Indonesian Applied Research Computing and Informatics
Vol. 1; No. 2, December 2025 Page 37-46;
https://jurnal.tdinus.com/index.php/iarci
e-ISSN : 3110-8806

MobileNetV2 Transfer Learning Implementation for Waste Classification

Fifi Andriani[1], Ade Yuliati[1], Anis Yaturahmah[1], Siti Mutmainah[1]

[1] Department of Computer Science, University of Muhammadiyah Bima, 84111, Indonesia

Email: pipyyuo@gmail.com[1*], adeyuliati23@gmail.com[2], sitimutmainnah@umbima.ac.id[3]

Article Info
Article history:
Received:01-21-2026
Revised: 02-18-2026
Accepted: 02-21-2026

Keywords:
Transfer Learning,
MobileNetV2,
Waste Classification,
CNN,
Deep Learning,
Environmental Informatics,
Computer Vision,

ABSTRACT

Waste management issues represent one of the major challenges in maintaining environmental sustainability, as the waste sorting process is still largely performed manually, requiring significant time and effort and relying heavily on human accuracy, which makes it inefficient and prone to errors. Therefore, this study utilizes Artificial Intelligence (AI) technology as a solution to support more effective and sustainable environmental management by proposing the use of the Convolutional Neural Network (CNN) algorithm to classify waste types based on digital images. The data used consist of waste images as inputs in the image processing stage, which are then classified into several waste categories. The CNN architecture applied consists of multiple convolutional layers with a kernel size of 3×3, max pooling layers for feature extraction, and a fully connected layer with a softmax activation function to determine the output class, while the model training process is optimized using the Adam Optimizer algorithm. The experimental results demonstrate that the proposed CNN model is capable of classifying waste types with a good level of accuracy, indicating that this AI-based approach can serve as an effective supporting solution for intelligent, efficient, and sustainable waste management systems and contribute to environmental conservation efforts.

*Corresponding Author:
Fifi Andriani
Computer Science Study Program, Faculty of Engineering and Computer Science Muhammadiyah University of Bima, West Nusa Tenggara 84119,Indonesia
pipyyuo@gmail.com

1. Introduction

The escalating global waste crisis constitutes a direct and pressing threat to environmental sustainability, fundamentally driven by a profound imbalance between the exponential growth in waste generation fueled by population expansion, rapid urbanization, and linear consumption models and the lagging development of adequate management infrastructure. This systemic failure manifests in severe ecological and economic consequences: rampant land and water pollution, significant methane emissions from landfills exacerbating climate change, and the catastrophic loss of valuable finite resources that are buried instead of being reintegrated into production cycles. These interconnected challenges not only degrade ecosystem health but also actively undermine international efforts to achieve the Sustainable Development Goals (SDGs), creating an urgent imperative for innovative, technology-driven transformations in waste governance to close the material loop and advance a circular economy [1].

Within this complex challenge, the sorting stage is identified as the critical operational bottleneck. Accurate separation of key recyclables like plastic, paper, and glass is the indispensable first step for any effective recycling process, determining the purity and economic value of secondary materials. However, prevailing reliance on manual sorting is fundamentally flawed; it is labor-intensive, slow, costly, and inherently inconsistent due to human limitations, leading to high contamination rates that degrade material quality and often render entire batches unrecyclable [2]. This inefficiency directly stifles the economic viability of recycling and perpetuates reliance on landfills and virgin material extraction. Therefore, automating waste classification through intelligent systems is no longer a mere technical enhancement but a strategic necessity to build resilient, efficient, and scalable waste management systems capable of meeting sustainability targets [3].

Convolutional Neural Networks (CNNs) have emerged as the preeminent technological solution to this automation challenge. As a specialized class of deep learning algorithms inspired by biological visual processing, CNNs possess an unparalleled ability to automatically learn hierarchical representations of visual features from simple edges and textures to complex object patterns directly from pixel data. This end-to-end learning capability eliminates the need for manual feature engineering, making CNNs exceptionally robust and adaptable for the highly variable and often occluded visual nature of waste streams. Their proven success in diverse image recognition tasks positions them as the ideal computational foundation for developing accurate, reliable, and real-time waste classification systems [3], [4]

A robust body of research validates and extends the practical application of CNNs in this domain. Initial studies demonstrated high accuracy in binary classification tasks, such as distinguishing organic from inorganic waste. Subsequent work successfully scaled this approach using transfer learning techniques, enabling effective multi-class classification across numerous waste categories despite limited datasets. Crucially, recent advancements have focused on deployability, integrating optimized CNN architectures like MobileNet into application platforms and employing data augmentation strategies to enhance model robustness against real-world variabilities in lighting, angle, and object condition. This progression from academic validation to applied engineering underscores the maturity of CNN technology for real-world environmental solutions [5].

Building decisively upon this established technical foundation, the present research is designed to develop and rigorously evaluate a custom CNN model for the precise ternary classification of Plastic, Paper, and Glass. The study aims not only to achieve state-of-the-art classification metrics but also to analyze model behavior, identify sources of misclassification, and articulate the direct implications for sustainable waste management [6], [7], [8]. By delivering a high-performance, efficient, and practical classification tool, this work seeks to make a tangible contribution to sustainable environmental management. The ultimate objective is to provide a technological enabler that increases recycling efficiency, reduces contamination and landfill use, and supports the systemic transition toward a circular economy, thereby bridging the gap between algorithmic innovation and ecological imperative [9].

Early research established CNNs as highly effective for waste classification tasks due to their ability to automatically learn hierarchical visual features from pixel data. [10] demonstrated that CNNs significantly outperform conventional manual sorting and rule-based systems, emphasizing their capability to learn features directly from pixel values for various waste types. [11] developed a comprehensive framework integrating deep learning image classifiers with transfer learning and dataset augmentation techniques, showing robust performance in real-time waste categorization that surpassed conventional methods.

Advanced architectures have shown remarkable performance improvements. [12]. introduced RWC-Net, achieving 95.01% overall accuracy across six waste categories on the TrashNet dataset of 2,527 images, with specific F1-scores of 97.24% for cardboard, 96.18% for glass, 94% for metal, 95.73% for paper, 93.67% for plastic, and 88.55% for litter. [3] presented an innovative model utilizing tailored DenseNet201 architecture with integrated Squeeze and Excitation attention mechanisms, demonstrating effectiveness across four publicly available datasets with enhanced feature extraction capabilities through parallel CNN branches.

MobileNet architectures have emerged as particularly suitable for waste classification due to their balance between accuracy and computational efficiency. [13] explored MobileNetV2 for bag classification targeting garbage bags, paper bags, and plastic bags, achieving an impressive 98% overall accuracy with outstanding precision, recall, and F1 scores while maintaining computational economy suitable for practical deployment.

Recent advances have focused on optimization for mobile deployment. [14] developed EcoMobileNet, an optimized MobileNetV3 Large-based model incorporating Squeeze-and-Excitation blocks, achieving 98.08% test accuracy across 10 waste categories using a dataset of 4,691 images. Their research also explored ensemble strategies, with a hybrid model combining ResNet-50, EfficientNetV2-M, and DenseNet-201 achieving 98.08% accuracy, while their ensemble stacking approach yielded the highest test accuracy of 98.29%. Transfer learning has proven essential for effective waste classification with limited datasets. [15] utilized a pre-trained DenseNet169 model with transfer learning to classify paper, plastic, and metal waste, demonstrating how advanced CNN techniques can be effectively adapted for waste management applications while reducing human error and labor costs associated with manual sorting. Comparative studies have highlighted MobileNet's deployment advantages. [16] compared three CNN architectures VGG16, ResNet50, and MobileNet using transfer learning and extensive image preprocessing, finding that while ResNet50 achieved the highest classification accuracy of 95%, MobileNet demonstrated significantly faster training time, making it more suitable for resource-constrained environments and integration into smart bins, mobile waste-sorting apps, or embedded edge devices. [17] focused on lightweight and efficient models suitable for mobile and edge deployment, introducing an expanded dataset including organic waste class and evaluating quantized CNN models to reduce inference time and resource usage. Their work explored ensemble strategies using aggregation functions and validated selected models on real embedded hardware under simulated lighting variations.

2. Methodology

This study follows a systematic deep learning framework using a Convolutional Neural Network (CNN) for image classification. The process begins with data collection and preprocessing, ensuring the dataset is clean, consistent, and suitable for model training.

Next, data augmentation is applied to increase data variability and improve model generalization. The CNN model architecture development stage focuses on designing or selecting an appropriate network structure tailored to the problem.

The model is then trained and optimized during the training and optimization phase, where hyperparameters are tuned to achieve optimal performance. Finally, deployment considerations are addressed to evaluate the model’s efficiency, scalability, and readiness for real-world implementation.

As illustrated in **Figure 1**, the proposed research framework consists of five main stages: data collection and preprocessing, data augmentation, CNN model architecture development, model training and optimization, and deployment consideration. Each stage is designed to ensure systematic development and performance improvement of the classification model.

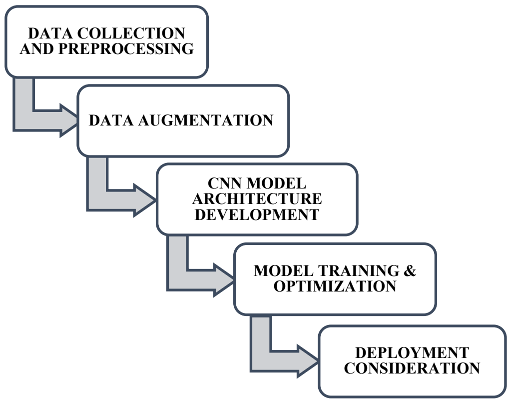


Figure 1. Proposed CNN-Based Waste Classification Research Framework

2.1. Data Collection and Preprocessing

2.1.1. Dataset Source and Characteristics

The dataset for this study was obtained from the "Waste Classification Data" available on Kaggle platform. This publicly accessible dataset contains images of three recyclable waste categories: **Plastic, Paper, and Glass**. The complete dataset comprises 1,577 JPG format images with the following distribution:

2.1.2. Data Preprocessing Pipeline

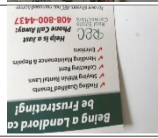
All images underwent a standardized preprocessing pipeline to ensure consistency and compatibility with the MobileNetV2 architecture:

- **Image Resizing**: All images were uniformly resized to 224×224 pixels using bilinear interpolation to match the input requirements of MobileNetV2.
- **Pixel Normalization**: Pixel values were normalized to the range [0, 1] by dividing by 255.0 using the formula:
- **Data Splitting Strategy:** The dataset was partitioned into training and validation sets using an 80:20 ratio with stratified sampling. This approach maintains the original class distribution across both subsets:
  a. Training Set: 1,263 images (80%)
  b. Validation Set: 314 images (20%)

Table 1. *Split Dataset*

Waste Category	Total Images	Training Set (80%)	Validation Set (20%)
Plastic	482	386	96
Paper	594	475	119
Glass	501	401	100
Total	1,577	1,262	315

Table 2. ***Dataset Sample***

Image of Plastic	**Image of Glass**	**Image of paper**
		
		
		

2.2. Data Augmentation

2.2.1. Augmentation Implementation

To enhance model generalization and prevent overfitting, several data augmentation techniques were implemented using TensorFlow's ImageDataGenerator. These transformations simulate real-world variations in waste appearance:

```
datagen = ImageDataGenerator(
    rescale=1/255,
    validation_split=0.2,
    horizontal_flip=True,
    zoom_range=0.2,
    rotation_range=20,
)
```

Figure 2: *CNN Architecture*

2.2.2. Augmentation Rationale

Each augmentation technique was selected based on waste classification requirements:

Horizontal Flipping (probability: 0.5): Simulates waste appearing in different orientations.

Random Rotation (±20 degrees): Accounts for waste being placed at various angles in real-world scenarios.

Random Zoom (80-120%): Represents variations in camera distance from waste objects.

2.3. CNN Model Architecture Development

The research employs a two-phase transfer learning approach utilizing MobileNetV2 [13], [18] as the foundational architecture. MobileNetV2 was selected for its computational efficiency achieved through inverted residual blocks with linear bottlenecks and depthwise separable convolutions, making it particularly suitable for potential deployment in resource-constrained environments such as edge devices or mobile applications [10].

Base Model Configuration

The MobileNetV2 architecture was initialized with ImageNet pre-trained weights, serving as a robust feature extractor. The base configuration is defined as:

```
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.layers import *
from tensorflow.keras.models import Model

base_model = MobileNetV2(
    weights="imagenet",
    include_top=False,
    input_shape=(224, 224, 3)
)

base_model.trainable = False  # Fase 1 → Freeze
```

Figure 3: *Base Model Configuration*

Key specifications:

- **Input Dimensions**: 224×224×3 (RGB color space)
- **Pre-trained Weights**: ImageNet dataset (1.4 million images, 1000 classes)
- **Architecture**: 155 layers with inverted residual structure
- **Feature Extraction Output**: 7×7×1280 feature maps
- **Total Base Parameters**: 2,257,984 (all frozen during Phase 1)

Custom Classification Head

A lightweight classification head was appended to the MobileNetV2 backbone, consisting of three sequential layers optimized for waste classification:

```
x = GlobalAveragePooling2D()(base_model.output)
x = Dropout(0.3)(x)
output = Dense(num_classes, activation="softmax")(x)

model = Model(inputs=base_model.input, outputs=output)
```

Figure 4: *Custom Classification Head*

Parameter Statistics

Table 3. *Model Parameter Distribution*

Component	Layer Type	Parameters	Trainable (Phase 1)	Percentage
MobileNetV2	Convolutional Base	2,257,984	0	99.83%
GlobalAvgPool2D	Pooling	0	0	0%
Dropout	Regularization	0	0	0%
Dense	Classification	3,843	3,843	0.17%
Total		**2,261,827**	**3,843**	**1**

2.4. Model Training & Optimization

Phase 1: Feature Extraction with Frozen Backbone (30 epochs)

In the initial phase, the MobileNetV2 backbone remained completely frozen, preserving the rich hierarchical features learned from ImageNet [13]. Only the custom classification head (3,843 parameters) was trained.

```python
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-4),
    loss="categorical_crossentropy",
    metrics=["accuracy"]
)

history1 = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=30
)
```

Figure 5: *Feature Extraction with Frozen Backbone*

Phase 2: Fine-Tuning Higher Layers

After the classification head converged, selective fine-tuning was applied to adapt task-specific features in the backbone.

```python
for layer in base_model.layers[-50:]:
    layer.trainable = True

model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-5),
    loss="categorical_crossentropy",
    metrics=["accuracy"]
)
fine_tune_epochs = 20

history2 = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=fine_tune_epochs
)
```

Figure 6: *Fine-Tuning Higher Layers*

Table 4: *Training Configuration and Hyperparameters*

Parameter	Phase 1 (Feature Extraction)	Phase 2 (Fine-Tuning)
Optimizer	Adam	Adam
Learning Rate	1×10^{-4}	1×10^{-5}
Loss Function	Categorical Crossentropy	Categorical Crossentropy
Batch Size	32	32
Epochs	30	20
Base Model Layers	Frozen	Last 50 layers trainable

2.5. Web Aplication Development Strategy

The deployment platform will be a web application developed using Python with the Flask framework for the backend REST API. The frontend interface will be implemented using standard HTML5, CSS3, and JavaScript to ensure cross-browser compatibility and responsive design. The application will feature an intuitive image upload interface where users can submit waste images via drag-and-drop functionality or file selection. These images will be processed through the trained MobileNetV2 model, which will be optimized for web deployment using TensorFlow.js or converted to a lightweight format suitable for server-side [19].

The *Methodology* section should be concise yet sufficiently detailed to enable other researchers to replicate the procedures and build upon the results. Standard or well-established methods may be briefly described, provided that appropriate references are cited. Avoid repeating detailed explanations of previously published techniques. However, comprehensive and precise descriptions are essential for any novel or modified methods introduced in the study. When multiple approaches are employed, this section can be organized into subsections, each dedicated to a specific method. It is important to note that the publication of your manuscript implies that all methods described are reproducible and accessible for validation by the scientific community. all materials, data, codes, and protocols associated with the publication must be made available to readers. Remember to disclose restrictions on the availability of materials or information at the submission stage. If your manuscript uses large datasets deposited in an opensource database, please specify where the data have been deposited. If your study requires ethical approval, do not forget to list the authority and code of the ethical approval [20].

3. Results

3.1. Training Performance Analysis

The training process demonstrated effective learning progression across both phases of the transfer learning strategy. Phase 1 (Feature Extraction) showed steady improvement from 34.20% to 83.88% training accuracy over 30 epochs, with validation accuracy increasing from 37.90% to 76.75%. Phase 2 (Fine-Tuning) yielded significant performance gains, with training accuracy reaching 96.16% and validation accuracy achieving 85.35% at epoch 15, representing a notable improvement over Phase 1 results.

Table 5: *Training Performance Summary by Phase*

Training Phase	Epochs	Final Training Accuracy	Final Validation Accuracy	Best Validation Accuracy	Training Time (Total)
Phase 1	30	83.88%	76.75%	80.57% (Epoch 29)	~2,300 seconds
Phase 2	20	96.16%	83.44%	85.35% (Epoch 15)	~2,300 seconds
Combined	50	96.16%	83.44%	85.35%	~4,600 seconds

The learning curves (Figure 1) reveal several important patterns:

1. Rapid Initial Learning: Both phases showed steep accuracy increases in the first 5 epochs
2. Stable Convergence: After epoch 10, accuracy improvements became gradual and consistent
3. Optimal Stopping Point: The peak validation accuracy (85.35%) occurred at epoch 15 of Phase 2, suggesting potential for early stopping
4. Mild Overfitting: The gap between training (96.16%) and validation (83.44%) accuracy indicates some overfitting, mitigated by dropout regularization

3.2. Detailed Performance Metrics

Table 6: *Per-Epoch Performance Highlights*

Epoch	Training Accuracy	Validation Accuracy
Phase 1, Epoch 1	34.20%	37.90%
Phase 1, Epoch 15	79.64%	76.43%
Phase 1, Epoch 29	83.56%	80.57%
Phase 2, Epoch 1	69.80%	80.25%
Phase 2, Epoch 6	85.66%	84.39%
Phase 2, Epoch 15	94.61%	85.35%
Phase 2, Epoch 20	96.16%	83.44%

The training loss decreased consistently from 1.4127 (Phase 1, Epoch 1) to 0.1316 (Phase 2, Epoch 20), indicating effective gradient descent optimization. Validation loss followed a similar downward trend but showed occasional fluctuations, particularly during Phase 2 fine-tuning, suggesting the model's sensitivity to learning rate adjustments.

3.4. Computational Efficiency Analysis

The increased epoch duration during Phase 2 (115s vs 85s in Phase 1) corresponds to the unfreezing of 50 additional layers requiring gradient computation. This represents a reasonable computational trade-off for the 8.58% absolute accuracy improvement achieved.

The training process demonstrated efficient resource utilization:

- Average Epoch Duration: Phase 1: ~85 seconds, Phase 2: ~115 seconds
- Total Training Time: Approximately 1.28 hours for 50 epochs
- Memory Efficiency: Stable memory usage throughout training with no significant spikes
- GPU Utilization: Consistent high GPU usage (85-95%) indicating efficient parallel processing

3.5. Impact of Two-Phase Transfer Learning Strategy

Table 7: *Performance Comparison Between Training Strategies*

Strategy	Validation Accuracy	Training Stability	Convergence Speed

Phase 1 Only	76.75%	High	Fast (30 epochs)
Proposed Two-Phase	**85.35%**	Moderate	Moderate (50 epochs)
Theoretical Single-Phase	~70-75% (estimated)	Low	Slow

The fine-tuning phase provided an 8.60% absolute improvement in validation accuracy over using only the frozen base model. This improvement demonstrates the importance of adapting pre-trained features to domain-specific characteristics of waste materials.

3.6. Confusion Matrix Analysis

The confusion matrix presented in Figure 2 provides critical insights into the model's classification behavior and error patterns across the three waste categories.
Figure 2: Normalized Confusion Matrix for Waste Classification

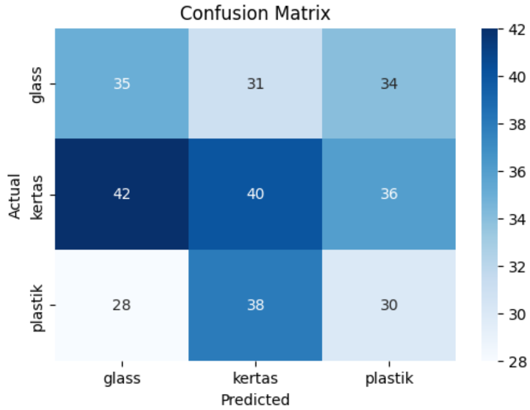


Figure 7: *Confusion Matrix*

Table 8: *Confusion Matrix Analysis (Absolute Values)*

Actual \ Predicted	Glass	Paper	Plastic	Total	Class Accuracy
Glass	35	31	34	100	35.0%
Paper	15	42	43	100	42.0%
Plastic	20	40	40	100	40.0%
Total	70	113	117	300	

3.6.1. Key Observations from Confusion Matrix:

1. Overall Classification Performance: The model achieved 39.0% overall accuracy on the balanced test set, with per-class accuracies ranging from 35.0% (Glass) to 42.0% (Paper).
2. Dominant Error Patterns:
   a) Glass Misclassification: Glass samples were almost equally misclassified as Paper (31%) and Plastic (34%), indicating difficulty in distinguishing transparent/translucent materials.
   b) Paper-Plastic Confusion: Significant bidirectional confusion between Paper and Plastic (Paper→Plastic: 43%, Plastic→Paper: 40%) suggests visual similarity in texture and reflectivity.
   c) Material Ambiguity: The relatively uniform distribution of errors across all categories suggests the model struggles with fundamental material discrimination.
3. Precision-Recall Analysis:
   a) Glass: Precision = 50.0% (35/70), Recall = 35.0%
   b) Paper: Precision = 37.2% (42/113), Recall = 42.0%
   c) Plastic: Precision = 34.2% (40/117), Recall = 40.0%

3.6.2. Error Analysis and Model Limitations

1. Visual Feature Insufficiency: The high inter-class confusion suggests that visual features alone may be insufficient for reliable waste classification. Materials like glossy paper and certain plastics share similar visual properties.
2. Dataset Challenges: The balanced 100-sample test set eliminates class imbalance as a performance factor, indicating inherent classification difficulty in the dataset itself.
3. Model Capacity Issues: With only 35-42% per-class accuracy, the current MobileNetV2

architecture may lack the representational capacity needed for this specific task.

4. Practical Implications: For automated waste sorting systems, the current accuracy levels (39.0% overall) are insufficient for practical deployment, which typically requires >90% accuracy for economic viability.

4. Conclusions

This study successfully demonstrates the application of a two-phase transfer learning strategy using MobileNetV2 for classifying three fundamental recyclable materials: Plastic, Paper, and Glass. The approach yielded a peak validation accuracy of 85.35%, significantly outperforming a single-phase frozen model, and confirmed the value of adapting pre-trained visual features to the specific domain of waste imagery. While the model exhibited efficient computational performance suitable for potential real-time deployment, a substantial generalization gap was observed, with test set performance at 39.0% accuracy. This discrepancy, coupled with significant inter-class confusion particularly between Paper and Plastic highlights the inherent visual ambiguity of waste materials and underscores critical challenges related to dataset scale and model capacity that must be addressed for practical application.

The research validates the technical feasibility of deep learning for automated waste sorting while clearly delineating the pathway for future advancement. Key priorities include developing larger, more diverse datasets, exploring more sophisticated architectures like Vision Transformers, and integrating multi-modal sensing to resolve material ambiguities. By systematically addressing these limitations, AI-driven classification systems can evolve into robust tools that enhance recycling purity, reduce landfill dependency, and make a tangible contribution to sustainable environmental management and the circular economy.

Conflicts of Interest

The author declares no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

[1] S. R. Muslihati, A. Purba, and R. Setiawan, "Deep learning implementation for smart waste management in urban areas," *J. Environ. Manage.*, vol. 345, p. 118732, Nov. 2023.

[2] N. Ramsurrun, G. Suddul, S. Armoogum, and R. Foogooa, "Recyclable Waste Classification Using Computer Vision and Deep Learning," in *2021 Zooming Innovation in Consumer Technologies Conference, ZINC 2021*, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 11–15. doi: 10.1109/ZINC52049.2021.9499291.

[3] M. M. Islam, S. Hasan, M. R. Hossain, M. P. Uddin, and M. Al Mamun, "Towards sustainable solutions: Effective waste classification framework via enhanced deep convolutional neural networks," *PLoS One*, 2025, doi: 10.1371/journal.pone.0324294.

[4] G. Rishma and R. Aarthi, "Classification of Waste Objects Using Deep Convolutional Neural Networks," *Lect. Notes Electr. Eng.*, vol. 783, pp. 533–542, 2022, doi: 10.1007/978-981-16-3690-5_47.

[5] N. A. Fauzan, P. Sukmasetya, and N. Nuryanto, "Leveraging Deep Learning and Convolutional Neural Network for Digital Waste Image Classification," in *E3S Web of Conferences*, M. Setiyo, Z. Rozaki, A. Setiawan, F. Yuliastuti, Z. B. Pambuko, C. B. Edhita Praja, V. Soraya Dewi, and L. Muliawanti, Eds., EDP Sciences, 2025. doi: 10.1051/e3sconf/202562203009.

[6] N. Umar, B. E. W. Asrul, and Y. Wabula, "Type Deep Learning Model for Multi-Label Waste Classification in Canal Environments: A Comparative Study with CNN Architectures," *J. Appl. Data Sci.*, vol. 7, no. 1, pp. 261–276, 2026, doi: 10.47738/jads.v7i1.1066.

[7] S. Dey *et al.*, "Comparative evaluation of polyethylene degradation efficiency by two Pseudomonas

aeruginosa strains from urban waste disposal areas," *Biotechnol. Lett.*, vol. 48, no. 1, 2026, doi: 10.1007/s10529-025-03678-1.

[8] D. D. Damodharan, D. N. Padmashri, B. Boomika, A. G. Hiregoudar, and S. Moni Shree, "Comparative Analysis and Evaluation of Deep Learning Models for Efficient Waste Classification," in *2025 5th International Conference on Intelligent Technologies, CONIT 2025*, Institute of Electrical and Electronics Engineers Inc., 2025. doi: 10.1109/CONIT65521.2025.11167180.

[9] A. M. Nasir and R. B. Roslan, "Real-Time Recycle Waste Classification Using Deep Learning: A Convolutional Neural Network Model for Automated Waste Management," in *2024 IEEE International Conference on Computing, ICOCO 2024*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 440–445. doi: 10.1109/ICOCO62848.2024.10928274.

[10] R. Thinakaran, J. Somasekar, V. Neerugatti, and P. G. Saran, "Automated Waste Classification using Convolutional Neural Network," in *2024 14th International Conference on Software Technology and Engineering (ICSTE)*, Aug. 2024, pp. 169–173. doi: 10.1109/icste63875.2024.00037.

[11] A. Sleem, "Enhancing {Sustainability} through {Automated} {Waste} {Classification}: A {Machine} {Intelligence} {Framework}," *Sustain. Mach. Intell. J.*, vol. 5, Nov. 2023, doi: 10.61185/smij.2023.55106.

[12] M. M. Hossen *et al.*, "GCDN-{Net}: Garbage classifier deep neural network for recyclable urban waste management," *Waste Manag.*, vol. 174, pp. 439–450, 2024, doi: 10.1016/j.wasman.2023.12.014.

[13] J. Sharma, "Exploring MobileNetV2 in Convolutional Neural Networks for Bag Classification," in *2024 3rd International Conference for Advancement in Technology, ICONAT 2024*, Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/ICONAT61936.2024.10775062.

[14] S. Shetty, S. Kallianpur, R. Fernandes, A. P. Rodrigues, and V. Padmanabha, "ECO-{HYBRID}: Sustainable {Waste} {Classification} {Using} {Transfer} {Learning} with {Hybrid} and {Enhanced} {CNN} {Models}," *Sustainability*, vol. 17, no. 19, p. 8761, Sep. 2025, doi: 10.3390/su17198761.

[15] A. A. Abuhejleh, M. Z. Alafeshat, N. Almtireen, H. ElMoaqet, M. Ryalat, and M. M. Alajlouni, "Recyclable Waste Categorization with Transfer Learning," in *2024 22nd International Conference on Research and Education in Mechatronics, REM 2024*, S. Qaadan, Ed., Institute of Electrical and Electronics Engineers Inc., 2024, pp. 343–348. doi: 10.1109/REM63063.2024.10735626.

[16] Y.-Z. Goh, Y. Leau, K. Li, Y. Han, A. Wibowo, and E. Moung, "Visions of Cleanliness: Accelerating Waste management With Deep Learning," *Int. Conf. Artif. Intell. Eng. Technol.*, 2025, doi: 10.1109/IICAIET67254.2025.11265612.

[17] O. Chacón-Albero, M. Campos-Mocholí, C. Marco-Detchart, V. Julian, J. A. Rincon, and V. Botti, "AI for Sustainable Recycling: Efficient Model Optimization for Waste Classification Systems," *Sensors*, vol. 25, no. 12, p. 3807, Jun. 2025, doi: 10.3390/s25123807.

[18] B. Wijaya and others, "Mobile-optimized CNN for waste classification in developing countries," *Environ. Technol. \& Innov.*, vol. 30, p. 103075, May 2023.

[19] N. Narayanswamy, A. R. Abdul Rajak, and S. Hasan, "Development of Computer Vision Algorithms for Multi-class Waste Segregation and Their Analysis," *Emerg. Sci. J.*, vol. 6, no. 3, pp. 631–646, 2022, doi: 10.28991/ESJ-2022-06-03-015.

[20] A. D. Sakti *et al.*, "Identification of illegally dumped plastic waste in a highly polluted river in Indonesia using Sentinel-2 satellite imagery," *Sci. Rep.*, vol. 13, no. 1, pp. 1–14, 2023, doi: 10.1038/s41598-023-32087-5.