YAYASAN AKRAB PEKANBARU
Akrab Juara : Jurnal Ilmu-ilmu Sosial
Volume 11 Nomor 2 Edisi Mei 2026 (460-472)
https://doi.org/10.58487/akrabjuara.v10i1.0000

44

APPLICATION OF CONVOLUTIONAL NEURAL NETWORKS FOR THE CLASSIFICATION OF ORGANIC AND INORGANIC WASTE IMAGES

Syifa Salsabila[1], Ahmad Fauzi[2*]
Universitas Bina Sarana Informatika
E-mail: Syifa234@gmail.com, ahmad.azy@bsi.ac.id
(Naskah diterima: 1 Maret 2026, disetujui: 31 Maret 2026)

Abstract

Waste management has become one of the most pressing environmental challenges due to the increasing volume of waste and the limited public awareness of proper waste segregation. The inability to distinguish between organic and inorganic waste often reduces the effectiveness of recycling and sustainable waste management practices. This study aims to develop an automatic image classification system based on the Convolutional Neural Network (CNN) method to identify organic and inorganic waste from digital images. The dataset consists of 25,077 images collected from publicly available sources and self-collected data, which were divided into 90% training data and 10% testing data. Before model training, the images underwent preprocessing techniques, including resizing, normalization, and data augmentation, to improve model performance and generalization. The CNN model was developed using the TensorFlow framework and achieved a training accuracy of 93.08% at the ninth epoch. Furthermore, the trained model was integrated into a Flask-based web application, enabling users to upload waste images and instantly receive classification results. The findings demonstrate that the proposed CNN-based system effectively classifies organic and inorganic waste images and has the potential to support intelligent waste management systems by improving the efficiency and accuracy of waste sorting. This research also highlights the applicability of deep learning techniques in addressing environmental issues through automated image recognition technology.
Keywords: *Convolutional Neural Network; Waste Classification; Deep Learning; TensorFlow.*

Abstrak

Pengelolaan limbah telah menjadi salah satu tantangan lingkungan yang paling mendesak karena volume limbah yang meningkat dan keterbatasan kesadaran publik tentang pemisahan limbah yang tepat. Ketidakmampuan membedakan antara limbah organik dan anorganik sering kali mengurangi efektivitas praktik daur ulang dan pengelolaan limbah berkelanjutan. Studi ini bertujuan mengembangkan sistem klasifikasi gambar otomatis berdasarkan metode Convolutional Neural Network (CNN) untuk mengidentifikasi limbah organik dan anorganik dari gambar digital. Dataset ini terdiri dari 25.077 gambar yang dikumpulkan dari sumber yang tersedia untuk umum dan data yang dikumpulkan sendiri, yang dibagi menjadi 90% data pelatihan dan 10% data pengujian. Sebelum pelatihan model, gambar menjalani teknik pra-pemrosesan, termasuk pengubahan ukuran, normalisasi, dan augmentasi data, untuk meningkatkan performa dan generalisasi model. Model CNN dikembangkan menggunakan

kerangka TensorFlow dan mencapai akurasi pelatihan sebesar 93,08% pada epoch kesembilan. Selain itu, model terlatih ini diintegrasikan ke dalam aplikasi web berbasis Flask, memungkinkan pengguna mengunggah gambar limbah dan langsung menerima hasil klasifikasi. Temuan menunjukkan bahwa sistem berbasis CNN yang diusulkan secara efektif mengklasifikasikan gambar limbah organik dan anorganik serta berpotensi mendukung sistem pengelolaan limbah cerdas dengan meningkatkan efisiensi dan akurasi pemilahan limbah. Penelitian ini juga menyoroti penerapan teknik pembelajaran mendalam dalam mengatasi masalah lingkungan melalui teknologi pengenalan gambar otomatis.
Kata kunci: Jaringan Saraf Konvolusional; Klasifikasi Limbah; Pembelajaran Mendalam; TensorFlow.

I. INTRODUCTION

The rapid growth of urbanization and population has significantly increased the volume of municipal solid waste worldwide, making waste management one of the most critical environmental issues. In Indonesia, improper waste disposal and inadequate waste segregation practices continue to contribute to environmental pollution, greenhouse gas emissions, and inefficient recycling processes. One of the primary challenges is the limited public awareness and ability to distinguish between organic and inorganic waste before disposal. Consequently, recyclable materials are often mixed with biodegradable waste, reducing the effectiveness of recycling systems and increasing the amount of waste sent to landfills. Effective waste classification at the source is therefore essential for improving sustainable waste management and supporting environmental conservation efforts.

Recent developments in Artificial Intelligence (AI), particularly Deep Learning, have provided promising solutions for automated image recognition and classification. Among various deep learning approaches, Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in computer vision applications due to their capability to automatically extract hierarchical features from images without requiring manual feature engineering. CNN-based methods have been successfully applied in numerous domains, including medical image analysis, object detection, agricultural monitoring, and waste classification. Their ability to recognize complex visual patterns makes CNN an effective approach for distinguishing different categories of waste based on image characteristics. Several previous studies have investigated waste classification using deep learning techniques and reported encouraging classification performance. However, many existing studies focus primarily on model development and evaluation without providing an accessible implementation for practical use by end users. In addition, differences in dataset characteristics and preprocessing techniques can significantly affect classification accuracy, indicating the need for further investigation into efficient model implementation for real-world applications. This study proposes an automated waste classification system based on a Convolutional Neural Network (CNN) to classify organic and inorganic waste images. The proposed approach employs image preprocessing techniques, including resizing, normalization, and data augmentation, before training the CNN model using the TensorFlow framework. The trained model is subsequently integrated into a Flask-based web application, enabling users to upload waste images and receive real-time classification results through a user-friendly interface. The main objective of this research is to develop an accurate and practical waste classification system that can support waste segregation activities. By combining deep learning techniques with a web-based implementation, this study is expected to contribute to the development of intelligent waste management systems while promoting greater public awareness of proper waste sorting practices.

II. LITERATURE REVIEW

Municipal solid waste management has become one of the most important environmental challenges worldwide because of the continuous increase in waste generation and the limited efficiency of conventional waste sorting methods. Manual waste segregation is labor-intensive, time-consuming, and prone to human error, reducing recycling effectiveness and increasing environmental pollution. Therefore, intelligent waste classification has attracted considerable attention as an effective solution for improving recycling systems and supporting sustainable environmental management (Wu et al., 2023; Shreya et al., 2023). Deep learning has significantly transformed image recognition by enabling computers to learn complex visual features directly from raw images. Among various deep learning algorithms, Convolutional Neural Networks (CNNs) are considered the most effective architecture for image classification because they automatically extract hierarchical spatial features through convolutional, pooling, and fully connected layers (LeCun et al., 2015). Compared with conventional machine learning approaches that require handcrafted feature extraction, CNNs provide higher accuracy and better generalization for image classification tasks (Goodfellow et al., 2016).

Recent studies have demonstrated the successful application of CNNs in intelligent waste identification and recycling. Wu et al. (2023) conducted a comprehensive review covering more than 350 studies and concluded that CNN-based methods have become the dominant approach for waste classification, object detection, and waste segmentation. Their review also highlighted that transfer learning architectures such as ResNet, MobileNet, DenseNet, and EfficientNet consistently outperform conventional CNN models while requiring fewer computational resources. Among lightweight CNN architectures, MobileNetV2 has gained significant attention because it utilizes depthwise separable convolution and inverted residual blocks to reduce computational complexity without substantially sacrificing classification performance. Oktayaessofa et al. (2024) reported that MobileNetV2 achieved excellent performance in classifying organic and non-organic waste while maintaining efficient inference speed, making it suitable for real-time applications and mobile deployment.

Transfer learning has become a common strategy for improving waste classification performance, particularly when training datasets are relatively small. Rayhan and Rifai (2024) compared several CNN architectures and found that DenseNet121 achieved an accuracy of 95.2%, while MobileNetV2 achieved 92% on multiclass waste classification. Their findings demonstrate that pretrained CNN models substantially outperform CNN models trained entirely from scratch. Image preprocessing is another critical factor influencing CNN performance. Common preprocessing operations include resizing, normalization, and data augmentation techniques such as image rotation, flipping, brightness adjustment, and zooming. These techniques increase dataset diversity, reduce overfitting, and improve model generalization to unseen images. Previous studies consistently reported that data augmentation contributes to significant improvements in classification accuracy, especially when datasets are imbalanced or limited in size (Shreya et al., 2023). TensorFlow has become one of the most widely adopted deep learning frameworks due to its flexibility in model development, training, optimization, and deployment. Likewise, Flask provides a lightweight web framework that enables CNN models to be integrated into web-based applications for real-time inference. Fauzan et al. (2026) demonstrated that integrating TensorFlow with Flask successfully produced an interactive waste classification dashboard capable of providing instant prediction results through a web interface.

Despite significant improvements in CNN-based waste classification, several challenges remain unresolved. Most previous studies primarily focused on maximizing classification accuracy while paying limited attention to deployment efficiency under real-world conditions. Furthermore, dataset diversity, illumination variation, background complexity, and class imbalance continue to affect model robustness and generalization performance (Wu et al., 2023; Lilhore et al., 2024).

Based on these findings, this research develops a CNN-based waste classification system using TensorFlow and deploys the trained model through a Flask-based web application. Unlike many previous studies that emphasize only model evaluation, this study combines image preprocessing, CNN-based classification, and practical web implementation to provide an accessible intelligent waste classification system for organic and inorganic waste. The proposed approach is expected to improve waste sorting efficiency while supporting the development of sustainable smart waste management systems

III. RESEARCH METHODOLOGY

This study employed an experimental research approach to develop and evaluate an image classification model for distinguishing organic and inorganic waste using a Convolutional Neural Network (CNN). The research consisted of four main stages: dataset preparation, image preprocessing, CNN model development, and web-based system implementation. The overall workflow is illustrated in Figure 1. The dataset used in this study consisted of 25,077 waste images, collected from publicly available datasets and self-collected image sources. The images were categorized into two classes: organic waste and inorganic waste. To evaluate the model objectively, the dataset was divided into 90% training data and 10% testing data. This data partition ensures that the trained model is evaluated using previously unseen images while maintaining sufficient training samples for model learning. Before training, all images underwent several preprocessing steps to improve model performance and reduce unnecessary variations. The preprocessing pipeline included:

a. Image resizing to produce a uniform input dimension.
b. Pixel normalization by scaling pixel values into the range of 0–1.
c. Data augmentation through random transformations, including horizontal flipping, rotation, zooming, and shifting.

These preprocessing techniques increase dataset diversity and reduce overfitting, enabling the CNN model to generalize better on unseen data.

Figure 1. Organic potato class sample

Figure 2. Sample of an inorganic tin compound

Table 1. Data Partitioning

Class	Training Data	Data Test	Quantity Data
Organik	12600	1401	14001
Anorganik	9964	1112	11111
Total	22564	2513	25077
Percentage	90%	10%	100%

The classification model was developed using the **TensorFlow** deep learning framework. This research employed the **MobileNetV2** architecture as the feature extraction backbone because of its lightweight computational requirements and high classification performance. The pretrained ImageNet weights were utilized through transfer learning to accelerate convergence and improve classification accuracy. The final classification layer was modified to produce two output classes representing organic and inorganic waste. The model was trained using the Adam optimizer with categorical cross-entropy as the loss function. Model performance was monitored using training accuracy and loss throughout **nine training epochs**.

The trained CNN model was evaluated using the testing dataset. Classification performance was measured using accuracy obtained from the prediction results. The evaluation process also utilized a confusion matrix to analyze prediction performance by identifying correctly and incorrectly classified images in each category. The confusion matrix provides information regarding True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), enabling comprehensive evaluation of the classification model. After the training process, the best-performing CNN model was deployed into a **Flask-based web application**. The application allows users to upload waste images through a browser interface, after which the trained model automatically predicts whether the uploaded image belongs to the organic or inorganic waste category. This implementation demonstrates the practical applicability of the proposed model for supporting intelligent waste management systems.

Figure 3. Research Methodology

IV. RESULTS AND DISCUSSION

The flowchart presents the overall research workflow of the proposed waste classification system. It describes the sequence of operations executed by the user and the system, from the initial image input to the final classification output. The workflow includes dataset preparation, image preprocessing, CNN model inference, and result visualization through a web-based interface. This flowchart provides a structured overview of the system implementation and facilitates understanding of the proposed methodology.

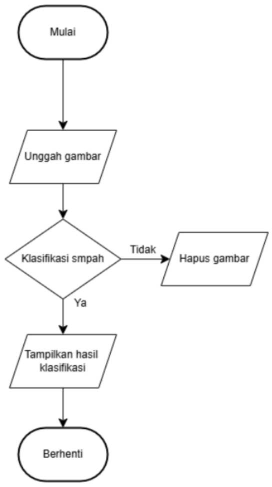

Figure 4. flowchart

The system flowchart illustrates the overall operational workflow of the proposed image-based waste classification system. As shown in Figure 2, the process begins with the Start node, indicating the initiation of user interaction with the application. The user is then prompted to upload an image of waste through the web interface. This uploaded image serves as the input for the classification process. After the image is successfully uploaded, the system performs waste classification using the pre-trained Convolutional Neural Network (CNN) model. During this stage, the input image undergoes preprocessing before being analyzed by the CNN model to extract relevant features and determine whether the waste belongs to the organic or inorganic category. Once the classification process is completed, the system evaluates whether the prediction has been successfully generated. If the classification is successful, the predicted waste category is displayed to the user through the web interface. The output provides immediate feedback regarding the identified waste type, allowing users to obtain classification results in real time.

Alternatively, if the user decides not to continue the classification process or chooses to remove the uploaded image, the system executes the image deletion function. This ensures that the uploaded data are discarded and no further processing is performed. Finally, the workflow terminates at the End node, indicating the completion of the interaction between the user and the proposed waste classification system.

Figure 5. Home Page Interface

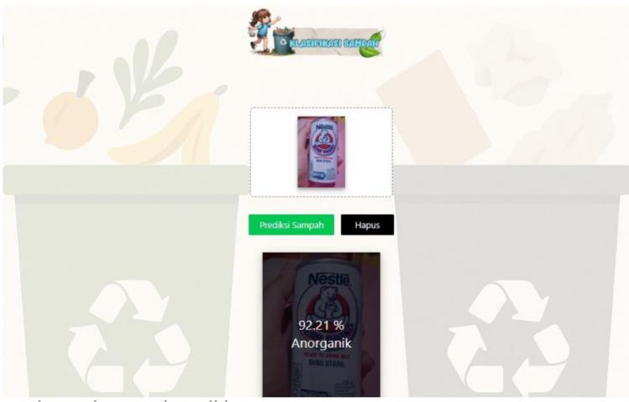

Figure 6. Prediction Result Interface

To evaluate the performance of the proposed CNN model during the training process, both accuracy and loss metrics were monitored for the training and validation datasets over nine epochs. Each epoch represents one complete iteration through the entire training dataset, allowing the model to progressively optimize its parameters through backpropagation. Table 2 presents the training results, including Training Accuracy, Validation Accuracy, Training Loss, Validation Loss, and the corresponding training time (seconds) for each epoch. These performance metrics provide a comprehensive evaluation of the model's learning behavior throughout the training process. Specifically, training and validation accuracy indicate the model's ability to correctly classify waste images, while the loss values measure the prediction error and convergence of the learning algorithm. By analyzing these metrics across all epochs, it is possible to assess the learning progression of the CNN model, determine whether the model has converged, and identify potential issues such as overfitting or underfitting. An increase in validation accuracy accompanied by a decrease in validation loss generally indicates that the model is learning meaningful representations and generalizing well to unseen data. Conversely, a significant gap between training and validation performance may suggest overfitting, where the model performs well on the training data but fails to generalize effectively to new samples.

This evaluation provides essential insights into the stability and effectiveness of the proposed CNN model before it is deployed for real-time waste classification through the web-based application.

Table 2. Training and Validation Performance of the CNN Model

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss	Training Time (s)
1	0.6774	0.6297	0.8489	0.3555	24
2	0.8691	0.3201	0.8841	0.2929	7
3	0.8963	0.2602	0.8963	0.2657	7
4	0.9102	0.2344	0.9038	0.2499	7
5	0.9108	0.2256	0.9063	0.2397	7
6	0.9199	0.2121	0.9109	0.2322	7
7	0.9182	0.2073	0.9129	0.2270	7
8	0.9267	0.1965	0.9145	0.2233	7
9	0.9308	0.1845	0.9151	0.2198	7

As shown in Table 2, the CNN model exhibited a consistent improvement throughout the nine training epochs. The training accuracy increased from 67.74% in the first epoch to 93.08% in the ninth epoch, while the training loss decreased substantially from 0.6297 to 0.1845. Similarly, the validation accuracy improved from 84.89% to 91.51%, accompanied by a reduction in validation loss from 0.3555 to 0.2198. These results indicate that the proposed model successfully learned discriminative features from the training data and achieved stable convergence during the training process. Furthermore, the relatively small gap between the training and validation accuracies suggests that the model generalized well to unseen data without exhibiting significant overfitting. The training time also became stable after the first epoch, requiring approximately 7 seconds per epoch, demonstrating the computational efficiency of the proposed MobileNetV2-based CNN architecture. Based on these observations, the model obtained its best performance at epoch 9, which was subsequently selected for deployment in the web-based waste classification system.

The training results were further analyzed by visualizing the changes in **accuracy** and **loss** values across all training epochs. These graphical representations provide a comprehensive overview of the learning behavior of the proposed CNN model throughout the training process. Specifically, the **training and validation accuracy curves** illustrate the model's improvement in correctly classifying waste images as the number of training epochs increases, while the **training and validation loss curves** demonstrate the reduction in prediction error during optimization. The accuracy and loss curves are valuable for evaluating the convergence and stability of the learning process. A consistent increase in accuracy accompanied by a gradual decrease in loss indicates that the model effectively learns representative features from the training data. Moreover, comparing the training and validation curves enables the identification of potential **overfitting** or **underfitting**. When both curves exhibit similar trends with only a small performance gap, the model is considered to generalize well to unseen data.

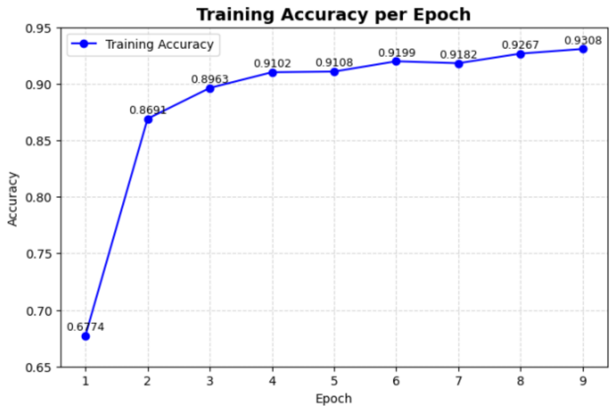

Figure 7. Training and validation accuracy

Figure 8 . validation loss over the nine training epochs

As illustrated in **Figure 7**, the training accuracy exhibited a steady upward trend throughout the training process. The accuracy increased from **67.74%** in the first epoch to **93.08%** in the ninth epoch, indicating that the proposed CNN model progressively learned meaningful features from the training dataset. This consistent improvement demonstrates the model's ability to optimize its parameters through iterative learning and effectively enhance its classification performance as the number of training epochs increased. In contrast, **Figure 8** shows a continuous decrease in the training loss during the same training period. The training loss was reduced from **0.6297** in the first epoch to **0.1845** in the final epoch, indicating a substantial reduction in prediction errors as the optimization process progressed. The gradual decline in the loss value suggests that the model converged successfully toward an optimal solution. Furthermore, the similarity between the training and validation performance observed in Table 1 indicates that the proposed model achieved good generalization capability. The absence of significant fluctuations in both the accuracy and loss curves during the final epochs suggests that the training process was stable and did not exhibit noticeable signs of overfitting. Therefore, the CNN model successfully learned representative features from the waste image dataset while maintaining reliable performance on unseen validation data. Overall, the accuracy and loss curves demonstrate that the proposed CNN model converged effectively after nine training epochs and produced a stable classification model suitable for deployment in the web-based waste classification application.

Table2. Testing Performance of the Proposed CNN Model

Test Accuracy (%)	**Test Loss**	**Evaluation Time (s)**
90.29	0.1264	7

Table 2 summarizes the performance of the proposed CNN model on the testing dataset. The model achieved a test accuracy of 90.29% with a test loss of 0.1264, demonstrating its ability to accurately classify unseen waste images. The relatively low test loss indicates that the model generated reliable predictions with minimal classification errors. Furthermore, the evaluation process required only 7 seconds, indicating that the proposed CNN model is computationally efficient and suitable for real-time deployment. The testing results confirm that the model maintains good generalization performance when applied to previously unseen data, making it appropriate for integration into the Flask-based web application for automatic waste classification.

V. CONCLUSION

This study proposed a Convolutional Neural Network (CNN)-based approach for the automatic classification of organic and inorganic waste images. The developed model was successfully trained using the TensorFlow framework and deployed as a Flask-based web application, enabling users to perform real-time waste classification through a simple image upload interface. Experimental results demonstrated that the proposed model achieved a training accuracy of 93.08% and a testing accuracy of 90.29%, with a test loss of 0.1264. The training and validation curves showed stable convergence throughout the nine training epochs, indicating that the model effectively learned discriminative image features while maintaining good generalization performance without significant overfitting. The findings confirm that CNN-based image classification is a reliable and effective approach for supporting automated waste sorting and has the potential to improve the efficiency of waste management systems. Furthermore, the relatively short evaluation time demonstrates that the proposed model is suitable for practical implementation in web-based applications requiring near real-time image classification. Although the proposed system achieved promising performance, several improvements can be explored in future research. Expanding the dataset with more diverse waste categories and environmental conditions is expected to enhance the robustness of the classification model. Future studies may also compare the proposed approach with more advanced deep learning architectures, such as EfficientNet, ConvNeXt, or Vision Transformer (ViT), to further improve classification accuracy and computational efficiency. In addition, incorporating comprehensive evaluation metrics, including precision, recall, F1-score, and ROC analysis, would provide a more complete assessment of model performance. Finally, deploying the proposed model on mobile devices or edge computing platforms could facilitate real-time intelligent waste classification in smart recycling and Internet of Things (IoT)-based waste management systems, thereby contributing to the development of sustainable environmental technologies.

REFERENCES

Fauzan, A. D., Al Hafizh, M. R., Rahayu, W. I., & Riza, N. (2024). Waste classification dashboard using TensorFlow and Convolutional Neural Network (CNN) for sustainable waste management. *Journal of Dinda: Data Science, Information Technology, and Data Analytics, 6*(1), 1–8. https://doi.org/10.20895/dinda.v6i1.9908

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778. https://doi.org/10.1109/CVPR.2016.90

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). MobileNets: Efficient convolutional neural networks for mobile vision applications. *arXiv Preprint arXiv:1704.04861*. https://arxiv.org/abs/1704.04861

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lilhore, U. K., Simaiya, S., Sharma, S. K., Ghosh, U., & Mahmoud, M. (2024). A smart waste classification model using hybrid CNN-LSTM with transfer learning for sustainable environments. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-023-16677-z

Oktayaessofa, E., Sari, C. A., Rachmawanto, E. H., & Yaacob, N. M. (2024). Classification of organic and non-organic waste with CNN-MobileNetV2. *Jurnal Teknik Informatika (JUTIF), 5*(4), 899–908. https://doi.org/10.52436/1.jutif.2024.5.4.2165

Rayhan, Y., & Rifai, A. P. (2024). Multi-class waste classification using convolutional neural networks. *Applied Environmental Research, 46*(2), 1–14. https://doi.org/10.35762/AER.2024021

Shreya, M., Yughan, V. N., Katyal, J., & Ramesh, R. (2023). Technical solutions for waste classification and management: A mini review. *Waste Management & Research, 41*(3), 356–370. https://doi.org/10.1177/0734242X221135262

Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. *International Conference on Learning Representations (ICLR).* https://arxiv.org/abs/1409.1556

Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. *Proceedings of the 36th International Conference on Machine Learning (ICML)*, 6105–6114.

Wu, T. W., Zhang, H., Peng, W., Lü, F., & He, P. J. (2023). Applications of convolutional neural networks for intelligent waste identification and recycling: A review. *Resources, Conservation and Recycling, 190*, 106813. https://doi.org/10.1016/j.resconrec.2022.106813

Zhang, X., Wang, Y., Liu, H., & Li, J. (2024). Intelligent waste classification based on improved convolutional neural networks. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-024-18939-w