

Densenet Architecture Implementation for Organic and Non-Organic Waste

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Abstract: Garbage is the result left over from the process of daily human activities and activities which are considered no longer suitable for use, ranging from household waste to large-scale industrial waste. Therefore, the classification of waste is important because the problem of waste disposal is increasing and the way of processing is wrong. This research focuses on the classification of organic and non-organic waste using the DenseNet architecture. The dataset is processed first and each image in the dataset is resized to 128x128 pixels before being used in the model. We then trained all DenseNet types namely DenseNet121, DenseNet169, DenseNet 201, and compared their performance. Based on the test results, all DenseNet models that were trained were able to produce good accuracy, precision, recall, and F1 scores in garbage classification. In particular, our designed DenseNet121 model achieves 93.1 accuracy, 94.08% precision, 94.00% recall, 94.03% F1 score and 1min 34s training time as the best among other models. These results prove that the DenseNet architecture can be used to classify organic and non-organic waste correctly.

Keywords: Computer Vision, Convolutional Neural Network, DenseNet, Image Classification, Waste, Organic and Non Organic Waste.

INTRODUCTION

Garbage is the result left over from the process of daily human activities and activities which are considered no longer suitable for use, ranging from household waste to large-scale industrial waste. Human activities and activities are the main factors for the emergence of waste and will have an adverse impact on human health and the surrounding environment if not handled properly (Syamsir & Pangestuty, 2020). The problem of waste disposal has continued to increase in recent years due to the large-scale production of consumer goods in almost every industry and current waste treatment is still limited to using simple waste treatment methods, namely placing them in temporary disposal sites (Malik et al., 2022). Then the waste is transported directly to the final disposal site without carrying out the sorting process in the processing process first which makes the process not in accordance with the rules of waste management procedures (Ode Rosnawati et al., n.d.)

Therefore, in the waste management process, it is necessary to separate waste into organic and non-organic waste. Organic waste is waste that comes from living things that is easily decomposed, while non-organic waste is synthetic waste that is difficult to decompose (Hurst et al., 2022). However, most people still have difficulty sorting organic and non-organic waste, so an application is needed to help socialize waste sorting to the community (Wong, 2022).

Research on the classification of organic and non-organic waste that has been done previously is by using the Backpropagation neural network method to implement an organic and non-organic waste classification system, where the accuracy of the system is 90% with an average prediction time of 42.9 ms. (Fantara et al., 2018). Another method that can be used is to use the Dense Convolutional Network

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(DenseNet) architecture, which connects each layer built with feedback control (Pardede & Putra, 2020). DenseNet is one of the Convolutional Neural Network (CNN) architectures which is the most widely used Machine Learning algorithm in learning image objects (Liao et al., 2023). CNN works by receiving input in the form of an image, that is, the input will be trained in several layers to produce output that can recognize the input object (Ramadhani et al., 2021). Currently DenseNet has several architectures such as DenseNet121, DenseNet169 and DenseNet201, where each architecture has its own characteristics. DenseNet121 is 33 MB, DenseNet169 is 57 MB, DenseNet201 is 80 MB (Saputra et al., 2023).

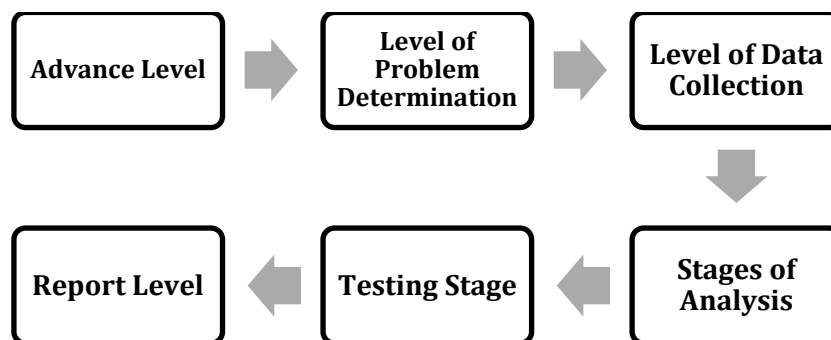
In this study, the number of images used in this study were 22,500 images of waste which would be processed using the Convolutional Neural Network (CNN) algorithm with the DenseNet architectural model consisting of DenseNet201, DenseNet121, and DenseNet169 to classify the two types of waste classes, namely organic waste and non-organic waste.

LITERATURE REVIEW

The following is a collection of previous studies that the researcher used as reference material in preparing the researcher's research proposal: Fahmi et al. succeeded in classifying waste using the Support Vector Machine model combined with the Convolutional Neural Network with an accuracy of 96.16% and a loss of 7.25% (Fahmi & Yudhana, 2023). Kurniawan et al. using the Xception architecture with Adam optimizer and a learning rate of 0.001 has an accuracy of 87.81% in the classification of inorganic waste (Kurniawan et al., 2023), Prakash et al. obtained accurate results from predicting liver lesions using the DenseNet architecture of 98.34%, sensitivity of 99.72%, and recall of 97.84%, and compared with other architectures with the result that DenseNet is more accurate and outperforms other architectures (Prakash et al., 2023).

METHOD

This type of research is an experimental type of research by applying the CNN algorithm with DenseNet architecture to classify organic and non-organic waste.



1. Advance Level
This research begins with a search for research references related to the research to be carried out, the references collected are in the form of a collection of previous studies.
2. Level of Problem Determination
Determine the formulation of the problem that occurs in the classification of types of waste. As well as determining the problem boundaries of this research which aims to focus the scope of research.
3. Level of Data Collection
This stage is carried out by collecting data on CNN based on the DenseNet architecture along with the datasets that will be tested in the research.
4. Stages of Analysis
This process analyzes the working process of the method used and the method of implementing the method used in the classification of organic and non-organic waste.
5. Testing Stage

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At this stage, data testing that has been collected into the application that was made before will be carried out.

6. Report Level

The last stage is the preparation of the report, the report is compiled in accordance with the provisions listed in the research writing guidelines.

RESULT

The training and validation process using a standard learning rate will stop until the 2nd epoch because the amount of data is large and there is no significant increase in the value of the loss resulting in overfitting. Each DenseNet model with the best loss validation value will be used at the testing stage to evaluate its performance in classifying organic and non-organic waste. Our DenseNet121 model for organic and non-organic waste classification only went through 2 training and validation periods. The DenseNet121 model with the best loss validation value was obtained in the 2nd epoch with the fastest training time than the other models in 1 minute 34 seconds. At that epoch, training accuracy was 95.01%, and loss validation was 0.1307. The graph of training loss vs validation loss on the number of epochs can be seen in Figure 2.

The DenseNet169 model for the classification of organic and non-organic waste went through 2 periods of training and validation and is the most stable model compared to other models. The best loss validation value achieved by DenseNet169 is 0.12 obtained in the 2nd epoch. In that epoch, the training accuracy was 95.5% and the training time was 1 minute 41 seconds. The graph of training loss vs validation loss on the number of epochs can be seen in Figure 3.

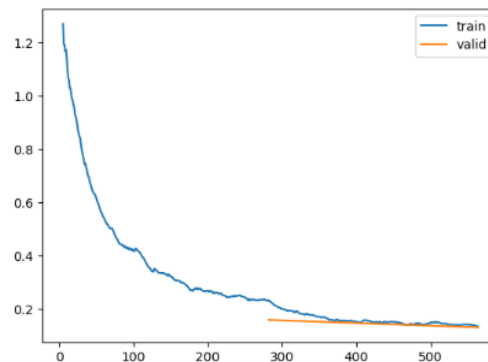


Figure 2. Training loss and loss validation from DenseNet121

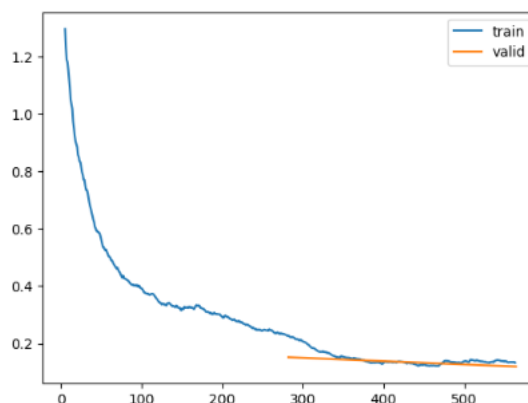


Figure 3. Training loss and loss validation from DenseNet169

Whereas for the DenseNet201 model, the loss validation reaches 0.11 which is the best loss result than the other models but the training time of 1 minute 49 seconds is the longest training time than the other models. The training accuracy obtained was 95.56%. The graph of training loss vs validation loss on the number of epochs can be seen in Figure 4.

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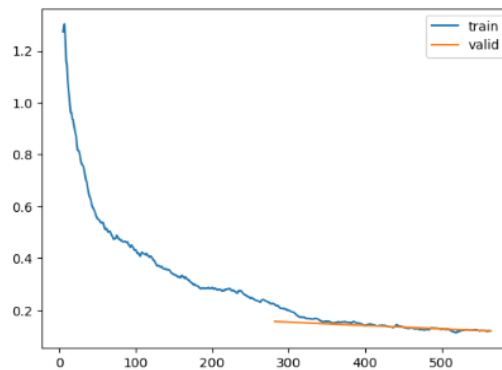


Figure 4. Training loss and loss validation from DenseNet201

Table 2. DenseNet performance on training set and validation set

Model	Loss		Percentage	
	Train	Val	Accuracy (%)	Time
DenseNet121	0.1346	0.1307	95.01	01:34
DenseNet169	0.1337	0.12	95.55	01:41
DenseNet201	0.121	0.1193	95.59	01:49

To find out and evaluate the model's performance in classifying junk images, the metrics we use are accuracy, precision, recall, and F1 score. The formula for these four metrics is as follows:

$$\text{Accuracy} = (\text{number of correctly classified images}(x)) / (\text{total number of images}(n)) \quad (1)$$

$$\text{Precision} = (\text{True Positive}(TP)) / (\text{True Positive}(TP) + \text{False Positive}(FP)) \quad (2)$$

$$\text{Recall} = (\text{True Positive}(TP)) / (\text{True Positive}(TP) + \text{False Negative}(FN)) \quad (3)$$

$$\text{F1-score} = 2 \times (\text{precision} \times \text{recall}) / (\text{precision} + \text{recall}) \quad (4)$$

Table 3. Accuracy, precision, recall, and F1 score on the testing set (%)

Model	Accuracy	Precision	Recall	Shoes-F1
DenseNet121	93.1	94.08	94.00	94.03
DenseNet169	91.5	93.44	95.51	93.44
DenseNet201	91.8	95.55	93.56	93.55

Accuracy, precision, recall, and F1 scores for all DenseNet models designed for the test set are shown in Table 3. DenseNet121 has the highest accuracy, namely 93.1%. The highest precision is 95.55% obtained using DenseNet201. In addition, all three DenseNet models also managed to achieve a precision of over 85%. DenseNet169 also achieved the best recall of 95.51%. As for the F1-score, DenseNet121 has the highest score of 94.03%. Based on the test results, our designed DenseNet121 can be considered as the best model for classifying organic and non-organic waste among other DenseNet models.

The best weight obtained from the training stage is used in the DenseNet121 model with the test set used in this study containing 22,500 trash images that have been resized to 128x128 pixels with the fastest training time. The results of the classification of organic and non-organic waste in the test set are presented in the confusion matrix in Figure 5 along with the test results in Figure 6.

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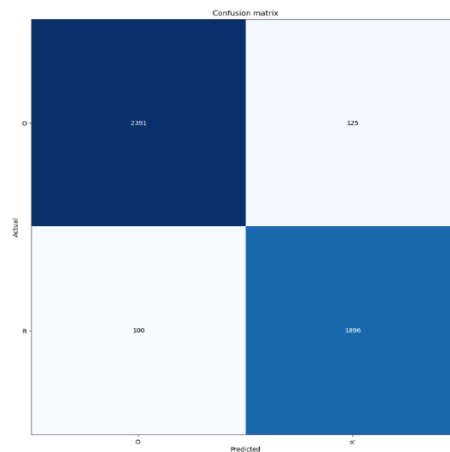


Figure 5. Confusion matrices of all DenseNet121 as the classification results

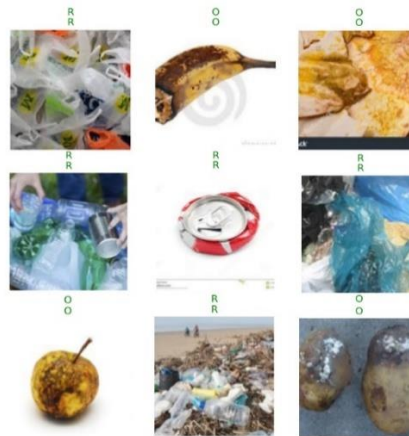


Figure 6. DenseNet121 test results on test data

Overall, all DenseNet models designed in this study achieved high accuracy, precision, recall and F1 scores. In other words, the DenseNet model has good performance and quality in classifying organic and non-organic waste. However, the designed model can still go wrong due to low epoch, and error/similarity of labels in the dataset. In addition, model classification performance can be further enhanced by utilizing advanced image preprocessing techniques.

DISCUSSIONS

Overall, all DenseNet models designed in this study achieved high accuracy, precision, recall and F1 scores. In other words, the DenseNet model has good performance and quality in classifying organic and non-organic waste. However, the designed model can still go wrong due to low epoch, and error/similarity of labels in the dataset. In addition, model classification performance can be further enhanced by utilizing advanced image preprocessing techniques.

CONCLUSION

In this study, we designed a model using the DenseNet architecture to classify organic and non-organic waste in our environment. We pre-process unbalanced datasets before using them to train, validate, and test all DenseNet models. To ensure that the process is smooth, we also apply rescaling, standard learning rates and small epochs to get optimal performance and time from large datasets. The test results show that the DenseNet121 model is the best among other models in the classification of organic and inorganic waste.

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