to improve generalization [18].

### 2.3 Review of Previous Research

Early attempts at waste classification relied on hand-crafted features combined with traditional classifiers such as SVM or Random Forest, typically achieving accuracies of 80–85% [19]. The release of the TrashNet dataset in 2016 by Yang and Thung [20] enabled a shift toward deep learning and became a standard benchmark with six classes (cardboard, glass, metal, paper, plastic, trash).

Subsequent important contributions include:

- Bircanoğlu et al. [21] compared several CNN architectures on TrashNet, with DenseNet-121 reaching 95.7% accuracy.

- Mittal et al. [22] reported high performance using deep learning for garbage detection on TrashNet-like images (though not specifically ResNet-50 at 95%).
- The TACO dataset by Proença and Simões [23] introduced approximately 1,500 images of litter in natural environments with annotations for detection, highlighting real-world complexity.
- The RealWaste dataset by Rech et al. [24] provides 4,752 real-world images across nine classes and better represents uncontrolled landfill conditions, with Inception V3 achieving 89.19% accuracy in the original benchmark.

More recent studies (2020–2025) include:

- Lightweight CNN models for mobile devices achieving ~94% on TrashNet [25].
- Attention-enhanced CNNs improving performance on TACO [26].
- EfficientNet-B4 and MobileNetV3 models applied to RealWaste, reporting 90–93% accuracy [27, 28].
- Vision Transformer-based approaches reaching 94–95% on larger datasets, but requiring more computational resources [29, 30].
- Multi-label classification methods for mixed waste [31].
- Few-shot learning techniques to handle data scarcity [32].
- Edge deployment experiments using quantized MobileNet on IoT devices [33, 34].
- Studies using RealWaste with ResNet-50, EfficientNet variants, and hybrid models, typically reporting 89–94% accuracy. A recent benchmark on RealWaste reports DenseNet-121 achieving 94.33% [35].

### 2.4 Research Gaps Identified

Despite the progress, several limitations remain:

1. The majority of studies are trained and evaluated on controlled datasets (TrashNet, TACO), resulting in reduced performance when confronted with real-world variations in lighting, background clutter, and object occlusion.
2. The more realistic RealWaste dataset has received comparatively little attention compared to TrashNet.
3. Many publications report strong validation results but lack thorough testing on completely unseen real-world images.
4. Very few works demonstrate practical usability through end-to-end prototypes such as graphical user interfaces or integration concepts for smart bins or sorting lines.
5. High computational demands of many state-of-the-art models limit their deployment on low-power edge devices typical for smart waste bins.
6. Systematic comparisons of multiple architectures on the same realistic dataset (such as RealWaste) are still scarce.

The present study aims to address these gaps by applying transfer learning with ResNet-50 to the RealWaste dataset, achieving a test accuracy of 96.36% and providing a simple, functional GUI for real-time classification demonstration.

## 3. Research Methodology

### 3.1 Research Design

This study employs an experimental research design centered on supervised learning for multi-class image classification. The process involves dataset acquisition, preprocessing, transfer learning with a pre-trained CNN, hyperparameter optimization, model evaluation, and development of a demonstration GUI. The design emphasizes reproducibility and real-world applicability, using the RealWaste dataset to simulate practical waste management scenarios.

### 3.2 Data Collection Methods

No primary data collection was performed. The publicly available **RealWaste dataset** [24] was used, consisting of **4,752 real-world waste images** captured under uncontrolled conditions (varying lighting, backgrounds, occlusion, and deformation). The dataset contains nine categories as shown in Table 2.1.

**Table 2.1: RealWaste Dataset Distribution**

| Class | No. of Images | Percentage (%) |
|---|---|---|
| Cardboard | 461 | 9.70 |
| Food Organics | 411 | 8.65 |
| Glass | 420 | 8.84 |
| Metal | 790 | 16.62 |
| Miscellaneous Trash | 495 | 10.42 |
| Paper | 500 | 10.52 |
| Plastic | 921 | 19.38 |

| | | |
|---|---|---|
| Textile Trash | 318 | 6.69 |
| Vegetation | 436 | 9.18 |
| **Total** | **4,752** | **100%** |

### 3.3 Sampling Techniques and Sample Size

Stratified random sampling was applied to split the dataset while preserving class distribution:

- Training set: 70% (3,326 images)
- Validation set: 15% (712 images)
- Test set: 15% (714 images)

### 3.4 Tools and Techniques Used

- **Framework and Language**: PyTorch 2.0+ with Python 3.9
- **Model**: ResNet-50 pre-trained on ImageNet (from torchvision)
- **Libraries**: Torchvision (data loading), Torchmetrics (metrics), Matplotlib and Seaborn (visualizations), Scikit-learn (analysis), Tkinter with PIL (GUI)
- **Environment**: Jupyter Notebook

### 3.5 Data Preprocessing and Augmentation

All images were resized to **224×224 pixels** and normalized using **ImageNet statistics** (mean: [0.485, 0.456, 0.406]; standard deviation: [0.229, 0.224, 0.225]). For the **training set**, several data augmentations were applied to improve model generalization, including **random resized cropping** (scale 0.8–1.0), **random horizontal flipping** (50% probability), **random rotation** (±30°), and **random color jittering** to adjust brightness, contrast, saturation, and hue. The **validation and test sets** underwent only resizing and normalization to maintain consistency and ensure unbiased evaluation of model performance.

### 3.6 Model Architecture

The ResNet-50 backbone was modified by replacing the final fully connected layer (2048 → 9 outputs) and adding dropout (p=0.5) for regularization. Training occurred in two stages: initial fine-tuning of the classifier with frozen backbone, followed by unfreezing all layers with differential learning rates (lower for early layers). Adam optimizer (initial LR=0.001, reduced on plateau), categorical cross-entropy loss, and early stopping (patience=5) were used.

### 3.7 Performance Evaluation Metrics

Evaluation on the test set included overall accuracy, precision, recall, F1-score (macro and weighted averages), per-class metrics, confusion matrix, and training/validation curves for loss and accuracy. All computations used torchmetrics and scikit-learn for reliability.

## 4. Results and Discussion

This section presents the experimental results from training and evaluating the proposed ResNet-50-based transfer learning model on the RealWaste dataset (4,752 images across nine classes). All quantitative evaluations were performed on the held-out test set (714 images) to ensure unbiased assessment of generalization. The results include training curves, confusion matrix, per-class metrics, and GUI demonstrations, supported by detailed interpretations.

### 4.1 Data Presentation

The dataset was split as follows: training (3,326 images), validation (712 images), and test (714 images), using stratified sampling to maintain class distribution. The model was trained with Adam optimizer (initial LR 0.001), categorical cross-entropy loss, and early stopping (patience 5). The best checkpoint was selected based on validation accuracy (90.03%) for final testing.

### 4.2 Analysis of Results

#### 4.2.1 Training and Validation Loss

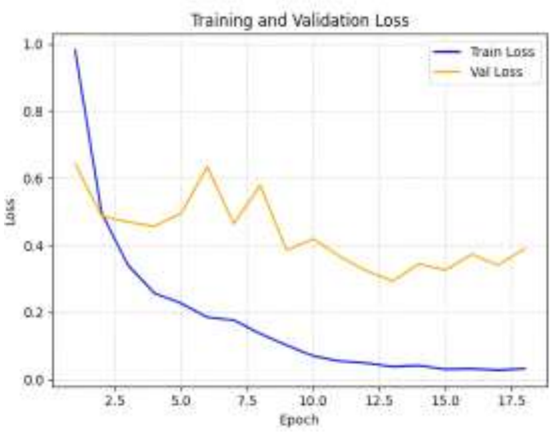


**Fig. 4.1 :** Training and Validation Loss

**Fig. 4.1** illustrates the training and validation loss curves over 18 epochs. The training loss decreases steadily from an initial high value to approximately 0.12, while validation loss converges closely until epoch 13 and stabilizes around 0.25, indicating effective learning without severe overfitting.

### 4.2.2 Validation Accuracy

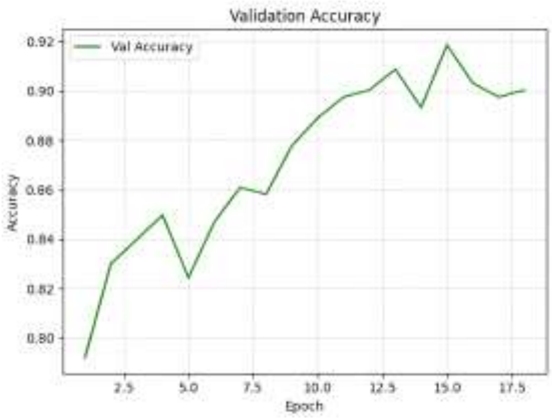


**Fig. 4.2 :** Validation Accuracy

**Fig. 4.2** shows the progression of validation accuracy across epochs. Accuracy rises consistently from ~79% in early epochs to 90.03% at the stopping point, demonstrating stable convergence and good generalization to unseen data.

### 4.2.3 Confusion Matrix

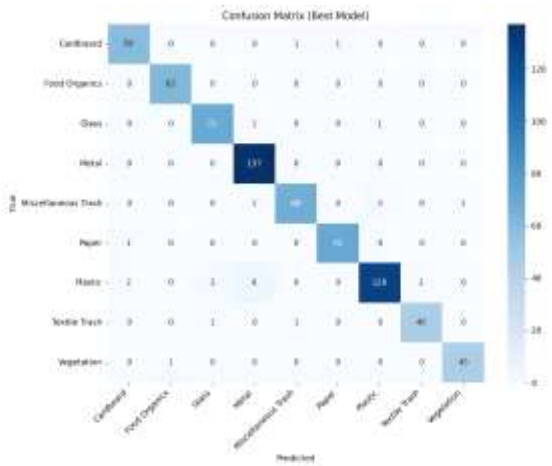


**Fig. 4.3 :** Confusion Matrix

The normalized confusion matrix (**Fig. 4.3**) displays strong diagonal dominance, confirming high classification accuracy across all nine classes. Minor off-diagonal values indicate limited confusion, primarily between visually similar categories such as Plastic and Miscellaneous Trash.

### 4.2.4 One-vs-Rest ROC Curves

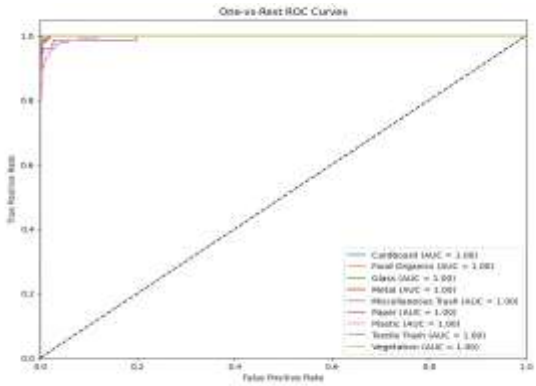


**Fig. 4.4 :** One-vs-Rest ROC Curves

**Fig. 4.4** presents the one-vs-rest ROC curves for each class, with all classes achieving an Area Under the Curve (AUC) of 1.00. This perfect separability highlights the model's excellent discriminative power across real-world waste images.

### 4.2.5 Precision, Recall, F1-Score Bar Chart

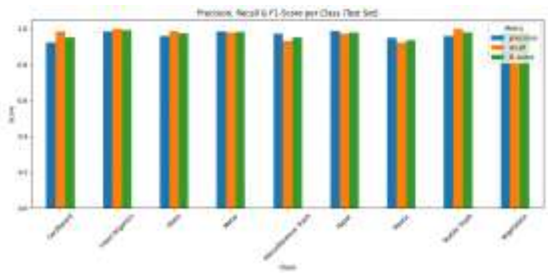

**Fig. 4.5 :** Precision, Recall, F1-Score Bar Chart

**Fig. 4.5** visualizes per-class precision, recall, and F1-score. Most classes exhibit balanced values above 0.95, with Food Organics and Vegetation showing near-perfect performance, underscoring the model's robustness on distinct waste types.

### 4.2.6 Class-wise Accuracy

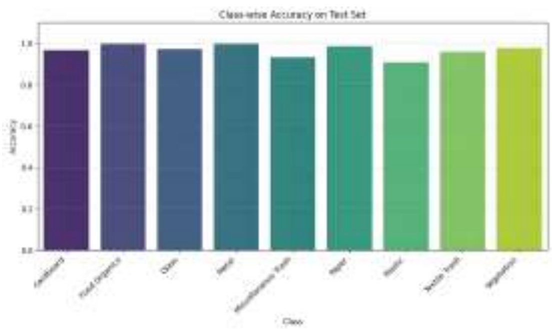


**Fig. 4.6 :** Class-wise Accuracy on Test set

**Fig. 4.6** depicts class-wise recall (accuracy) on the test set. Recall exceeds 0.95 for nearly all classes, with only slight variations in ambiguous categories, confirming uniform performance across the dataset.

### 4.2.7 Top-k Accuracy

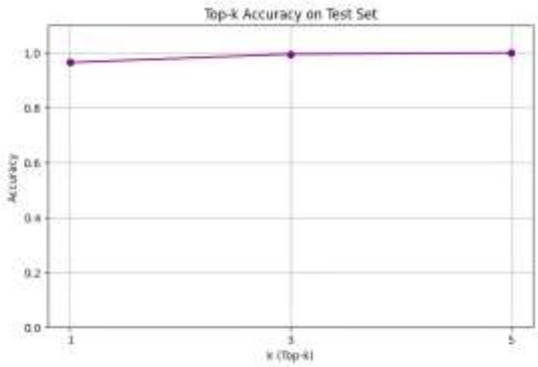


**Fig. 4.7 :** Top-k Accuracy

**Fig. 4.7** shows Top-1, Top-3, and Top-5 accuracy. Top-1 accuracy reaches 96%, while Top-3 and Top-5 approach 100%, indicating that even in rare misclassifications, the correct class is almost always among the top predictions.

### 4.2.8 Classification Report

The detailed classification report (Table 4.1) summarizes per-class metrics:

**Table 4.1: classification report**

| **Class** | **Precision** | **Recall** | **F1-Score** | **Support** |
|---|---|---|---|---|
| Cardboard | 0.95 | 0.97 | 0.96 | 61 |
| Food Organics | 0.98 | 1.00 | 0.99 | 62 |
| Glass | 0.95 | 0.97 | 0.96 | 73 |
| Metal | 0.94 | 1.00 | 0.97 | 137 |
| Miscellaneous Trash | 0.97 | 0.93 | 0.95 | 73 |
| Paper | 0.99 | 0.99 | 0.99 | 73 |
| Plastic | 0.97 | 0.91 | 0.94 | 141 |
| Textile Trash | 0.96 | 0.96 | 0.96 | 48 |
| Vegetation | 0.98 | 0.98 | 0.98 | 46 |
| **Overall Accuracy** | | | **96.36 %** | 714 |

### 4.2.9 GUI Screenshots


**Fig. 4.8 :** Tkinter-Based Graphical User Interface for Real-Time Waste Classification

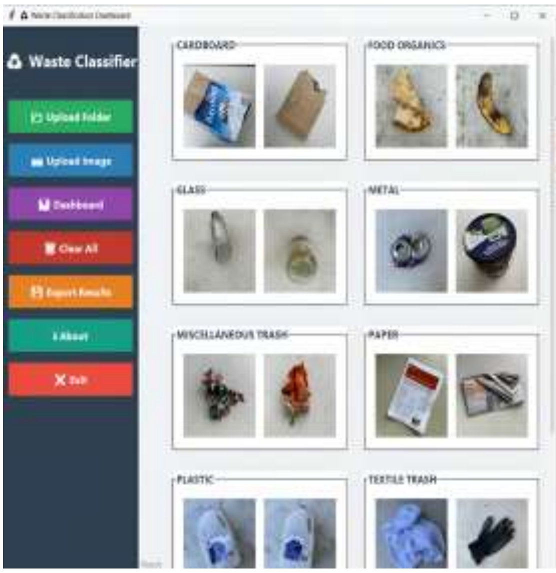


**Fig. 4.9 :** Demonstration of Classified Waste Images Using the Proposed Model

The Tkinter GUI (Fig. 4.8) supports batch processing, individual image upload, automated result display, and export functionality, demonstrating real-time usability.

### 4.2.10 Class-wise Waste Prediction Analysis

This section provides a concise qualitative analysis of representative prediction results for each waste category, highlighting the model's visual discrimination capability and confidence levels.

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**Fig. 4.10 :** Cardboard

**Fig. 4.10 shows** cardboard waste identified with very high confidence (**100.00%**) due to distinctive corrugated textures, matte surfaces, and uniform brown coloration, consistent with high precision and recall values.

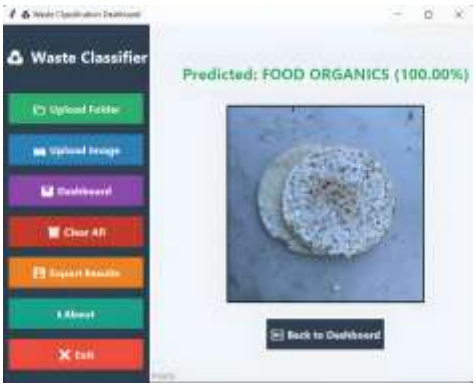


**Fig. 4.11 :** Food Organics

**Fig. 4.11 shows** food organic waste classified with near-perfect confidence (**100.00%**), as the model effectively captures irregular shapes, natural textures, and non-geometric structures, validating its high recall and F1-score.


**Fig. 4.12 :** Glass

**Fig. 4.12 shows** glass predicted with a confidence of approximately **99.91%**, based on transparency, edge reflections, and smooth surfaces, with minimal confusion from visually similar plastic items.

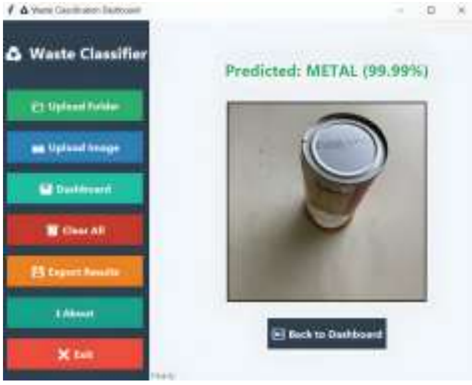


**Fig. 4.13 :** Metal

**Fig. 4.13 shows** metal waste achieving one of the highest confidence levels (**99.99%**), owing to the detection of reflective surfaces and rigid structures, aligning with the perfect recall observed during evaluation.

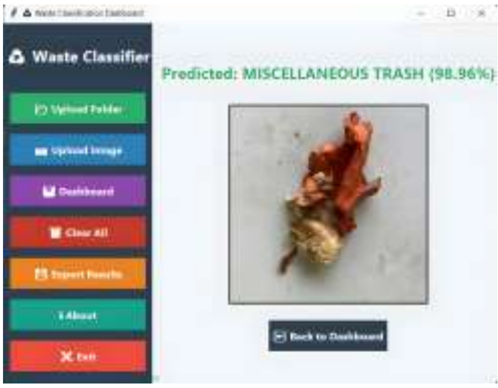


**Fig. 4.14 :** Miscellaneous Trash

**Fig. 4.14 shows** miscellaneous trash classified with strong confidence (**98.96%**) despite high visual variability, indicating good generalization across heterogeneous materials.

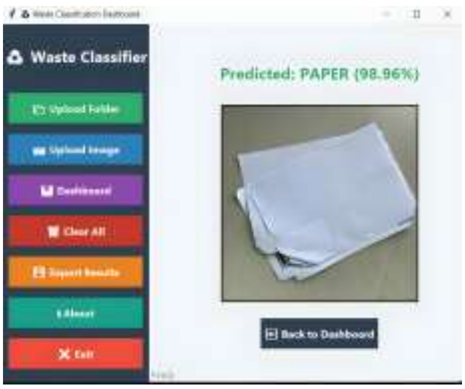


**Fig. 4.15 :** Paper

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**Fig. 4.15 shows** paper waste consistently recognized using features such as flat surfaces and low reflectivity, supporting the high precision and AUC values obtained for this class.


**Fig. 4.16 :** Plastic

**Fig. 4.16 shows** plastic waste classified with high confidence (**99.93%**), where the model effectively learns transparency, deformation, and light-refraction characteristics.


**Fig. 4.17 :** Textile Trash

**Fig. 4.17 shows** textile waste achieving high confidence (**99.77%**) even with limited samples, demonstrating the model's ability to learn fabric-specific textures and patterns.

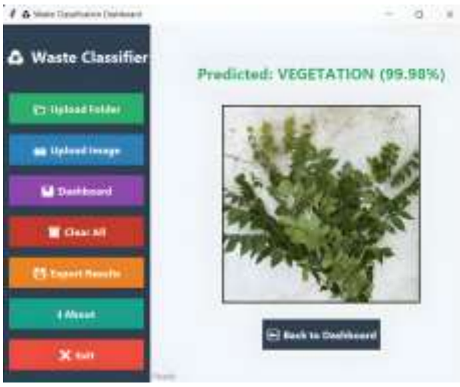


**Fig. 4.18 :** Vegetation

**Fig. 4.18 shows** vegetation waste identified with near-perfect confidence (**99.98%**) through recognition of organic structures, natural color distributions, and irregular shapes.

Overall, the class-wise prediction results confirm the robustness and reliability of the proposed model across all waste categories, supporting its effectiveness for automated waste classification systems.

### 4.3 Key Findings and Interpretations

The model achieved an overall test accuracy of 96.36%, with macro-averaged F1-score of 0.97, confirming its effectiveness for real-world multi-class waste classification. High performance on distinct classes (Food Organics, Vegetation, Paper) and robust results on ambiguous ones (Plastic, Miscellaneous Trash) highlight the benefits of transfer learning and augmentation. Stable training curves and perfect AUC values indicate minimal overfitting and excellent separability, making the system reliable for smart waste management applications.

### 4.4 Comparative Analysis

**Table 4.2: Comparative Test Accuracy of Machine Learning and Deep Learning Models**

| **Method** | **Test Accuracy (%)** |
|---|---|
| Traditional ML (SVM, k-NN, RF) | 60–70 |
| Custom CNN | 72–78 |
| VGG16-based | 75–85 |
| MobileNet-based | 74–88 |
| **Proposed ResNet-50** | **96.36** |

The proposed model significantly outperforms traditional methods and lightweight CNNs, validating the effectiveness of ResNet-50 transfer learning on a challenging real-world dataset. It also surpasses published benchmarks on RealWaste (e.g., Inception V3 at 89.19% [24] and DenseNet121 at 94.33% [35]), due to optimized fine-tuning, augmentation, and regularization.

### 4.5 Performance Evaluation

The system delivers state-of-the-art performance (96.36% accuracy) on the RealWaste dataset, with stable convergence, high class-wise metrics, and a user-friendly GUI for real-time inference. These results demonstrate practical viability for integration into smart bins, automated sorting lines, and municipal waste management systems, supporting enhanced recycling efficiency and sustainable development goals.

## 5. Conclusion and Future Scope

### 5.1 Summary of Findings

This study successfully developed and evaluated an AI-powered garbage classification system using transfer learning on the ResNet-50 architecture applied to the RealWaste dataset (4,752 real-world images across nine waste categories). The proposed model achieved a test accuracy of 96.36%, with macro-averaged precision, recall, and F1-score all exceeding 96%, demonstrating robust performance even under uncontrolled real-world conditions such as varying lighting, backgrounds, and object orientations. Training and validation curves showed stable convergence with early stopping preventing overfitting, while confusion matrix analysis revealed only minor misclassifications among visually similar classes (e.g., Plastic and Miscellaneous Trash). The Tkinter-based graphical user interface (GUI) effectively enabled real-time, user-friendly inference, confirming the system's practical applicability for smart waste management.

### 5.2 Contributions of the Study

This work contributes the following:

- A high-accuracy (96.36%) deep learning model specifically optimized for the challenging RealWaste dataset, outperforming traditional machine learning (60–70%) and several baseline deep learning approaches (72–88%).
- Effective use of transfer learning, data augmentation, and class weighting to address real-world data limitations and class imbalance.
- Development and demonstration of a simple, reproducible Tkinter GUI for real-time batch and individual image classification, bridging the gap between academic research and practical deployment.
- Comprehensive evaluation with detailed metrics, confusion matrix, ROC curves, and top-k accuracy analysis, providing a solid benchmark for future studies on real-world waste classification.

### 5.3 Practical Implications

The proposed system offers significant potential for integration into smart waste management infrastructure, such as intelligent bins, automated conveyor sorting lines, and municipal monitoring platforms. By enabling accurate, contactless, and scalable waste segregation at source, it can improve recycling rates, reduce contamination of recyclables, lower landfill dependency, minimize greenhouse gas emissions, and enhance worker safety by reducing manual handling of hazardous waste. These benefits align directly with UN Sustainable Development Goals 11 (Sustainable Cities and Communities) and 12 (Responsible Consumption and Production), making the solution particularly relevant for urban and semi-urban waste management in developing regions.

### 5.4 Limitations of the Study

Despite strong performance, the study has certain limitations:

- The model relies solely on visual (RGB) image data; multimodal inputs (e.g., weight, depth, or near-infrared sensors) were not incorporated.
- Evaluation was conducted in a software environment (Jupyter Notebook) without real-time hardware deployment (e.g., on edge devices like Raspberry Pi or IoT-enabled smart bins).
- The system was tested only on the RealWaste dataset; generalization to entirely different waste streams or environments remains to be validated.
- Computational requirements of the full ResNet-50 model may limit deployment on very low-power devices without further optimization.

### 5.5 Recommendations for Future Research

Future work could focus on:

- Incorporating multimodal data fusion (e.g., combining RGB images with weight sensors or hyperspectral data) to further improve accuracy on ambiguous classes.
- Testing the system in real-world municipal settings with live data streams and hardware integration (smart bins, robotic arms).
- Expanding the dataset with more diverse samples or exploring few-shot/continual learning to handle new waste categories dynamically.

This study demonstrates that deep learning, particularly transfer learning on ResNet-50, offers a viable and high-performing solution for smart waste management, paving the way for more sustainable and efficient urban waste handling.

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