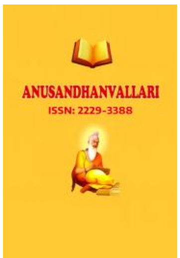

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AI Powered Waste Management System

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Abstract—Waste mismanagement remains a significant environmental and public health challenge, particularly in rural and semi-urban regions where structured waste segregation systems are limited. The increasing diversity of waste materials further complicates manual segregation, leading to inefficient recycling, environmental pollution, and health risks. To address these challenges, this paper presents an AI-powered automated waste classification system based on MobileNetV2 and transfer learning for fine-grained multi-class waste categorization. The proposed system classifies waste into thirteen categories, including recyclable, organic, hazardous, and non-waste classes. A multi-source dataset is constructed by combining a publicly available garbage classification dataset with non-waste images from the CIFAR-10 dataset to improve robustness under real world conditions. Image preprocessing and data augmentation techniques are employed to enhance generalization across varying environmental conditions. Experimental evaluation demonstrates that the proposed MobileNetV2-based model achieves a test accuracy of 94.62%, along with strong precision, recall, and F1-score across most classes. The lightweight architecture and efficient training strategy make the system suitable for deployment on low-cost and resource constrained devices, enabling scalable and sustainable waste management solutions aligned with national initiatives such as Swachh Bharat Abhiyan and Digital India.

Index terms—Waste Management, Deep Learning, Transfer Learning, MobileNetV2, Multi-Class Classification, Smart Waste Systems

I. Introduction

Waste mismanagement has emerged as a major environmental and public health concern, particularly in rural and semi-urban regions where structured waste disposal systems are limited. The lack of systematic segregation across diverse waste materials—including organic, recyclable, and hazardous waste—contributes to soil and water contamination, unhygienic surroundings, and increased health risks. Manual segregation, although practiced in some areas, is labor-intensive, unsafe, and inconsistent, making it unsuitable for large-scale deployment.

Recent advancements in Artificial Intelligence (AI) and Computer Vision have enabled automated waste classification systems that improve segregation accuracy and operational efficiency. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong performance in visual recognition tasks [1]–[3]. By leveraging such models, waste segregation can be automated at the source, enabling cleaner environments and more efficient downstream recycling processes.

Furthermore, the availability of lightweight deep learning architectures designed for mobile and embedded platforms—such as MobileNetV2 and EfficientNet—makes real-time, on-device inference feasible in low-resource settings [4], [5]. This research focuses on developing a deployable, low-power AI-based waste classification system capable of performing fine-grained multiclass waste segregation, making it suitable for rural smart waste management applications.

The contributions of this work are:

- Development of a MobileNetV2-based transfer learning model for thirteen-class waste classification, covering recyclable, organic, hazardous, and non-waste categories.
- Construction of a multi-source dataset integrating a garbage classification dataset and non-waste samples to improve real-world robustness.
- Implementation of an image preprocessing and data augmentation pipeline to enhance generalization under varying environmental conditions.
- Design of an automated waste segregation framework suitable for deployment in low-power rural smart bins.
- Comprehensive evaluation using accuracy, precision, recall, F1-score, confusion matrix, and ROC curve analysis.

II. Related Work

A. Traditional Waste Management Approaches

Early smart waste systems employed RFID tags and sensor-based monitoring to assist in waste collection and scheduling [6], [7]. IoT-driven waste management systems further improved route optimization and bin-level monitoring [8], [9]. However, these approaches primarily focus on logistics and do not address the challenge of automated waste segregation. Manual sorting remains common in many regions, exposing workers to hazardous waste and underscoring the need for safe and automated alternatives [10].

B. Machine Learning for Waste Classification

Classical machine learning methods utilized handcrafted features combined with classifiers such as Support Vector Machines (SVMs) and Random Forests to categorize waste. While effective in constrained environments, these methods struggle with real-world variability in lighting, background, and object appearance [?]. Their dependence on manual feature engineering limits scalability and adaptability.

C. Deep Learning-Based Waste Classification

Deep learning approaches have significantly advanced waste classification accuracy. CNN-based models have shown promising results in identifying recyclable and non-recyclable waste [11]–[13]. Transfer learning techniques leveraging pretrained architectures such as EfficientNet and MobileNetV2 enable improved performance when labeled data is limited [5]. Data augmentation and generative techniques further enhance robustness [14]. However, many studies focus on coarse-grained classification and urban-centric datasets, limiting applicability in rural contexts.

D. Lightweight Models for Edge Deployment

Lightweight architectures such as MobileNetV2 are designed for efficient inference on resource-constrained devices [4]. Their reduced computational footprint enables deployment in embedded systems and smart bins where power and connectivity are limited, making them suitable for scalable rural waste management applications [15].

III. Problem Statement

Rural regions often lack structured waste management infrastructure and awareness. Waste is commonly disposed of as mixed garbage, resulting in environmental pollution, health hazards, reduced recyclability, and increased risk for manual waste handlers. An automated, low-cost, and scalable waste classification system is required to enable source-level segregation without reliance on skilled labor.

IV. Proposed Methodology

A. Dataset Description

A curated multi-source dataset of labeled waste images was constructed to support fine-grained multi-class waste classification. The primary waste dataset was sourced from a publicly available garbage classification dataset containing categories such as plastic, metal, paper, cardboard, glass variants, biological waste, batteries, clothes, shoes, and trash. To enhance real-world robustness, a *Non-Waste* class was introduced using images from the CIFAR-10 dataset.

The final dataset consists of thirteen distinct classes and was divided into training and testing subsets using an 80/20 split. This design enables the model to distinguish waste from non-waste objects commonly encountered in uncontrolled environments.

B. Preprocessing

All images were resized to 224 × 224 pixels to match the input requirements of MobileNetV2 and normalized to the range $[0,1]$ using:

$$I_{\text{norm}} = \frac{I}{255}.$$

To enhance robustness against variations in illumination, orientation, and background clutter, data augmentation techniques such as horizontal flipping, random rotation, and zoom perturbations were applied during training. These operations help mitigate overfitting and improve generalization.

C. Model Architecture

The ImageNet-pretrained MobileNetV2 [4] architecture was employed as a fixed feature extractor using transfer learning. The convolutional layers were frozen during initial training to preserve pretrained representations. Extracted features were passed through a lightweight classification head consisting of:

- GlobalAveragePooling2D layer,
- Dense layer with 128 ReLU units,
- Dropout layer with a rate of 0.5,
- Final Dense layer with 13 outputs and softmax activation. The softmax function computes class probabilities as:

$$p(y = i|x) = \frac{e^{z_i}}{\sum_{j=1}^{13} e^{z_j}}.$$

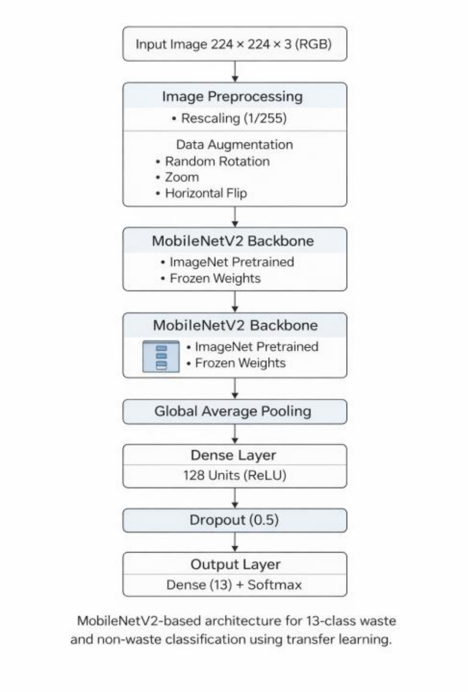

Fig. 1: MobileNetV2-based architecture for 13-class waste classification.

D. Training Strategy

The model was trained using the Adam optimizer [16] with a learning rate of 1×10^{-4} and categorical cross-entropy loss. A batch size of 16 was selected to balance memory usage and training stability. Early stopping and learning rate reduction strategies were applied by monitoring validation loss to prevent overfitting and improve convergence behavior. The training pipeline was implemented using TensorFlow/Keras [17].

V. Evaluation Metrics

Model performance was evaluated using standard multiclass classification metrics derived from the confusion matrix, including accuracy, precision, recall, specificity, and F1-score. These metrics provide a comprehensive quantitative assessment of both overall classification performance and class-wise prediction reliability, which is essential for automated waste management systems operating in real-world environments.

Let *TP*, *TN*, *FP*, and *FN* denote the number of true positives, true negatives, false positives, and false negatives, respectively.

A. Accuracy

Accuracy represents the overall proportion of correctly classified samples across all classes and is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

B. Precision

Precision measures the correctness of positive predictions by indicating the proportion of true positive predictions among all predicted positives:

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$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

C. Recall

Recall, also known as sensitivity, evaluates the ability of the model to correctly identify actual positive samples:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

D. Specificity

Specificity measures the model's capability to correctly identify negative samples and is defined as:

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4}$$

E. F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation metric that is particularly useful in the presence of class imbalance:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

F. Macro-Averaged Metrics

For the proposed multi-class waste classification task, macroaveraged metrics were reported to ensure that each class contributes equally to the overall evaluation, regardless of class frequency. Macro-averaging is computed as:

$$\text{Metric}_{\text{macro}} = \frac{1}{C} \sum_{i=1}^{C} \text{Metric}_i \tag{6}$$

where C denotes the total number of classes.

VI. Results And Discussion

TABLE I: Model Performance Metrics

Metric	Value (%)
Accuracy	94.62
Precision (Macro)	93.88
Recall (Macro)	93.21
F1-score (Macro)	93.54

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A. Learning Curves

Figures 2 and 3 illustrate training and validation accuracy and loss across epochs. The smooth convergence trends indicate effective optimization and minimal overfitting.

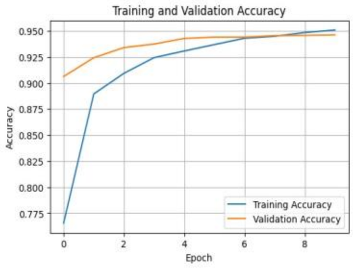

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Fig. 2: Training and validation accuracy across epochs.

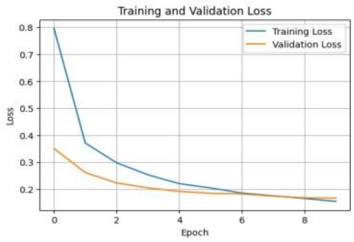

Fig. 3: Training and validation loss across epochs.

B. Confusion Matrix Analysis

The confusion matrix shown in Fig. 4 provides a detailed class-wise evaluation of the proposed waste classification model. Each row of the matrix represents the true class labels, while each column corresponds to the predicted class labels. Diagonal elements indicate correct predictions, whereas off-diagonal entries represent misclassifications.

Overall, the confusion matrix confirms balanced class-wise performance and validates the effectiveness of the proposed

MobileNetV2-based model for multi-class waste classification.

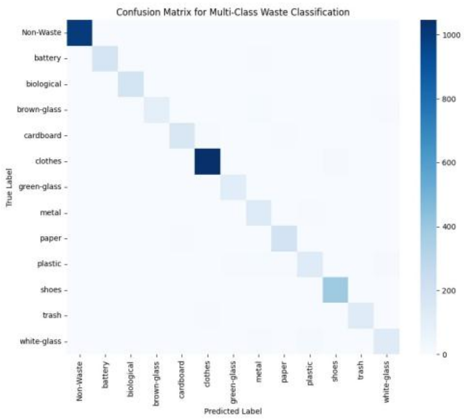

Fig. 4: Confusion matrix for the 13-class waste classifier.

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C. ROC Curve Analysis

Receiver Operating Characteristic (ROC) analysis was performed using a one-vs-rest strategy to evaluate the discriminative capability of the model across all thirteen classes. The macro-averaged ROC curve, presented in Fig. 5, summarizes the overall classification performance by aggregating class-wise true positive rates and false positive rates.

The high Area Under the Curve (AUC) values indicate that the proposed model effectively separates waste categories from one another over a wide range of decision thresholds. This strong discriminative performance demonstrates the robustness of the learned feature representations and supports the model's suitability for real-world deployment, where classification confidence and reliability are critical.

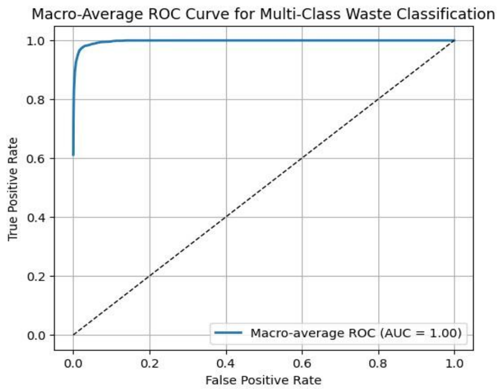

Fig. 5: Macro-averaged ROC curve for multi-class waste classification.

D. Interpretation of Results

The proposed model achieves strong overall performance, with a test accuracy of 94.62% and a macro-averaged F1score of 93.54%, indicating balanced and reliable classification across all thirteen categories. Misclassifications primarily occur between visually similar waste items such as different glass variants, which is expected in real-world waste streams.

E. Strengths and Limitations

The primary strengths of the proposed system include high accuracy with a lightweight architecture, robustness to visual variability through augmentation, and suitability for embedded deployment. Limitations include dataset diversity constraints and challenges in distinguishing visually ambiguous waste items.

VII. Conclusion

This work presents an AI-powered waste classification system using MobileNetV2-based transfer learning for finegrained multi-class waste segregation. The proposed model effectively classifies waste into thirteen categories while maintaining computational efficiency suitable for low-cost embedded deployment. The achieved accuracy of 94.62% demonstrates the effectiveness of transfer learning in addressing real-world waste management challenges. The system offers a scalable and practical solution for intelligent waste segregation aligned with sustainable development goals.

VIII. Future Scope

\Future enhancements include expanding the dataset with field-collected rural waste images, applying model compression techniques for faster inference, integrating multimodal sensing, and deploying the system in real-time smart-bin environments.

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