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Detection of Inorganic Waste Using Convolutional Neural Network Method

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Abstract

Waste, encompassing both domestic and industrial materials, presents a significant environmental challenge. Effectively managing waste requires accurate identification and classification. Convolutional Neural Networks (CNNs), particularly the Residual Network (ResNet) architecture, have shown promise in image classification tasks. This research aims to utilize ResNet to identify types of waste, contributing to more efficient waste management practices. The ResNet101 architecture, comprising 101 layers, is employed in this study for waste classification. The dataset consists of 2527 images categorized into six classes: Cardboard, Glass, Metal, Paper, Plastic, and Trash. The ResNet model is pre-trained, leveraging existing knowledge to enhance classification accuracy. The dataset is divided into training and testing sets to evaluate the model's performance. The testing results, evaluated using a Confusion Matrix, demonstrate strong performance in waste classification. The ResNet101 model achieves 92% accuracy in detecting inorganic waste objects within the training dataset and maintains a high accuracy of 90% on the testing dataset. This indicates the effectiveness of the ResNet architecture in accurately identifying various types of waste, contributing to improved waste management efforts. he utilization of ResNet101 for waste classification yields promising results, with high accuracy rates observed across both training and testing datasets. By effectively identifying types of waste, this approach facilitates more efficient waste management practices, enabling better resource allocation and environmental conservation. Further research and application of CNN architectures in waste management could lead to enhanced sustainability efforts and improved waste-handling strategies.

Keywords: Waste, Image Classification, CNN, ResNet

1. INTRODUCTION

Waste, defined as material that is no longer useful and often detrimental to the environment, presents a pressing challenge in modern society [1], [2]. In particular, inorganic waste, which includes materials resistant to decomposition such as

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cardboard, glass, metal, plastic, and paper, poses significant environmental risks due to its persistence in the environment [3]. Despite its detrimental effects, waste management remains a neglected aspect of human activity, often stemming from indifference to environmental concerns. To mitigate the adverse impacts of waste accumulation, various methods, including more efficient waste management and recycling initiatives, have been implemented [4].

Recent advancements in artificial intelligence (AI) have spurred research efforts to develop automated systems for waste classification and management. Previous studies, such as the work conducted by Mindy Yang [5] and colleagues using the Convolutional Neural Networks (CNNs) method with the AlexNet model, have achieved notable success in classifying trash for recyclability status. Similarly, Jihan Nuraini et al. [6] employed the Base ResNet-50 architecture to classify waste types with high accuracy, showcasing the potential of AI-driven approaches in waste management. Additionally, Stephen et al. [7] demonstrated the efficacy of CNNs with transfer learning, particularly the ResNet50 model, in waste classification tasks. P. N. Ma'rifah, et al [8] utilized the CNN ResNet architecture, achieving a classification accuracy of 77% for waste classification. Similarly, Z. M. A. Amin, et all [9] achieved a classification accuracy of 92.5% using the ResNet50 architecture for the same purpose in 2021. These studies collectively underscore the versatility and efficacy of CNN-based approaches in addressing the challenges of waste classification and management.

In this study, we aim to contribute to the advancement of waste management technology by employing the CNN architecture approach of ResNet101 to detect images of inorganic waste objects. Building upon the successes of previous research, particularly the work by Ulfah Nur et al., who achieved perfect object detection in images using the ResNet101 architecture, our research seeks to further refine and extend the application of AI techniques in waste classification. By leveraging the deep learning capabilities of CNNs, we endeavor to enhance the accuracy and efficiency of waste detection and separation processes, ultimately contributing to more effective waste management practices.

2. METHOD

This research follows an experimental approach using the CNN method to classify types of inorganic waste. The research activities consist of three stages: Dataset Collection, Data Preprocessing, and Classification [10], [11] using the CNN Method.

2.1. Dataset

The dataset of inorganic waste was obtained from Kaggle.com, consisting of six classes: Cardboard, Glass, Metal, Paper, Plastic, and Trash. The total dataset

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comprises 2,527 images. Table 1 shows the labeled classes along with the respective amount of data for each class.

Table 1. Dataset

Class	Label	Total
Cardboard	0	403
Glass	1	501
Metal	2	410
Paper	3	594
Plastic	4	482
Trash	5	137
	Total	2.527

In Figure 1, there are representations of each shape based on the six classes adopted in this study.

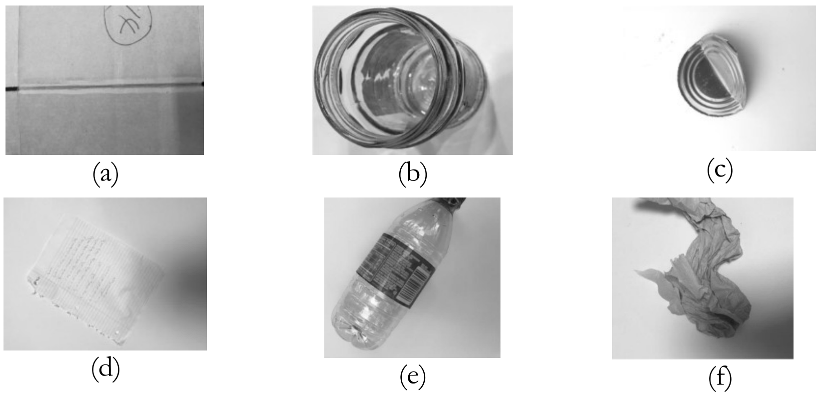

Figure 1. Dataset based on classes (a) Cardboard, (b) Glass, (c) Metal, (d) Paper, (e) Plastic, (f) Trash.

2.2. Data Processing

First, the dataset is collected by copying images. Then, the dataset is divided into training data, which accounts for 70%, and validation data, which accounts for 30%. The next step is data augmentation, where this process modifies existing data by adding brightness, performing horizontal flip, vertical flip, and adding blur to the image data previously divided. Augmentation greatly influences the improvement of the classification model. After that, the process involves data loading for classification by resizing the images to 224x224 pixels according to the input of ResNet101. The previously divided training, validation, and test data are combined, with a total of 2019 training sets, 252 validation sets, and 256 test sets. Finally, in the CNN classification model stage, the use of the ResNet101 model with additional layers is proposed.

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2.3. Convolutional Neural Network Classification.

The choice of using CNN, specifically the ResNet101 architecture, as the solution in this study is well-justified due to several key reasons. Firstly, CNNs are renowned for their efficacy in processing and analyzing image data. With the ability to detect and recognize objects within images, CNNs offer a robust framework for image classification tasks. This is particularly relevant in the context of waste identification, where accurately distinguishing between different types of waste materials is crucial for effective waste management [12], [13].

Moreover, CNNs are characterized by their deep neural network architecture, which enables them to learn intricate features and patterns within images. The deep layers of a CNN, including Convolution, ReLU Activation, Pooling, and Fully Connected layers, facilitate hierarchical feature extraction, allowing the model to discern subtle variations and nuances in the input data. This depth contributes to the CNN's ability to achieve high accuracy rates in image classification tasks, often surpassing 90% [14], [15].

Furthermore, the ResNet101 architecture specifically offers several advantages that make it a suitable choice for this study. ResNet, short for Residual Network, introduces skip connections that bypass certain layers, mitigating the vanishing gradient problem and facilitating the training of deeper networks. This architectural innovation allows ResNet models to effectively learn from a wide range of image data, making them well-suited for complex classification tasks such as waste identification [16].

The selection of CNN, particularly the ResNet101 architecture, as the solution in this study is justified by its proven effectiveness in image classification tasks, its ability to learn intricate features within images, and the specific advantages offered by the ResNet architecture. By leveraging these capabilities, the study aims to accurately identify types of waste, contributing to more efficient waste management practices.

3. RESULTS AND DISCUSSION

In this stage, data processing will be conducted using the collected data. The data in question is waste data from six classes, each class having approximately ±400 data points, divided into six classes: Cardboard, Glass, Metal, Paper, Plastic, and Trash. The data will be split into 70% training data and 30% testing data or validation data. The collected data will undergo data processing, including image resizing, and ultimately will be processed into a training model for use in the waste class recognition process.

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3.1. Dataset

In Figure 1, the dataset used in this research, consisting of six classes: Cardboard, Glass, Metal, Paper, Plastic, and Trash, is presented. The data collection involved searching for images based on the types of waste, which were then edited to fit the testing requirements. The representation of waste data by class and the total dataset is displayed in Figure 1 above. The application utilized is Python on Google Colab. Google Colab was chosen due to its high accessibility, integration with Google Drive, and provision of a powerful online Python development environment without requiring additional software installation. Additionally, Google Colab facilitates real-time collaboration and provides access to powerful computational resources for free. [17].

3.2. ResNet101 Modeling

After preprocessing and preparing the data for classification using the CNN method, this research proceeds with employing ResNet101, a modeling technique within CNN, for waste dataset classification. The dataset comprises six classes: Cardboard, Glass, Metal, Paper, Plastic, and Trash. The initial process involves utilizing TensorFlow with ResNet101 modeling, as depicted in Figure 2. In this research, TensorFlow is used to simplify and accelerate the training and testing processes. TensorFlow is widely utilized in CNN-based research.

```
from tensorflow.keras.applications import ResNet101

# Create ResNet-101 model without loading weights
resnet101_model = ResNet101(weights='imagenet', include_top=True)

# Display model summary
resnet101_model.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet101_weights_tf_dim_ordering_tf_kernels.h5
179648224/179648224 [==============================] - 1s 0us/step
Model: "resnet101"
__________________________________________________________________________________________________
 Layer (type)                Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]  0         []

 conv1_pad (ZeroPadding2D)   (None, 230, 230, 3)   0          ['input_1[0][0]']
```

Figure 2. Model Resnet101

The next step involves defining the dataset classes, which consist of six classes: Cardboard, Glass, Metal, Paper, Plastic, and Trash. The training process is conducted with 100 epochs, as indicated in Figure 3.

```
model_ft = train_model(model_ft, criterion, optimizer_ft, exp_lr_scheduler,num_epochs=EPOCHS)
```

```
Epoch 0/99
----------
train Loss: 1.2869 Acc: 0.5339
val Loss: 1.2076 Acc: 0.5556

Epoch 1/99
----------
```

Figure 3. Epoch Model Resnet101

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Figure 3 shows that the threshold accuracy for the first epoch is 0.55 or 55%. Next, TensorBoard is executed to visualize the accuracy level from the accuracy results, as depicted in Figure 4.

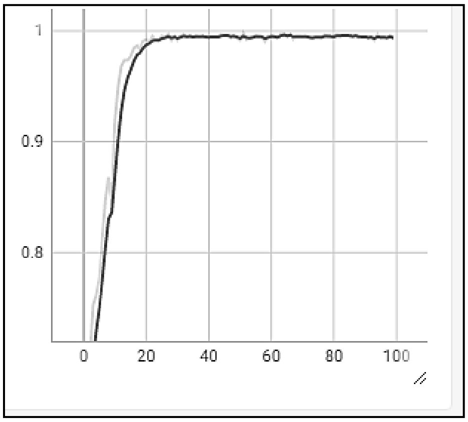

Figure 4. Accuracy

In Figure 4, it can be observed that the evaluation results are depicted, with the x-axis representing the epochs and the y-axis representing the accuracy values. The accuracy values for the data tend to stabilize, indicating that the model is good and optimal. The training accuracy reaches 0.9, and from epoch 0 onwards, it tends to stabilize and continues to increase. Next, the visualization of the training loss will be shown in Figure 5 below. Figure 5 illustrates the loss graph from the learning process, where the x-axis represents the Epoch, and the y-axis represents the Loss along with its accuracy values. The error values for the training data start at around 0.6 and continue to decrease up to epoch 100, while the validation data tends to decrease significantly.

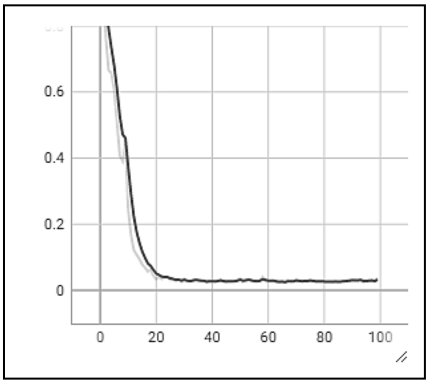

Figure 5. Loss

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The researcher has conducted testing after going through the training process and model formation. Next, the researcher will discuss the results of the testing that has been conducted.

1) Training and Testing Accuracy

The accuracy values from the training and testing processes using the CNN ResNet101 method for inorganic waste images as previously determined can be seen in Table 2. The accuracy obtained from the training data is 92%, while the accuracy from the testing data is 90%.

Table 2. Accuracy Results for Train and Test

Data	Total	Accuracy (%)
Training	2019	92
Testing	256	90

2) Testing Results

The researcher used 10 image objects in the testing process, and their respective accuracies can be seen in Table 3 below. The images displayed in the table do not have specific criteria. This testing result is for images classified under the Glass class.

Table 3. Testing Results

No	Image	Size	Accuracy (%)
1	 glass1.jpg	512 x 384	90,29
2	 glass2.jpg	512 x 384	91,90

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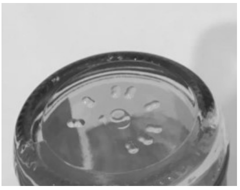
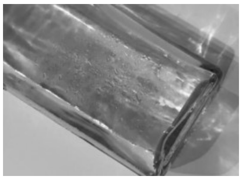
No	Image	Size	Accuracy (%)
3	 glass3.jpg	512 x 384	92,44
4	 glass4.jpg	512 x 384	92,07
5	 glass5.jpg	512 x 384	92,42
6	 glass6.jpg	512 x 384	91,98
7	 glass7.jpg	512 x 384	91,06
8	 glass8.jpg	512 x 384	92,17

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No	Image	Size	Accuracy (%)
9	 glass9.jpg	512 x 384	90,12
10	 glass10.jpg	512 x 384	91,44

Table 3 shows that the position of image capture affects the accuracy value obtained. For example, the image glass9.jpg has the lowest accuracy value, which is 90.12%, while the image glass3.jpg has the highest accuracy value, which is 92.44%. Some of the testing results on the waste images used as testing data, as shown in Table 3, demonstrate a detection accuracy rate of above 90%. The average accuracy value obtained from the detection of waste images using testing data is 91.585%. This proves that the system developed can detect waste taken from various angles and in various sizes and shapes from image data.

In Table 4, a comparative analysis of studies utilizing ResNet CNN architectures for waste classification is presented. In the study conducted by Z.M. A. Amin, et all [9] in 2021, an accuracy of 92.5% was achieved using the ResNet50 architecture. Subsequently, in 2023, P. N. Ma'arifah, et al [8] employed the ResNet101 architecture and achieved an accuracy of 77% for waste classification. In our study, leveraging the same ResNet101 architecture utilized by P. N. Ma'arifah, et al, we attained an improved accuracy of 90%. This indicates that our approach builds upon previous research efforts and yields superior results in waste classification using ResNet CNN architectures.

Table 4. Comparative Analysis of Studies

Author/Year	Architecture	Accuracy
Z. M. A. Amin, et al [9], 2021	Resnet50	92.5%
P. N. Ma'rifah, et al [8], 2023	Resnet 101	77%
Ourstudy	Resnet 101	90%

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4. CONCLUSION

The CNN ResNet101 model employed in this study has exhibited commendable performance in the classification of inorganic waste types. Specifically, the model achieved an impressive accuracy rate of 92% during the training phase and maintained a high accuracy of 90% during the testing phase, in effectively detecting objects within images of inorganic waste materials. This robust performance underscores the efficacy of the CNN ResNet101 architecture in accurately identifying and classifying waste materials, thereby contributing to the advancement of waste management practices. By leveraging deep learning techniques and the hierarchical feature extraction capabilities of CNNs, the model demonstrates its ability to discern subtle distinctions between different types of inorganic waste, aiding in the efficient sorting and processing of waste materials. The results obtained in this study not only validate the suitability of the CNN ResNet101 model for waste classification tasks but also highlight its potential for broader applications in environmental conservation and sustainability efforts. By harnessing the power of deep learning and convolutional neural networks, this research contributes to the development of automated systems capable of efficiently managing waste streams, ultimately leading to a cleaner and more sustainable environment.

REFERENCES

[1] R. D. Ramadhani, A. N. A. Thohari, C. Kartiko, A. Junaidi, T. G. Laksana, and N. A. S. Nugraha, "Optimasi Akurasi Metode Convolutional Neural Network untuk Identifikasi Jenis Sampah," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 5, no. 2, pp. 312–318, 2021.
[2] H. I. Abdel-Shafy and M. S. M. Mansour, "Solid waste issue: Sources, composition, disposal, recycling, and valorization," *Egypt. J. Pet.*, vol. 27, no. 4, pp. 1275–1290, 2018.
[3] T. Noor *et al.*, "Types, sources and management of urban wastes," in *Urban ecology*, Elsevier, 2020, pp. 239–263.
[4] P. Singh and V. P. Sharma, "Integrated plastic waste management: environmental and improved health approaches," *Procedia Environ. Sci.*, vol. 35, pp. 692–700, 2016.
[5] M. Yang and G. Thung, "Classification of trash for recyclability status," *CS229 Proj. Rep.*, vol. 2016, no. 1, p. 3, 2016.
[6] J. Nuariputri and P. Sukmasetya, "Klasifikasi Jenis Sampah Menggunakan Base ResNet-50," *J. Ilm. KOMPUTASI*, vol. 22, no. 3, pp. 379–386, 2023.
[7] S. Stephen, R. Raymond, and H. Santoso, "Applikasi Convolution Neural Network Untuk Mendeteksi Jenis-jenis Sampah," *Explor. J. Sist. Inf. dan Telemat. (Telekomunikasi, Multimed. dan Inform.*, vol. 10, no. 2, 2019.
[8] P. N. Ma'rifah, M. Sarosa, and E. Rohadi, "Comparison of Faster R-CNN ResNet-50 and ResNet-101 Methods for Recycling Waste Detection."

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[9] Z. M. A. Amin, K. N. Sami, and R. Hassan, "An approach of classifying waste using transfer learning method," *Int. J. Perceptive Cogn. Comput.*, vol. 7, no. 1, pp. 41–52, 2021.
[10] S. Liu, J. Zhang, Y. Xiang, W. Zhou, and D. Xiang, "A study of data pre-processing techniques for imbalanced biomedical data classification," *Int. J. Bioinform. Res. Appl.*, vol. 16, no. 3, pp. 290–318, 2020.
[11] F. Kamiran and T. Calders, "Data preprocessing techniques for classification without discrimination," *Knowl. Inf. Syst.*, vol. 33, no. 1, pp. 1–33, 2012.
[12] F. F. Maulana and N. Rochmawati, "Klasifikasi Citra Buah Menggunakan Convolutional Neural Network," *J. Informatics Comput. Sci.*, vol. 1, no. 02, pp. 104–108, 2019.
[13] Z. Xu, K. Sun, and J. Mao, "Research on ResNet101 network chemical reagent label image classification based on transfer learning," in *2020 IEEE 2nd International Conference on Civil Aviation Safety and Information Technology (ICCASIT*, 2020, pp. 354–358.
[14] M. A. Hanin, R. Patmasari, and R. Y. N. Fuâ, "Sistem Klasifikasi Penyakit Kulit Menggunakan Convolutional Neural Network (cnn)," *eProceedings Eng.*, vol. 8, no. 1, 2021.
[15] Q. Zhang, "A novel ResNet101 model based on dense dilated convolution for image classification," *SN Appl. Sci.*, vol. 4, pp. 1–13, 2022.
[16] S. Vaishali and S. Neetu, "Enhanced copy-move forgery detection using deep convolutional neural network (DCNN) employing the ResNet-101 transfer learning model," *Multimed. Tools Appl.*, vol. 83, no. 4, pp. 10839–10863, 2024.
[17] R. G. Guntara, "Deteksi Atap Bangunan Berbasis Citra Udara Menggunakan Google Colab dan Algoritma Deep Learning YOLOv7," *J. Manaj. Sist. Inf.*, vol. 2, no. 1, pp. 9–18, 2023.