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Transfer Learning-Based Convolutional Neural Network for Classifying Organic and Recyclable Waste

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Abstract

The problem of waste management continues to increase along with population growth and lifestyle changes, highlighting the need for a fast and accurate waste classification system to support recycling processes. This study implements a transfer learning approach using seven Convolutional Neural Network (CNN) architectures: MobileNet, MobileNetV2, Xception, EfficientNetB0, VGG16, VGG19, and ResNet50 to classify waste into two categories: organic and recyclable. Each model is modified by adding a Global Average Pooling layer followed by a fully connected layer with 256 neurons before the output layer. The models are trained twice using 30 epochs, a batch size of 2, the Adam optimizer, and a learning rate of 0.0001. Experimental results show that ResNet50 achieves the best performance, with an accuracy of 89.84%, precision of 96.34%, recall of 82.82%, and an F1-score of 89.07%, followed by MobileNet with an accuracy of 89.25%. In contrast, Xception demonstrates the lowest performance, with an accuracy of 83.81%. Analysis of training and validation curves indicates that ResNet50 and MobileNet exhibit better stability and lower overfitting tendencies compared to other models.

Keywords: *CNN, global average pooling, organic, recyclable, transfer learning*

INTRODUCTION

Effective waste management has become a major challenge in many countries, particularly due to the increasing volume and diversity of waste generated by modern societies. Waste sorting plays a crucial role in recycling and further processing; however, manual methods have proven to be inefficient, error-prone, and time-consuming, while also requiring significant human effort. Therefore, the development of artificial intelligence-based waste classification technologies has become a primary focus in various studies to support faster, more accurate, and sustainable waste management systems. In recent years, various deep learning and machine learning approaches have been widely applied to improve the accuracy of waste classification. Previous studies have shown that transfer learning is one of the most commonly used methods due to its ability to extract more representative and high-level visual features. For instance, several studies have demonstrated that pre-trained Convolutional Neural Network (CNN) architectures can significantly enhance classification performance, even with limited datasets (H. Santoso et al., 2024) integrated EfficientNet with PCA and successfully achieved an accuracy of 99.07%, while (Ananda & Setyawan, 2026) used EfficientNet-B0 to classify six categories of industrial waste with 91.94% accuracy. Furthermore, several more complex CNN models also showed promising results: (Islam et al., 2025) proposed ECCDN-Net which combines DenseNet201 and ResNet18 and achieved an accuracy of 96.10%, while (B. D. Santoso & Nafi'iyah, 2024) modified ResNet-50 and obtained an accuracy of 93.85%.

The use of various other CNN architectures also makes significant contributions: (Muslihati et al., 2024) showed that transfer learning VGG16, Xception, and NasNet Mobile were able to achieve an accuracy of 96.43%, while the research (Kurniawan et al., 2023) using Xception with Adam optimizer and a small learning rate to achieve an accuracy of 87.81%. In addition, several studies have demonstrated the importance of model adaptation to real-world conditions, as shown by (Wedha et al., 2024) with 73% accuracy across various waste categories and (Altikat et al., 2022) which achieved up to 70% accuracy on the DCNN architecture. On the other hand, hybrid methods and feature engineering-based approaches also showed competitive results: (Toğaçar et al., 2020) combining AutoEncoder, CNN, Ridge Regression, and SVM to achieve 99.95% accuracy. (Dahyoung Yenuargo et al., 2024) using SVM with RBF kernel after SqueezeNet feature extraction and achieved 97.9% accuracy. A similar finding was also seen in the study (Nisa et al., 2022) which implemented GLCM and Color Moments and achieved an accuracy of up to 85.43% on the TrashNet dataset.

Besides architectural development, dataset improvement also plays a big role: (Zhang et al., 2021) building a more realistic NWNU-TRASH dataset so that the applied DenseNet169 model can achieve accuracy above 82%. Some studies also focus on practical implementations, such as (Arifin et al., 2023) which implemented ANN on Arduino UNO and achieved 100% accuracy, as well as (Agustiani et al., 2025) which shows the effectiveness of EfficientNetB3 with 93% accuracy on the smart bin system.

Although numerous studies have demonstrated promising results, several challenges remain, including data imbalance, high variability of waste objects, and the need for more efficient yet accurate models. Therefore, this study implements transfer learning using several modern CNN architectures, namely MobileNet, MobileNetV2, Xception, EfficientNetB0, VGG16, VGG19, and ResNet50, with the addition of a Global Average Pooling layer, a fully connected layer consisting of 256 neurons, and a two-class output (organic and recyclable). This approach is expected to produce a model that is not only accurate but also efficient, making it suitable for implementation in image-based automated waste sorting systems.

LITERATURE REVIEW

The development of artificial intelligence-based waste classification systems has continued to advance in response to the growing need for more efficient and accurate waste management. Various machine learning and deep learning approaches have been developed to improve the performance of waste detection and classification across diverse conditions and category types.

Transfer learning-based approaches have been widely adopted due to their ability to extract features more effectively. A study by (H. Santoso et al., 2024) combined EfficientNet with Principal Component Analysis (PCA) for dimensionality reduction and achieved a very high accuracy of 99.07%. Meanwhile, (Ananda & Setyawan, 2026) utilized EfficientNet-B0 to classify six types of industrial waste and obtained an accuracy of 91.94%, demonstrating its effectiveness in multi-class classification tasks. (Malik et al., 2022) further performed fine-tuning on EfficientNet-B0 and showed that the optimized model could achieve performance comparable to EfficientNet-B3 while requiring significantly lower computational resources. In addition, (Agustiani et al., 2025) demonstrated the effectiveness of EfficientNet-B3 for classifying six waste categories, achieving an accuracy of 93%, indicating its potential for implementation in smart bins and automated sorting systems.

In other deep learning architectures, (Islam et al., 2025) introduced the ECCDN-Net model, which combines the capabilities of DenseNet201 and ResNet18. Using a dataset of 24,705 images for binary classification, the model achieved an accuracy of 96.10%, outperforming several pre-trained models. Similarly, (B. D. Santoso & Nafi'iyah, 2024) adapted ResNet-50 for classifying 12 types of waste and achieved an accuracy of 93.85% using the Adadelta optimizer. (Muslihati et al., 2024) also reported high performance, achieving an accuracy of 96.43% by utilizing VGG16, Xception, and NasNet Mobile architectures for binary classification. Lightweight CNN architectures have also been widely explored; for example, (Sadida Aulia et al., 2024) used MobileNet for household waste classification and achieved an accuracy of 86-88% on training and testing data. Meanwhile, (Ety Sutanty et al., 2023) modified the VGG16 architecture by adding a Global Average Pooling layer and dense layers, resulting in accuracies of 82.89% on training data and 84.62% on validation data.

Beyond CNN architectures, several studies have explored hybrid approaches. (Toğaçar et al., 2020) combined AutoEncoder, CNN, Ridge Regression, and Support Vector Machine (SVM), achieving an accuracy of 99.95%. Another approach by (Li & Chen, 2023) integrated CNN with Graph-LSTM for classifying six types of waste on an industrial conveyor system, achieving an accuracy of 97.5%. SVM-based methods remain relevant, particularly for binary classification tasks. (Nisa et al., 2022) utilized Gray-Level Co-occurrence Matrix (GLCM) and Color Moments features on the TrashNet dataset, achieving an average accuracy of 78.87% and 70% on new test data. (Dahyoung Yenuargo et al., 2024) employed SVM with Radial Basis Function (RBF) and Polynomial kernels after feature extraction using SqueezeNet, where the RBF kernel achieved the highest accuracy of 97.9%.

Several studies have also focused on dataset improvement and architectural optimization. (Zhang et al., 2021) developed the NWNU-TRASH dataset, which is more balanced and realistic, and applied DenseNet169 with transfer learning, achieving an accuracy above 82%. (Wedha et al., 2024) implemented transfer learning-based CNN models across various waste categories and achieved an accuracy of 73% under real-world conditions. (Kurniawan et al., 2023) used the Xception architecture and identified the optimal configuration using the Adam optimizer with a learning rate of 0.001, resulting in an accuracy of 87.81%. In sensor-based approaches, (Arifin et al., 2023) demonstrated that an Artificial Neural Network (ANN) implemented on an Arduino UNO with three different sensors could classify organic and inorganic waste with 100% accuracy. Meanwhile, (Alamsyah et al., 2023) highlighted the importance of training data size, where accuracy increased from 68% to 83% as the dataset expanded from 60 to 600 images. Overall, previous studies indicate that deep learning approaches, particularly CNN and EfficientNet architectures, achieve excellent performance in waste classification tasks. However, challenges remain, including dataset imbalance, background variability, computational requirements, and adaptability to real-world conditions.

DATASET

This study utilizes the Waste Classification Data dataset obtained from the public platform Kaggle, which provides a collection of images for waste classification tasks. The dataset consists of two main categories: Organic (O) and Recyclable (R). Each image is stored in common formats (.jpg/.png) and exhibits various conditions, including differences in lighting, background, object orientation, and visual clarity.

The dataset was sourced from a public Kaggle repository developed as a benchmark for computer vision-based waste classification research. It has been widely used in previous studies (Toğaçar et al., 2020), (Ibnul Rasidi et al., 2022), (Dahyoung Yenuargo et al., 2024), (Chhabra et al., 2024), (Islam et al., 2025) due to its diversity in object shapes and environmental conditions, making it suitable for training deep learning models.

In this study, the dataset was balanced to ensure an equal number of images in each class, thereby reducing bias during the training process. The data were divided into two subsets: training and testing. The detailed distribution of the dataset is presented in Table 1. The Organic (O) class consists of biodegradable waste, such as food scraps, leaves, decaying fruits, and other kitchen residues. Images in this category generally exhibit irregular shapes, varying colors, and diverse conditions (e.g., wet, dry, decomposed, or mixed with other materials). In contrast, the Recyclable (R) class includes inorganic waste such as plastic bottles, cans, glass, cardboard, and other recyclable materials. Objects in this category tend to have more defined shapes, consistent textures, and relatively stable colors.

Table 1. Dataset Distribution

Class	Training	Testing	Total
Organic (O)	9999	1112	11111
Recyclable (R)	9999	1112	11111
Total	19998	2224	22222

METHOD

The research stages are illustrated in Figure 1. The study begins with a literature review covering previous waste classification methods, the application of transfer learning in image classification, and modern CNN architectures, including MobileNet, EfficientNet, Xception, VGG, and ResNet. The dataset is then collected from Kaggle, followed by data balancing to ensure an equal number of samples in each class and dataset splitting into training and testing sets.

The model development stage involves constructing several CNN architectures, namely MobileNet, MobileNetV2, Xception, EfficientNetB0, VGG16, VGG19, and ResNet50. Each model is modified by adding a classification head consisting of a Global Average Pooling (GAP) layer, a Dense layer with 256 neurons using ReLU activation, and a Sigmoid output layer for binary classification (Organic and Recyclable).

The testing and evaluation process includes the calculation of performance metrics such as Accuracy (Equation 1), Precision (Equation 2), Recall (Equation 3), and F1-score (Equation 4) (Zhang et al., 2021). Furthermore, a comparative analysis is conducted to evaluate the performance of each model and determine the best-performing architecture.

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

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - score = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

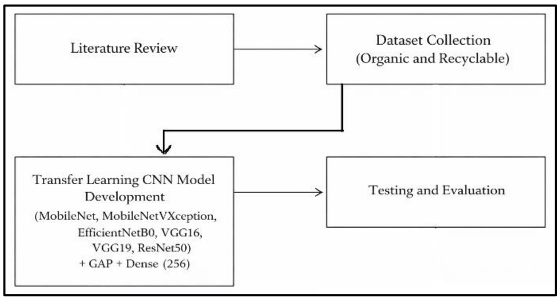

Figure 1. Research Stages

RESULTS AND DISCUSSION

The experiments were conducted using seven transfer learning models MobileNet, MobileNetV2, Xception, EfficientNetB0, VGG16, VGG19, and ResNet50 with the same training configuration: 30 epochs, a batch size of 2, and the Adam optimizer with a learning rate of 0.0001. The training and evaluation processes were performed twice to ensure performance consistency. The average results of the evaluation metrics are presented in Table 2.

In terms of accuracy, the top-performing models are ResNet50 (89.84%), MobileNet (89.25%), and VGG19 (88.76%). These models demonstrate better generalization capability compared to others in distinguishing between Organic and Recyclable waste. In contrast, Xception achieved the lowest accuracy (83.81%), indicating that this architecture is less optimal for a binary classification task with a limited dataset.

Table 2. Model Evaluation

Model	Acc (%)	Precision (%)	Recall (%)	F1-score (%)
MobileNet	89.25	91.61	86.42	88.94
MobileNetV2	85.39	89.95	79.68	84.50
Xception	83.81	88.29	77.97	82.81
EfficientNetB0	87.46	93.80	80.22	86.48
VGG16	86.92	94.96	77.97	85.63
VGG19	88.76	93.80	83.00	88.07
ResNet50	89.84	96.34	82.82	89.07

Precision reflects the model’s ability to correctly predict the positive class. The best-performing models in terms of precision are ResNet50 (96.34%), VGG16 (94.96%), and EfficientNetB0 and VGG19 (93.80%). The high precision values indicate that these models produce relatively few false positives, meaning they rarely misclassify samples into incorrect classes.

The highest recall values are achieved by MobileNet (86.42%), ResNet50 (82.82%), and VGG19 (83.00%). This suggests that MobileNet produces the fewest false negatives and is more capable of detecting all target samples. Conversely, the lowest recall values are observed in MobileNetV2 (79.68%) and Xception (77.97%), indicating that a considerable number of relevant samples are missed.

The F1-score provides an overall performance measure by combining precision and recall. The top three models are ResNet50 (89.07%), MobileNet (88.94%), and VGG19 (88.07%). These models demonstrate the best balance between prediction accuracy (precision) and detection capability (recall).

Overall, ResNet50 is the most stable and superior model across nearly all evaluation metrics, making it the most effective architecture for binary classification on this dataset.

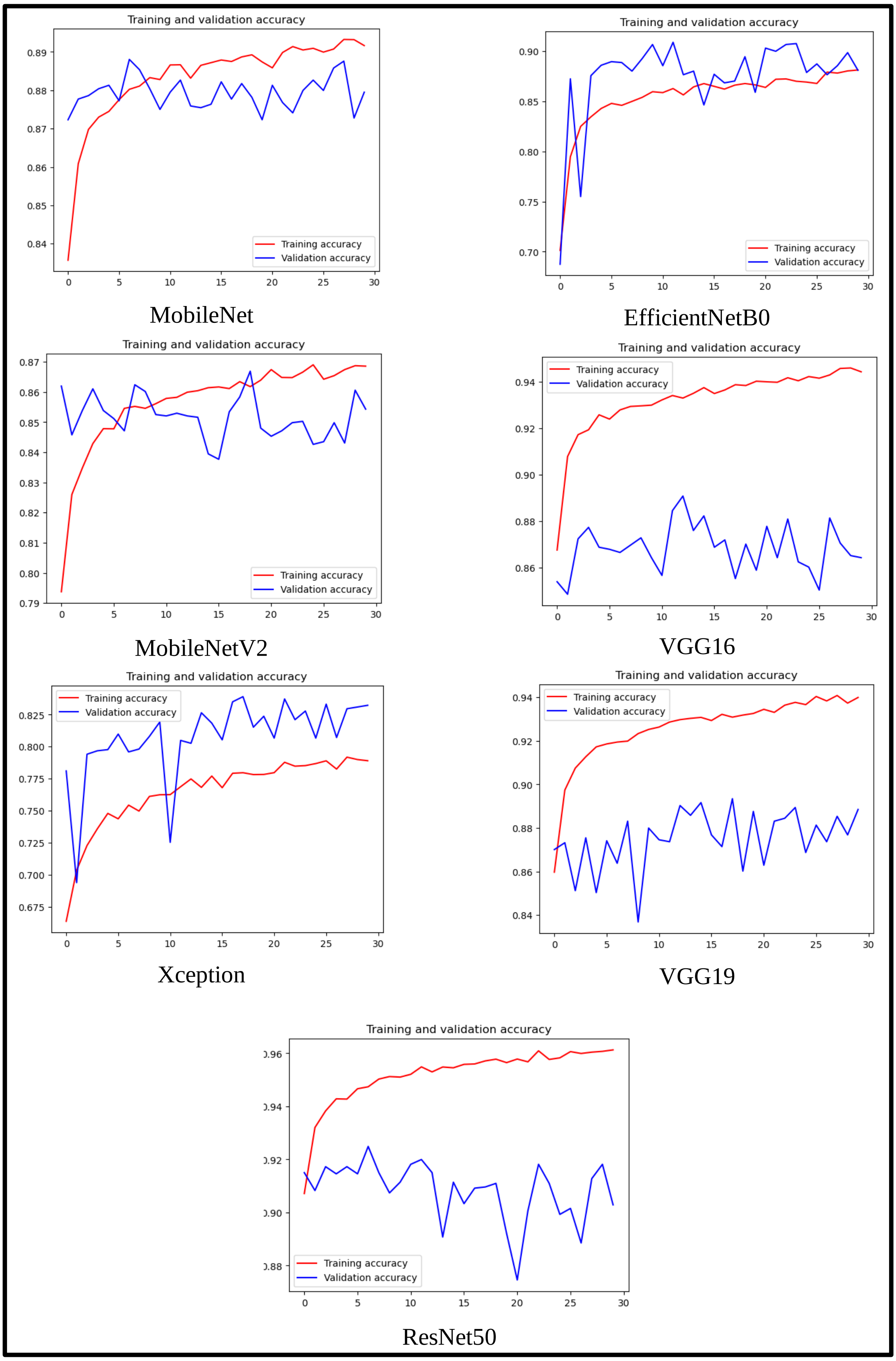

Figure 2 Model Training and Validation Graph

MobileNet ranks second, with a high F1-score and the best recall, making it suitable when maximizing detection is the primary objective. VGG19 also shows strong and consistent performance, serving as a reliable alternative. In contrast, Xception and MobileNetV2 tend to have lower recall and F1-scores, making them less optimal for this classification task.

Figure 2 presents the accuracy curves for both training and validation processes across the seven transfer learning architectures. In general, all models exhibit a consistent increase in training accuracy as the number of epochs increases, indicating that the training process is well-conducted. However, performance variations among models can be observed from the stability of the validation curves and the gap between training and validation accuracy.

MobileNet shows a stable pattern between training and validation accuracy, with no significant gap, indicating that the model does not suffer from overfitting. This consistency supports its achieved accuracy of 89.25%. MobileNetV2 demonstrates more fluctuations in the validation curve compared to the training curve. This suggests that MobileNetV2 is slightly more sensitive to variations in validation data, resulting in lower performance (85.39%) compared to MobileNet.

Xception exhibits relatively high fluctuations, particularly during the early epochs. The gap between training and validation curves is noticeable at several points, indicating instability in generalization. This is consistent with its lowest accuracy of 83.81%.

EfficientNetB0 shows stable training performance with high accuracy; however, the validation curve occasionally fluctuates. This indicates a slight tendency toward overfitting due to the model's architectural complexity. Nevertheless, its performance remains competitive, achieving an accuracy of 87.46%.

VGG16 demonstrates a rapid increase in training accuracy, while the validation curve tends to plateau after several epochs. A clear gap between training and validation indicates overfitting. This explains why the model has relatively low recall despite high precision.

VGG19 exhibits more stable behavior compared to VGG16. The validation curve shows a more consistent upward trend with a smaller gap, resulting in higher accuracy (88.76%). This suggests that VGG19 has better generalization capability than VGG16 on this dataset.

ResNet50 presents the most stable and balanced curves between training and validation. The accuracy increases gradually without sharp fluctuations. This pattern indicates that the model effectively captures feature patterns without overfitting, which aligns with its highest accuracy of 89.84%.

Overall, the experimental results indicate that ResNet50, MobileNet, and VGG19 are the most suitable architectures for classifying organic and recyclable waste, as they demonstrate more stable performance and higher evaluation metrics compared to other models.

Based on the overall curve patterns, ResNet50 and MobileNet exhibit the most stable and balanced behavior, indicating strong generalization. In contrast, VGG16 and Xception show signs of overfitting or validation instability. EfficientNetB0 and VGG19 demonstrate moderate fluctuations but remain competitive. Overall, the training and validation curves indicate that all models are able to learn effectively, although their stability varies across architectures.

Table 3 Comparison of Evaluation with Previous Research

Model	Class	Evaluation
DenseNet169 (Zhang et al., 2021)	Dataset NWNU-TRASH, class: Glass, Fabric, Paper, Plastic, Metal	Acc 82%
EfficientNetB3 (Agustiani et al., 2025)	Class: Battery, Glass, Metal, Organic, Paper, Plastic	Acc 93%
Merge CNN+Ridge Regression+ SVM (Toğaçar et al., 2020)	Class: Organic, Recyclable	Acc 99.95%
EfficientNet-B0 (Malik et al., 2022)	Many classes	Acc 74%-84%

Model	Class	Evaluation
SqueezeNet feature extraction, SVM classification (Dahyoung Yenuargo et al., 2024)	Class: Organic, Recyclable	Kernel RBF acc 97.9%
VGG-16 by adding GlobalAveragePooling2D and dense layer (Ety Sutanty et al., 2023)	Many classes	Acc 84.62%
CNN and Graph-LSTM (Li & Chen, 2023)	Many classes	Acc 97.5%
CNN MobileNet (Sadida Aulia et al., 2024)	Class: Anorganic, B3, Organic	Acc 86-88%
GLCM feature extraction and SVM classification (Alamsyah et al., 2023)	Class: Cardboard, Glass, Metal, Paper, Plastic, Trash	Acc 68-83%
GLCM and color Moment feature extraction, SVM classification (Nisa et al., 2022)	Many classes	Acc 78.87%-85.43%
Deep learning CNN: VGG16, VGG19, MobileNetV2, DenseNet121, and EfficientNetB0 (Chhabra et al., 2024)	Class: Organic, Recyclable	Acc 93.28%
Deep Convolutional Neural Network (Altikat et al., 2022)	Class: Glass, Organic, Paper, Plastic	Acc 70%
Xception (Kurniawan et al., 2023)	Many classes	Acc 87.81%
VGG16, Xception and NasNet Mobile (Muslihati et al., 2024)	Class: organik and non-organik	Acc 96.43%
EfficientNetB0 (Ananda & Setyawan, 2026)	Many classes	Acc 91.94%

Table 3 presents a comparison of the performance of various waste classification methods developed in previous studies. In general, the results show that accuracy varies significantly depending on the model architecture, feature extraction techniques, number of classes, and the complexity of the dataset used.

From the overall comparison, it can be observed that models with fewer classes (2-3 classes) tend to achieve higher accuracy, while datasets with a larger number of classes or higher visual complexity generally result in lower accuracy. In addition, modern transfer learning-based models such as EfficientNet, ResNet, MobileNet, and modified VGG consistently demonstrate superior performance, particularly when combined with optimization techniques or additional feature extraction methods.

CONCLUSION

This study demonstrates that transfer learning-based CNN methods are effective for classifying organic and recyclable waste. Among the seven architectures evaluated, ResNet50 achieves the best performance, with the highest accuracy (89.84%) and the most consistent training-validation stability. MobileNet also shows competitive performance, achieving an accuracy of 89.25% with good generalization capability. Other models, such as VGG16, VGG19, EfficientNetB0, and MobileNetV2, produce satisfactory results but exhibit tendencies toward overfitting or validation fluctuations. Meanwhile, Xception delivers the lowest performance in this experiment.

Overall, the results indicate that the choice of CNN architecture significantly affects classification performance, and that the addition of Global Average Pooling and a dense layer enhances the model’s ability to recognize the two main waste classes. Future research is recommended to increase dataset diversity, balance class distribution, and explore advanced data augmentation techniques or full fine-tuning strategies to achieve higher accuracy and improved model stability in waste classification tasks.

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