International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Classification Organic and Inorganic Waste with Convolutional Neural Network Using Deep Learning

Abba Suganda Girsang[1], Handy Pratama[2], Leody Pra Santo Agustinus[3]

Submitted: 13/11/2022 **Accepted:** 15/02/2023

Abstract: The amount of waste worldwide continues to increase every year. Data shows that global waste production has continued to increase from two million tons per year to 381 million tons per year over the last 65 years. The biggest problem in decomposing waste is waste that has not been sorted, so organic and inorganic waste cannot be recycled directly. Organic waste can be recycled into organic fertilizer, which is useful for farmers, while inorganic waste can be processed into items that can be reused, such as flowerpots, handicrafts, and others. This research aims to make the waste sorting process faster and more efficient using deep learning. The first step in conducting this research was to collect datasets with two categories, namely organic and inorganic, which were divided into three parts, namely training, testing, and validation. To find the best learning outcomes, preprocessing and hyperparameter testing are needed. The models used are MobileNet, VGG16, and Xception. In this study, the MobileNet model produced an accuracy of 93.35%, which is the best result of the others.

Keywords: *Deep Learning, Iimage Classification, Convolutional Neural Networks, Waste Classification*

1. Introduction

Waste is a global problem experienced by every country because waste takes a very long time and is difficult to decompose, especially plastic and rubber waste. Problems arise when all the waste is mixed without being sorted before being thrown into the trash. This requires waste to be sorted manually first before being processed. It takes a very long time during the separation process between organic waste and inorganic waste. Organic waste can be reprocessed into fertilizer and animal feed, while inorganic waste such as plastic and rubber can be processed into recycled raw materials.

By utilizing current technological developments, it is not impossible to design a program to classify organic and inorganic waste. Making machine learning for classifying can use a Convolutional Neural Network (CNN). In previous research conducted by William, Revikasha, Rivandi, & Novita published a paper entitled "Waste Classification Using EfficientNet-B0", which conducted research on waste sorting using EfficientNet-B0. [2] In this study, we used CNN with the MobileNet, VGG-16, Xception, and ResNet-50 models. There are some of the best layers in each model that can be determined by testing the bottleneck layer.

To reduce validation loss, GAP (Global Average Pooling) will be added into each model in the last layer. The dataset used for training consists of 5000 images with an accuracy of up to 93.35%. The accuracy of this CNN model can still be improved to produce better results. One way to improve its accuracy is by optimizing hyperparameters. The execution of hyperparameters takes a long time because, to get the best results, a lot of experiments are needed.

2. Related Work

Classification of waste types is one of the methods used to identify waste based on its type. By using a database of previously stored waste images, the waste recognition system can identify the type of waste in the existing database. The introduction of waste types can be identified by combining features such as color and texture [3]. Proposed an experimental project that uses the faster model of R-CNN for classifying waste into 3 categories, namely paper, recycled materials, and soil, which gets an average precision of 68% [4]. Proposing to use the Resnet-50 model with an accuracy of 87% to classify waste into four categories: glass, metal, paper, and plastic [5]. Deploys a support vector machine (SVM) and a convolutional neural network to classify waste into six categories and obtains an accuracy level of 63% for SVM and 73% for CNN [6]

[1] Computer Science Department, BINUS Graduate Program –Master of Computer Science, Bina Nusantara University, Jakarta 11380, Indonesia
ORCID ID: 0000-0003-4574-3679
[2]Computer Science Department, BINUS Graduate Program –Master of Computer Science, Bina Nusantara University, Jakarta 11380, Indonesia
[3]Computer Science Department, BINUS Graduate Program –Master of Computer Science, Bina Nusantara University, Jakarta 11380, Indonesia
** Corresponding Author Email: handy.pratama@binus.ac.id*

2.1. Deep Learning

Deep learning is a set of algorithms in machine learning that attempts to learn important features from raw data automatically. Like Deep Neural Networks (DNN), which also consist of artificial neurons arranged in the form of artificial layers arranged in input, hidden, and output layers [7]. Deep learning consists of multiple representation learnings; representation learning is a set of approaches that allow a machine to take raw data and automatically detect or determine the classification of items built using simple but nonlinear modules. Later in the decade, machine learning techniques necessitated the development of raw data extractors into mature data (such as image data in which pixel values are converted to internal representation data), from which data can be used to classify or detect patterns in input images.

2.2. Transfer Learning

Transfer learning is a machine learning method that reuses a trained model. Transfer learning is also a method that can help reduce the size of the required training dataset [8]. This model is important when you have such a large data set, which saves training time. Although transfer learning provides a solution for determining the number of datasets required, it is also important to determine the number of datasets required in the model to achieve the same or better accuracy than the original model. To find out how many data sets are needed, you can usually use two types of data sets, Tiny-Imagenet and Multiplaces2 [9].

2.3. Xception

Xception or Xtreme inception is a Convolutional Neural Network architecture consisting of deeply separable linear stacks with residual connections, it is an update of the Inception model and design with a more robust architecture. In figure 1, the exception architecture has 36 convolutional network layers that form the basis of feature extraction from the network. Then the 36 layers are organized into 14 modules, which have residual connections that make the architecture easy to define and modify. [10]

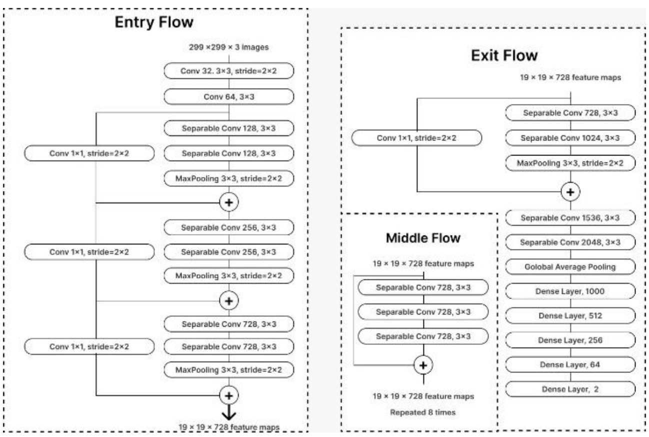

Fig. 1. Xception Architecture

2.4. MobileNet V1

MobileNet is a Convolution Neural Network (CNN) architectural model that explicitly focuses on image classification for mobile device application development by lowering model size and complexity through limited hardware resources. MobileNet V1 was developed using depthwise separable convolution. By using depth-wise separable convolutions, MobileNet V1 can reduce parameters by seven times with a decrease in accuracy of only 1% compared to using traditional convolutions [11]. Figure 2 depicts a depthwise separable convolution split into two, depthwise convolution and pointwise convolution, followed by ReLu and Batch noma. Each block layer is stacked to build the MobileNet V1 architecture, which consists of 28 layers [12].

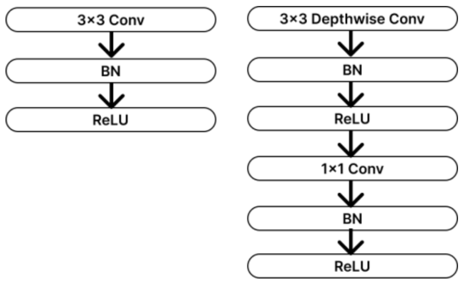

Fig. 2. Depthwise Separable Convolution

2.5. VGG16

VGG16 is a learning model that uses a large number of small convolutions and pooling operations so that it can extract more implicit features. Figure 3 represents the VGG16 architecture consisting of 16 custom layers consisting of a 3 x 3 kernel sized filter that helps the model learn more complex features by increasing the network depth and followed by three fully connected layers.

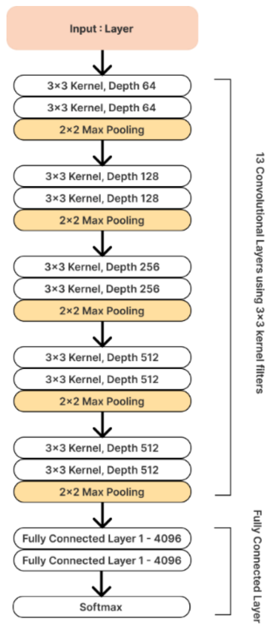

Fig. 3. VGG16 Architecture

3. Proposed Method

In conducting this research, the first thing to do was collect a public dataset of organic and inorganic waste. Then the dataset is divided into 3 parts, namely: training data, testing data, and validation data with the comparison data being 70:15:15.

Table 1. The Statistic of Dataset

No.	Classes	Organic	Inorganic
1.	Training	1092	582
2.	Testing	235	126
3.	Validation	235	126
4.	Total		2400

Labeling will be given based on the category of waste, namely organic waste and inorganic waste. After that, the data scale is changed to 224 x 224 pixels and gives an index of 0 for inorganic waste data and an index of 1 for organic waste. The data training process is carried out by determining the model to be used and several parameters used during the training process, such as the learning rate, class mode, batch size, and the number of training periods. The deep learning models used in this study are MobileNet, Xception and VGG-16

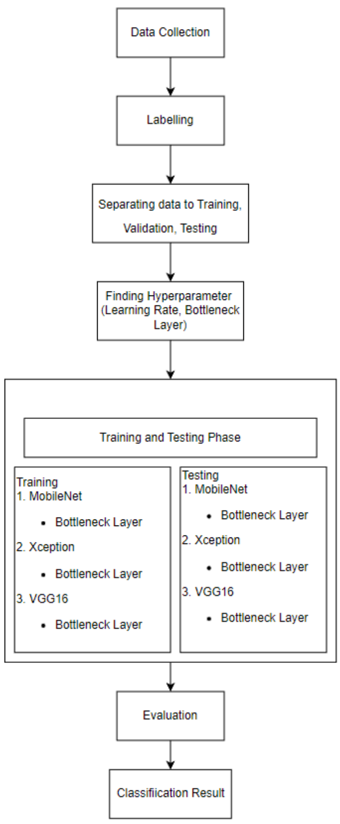

Fig. 4. Proposed Method

4. Experiment Result

4.1. Datasets

The waste dataset that has been chosen and sorted according to the type of waste is in the form of organic waste and inorganic waste and was taken from the Kaggle database. The data used are 2400 images divided into three parts: training data, testing data, and test data and data validation with image comparison 70:15:15. The dataset images are mostly in .jpg format. The following are some examples of datasets in each class, namely organic waste and inorganic waste.

Fig. 5. Sample Dataset

4.2. Hyperparameter

To get the best hyperparameter, we found the best hyperparameter by concluding that the best learning rate we use is 0.00001. The model that we use to perform the hyperparameter search process is MobileNet. This is because MobileNet has the shortest runtime, so it can save time. After testing, the learning rate of 0.00001 produces the best results in the validation and testing processes.

4.3. Deep Learning Model Implementation

The models used in this study are MobileNet, Xception, and VGG16 using the bottleneck layer. Table 2 is the result of the validation and testing of three deep learning models. As a result, the MobileNet model has the best accuracy compared to other models because it has the smallest difference in accuracy, so there is no deficiency in validation and testing.

Table 2. Validation and Testing Result

Model	Validation (%)	Testing (%)
MobileNet	93.18%	93.35%
Xception	91.48%	93.63%
VGG16	90.62%	91.69%

4.3.1. MobileNet V1

The MobileNet model has a validation accuracy value of 93.18% and a testing accuracy value of 93.35%. The Confusion Matrix of the MobileNet test model is displayed on Figure 6.

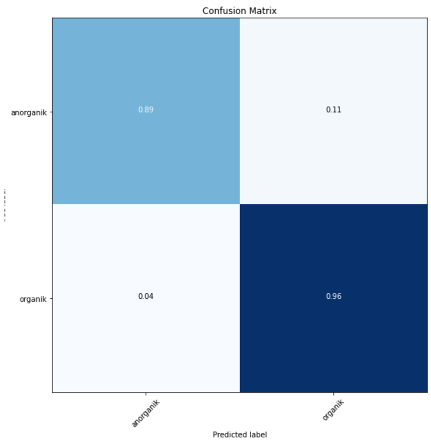

Fig. 6. Confusion Matrix MobileNet

In the table below, there are details of the classification results for the dataset that has been tested. Testing is done using the MobileNet model. The average accuracy generated using this MobileNet model is 93%, the average recall is 93%, and the average f1-score is 93%, as shown in table 3.

Table 3. Precision, recall, and f1-score for MobileNet

Class	Precision	Recall	F1-Score	Support
Organic	0.92	0.89	0.90	126
Inorganic	0.94	0.96	0.95	235
Accuracy			0.93	361
Average	0.93	0.93	0.93	361

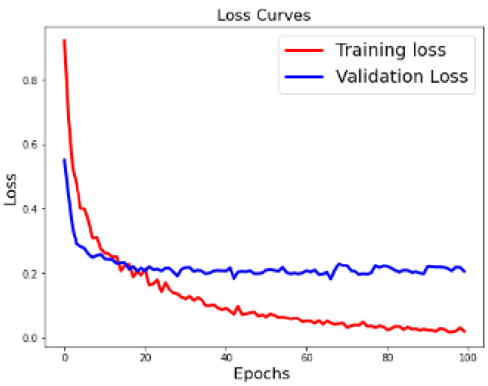

Fig. 7. Training Loss and Validation Loss MobileNet

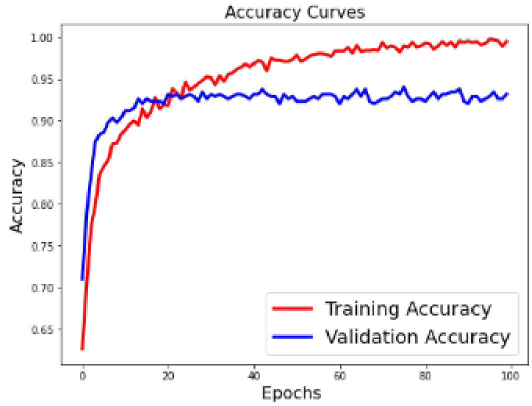

Fig. 8. Training Accuracy and Validation Accuracy MobileNet

4.3.2. VGG16

The VGG16 model has a validation accuracy value of 90.62% and a testing accuracy value of 91.69%. The Confusion Matrix of the VGG16 test model is displayed on Figure 9.

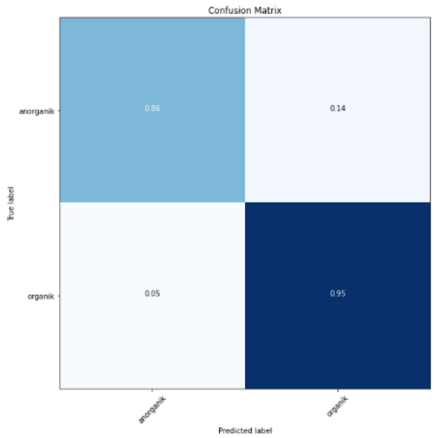

Fig. 9. Confusion Matrix VGG16

In the table below, there are details of the classification results for the dataset that has been tested. Testing is done using the VGG16 model. The average accuracy generated using this VGG16 model is 91%, the average recall is 90%, and the average f1-score is 91%, as shown in table 4.

Table 4. Precision, recall, and f1-score for VGG16

Class	Precision	Recall	F1-Score	Support
Organic	0.90	0.86	0.88	126
Inorganic	0.94	0.95	0.94	235
Accuracy			0.92	361
Average	0.91	0.90	0.91	361

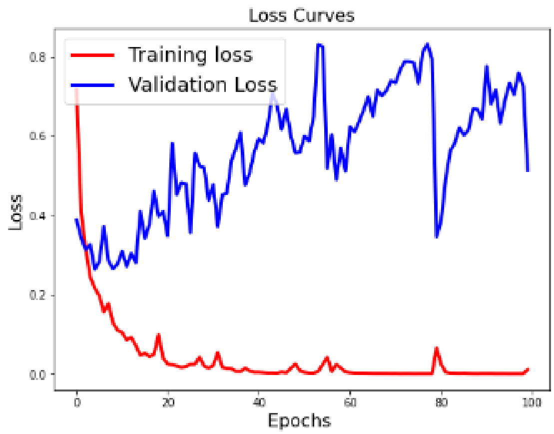

Fig. 10. Training Loss and Validation Loss VGG16

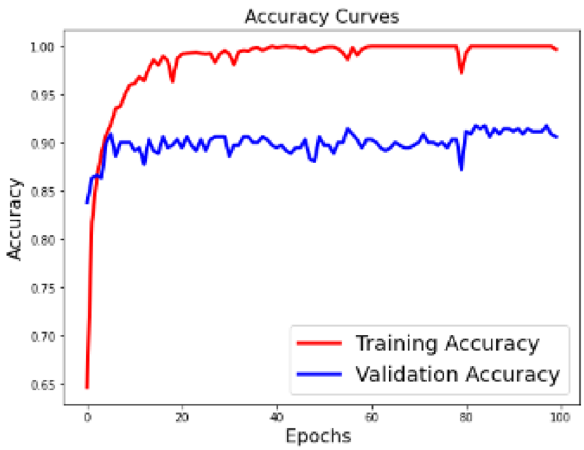

Fig. 11. Training Accuracy and Validation Accuracy VGG16

4.3.3. Xception

The Xception model has a validation accuracy value of 91.48% and a testing accuracy value of 93.63%. The Confusion Matrix of the Xception test model is displayed on Figure 8.

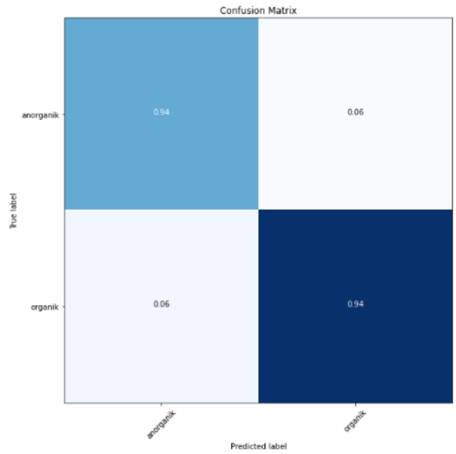

Fig. 12. Confusion Matrix Xception

In the table below, there are details of the classification results for the dataset that has been tested. Testing is done using the Xception model. The average accuracy generated using this Xception model is 94%, the average recall is 94%, and the average f1-score is 94%, as shown in table 5.

Table 5. Precision, recall, and f1-score for Xception

Class	Precision	Recall	F1-Score	Support
Organic	0.89	0.94	0.91	126
Inorganic	0.96	0.94	0.95	235
Accuracy			0.94	361
Average	0.94	0.94	0.94	361

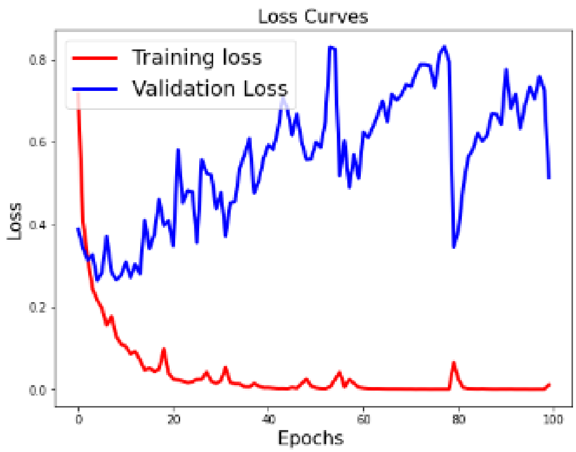

Fig. 13. Training Loss and Validation Loss Xception

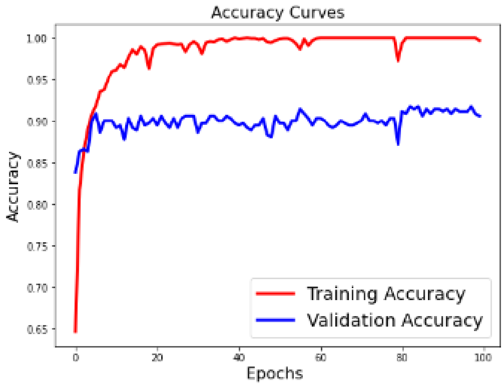

Fig. 14. Training Accuracy and Validation Accuracy Xception

5. Conclusion

In this research, we search for the best hyperparameter by concluding that the best learning rate we use is 0.00001. The learning rate of 0.00001 produces the best testing and validation results. We use three types of deep learning models to classify organic and inorganic waste, namely MobileNet, VGG-16, and Xception. Of the three models, it can be concluded that the MobileNet model produces the model with the best accuracy, with validation accuracy reaching 93.18% and testing accuracy reaching 93.35%. This method can not only be used to classify organic and inorganic waste but can be used for other classifications using different datasets. The author's suggestion for future work is to develop a garbage classification model using the YOLO algorithm, which can detect garbage objects more accurately.

References

[1] Pratami, S., Hertati, L., Puspitawati, L., Gantino, R., & Ilyas, M. (2021). Teknologi Inovasi Pengolahan Limbah Plastik Menjadi Produk UMKM Guna Menopang Ekonomi Keluarga Dalam Mencerdaskan Keterampilan Masyarakat. In GLOBAL ABDIMAS: Jurnal Pengabdian Masyarakat (Vol. 1, Issue 1, pp. 1–11). Perkumpulan Intelektual Madani Indonesia. https://doi.org/10.51577/globalabdimas.v1i1.59

[2] W. Mulim, M. F. Revikasha, Rivandi and N. Hanafiah, "Waste Classification Using EfficientNet-B0," 2021 1st International Conference on Computer Science and Artificial Intelligence (ICCSAI), 2021, pp. 253-257, doi: 10.1109/ICCSAI53272.2021.9609756.

[3] Zhang Q, Yang Q, Zhang X, Bao Q, Su J, Liu X. Waste image classification based on transfer learning and convolutional neural network. Waste Manag. 2021 Nov;135:150-157. doi: 10.1016/j.wasman.2021.08.038. Epub 2021 Sep 8. PMID: 34509053.

[4] Thung G, Yang M 2016 Classification of trash for recyclability status. CS229 Project Report URL: cs229.stanford.edu/proj2016/report/ThungYang-ClassificationOfTrashForRecyclabilityStatus-report.pdf

[5] Olugboja Adedeji, Zenghui Wang, Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network, Procedia Manufacturing, Volume 35, 2019, Pages 607-612, ISSN 2351-9789, https://doi.org/10.1016/j.promfg.2019.05.086.

[6] Rad, M.S. et al. (2017). A Computer Vision System to Localize and Classify Wastes on the Streets. In: Liu, M., Chen, H., Vincze, M. (eds) Computer Vision Systems. ICVS 2017. Lecture Notes in Computer Science(), vol 10528. Springer, Cham. https://doi.org/10.1007/978-3-319-68345-4_18

[7] G. Hinton et al., "Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups," in IEEE Signal Processing Magazine, vol. 29, no. 6, pp. 82-97, Nov. 2012, doi: 10.1109/MSP.2012.2205597.

[8] Schneider, S., Taylor, G. W., & Kremer, S. (2018, May). Deep learning object detection methods for ecological camera trap data. In 2018 15th Conference on computer and robot vision (CRV) (pp. 321-328). IEEE.

[9] Soekhoe, D., Putten, P. V. D., & Plaat, A. (2016, October). On the impact of data set size in transfer learning using deep neural networks. In International symposium on intelligent data analysis (pp. 50-60). Springer, Cham.

[10] Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1251-1258).

[11] Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861

[12] Biswas, D., Su, H., Wang, C., Stevanovic, A., & Wang, W. (2019). An automatic traffic density estimation using Single Shot Detection (SSD) and MobileNet-SSD. Physics and Chemistry of the Earth, Parts A/B/C, 110, 176-184.