DEEP LEARNING-BASED IDENTIFICATION OF ORGANIC AND INORGANIC WASTE TO ADDRESS WASTE GENERATION

MHD Rizky [1]; Hirzi Ubaidillah[2]; Sri Hadianti [3*]; Daning Nur Sulistyowati[4]; Ridan Nurfalah[5]

Informatics, Faculty of Technology Information[1,2,3]
Information Systems, Faculty of Technology Information[4,5]
Universitas Nusa Mandiri, Jakarta, Indonesia[1,2,3,4,5]
https://nusamandiri.ac.id/?
12230122@nusamandiri.ac.id[1], 12230126@nusamandiri.ac.id[2], sri.shv@nusamandiri.ac.id[3*],
daning.dgs@nusamandiri.ac.id[4], ridan.rlh@nusamandiri.ac.id[5]

(*) Corresponding Author

The creation is distributed under the Creative Commons Attribution-NonCommercial 4.0 International License.

Abstract— *Solid waste issues in Indonesia show a significant increasing trend. Based on the National Waste Management Information System (SIPSN) data, waste generation in 2024 is estimated to reach 37 million tons. The main challenge in managing this volume lies in the inefficiency of sorting organic and inorganic waste, which is predominantly done manually. This study aims to analyze and apply Deep Learning technology as an automation solution to accelerate the waste identification process. The method employed is Transfer Learning on the DenseNet121 Convolutional Neural Network (CNN) architecture, optimized using the AdamW algorithm and image data augmentation. The dataset consists of two main categories (organic and inorganic) split by an 80:20 ratio. Experimental results show that the developed model is capable of recognizing waste types with a validation accuracy reaching 98.79%. The model's ability to precisely distinguish visual waste characteristics is expected to be implemented in smart waste management systems to reduce waste residue ending up in landfills.*

Keywords: *Deep Learning, DenseNet121, Image Processing, Transfer Learning, Waste Generation.*

Intisari— Permasalahan limbah padat di Indonesia menunjukkan tren peningkatan yang signifikan. Berdasarkan data Sistem Informasi Pengelolaan Sampah Nasional (SIPSN), timbulan sampah pada tahun 2024 diestimasi mencapai angka 37 juta ton. Tantangan utama dalam pengelolaan volume sampah ini terletak pada inefisiensi pemilahan antara sampah organik dan anorganik yang masih dilakukan secara manual. Penelitian ini bertujuan untuk menganalisis dan menerapkan teknologi Deep Learning sebagai solusi otomatisasi guna mempercepat proses identifikasi sampah. Metode yang digunakan adalah Transfer Learning pada arsitektur Convolutional Neural Network (CNN) DenseNet121, yang dioptimalkan menggunakan algoritma AdamW dan augmentasi data citra. Dataset terdiri dari dua kategori utama (organik dan anorganik) yang dibagi dengan rasio 80:20. Hasil eksperimen menunjukkan bahwa model yang dikembangkan mampu mengenali jenis sampah dengan akurasi validasi mencapai 98.79%. Kemampuan model dalam membedakan karakteristik visual sampah secara presisi ini diharapkan dapat diimplementasikan pada sistem manajemen sampah cerdas untuk mengurangi residu sampah yang berakhir di TPA.

Kata Kunci: *pembelajaran mendalam, DenseNet121, pengolahan citra, pembelajaran transfer, timbulan sampah.*

INTRODUCTION

The issue of solid waste has become a global crisis that continues to escalate alongside population growth and urbanization. Recent research predicts that global waste volumes will continue to rise significantly between 2020 and 2030 (Group, 2024). This phenomenon is also clearly evident in Indonesia. According to data from the National Waste Management Information System (SIPSN) of the Ministry of Environment and Forestry (KLHK), the volume of national waste generation fluctuates but tends to remain high. In 2024, estimated waste generation reached approximately 37 million tons (Abedin *et al.*, 2025). This data indicates that the burden of waste management is becoming increasingly heavy year by year and requires serious attention.

The primary challenge in managing such large volumes of waste lies in the initial sorting stage. To date, separating organic waste such as food scraps and foliage from inorganic waste such as plastic, metal, and glass remains a hurdle for the community. The mixing of these waste types complicates the recycling process and increases the volume of residual waste ending up in landfills. This difficulty often stems from a lack of adequate facilities and a reliance on manual sorting methods, which are prone to human error caused by physical or visual fatigue (Siddiqua *et al.*, 2022).

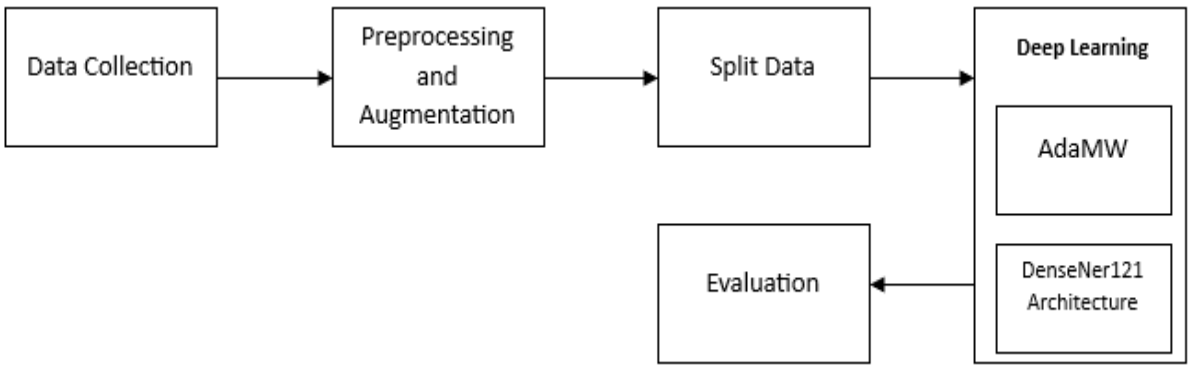
The development of deep learning-based systems offers a promising solution to overcome limitations in the waste identification process. Previous studies have demonstrated that Convolutional Neural Network (CNN) architectures, such as MobileNet and VGG16, are capable of recognizing visual patterns in waste images (Kumala, Sari and Rachmawanto, 2025), (Abdu, Halim and Noor, 2022). However, the heterogeneous characteristics of waste, including variations in texture, shape, size, and visual appearance, require an appropriate learning architecture and training strategy to achieve reliable classification performance. Models with limited feature extraction capabilities may have difficulty distinguishing visually similar waste materials, whereas more complex models may be susceptible to overfitting when the available training data are limited (Aliferis and Simon, 2024). These considerations indicate the importance of investigating an appropriate combination of network architecture, optimization strategy, and data augmentation for waste classification.

This research addresses this issue by investigating a transfer learning-based classification approach using the DenseNet121 architecture, AdamW optimizer, and image augmentation for distinguishing organic and inorganic waste. DenseNet121 was selected because its dense connectivity facilitates feature reuse and information propagation across network layers, making it suitable for extracting discriminative visual features from waste images (Hou *et al.*, 2024). AdamW was employed as the optimization strategy because its decoupled weight decay mechanism can support effective model parameter learning and generalization (Reyad and Sarhan, 2023), while image augmentation was applied to increase the diversity of training samples and reduce the risk of overfitting. Therefore, the contribution of this study is not solely the use of DenseNet121, but the investigation of this integrated training configuration for binary waste classification and its performance based on accuracy, precision, recall, F1-score, confusion matrix, and learning-curve analysis. This study aims to provide an experimentally evaluated deep learning approach that can support the automated identification of organic and inorganic waste and potentially facilitate intelligent waste sorting systems.

This approach can provide a more accurate and stable automated identification solution. The aim of this study is to describe an identification method that can be applied to facilitate the sorting process of organic and inorganic waste through intelligent computing.

MATERIALS AND METHODS

The research stages involved collecting images of organic and inorganic waste, followed by image preprocessing and augmentation to enhance data diversity. Subsequently, the data was split into training and validation sets. The core phase involved developing a Deep Learning model using the DenseNet121 architecture, accompanied by hyperparameter optimization. The final stage was the evaluation of model performance using a confusion matrix. The research workflow is illustrated in Figure 1.



Source: (Research Results, 2026)

Figure 1. Research Flow

Data collection

At this stage, the data used in the research consists of waste images classified into two categories organic and inorganic waste using a transfer learning approach (Poudel and Poudyal, 2022). The dataset used in this study was obtained from the Kaggle platform, specifically the Recyclable and Household Waste dataset, published by Alistair King and available at https://www.kaggle.com/code/alistairking/recyclable-and-household-waste-classification-code/input. Organic waste images include food scraps, leaves, and other biological waste, whereas inorganic waste images include plastic, bottles, cans, and other non-biological materials. The images are provided in .jpg, .jpeg, and .png formats and vary in image size, shooting angle, background, and lighting conditions. These variations represent diverse real-world image acquisition conditions. No additional images were collected directly by the researchers. Examples of organic and inorganic waste images are presented in Figure 2.



(a) (b)

Source: (Research Results, 2026)
Figure 2. (a) Plastic (Inorganic), (b) Vegetable Waste (Organic)

Image Preprocessing and Augmentation

Preprocessing was performed to align the image input format with the model architecture. All images were resized to 224 × 224 pixels, and pixel intensity values were normalized to the 0–1 range by rescaling the pixel values by 1/255. Data augmentation was subsequently applied to the training set using ImageDataGenerator. The augmentation configuration included a rotation range of 20°, width and height shift ranges of 0.2, a zoom range of 0.2, and horizontal flipping enabled (horizontal_flip=True). Data augmentation was applied only to the training set to increase image diversity and reduce the risk of overfitting.



Source: (Research Results, 2026)
Figure 3. Resizing the Image



Source: (Research Results, 2026)
Figure 4. Image rotation



Source: (Research Results, 2026)
Figure 5. Zooming In/Out on the Image



Source: (Research Results, 2026)
Figure 6. Horizontal Flip

Data Splitting

This stage is carried out to split the data into two independent sets in order to prevent data leakage during the training process (Apicella, Isgrò and Prevete, 2025). Data dibagi menggunakan rasio 80:20, di mana 80% data dialokasikan sebagai data latih (*training set*) untuk pembelajaran model, dan 20% data dialokasikan sebagai data validasi (*validation set*) untuk pengujian performa model secara objektif (Arashpour, 2023).

Deep Learning

The deep learning method employed in this study was a Convolutional Neural Network (CNN) based on the DenseNet121 architecture using a transfer learning approach. DenseNet121 was initialized with weights pretrained on the ImageNet dataset and used as the feature extraction backbone. During the training process, the pretrained DenseNet121 layers were frozen; therefore, their weights were not updated, and only the newly added classification layers were trainable.

The original classification layer of DenseNet121 was replaced with a custom classification head consisting of a Global Average Pooling 2D layer, followed by a Dropout layer with a rate of 0.5, a fully connected Dense layer containing 256 neurons with ReLU activation, and another Dropout layer with a

Techno Nusa Mandiri: Journal of Computing and Information Technology
Vol. 23, No. 2 September 2026 | DOI https://doi.org/10.33480/techno.v23i2.8999

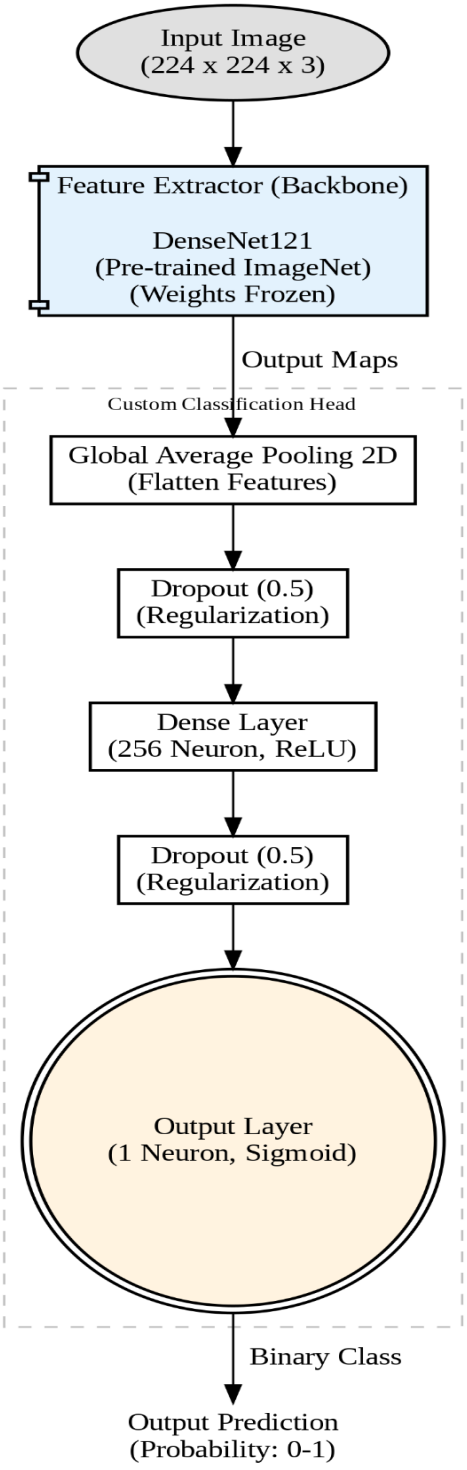
rate of 0.5. Finally, a single-neuron output layer with a sigmoid activation function was used for binary classification between organic and inorganic waste. The input images were resized to 224 × 224 pixels with three color channels, resulting in an input dimension of 224 × 224 × 3. The architecture used in this study is illustrated in Figure 7.

Hyperparameter Optimization

Hyperparameter optimization is a systematic process for determining the optimal combination of non-trainable parameter configurations to achieve peak model performance and prevent the model from becoming trapped in local minima. Within the TensorFlow framework employed here, various optimization algorithms are available. In this study, the training scenario was implemented using the AdamW (Adam with Weight Decay) optimization algorithm with an initial learning rate of 1×10^{-4} (Reyad and Sarhan, 2023). The choice of AdamW is based on its superior generalization capabilities compared to standard Adam, achieved through a decoupled weight decay mechanism. Additionally, computational efficiency is enhanced by implementing a Mixed Precision Policy, which combines float16 and float32 data types to accelerate GPU computation times (Dörrich, Fan and Kist, 2023). The loss function employed is Binary Cross-entropy, consistent with the use of Sigmoid activation in the final layer, alongside a Dropout regularization technique set to 0.5 to minimize the risk of overfitting during the weight learning process (Ahmed, Dahmani and Hassanien, 2024).

Evaluation

A comprehensive evaluation process is conducted after the model completes the training phase based on the established hyperparameter scenarios. The evaluation aims to assess the model's validity and reliability in classifying new data (validation data). The primary measurement instrument used in this study is the Confusion Matrix, a matrix that maps the comparison between the model's predicted classes and the actual class labels (Heydarian and Doyle, 2022). *The confusion matrix serves as the basis for calculating performance metrics, including Accuracy, Precision, Recall, and F1-Score. Accuracy represents the percentage of correct predictions across the entire dataset. Precision measures the model's accuracy in predicting the positive class, whereas Recall measures the model's sensitivity in retrieving all existing positive class samples. The F1-Score provides the harmonic mean of precision and recall, serving as a crucial indicator in cases of data imbalance. Model stability analysis is conducted by examining the learning curve* (Sujon *et al.*, 2025). The convergence of the loss curves for the training and validation data will serve as the primary indicator for determining whether the resulting model is overfitting a condition where the model achieves high accuracy during training but performs poorly when tested on validation data.



Source: (Research Results, 2026)

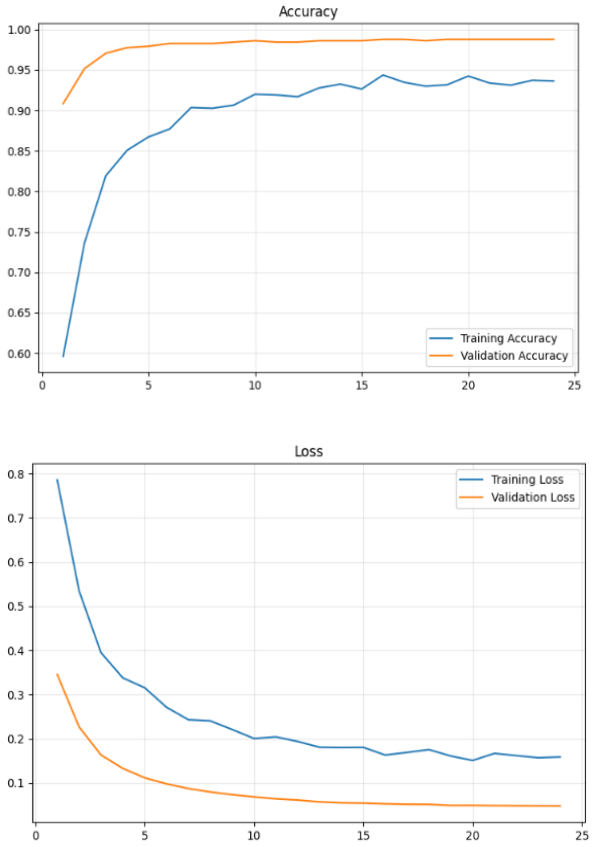
Figure 7 DenseNet121 Architecture

RESULTS AND DISCUSSION

Model testing was conducted using a predefined training scenario, specifically by splitting the data into 80% training data and 20% validation data. The training process was executed in a T4 GPU computing environment for a maximum of 25 epochs; however, an Early Stopping mechanism automatically halted training once the model reached an optimal point, thereby ensuring efficiency in time and resource usage.

Learning Curve Analysis

The graph in Figure 8 illustrates the model's learning dynamics during the training phase. It can be observed that the accuracy curves for both the training and validation data show steady improvement and closely track one another, with a minimal gap. The stability of these curves, combined with the low validation loss, indicates that the model does not exhibit significant overfitting. The applied data augmentation techniques contributed to increasing the diversity of the training data, thereby supporting the model's ability to recognize general patterns in the validation data.



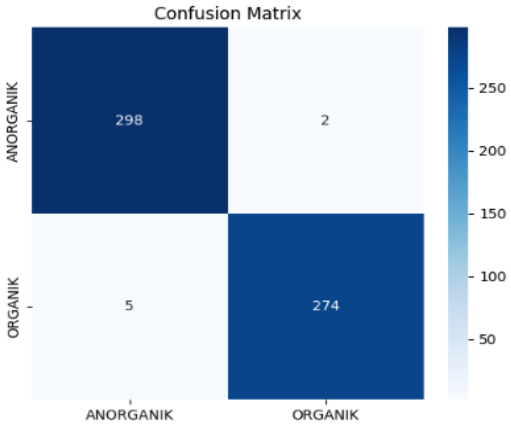
Source: (Research Results, 2026)

Figure 8. Graph Comparing Accuracy and Loss

The stability of this graph, combined with a low validation loss value, indicates that the model is not overfitting. The applied data augmentation techniques proved effective in enriching the diversity of the training data, enabling the model to successfully recognize general patterns in waste images within the test data.

Confusion Matrix Evaluation

Classification performance was further analyzed using a confusion matrix to examine the distribution of predictions across the 579 test data samples. As shown in Figure 9, the model was able to identify both classes with high precision.



Source: (Research Results, 2026)

Figure 9. Confusion Matrix of Model Classification Results

Misclassification rates were very low for both categories. This demonstrates that the texture features extracted by the DenseNet121 architecture are highly representative for distinguishing the physical characteristics of organic waste materials (such as food scraps or foliage) from inorganic ones (such as plastic or metal).

Model Performance Based on Metrics

The quantitative results of the model testing are summarized in Table 1. Based on the final classification report, the model achieved a validation accuracy of 98.79%.

Table 1. Model Performance Test Results

Kelas Target	Precision	Recall	F-1 Score
Anorganik	0,99	0,99	0,99
Organik	0,99	0,98	0,99
Akurasi Total	98,79%		

Source: (Research Results, 2026)

The recall value for the Inorganic class reached 0.99, indicating that the model is highly sensitive in detecting inorganic waste. This capability is crucial for automated waste sorting systems to ensure that plastic or metal waste does not end up in the composting (organic) processing facility, where it

Techno Nusa Mandiri: Journal of Computing and Information Technology
Vol. 23, No. 2 September 2026 | DOI https://doi.org/10.33480/techno.v23i2.8999

could contaminate the final recycled product. Conversely, a precision value of 0.99 for the Organic class demonstrates a high level of confidence when the system identifies an object as wet waste. The weighted average F1-score of 0.99 confirms the model's excellent performance balance in handling both classes.



Source: (Research Results, 2026)

Figure 10. Detected and Undetected

The DenseNet121-based transfer learning approach achieved a validation accuracy of 98.79%, with precision, recall, and F1-score ranging from 0.98 to 0.99. These findings indicate that the model was able to distinguish organic and inorganic waste effectively under the validation conditions used in this study. The small difference between the training and validation learning curves also suggests that the model maintained relatively stable generalization performance.

Previous studies have also demonstrated the applicability of transfer learning for image-based waste classification. (Kumala, Sari and Rachmawanto, 2025) investigated MobileNetV2 and VGG16 architectures for multi-class waste classification, while (Poudel and Poudyal, 2022) applied a CNN-based transfer learning approach for waste material classification. In contrast, the present study employed DenseNet121 as a pretrained feature extractor combined with AdamW, image augmentation, and a binary classification head for distinguishing organic and inorganic waste.

The dense connectivity of DenseNet121 facilitates feature reuse across layers, which may support the extraction of discriminative visual features from heterogeneous waste images.

Nevertheless, direct numerical comparison with previous studies should be interpreted cautiously because differences in dataset size, waste categories, number of classes, image acquisition conditions, data splitting strategies, and experimental configurations can substantially affect classification performance. Furthermore, the present study focuses only on binary classification of organic and inorganic waste. Therefore, the obtained accuracy should not be interpreted as evidence that DenseNet121 universally outperforms other architectures such as MobileNetV2 or VGG16. Future studies could evaluate these architectures using the same dataset and experimental protocol to provide a more controlled comparison.

CONCLUSION

Based on the conducted testing and analysis, this study successfully developed an automated waste identification model using Deep Learning. Implementing Transfer Learning on the DenseNet121 architecture optimized with AdamW proved highly effective in distinguishing between organic and inorganic waste images. The developed model achieved a final validation accuracy of 98.79%, with balanced precision and recall values exceeding 0.98. The experimental results demonstrate that the DenseNet121-based transfer learning approach, combined with AdamW optimization and image augmentation, achieved a validation accuracy of 98.79%. The model obtained precision, recall, and F1-score values ranging from 0.98 to 0.99, while the confusion matrix showed only a small number of misclassified organic and inorganic waste images. The relatively small gap between the training and validation learning curves further indicates stable generalization under the experimental conditions.

The proposed approach demonstrates competitive classification performance. Nevertheless, direct numerical comparison should be interpreted cautiously because of differences in the number of waste classes, dataset characteristics, and experimental settings. Future research should therefore evaluate DenseNet121, MobileNetV2,

VGG16, and other transfer learning architectures using the same dataset and evaluation protocol to establish a more controlled architectural comparison. Integrating this model into waste processing infrastructure is expected to minimize manual sorting errors (human error) and accelerate recycling processes, ultimately contributing to a reduction in residual waste volumes in Indonesia. For future development, it is recommended to expand the dataset to include extreme outdoor lighting conditions, thereby testing the model's robustness in real-world, open-field deployment scenarios. Additionally, incorporating more specific categories such as paper, glass, and hazardous (B3) waste is advised to support a more comprehensive circular economy system.

REFERENCE

Abdu, H., Halim, M. and Noor, M. (2022) 'A Survey on Waste Detection and Classification Using Deep Learning', *IEEE Access*, 10(November), pp. 128151–128165. doi: 10.1109/ACCESS.2022.3226682.

Abedin, T. *et al.* (2025) 'From waste to worth : advances in energy recovery technologies for solid waste management', *Clean Technologies and Environmental Policy*, 27(11), pp. 5963–5989. doi: 10.1007/s10098-025-03204-x.

Ahmed, R., Dahmani, N. and Hassanien, A. E. (2024) 'Early Detection and Categorization of Cervical Cancer Cells Using Smoothing Cross Entropy-Based Multi-Deep Transfer Learning', *IEEE Access*, 12(November), pp. 157838–157853. doi: 10.1109/ACCESS.2024.3485888.

Aliferis, C. and Simon, G. (2024) *Overfitting , Underfitting and General Model Overconfidence and Under- - Performance Pitfalls and Best Practices in Machine Learning and AI*.

Apicella, A., Isgrò, F. and Prevete, R. (2025) 'machine learning and transfer learning', *Artificial Intelligence Review*, 58(339), pp. 1–58.

Arashpour, M. (2023) 'Predicting individual learning performance using machine - learning hybridized with the teaching - learning - based optimization', *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, (April 2022), pp. 83–99. doi: 10.1002/cae.22572.

Dörrich, M., Fan, M. and Kist, A. M. (2023) 'Impact of Mixed Precision Techniques on Training and Inference Efficiency of Deep Neural Networks', *IEEE Access*, 11.

Group, W. B. (2024) *Global Snapshot of Solid Waste Management toward Circularity until 2050*. Available at: https://www.worldbank.org/en/publication/what-a-waste (Accessed: 7 September 2026).

Heydarian, M. and Doyle, T. E. (2022) 'MLCM : Multi-Label Confusion Matrix', *IEEE Access*, 22, pp. 19083–19095.

Hou, Y. *et al.* (2024) 'The application of improved densenet algorithm in accurate image recognition', *Scientific Reports*, pp. 1–14. doi: 10.1038/s41598-024-58421-z.

Kumala, R. A., Sari, C. A. and Rachmawanto, E. H. (2025) 'A Comparison of MobileNetV2 and VGG16 Architectures with Transfer Learning for Multi-Class Image-Based Waste Classification', 9(4), pp. 1610–1624.

Poudel, S. and Poudyal, P. (2022) *Classification of Waste Materials using CNN Based on Transfer Learning*, *Forum for Information Retrieval Evaluation (FIRE '22), December 9â•fi13, 2022, Kolkata, India*. Association for Computing Machinery. doi: 10.1145/3574318.3574345.

Reyad, M. and Sarhan, A. M. (2023) 'A modified Adam algorithm for deep neural network optimization', *Neural Computing and Applications*, 35(23), pp. 17095–17112. doi: 10.1007/s00521-023-08568-z.

Siddiqua, A. *et al.* (2022) 'An overview of the environmental pollution and health effects associated with waste landfilling and open dumping', *Environmental Science and Pollution Research*, pp. 58514–58536. doi: 10.1007/s11356-022-21578-z.

Sujon, K. M. *et al.* (2025) 'Accuracy, precision, recall, f1-score, or MCC? empirical evidence from advanced statistics, ML, and XAI for evaluating business predictive models', *Journal of Bi*, 12(268).