A Convolutional Neural Network Approach for Multi-Class Waste Image Classification

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Abstract. Waste management has become an increasingly important global issue, requiring effective solutions to support proper waste sorting and recycling processes. Manual waste classification is often inefficient and prone to human error, particularly when dealing with large volumes of waste. In recent years, image classification using deep learning techniques has emerged as a promising approach to automatically identify different types of waste based on their visual characteristics. This study aims to develop and implement a Convolutional Neural Network (CNN) model for multi-class waste image classification. The proposed model utilizes a transfer learning approach based on the EfficientNetV2 architecture. The model was trained using a publicly available waste image dataset obtained from Kaggle consisting of 4,752 images across multiple waste categories. The research process includes data preprocessing, image augmentation, model training, and a series of experimental scenarios to analyze the influence of different hyperparameter configurations, including variations in dropout rate, fine-tuning layers, learning rate, dense layer structures, and L2 regularization. Experimental results show that the best-performing configuration, which applies dropout rates of 0.3 and 0.2, achieved an accuracy of 94.03% with a weighted F1-score of 0.9399. To further evaluate the model's practical performance, the selected model was tested using 30 real-world waste images captured directly from the surrounding environment. The testing results indicate that the proposed CNN model is capable of classifying waste images effectively and demonstrates promising potential for implementation in automated waste sorting systems.
Keywords: Convolutional Neural Network, EfficientNetV2, Waste Image Classification, Deep Learning, Multi-Class Classification

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1. Introduction

Waste management has become a critical environmental issue due to the increasing volume of waste generated globally. In Indonesia, approximately 18 million tons of waste were produced in 2023, with a significant portion not properly managed. Ideally, waste should be sorted at the source to support recycling and sustainable processing. However, waste segregation at the community level remains low due to limited awareness and inconsistent sorting behavior (Dewi et al., 2024), (Ibnul Rasidi et al., 2022). To address this issue, artificial intelligence (AI), particularly Convolutional Neural Networks (CNN), has been widely applied in image classification due to its ability to extract discriminative visual features (Girsang et al., 2023). Several studies have demonstrated the effectiveness of CNN in waste classification. For instance, a CNN-based system has been implemented for real-time classification of organic and inorganic waste (Ramadhani et al., 2020), while other studies using architectures such as MobileNet, VGG16, and Xception achieved accuracy up to 93.35% (Girsang et al., 2023). In addition, web-based classification systems and transfer learning approaches have also shown promising results in both binary and multi-class waste classification tasks (Nugraha et al., 2025), (Putri Vandalis et al., 2024), (Vidiadivani & Suhartana, 2024).

Despite these advancements, several limitations remain. Most studies focus primarily on model accuracy, with limited analysis of hyperparameter configurations and their impact on model performance and generalization. In addition, evaluation across multiple experimental scenarios and analysis of misclassification between visually similar classes are still limited. Therefore, this study aims to develop and evaluate a CNN-based model for multi-class waste image classification using a transfer learning approach based on EfficientNetV2. The study systematically analyzes the effect of various hyperparameter configurations and evaluates model performance using standard metrics. Furthermore, the proposed model is implemented in a web-based system and evaluated using real-world waste images to assess its applicability in practical scenarios.

2. Method

This study employs a deep learning approach using a Convolutional Neural Network (CNN) for multi-class waste image classification. CNN is widely used in image processing tasks due to its ability to automatically extract complex features from images (Raup et al., 2022).

2.1 Dataset Preparation

The dataset used in this research was obtained from a public Kaggle repository and consists of 4,752 images categorized into nine classes: cardboard, food organics, glass, metal, paper, plastic, textile, vegetation, and miscellaneous trash.

(a) Cardboard (b) Food Organics (c) Glass

(d) Metal (e) Paper (f) Plastic

(g) Textile (h) Vegetation (i) Miscellaneous

Figure 1. Sample of Waste Image Dataset Across

Each category represents different types of waste materials with distinct visual characteristics such as color, texture, and shape. This diversity is important to ensure that the model can learn discriminative features for multi-class classification tasks. Previous studies have shown that Convolutional Neural Networks (CNN) perform effectively in waste classification problems due to their ability to capture spatial features (Girsang et al., 2023).

In this research, the dataset consists of multiple waste categories. However, two classes, namely *food organics* and *vegetation*, were merged into a single class due to their similar characteristics. This merging process was conducted to reduce class ambiguity and improve classification performance. As a result, the final dataset used in this research consists of eight classes. This approach also helps in improving class balance and reducing misclassification between visually similar categories.

In this research, the dataset is divided into training and validation sets using a random split approach. The training dataset is used to train the model, while the validation dataset is used to evaluate model performance during the training process.

Table 1. Dataset Distribution for Training and Validation

Dataset Type	Number of Images
Training	3798
Validation	954
Total	**4752**

The validation set is used to evaluate model performance during training and to monitor potential overfitting. No separate test set is used, as real-world testing is conducted using independently collected data to assess model generalization.

2.2 Data Preprocessing

All images are resized to match the input requirements of the EfficientNetV2 model and normalized to improve training stability. Data augmentation is applied to enhance generalization, including rotation (45°), width and height shifting (0.25), shear (0.25), zoom (0.3), brightness adjustment (0.7–1.3), and horizontal and vertical flipping. Additional configurations include channel shifting (0.2) and nearest fill mode. These techniques help the model learn robust features under various conditions.

Figure 2. Example of Data Augmentation Techniques

Figure 2 illustrates examples of the data augmentation process applied in this research. These transformations help the model learn more robust features and improve performance when encountering variations in real-world data.

2.3 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning model widely used for image classification tasks due to its ability to automatically extract relevant features from input data. CNN consists of

several layers, including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification (Nurhakiki & Yahfizham, 2024).
In this research, CNN is utilized to learn visual patterns from waste images and classify them into predefined categories.

2.4 EfficientNetV2
In this research, the Convolutional Neural Network (CNN) model is implemented using a transfer learning approach based on the EfficientNetV2 architecture. EfficientNetV2 is a deep learning model designed to achieve high classification accuracy while maintaining computational efficiency through an optimized scaling method (Maulana et al., 2025).

The EfficientNetV2 architecture improves conventional CNN models by applying a compound scaling strategy that simultaneously adjusts network depth, width, and input resolution. In this research, the pre-trained EfficientNetV2 model is utilized as a feature extractor and fine-tuned to adapt to the specific task of multi-class waste classification. To accommodate the classification task, several additional layers are integrated on top of the base model. A Global Average Pooling layer is used to reduce the spatial dimensions of the feature maps, followed by fully connected layers that learn higher-level representations of the extracted features. A dropout layer is incorporated to reduce overfitting and improve model generalization (Wardani & Leonardi, 2023). Finally, a softmax activation function is applied in the output layer to produce probability distributions across the eight waste categories.

The proposed architecture is designed to balance accuracy and computational efficiency, making it suitable for real-world waste classification applications. By leveraging EfficientNetV2 and transfer learning, the model is expected to achieve improved performance compared to conventional CNN approaches.

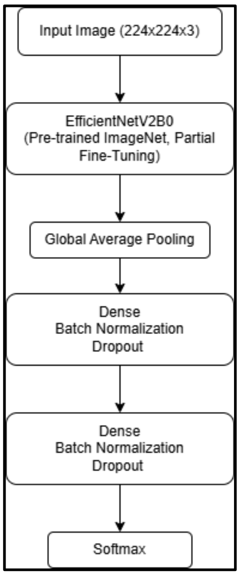

Figure 3. Proposed EfficientNetV2-Based Model Architecture

Figure 3 illustrates the proposed EfficientNetV2-based model architecture used in this research. The model utilizes a pre-trained EfficientNetV2 as a feature extractor, followed by additional layers including global average pooling, fully connected layers, dropout, and a softmax classifier for multi-class classification.

2.5 Model Training

The model training process is conducted to optimize the performance of the proposed EfficientNetV2-based architecture for multi-class waste classification. The training dataset is used to train the model, while the validation dataset is utilized to evaluate model performance during the training process.

In this research, multiple experimental configurations were conducted to evaluate the effectiveness of the model. Several key hyperparameters were systematically varied, including the learning rate, the number of neurons in the dense layers, dropout rates, and fine-tuning strategies applied to the EfficientNetV2 backbone. The fine-tuning parameter refers to the layer index from which the base model begins to be unfrozen. For example, a value of 100 indicates that layers before this index are kept frozen, while layers from index 100 onward are set to be trainable. These variations were designed to analyze their impact on model performance and to determine the most optimal configuration. The model is trained using a categorical cross-entropy loss function, which is suitable for multi-class classification problems. An adaptive optimization algorithm is employed to update model weights during training, allowing efficient convergence. The training process is carried out over several epochs using a fixed batch size, and model performance is monitored using accuracy metrics on both training and validation datasets. To prevent overfitting, early stopping or model checkpointing techniques can be applied during the training process.

Based on the experimental results, the best-performing configuration is selected and used as the final model in this research. The configuration of this final model is summarized in Table 2.

Table 2 Training Configuration (Final Model)

Parameter	Value
Input Size	224x224x3
Batch Size	16
Epoch	150
Optimizer	Adam
Learning Rate	0.0001
Loss Function	Categorical Crossentropy
Output	8 Classes

Furthermore, the trained model is deployed and tested using real-world data collected directly from the environment to evaluate its performance in practical scenarios.

2.6 Deployment

The trained model is deployed in a web-based system using the Flask framework. The system allows users to upload waste images and receive classification results along with prediction confidence. This implementation demonstrates the applicability of the proposed model in real-world scenarios.

3. Results and Discussion

This section presents the results obtained from both experimental evaluations and real-world testing of the proposed model. The evaluation is conducted in two stages, namely experimental testing using validation data and deployment testing using real-world waste images. The results are further analyzed to assess the performance and robustness of the model under different conditions.

3.1 Experimental Results

This section presents the results obtained from multiple experimental configurations conducted to evaluate the performance of the proposed model. A total of 12 experiments were performed by

systematically varying several key hyperparameters, including learning rate, dense layer configuration, dropout rate, fine-tuning strategy, and L2 regularization. Each experiment was evaluated using the validation dataset, and model performance was measured based on accuracy, precision, recall, and F1-score. These metrics were used to provide a comprehensive evaluation of the model's classification performance.
The results of all experimental scenarios are summarized in Table 3.

Table 3 Experimental Results

Exp	Configu-ration	LR	Dense	Dropout	Fine-tune (Layer Index)	L2	Accuracy (%)	Precision	Recall	F1-score
1	Baseline	0.001	256	0.5	150	0.01	93.92	0.9407	0.9392	0.9392
2	Finetune 100	0.001	256	0.5	100	0.01	93.19	0.9341	0.9319	0.9323
3	Finetune 180	0.001	256	0.5	180	0.01	91.82	0.9193	0.9182	0.9182
4	Dropout (0.3 & 0.2)	0.001	256	0.3 / 0.2	150	0.01	94.03	0.9402	0.9403	0.9399
5	Dropout (0.6 & 0.5)	0.001	256	0.6 / 0.5	150	0.01	93.50	0.9372	0.9350	0.9353
6	LR 0.0005	0.0005	256	0.5	150	0.01	93.50	0.9359	0.9350	0.9350
7	LR 0.00005	0.00005	256	0.5	150	0.01	89.62	0.9006	0.8962	0.8973
8	Dense (512 & 256)	0.001	512/ 256	0.5	150	0.01	93.71	0.9384	0.9371	0.9374
9	Dense (128 & 64)	0.001	128/ 64	0.5	150	0.01	92.24	0.9268	0.9224	0.9234
10	L2 0.01	0.001	256	0.5	150	0.01	93.29	0.9348	0.9329	0.9333
11	L2 0.0001	0.001	256	0.5	150	0.0001	91.72	0.9217	0.9172	0.9181
12	Combined	0.0001	512/ 256	0.3/0.2	150	0.001	93.08	0.9325	0.9308	0.9309

Based on the results presented in Table 3, it can be observed that different hyperparameter configurations produce varying levels of classification performance. In particular, changes in dropout configuration, learning rate, and fine-tuning strategy show noticeable effects on model accuracy and overall performance.

The highest accuracy of 94.03% is achieved in Experiment 4, which applies a dropout configuration of 0.3 and 0.2. This result indicates that an appropriate dropout setting can effectively improve model generalization and prevent overfitting. In contrast, lower performance is observed in configurations with extremely small learning rates, such as in Experiment 7, suggesting that overly small learning rates may hinder the learning process. Overall, these results demonstrate that careful tuning of hyperparameters plays a crucial role in achieving optimal model performance. The best-performing configuration is selected for further evaluation in real-world testing.

To further evaluate the performance of the best-performing model, a confusion matrix and classification report are analyzed to provide a detailed evaluation across all classes

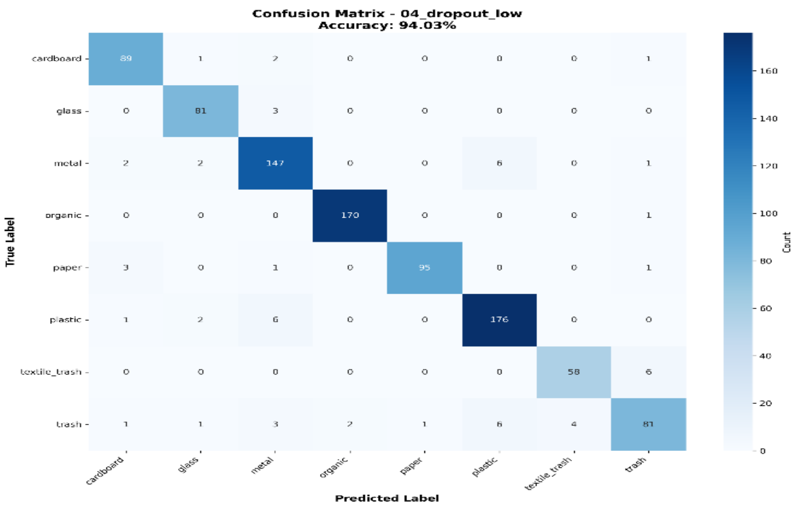

Figure 4. Confusion Matrix of The Best Model

Figure 4 presents the confusion matrix of the selected model. The results show that most classes are correctly classified, as indicated by the high values along the diagonal. However, some misclassifications occur between visually similar classes, such as plastic and metal, as well as textile and miscellaneous trash.

Table 4 Classification Report of the Best Model

Class	Precision	Recall	F1-Score
Cardboard	0.9271	0.9570	0.9418
Glass	0.9310	0.9643	0.9474
Metal	0.9074	0.9304	0.9187
Organic	0.9884	0.9942	0.9913
Paper	0.9896	0.9500	0.9694
Plastic	0.9362	0.9514	0.9437
Textile	0.9355	0.9062	0.9206
Miscellaneous	0.8901	0.8182	0.8526

Table 4 presents the classification report of the model, including precision, recall, and F1-score for each class. The model achieves high performance across most categories, particularly in the organic class, which shows the highest F1-score. In contrast, the miscellaneous trash class exhibits relatively lower performance, indicating that this category is more challenging to classify accurately.

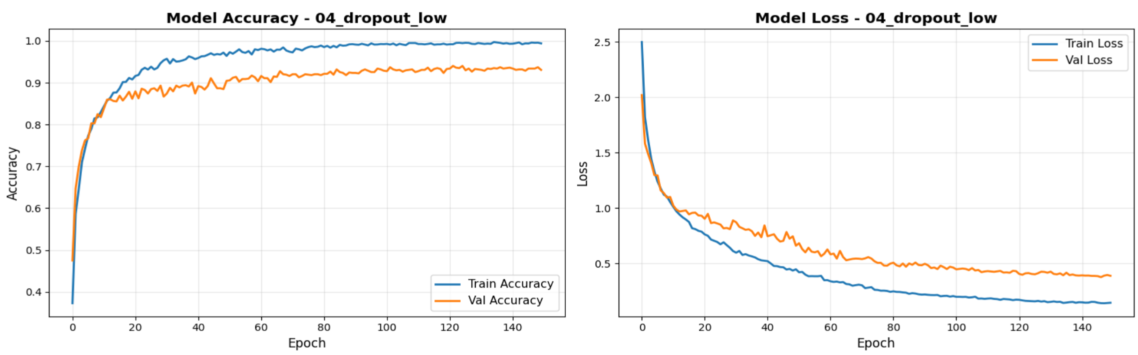

Figure 5. Training and validation accuracy and loss curves

Figure 5 presents the training and validation accuracy and loss curves of the proposed model. The results show that the model converges effectively, as indicated by the steady increase in both training and validation accuracy and the consistent decrease in loss values over the training epochs.

The training accuracy reaches nearly 99%, while the validation accuracy stabilizes around 94%, indicating that the model achieves high performance. Although a slight gap between training and validation accuracy is observed, this difference remains relatively small and suggests only mild overfitting.

Furthermore, the loss curves demonstrate a smooth and continuous decline without significant fluctuations, indicating stable training behavior. Overall, these results confirm that the model is well-optimized and capable of generalizing effectively to unseen data.

3.2 Real-World Testing

To further evaluate the performance of the proposed model, real-world testing was conducted using 30 waste images collected directly from the environment. These images represent eight waste categories, namely cardboard, organics, glass, metal, plastic, paper, textile, and miscellaneous trash. This evaluation aims to assess the model's ability to generalize beyond the validation dataset and perform effectively in practical scenarios.

The best-performing model obtained from the experimental phase (Experiment 4) was deployed into a web-based system. This system enables users to upload waste images and receive classification results along with confidence scores in real time. The results of the real-world testing are summarized in Table 5.

Table 5 Real-World Testing Results by Category

Category	Total Data	Correct	Incorrect	Accuracy (%)
Cardboard	4	4	0	100
Organics	7	5	2	71,43
Glass	4	4	0	100
Metal	4	3	1	75
Plastic	5	3	2	60
Paper	4	3	1	75
Textile	4	4	0	100
Total	**30**	**24**	**6**	**80**

Based on the results, the model achieves an overall accuracy of 80.00% on real-world data. Several categories, such as cardboard, glass, and textile, achieve perfect classification accuracy, indicating that the model performs very well on visually distinctive objects. However, lower performance is observed in certain categories, particularly organics and plastic. Misclassifications occur in cases where objects have similar visual characteristics or ambiguous features. These results suggest that the model still faces challenges when applied to real-world conditions with complex variations.

Overall, the results indicate that the proposed model is capable of performing waste classification in practical scenarios. Despite some misclassifications, the model shows strong potential for real-world implementation, particularly in applications that support waste sorting and environmental management.

3.3 Discussion

The results from both experimental evaluation and real-world testing demonstrate that hyperparameter configuration plays a crucial role in model performance. The highest accuracy of

94.03% is achieved using a dropout configuration of 0.3 and 0.2, indicating its effectiveness in reducing overfitting and improving generalization.

In contrast, extremely small learning rates, such as 0.00005, lead to lower performance, suggesting that slow optimization hinders effective convergence. Similarly, larger dense layer configurations provide better feature representation compared to smaller ones.

The confusion matrix and classification report show consistent performance across most classes, with the organic category achieving the highest F1-score. However, lower performance is observed in the miscellaneous trash category, likely due to its high variability and less distinctive features.

In real-world testing, the model achieves an accuracy of 80.00%, which is lower than the validation accuracy. This gap indicates reduced generalization under real-world conditions, influenced by variations in lighting, background, and object orientation. Misclassification commonly occurs between visually similar categories, such as organics and plastic, consistent with the confusion matrix findings.

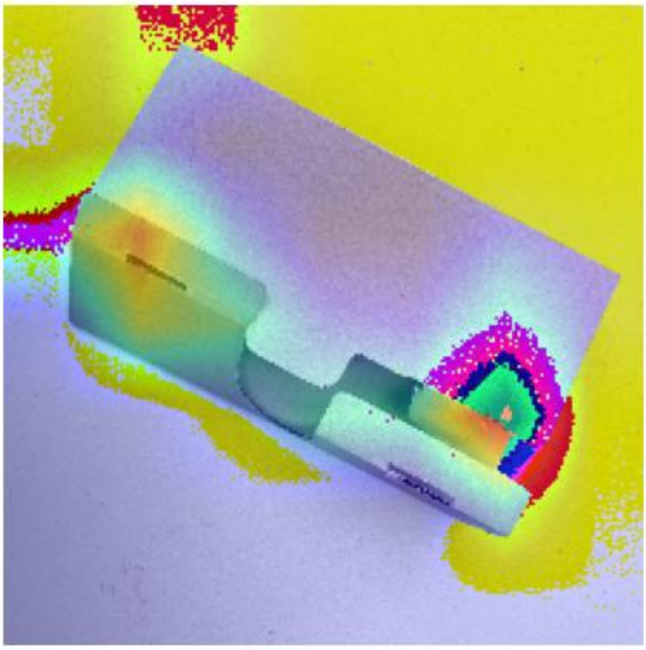

Figure 6. Grad-CAM visualization highlighting important regions used by the model for classification

To further analyze the model's decision-making process, Grad-CAM visualization is applied, as shown in Figure 6. The results indicate that the model focuses on specific object regions rather than the entire image, highlighting meaningful and localized features. This suggests that the model emphasizes relevant object characteristics and demonstrates good interpretability aligned with human perception.

Overall, the model achieves high accuracy under controlled conditions but is affected by environmental variability in real-world scenarios. Despite this, the model shows strong potential for practical waste classification applications. This study has several limitations, including the relatively small real-world dataset of 30 images, which may not fully represent real-world variability. Future work should expand the dataset and incorporate more diverse environmental conditions to improve model robustness.

4. Conclusion

This study successfully developed a multi-class waste image classification model using a Convolutional Neural Network (CNN) with a transfer learning approach based on EfficientNetV2. The proposed model achieved a high accuracy of 94.03% and a weighted F1-score of 0.9399, demonstrating its effectiveness in classifying waste images. The results also indicate stable performance across different experimental scenarios, confirming the model's generalization capability. Real-world testing further shows that the model can be applied in practical scenarios, although some misclassification occurs in visually similar categories. Compared to previous studies, such as Girsang et al. (2023) with an accuracy of 93.35%, the proposed model demonstrates slightly improved performance. This improvement is attributed to the use of EfficientNetV2 combined with systematic hyperparameter tuning.

Despite these promising results, several limitations remain, particularly the limited size of the real-world dataset and the use of validation data for model evaluation, which may introduce optimistic bias. Therefore, future work should focus on expanding the dataset, improving data diversity, and applying more robust evaluation methods such as independent test sets or cross-validation. In addition, further development of the system into other platforms, such as mobile applications, may enhance its practical applicability.

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