

Traspoter Application Development: Website-Based Automatic Garbage Classification Using CNN Method

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Abstract. *This research focuses on the development of automatic waste classification by applying the Convolutional Neural Network (CNN) method in a web-based application. This system is designed to help the waste management process through automatic sorting between organic and inorganic waste, so that it can support recycling efforts and reduce environmental impacts. In its application, this application utilizes the CNN algorithm to analyze images and recognize the type of waste with good accuracy. The development uses technologies such as Python and OpenCV to ensure efficient processing of image data, with the CNN model trained using a dataset of 22,564 images. Test results show excellent accuracy, reaching 99.27% for organic waste and 98.72% for inorganic waste.*

Keywords *Automatic Garbage Classification, Recycling, CNN, Python, OpenCV*

1. INTRODUCTION

Traspoter is the name of the app that describes its main role as a "transporter" or "mover" of information about waste to support more appropriate sorting. The app works to identify and classify waste into appropriate categories, assisting users in "transporting" waste towards more effective management, including recycling options. The name reflects the ease and efficiency provided to users to make eco-friendly decisions.

Waste is a serious problem in many countries, including Indonesia. Based on a report (Ibnul Rasidi et al., 2022), the volume and type of waste in Indonesia continues to increase every year along with population growth. Data from the National Waste Management Information System (SIPSN) in 2021 shows that the amount of waste generation reached 24.67 million tons per year, with a reduction of 13.38% or around 3.3 million tons from the previous year. However, only 50.43% or around 12.44 million tons of waste were successfully managed (SIPSN, 2021). This is equivalent to a daily waste production of around 67,590 tons or 0.25 kg per person. This condition illustrates the waste emergency situation in Indonesia (Ibnul Rasidi et al., 2022).

Waste is divided into two types based on its nature, namely inorganic and organic waste. Inorganic waste includes materials such as metals, broken glass, and plastics that are difficult to decompose, while organic waste includes materials that can decompose such as kitchen scraps, leaves, and fruits (Zayadi & Hayat, n.d.2018). The lack of public knowledge and

awareness in waste management often causes these two types of waste to be mixed in the surrounding environment.

The Transporter application is designed to perform automatic classification of waste. Classification, according to (Qasim & Khan, 2022), is the process of assessing a data object to group it into a particular class from several types of available classes. In this application, waste classification is done automatically, utilizing the principle of automation which is defined by (Sutarno & Gaffar, 2023) as a discipline that transforms manual work into automatic. This approach facilitates the overall waste management process.

Transporter was developed as a web-based application to provide wider access to users. Through the web platform, this application allows users to manage information and perform waste management functions more effectively and efficiently. As explained by (Firmansyah et al., 2024), a website is a medium that can accommodate various information, including text, sound, images, and animation, which can be accessed via the internet.

In addition, this application relies on Convolutional Neural Network (CNN) technology to improve accuracy in the classification of garbage objects. CNN, according to (Nasution & Herdianto, 2022), is a development of neural networks designed to improve the weaknesses in these networks, especially in object classification tasks. The combination of these technologies supports the efficiency and accuracy of waste management through the Transporter application.

2. THEORETICAL STUDY

1. Automatic Waste Classification

Automatic waste classification is a system that uses certain sensors or technology to identify and separate types of waste based on predetermined categories, such as organic and non-organic (Anas et al., 2023). With this system, the classification does not need to be done manually again.

2. Python

Python is an arguably high-level programming language, developed by Guido Van Rossum and introduced to the public in 1991. In recent years, Python has gained significant popularity among programming languages. In addition, Python is also a versatile language; for example, it can be used in the field of Deep Learning. Python was chosen for research purposes due to its ease of use, and its open source nature (Alfarizi et al., 2023).

3. CNN (Convolutional Neural Network)

To solve the waste sorting problem, we can utilize Machine Learning technology, especially CNN (Abror, 2020). CNN is an algorithm that is often used for image data processing (Xin & Wang, 2019). With the application of CNN, it is expected that garbage can be sorted more accurately (Sungheetha, 2021). This website takes photos of garbage taken by users, then uses CNN algorithm to identify the type of garbage. The results of this identification are then presented to the user through a website that is convenient to use, and allows the user to distinguish the appropriate category of garbage for disposal based on its classification.

4. OpenCV

OpenCV, or Open Source Computer Vision Library, is an open source library developed by Intel to support various digital image processing applications. This library offers various functions, such as object detection, motion tracking, and facial recognition, which make it easier to implement computer vision technology in application development (Anas et al., 2023).

3. METHODS

This research applies a web-based application development method using the Convolutional Neural Network (CNN) algorithm. The main focus of this research is to classify waste into organic and inorganic categories, enabling automatic identification of waste types based on input in the form of images and real objects. The dataset used by the model is taken from the *Waste Classification* dataset. The data used to train the model is taken from the Kaggle platform, a site that provides various datasets to support research (Ibnul Rasidi et al., 2022).

The initial stage of the research involves the preparation of the data required to develop the application system; next, the model design and selection of appropriate algorithms for testing is carried out, if the data check is successful it will proceed to the integration stage of the model with the application. Once this stage is completed, the application will then enter into a thorough evaluation stage, which is fundamentally designed to identify and correct any flaws or limitations that may exist in the application, ensuring that it operates at its optimal capacity. Ultimately, this stage not only enhances the overall functionality of the application but also the refinement and improvement of the overall user experience.

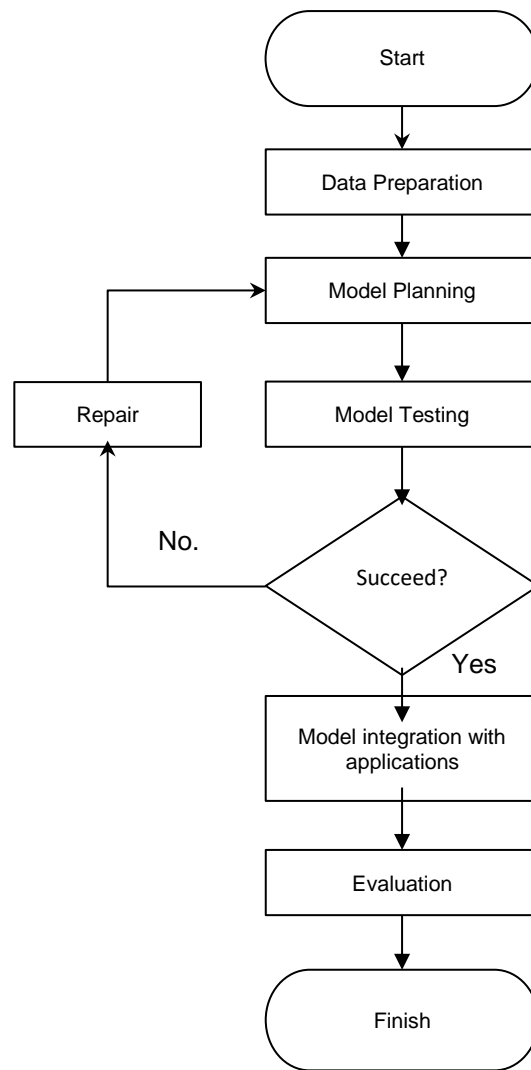


Figure 1. Research Stages Diagram.

4. RESULTS

In this section we implement the Traspoter application and produce an automatic waste classification system, the following are the stages and results obtained:

A. Data Collection

The dataset used in this system is the *Waste Classification Data* available on the Kaggle platform (Ibnul Rasidi et al., 2022). This dataset consists of a collection of classified images divided into two groups, namely organic and inorganic. The data was collected in image formats of varying resolutions, which were suitable for use in the development with the Convolutional Neural Network (CNN) algorithm. The total number of images from this dataset consists of 25,077 images, which are divided into two groups; training data of 22,564 images (90%) and testing data of 2,513 images (10%).

```
[ ] # 2. Preprocessing Data menggunakan ImageDataGenerator
# Image augmentation untuk mengurangi overfitting
train_datagen = ImageDataGenerator(
    rescale=1.0/255.0,      # Normalisasi pixel ke [0, 1]
    rotation_range=20,      # Rotasi gambar acak
    width_shift_range=0.2,  # Pergeseran gambar secara horizontal
    height_shift_range=0.2, # Pergeseran gambar secara vertikal
    shear_range=0.2,       # Shear gambar
    zoom_range=0.2,        # Zoom gambar
    horizontal_flip=True,   # Membalik gambar secara horizontal
    fill_mode='nearest'    # Pengisian piksel kosong
)

test_datagen = ImageDataGenerator(rescale=1.0/255.0)

[ ] # 3. Menyiapkan generator untuk melatih model
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(150, 150), # Ukuran gambar yang diinginkan
    batch_size=32,
    class_mode='binary'     # Karena hanya ada 2 kelas: Organik dan Anorganik
)

test_generator = test_datagen.flow_from_directory(
    test_dir,
    target_size=(150, 150),
    batch_size=32,
    class_mode='binary'
)

➡ Found 22564 images belonging to 2 classes.
Found 2513 images belonging to 2 classes.
```

Figure 2. Preprocessing training data and test data.

B. Data Training

The model training process uses Convolutional Neural Network (CNN) by utilizing training data of 22,564 images. covering images for organic class as many as 12,565 images and inorganic class as many as 9,999 images to increase data variation and reduce overfitting. the model was trained for 20 *epochs* with batch size 32, using *binary crossentropy* function as *loss function* and *Adam* optimizer.

```

Epoch 1/20
706/706 [=====] - 141s 191ms/step - loss: 0.4478 - accuracy: 0.8045 - val_loss: 0.3455 - val_accuracy: 0.8496
Epoch 2/20
706/706 [=====] - 121s 172ms/step - loss: 0.3979 - accuracy: 0.8287 - val_loss: 0.3385 - val_accuracy: 0.8786
Epoch 3/20
706/706 [=====] - 124s 175ms/step - loss: 0.3744 - accuracy: 0.8422 - val_loss: 0.3153 - val_accuracy: 0.8774
Epoch 4/20
706/706 [=====] - 149s 210ms/step - loss: 0.3535 - accuracy: 0.8544 - val_loss: 0.2940 - val_accuracy: 0.8806
Epoch 5/20
706/706 [=====] - 140s 198ms/step - loss: 0.3492 - accuracy: 0.8582 - val_loss: 0.2839 - val_accuracy: 0.8818
Epoch 6/20
706/706 [=====] - 132s 187ms/step - loss: 0.3330 - accuracy: 0.8636 - val_loss: 0.2505 - val_accuracy: 0.9037
Epoch 7/20
706/706 [=====] - 131s 185ms/step - loss: 0.3191 - accuracy: 0.8699 - val_loss: 0.2967 - val_accuracy: 0.8949
Epoch 8/20
706/706 [=====] - 124s 176ms/step - loss: 0.3202 - accuracy: 0.8685 - val_loss: 0.2480 - val_accuracy: 0.9033
Epoch 9/20
706/706 [=====] - 132s 186ms/step - loss: 0.3168 - accuracy: 0.8729 - val_loss: 0.2827 - val_accuracy: 0.8981
Epoch 10/20
706/706 [=====] - 127s 179ms/step - loss: 0.3059 - accuracy: 0.8750 - val_loss: 0.2323 - val_accuracy: 0.9133
Epoch 11/20
706/706 [=====] - 122s 173ms/step - loss: 0.3038 - accuracy: 0.8793 - val_loss: 0.2618 - val_accuracy: 0.9069
Epoch 12/20
706/706 [=====] - 121s 171ms/step - loss: 0.2894 - accuracy: 0.8833 - val_loss: 0.2648 - val_accuracy: 0.9037
Epoch 13/20
706/706 [=====] - 123s 174ms/step - loss: 0.2915 - accuracy: 0.8833 - val_loss: 0.2314 - val_accuracy: 0.9196
Epoch 14/20
706/706 [=====] - 118s 167ms/step - loss: 0.2865 - accuracy: 0.8837 - val_loss: 0.2656 - val_accuracy: 0.9081
Epoch 15/20
706/706 [=====] - 107s 152ms/step - loss: 0.2840 - accuracy: 0.8881 - val_loss: 0.2200 - val_accuracy: 0.9188
Epoch 16/20
706/706 [=====] - 98s 139ms/step - loss: 0.2800 - accuracy: 0.8892 - val_loss: 0.2666 - val_accuracy: 0.8973
Epoch 17/20
706/706 [=====] - 108s 152ms/step - loss: 0.2807 - accuracy: 0.8886 - val_loss: 0.2333 - val_accuracy: 0.9129
Epoch 18/20
706/706 [=====] - 98s 138ms/step - loss: 0.2710 - accuracy: 0.8921 - val_loss: 0.2408 - val_accuracy: 0.9101
Epoch 19/20
706/706 [=====] - 101s 143ms/step - loss: 0.2676 - accuracy: 0.8938 - val_loss: 0.2418 - val_accuracy: 0.9101
Epoch 20/20
706/706 [=====] - 100s 141ms/step - loss: 0.2671 - accuracy: 0.8946 - val_loss: 0.2250 - val_accuracy: 0.9160

```

Figure 3. Training Model.

The training results show a graph of training accuracy that increases consistently at each epoch. In contrast, the validation accuracy shows a fluctuating pattern, indicating a limitation in the amount of validation data used, thus affecting the generalization of the model. The following graphs display the results of Training and Validation Accuracy as well as Training and Validation Loss in Figure 4 and Figure 5. Based on these results, the model performed quite well during the training process. The accuracy on the training data continues to increase steadily, while the validation accuracy fluctuates slightly but remains at a high level. These results show that the model has a fairly good generalization ability, although there are still opportunities for further improvement.

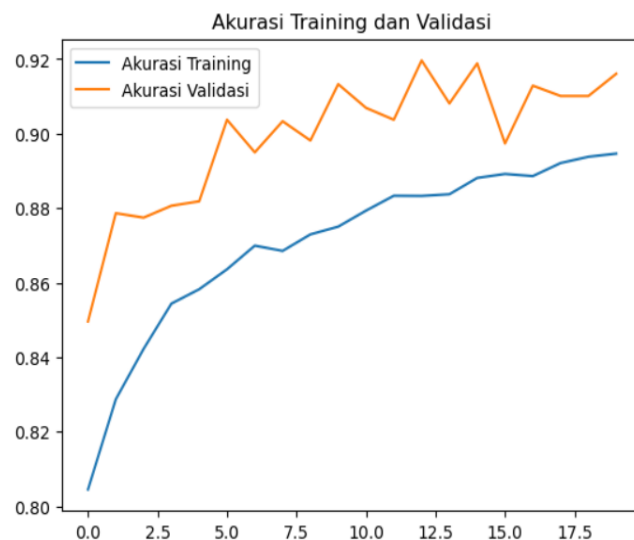


Figure 4. Accuracy Chart of Training and Validation.

In Figure 4, the training accuracy increases gradually from the beginning of training with a value of around 0.80 until it reaches 0.90 at the end of training. The validation accuracy shows a fairly high performance since the beginning of training, with an average of above 0.90. Small fluctuations in validation accuracy indicate that the model can still be optimized to obtain more stable results.

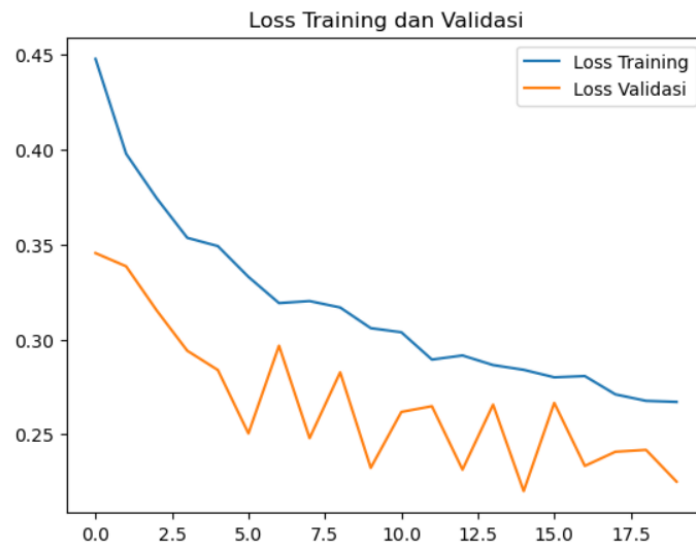
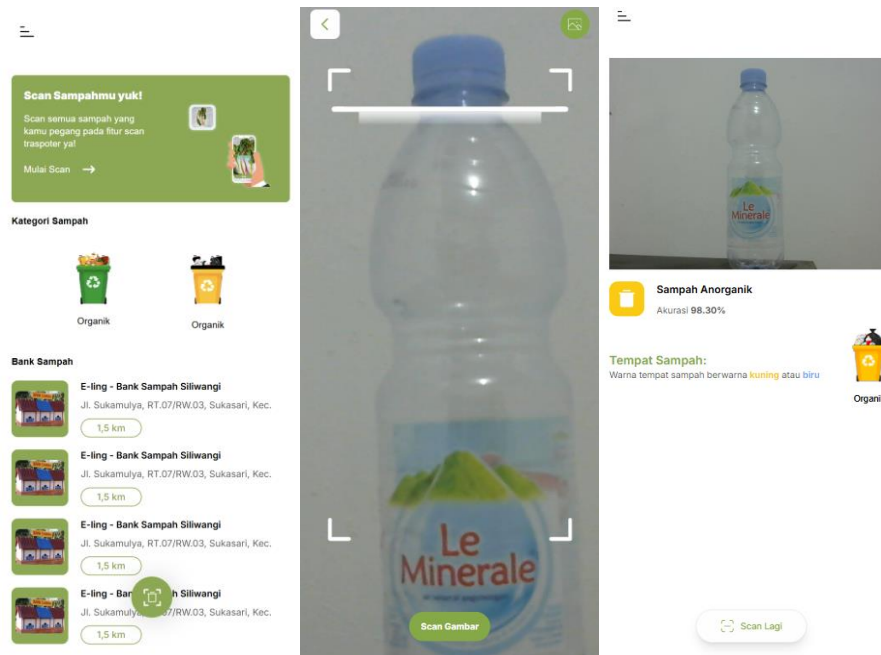


Figure 5. Loss Training and Validation Graph.

In Figure 5, the training loss value consistently decreases from the beginning of training until it reaches a value of about 0.25 at the end of training. Meanwhile, the validation loss value shows a similar decreasing pattern, with the final value being around 0.23. Although there are slight variations at some epoch points, the model is proven to learn and recognize patterns from the data effectively without experiencing significant overfitting.

C. Model Integration with Applications

The Traspoter application implementation process involves several stages of development. Frontend development is designed using HTML, Tailwind CSS. Then on the Backend the application has been developed using python with nextjs. The interface provides a Scan Trash feature by uploading a photo of trash in the *gallery* or choosing to take a picture directly through the camera. After making a choice, the application will immediately scan the image and will be classified by the system. If the classification process is complete, the system will display results such as the type of organic or inorganic waste.



Gambar 6. Application Implementation and Garbage Classification Results.

D. Test Run

In this testing phase we tried as many as 20 images of garbage of different types and conditions. Table 1 shows the results of the test on the Traspoter application.

Table 1. Application Test Results

Type of Waste	Data	Correct	Wrong	Accuracy	Error
Inorganic	10	10	0	98,72%	1,28%
Organic	10	10	0	99,27%	0,73%

The test results of the Traspoter application show a very good level of accuracy in classifying organic and inorganic waste. The average accuracy for organic waste reached 99.27% with an error rate of 0.73%, while for inorganic waste, the accuracy reached 98.72% with an error rate of 1.28%. The system successfully classified various types of waste with consistent performance, such as eggshells, rotten rice, cardboard, and cans. However, there are some waste types that have higher error rates, such as mango peels (95.46%) and light bulbs (95.35%), indicating the need for further optimization.

5. CONCLUSION

This research successfully developed a web-based application called Traspoter using Convolutional Neural Network (CNN) technology for automatic waste classification. The CNN method used in this research is proven to be able to identify the type of waste quickly

and accurately as evidenced by the training and trial data. This application can recognize organic and inorganic waste with a very good accuracy rate, namely 99.27% for organic waste and 98.72% for inorganic waste. These results show that the Traspoter application can be a solution in supporting waste management effectively. Future research can be focused on optimizing the CNN architecture and increasing the amount of data in the dataset to increase the accuracy rate and reduce potential errors in classification. This application is expected to have a major impact on waste management and encourage the creation of a clean and healthy environment.

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