



Research Article

Classification Of Organic And Inorganic Waste Using Resnet50

I Kadek Mahesa Chandra Qinantha ^{1,*}, I Gusti Agung Indrawan ², I Putu Satria Udyana Putra ³, I Gusti Ayu Agung Mas Aristamy ⁴, Ayu Gede Willdahlia ⁵

¹ Institut Bisnis dan Teknologi Indonesia, Bali 80225, Indonesia, mahesachandra242@gmail.com

² Institut Bisnis dan Teknologi Indonesia, Bali 80225, Indonesia, agung.indrawan@instiki.ac.id

³ Institut Bisnis dan Teknologi Indonesia, Bali 80225, Indonesia, satria@instiki.ac.id

⁴ Institut Bisnis dan Teknologi Indonesia, Bali 80225, Indonesia, agungmas.aristamy@instiki.ac.id

⁵ Institut Bisnis dan Teknologi Indonesia, Bali 80225, Indonesia, willdahlia@instiki.ac.id

Correspondence should be addressed to I Kadek Mahesa Chandra Qinantha; mahesachandra242@gmail.com

Received 17 January 2025; Accepted 20 May 2025; Published 31 July 2025

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Abstract:

Waste generation, particularly from organic and inorganic sources, has become a growing environmental issue, especially in culturally unique regions like Bali where traditional offerings contribute to organic waste volumes. Despite regulations such as Gianyar Regency Regulation No. 76 of 2023 mandating source-level separation, on-ground implementation remains inconsistent due to low public awareness and operational limitations. This study addresses the challenge by developing an automated image-based classification system using the ResNet50 deep learning architecture to distinguish between organic and inorganic waste. A total of 200 images were collected 100 per class using smartphone cameras, and the dataset was expanded to 1,400 images through geometric data augmentation techniques such as rotation, flipping, and zooming. Images were resized to 224x224 pixels and evaluated using K-Fold Cross Validation to ensure model stability. The model was trained using transfer learning and tested under two conditions with and without augmentation while optimizing hyperparameters such as learning rates (0.0001 and 0.00001) and optimizers (Adam and SGD). The results demonstrate that augmentation significantly enhanced model performance, with the augmented model achieving an average accuracy of 99.25%, precision of 99.32%, recall of 99.25%, and F1-score of 99.25%, compared to 89.88% accuracy in the non-augmented model. These findings confirm that ResNet50, when combined with geometric augmentation and proper preprocessing, offers a robust, accurate, and scalable solution for waste classification tasks. This research contributes to the advancement of AI-driven environmental technologies and offers a potential framework for smart waste management systems, with future directions including real-time deployment, multi-class classification, and expansion to more diverse and real-world datasets.

Keywords: Deep Learning; Image Augmentation; ResNet50; Sustainable Environment; Transfer Learning; Waste Classification.

1. Introduction

Waste has become an increasingly complex environmental issue in line with the growing population and expanding human activities across various sectors of life [1], [2]. In Bali, this phenomenon takes on unique characteristics due to local traditions and cultural practices that contribute specific types of waste, such as canang (Balinese offerings), which are classified as organic waste. Moreover, the volume of inorganic waste such as plastic bottles, cans, and plastic bags continues to rise in response to modern lifestyle habits. If not managed properly, both types of waste can seriously impact environmental quality, public health, and the balance of natural ecosystems [3], [4], [5]. Therefore, waste separation at the source becomes a crucial first step in mitigating these negative effects and promoting sustainable waste management practices.

In response to these challenges, the Gianyar Regency Government in Bali issued Regional Regulation No. 76 of 2023, mandating that every household must separate their waste at the source. This regulation also prohibits the disposal of mixed waste at the Temesi Landfill starting from May 1, 2024. The policy aims to encourage behavioral change within the community while integrating Balinese local wisdom into the waste management system. However, its effectiveness in practice remains limited, primarily due to insufficient enforcement and inconsistent implementation across different villages and districts [6]. This indicates a gap between formal policy and actual execution at the grassroots level.

Various national and local surveys have revealed a low level of public compliance with waste sorting practices. Data from the Central Statistics Agency in 2022 showed that 39.92% of households in Indonesia acknowledged the importance of separating waste but had not adopted the practice in daily life. Meanwhile, a GoodStats survey (2024) reported that only 31.4% of respondents consistently sorted wet and dry waste. Key barriers identified in these studies include a lack of public education, the absence of clear technical guidelines, and a general perception that waste sorting is cumbersome and time-consuming [7]. These findings highlight the need for more practical and engaging approaches to foster environmentally responsible behavior within communities.

To address these challenges, artificial intelligence (AI) technologies offer an innovative solution that can enhance the efficiency of waste management efforts. One of the most promising AI technologies in this context is the Convolutional Neural Network (CNN), known for its ability to recognize visual patterns and classify objects based on digital imagery. CNNs can be used to identify types of waste through camera input or images, allowing for automatic waste classification without manual feature extraction [8]. This reduces the burden on individuals, speeds up the sorting process, and minimizes errors in waste identification. Previous studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in image-based waste classification. [9] Optimized DenseNet121 using a genetic algorithm, achieving 99.6% accuracy, while [10] developed an automated classification system to enhance waste management efficiency. [11] Applied a TensorFlow-based CNN model to classify organic and inorganic waste, and [12] used transfer learning with MobileNetV2 and DenseNet121 to classify waste categories with high accuracy. These studies collectively highlight the potential of CNN-based models to significantly improve the speed, accuracy, and automation of waste classification model.

In this research, the ResNet-50 architecture is selected as the primary model due to its strengths in addressing the vanishing gradient problem through residual learning. This architecture enables deeper network training and more effective recognition of complex visual features with high accuracy. ResNet-50 has proven its effectiveness in various image classification tasks and is widely adopted in computer vision applications. By leveraging this model, the classification of organic and inorganic waste can be performed more accurately, quickly, and reliably at the community level. Furthermore, the model is expected to serve as a reference for future AI-based waste classification system development and act as an educational tool to raise public awareness of the importance of sustainable waste management.

2. Method:

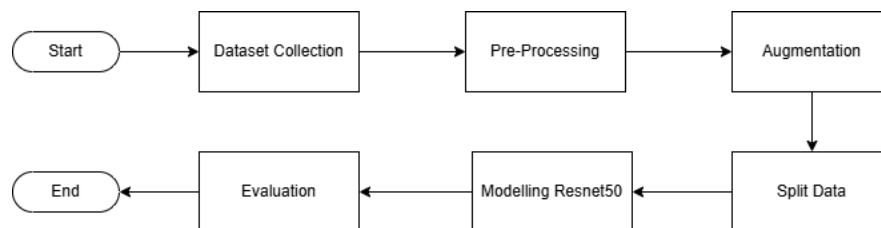


Figure 1. Research Flow

Figure 1 illustrates the research workflow for classifying waste images using the ResNet50 model. The process begins with data collection, consisting of 200 images, 100 images for each of the two classes: organic and inorganic. This is followed by a preprocessing stage, including image resizing and normalization to standardize the data format. Next, image augmentation techniques are applied to artificially increase data diversity, enhancing the model's robustness to input variations. The prepared

data is then split into training and testing sets. The ResNet50 model is trained using a transfer learning approach. In the final stage, the model's performance is evaluated using several metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of the classification.

Data Collection

The primary data used in this study was collected by capturing photos of organic waste, such as dried leaves and leftover canang offerings, at the homes of Hindu residents in Bali, as well as inorganic waste, such as plastic bottles and plastic bags, found in scavenger settlements. All photos were taken using a mobile phone camera. The dataset consists of 200 images, with 100 images of organic waste and 100 images of inorganic waste. Photos were taken from various angles, including front, back, and side views.

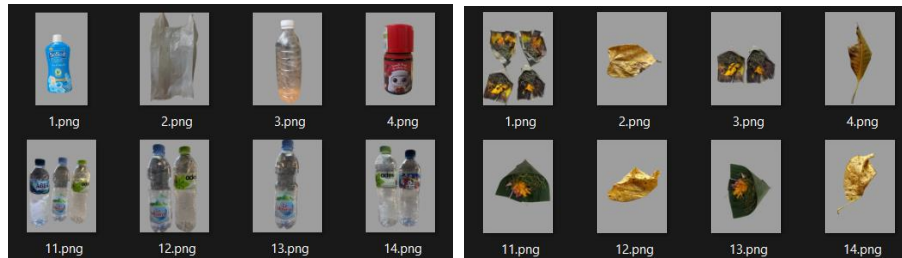


Figure 2. Sample Dataset

Pre-processing

Preprocessing is the initial step in image processing, aimed at preparing raw images before proceeding to further analysis. This stage is carried out to align the data with the model's requirements, reduce visual noise, standardize the scale, and ensure consistent image dimensions. In this study, preprocessing was performed by resizing all images to 224×224 pixels [13], [14]. This dimensional consistency enhances the performance of transfer learning, ensures uniform input, and reduces computational load without sacrificing essential image information. The 224×224 pixel image size has been proven effective in various deep learning studies, such as in OCT image classification using ResNet and GoogLeNet architectures [15], as well as in handwritten character recognition using transfer learning with ResNet50 [16], [17]. These studies demonstrate that using standard sizes like 224×224 not only maintains high classification accuracy but also improves the efficiency of the model training process.

Augmentation

Data augmentation is a technique used in deep learning model training to increase the quantity and diversity of training data by modifying original images through various transformations such as rotation, flipping, random cropping, lighting adjustments, and color changes, without altering their class labels. The primary goal of this method is to expand data distribution to minimize overfitting and enhance the model's ability to generalize to new data, especially when training data is limited [18]. In specific applications like image captioning, augmentation has been proven to enrich visual diversity and significantly improve model accuracy [19]. Moreover, recent methods such as the Random Augmentation Pipe and GAN-based transformation combinations have demonstrated significant improvements in image classification, even with limited datasets [20], [21]. In this study, the applied augmentation technique is geometric transformation, which introduces positional variations of objects using rotation, flipping, zooming, and translation. This approach increases positional diversity in the dataset, enabling the model to better handle variations in perspective, size, and object orientation in real-world data. From the original 200 images, the dataset was expanded to 1,400 images through augmentation.

K-fold Cross Validation

K-Fold Cross Validation is a widely used validation method in the training and evaluation of machine learning models, including deep learning, to address overfitting issues and ensure good model generalization. This technique divides the dataset

into k parts (folds), where training is performed on $k-1$ parts, while the remaining part is used for testing. This process is repeated k times so that each fold serves once as the test set, and the average of all evaluation results is used as the model's performance estimate. The main advantage of this method lies in its efficient use of data particularly valuable when dealing with limited datasets as all data is used for both training and testing [22]. In addition, k -fold provides a more stable estimate of model performance compared to a single train-test split [23], [24]. This method is also applied in reinforcement learning and deep learning to assess task difficulty in automated curriculum learning scenarios [25]. When properly implemented, K-Fold Cross Validation not only enhances model accuracy but also assists in selecting the most appropriate model for the given problem and dataset.



Figure 3. K-Fold Cross Validation

ResNet50

ResNet50 is one of the most well-known convolutional neural network (CNN) architectures in the field of deep learning, recognized for its efficiency in handling large-scale image classification tasks. This architecture comprises 50 layers and was introduced to address the vanishing gradient problem, which frequently occurs in very deep networks. The core strength of ResNet50 lies in its use of residual blocks or shortcut connections, which enable information to flow more directly from the earlier layers to the later ones without degradation, thereby accelerating training convergence and improving accuracy [26], [27]. In various studies, ResNet50 has demonstrated outstanding performance in image classification tasks, such as recognizing fresh and rotten fruits [28], detecting plant diseases [29], and classifying artworks [30]. This architecture is also highly suitable for transfer learning, as its pretrained weights on large datasets such as ImageNet can be reused for new classification tasks, saving both time and computational resources [27], [31]. With its combination of depth, efficiency, and generalization capability, ResNet50 remains a popular choice in modern computer vision applications.

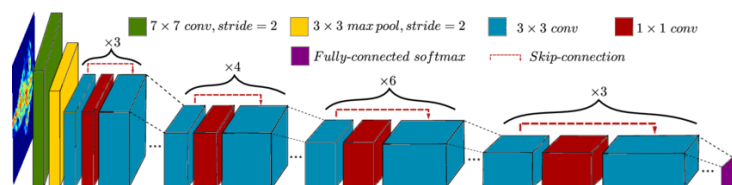


Figure 4. Resnet50 Architecture

Evaluation

The confusion matrix is an essential evaluation tool in machine learning and deep learning used to measure the performance of classification models. It displays the model's prediction outcomes in a table that highlights the number of correct and incorrect predictions for each class, divided into four key components: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). From this matrix, various evaluation metrics such as accuracy, precision, recall, and F1-score can be calculated, offering a thorough insight into the model's ability to correctly and incorrectly identify patterns. Beyond assessing a

single model, the confusion matrix can also be applied to compare the performance of multiple models, for example through the use of a relative confusion matrix, which provides a more detailed visualization of prediction differences [32].

3. Results and Discussion

Results

The ResNet50 model was trained by experimenting with various hyperparameters, including learning rates of 0.0001 and 0.00001, and by applying both Adam and SGD optimization algorithms. A grid search approach was employed to determine the optimal combination of these parameters. Furthermore, the training process was carried out under two distinct conditions: one incorporating data augmentation and the other without it. The following table summarizes the model's training outcomes using the most effective hyperparameter configuration.

Table 1. Evaluation Results of Restnet50 Data Model

Model	Learning Rate	Optimizer	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
Resnet50 Without Augmentation	0.0001	adam	90.00%	91.67%	90.00%	89.90%
	0.0001	sgd	90.00%	90.00%	90.00%	90.00%
	0.00001	adam	97.50%	97.62%	97.50%	97.50%
Resnet50 With Augmentation	0.00001	sgd	85.00%	85.35%	85.00%	84.96%
	0.0001	adam	99.29%	99.30%	99.29%	99.29%
	0.0001	sgd	99.64%	99.65%	99.64%	99.64%
	0.00001	adam	86.07%	86.09%	86.07%	86.07%
	0.00001	sgd	86.43%	87.19%	86.43%	86.36%

Table 2. Evaluation Fold Validation of Restnet50 Without Augmentation Data Model

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	87.50%	90.00%	87.50%	87.30%
2	100.00%	100.00%	100.00%	100.00%
3	93.75%	94.44%	93.75%	93.73%
4	81.25%	86.36%	81.25%	80.57%
5	93.75%	94.44%	93.75%	93.73%
6	100.00%	100.00%	100.00%	100.00%
7	87.50%	90.00%	87.50%	87.30%
8	81.25%	86.36%	81.25%	80.57%
9	68.75%	80.77%	68.75%	65.37%
10	100.00%	100.00%	100.00%	100.00%
Rata-rata	89.88%	91.84%	89.88%	88.86%

Table 3. Evaluation Fold Validation of Restnet50 With Augmentation Data Model

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	100.00%	100.00%	100.00%	100.00%
2	98.21%	98.21%	98.21%	98.21%
3	100.00%	100.00%	100.00%	100.00%
4	100.00%	100.00%	100.00%	100.00%
5	100.00%	100.00%	100.00%	100.00%
6	99.11%	99.12%	99.11%	99.11%
7	100.00%	100.00%	100.00%	100.00%

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
8	100.00%	100.00%	100.00%	100.00%
9	98.21%	98.28%	98.21%	98.21%
10	97.32%	97.46%	97.32%	97.32%
Rata-rata	99.25%	99.32%	99.25%	99.25%

Based on the evaluation results in **Table 1**, the ResNet50 model demonstrates excellent performance in image classification tasks both with and without data augmentation. For the model without augmentation, the best performance was achieved using a learning rate of 0.00001 and the Adam optimizer, yielding 97.50% for accuracy, precision, recall, and F1-score. Meanwhile, the use of data augmentation significantly improved performance, with the combination of learning rate 0.0001 and SGD optimizer reaching 99.64% accuracy. This finding is further supported by the 10-fold validation results shown in **Tables 2** and **3**. **Table 2**, representing the model without augmentation, recorded average scores of 89.88% accuracy, 91.84% precision, 89.88% recall, and 88.86% F1-score. In contrast, **Table 3**, which shows the augmented model, reports a notable increase in all evaluation metrics with an average of 99.25%. These results suggest that data augmentation can enhance the model's generalization capabilities and lead to more consistent and accurate classification outcomes.

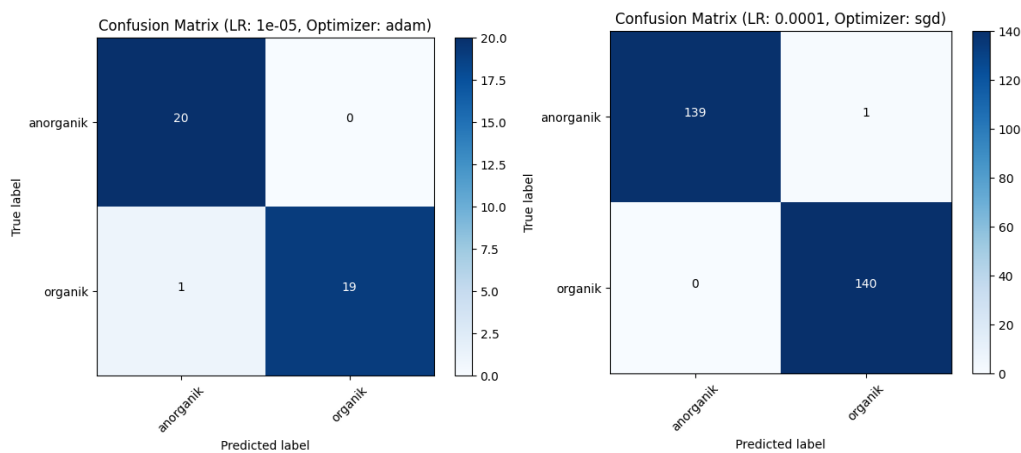


Figure 5. Confusion Matrix Result Without Augmentation Data and With Augmentation Data

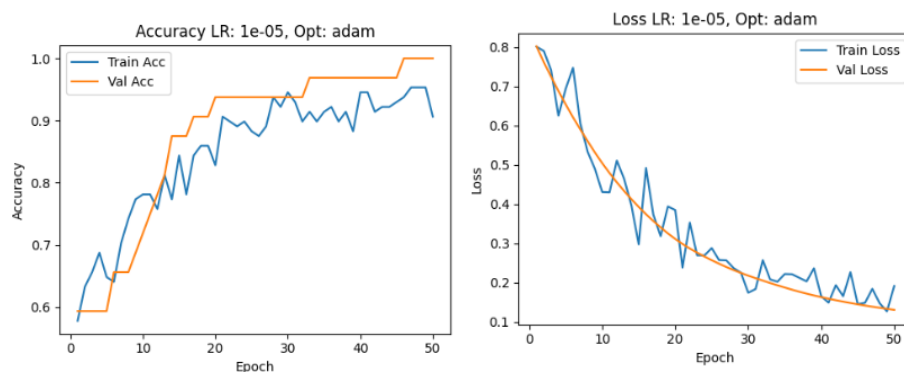


Figure 6. Accuracy and Loss Without Augmentation Data

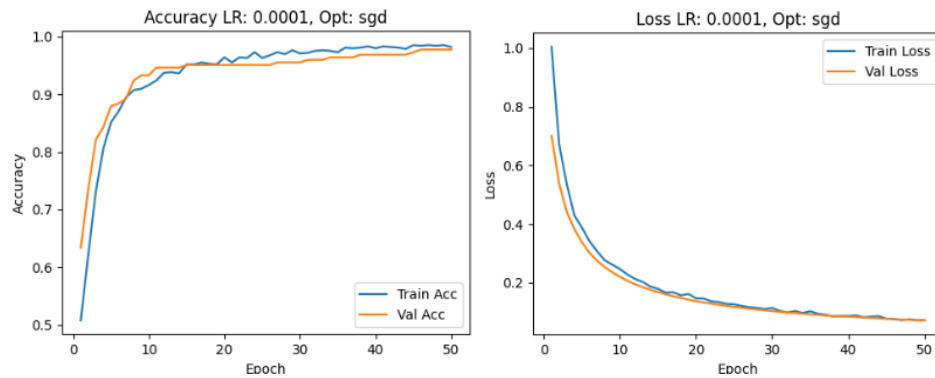


Figure 7. Accuracy and Loss with Augmentation Data

Discussion

The results of this study confirm that applying data augmentation significantly enhances the performance of the ResNet50 model in classifying organic and inorganic waste. Without augmentation, the model achieved its highest performance using the Adam optimizer with a learning rate of 0.00001, resulting in 97.50% accuracy. However, the incorporation of geometric transformations, such as rotation, zooming, and flipping, enabled the model to better recognize positional and visual variations, which led to a substantial increase in classification performance reaching up to 99.64% accuracy. Furthermore, the application of 10-Fold Cross Validation provided a thorough evaluation of the model's stability across different data partitions. The average evaluation metrics for the augmented model accuracy, precision, recall, and F1-score all exceeded 99%, demonstrating its consistency and robustness. These findings indicate that image augmentation is a crucial strategy when working with limited datasets and can significantly improve the reliability of visual-based classification in waste management. For future research, it is recommended to explore multi-class classification of waste types, increase dataset diversity by collecting images from public environments, and evaluate the performance of alternative lightweight architectures for real-time implementation.

4. Conclusion

This study successfully applied the ResNet50 deep learning model to classify organic and inorganic waste using image-based data. The use of geometric image augmentation led to a significant improvement in classification accuracy and model generalization, especially when validated through K-Fold Cross Validation. The augmented model achieved an average accuracy of 99.25%, surpassing the non-augmented model, which averaged 89.88%. These results demonstrate that ResNet50, combined with appropriate preprocessing and augmentation techniques, is highly effective for visual-based classification tasks in environmental contexts. Future research may further refine this approach by expanding the dataset, exploring other deep learning architectures, and adapting the model for broader applications in waste identification and management.

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