REKAYASA
Journal of Science and Technology
https://journal.trunojoyo.ac.id/rekayasa

Rekayasa, 2024; 17(3): 380-386
ISSN: 0216-9495 (Print)
ISSN: 2502-5325 (Online)

# Plastic Waste Identification using ResNet-50: A Deep Learning Approach

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DOI: https://doi.org/10.21107/rekayasa.v17i3.26456
Submitted July 10th 2024, Accepted December 4th 2024, Published December 27th 2024

**Abstrak**

Sampah plastik merupakan masalah lingkungan yang signifikan dan menyumbang sebagian besar dari total sampah. Pengelolaan sampah yang tidak tepat dapat menyebabkan permasalahan lingkungan seperti polusi udara, kerusakan lingkungan laut, dan kontribusi terhadap perubahan iklim. Permasalahan tersebut dapat dikurangi dengan strategi pemilahan sampah yang efektif. Namun, metode pemilahan sampah secara tradisional memerlukan waktu dan biaya yang mahal. Untuk mengatasi permasalahan tersebut, diperlukan solusi alternatif, salah satunya adalah dengan memanfaatkan teknologi kecerdasan buatan. Metode berbasis pembelajaran mendalam dapat secara otomatis mengidentifikasi dan mengklasifikasikan berbagai jenis sampah plastik dan non plastik menggunakan pola dari gambar digital. Penelitian ini mengimplementasikan ResNet50, salah satu metode berbasis *Convolutional Neural Networks* untuk menglasifikasikan sampah plastik dan non-plastik. ResNet50 dilatih pada *multi-source* dataset dengan total data sebanyak 4000 gambar. Implementasi ResNet50 memberikan hasil performa yang sangat baik dengan nilai akurasi, F1-score, *recall*, dan *presicion* sebesar 0,99. Hasil tersebut menunjukkan bahwa ResNet50 dapat mengklasifikasikan secara tepat sampah plastik dan non-plastik dengan akurasi yang tinggi. Hasil ini juga menunjukkan potensi penggunaan pembelajaran mendalam sebagai alternatif solusi dalam pemilihan sampah. Dengan memanfaatkan metode identifikasi berbasis kecerdasan buatan, proses pemilahan sampah dapat dilakukan dengan lebih cepat, lebih akurat, dan hemat biaya. Hal tersebut juga berdampak pada upaya pengurangan kerusakan lingkungan sekaligus mendukung terciptanya solusi yang berkelanjutan. Mengintegrasikan teknologi berbasis kecerdasan buatan ke dalam sistem pemilahan sampah dapat menghasilkan solusi yang lebih efisien dan ramah lingkungan untuk pengelolaan sampah.

**Kata Kunci:** *convolutional neural networks*, identifikasi sampah, Resnet-50, sampah plastik

**Abstract**

*Plastic waste is a significant environmental concern, constituting a major portion of the global waste stream. Improper disposal and accumulation have led to severe environmental challenges, including pollution, harm to marine life, and contributions to climate change. Effective waste management strategies are essential to mitigate these issues. However, manual sorting methods are both time-consuming and costly, requiring substantial human effort and financial investment. To address these limitations, automated solutions utilizing advanced technologies like artificial intelligence have gained increasing attention. Deep learning-based method can automatically identify and classify various types of plastic waste using computer-captured image patterns. This study explores the application of ResNet50, a state-of-the-art deep learning model, for the classification of plastic and non-plastic waste. A robust dataset comprising 4,000 diverse images of waste materials was employed for model training and validation. ResNet50, with its advanced architecture designed for image recognition tasks, demonstrated exceptional performance, achieving an accuracy, precision, recall, and F1-score of 0.99. These results highlight the model's ability to precisely and reliably differentiate between plastic and non-plastic waste categories. The findings of this research underscore the potential of deep learning-based approaches in revolutionizing waste management practices. By leveraging automated classification methods, waste sorting can become significantly faster, more accurate, and cost-effective. This has far-reaching implications reducing environmental harm and fostering a more sustainable future. The results demonstrate that integrating AI technologies into waste management systems can lead to efficient and environmentally friendly solutions for tackling plastic waste challenges.*

***Key words**: convolutional neural networks, plastic waste, Resnet-50, waste identification*

## INTRODUCTION

Waste can be broadly divided into biodegradable and nonbiodegradable categories. Non-biodegradable wastes, such as plastics, cannot be decomposed by natural processes and pose significant environmental risks. Plastic waste alone accounts for 18.4% of the total waste, making it the second-largest category after food waste, and a major global environmental concern (Kementerian Lingkungan Hidup dan Kehutanan Republik Indonesia, 2024). By 2050, global waste is expected to reach 46 billion tons (Maalouf & Mavropoulos, 2023). Proper waste management is crucial for reducing the adverse effects on human health and the environment (Fadhullah et al., 2022; Sari et al., 2023). Strategies, such as reducing, reusing, and recycling waste, are required. However, these processes require meticulous sorting of waste materials, which is typically performed manually. While manual sorting allows for thorough and detailed categorization, it is both time-consuming and costly. Therefore, automated waste sorting machines are required to enhance efficiency and reduce costs.

Advancements in technology, particularly Artificial Intelligence (AI), have immense potential to revolutionize plastic waste management, enhancing both productivity and quality, while accelerating the waste disposal process (Alsabt *et al.*, 2024, 2024; Sharma & Vaid, 2021). AI can automatically identify and classify various types of plastic waste using computer-captured image patterns, which can significantly improve efficiency (Cheema *et al.*, 2022; Ramos *et al.*, 2024). This method enables precise classification and identification of waste types and presents a promising alternative to traditional manual sorting. AI-driven technology is set to provide innovative solutions for future waste management (Fang *et al.*, 2023). One AI-based method is deep learning, which uses multilayer neural networks to autonomously extract features from data without human involvement (Alzubaidi *et al.*, 2021; Sarker, 2021; Taye, 2023b). A notable deep learning technique is Convolutional Neural Networks (CNN) (Taye, 2023a), designed to perform feature extraction from data structured in arrays, such as images. CNNs have been widely employed in image and video recognition, image classification, and image segmentation (Dafid *et al.*, 2021; Musa *et al.*, 2023; Shabrina *et al.,* 2023; Shabrina & Brian, 2023; Zhao *et al.*, 2024), making them highly effective for sorting waste management tasks.

Numerous researchers have effectively utilized deep learning and CNN for waste classification (Wu *et al.*, 2023). Sami et al. compared four algorithms, CNN, SVM, Random Forest, and Decision Tree, to classify six waste classes: glass, metal, paper, cardboard, plastic, and general waste. The CNN achieved the highest accuracy of approximately 90%, whereas the SVM showed an excellent performance with an accuracy of 85%. In contrast, Decision Tree and Random Forest achieved 65% and 55%, respectively (Sami *et al.*, 2020). Ozkaya and Seyfi utilized fine-tuned models, such as AlexNet, VGG16, GoogLeNet, and ResNet, to classify six different types of trash. They employed two types of classifiers, Support Vector Machines (SVM) and softmax, with the highest accuracy of 97.86% achieved by combining GoogLeNet and SVM (Ozkaya & Seyfi, 2019). Middya et al. aimed to identify and categorize waste items into ten different classes, including bottles, cups, masks, and cardboard. Their approach employed Faster Region-based CNN with Inception-V2 as the foundation for feature extraction, achieving a significant mean average precision (mAP) of 92% (Middya *et al.*, 2021). Malik *et al*. used transfer learning techniques with the EfficientNetB0 model to improve the classification accuracy of solid waste images to 85% (Malik et al., 2022). Wang classified domestic garbage into hazardous garbage, recyclable garbage, kitchen waste, and other waste using VGG16. The VGG16 network-based garbage classification system attained an accurate classification rate of 81.1% (Wang, 2020).

However, previous research has not specifically focused on classifying plastic and non-plastic wastes, and the accuracy of these models has been somewhat limited. To address these gaps, this study proposes the use of ResNet50 to classify plastic and non-plastic waste. ResNet50 was selected because of its high accuracy and straightforward implementation (He *et al.*, 2016). The model was trained using a multi-source dataset that represents plastic and non-plastic waste, as referenced in (Ahdita, 2019; Kumsetty *et al.*, 2022; Serezhkin, 2020). This approach aims to enhance the accuracy and provide a more targeted solution.

## METHODS

Figure 1 illustrates the workflow of this study. Dataset preparation is the initial step, which involves the collection and preprocessing of images to ensure a uniform size and format. The dataset was subsequently divided into three separate subsets for training, validation, and testing. ResNet50 was implemented to train the dataset. The evaluation of the model's performance was conducted using various metrics, including accuracy, F1-score, recall and precision, to assess its ability to accurately classify plastic and non-plastic waste.

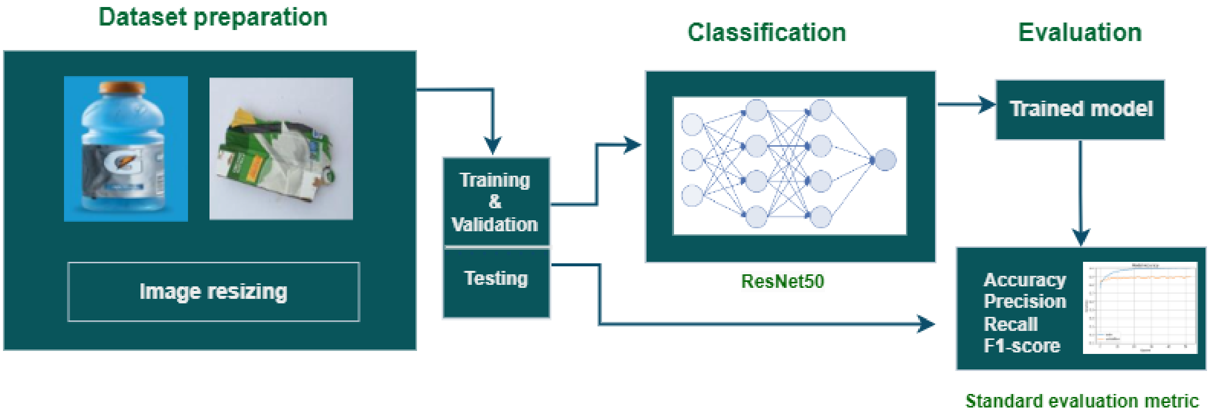


Figure 1. Workflow of this study

**Dataset Preparation**

The dataset was collected from several sources (Ahdita, 2019; Kumsetty et al., 2022; Serezhkin, 2020), resulting in up to 4000 images. There are two classes in the dataset: plastic and non-plastic, with 2000 images per class. The images were selected based on the following specific criteria: plastic bottle waste images representing the plastic category and cardboard images representing the non-plastic category. The dataset was subsequently split into three parts: training, validation, and testing, with a ratio of 80:10:10. The training set comprised 1600 images for each class, while the testing set consisted of 200 images and the validation set had 200 images. After the split, the images were resized to 224 × 224 pixels to satisfy the input requirements of ResNet50.

**ResNet50 Architecture**

ResNet, also known as a Residual Network, is an evolution of VGGNet (Simonyan & Zisserman, 2015) that aims to solve the problem of vanishing gradients that are common in deep CNN algorithms. To overcome the vanishing gradient problem prevalent in CNN architectures, ResNet integrates residual connections and implements connections that directly connect the input and output models, thereby enabling neural networks to learn residual mappings from existing data. ResNet50 has 50 neural network layers, enabling the model to learn more complex functions and patterns from data (He et al., 2016). Table 1 shows the architecture of ResNet50.

Table 1. ResNet-50 Architecture

| Layer Name | Output size | Detailed of the layer |
|---|---|---|
| Conv1 | 112 x 112 | $7x7, 64, stride\ 2$ |
| Conv2_x | 56x65 | $3x3$ max $pool. Stride\ 2$ |
| | | $\begin{bmatrix} 1x1, 64 \\ 3x3, 64 \\ 1x1, 256 \end{bmatrix} x3$ |
| Conv3_x | 28x28 | $\begin{bmatrix} 1x1, 128 \\ 3x3, 128 \\ 1x1, 512 \end{bmatrix} x4$ |
| Conv4_x | 14x14 | $\begin{bmatrix} 1x1, 256 \\ 3x3, 256 \\ 1x1, 1024 \end{bmatrix} x6$ |
| Conv5_x | 7x7 | $\begin{bmatrix} 1x1, 512 \\ 3x3, 512 \\ 1x1, 2048 \end{bmatrix} x3$ |
| | $1x1$ | $average\ pool. 1000 - d\ fc, softmax$ |
| FLOPS | $3.8\ x\ 10^9$ | |

This study implements a transfer learning approach that allows the model to learn new features from another dataset while leveraging the rich features learned from previously trained data, that is, ImageNet data. Transfer learning is implemented by freezing all the layers above a specific layer and retaining the final layer. Modifications were made to the final layer by introducing dropout and GlobalAveragePooling2D parameters, which were changed from AveragePooling. These adjustments were implemented to prevent prolonged training and to mitigate potential overfitting. Additionally, the dense layer is configured to use the sigmoid function, resulting in the creation of two classes at the end of the layer, as the research only requires classification into two classes

**Model Implementation**

Hyperparameters play a crucial role in optimizing the performance and controlling the behavior of the model (J. Wu et al., 2019). This study employed the Adam optimizer, which is known for its straightforward implementation and computational efficiency (Kingma & Ba, 2017). $\beta_1$ and $\beta_2$ values in the Adam optimizer were set at 0.9 and 0.999, respectively. The epsilon value was set as $10^{-7}$ with a learning rate of 0.001. The training process spanned for 25 epochs and employed a batch size of 16. Additionally, an EarlyStopping callback is implemented to prevent overfitting, ensuring that the training halts if the performance on the validation set ceases to improve. The training process was implemented using Google Colab Pro, which was equipped with an Intel Xeon Processor operating at a speed of 2.3GHz, an A100 Nvidia GPU accompanied by 40GB of RAM, and 83.5GB of memory.

**Metric Evaluation**

One method for assessing model performance is the accuracy score, which measures the correctness of a model based on accurate predictions during the prediction process. A high accuracy score indicated the precision of the model in predicting the given data. Precision indicates the proportion of correct positive predictions made by a model. Another essential metric is recall, which calculates the proportion of accurate positive predictions relative to the total number of actual positive cases. The F1-score takes into account both precision and recall value, providing an even-handed assessment of the model's efficiency by calculating their combined average. Equations (1)–(4) show all evaluation metrics used in this study, with TP, TN, FP, and FN referring to true positives, true negatives, false positives, and false negatives, respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$Recall = \frac{TP}{TP + FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$Precision = \frac{TP}{TP + FP} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

## RESULT AND DISCUSSION

The results of the deep learning model for classifying plastic and non-plastic waste, as presented in Table 2, demonstrate outstanding performance across a range of evaluation metrics. The training loss was low at 0.01, indicating a minimal error in the model predictions of the training data. The training accuracy was exceptionally high, at 99.62%, demonstrating that the model effectively learned from the training dataset. Additionally, the validation loss is relatively low at 0.429, suggesting that the model is not overfitting and can be generalized well to new, unseen data. This is further supported by the validation accuracy of 99.25%, which is only slightly lower than the training accuracy, indicating a consistent performance across different data subsets. The test accuracy of 99% confirms the model's ability to classify plastic and non-plastic waste with high precision using completely new data. The precision and recall metrics, both at 99.5%, highlight the effectiveness of the model in correctly identifying positive cases (e.g., correctly identifying plastic waste) and capturing all relevant instances. The F1-Score, which combines precision and recall, also stands at 99.5%, underscoring the balanced performance and high overall accuracy of the model. These results suggest that the model is highly effective in distinguishing between plastic and nonplastic waste, making it a valuable tool for automated waste sorting and management.

Table 2. Model performance results

| Metric | Results |
|---|---|
| Train Loss | 0.01 |
| Validation Loss | 0.429 |
| Train Accuracy | 0.9962 |
| Validation Accuracy | 0.9925 |
| Test Accuracy | 0.99 |
| Recall | 0.995 |
| Precision | 0.995 |
| F1-Score | 0.995 |

Figure 2 shows the learning curves obtained from these results. The training accuracy graph shows a clear upward trend as the number of epochs increases, indicating that the model learns effectively from the training data. This is expected, as the model gradually improves its understanding and predictions through repeated exposure to the training dataset. The validation accuracy also increased with epochs, albeit to a lesser extent than that of the training accuracy. This disparity suggests potential overfitting, where the model becomes too tailored to the training data and performs less effectively on the unseen data.

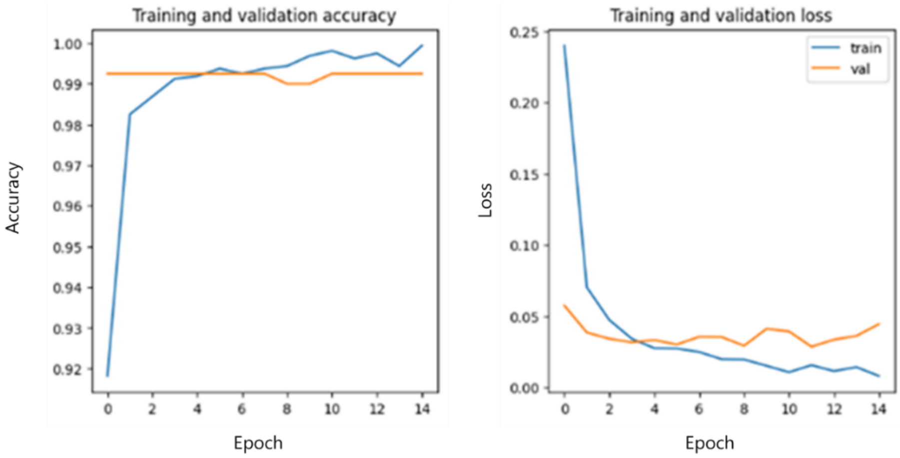


Figure 2. Accuracy and Loss Curves

In the training loss graph, a consistent decrease in the training loss with increasing epochs was observed, signifying the improved performance of the model. However, the validation loss, while generally decreasing, exhibited more fluctuations than the training loss. This variability in the validation loss further hints at overfitting, as the model's performance on the validation data is less stable. Overall, the graphs indicate that, while the model is learning, there is a risk of overfitting. Overfitting may occur if the model is too complex for a given dataset or if it has not been trained for an adequate number of epochs. To mitigate overfitting, several strategies can be employed: reducing the model complexity by using fewer layers or neurons, applying dropout to prevent neurons from co-adapting excessively, collecting more training data to provide a more robust learning base, and training the model for a suitable number of epochs. The authors suggest that expanding the dataset through augmentation and other preprocessing techniques will enhance the results.

The performance of the ResNet50 implemented in this study significantly outperforms the results reported in previous research on automated waste classification, as summarized in Table 3. Sami et al. employed a traditional CNN model and achieved an accuracy of 90%. Similarly, Malik et al. (2022) utilized the EfficientNetB0 model reported an accuracy of 85%. In contrast, more advanced architectures such as GoogleNet combined with SVM, as utilized by Ozkaya and Setfi (2019), reported a higher accuracy of 97.86%, showcasing the effectiveness of hybrid approaches. However, this method required more computational resources and complex model integration. Wang (2020) adopted VGG16 and achieved an accuracy of 81.6%. Compared to these studies, ResNet50 implemented in this research demonstrates superior accuracy at 99%, benefiting from its residual learning framework, which allows for training deeper networks without the risk of vanishing gradients. These findings highlight the potential of ResNet50 as a highly effective solution for waste classification, surpassing the accuracy levels reported in previous studies.

Tabel 3. Comparison with other studies

| **Author** | **Method** | **Accuracy** |
|---|---|---|
| Sami et al., 2020 | CNN | 90% |
| Ozkaya & Setfi, 2019 | GoogleNet & SVM | 97.86% |
| Malik et al., 2022 | EfficientNetB0 | 85% |
| Wang, 2020 | VGG16 | 81.6% |
| *Ours* | *ResNet50* | *99%* |

## CONCLUSIONS

The proposed study suggests the application of ResNet-50, a deep learning approach, for identifying plastic and non-plastic waste. The training dataset for the model comprised 4000 images, which were divided evenly between 2000 images per class. The ResNet50 model achieved remarkable results, with accuracy, precision, recall, and F1-score of 0.99. The proposed method showcases the potential of AI-driven technology to offer efficient and cost-effective waste management solutions, particularly for the identification of plastic and non-plastic waste.

## ACKNOWLEDGEMENT

The authors would like to thank Universitas Multimedia Nusantara for the support during this study

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