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# Classification of Organic and Non-Organic Waste Using Convolutional Neural Network (CNN)

**Muhammad Farhan[1*], Mhd Farhan Aditiya[2], Dafa Ikhwanu Shafa[3], Supiyandi[4], Aidil Halim Lubis[5]**

[*1),2),3),5)]Universitas Islam Negeri Sumatera Utara, Jl. Lapangan Golf, Desa Durian Jangak, Kecamatan Pancur Batu, Kabupaten Deli Serdang, Sumatera Utara, 20353
[4)]Universitas Pembangunan Panca Budi, Jl. Jend. Gatot Subroto Km 4,5, Sei Sikambing, Medan, Sumatera Utara, 20122
[*1]*email : mf888943@gmail.com*
[2]*email: farhanaditya503@gmail.com*
[3]*email : dafaikhwanu334@gmail.com*
[4]*email : supiyandi.mkom@gmail.com*
[5]*email : aidilhalimlubis@uinsu.ac.id*

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***ABSTRACT*** *– The increase in waste volume in Indonesia, which reached emergency levels in 2024, requires technological solutions that can assist in the sorting process quickly and accurately. Previous research on CNN-based waste classification generally focused on recyclable waste categories with many classes and used structured datasets, which did not adequately represent real-world waste conditions, especially organic waste, which has more varied shapes and conditions. Based on this gap, this study proposes a Convolutional Neural Network (CNN) model for classifying two main categories—organic and inorganic—using 25,077 images and direct testing on field samples. The model was trained using the Adam optimizer and categorical crossentropy loss. The results show high accuracy for inorganic waste (96%), but lower accuracy for organic waste (62%) due to the complexity of texture and natural damage. This study contributes to the field of informatics through the application of more applicable and realistic deep learning for automatic waste sorting systems, as well as opening up opportunities for the development of model architectures that are more adaptive to waste conditions in the actual environment.*

***Keywords*** *– Convolutional Neural Networks, Deep Learning, Image Classification, Organic and Inorganic Waste, Waste Classification*

# *Klasifikasi Sampah Organik dan Non Organik Menggunakan Convolutional Neural Network (CNN)*

***ABSTRAK*** *– Peningkatan volume sampah di Indonesia hingga mencapai status darurat pada tahun 2024 menuntut solusi teknologi yang mampu membantu proses penyortiran secara cepat dan akurat. Penelitian terdahulu mengenai klasifikasi sampah berbasis CNN umumnya berfokus pada kategori sampah daur ulang dengan banyak kelas dan menggunakan dataset terstruktur, sehingga kurang merepresentasikan kondisi sampah nyata, terutama sampah organik yang memiliki bentuk dan kondisi lebih bervariasi. Berdasarkan gap tersebut, penelitian ini mengusulkan model Convolutional Neural Network (CNN) untuk klasifikasi dua kategori utama—organik dan anorganik—menggunakan 25.077 citra serta pengujian langsung pada sampel lapangan. Model dilatih menggunakan optimizer Adam dan loss categorical crossentropy. Hasilnya menunjukkan akurasi tinggi pada sampah anorganik (96%), namun lebih rendah pada sampah organik (62%) akibat kompleksitas tekstur dan kerusakan alami. Penelitian ini memberikan kontribusi pada bidang informatika melalui penerapan deep learning yang lebih aplikatif dan realistis untuk sistem penyortiran sampah otomatis, serta membuka peluang pengembangan arsitektur model yang lebih adaptif terhadap kondisi sampah di lingkungan sebenarnya.*

***Kata Kunci*** *- Convolutional Neural Network, Deep Learning, Klasifikasi Gambar, , Klasifikasi Sampah, Organik, Pengolahan Sampah, Sampah Anorganik*

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## 1. INTRODUCTION

The issue of waste has become an increasingly pressing environmental issue as time goes by, both nationally and globally. In Indonesia, this issue reached a critical point in 2024, when the country was declared to be in a state of waste emergency. Based on SIPSN data in 2024, during that period, the volume of waste increased significantly to around 38,170 million tons/year, with 33.68% of waste being managed and 66.32% of waste being unmanaged. This means that around 25,316,514.65 tons/year were not properly managed. This is a major issue that warrants attention, as it has the potential to cause serious impacts on the environment and public health [1].

Waste management needs to be carried out in a balanced and controlled manner, because imbalances in its management have the potential to cause damage and environmental pollution. Greater risks can arise when waste is not handled properly, which ultimately has a negative impact on the quality of human life. Therefore, maintaining a healthy environment now and in the future requires increased awareness and the implementation of good waste management practices in real life, in order to prevent pollution and support the welfare of the community [2].

Waste types can be classified based on their constituent materials, level of hazard, and source or location where the waste is generated, such as from industrial or household activities. In addition, waste can also be grouped into two main categories, namely organic waste and inorganic waste [3]. Among the various types of waste, Municipal Solid Waste (MSW) is the most widely produced category. This type of waste comes from household activities, offices, hotels, schools, and various other facilities. According to data from the United States Environmental Protection Agency (EPA), the amount of MSW continued to increase from 1960 to 2012. In 1960, the amount was recorded at around 88 million tons, and increased significantly to 250 million tons in 2012 [4].

To address the issue of waste, various efforts have been made, such as more efficient waste management, recycling activities, and reducing the use of disposable materials. Recycling is one method that provides significant benefits to the environment while also having the potential to boost the country's economy. These efforts can create new job opportunities, preserve the environment, and improve public health because the environment becomes cleaner and free from waste accumulation.

One of the most commonly used learning methods for image classification tasks is Convolutional Neural Network (CNN). This method performs well in grouping image collections and in performing real-time image recognition in various applications [5][6][7]. This method is a further development of Multilayer Perceptron (MLP), making it more effective in handling visual data [8]. The CNN process consists of two main stages. First, the feature extraction layer, which extracts important features from the image and stores them as feature representations. Second, the fully connected layer, which utilizes these features to classify objects in the previously processed image [9].

According to Azis, F. A., Suhaimi, H., and Abas, E., who researched the classification of recyclable waste using the CNN algorithm, the process involves extracting a number of features from the image dataset, grouping the data, and then utilizing the information obtained to classify the images into six categories, namely cardboard, glass, metal, paper, plastic, and other waste [5].

Previous research [10] compared CNN and SVM for waste classification by reducing the image size from 256×256 to 32×32 using the AlexNet architecture. As a result, SVM achieved an accuracy of 94.8%, higher than CNN, which achieved 83%. Maeda-Gutiérrez V also compared various architectures such as AlexNet, GoogleNet, Inception V3, ResNet18, and ResNet50, and found that GoogleNet provided the highest accuracy of 99.72% through fine-tuning, while Inception V3 showed the lowest performance [11].

Previous studies have used CNNs for waste classification, but most still focus on recyclable waste categories with many classes and use structured datasets that do not reflect the actual conditions of waste in the field. In addition, model performance is generally tested on balanced data, which does not address the challenges of organic waste, which has more complex variations in shape and condition. Seeing this gap, this study focuses on the classification of two main categories-organic and non-organic—using a large dataset and direct testing on real samples to produce a model that is more relevant and applicable in waste sorting systems.

Based on the issues described above, this study aims to classify organic and non-organic waste using image processing methods based on Convolutional Neural Network (CNN). This study also focuses on obtaining optimal model evaluation results through measuring accuracy, precision, recall, and F1-score values.

## 2. RESEARCH METHOD

In this study, a Convolutional Neural Network CNN) model was used to classify organic and inorganic waste. The dataset used was Waste Classification Data downloaded from the Kaggle website, which provides various datasets for research purposes [12]. The data analyzed consisted of images of organic and inorganic waste. The complete research flow can be seen in Figure 1.

The initial stage of this research is to collect and analyze the data needed for program development. Once the data has been collected and analyzed, the process continues with the design of an application to determine the most appropriate solution to the problem. The next stage is coding, which is the process of building and creating the program. Once the program has been created, it is tested. If any failures or incompatibilities are found, the program is corrected and retested until it functions properly. After passing the test, the program is implemented on the actual object as a second stage of testing. When the entire process runs smoothly, an evaluation stage is carried out to review the prog ram's shortcomings and weaknesses so that they can be corrected.

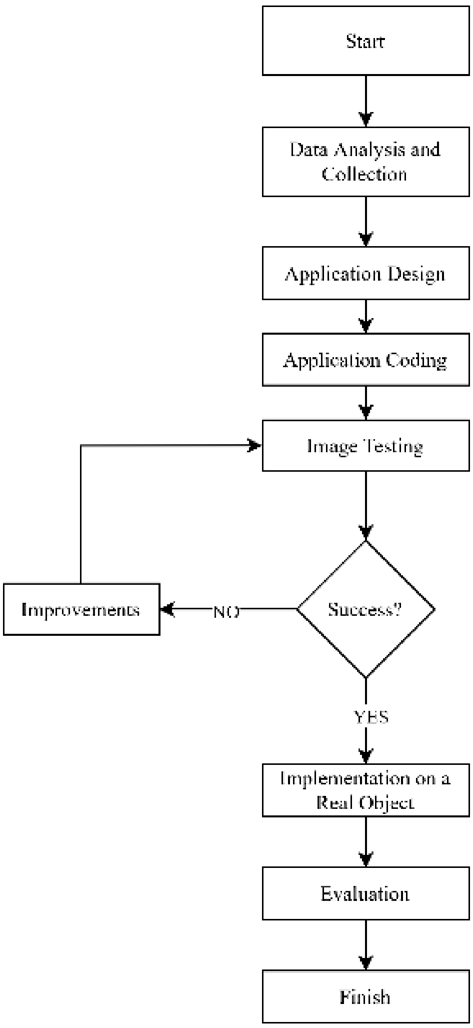


Figure 1. Research Stages [13]

1. Deep Learning

Deep learning is a representation learning method that enables computer models with multiple processing layers to learn data at various levels of abstraction [14]. Deep learning is a learning method that utilizes multi-layered artificial neural networks, whose structure mimics the way the human brain works through connections between neurons. This approach uses multi-level non-linear transformations to learn complex patterns, so it can be seen as a development of machine learning based on artificial neural networks [15].

Deep learning has also become a new branch of machine learning that is increasingly popular thanks to advances in GPU acceleration technology [16]. This method is particularly suitable for use in computer vision, including object classification tasks in images. One of the most commonly used machine learning approaches for image classification is the Convolutional Neural Network (CNN).

2. Convolutional Neural Network

Convolutional Neural Network (CNN) is a type of Artificial Neural Network (ANN) specifically designed to process data in the form of images, videos, and sounds [17]. CNN works on a principle similar to ANN, which is to mimic the workings of human brain cells, but each neuron in CNN is represented in two dimensions, making the process simpler.

CNN works on a principle similar to ANN, which is to mimic the workings of human brain cells, but each neuron in CNN is represented in two dimensions, making the process simpler. Convolutional Neural Network (CNN) is an advancement of the Multi Layer Perceptron (MLP) architecture that is specifically designed to process two-dimensional data. As part of Deep Neural Network, CNN is widely used in image processing because it is capable of recognizing patterns, detecting objects, and extracting features automatically through its convolutional layers [18][19].

CNN is a type of deep neural network that has many layers, making it effective for image data processing. The CNN architecture generally consists of several main components, such as convolution layers, activation (ReLU) layers, pooling layers, and fully connected layers that work together to extract features and generate accurate predictions [20].

## 3. RESULTS AND DISCUSSION

1. Data Collection

The data used in this study consists of .jpg images obtained from the Kaggle website. A total of 25,077 images were collected and divided into two data groups. For the training data, the organic class had 12,565 images, while the recycle class had 9,999 images, bringing the total training data to 22,564 images (90%) with two classes, as shown in Figure 2. Meanwhile, in the test data, the organic class consists of 1,401 images and the recycle class consists of 1,112 images, bringing the total test data to 2,513 images (10%) with two classes.

**Preprocessing The Training Data**

```
training_generator = training.flow_from_directory(
    'DATASET/TRAIN',
    target_size=(150, 150),
    shuffle=True,
    class_mode='binary',
    batch_size=20,
)

... Found 22564 images belonging to 2 classes.
```

**Preprocessing The Test Data**

```
validation_generator = validation.flow_from_directory(
    'DATASET/TEST',
    target_size=(150, 150),
    shuffle=True,
    class_mode='binary',
    batch_size=20,
)

... Found 2513 images belonging to 2 classes.
```

Figure 2. Preprocessing data train dan data test

2. Data Training

The training data used covers 90% of the entire dataset, consisting of 22,564 images divided into two classes. At this stage, the model was compiled using the compile function with the configuration optimizer = 'adam', loss = 'categorical_crossentropy', and metrics = ['accuracy']. The training process was carried out with the parameters x = training_set, validation_data = test_set, and a total of 4 epochs. The training results are shown in Figure 3.

```
history = model.fit(
    training_generator,
    validation_data = validation_generator,
    batch_size=32,
    verbose=True,
    epochs=4
)

... /usr/local/lib/python3.12/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset
  self._warn_if_super_not_called()
Epoch 1/4
1129/1129 ━━━━━━━━━━━━━━━━━━━━ 591s 521ms/step - accuracy: 0.7504 - loss: 0.5156 - val_accuracy: 0.8436 - val_loss: 0.3782
Epoch 2/4
1129/1129 ━━━━━━━━━━━━━━━━━━━━ 590s 522ms/step - accuracy: 0.8149 - loss: 0.4225 - val_accuracy: 0.8170 - val_loss: 0.4439
Epoch 3/4
1129/1129 ━━━━━━━━━━━━━━━━━━━━ 586s 519ms/step - accuracy: 0.8282 - loss: 0.3958 - val_accuracy: 0.8639 - val_loss: 0.3270
Epoch 4/4
1129/1129 ━━━━━━━━━━━━━━━━━━━━ 593s 525ms/step - accuracy: 0.8371 - loss: 0.3782 - val_accuracy: 0.8703 - val_loss: 0.3190
```

Figure 3. Training results

The graphs in Figures 4 and 5 show Training and Validation Accuracy as well as Training and Validation Loss. From these graphs, it can be seen that the accuracy on the training data is quite high, but the accuracy on the validation data is still not optimal. This is due to the limited number of samples in the validation data, which only covers 10% of the total 25,077 images. Some possible solutions include increasing the number of image samples for the validation data, increasing the number of epochs, and modifying the CNN model architecture.

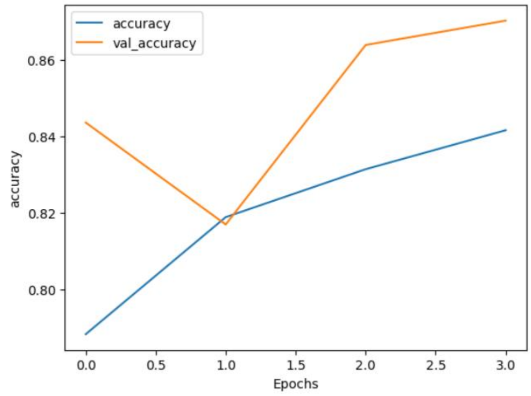



Figure 4. Training And Validation Accuracy Graph

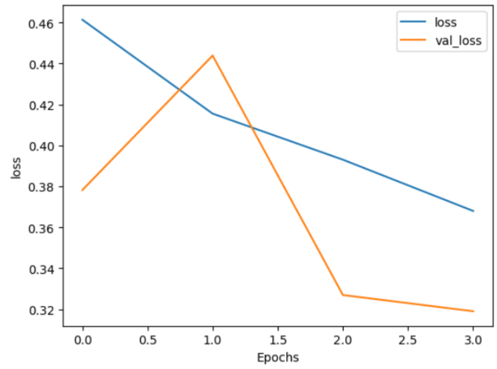



Figure 5. Training And Validation Loss Graph

3. Implementation and Testing

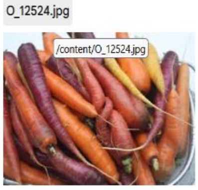
During the testing phase, samples were taken from a dataset containing images of various types of waste. Samples were taken randomly, covering images of both organic and inorganic waste, as well as various conditions of waste—both those that were still intact and those that were damaged or decayed.

The system was designed to be implemented in landfills in the form of a device resembling an X-ray machine. The working principle is similar to X-ray or radiography examinations, which utilize electromagnetic radiation to produce images. The system is designed to work automatically to sort waste using AI technology based on a deep learning approach.

Table 1 shows examples of waste classification identification results using the CNN method.

Table 1. Results Of Identification Using The Cnn Method

| Description | Prediction Results |
|---|---|
| In the image above, the prediction result shows that the image is categorized as organic waste. | O_185.jpg  |

| Description | Prediction Results |
|---|---|
| The image on the right shows the prediction resultthat the image is categorized as inorganic waste. |  |
| In the image above, the prediction result shows that the image is categorized as organic waste. |  |
| The image on the right shows the prediction resultthat the image is categorized as inorganic waste. |  |

4. Testing

During the testing phase, we used 40 data samples consisting of various types and conditions of waste. This step was taken to ensure that the system would function properly when applied in real-world conditions, given that the shape and condition of waste in the field often varies. Table 2 shows the test results, which include the prediction accuracy rate and error percentage for each type of waste condition.

Table 2. Test Results

| Condition Trash | Data | Correct | Incorrect | Accuracy | Error |
|---|---|---|---|---|---|
| Non Organic | 40 | 38 | 2 | 96% | 4% |
| Organic | 40 | 21 | 19 | 62% | 38% |

## 4. CONCLUSION

This study proves that an informatics approach using Convolutional Neural Networks (CNN) can make a significant contribution to solving waste sorting problems. The CNN model developed is capable of automatically extracting visual features, thereby reducing dependence on slow and inconsistent manual processes. Testing shows excellent performance for inorganic waste, although there are still challenges in recognizing organic waste with more diverse characteristics. Through data quality improvement, model architecture expansion, and augmentation techniques, this system has the potential to become an effective informatics solution to support waste processing automation in real facilities. Thus, this research makes a real contribution to the field of applied informatics, particularly in the integration of computer vision technology to support sustainability and efficiency in environmental management.

## 5. SUGGESTIONS AND FEEDBACK

Based on the results of the research that has been conducted, there are still several aspects that can be improved to obtain more optimal model performance. The amount of data, especially in the organic class, needs to be increased so that the model has better generalization capabilities, given the more complex variations in the shape and condition of organic waste. The use of data augmentation techniques can be an alternative to enriching data variation without having to manually increase the number of images. In addition, increasing the number of epochs and adjusting the CNN architecture, such as adding layers or using pre-trained models, can help improve accuracy, especially in conditions where waste is difficult to recognize. For implementation in the field, the system also needs to be tested in more diverse environments in order to assess the robustness of the model against lighting, image capture angles, and unexpected waste conditions. Overall, further development is highly recommended so that this deep learning-based waste sorting system can be implemented more effectively and reliably on an industrial scale and in waste processing facilities.

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