Performance Analysis of Low-Computational Computer Vision Techniques for Recyclable Waste Identification.

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ABSTRACT

Waste management on the low-resource setting is also a serious issue because of the shortage of infrastructure, and the lack of access to modern technologies, and the use of manual sorting of waste leads to environmental pollution and ineffective recycling. Although deep learning-based image classification has demonstrated the potential of automating waste, the majority of studies emphasize high-computation models, which cannot be used in resource-constrained environments. The research gap is a significant lack of systematic comparisons on both classification and computational efficiency of low-computational convolutional neural network (CNN) models. This study aim to examine the appropriateness of lightweight CNN models in the identification of recyclable wastes with a tradeoff between accuracy and resource consumption. Three low-computational CNN models, namely EfficientNet-Lite, MobileNetV2, and SqueezeNet, were trained and tested using publicly available datasets, such as TrashNet. Accuracy and F1-score were used to measure the classification performance, and latency, memory usage, and model size were used to measure computational efficiency. Findings show that EfficientNet-Lite had the best accuracy (92.4) and F1-score (92.0) but used more memory and inference time whereas MobileNetV2 provided a reasonable compromise between performance and efficiency. SqueezeNet was the lightest and the fastest model but with a lesser classification reliability. These results give practical recommendations on the design of AI-powered waste management in low-resource settings. This study helps to advance sustainable recycling efforts because it emphasizes the existence of the accuracy-latency-memory trade-offs of lightweight CNNs and informs practitioners and researchers on the need to use the right model whenever deploying lightweight CNNs to mobile, edge, or embedded applications in developing regions.

Keywords: Recyclable Waste Identification**,** Low-Computational CNN**,** Computer Vision**,** Resource-Constrained Environments.

INTRODUCTION

Proper waste separation and recycling is one of the major problems in the world especially with the increasing rate of urbanization and population, which still increases the levels of solid waste (Ebikapade & Baird, 2016). In a low-resource setting or any developing environmental setting, poor waste sorting practices are responsible in environmental pollution, overuse of landfills, and loss of recyclable resources that could be used to build circular economy projects. The manual waste segregation process is also prone to errors and labor intensive, which can be easily scaled, thus demonstrating the necessity of automated and smart waste management solutions that would help achieve more efficient and sustainable recycling. New technologies in computer vision and artificial intelligence (AI) have already shown the high potential of it in waste recognition and sorting (Nahiduzzaman et al., 2025). Image recognition systems with deep learning, particularly convolutional neural networks (CNNs) have been shown to attain accuracy on a large scale in classifying between recyclable and non-recyclable materials by learning intricate visual structures on large datasets. Such systems provide a bright future of automated waste segregation where decision-making is quicker and human interactions are minimized in all processes of waste management (Taglay et al., 2025). Yet, most of the state-of-the-art deep learning models are computationally intensive, which demands large processing power, memory, and energy. These are limitations that restrict their use in low-resource environments where high-end hardware, consistent power supply and internet accessibility are frequently limited (Patil et al., 2024). Consequently, the implementation of the

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traditional deep learning models into the real-life waste management system in such settings is still not feasible. This difficulty has encouraged the development of increasing interest in low-computational CNN methods to trade-off classification performance and efficiency (Shahab et al., 2022). MobileNet, SqueezeNet and EfficientNet-Lite are lightweight architectures that have smaller model size, low latency, and low memory consumption, which is suitable to deploy on mobile and embedded devices. This study will attempt to undertake a thorough performance study on low-computational computer vision methods of recyclable waste detection (Bauravindah & Fudholi, 2024). The main contribution is the comparative analysis of the chosen lightweight CNN models in terms of their accuracy, latency of inference, and memory footprint, thus giving useful information on their applicability to resource-constrained waste management processes.

Problem Statement

The use of artificial intelligence in waste management is increasing, the adoption of high-performance AI systems is still elusive in the developing and low-resource areas. The current waste classification solutions are based on computationally expensive deep learning models and need such attributes as powerful hardware, large memory capacity, stable electricity, and permanent access to the internet (Qu, 2022). These conditions drastically reduce the application of these in actual waste segregation systems where resources are limited. As a result, such environments still rely on manual sorting procedures that are not very efficient in waste identification, achieving low results in recycling and causing even more harm to the environment (Sudha et al., 2016). The urgency is thus to have waste classification models that are capable of sustaining reasonable accuracy whilst being run with stringent computational requirements. One of the biggest challenges is the design of systems capable of operating with a low amount of memory, low processing capabilities, and low power usage (Sayem et al., 2024). Unless these limitations are tackled, the practical utility of AI-based waste recognition cannot be achieved in the areas where it is most necessary. It fills this gap by considering the low-computational computer vision methods, which provide an effective compromise between performance and resource efficiency in identifying recyclable waste.

LITERATURE REVIEW

AI-Based Waste Classification Systems

The use of AI-based waste classification systems has been an emerging topic of research due to the increasing investigations in automated methods of enhancing waste determine and recycling (Nasir & Al-Talib, 2023). The majority of existing works use image-based methods that rely on computer vision and deep learning algorithms to detect and classify various types of waste materials which include plastic, paper, metal, glass, and organics (Malik et al., 2022). The leading models in this field are convolutional neural networks (CNNs), which are characterised by high levels of discriminative visual features of waste images. Simple architectures like VGGNet, ResNet, Inception, and DenseNet have been extensively used and they have been found to have high classification accuracy when trained on standard datasets like TrashNet, TACO and WasteNet (Mao et al., 2021). Several research have examined how transfer learning can be used, in which pre-trained CNNs can be fine-tuned to waste data to minimize training time and enhance performance. Such methods have shown promising performances especially in restricted environments where there exists adequate computation resources (Kartik et al., 2023). Moreover, data augmentation methods are usually employed to enhance the model resistance to changes in the waste appearance and include rotation, scaling, and lighting reconfiguration. Studies that are even more recent have started to deal with the aspect of practical deployment with the introduction of lightweight and mobile-friendly waste classification models (William et al., 2024). MobileNet, SqueezeNet and EfficientNet variants of architectures have been explored due to their smaller parameter size and accelerated inference speed. It has also been observed that some of the studies have incorporated waste classification models into smart bins, mobile applications as well as edge devices in order to support real-time waste sorting (Frost et al., 2025). Nonetheless, in spite of these improvements the current literature tends to focus more on the accuracy of the classification rather than the computation efficiency. Deep comparative studies that collectively assess accuracy, latency, and memory consumption are still scarce, especially regarding low-resource settings. Such a gap demonstrates the necessity of systematic performance appraisal of the low-computational AI-based waste classification systems.

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Review of Related Works

In this section, this study examine some of the previous approaches used by researchers for Image Classification of Recyclable Waste for Low-Resource Environments. Below are brief review of research studies that have been conducted using these approaches.

Yadav (2025) proposes an AI-driven system to improve urban waste management through automated waste recognition, sorting, and optimized collection routing. The system applies deep learning techniques, particularly convolutional neural networks, to classify recyclable materials from image data with high accuracy. Designed for low-power devices, it is suitable for resource-constrained environments. Image augmentation and normalization enhance model reliability. Results show improved sorting efficiency, reduced landfill use, optimized collection schedules, and lower environmental impact. The study demonstrates that AI can modernize urban recycling systems and supports its adoption for sustainable waste management and resource conservation.

Sivakumar et al. (2025) propose a CNN-based automated waste classification system to improve recycling efficiency and reduce reliance on manual sorting. The model is trained on diverse waste images to enhance generalization and uses data augmentation to prevent overfitting. Results show high classification accuracy, reduced sorting errors, and improved waste management efficiency. The study concludes that CNN-based artificial intelligence systems are reliable tools for waste classification and can significantly enhance recycling processes while contributing to environmental protection and sustainable waste management.

Hossen et al. (2024) propose RWC-Net, a deep learning model for classifying six waste categories using the TrashNet dataset. Trained with data augmentation and optimized using Adam, the model achieved 95.01% accuracy, outperforming established architectures such as ResNet50 and MobileNet-v2. High F1-scores across all classes demonstrate robustness. Score-CAM enhances interpretability by highlighting decision regions. The study confirms RWC-Net's reliability for automated waste sorting and recommends extending it to more waste types and real-world recycling applications.

Ahmad, Khan, and Al-Fuqaha (2020) propose a double-fusion approach to improve image-based waste classification by combining features and outputs from multiple CNNs, including AlexNet, VGGNet, GoogleNet, and ResNet. Using the TrashNet dataset, the method integrates early and late fusion strategies with optimized weighting through particle swarm optimization. Results show a 3.58% accuracy improvement over single models and conventional fusion techniques. The study demonstrates that multi-CNN feature integration significantly enhances classification reliability for automated waste management systems.

Sayem et al. (2024) propose a deep learning-based system to automate waste sorting and improve recycling efficiency. Using CNNs trained on diverse waste images with augmentation and object detection techniques, the system accurately classifies and detects various waste types. Evaluated via accuracy, precision, recall, and F1-score, it demonstrates high reliability and performance. The approach reduces human labor, enhances sorting efficiency, and can be applied in automated recycling facilities, showing that deep learning effectively supports sustainable and efficient waste management practices.

Sallang et al. (2021) develop a CNN-based waste classification system using TensorFlow Lite for lightweight deployment on IoT devices with LoRa-GPS for real-time location monitoring. Trained on diverse waste images, the model accurately classifies waste while enabling remote tracking and management. Designed for smart cities, it reduces resource usage and automates sorting. The combination of lightweight deep learning and IoT improves waste collection efficiency, provides immediate data for monitoring, and supports scalable, low-power smart waste management systems with potential for further expansion.

Chhabra et al. (2024) develop a DCNN-based system to classify household waste into organic and recyclable materials, improving on standard CNNs through hyperparameter tuning and architectural enhancements. Using 25,077 images, the model achieved 93.28% accuracy with low MDR (2.6%) and FDR (4.5%), outperforming VGG16, VGG19, MobileNetV2, DenseNet121, and EfficientNetB0. The system automates sorting, reduces manual labor, promotes sustainability, and enhances recycling efficiency, demonstrating that advanced deep learning models can effectively support smart waste management in urban environments.

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Malik et al. (2022) develop an EfficientNet-B0-based model to classify municipal solid waste into bio, plastic, glass, metal, and paper. Optimized with transfer learning and trained on ImageNet, the system achieves accuracy comparable to EfficientNet-B3 but with fewer parameters and greater efficiency. Lightweight and resource-efficient, it can operate in varied environments, enabling automated, adaptable waste sorting. The model enhances waste management, supports deployment in resource-limited settings, and shows potential for further improvement to handle more waste types and real-time applications.

Yang and Li (2020) develop WasNet, a lightweight CNN for accurate waste classification in low-resource environments. Integrated with smart bins, a mobile app, and a centralized platform, it automates waste sorting and management. Using data augmentation and attention modules (SE, CBAM), WasNet achieves high accuracy on multiple datasets (TrashNet 96.1%, Huawei 82.5%). With only 1.5 million parameters, it outperforms ShuffleNet-V2 and MobileNetV3-Small. The system enhances sustainable waste disposal, reduces manual labor, and enables efficient municipal waste monitoring and decision-making.

METHODOLOGY

Dataset Description

To assess the performance of computer vision-based approaches with low computational requirements for the identification of the recyclable waste in low resources environments, this study used publicly available recyclable waste image datasets, which is mostly the TrashNet dataset. The TrashNet dataset consists of labeled waste images of types plastic, paper, cardboard, glass, metal, and organic waste materials, divided into two classes: recyclable and non-recyclable. The data set was chosen due to its visual diversity, multiple type of waste, and balanced representation, which is ideal for supervised image classification tasks. The data set was preprocessed with quality assessment to exclude the blurred, duplicate, low-resolution, corrupted image data that may have a negative impact on the model learning process before experimentation. The final dataset distribution was designed to be representative in terms of waste category and minimize classification bias to dominant waste classes. About 70% of the pictures were used for training the model, 15% for validation, and 15% for testing. That dataset splitting was stratified was carried out in order to ensure that the proportions of each waste category were the same across each of the subsets. The training dataset was used to learn the features and optimize the parameters, the validation dataset was used to tune hyper-parameters and avoid overfitting when training. The testing data set was set aside specifically to assess the performance of the final model as an unbiased testing of the model. Also, some other augmentation techniques were added to enhance the diversity of the dataset and the generalization of the model, particularly for the less numerous categories of waste. This pre-processing stage enabled the models to adequately classify recycled materials in different environmental conditions which can be encountered in waste management systems in practice.

Image Preprocessing Methods

To enhance the quality of images, standardise the input size, minimise computational complexity and increase the robustness of the lightweight CNN models, the images were processed. The datasets consist of images taken with varying lighting, background, orientation and resolution so there was a need to preprocess the data to make it more uniform for model training**.** To bring all images to a common size, the first pre-processing step was to resize them all to 224 × 224 pixels required by MobileNetV2, SqueezeNet and EfficientNet-Lite architectures. Resize also shortened training and inference time, and memory usage. After resizing, the intensity values of the pixels were normalized by scaling the values between 0 and 1. This normalization has enhanced the numerical stability in the optimization process and faster CNN model convergence. Images that were visually distorted or of low quality, which might cause classification mistakes, were filtered out. Images of waste were selectively processed with gaussian smoothing and image sharpening to highlight the objects and edges in the waste images. In order to enhance the generalization of the model and reduce overfitting, several data augmentation techniques were used on the images to be used for training. These were random rotation, horizontal flipping, zoom scaling, brightness adjustment, cropping and translation transformations. To simulate object positioning variations, rotations of −20° to +20° were applied to the objects; brightness adjustments allowed models to adapt to different lighting conditions that typically occur outdoors during waste disposal. The data set was further varied by flipping the images horizontally and performing zoom transformations, which further enhanced the ability of the

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model to identify recyclable materials from various angles.Data was further varied by horizontally flipping the images and performing Zoom transformations, which further enhanced the ability of the model to identify the recyclable materials from various angles. Only the training set was data augmented to avoid information leakage during validation and testing. All CNN models were given consistent and optimised image inputs using the pre-processing pipeline, which can be implemented in a real-time resource-constrained system for lightweight classification**.**

Model Selection and Training Configurations

The study focused on three lightweight convolutional neural network architectures, namely MobileNetV2, SqueezeNet, and EfficientNet-Lite, because of their low computational requirements, reduced parameter sizes, and suitability for deployment on mobile, embedded, and edge devices. MobileNetV2 was chosen since it incorporates the depthwise separable convolutions and inverted residual blocks, which help to control the number of computational operations without sacrificing the classification accuracy. SqueezeNet was chosen because of its very small parameters with its fire modules that can cut down on the complexity of the network with no significant loss of performance. Its efficient network depth, width and resolution for efficient feature extraction allowed EfficientNet-Lite to be selected. Experiments were performed in Python and TensorFlow Lite as the main frameworks to implement the model. The reason for using TensorFlow Lite is its ability for lightweight deployment on low-resource mobile and embedded systems. Supporting libraries employed for image processing, image visualization and evaluation procedures include NumPy, OpenCV, Matplotlib and Scikit-learn. To simulate the real-life deployment scenario of such edge devices, the training experiments were carried out on a middle-of-the-road laptop with an Intel Core i7 processor and 16 GB of RAM. The processing parameters and the way the datasets were split were the same for both CNN models to ensure an apples-to-apples comparison. The lightweight CNN models were used with transfer learning, where the models pretrained on the ImageNet dataset were fine-tuned on the recyclable waste dataset. This method not only saved training time, but also enhanced classification accuracy, particularly when the number of data points was small. For training, the final classification layers were replaced by customized fully connected layers, based on waste categories of the dataset. Adam optimizer has been employed due to its adaptive learning feature and its consistent convergence. The starting learning rate was 0.001 and the number of images per batch was 32. To avoid overfitting and enhance the stability of models, early stopping and the learning rate reduction callbacks were applied. The training was performed for 50 epochs but was automatically stopped after a few epochs if the validation loss did not show any improvement. The fully connected layers also used the dropout method to prevent overfitting and to enhance the generalization of the model. To determine the best configuration for each lightweight CNN model, hyperparameter tuning was performed, and the validation loss and the F1-score were used as optimization function**.**

Experimental Setup and Deployment Simulation

The experimental setup was designed to simulate realistic deployment scenarios for recyclable waste identification systems deployed in low-resource environments. The light-weight CNN models were assessed not only with respect to the classification accuracy, but also with respect to the computational efficiency under a hardware limit, which is mostly observed in the developing region. The experiments were carried out in two computational settings. The first environment was a standard laptop system with which to train the model and perform initial testing, and the second environment simulated edge deployment with light computational constraints. During deployment simulations, TensorFlow Lite optimization techniques like model quantization and reduced precision inference were used to reduce memory usage and inference latency. The processing of image streams sequentially in real time was used to perform real-time inference experiments, thus emulating automated waste sorting operations in smart bins and recycling facilities. The system performed a classification speed, memory allocation, processor utilization and model loading times measurement during the inference process. These experiments were conducted to assess the feasibility of the light weight CNN models in the real world waste management system having less hardware.

Evaluation Procedures and Performance Metrics

The evaluation process aimed to evaluate the classification performance and the computational efficiency of the lightweight CNN models for the purpose of waste identification in recyclable waste streams. To make the model performance comparison comprehensive, a mix of the classification metrics and resource-efficiency metrics were used. The metrics used to assess the classification performance were accuracy, precision, recall and F1-score. The accuracy was calculated as the total percentage of correctly classified waste images, and precision as the number of correctly identified recyclable images divided by the number of all predicted recyclable output images. The models were evaluated using recall to correctly identify the actual instance of recyclable waste and precision and recall were measured using the F1-score. To visualize the classification results for all the waste components, the confusion matrix was created for each CNN model. Also, to identify the pattern of misclassification between the recyclable waste component, plastic, paper, and glass, the confusion matrix was created. Latency, memory usage and model size were measured to assess the computational efficiency. Latency was the average time (in milliseconds) it took to classify an image and was measured in milliseconds. The amount of RAM used during the inference process was used as a measure of memory usage, and the overall memory footprint of each lightweight CNN architecture was used as a measure of model size. These statistics were essential because in low resource areas, often there are computational and storage constraints. Multiple experimental runs were performed under the same conditions and average values reported to enhance the repeatability and reliability of the results. The experiments were performed on the same hardware and processing pipeline with the same dataset partitionings to fairly compare the models across the architectures. The evaluation framework hence offered a clear and repeatable method of evaluating the applicability of low-computational computer vision methods to the identification of recyclable waste in resource-poor settings.

RESULTS

Table 1: Classification Performance Comparison

CNN Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MobileNetV2	91.2	90.5	91.0	90.7
SqueezeNet	87.5	86.8	87.0	86.9
EfficientNet-Lite	92.4	92.0	92.1	92.0

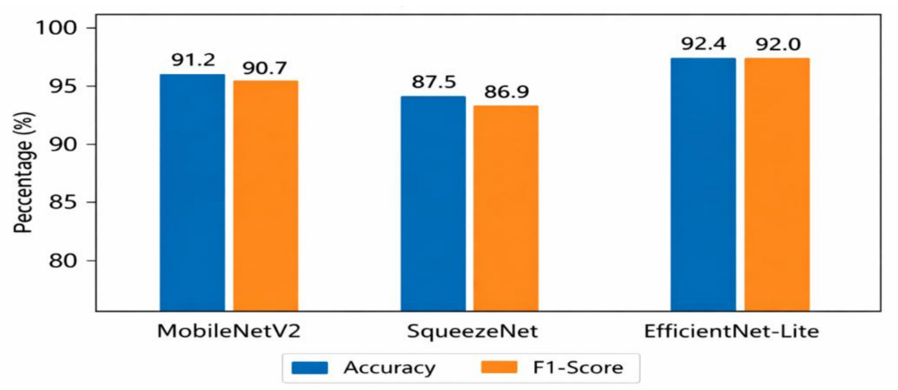

Figure 1: graph of Classification Performance Comparison

Figure 1 shows the performance of three low-computational CNN models, which are MobileNetV2, SqueezeNet, and EfficientNet-Lite, in classifying recyclable wastes. EfficientNet-Lite attains the best performance with 92.4% accuracy and 92.0% F1-score and, thus, a better balance between the precision and the recall. MobileNetV2 has a slightly lower accuracy of 91.2 and F1-score of 90.7, showing a competitive capability of classification. SqueezeNet has the lowest values, 87.5% accuracy and 86.9% F1-score, but it has the advantage of lightweight architecture. In general, the graph shows that there is a trade-off point between the complexity of

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models and performance, with EfficientNet-Lite offering the best classification performance when deployed in low-resource settings.

Table 2: Evaluation Metric

CNN Model	Accuracy (%)	F1-Score (%)	Latency (ms)	Memory Usage (MB)	Model Size (MB)
MobileNetV2	91.2	90.7	18	120	14
SqueezeNet	87.5	86.9	12	90	**5**
EfficientNet-Lite	92.4	92.0	22	140	120

Table 2 shows trade-offs between classification and computational efficiency between low-computational CNN models used to identify recyclable waste. EfficientNet-Lite has the highest accuracy (92.4%), F1-score (92.0%), and is the most efficient in terms of classification, 22 ms latency, 140 MB memory use, and 20 MB model size. SqueezeNet is the smallest, and its latency (12 ms), memory (90 MB), and model size (5 MB) are the lowest, but the accuracy (87.5) and F1-score (86.9) are worse. MobileNetV2 offers a trade-off between performance (91.2% accuracy) and moderate latency and memory usage, which enables it to be deployed successfully in limited resources.

DISCUSSION

The findings show evident differences in performance of the low-computational CNN models that have been evaluated. EfficientNet-Lite had the best accuracy (92.4), F1-score (92.0), which implies that it has a high capacity of detecting recyclable waste with the least misclassifications. The difference in its performance and computational requirements (slightly higher latency of 22 ms and memory consumption of 140 MB) indicates the trade-off but implies that this model may be deployed in the environment with moderate hardware requirements. MobileNetV2, with 91.2 and 90.7 accuracy and F1-score, provides a compromise between the performance of classification and efficiency as well as it is very appropriate in a mobile environment or edge deployments where resources are more likely to be a bottleneck. Although SqueezeNet is the fastest and lightest model (12 ms latency, 90 MB memory, 5 MB model size), it is the least accurate (87.5%) and F1-score (86.9%), meaning that it might not work well in settings where there is a need to ensure high classification reliability. These results are in line with existing literature that lightweight CNN models can achieve acceptable accuracy, much smaller model size and lower computational cost. The past studies tended to emphasise one of the two; accuracy or efficiency, though this paper emphasises the need to consider both together especially in cases of low resources deployment. In a more pragmatic viewpoint, these models allow real-time or near real-time recyclable wastes to be identified in an environment with inferential computing capability, like developing areas or intelligent recycling receptacles. EfficientNet-Lite can be used with centralized or semi-automated sorting systems, MobileNetV2 can be implemented in handheld devices or mobile devices, and SqueezeNet can be deployed on devices with limited resources when speed and memory consumption are extremely important. In general, these findings can be used to implement practical suggestions to create sustainable waste management systems based on AI.

CONCLUSION

This study compared the results of low-computational convolutional neural network (CNN) models, namely, EfficientNet-Lite, MobileNetV2 and SqueezeNet in recyclable waste recognition in low-resource settings. These findings suggest that EfficientNet-Lite has the best classification accuracy (92.4%), F1-score (92.0%), which proves its high potential to identify correctly the recyclable materials. MobileNetV2 provided a trade-off on performance and efficiency with a slightly lower accuracy (91.2) but medium latency and memory consumption due to which it could be deployed to a mobile or edge environment. Although SqueezeNet has the highest inference (12 ms) and minimum memory footprint (90 MB), its accuracy (87.5%) was relatively lower, which is an indicator of the trade-off between the simplicity of the model and its ability to classify. This study adds to the AI and sustainable waste management by delivering a comparative analysis of the low-computational CNNs

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on a systematic basis, focusing on the classification and computational efficiency. These lessons are especially useful when developing AI-based waste sorting systems in resource-limited environments, i.e. developing countries or smart bins. This study helps to show that scalable, inexpensive, and sustainable solutions to automated recycling can be achieved by showing how low-weight models can achieve high accuracy and reduce hardware needs. To practitioners, the results suggest the use of CNN models depending on deployment factors: EfficientNet-Lite with semi-automated systems or centralized systems, MobileNetV2 with mobile apps, and SqueezeNet with ultra-low-resource systems. In the eyes of researchers, future studies may include hybrid or quantized models, larger and more diverse data and combination with multimodal sensors to further improve the performance, reliability, and applicability in real world waste management situations.

REFERENCE

1. Ahmad, K., Khan, K., & Al-Fuqaha, A. (2020). Intelligent fusion of deep features for improved waste classification. IEEE Access, 8, 96495-96504. Retrieved from https://doi.org/10.1109/ACCESS.2020.3023092.
2. Bauravindah, A., & Fudholi, D. (2024). Lightweight steganalysis models: MobileNet, ShuffleNet, EfficientNet. Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 8(6), 737-747. https://doi.org/10.29207/resti.v8i6.6091
3. Chhabra, M., Sharan, B., Elbarachi, M., & Kumar, M. (2024). Intelligent Waste Classification Approach Based on Improved Multi-Layered Convolutional Neural Network. Multimedia Tools and Applications, 83, 84095–84120. https://doi.org/10.1007/s11042-024-18939-w
4. Ebikapade, A., & Baird, J. (2016). Understanding waste and waste management. Journal of Management and Sustainability, 6(4), 88. https://doi.org/10.5539/jms.v6n4p88
5. Frost, A., Jean, G., & Ailyn, D. (2025). Lightweight CNNs for edge computing in resource-limited settings. Retrieved from https://www.researchgate.net/publication/395767938
6. Hossain, M. A., Ferdous, N., & Ferdous, E. (2024). Crisis-driven Disruptions in Global Waste Management: Impacts, Challenges, and Policy Responses Amid COVID-19, Russia-Ukraine War, Climate Change, and Colossal Food Waste. Environmental Challenges, 14, 100807. Retrieved from https://doi.org/10.1016/j.envc.2023.100807.
7. Kartik, K., Ahmed, T., Ghosh, S., Gupta, R., & Tripathi, A. (2023). Transfer learning with CNNs on small datasets. In Proceedings of the International Conference on Machine Learning and Applications (pp. 1087-1099). CC BY 4.0 license.
8. Malik, M., Sharma, S., Uddin, M., Chen, C. L., Wu, C. M., Soni, P., & Chaudhary, S. (2022). Waste Classification for Sustainable Development Using Image Recognition with Deep Learning Neural Network Models. Sustainability, 14(12), 7222. Retrieved from https://doi.org/10.3390/su14127222.
9. Mao, W., Chen, W., Wang, C., & Lin, Y. (2021). Optimized CNN for recycling waste classification. Resources, Conservation and Recycling, 164, 105132. https://doi.org/10.1016/j.resconrec.2020.105132
10. Nahiduzzaman, M., Ahamed, M., Naznine, M., Karim, M., Kibria, H., Ayari, M., Khandakar, A., Ashraf, A., Ahsan, M., & Haider, J. (2025). Deep learning for automated waste classification. Knowledge-Based Systems, 310, 113028. https://doi.org/10.1016/j.knosys.2025.113028
11. Nasir, I., & Al-Talib, G. (2023). AI techniques for waste classification: A literature review. Technium: Romanian Journal of Applied Sciences and Technology, 5, 49-59. https://doi.org/10.47577/technium.v5i.8345
12. Patil, D., Rane, N., Desai, P., & Rane, J. (2024). Machine learning and deep learning: An overview. In Machine Learning and Deep Learning (pp. 11-30). ISBN: 978-81-981367-4-9.
13. Qu, D. (2022). AI in university waste classification management. In Advances in Artificial Intelligence and Applied Mathematics (pp. 287-296). Springer, Cham. https://doi.org/10.1007/978-3-030-97196-0_27
14. Sallang, N. C. A., Islam, M. T., Islam, M. S., & Arshad, H. (2021). A CNN-based smart waste management system using TensorFlow lite and LoRa-GPS shield in Internet of Things environment. IEEE Access, 9, 153560-153574. Retrieved from https://doi.org/10.1109/ACCESS.2021.3055128.
15. Sayem, F. R., Islam, M. S. B., Naznine, M., Nashbat, M., Hasan-Zia, M., Kunju, A. K. A., ... & Chowdhury, M. E. (2024). Enhancing Waste Sorting and Recycling Efficiency: Robust Deep Learning-

Based Approach for Classification and Detection. Neural Computing and Applications, 1–17. Retrieved from https://doi.org/10.1007/s00521-024-06994-8.

16. Shahab, S., Anjum, M., & Umar, M. (2022). Deep learning in solid waste management: A review. International Journal of Advanced Computer Science and Applications, 13. https://doi.org/10.14569/IJACSA.2022.0130347
17. Sudha, S., Vidhyalakshmi, M., Pavithra, K., Sangeetha, K., & Swaathi, V. (2016). Deep learning for eco-friendly waste classification. In 2016 International Conference on Technological Innovations in Management, Engineering, and Sciences (TIARE) (pp. 65-70). IEEE. https://doi.org/10.1109/TIAR.2016.7801215
18. Taglay, D., Rigor, J., Royo, R., & Fernandez, R. (2025). CNN-based image recognition for recyclables. International Journal of Latest Technology in Engineering Management & Applied Science, 14, 606-617. https://doi.org/10.51583/IJLTEMAS.2025.1409000073
19. William, Lily & Ayodele, Harry & Blake, Harrison. (2024). Evaluating the Impact of Data Augmentation Techniques on Model Performance. https://www.researchgate.net/publication/389357090_Evaluating_the_Impact_of_Data_Augmentation_Techniques_on_Model_Performance/citation/download
20. Yang, Z., & Li, D. (2020). WasNet: A neural network-based garbage collection management system. IEEE Access, 8, 103984-103993. Retrieved from https://doi.org/10.1109/ACCESS.2020.3021510.