

Waste Classification using VGG-16 and ResNet-50

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Abstract - The increase in solid waste has made waste management a major challenge in today's world. Manual waste segregation is slow and often inaccurate because it depends on human effort, which can lead to mistakes. To overcome these problems, automated and software-based waste classification systems are becoming increasingly important.

Convolutional Neural Networks (CNN) are used in this project to create a waste classification system. Two deep learning models, VGG-16 and ResNet-50, are used throughout the implementation in a Kaggle Notebook environment. The waste image dataset is gathered from Kaggle and preprocessed using data augmentation techniques, pixel value normalization, and image resizing. Next, training and testing sets are created from the dataset. The VGG-16 and ResNet-50 models are both trained to categorize waste images into various pre-established groups. Accuracy, loss graphs, precision values, and confusion matrices are used to assess the models' performance. The results show that ResNet-50 achieves better accuracy and lower loss because of its deeper network and residual learning capability, while VGG-16 offers a stable and dependable baseline performance. All things considered, this project shows an efficient and dependable software-based method for automated waste classification, which can promote improved recycling and waste disposal procedures.

Keywords: Waste Classification, Convolutional Neural Network (CNN), VGG-16, ResNet-50, Deep Learning, Kaggle Notebook, Image Processing, Solid Waste Management, Recycling Automation, Residual Learning, Transfer Learning, Supervised Learning, Computer Vision.

I INTRODUCTION

Globally, solid waste generation has increased dramatically as a result of growing urbanization, industrialization, and consumer consumption. In the Third World, where waste is currently mostly picked by hand, waste management has grown to be a significant environmental and social concern. Waste segregation by hand is extremely time-consuming, labor-intensive, and prone to mistakes.. These problems lower recycling efficiency and aggravate environmental pollution. One such solution to these issues is automated waste classification with artificial intelligence.

In recent years, deep learning based models (most often convolutional neural networks (CNNs)) have performed excellently in the image classification task as they can learn relevant features from images without too much human

intervention. In addition, deeper network structures and better learning strategies can achieve higher accuracy, such as VGG-16 and ResNet-50. These models are suitable for applications where detailed image processing is needed, e.g. differentiate various waste types.

In this work, a CNN based waste classifier system will be developed with VGG-16 and ResNet-50 models. All this code is being done in a Kaggle Notebook environment. A garbage image dataset from Kaggle is pre-processed as the initial and training /testing images on both methods. The performance of the models is compared based on accuracy, loss, and classification efficiency. Overall, this project demonstrates how deep learning can be effectively used to improve waste segregation.

II LITERATURE REVIEW

1. "Enhanced Garbage Classification Using a Lightweight ResNet-50 Variant" by Li et al., 2025. The authors redesigned parts of ResNet-50 using depth wise separable convolutions and feature fusion to reduce parameters while increasing accuracy.
2. "An Intelligent Deep Learning based Classification" by Ishaque, N. B. M in 2025. This demonstrates YOLOv3 detection + ResNet-50 classification pipeline with very high accuracy and discusses how object detection + classifier fusion helps practical systems.
3. "A CNN-Based Intelligent Waste Sorting Model for Sustainable Environment" by Sayed et al., 2024. The authors used an improved CNN architecture, along with data balancing and augmentation, to classify waste categories. The study reports high accuracy (up to 95.9%) on the TrashNet dataset.
4. "Enhanced convolutional neural network methodology for solid waste classification" by Itam, D. H (2024). Focuses on image resizing, augmentation and hyper-parameter tuning to boost standard CNN / transfer-learning models for waste classification tasks. Useful for augmentation & preprocessing design.
5. "Intelligent waste classification" by Chhabra, M in 2024. The work compares the outcomes with ResNet-based models to demonstrate improved performance and

enhances the model structure to better differentiate between organic and recyclable waste.

III PROPOSED SYSTEM

The proposed system uses deep learning techniques like VGG-16 and ResNet-50 convolutional neural network models to implement an automatic waste classification model. The system's goal is to automatically classify waste into two categories: organic (class 1) and recyclable (class 2). The Kaggle labeled waste image dataset is used to train the model. Prior to processing for learning, the dataset is preprocessed (pre-training), which includes resizing the images and normalizing the values. After that, the models are tested and trained to see how well they can recognize different kinds of waste.

A. Key Components

1. Dataset Acquisition: Waste photos are gathered from a Kaggle dataset that is already accessible. The combined waste categories in the dataset have been filtered and labeled into two groups:

- Organic waste
- Recyclable waste

2. Feature Extraction and Model Training: To increase learning and accuracy, the project makes use of VGG-16 and ResNet-50 models that have already been trained on the ImageNet dataset. The final layers are modified for binary classification Models learn features such as:

- Texture
- Shape
- Color patterns

Structural differences between organic and recyclable waste

3. Software Requirements

- Kaggle Notebook
- Python 3.x
- GPU runtime

Libraries:

- TensorFlow / Keras for CNN implementation.
- OpenCV for image capture and preprocessing.
- NumPy, Pandas, Matplotlib for data handling and visualization.
- Scikit-learn, OS for utility and to access directory paths.

IV SYSTEM DESIGN

A. system architecture description

The system architecture for the project "Waste Classification Using VGG-16 and ResNet-50" is designed as a modular, layered deep-learning pipeline. It ensures effective data processing, model training, prediction generation, and performance comparison between two powerful CNN architectures.

The architecture integrates all major components — data acquisition, preprocessing, feature extraction, training, evaluation, and output generation — in a clear and organized manner.

Data Flow Summary:

Input Dataset → Dataset Preprocessing → Train-Test Split → Feature extraction and model training → Classification Module → Performance evaluation → Output module.

System Workflow Overview:

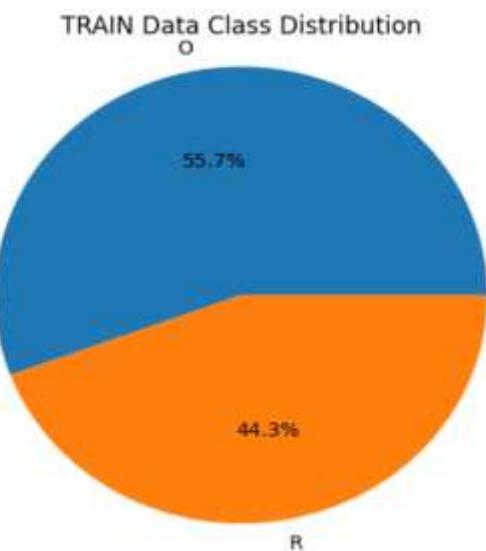
A layered architecture is used to implement the Waste Classification using VGG16 and ResNet50. The stages of the workflow are as follows:

1. Input Dataset: The dataset used in this project comes from Kaggle and includes a variety of waste photos. The images are divided into two groups: Food scraps and recyclable waste, which includes plastic, paper, metal, and evorita, appear to be major contributors to waste pollution. Several hundred to several thousand color JPG or PNG images are included in the datasets. Every picture is grouped into a folder based on its type. These annotated images serve as training and testing data for the CNN model and are ultimately used as input by the waste classification system.



2. Dataset Preprocessing: Before model training, the waste images are prepared so the CNN models can use them appropriately. Each image is resized to 224×224 pixels, the input size required by VGG-16 and ResNet-50. The pixel values of the images are also normalized to a range between 0 and 1, which helps the models learn faster and perform better during training. Data augmentation methods, such as rotation, flipping, and zooming, are also used to increase dataset variability and prevent overfitting in order to enhance the models' capacity to generalize to new images.

3. Train-Test split: After preprocessing, the dataset is separated into training, validation, and testing sets. Usually, 70% of the images are used for training, 10% for validation, and 20% for testing. Using the training set, the CNN models are trained to categorize waste photos. During training, the validation set is used to check for overfitting and modify model settings. Finally, the testing set is used to assess how well the training models perform on new, unseen images.



4. Feature extraction and model training: During feature extraction, the VGG-16 and ResNet-50 models are applied to the preprocessed waste images. The convolution layers of these models automatically extract important visual information from the images, such as edges, textures, and shapes, which help differentiate different types of waste. These learned characteristics are used by the final classification layers to identify whether the waste is organic or recyclable. In order to learn, the models continuously adjust their internal weights using the training data. Performance is concurrently assessed using the validation set to avoid overfitting. The training process is repeated several times until the models achieve stable accuracy and loss values.

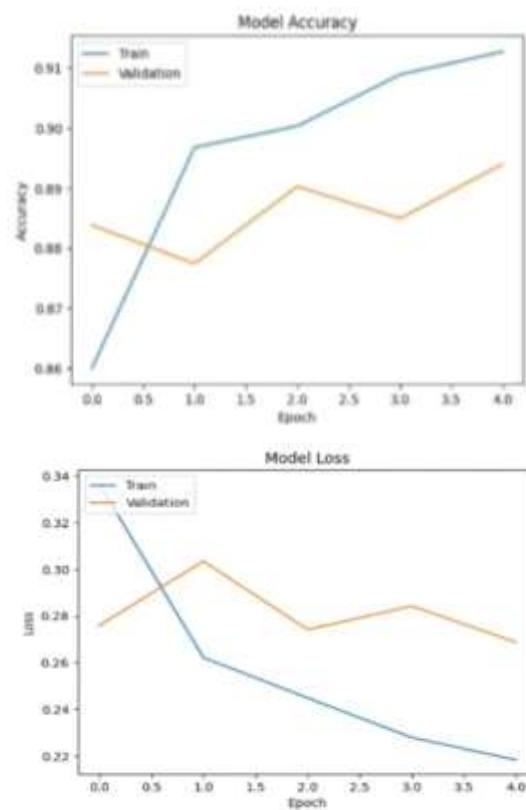
5. Classification module: The classification module applies fully connected layers to the features learned by the trained CNN models in order to make a final decision. These learned patterns are used to classify each input image as either recyclable or organic. A softmax function is used to calculate the probability of each category, and the category with the highest probability is selected as the result. This module acts as the system's decision-making component and selects the type of waste shown in each image.

6. Output module: The output module shows the model's final output. It indicates whether the waste image is organic or recyclable. In addition to the predicted category, the model may display a confidence value that shows how certain the model is about its prediction. Because the results are presented in an understandable manner, they are useful for automation and decision-making in waste management systems.

V RESULTS AND DISCUSSION

The experimental results clearly show how the two CNN models used in this project, VGG-16 and ResNet-50, performed differently. During training, VGG-16 showed stable learning and was able to extract basic and intermediate visual features from waste images. However, because of its deep and sequential structure with numerous parameters, it required more training time and processing power. Despite achieving good accuracy on the training set, VGG-16 showed a slight overfitting during validation, suggesting that the model did not

fully generalize to new, unseen images. On the other hand, ResNet-50 performed better overall. By using residual connections to help overcome common training issues like vanishing gradients, the model was able to train deeper layers more successfully. As a result, ResNet-50 performed better than VGG-16 in terms of convergence speed, training and validation loss, and classification accuracy. The confusion matrix results showed that ResNet-50 made fewer classification errors, especially when organic and recyclable waste had similar visual characteristics. Additionally, ResNet-50 showed excellent stability on training and validation datasets, sustaining steady performance over training epochs. Overall, the comparison shows that ResNet-50 outperforms VGG-16 in terms of accuracy, dependability, and generalization to new data. This facilitates the use of deep CNN models for intelligent and scalable waste management systems and makes ResNet-50 a more appropriate and effective model for practical waste classifications.



CONCLUSION

In this project, a deep learning-based waste classification system was developed using two prominent CNN architectures, VGG-16 and ResNet-50, to automatically categorize waste into Organic and Recyclable classes. The system was developed using the Kaggle platform with a labeled waste image dataset. Important steps such as image preprocessing, data augmentation, and dataset splitting were applied to improve model performance. Both VGG-16 and ResNet-50 models were trained and tested. The results show that VGG-16 is able to extract useful features consistently, but it requires more computational power and shows slight overfitting. ResNet-50, on the other hand, achieves greater accuracy, faster training, and better performance on new data due to its residual learning

approach. It is evident from the comparison that ResNet-50 is better suited for automated waste classification systems in the real world. All things considered, this project shows how sophisticated CNN models can be applied to create intelligent waste sorting systems that lessen manual labor, increase recycling effectiveness, and promote ecologically friendly behaviors.



1/1 ————— 0s 44ms/step
The image belongs to **Recycle waste** category

REFERENCES

- [1] Ngoc-Bao-Quang Nguyen, Tuan-Minh Do, Cong-Tam Phan & Thi-Thu-Hong Phan (2025). Towards Accurate and Efficient Waste Image Classification: A Hybrid Deep Learning and Machine Learning Approach.
- [2] Li et al. (2025). Enhanced ResNet-50 for garbage classification: Feature fusion and depth-separable convolutions.
- [3] Debojoyoti Ghosh, Soumya K. Ghosh & Adrijit Goswami (2025). Neuroplastic Modular Framework: Cross-Domain Image Classification of Garbage and Industrial Surfaces.
- [4] Zhanshan Qiao (2024). Advancing Recycling Efficiency: A Comparative Analysis of Deep Learning Models in Waste Classification.
- [5] Chhabra, M. (2024). Intelligent waste classification approach.
- [6] Fangfang Wu & Hao Lin. (2022). Effect of Transfer Learning on the Performance of VGGNet-16 and ResNet-50 for the Classification of Organic and Residual Waste.
- [7] Md Atikuzzaman, Md Parvez Hossain, Md Zahidul Islam & Syed Ahsanul Kabir. (2022). Comparative Analysis of Convolutional Neural Networks for Trash Classification.