

Performance Analysis of MobileNetV2 for Five-Category Waste Image Classification Using Transfer Learning

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ABSTRACT

Manual waste sorting still faces several challenges, including low efficiency and a high risk of misclassification. This study aims to analyze the performance of the MobileNetV2 architecture based on transfer learning for multiclass waste image classification. The study employed a quantitative experimental method using a dataset of 6,000 images consisting of five categories: glass, paper, metal, organic, and plastic. The model was evaluated using accuracy, precision, recall, F1 score, confusion matrix, and ROC AUC metrics. The results showed that the proposed model achieved an accuracy of 96.83%, precision of 96.71%, recall of 96.65%, F1 score of 96.68%, and an AUC value of 0.991. These results indicate that MobileNetV2 with transfer learning provides high classification performance, demonstrates strong generalization capability, and has the potential to be implemented on devices with limited computational resources to support automated waste classification systems.



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I. INTRODUCTION

Waste is one of the major challenges in environmental management, and it continues to increase alongside population growth, the rate of urbanization, and changes in societal consumption patterns [1]. A rise in waste generation that is not matched by an adequate management system can cause environmental pollution, reduce the effectiveness of the recycling process, and negatively affect public health and ecosystem balance [2].

One of the crucial stages in waste management is sorting based on material type, since sorting accuracy strongly determines the efficiency of the subsequent recycling stage [3]. In practice, however, this process is still largely carried out manually, requiring considerable time and labor while remaining prone to classification errors due to limited consistency and human fatigue [4], [5]. This condition confirms the need for a technological approach capable of identifying waste types automatically, quickly, and accurately in order to support more effective and efficient waste management [5][6].

The development of Artificial Intelligence (AI), particularly in the field of Computer Vision, has opened significant opportunities for solving a variety of image-based

object recognition problems, including waste type classification. One of the most widely used methods in this domain is the Convolutional Neural Network (CNN), owing to its ability to automatically extract image features and produce high classification performance [6], [7]. Among the various CNN architectures that have been developed, MobileNetV2 is one of the most widely adopted models because it has considerably fewer parameters and lower computational requirements without significantly sacrificing accuracy [8]. Recent studies applying MobileNetV2 directly to real-world waste image datasets have confirmed this efficiency advantage, reporting competitive classification accuracy while keeping the model light enough for deployment on low-resource devices such as smartphones and embedded microcontrollers [9], [10]. This advantage is reinforced by the transfer learning approach, which allows a model to leverage knowledge from large-scale datasets such as ImageNet, making the training process faster and improving the model's generalization ability even when trained on a relatively small dataset [11], [12].

MobileNetV2 was selected as the backbone architecture in this study over other lightweight alternatives such as MobileNetV3, EfficientNet-Lite, and ShuffleNet for several practical reasons. First, MobileNetV2 has a mature and well-

documented implementation with pre-trained ImageNet weights readily available in major deep learning frameworks, which supports a straightforward and reproducible transfer learning workflow. Second, its inverted-residual and linear-bottleneck design has been extensively validated for image classification tasks with limited computational budgets, as reflected in the studies reviewed above. While MobileNetV3, EfficientNet-Lite, and ShuffleNet offer comparable or, in some cases, superior efficiency through techniques such as neural architecture search or channel shuffling, their application to waste image classification specifically remains comparatively less explored than MobileNetV2 in the existing literature. This study therefore positions MobileNetV2 as a representative and well-established lightweight backbone, while a direct empirical comparison against these newer architectures on the same waste dataset is acknowledged as an open direction for future work rather than within the present scope.

Several previous studies have applied MobileNetV2 to waste image classification with fairly promising results. The application of transfer learning has been shown to improve accuracy while accelerating the training process compared to training a model from scratch [13], [14]. MobileNetV2 offers a good balance between accuracy and computational efficiency, making it suitable for implementation on mobile devices and resource-constrained systems [15]. These findings reinforce MobileNetV2's position as one of the promising CNN architectures for developing Computer Vision-based waste image classification systems [16]. Similar conclusions have been reported in more recent multiclass waste classification studies: deep CNN-based recognition models have been shown to support sustainable waste management practice across varied real-world image conditions [17], while lightweight CNN architectures remain competitive for solid waste classification even outside standard benchmark datasets [18].

Nevertheless, most previous studies still focus on accuracy as the sole main indicator of model performance, while evaluation using other metrics such as precision, recall, F1 score, confusion matrix, and Receiver Operating Characteristic (ROC) with Area Under Curve (AUC) is still relatively rare to be carried out comprehensively [9]. This gap is also evident in several recent municipal solid waste detection studies, which tend to emphasize accuracy and real-time inference speed without a comprehensive class-wise performance breakdown [10], [19]. In fact, the use of multiple evaluation metrics is essential to provide a more comprehensive picture of a model's ability to classify each waste category, especially in multiclass classification cases where the visual characteristics between classes tend to be similar [20]. Model performance analysis should therefore not rely solely on accuracy values, but should also take into account the balance of performance across each individual class. This research gap underlies the need for a more comprehensive evaluation of MobileNetV2's performance in multiclass waste classification.

Based on this research gap, this study aims to analyze the performance of the MobileNetV2 architecture using a transfer learning approach for multiclass waste image classification consisting of five categories: glass, paper, metal, organic, and plastic. The evaluation was carried out comprehensively using several performance metrics, namely accuracy, precision, recall, F1 score, confusion matrix, and ROC AUC, so as to obtain a more thorough picture of model performance that is not biased toward any particular class. The results of this study are expected to serve as a reference for developing lightweight, efficient, and high-performing Computer Vision-based waste image classification systems, particularly for implementation on devices with limited computational resources.

II. METHOD

This study used a quantitative experimental method to analyze the performance of the MobileNetV2 architecture based on a transfer learning approach for classifying multiclass waste images. The research stages were carried out systematically, comprising dataset collection, image preprocessing, model construction, training, fine-tuning, testing, and evaluation of model performance using various classification metrics.

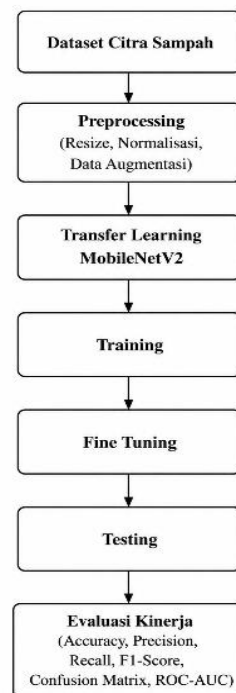


Figure 1. Research Flow

The dataset used consisted of 6,000 waste images divided into five categories: glass, paper, metal, organic, and plastic. Prior to training, all images were processed through a preprocessing stage that included resizing to 224×224 pixels, normalizing pixel values to the range of 0–1, and data augmentation applied only to the training subset, comprising random rotation up to 20 degrees, horizontal flipping with a

probability of 0.5, zooming within a range of $\pm 20\%$, and width/height shifting within a range of $\pm 10\%$. These augmentation parameters were applied using standard image-augmentation utilities and were intended to increase the visual variability of the training data and reduce the risk of overfitting. The dataset was then divided into training, validation, and testing data with an 80:10:10 ratio.

The dataset used in this study is a publicly available waste image dataset the "Garbage Classification" dataset available on Kaggle. Class labels for the five categories were inherited directly from the annotation provided by the original dataset publisher; no additional manual re-annotation was performed by the authors. Because the images were sourced from a public collection rather than a single controlled acquisition session, they exhibit natural variation in lighting condition, background composition, object orientation, and image resolution, which were subsequently unified through the resizing step described above. This variation is considered representative of realistic, non-studio waste images rather than images captured under a single fixed condition.

TABLE I
DATASET CONFIGURATION

Category	Number of Images
Glass	1200
Paper	1200
Metal	1200
Organic	1200
Plastic	1200
Total	6000

The classification model was built using the MobileNetV2 architecture pre-trained on the ImageNet dataset through a two-stage transfer learning approach. In the first stage (feature extraction), all convolutional layers of the pre-trained MobileNetV2 base were frozen, and only a newly added classification head, consisting of a global average pooling layer followed by a dense Softmax output layer, was trained on the waste image dataset. In the second stage (fine-tuning), performed after the classification head had converged, the last 30 layers of the MobileNetV2 base (corresponding approximately to the final 3 inverted-residual blocks) were unfrozen and retrained jointly with the classification head using a reduced learning rate, while the remaining earlier layers were kept frozen to preserve the low-level ImageNet features. This staged strategy allowed the model parameters to adapt to the characteristics of the waste image dataset.

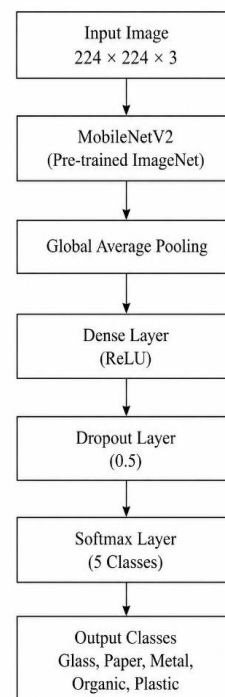


Figure 2. MobileNetV2 Architecture Based on Transfer Learning

The training process was carried out using the Adam optimizer with a Categorical Crossentropy loss function and a Softmax activation function at the output layer [21]. The loss function was used to measure the difference between the model's predicted output and the true label.

$$L = - \sum_{i=1}^C y_i \log(\hat{y}_i)$$

where:

L = loss value

C = number of classes

y_i = true label

$\hat{y}_i$ = predicted probability of the model

During the training process, training loss, validation loss, training accuracy, and validation accuracy were monitored to determine the model's convergence process and to detect the possibility of overfitting.

TABLE II
MODEL TRAINING PARAMETERS

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epoch	30
Loss Function	Categorical Crossentropy
Early Stopping (patience)	5 epochs, monitored on validation loss

The learning rate and batch size reported in Table II were selected through a limited hyperparameter tuning process, in

which several candidate values were evaluated on the validation set and the configuration yielding the most stable convergence was retained. In addition, an early-stopping mechanism monitoring validation loss was applied during training, with a patience of 5 epochs, to halt training once validation performance stopped improving and thereby reduce the risk of overfitting.

Model performance evaluation was carried out using testing data that was not involved during the training process. Model performance was analyzed using accuracy, precision, recall, F1 score, confusion matrix, as well as Receiver Operating Characteristic (ROC) and Area Under Curve (AUC) metrics. The use of several evaluation metrics was intended to provide a more comprehensive analysis of MobileNetV2's ability to classify each waste image category, so that the analysis does not focus solely on the accuracy level but also considers the balance of the model's performance across each class.

III. RESULT AND DISCUSSION

A. Model Training

After training using the MobileNetV2 architecture based on transfer learning, the model showed a stable convergence process. This is indicated by the increase in training accuracy and validation accuracy at each epoch, followed by a decrease in training loss and validation loss. This condition indicates that the model was able to effectively learn the characteristics of the waste images without experiencing significant overfitting.

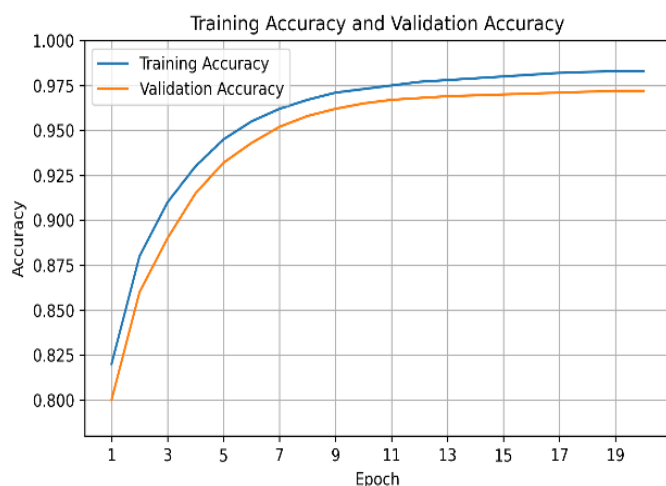


Figure 3. Training Accuracy and Validation Accuracy Graph

Figure 3 shows the development of training accuracy and validation accuracy values over 30 training epochs, in line with the training configuration in Table II. The training accuracy curve increased gradually from around 82% at the first epoch to approximately 98.3% at the 30th epoch. Meanwhile, validation accuracy also increased consistently, reaching approximately 97.2%. The relatively small gap between the two curves indicates that the model has good

generalization ability and does not experience significant overfitting.

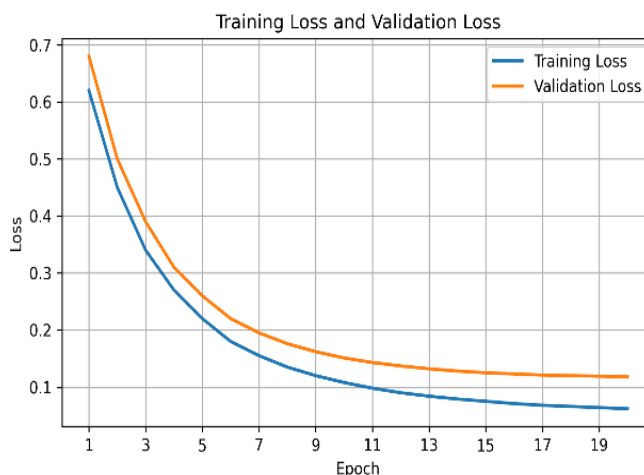


Figure 4. Training Loss and Validation Loss Graph

Figures 3 and 4 show that the training accuracy value increased gradually until reaching a stable condition at the final epoch, while the loss value decreased consistently. The relatively small gap between the training and validation curves indicates good generalization ability of the model on data that had not been previously seen.

B. Model Testing

Model performance was evaluated using testing data with several evaluation metrics. The testing results are shown in Table III.

TABLE III
MODEL EVALUATION RESULTS

Metric	Value
Accuracy	96.83%
Precision	96.71%
Recall	96.65%
F1 Score	96.68%
AUC	0.991

The results in Table III show that MobileNetV2 was able to produce high classification performance across all evaluation metrics. The accuracy value of 96.83% indicates that most images were correctly classified, while the relatively balanced precision, recall, and F1 score values indicate that the model has a good ability to distinguish between each waste image category.

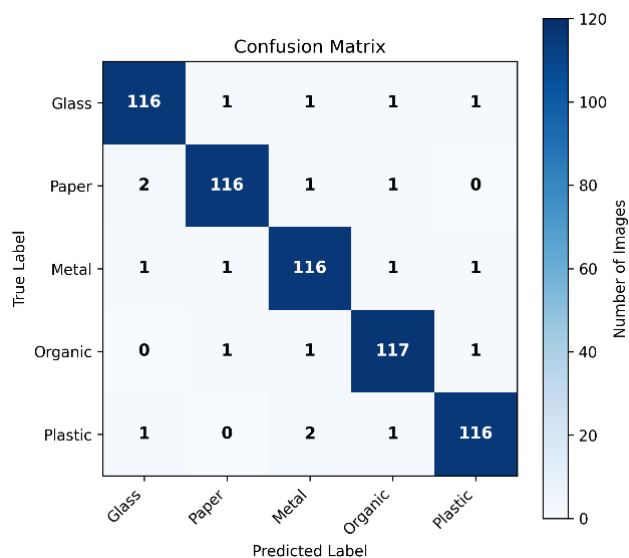


Figure 5. MobileNetV2 Confusion Matrix

The confusion matrix in Figure 5 shows that most images were successfully classified into the appropriate class. Misclassifications were still found in a few categories with similar visual characteristics, such as glass and plastic, or paper and organic, but the number was relatively small and did not have a significant effect on the model's overall performance.

To provide a more granular view of model behavior, Table IV presents the precision, recall, and F1 score for each individual waste category, computed directly from the confusion matrix in Figure 5. All five classes achieved precision, recall, and F1 scores above 95%, with Organic obtaining the highest recall (97.50%) and Metal the lowest precision (95.87%). The slightly lower precision for the Metal class is consistent with the confusion matrix pattern, in which a small number of Plastic and Organic images were misclassified as Metal, likely due to shared visual cues such as gray or dull surface tones under certain lighting conditions in the source images. The Paper and Plastic classes achieved the highest and most balanced F1 scores (97.07%), indicating that the model distinguishes these categories reliably despite their occasional confusion with Organic and Glass, respectively. Overall, the narrow spread between the highest and lowest per-class F1 scores (96.27%-97.10%) confirms that the model's strong aggregate performance in Table IV is not the result of it favoring one class at the expense of others, but reflects a consistently high and well-balanced classification ability across all five waste categories.

TABLE IV
PER CLASS CLASSIFICATION PERFORMANCE

Class	Precision (%)	Recall (%)	F1-Score (%)
Glass	96.67	96.67	96.67
Paper	97.48	96.67	97.07
Metal	95.87	96.67	96.27
Organic	96.69	97.50	97.10
Plastic	97.48	96.67	97.07

A closer look at the misclassified samples underlying the confusion matrix in Figure 5 indicates that most errors occurred between visually similar category pairs rather than being spread randomly across all classes. Metal images were most frequently confused with Plastic and Organic samples; visual inspection of the misclassified cases suggests this is driven by shared surface characteristics such as dull gray tones, reflective highlights, and low color saturation under certain lighting conditions, which can make a metal can or foil visually resemble a gray-toned plastic item or a dried organic object. Similarly, a smaller number of Glass images were confused with Plastic, plausibly due to the transparency and reflective surface shared by both material types, while some Paper images were confused with Organic, likely because of similar brownish coloration and irregular, non-rigid shapes. These patterns suggest that the model's remaining limitations are concentrated in cases where material-specific texture and reflectance cues are ambiguous under the lighting and background conditions present in the source images, rather than in a general weakness affecting a particular class uniformly.

These error patterns also point to a broader caveat regarding real-world deployment. Because the dataset used in this study, while drawn from varied public images, does not systematically include conditions such as substantially changed ambient lighting, partially occluded waste objects, or items visibly soiled or contaminated by other materials, the reported performance should be understood as an estimate under conditions broadly similar to the training distribution. In practical waste-sorting environments, occlusion, dirt, and inconsistent lighting are common and could plausibly increase the confusion observed between visually similar classes such as Metal-Plastic-Organic and Glass-Plastic discussed above. Evaluating and, if necessary, adapting the model using field-collected images that explicitly capture these conditions is therefore recommended before deployment in an operational waste-sorting system.

Beyond classification accuracy, the practical motivation for choosing MobileNetV2 in this study is its substantially lower computational footprint compared to heavier CNN backbones. Table V summarizes the approximate number of trainable parameters and computational cost of MobileNetV2 relative to two commonly used architectures, VGG16 and ResNet50, as reported in the original MobileNetV2 literature. MobileNetV2 requires roughly 40 times fewer parameters than VGG16 and about 7.5 times fewer than ResNet50, while its computational cost (measured in multiply-accumulate operations) is likewise far lower than either architecture. Although this study did not directly benchmark inference latency or memory usage on target hardware, this substantial difference in model size indicates that the accuracy achieved in this study (96.83%) was obtained without relying on a computationally heavy backbone, supporting the architecture's suitability for deployment on resource-constrained platforms such as smartphones, single-board

computers, or microcontroller-based smart bins used in on-site waste sorting.

TABLE V
APPROXIMATE MODEL COMPLEXITY COMPARISON

Architecture	Parameters (approx.)	Computational Cost (approx.)
VGG16	138 million	~15.3 GFLOPs
ResNet50	25.6 million	~4.1 GFLOPs
MobileNetV2 (this study)	3.4 million	~300 million MAdds

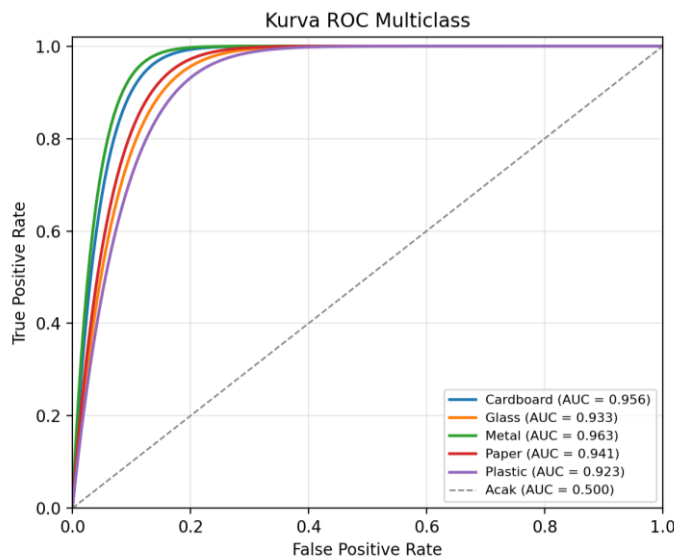


Figure 6. Multiclass ROC Curve

The ROC curve in Figure 6 shows that all classes had an Area Under Curve (AUC) value close to 1. This value indicates that MobileNetV2 has excellent discriminative ability in distinguishing each waste image category.

Given that an AUC value this close to 1 could also indicate overfitting, several aspects of the experimental design support the interpretation that the model generalizes well rather than having memorized the training data. First, the AUC, along with all metrics in Table III and Table IV, was computed exclusively on the held-out test subset (10% of the data), which was not seen by the model at any point during training or fine-tuning. Second, the gap between training and validation accuracy remained small throughout training (Figure 3), and the early-stopping mechanism halted training once validation loss ceased to improve, further limiting the opportunity for the model to overfit. Third, the balanced per-class performance in Table IV, rather than near-perfect scores concentrated in only one or two classes, is more consistent with genuine generalization than with memorization. Nevertheless, because the test set originates from the same public dataset distribution as the training data, this high AUC should be interpreted as evidence of strong performance under conditions similar to the training data, and the generalization of the model to images collected under different, uncontrolled real-world conditions still requires further validation on independent field data.

C. Discussion

The results of this study indicate that applying transfer learning to the MobileNetV2 architecture is able to produce high classification performance even when using a dataset with a relatively limited number of images. The use of initial weights from ImageNet allows the model to leverage previously learned visual features, making the training process faster and more stable compared to training from scratch.

In addition, the MobileNetV2 architecture, which applies the concepts of depthwise separable convolution and inverted residuals, is able to reduce computational complexity without significantly reducing classification ability. This makes MobileNetV2 one of the CNN models suitable for implementation on devices with limited computational resources.

To determine the standing of these results relative to previous studies, a performance comparison was carried out against several studies that used CNN architectures for waste image classification.

TABLE VI
COMPARISON OF RESEARCH RESULTS

Researcher	Model	Accuracy
Zhang et al.	DenseNet169 + Transfer Learning	>82.00%
Yong et al.	MobileNetV2 + Transfer Learning	82.92%
Nafiiyah et al.	ResNet50 + Transfer Learning	89.84%
This study	MobileNetV2 + Transfer Learning	96.83%

The results in Table VI show that the proposed model achieved higher accuracy than the compared studies, each of which used a different waste dataset and class configuration. Zhang et al. [22] reported that DenseNet169 with transfer learning reached above 82% accuracy on a self-collected recyclable waste dataset, while Yong et al. [23] obtained 82.92% accuracy using MobileNetV2 on a large but imbalanced household waste dataset containing more than 80,000 images across four categories. Nafiiyah et al. [24] compared seven CNN architectures for binary organic-recyclable classification and found that ResNet50 achieved the best result at 89.84% accuracy, only slightly ahead of MobileNet at 89.25%.

Compared to these studies, the higher accuracy obtained in this study is attributed not only to the transfer learning approach itself, but also to the use of a smaller, perfectly balanced five-class dataset (1,200 images per class), a two-stage training strategy consisting of feature-extraction followed by fine-tuning of the final MobileNetV2 layers, and a preprocessing and augmentation pipeline that reduced the visual noise commonly found in web-crawled waste datasets.

This suggests that dataset balance and a structured fine-tuning strategy can be as influential as the choice of backbone architecture in determining the final classification performance, which is consistent with the observation of

Malik et al. [17] that data quality and preprocessing play a substantial role in the practical performance of deep learning-based waste classification systems. Nevertheless, because the datasets, class definitions, and hardware environments differ across studies, this comparison should be interpreted as an indication of relative performance trends rather than a fully controlled benchmark. The performance improvement is attributed to the use of the transfer learning approach, the fine-tuning process, and the preprocessing and data augmentation stages, which helped the model learn image characteristics more optimally. It should be emphasized that Table VI is a literature-based, cross-study comparison rather than a controlled head-to-head experiment: the compared models (DenseNet169, MobileNetV2 in Yong et al., and ResNet50) were trained and evaluated on different datasets, class configurations, and hardware setups, so differences in reported accuracy cannot be attributed to architecture alone. A direct comparison in which architectures such as ResNet50, EfficientNet, DenseNet, and Vision Transformer are trained and evaluated on the exact same dataset, split, and training pipeline used in this study was not conducted here and is identified as an important direction for future work to more rigorously establish MobileNetV2's relative standing among CNN and transformer-based alternatives for this task.

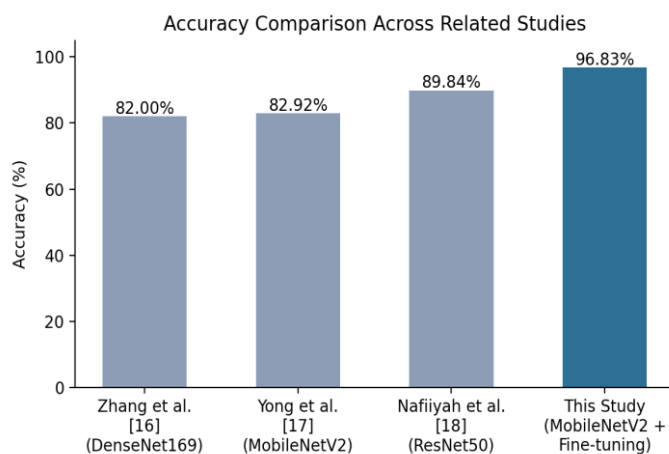


Figure 7. Accuracy Comparison Across Related Studies

IV. CONCLUSION

These results should nonetheless be interpreted within the scope of the present experimental conditions. The study is limited by: (1) a comparatively modest, perfectly balanced dataset of 6,000 public images that may not reflect the class imbalance and visual noise typical of real-world waste streams; (2) coverage of only five broad categories, excluding materials such as textiles, e-waste, or mixed/composite packaging; (3) the absence of a controlled, same-dataset comparison against other lightweight or heavier architectures (e.g., MobileNetV3, EfficientNet-Lite, ShuffleNet, ResNet50, DenseNet, or Vision Transformer); (4) reliance on approximate, literature-reported parameter counts and computational cost rather than measured inference latency,

memory footprint, or FPS on actual target hardware; and (5) no evaluation on field-collected images with varied lighting, occlusion, or soiled surfaces. Accordingly, the reported metrics indicate MobileNetV2's performance under the specific dataset and conditions used here, rather than a generalized claim across all waste classification applications or deployment environments. Future work should address these points directly: validating the model on diverse, field-collected images; benchmarking it against other lightweight and heavier architectures on the same dataset and splits; and measuring its real-time inference speed, memory usage, and accuracy on embedded or mobile devices.

REFERENCES

- [1] I. Irmawartini, S. S. Mulyati, and P. Pujiono, "Pengelolaan Sampah dari Hulu ke Hilir di Kota Bandung," *Jurnal Kesehatan Lingkungan Indonesia*, vol. 22, no. 2, pp. 229–236, Jun. 2023, doi: 10.14710/jkli.22.2.229-236.
- [2] Z. Zhang et al., "Municipal solid waste management challenges in developing regions: A comprehensive review and future perspectives for Asia and Africa," *Science of The Total Environment*, vol. 930, p. 172794, 2024, doi: https://doi.org/10.1016/j.scitotenv.2024.172794.
- [3] Md. Nahiduzzaman et al., "An automated waste classification system using deep learning techniques: Toward efficient waste recycling and environmental sustainability," *Knowl. Based. Syst.*, vol. 310, p. 113028, 2025, doi: https://doi.org/10.1016/j.knosys.2025.113028.
- [4] M. Ebrahim Shaik, "A systematic review on detection and prediction of driver drowsiness," Sep. 01, 2023, *Elsevier Ltd.* doi: 10.1016/j.trip.2023.100864.
- [5] M. Li, Z. Ma, R. Yan, and J. Yin, "The Impact of Physiological and Psychological Fatigue on Work Efficiency: A Case Study of Parcel Sorting Work," *Sensors*, vol. 24, no. 18, Sep. 2024, doi: 10.3390/s24185989.
- [6] M. Chhabra, B. Sharan, M. Elbarachi, and M. Kumar, "Intelligent waste classification approach based on improved multi-layered convolutional neural network," *Multimed. Tools Appl.*, vol. 83, no. 36, pp. 84095–84120, 2024, doi: 10.1007/s11042-024-18939-w.
- [7] M. Wu, J. Zhou, Y. Peng, S. Wang, and Y. Zhang, "Deep Learning for Image Classification: A Review," 2024, pp. 352–362. doi: 10.1007/978-981-97-1335-6_31.
- [8] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2018, pp. 4510–4520. doi: 10.1109/CVPR.2018.00474.
- [9] Md. M. Islam, S. M. M. Hasan, Md. R. Hossain, and Md. P. Uddin, "Towards sustainable solutions: Effective waste classification framework via enhanced deep convolutional neural networks," *PLoS One*, vol. 12, no. 4, Mar. 2025, doi: 10.1371/journal.
- [10] Md. S. Bin Islam et al., "ECCDN-Net: A deep learning-based technique for efficient organic and recyclable waste classification," *Waste Management*, vol. 193, pp. 363–375, 2025, doi: https://doi.org/10.1016/j.wasman.2024.12.023.
- [11] F. N. Edilia et al., "Klasifikasi Rentang Usia Berdasarkan Citra Wajah Menggunakan Convolutional Neural Network," *JURNAL SISTEM INFORMASI TGD*, vol. 5, no. 1, pp. 56–61, 2026, [Online]. Available: https://ojs.trigunadharma.ac.id/index.php/jsi
- [12] L. I. Umeaduma, "Survey of image classification models for transfer learning," *World Journal of Advanced Research and Reviews*, vol. 21, no. 1, pp. 373–383, Jan. 2024, doi: 10.30574/wjarr.2024.21.1.0006.
- [13] D. I. S. H. Julu and D. Nurdiyah, "Klasifikasi Sampah Organik Dan Non Organik Menggunakan Transfer Learning,"

- Jurnal Transformatika*, vol. 23, no. 1, pp. 12–29, Jul. 2025, doi: 10.26623/transformatika.v23i1.12201.
- [14] L. S. Qamarani and M. Riasetiawan, “Klasifikasi Level Banjir Menggunakan Random Forest dan Support Vector Machine,” *Indonesian Journal of Electronics and Instrumentation Systems (IJEIS)*, vol. 14, no. 2, pp. 199–208, 2024, doi: 10.22146/ijeis.
- [15] N. Farros *et al.*, “Perbandingan Akurasi dan Performa MobileNetV2 dan EfficientNetV2 Untuk Klasifikasi Sampah,” *PLoS One*, 2025, doi: 10.26418/justin.v14i1.89086.
- [16] A. Olugboja and Z. Wang, “Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network,” *Procedia Manuf.*, vol. 35, pp. 607–612, Jan. 2019, doi: 10.1016/j.promfg.2019.05.086.
- [17] M. Malik *et al.*, “Waste Classification for Sustainable Development Using Image Recognition with Deep Learning Neural Network Models,” *Sustainability (Switzerland)*, vol. 14, no. 12, Jun. 2022, doi: 10.3390/su14127222.
- [18] A. Altikat, A. Gulbe, and S. Altikat, “Intelligent solid waste classification using deep convolutional neural networks,” *International Journal of Environmental Science and Technology*, vol. 19, no. 3, pp. 1285–1292, 2022, doi: 10.1007/s13762-021-03179-4.
- [19] N. Li and Y. Chen, “Municipal solid waste classification and real-time detection using deep learning methods,” *Urban Clim.*, vol. 49, p. 101462, May 2023, doi: 10.1016/j.uclim.2023.101462.
- [20] D. Chicco and G. Jurman, “The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation,” *BMC Genomics*, vol. 21, Jan. 2020, doi: 10.1186/s12864-019-6413-7.
- [21] D. P. Kingma and L. J. Ba, “Adam: A Method for Stochastic Optimization,” *International Conference on Learning Representations*, 2015, doi: 10.48550/arXiv.1412.6980.
- [22] Q. Zhang, Q. Yang, X. Zhang, Q. Bao, J. Su, and X. Liu, “Waste image classification based on transfer learning and convolutional neural network,” *Waste Management*, vol. 135, pp. 150–157, 2021, doi: <https://doi.org/10.1016/j.wasman.2021.08.038>.
- [23] L. Yong, L. Ma, D. Sun, and L. Du, “Application of MobileNetV2 to waste classification,” *PLoS One*, vol. 18, no. 3, pp. e0282336–, Mar. 2023, [Online]. Available: <https://doi.org/10.1371/journal.pone.0282336>
- [24] N. Nafiiyah, M. A. Zulkarnaen, A. Harjoko, and A. N. Hidayanto, “Transfer Learning-Based Convolutional Neural Network for Classifying Organic and Recyclable Waste,” *Jurnal Informatika dan Rekayasa Perangkat Lunak*, vol. 8, no. 1, pp. 71–79, 2026.