

RecycleVision AI: Automated Waste Classification using Deep Learning and Explainable AI

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Abstract — Waste management has emerged as a critical environmental concern due to rapid urbanization and increasing consumption patterns. Traditional waste segregation methods rely heavily on manual processes, which are inefficient, error-prone, and hazardous to human health. To address these challenges, this paper proposes RecycleVision AI, an intelligent waste classification system based on deep learning and computer vision techniques. The system utilizes the MobileNetV2 architecture with transfer learning to classify waste images into six categories: plastic, paper, glass, metal, cardboard, and general trash. A key contribution of this work is the integration of Explainable Artificial Intelligence using Grad-CAM, which provides visual insights into the model's decision-making process by highlighting important image regions. The system is implemented using TensorFlow and deployed via a Streamlit-based web interface, enabling users to upload images and receive real-time classification results along with confidence scores and visual explanations. The proposed solution demonstrates high accuracy, computational efficiency, and usability, making it suitable for real-world waste management applications. It contributes to sustainable development by improving waste segregation efficiency and promoting responsible recycling practices.

Keywords: Waste Classification; Deep Learning; MobileNetV2; Computer Vision; Explainable AI; Grad-CAM.

1. Introduction

The rapid growth of population and industrial activities has led to a significant increase in solid waste generation across the globe. Inefficient waste management practices have resulted in environmental degradation, resource depletion, and increased health risks. A large portion of generated waste consists of recyclable materials such as plastic, paper, glass, and metals, which often remain unsegregated due to the limitations of manual sorting systems. Manual waste classification is labor-intensive, time-consuming, and prone to errors caused by human fatigue and inconsistency. Moreover, workers involved in waste segregation are exposed to hazardous substances, making the process unsafe.

As waste volumes continue to grow, traditional approaches become economically and operationally unsustainable. Recent advancements in Artificial Intelligence, particularly in deep learning and computer vision, have enabled automated solutions for visual recognition tasks. Convolutional Neural Networks (CNNs) have proven highly effective in image classification applications and can be leveraged to automate waste segregation processes. RecycleVision AI is proposed as an intelligent solution that automates waste classification using a pre-trained MobileNetV2 model. The system enhances transparency by incorporating Explainable AI techniques such as Grad-CAM, allowing users to understand the reasoning behind predictions. With a user-friendly web interface built using Streamlit, the system ensures accessibility and real-time interaction, making it suitable for both domestic and industrial applications.

2. Literature Survey

Artificial Intelligence in waste management has evolved from traditional image processing techniques such as color histograms and edge detection to advanced deep learning methods. Earlier approaches required manual feature extraction and struggled with real-world variations, leading to inconsistent performance.

With the rise of Convolutional Neural Networks, waste classification accuracy has significantly improved due to their ability to learn hierarchical image features automatically. Among these, MobileNetV2 is widely used for its lightweight architecture, making it suitable for resource-constrained environments while maintaining high accuracy.

Transfer learning using large datasets like ImageNet further enhances performance even with limited training data. However, deep learning models are often considered opaque in their decision-making. To improve transparency, techniques like Grad-CAM are used to generate heatmaps that highlight important regions influencing predictions, making the model more interpretable and trustworthy. Modern tools such as TensorFlow and Streamlit enable easy deployment of interactive AI systems.

Despite advancements, challenges remain, including limited datasets, sensitivity to image quality, and lack of real-time and user-friendly solutions. RecycleVision AI addresses these gaps by combining an efficient model, explainable AI, and an intuitive interface to deliver a scalable and practical waste classification system.

3. Proposed System

RecycleVision AI is an intelligent waste classification system designed to automate waste segregation using deep learning and computer vision. It addresses the inefficiencies of manual sorting by providing an accurate, scalable, and user-friendly solution for real-time classification. The system works through image classification: users upload an image of a waste item, and the model predicts its category. It classifies waste into six types—cardboard, glass, metal, paper, plastic, and trash—covering common real-world recyclable materials. The system is built on three main components: deep learning-based classification, explainable AI, and a web-based interface. The classification module uses a fine-tuned MobileNetV2 model with transfer learning to achieve high accuracy. To improve transparency, Grad-CAM is integrated to generate heatmaps showing the regions influencing predictions. The application is deployed using Streamlit, providing an interactive interface where users can easily upload images and view results instantly.

3.1 System Architecture

The architecture of RecycleVision AI follows a modular design, where each component performs a specific function in the classification pipeline. This modular approach improves system scalability, maintainability, and performance. The system architecture, as shown in Fig. 1, consists of the following layers: the User Interface Layer provides interaction between the user and the system; the Image Ingestion Layer validates the uploaded image format; the Preprocessing Layer resizes the image to 224×224 pixels and normalizes it; the Deep Learning Inference Layer uses MobileNetV2 for feature extraction and classification; the Explainable AI Layer applies Grad-CAM to generate interpretable heatmaps; and the Results Layer presents the predicted category, confidence score, heatmap, and recycling recommendation.

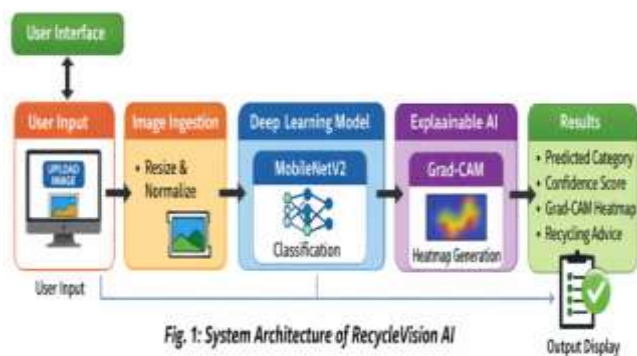


Fig. 1: System Architecture of RecycleVision AI

3.2 System Flow

The workflow of the proposed system follows a sequential pipeline. The user uploads an image through the interface, which is then preprocessed through resizing and normalization. The MobileNetV2 model performs classification and generates a prediction along with a confidence score. Grad-CAM subsequently produces a visual explanation by highlighting the important regions that influenced the classification decision. Finally, all results including the predicted category, confidence score, heatmap visualization, and recycling recommendation are displayed to the user.

3.3 UML Diagrams

3.3.1 Use Case Diagram

The Use Case Diagram in Fig. 2 represents the interaction between the User and the RecycleVision AI system. The user can upload waste images, view image previews, receive predictions with confidence scores, view Grad-CAM heatmaps, and access recycling suggestions. The system internally performs preprocessing, classification, and visualization processes.

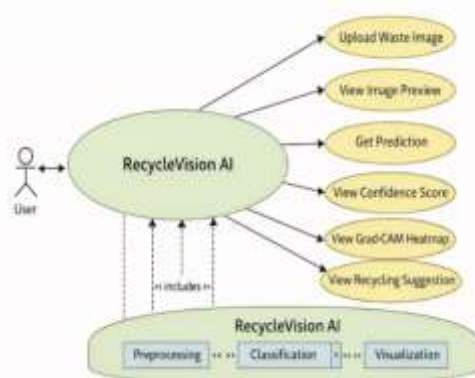


Fig. 2: Use Case Diagram of RecycleVision AI

3.3.2 Class Diagram

The Class Diagram in Fig. 3 shows the structural components of the system and relationships between different classes. The key classes include ImageUploader for handling file uploads and previews, ImagePreprocessor for resizing and normalizing images, WasteClassifier that encapsulates the MobileNetV2 model for classification, GradCAMGenerator for producing heatmaps, StreamlitApp as the main application controller, RecyclingAdvisor for generating recycling suggestions, and ClassificationResult for encapsulating output data. Each class performs a specific function, ensuring modularity and maintainability.

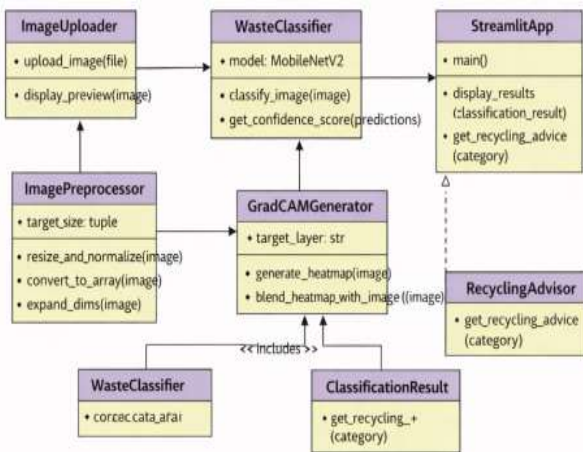


Fig. 3: Class Diagram of RecycleVision AI

3.3.3 Sequence Diagram

The Sequence Diagram in Fig. 4 illustrates the step-by-step interaction between system components during the classification process. The user uploads an image through the StreamlitApp, which forwards it to the Image Preprocessor for resizing and normalization. The preprocessed image is then sent to the Waste Classifier for prediction, while simultaneously the GradCAM Generator creates a visual explanation. The results are aggregated and displayed back to the user through the application interface.

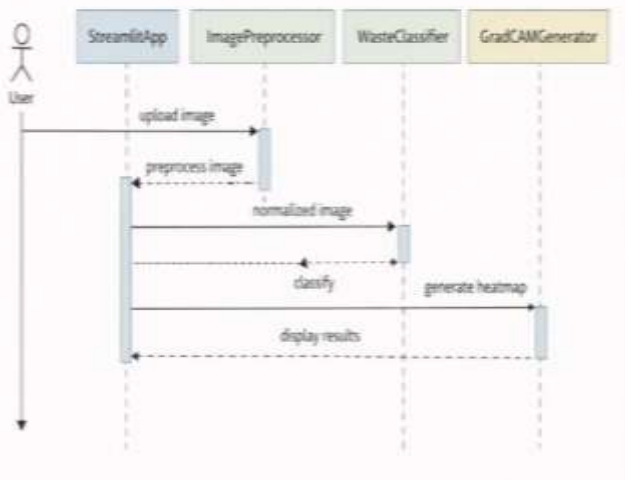


Fig. 4: Sequence Diagram of RecycleVision AI

4. Implementation

The implementation of RecycleVision AI is designed using a modular architecture to ensure scalability, maintainability, and efficient performance. Each module is responsible for a specific task in the waste classification pipeline, enabling seamless integration and independent testing.

4.1 System Modules

The system is divided into five major modules: Image Input Module, Preprocessing Module, Classification Module, Explainable AI Module, and Visualization Module. The Image Input Module acts as the entry point of the system, implemented using a Streamlit-based web interface that allows users to upload waste images in JPEG and PNG formats. This module validates the uploaded file, ensures compatibility, displays a preview, and incorporates error handling for invalid or corrupted inputs. The Preprocessing Module prepares the input image for classification by resizing it to 224×224 pixels, normalizing pixel values to the range [0,1], converting the image into a numerical array format, and expanding dimensions for model compatibility. These steps ensure consistency between training and testing data. The Classification Module is the core component utilizing MobileNetV2 trained with transfer learning. The architecture includes feature extraction layers, global average pooling, fully connected dense layers, and softmax activation for multi-class classification. The module predicts one of the six waste categories and provides a confidence score.

The Explainable AI Module incorporates Grad-CAM to generate heatmaps that highlight important image regions influencing the model’s decision. This improves transparency and increases user trust in AI-based predictions. The Visualization Module presents results in a user-friendly format, displaying the predicted waste category, confidence score, Grad-CAM heatmap visualization, probability distribution across all categories, and recycling recommendations.

4.2 Implementation Tools

The system is developed using Python as the core programming language, TensorFlow and Keras as the deep learning framework, OpenCV for image processing tasks, NumPy for numerical computation, and Streamlit for the web-based deployment interface. These tools provide a robust environment for developing and deploying AI-based applications efficiently.

5. Testing and Evaluation

Testing plays a crucial role in ensuring the reliability, accuracy, and efficiency of the RecycleVision AI system. A comprehensive testing strategy was adopted including unit testing, integration testing, system testing, and user acceptance testing. Unit testing validated the functionality of individual components in isolation, ensuring each module performs correctly. Integration testing verified the seamless data flow between modules in the pipeline architecture, including file upload functionality, image preview display, prediction and confidence display, and heatmap

visualization rendering. System testing evaluated the complete system under real-world conditions.

Accuracy was measured using metrics such as precision, recall, and F1-score on a test dataset, where the model achieved high performance due to transfer learning with MobileNetV2. Performance testing assessed image processing time, model inference time, heatmap generation, and overall response time, with results showing fast responses suitable for real-time use. Robustness testing examined system behavior under challenging conditions such as low lighting, blur, and complex backgrounds, where the system maintained stable performance. User Acceptance Testing ensured the system meets user expectations. Users uploaded waste images, viewed classification results, interpreted Grad-CAM visualizations, and followed recycling suggestions. Feedback indicated that the system is intuitive, clear, and useful for real-world waste classification. The overall performance evaluation confirmed a strong balance between accuracy and computational efficiency, making the system suitable for both academic use and real-world deployment.

6. Conclusion

RecycleVision AI provides an intelligent solution for automated waste classification using deep learning and computer vision. The use of MobileNetV2 with transfer learning ensures high accuracy with efficient performance, while Grad-CAM adds transparency by explaining predictions through visual heatmaps. The Streamlit-based interface makes the system easy to use and accessible to a broad range of users. Overall, it offers a practical, efficient, and sustainable approach to improving waste management and promoting responsible recycling practices.

7. Future Enhancements

Several enhancements can be pursued to extend the capabilities of RecycleVision AI. Integration of real-time webcam-based waste classification would enable continuous monitoring. Development of a mobile application would provide wider accessibility for end users. The waste categories can be expanded to include e-waste, organic waste, and hazardous waste for more comprehensive coverage. Integration with IoT-enabled smart bins would facilitate automated segregation at the point of disposal. Deployment on cloud platforms would ensure scalability and multi-user access. Implementation of advanced explainability techniques such as SHAP and LIME could further enhance model interpretability. Finally, improving model accuracy using larger and more diverse datasets would strengthen classification performance across varied real-world conditions.

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