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CLASSIFICATION OF ORGANIC AND NON-ORGANIC WASTE WITH CNN-MOBILENET-V2

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Abstract

Data from the Ministry of Environment and Forestry shows that the amount of organic and non-organic waste in 2023 has started to decline compared to the previous year. However, waste management in the central landfill is still not optimal. This is a problem for the community and the environment because it can cause pollution and disrupt public health around the disposal site. The reason for the difficulty of waste management at the landfill is that people still dispose of waste without separating it first. In addition, it is also due to a lack of public awareness and knowledge. One of the things that can be done to help overcome the problem of waste and its management is to develop an application that can help people understand the importance of waste selection and facilitate socialization in the community. For that, a model is needed that can classify waste based on its type with accurate accuracy. In this study, we propose a deep learning model, CNN with mobilenetV2 architecture, to classify organic and non-organic waste. This model uses a dataset consisting of 4380 images of organic and non-organic waste. Then 3 preprocessing stages were carried out, namely resize, normalization, and augmentation. From this process, data training was carried out and researchers obtained model evaluation results with 98.47% accuracy, 97% precision, 97% recall, and 97% F1 Score evaluation results. These results show that the proposed model is categorized as excellent.

Keywords: *CNN, MobilenetV2, organic and non-organic waste classification.*

1. INTRODUCTION

Waste is a crucial problem for the whole world [1]-[2], including Indonesia. This is because everyday waste is generated from activities carried out by the community[3], be it from households, industries, markets, and shopping centers. In 2023, the Ministry of Environment and Forestry noted that Indonesia produces yearly waste piles of around 17 tons. This number has certainly decreased from the previous year. However, even though the number has decreased, the management efforts that can be carried out are only around 67.4%. This means that there is around 32.6% unmanaged waste. This certainly shows that waste is still a serious problem. Because if waste management is not done optimally, it will cause environmental pollution and disruption of public health[4].

In waste management efforts, the community needs to increase attention and take concrete actions as a form of support so that waste management can be carried out optimally[5]-[6]. However, this is still difficult to do because people dispose of waste without separating it by classifying waste by type[7][8]. Therefore, it is necessary to take the right steps to guide the community to be able to sort waste correctly and according to its type, namely organic and non-organic waste. This is very useful because organic waste can be managed into fertilizer[9] while non-organic waste can be managed or recycled again [10]-[11] so that it has a selling value[12]. In addition to having a selling point recycling[13] waste can help solve environmental problems[14].

According to research conducted by Joni Wong, most people still experience confusion in sorting waste based on its nature so applications are needed that can help them and can provide proper education to them[15]. This factor requires an effective solution that can provide suggestions that facilitate the individual selection process. For this reason, it is necessary to design an algorithm model to build an application that can provide classification results with high accuracy and is lighter when developed into an application[16]-[17].The use of Deep Learning technology such as CNN can be the best solution at this time. [1]

CNN is a deep-learning algorithm model that can be used to classify image data[6][18]. In research conducted by Abdul Rasidi et all, the use of the CNN model for the classification of non-organic waste resulted in an accuracy of 92%[19], and the same result was obtained by Kartiko et all[20]. However, according to Yong L et al in research using Mobile net to classify garbage compared to using only conventional CNN models. Because the mobile net can classify with an accuracy of 15.42% higher than CNN the trained model is also quite light[21]. This makes MobileNetV2 very suitable when used with limited device sources such as mobile applications. In addition, based on research conducted by Oktafiandi H using 2527 garbage datasets using the mobile net, the accuracy is 93%[22] . The research conducted by Reza Fahcruroji et all using a dataset of 2773 to classify waste gets 96% accuracy[18].

Therefore researchers are trying to develop a model that can be used for waste identification using MobileNetV2 which aims to get high accuracy and be able to educate the public to do better waste sorting.

2. RESEARCH METHODS

2.1. Research flow

In the Figure 1 diagram, there are several stages of this research flow consisting of data collection, pre-processing, training and validation, CNN modeling with mobile net V2 architecture, evaluation, and classification. At the first flow stage, researchers will collect datasets of organic and non-organic waste images from various sources. At the second flow stage, researchers will use Python coding to resize photos with resize and normalization techniques. In the third flow stage, researchers will divide the image data from pre-processing into 2 image data, namely train and validation data. The third stage of the flow of this research is modeling the training data will be applied to the model using CNN architecture, namely mobilenetv2. In the fourth stage, researchers will evaluate the modeling results using test data with a classification and confusion matrix. In the fifth stage, visualize the classification results based on the label.

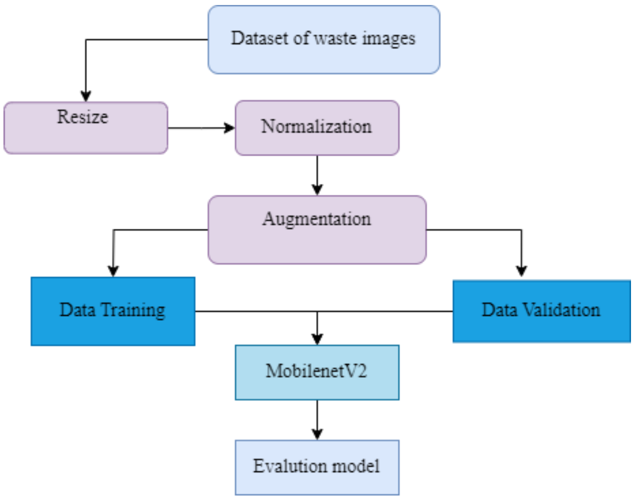

Figure 1 Research flow chart

2.2. Data collection

This research uses collab as a tool to conduct experiments with the T4 configuration. For the dataset itself, researchers collected it from Kaggle which amounted to 14180 with 12 image labels consisting of clothing, shoes, cardboard, plastic, metal, paper, biological, batteries, green colored glass, white colored glass, brown colored glass, and other waste. However, to classify the data of organic waste images and non-organic images, the researcher changed 12 image labels into 2 labels by grouping them based on their nature. The nature of waste is divided into organic and non-organic waste. The data was reduced to 2190 organic datasets and 2190 non-organic datasets.

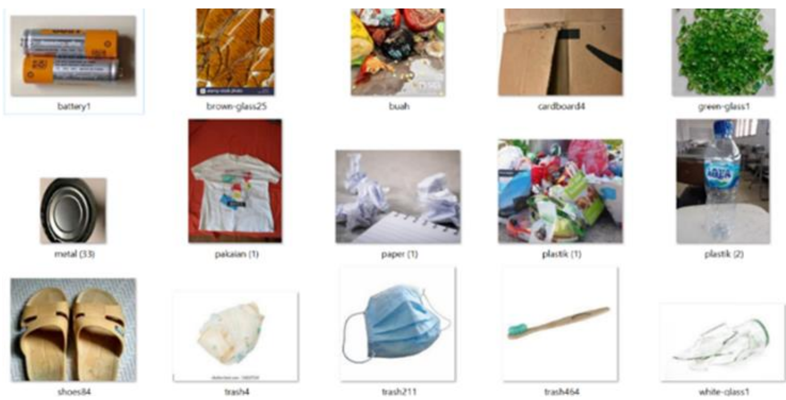

Figure 2 Data Collection

2.3. Pre-processing

Pre-processing is a stage where inappropriate data will be deleted [23] or changed using techniques or done manually so that the model can work properly. While in research preprocessing is done because the image data obtained from Kaggle has an unequal size so it is necessary to resize and normalize to ensure the image is in the same pixel scale so that it can improve the performance of the algorithm. Pre-processing techniques that will be used on this data are resizing, Normalization, and augmentation. Resize is a technique used to change the size or scale of the image. at this stage, the image that originally had different pixel sizes (175x175, 260x 260, 435x182, 220x220) and sizes (32kb, 4 kb, 16 kb) will be converted into an image with a size of 200 x 200, and a dimension scale of 0.3 Then Normalization is a technique used to normalize images in a certain standard range. Image data will be divided based on its pixel value by a factor of 1/255 in the image generator.

Augmentation is one of the most widely used image processing techniques to change the shape and position of the image from the original image with the aim that the machine can learn different image data [24]. In this process using the library from TensorFlow, the Keras preprocessing layer uses layers such as the use of Random Flip ("horizontal"), Random Rotation (0.2), RandomZoom (0.2), RandomFlip("horizontal"), Random Contrast (0.2). In the first layer, the image will be randomly flipped to perform a random return on the image, and the image will be returned horizontally adjusted to the requested input. In the second layer, the image will become Random Rotation (0.2) so that in this layer the image will perform a random rotation on the image with a total image rotation of 72 degrees from the initial image. In the third layer random flip horizontally has the same function as the first layer. In the last layer, namely the fourth layer Random Contrast (0.2) the image will be randomly contrasted up to 20%. All these techniques are used to increase the diversity of the dataset [11] and as one of the strategies to prevent overfitting [23] -[25].

2.4. Data Training

Training data is a collection of data that is trained using programming algorithms to facilitate the modeling process. At this stage, organic and non-organic waste image data will be divided into 2 parts, namely data that is more in number to be trained and data with a smaller amount to be validated. The division will use the flow from the directory mode of the Image processor object which is part of the Keras library so that by using this method the image is randomized and divided automatically with the split validation parameter and binary class mode for binary classification. while the test data for the classification part uses data that is not randomized with the False shuffle command.

2.5. Mobile Net V2

Mobile Net V2 is a CNN architecture used to classify images by focusing on mobile device development[8]-[26]. Mobile Net V2 was introduced by Google for the first time in 2018, one year after the first Mobile Net introduced by Howard in 2017. The MobileV2 architecture is designed to allow for a reduction in the number of parameters while improving network performance compared to Mobilenet V1[27]. This model was chosen because previous research conducted by L Yong et all shows that the performance of the model using the mobile net v2 architecture can work well and has its advantages in testing image data with various model sizes.[18].

Table 1 block residual block [28]

Input	operator	output
h x w x tk (1)	Convd2 , ReLu6	h x w x tk (4)
h x w x tk (2)	Dwise, ReLu6	$\frac{h}{s} \times \frac{w}{s}$ x tk (5)
$\frac{h}{s} \times \frac{w}{s}$ x tk (3)	Linear, conv2	$\frac{h}{s} \times \frac{w}{s}$ x k' (6)

MobileNet has 2 types of blocks in it, namely block 1 residual step and block 2 downsizing step. Research [28] uses a block structure where each block has 3 layers of bottleneck residual blocks namely input (1), (2), (3) using Convd2, Relu6, Dwise, and Linear operators. This architecture contains 32 dense (fully connected) initial layers and 19 residual bottlenecks [29]. In addition, the use of Rectified Linear Unit (ReLu) is most widely used in neural networks. However, in this study, ReLu6 is the activation function that will be used in the MobileNet neural network. This is because in research[21] Previous work shows that ReLu6 has better speed in training than others. Relu6 calculation with formula (1):

$$ReLU6 = min(max(x, 0), 6) \quad (1)$$

Linear functions are used because the residual structure of mobilenetv2 has low-dimensional features, so activation functions are used to prevent the destruction of much of the required information[21]. With formula (2):

$$y = b + \sum_i x_i w_i \quad (2)$$

However, in this study, as shown in Figure 3, researchers used a simple CNN to test along with defining the mobilenetv2 architecture model as a base. The following is an explanation of the layers that will be used in this architecture:

a. The first layer calls the mobile net model with the previously defined.

b. The second layer of layers is called the augmentation preprocessing was defined earlier.

c. The third layer uses layers keras Dropout 0.5 is used to prevent the model from overfitting so that it is not able to provide correct accuracy with the formula:

$$drop\ out = 1 - r \tag{3}$$

d. The fourth layer calls flatten to convert the output of the model that displays the matrix dimension into one dimension with a vector ((n).

e. The fifth dan sixth layer uses a dense layer with activated Relu6. The dense layer is used so that each layer is interconnected with each neuron while activated relu6 will be used to prevent gradient relief during training.

f. The seventh layer uses dense with activated sigmoid to output the classification results of each class. Sigmoid is used by defining binary, namely 0 and 1. because this study only uses 2 class labels.

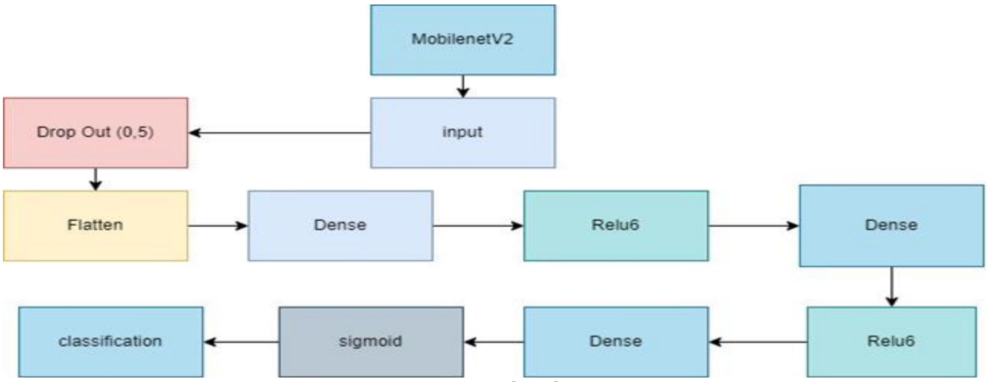

Figure 3 Proposed Architecture

2.6. Evaluasi

In this stage, the model and classification will be evaluated using the Sklearn Matrics library to create a report of the score classification. The parameters that will be used in the score classification report are y_pred, y_true, target, and label_class. Then these parameters will be returned in the form of reports precision (4), recall (5), f1 score (6), support, macro average, and weighted average.

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

The precision calculation is calculated based on the true positive (TP) with the ratio of true positive and false negative (TP and Fp). By measuring this score, it is known that classifications that are not organic and non-organic waste are detected as actual organic and non-organic waste.

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

Recall is a calculation based on true positives (TP) with True Positive (TP) and False Negative (FN) comparators. By measuring this score, it is possible to classify all organic and non-organic waste without being missed.

$$F1\ Score = 2\ x\ \frac{precision\ x\ recall}{Precision\ +recall} \tag{6}$$

The calculation f1 score is done by combining the calculation of precision and recall. The purpose of this calculation is to ensure that the precision and recall calculations for classifying organic and non-organic waste are correct.

3. RESULTS AND DISCUSSION

3.1. Waste Detection

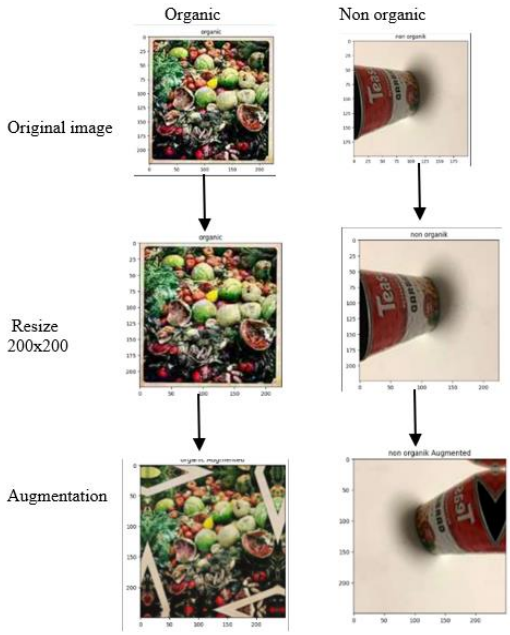

Figure 4 Preprocessing stages

In Figure 4 the preprocessing stage image, there are inputs from two organic and non-organic waste image labels, each of which still has a different size so it needs to be resized. Resize is done by reducing the size of the image from the previous size or equalizing the garbage image so that when processing the image can be processed faster but the quality of the image is still clearly visible. Furthermore, the normalization process is carried out to ensure that the image as a training model will be used moreably and in the same range. Furthermore, the augmentation stage is used to perform transformations such as reversal, rotation, zoom, and random image contrast adjustment to produce the output of several images that have different directions that can face one direction, have different rotations, recognize larger and smaller objects, and help adjust light contrast.

3.2. Waste Classification

In the classification stage, the CNN-mobile net V2 algorithm is the method used. To define the classification task using a neural network, where the mobile architecture will be preloaded to perform image model recognition, layers dropout is used to prevent overfitting of the model, flatten, layers dense 32 with activation relu6, dense 2 with binary to define 2 classes used with 6 different training times.

Table 2 Result of Training Eksprimen

Train	Data	epoch	precision	recall	F1-score	accuracy
3504	876	20	97%	97%	97%	96,91%
		25	97%	97%	97%	97,14%
3724	656	20	97%	97%	97%	96,95%
		25	97%	97%	97%	98,47%
3066	1314	20	96%	96%	96%	96,16%
		25	97%	97%	97%	96,70%

In Table 2, based on six experiments conducted six different times, three different dataset sizes, and two different epochs, the percentages of accuracy, precision, recall, and f1-score are obtained. In the first experiment using the first dataset, 80% of the data is obtained (3504 images), and 20% validation (876 images) using an epoch of 20 obtained 96,91% accuracy, 97% precision, 97% recall, and 97% F1 score. In the second experiment, using the first dataset for train and validation only differentiated the epoch to 25 obtained 97.14% accuracy, 97% precision, 97% recall, and 97% F1 Score. In the third experiment using the second dataset with 85% train data (3724 images from two classes), 15 validation data (656 from 2 classes), and 20 epochs, the accuracy is 96.95%, precision 97%, recall 97%, and F1 Score 97%, 96.95% accuracy, 97% precision, 97% recall, and 97% F1 Score were obtained. The fourth experiment using the third dataset with epoch 25 obtained 98.47% accuracy, 97% precision, 97% recall, and an F1 score of 97%. In the fifth experiment using the second dataset with data train 70 (3066 images from two classes) and validation 15 (1314 images from two classes) and epoch 20 obtained accuracy 96.16%, precision 96%, recall 96%, and F1 Score 96%. The last experiment using a dataset that has been trained in the fifth experiment with epoch 25 obtained an accuracy of 96.70%, a precision of 97%, a recall of 97%, and an F1 score of 97%.

Figure 6 shows experimental results from the test data used to obtain accuracy, precision, recall, and f1 scores. The first experiment using 876 test data to evaluate the model showed that the model used was able to classify with 97.14% accuracy with details of actual organic waste classification 432, classification of non-organic waste while classification of no organic waste was 19 and no non-organic waste was 6. The second experiment using 876 test data to evaluate the model showed that the model was able to classify with 96.23% accuracy with details of the classification of 432 actual organic waste, 419 classifications of actual non-organic waste, 19 non-actual organic waste, and 6 non-actual non-organic waste. The third experiment using 625 test data to evaluate the model shows that the model can classify with an accuracy of 96.95% with details of classifying actual organic waste are 312, actual non-organic waste as 324, non-actual organic waste there are 4, and non-actual organic waste at there are 12. Experiment four using 625 test data, also shows that the model can produce an accuracy of 98.47% with details of classifying actual organic waste 312, actual non-organic waste there are 324, non-actual organic waste there are 4, and non-actual organic waste there are 16. In the fifth experiment using 1094 test data, the model got 96.16% accuracy with details of classifying actual organic waste being 536, non-organic waste being 515, organic waste not 32, and non-organic waste, not 11. In the sixth experiment from 1094 test data from 2 classes, the model gets 96.70% accuracy with details of the actual organic waste classification results there are 542 actual non-organic waste there are 516, non-actual organic waste there are 32, and non-actual organic waste there are 5. Based on the results of the visualization of the six experiments above, dark blue images on both digital have high and correct classification results and show good performance in classifying organic and non-organic waste.

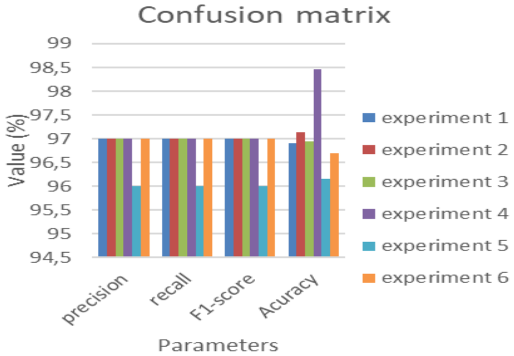

Figure 5 Result of Confusion Matrix

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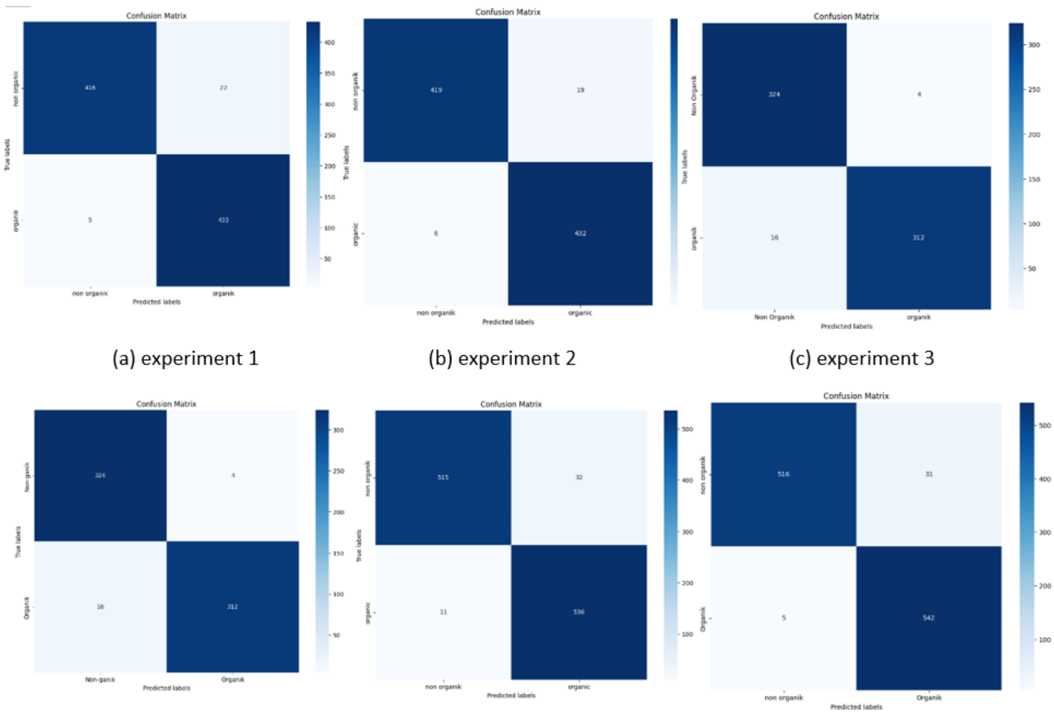

(a) experiment 1 (b) experiment 2 (c) experiment 3

(d) experiment 4 (e) experiment 5 (f) experiment 6

Figure 6 Confusion matrix results of experiments 1-6 based on data classification capabilities

4. DISCUSSION

In Table 3 of this study, researchers used several comparisons with the same model but different datasets. In research[22] by using the MobileNet model to get 93% accuracy. in research [21] by using the MobilenetV2 model gets 82.93% accuracy. In research[18] by using the MobileNet model to get 83.2% accuracy. in research[8] by using the MobilenetV2 model to get 93% accuracy. In research[30] by using SDD-Mobilenet obtained an accuracy of 94%. In research[31] using the MobileNet model gets 96% accuracy. Meanwhile, the test results in this study using MobileNetV2 get an accuracy of 98.47%.

Figure 7 shows that the model displays the visualization of several images with classification labels taken randomly from the training results using Matliplob. This result also shows the correct classification results based on the category on the test data even though the shape of the object is different

Figure 7 Visualization of several images with classification labels

Table 3 Previous journal references

Result of Training				
work	**Model**	**accuracy**	**precision**	**recall**
[22]	Mobilenet	93%	92%	90%
[21]	MobilenetV2	82,92%	96,25%	97,25%
[18]	Mobilenet	83,2	-	-
[8]	MobilenetV1	93%	93%	93%
[30]	SDDMobilenet	94%	96%	91,98%
[31]	MobileNet	96%	-	-
Our experiment	MobilenetV2	98,47%	97%	97%

This research is far from perfect so it can still be updated and refined to achieve accurate accuracy and the model is not overfitting. This is due to the use of datasets that are used in small quantities, only slightly more than the datasets used in previous studies and collected through public sites. As well as the application of preprocessing is still simple and needs to be improved. In this study, researchers used CNN

Architectures, namely Mobilenet V2, not other Architectures such as ResNet, DesNet, Vgg16, and Googlenet.

5. CONCLUSION

The research has been done using 4380 datasets of organic and non-organic waste images which are then reduced and equalized images with a size of 200 x 200 and jpg format. This detection process starts from the stages of data selection, image preprocessing, training, modeling, and architecture proposed and evaluated. The research results obtained from conducting six experiments found that the highest accuracy was obtained 98.47% of the dataset size train 85%, validation 15%, and epoch 25 with recall 97%, precision 97%, and f1-score 97%. This shows that our proposed model is categorized as very good from previous research. Previous research got 96% accuracy. Then the classification metrics also show that the model can classify actual organic waste there are 312, actual non-organic waste there is 324, non-actual organic waste there is 4, and non-actual non-organic waste there is 16 out of 656 test data.

For future research, researchers can add many datasets to achieve satisfactory results. The preprocessing used must also be different such as stretching and histograms, adding different speeds, and different image sizes, and using the latest mobile netV3 architecture model.

REFERENCES

[1] S. Majchrowska *et al.*, "Deep learning-based waste detection in natural and urban environments," *Waste Management*, vol. 138, 2022, doi: 10.1016/j.wasman.2021.12.001.

[2] Dr. A. Oberoi, "'A Design of Novel Method for Classification of Waste Materials with its location using Deep Learning and Computer Vision for Smart Cities,'" *International Journal of Innovative Research in Computer Science & Technology*, 2021, doi: 10.55524/ijircst.2021.9.6.71.

[3] R. Holiyanti, S. Wati, I. Fahmi, and C. Rozikin, "Pendeteksi Sampah Metal untuk Daur Ulang Menggunakan Metode Convolutional Neural Network," *Jurnal Teknik Informatika dan Sistem Informasi*, vol. 8, no. 1, 2022, doi: 10.28932/jutisi.v8i1.4492.

[4] V. Kaya, "Classification of waste materials with a smart garbage system for sustainable development: a novel model," *Front Environ Sci*, vol. 11, 2023, doi: 10.3389/fenvs.2023.1228732.

[5] T. Gupta *et al.*, "A deep learning approach based hardware solution to categorize garbage in environment," *Complex and Intelligent Systems*, vol. 8, no. 2, 2022, doi: 10.1007/s40747-021-00529-0.

[6] Z. Feng, J. Yang, L. Chen, Z. Chen, and L. Li, "An Intelligent Waste-Sorting and Recycling Device Based on Improved EfficientNet," *Int J Environ Res Public Health*, vol. 19, no. 23, 2022, doi: 10.3390/ijerph192315987.

[7] L. Cao and W. Xiang, "Application of Convolutional Neural Network Based on Transfer Learning for Garbage Classification," 2020.

[8] A. S. Girsang, H. Pratama, L. Pra, and S. Agustinus, "International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING Classification Organic and Inorganic Waste with Convolutional Neural Network Using Deep Learning," *Original Research Paper International Journal of Intelligent Systems and Applications in Engineering IJISAE*, vol. 2023, no. 2, pp. 343–348, 2023, [Online]. Available: www.ijisae.org

[9] Y. Narayan, "DeepWaste: Applying Deep Learning to Waste Classification for a Sustainable Planet," Jan. 2021, [Online]. Available: http://arxiv.org/abs/2101.05960

[10] A. Namoun, B. R. Hussein, A. Tufail, A. Alrehaili, T. A. Syed, and O. Benrhouma, "An Ensemble Learning Based Classification Approach for the Prediction of Household Solid Waste Generation," *Sensors*, vol. 22, no. 9, 2022, doi: 10.3390/s22093506.

[11] N. Nnamoko, J. Barrowclough, and J. Procter, "Solid Waste Image Classification Using Deep Convolutional Neural Network," *Infrastructures (Basel)*, vol. 7, no. 4, 2022, doi: 10.3390/infrastructures7040047.

[12] Y. Mulyani, R. Kurniawan, P. B. Wintoro, M. Komarudin, and W. M. Al-Rahmi, "International Journal of Aviation Science and Engineering AVIA Systematic Comparison of Machine Learning Model Accuracy Value Between MobileNetV2 and XCeption Architecture in Waste Classification System," vol. 4, no. 2, pp. 75–82, 2022, doi: 10.47355/AVIA.V4I2.70.

[13] J. Bobulski and M. Kubanek, "Deep Learning for Plastic Waste Classification System," *Applied Computational Intelligence and Soft Computing*, vol. 2021, 2021, doi: 10.1155/2021/6626948.

[14] A. P. Siva Kumar and K. Buelaevanzalina, "an Efficient Classification of Kitchen Waste Using Deep Learning Techniques," *Turkish Journal of Computer and Mathematics Education*, vol. 12, no. 14, 2021.

[15] J. Wong, "Aplikasi Klasifikasi Sampah Organik dan Non Organik dengan Metode

GLCM Dan LS-SVM," *Bulletin of Computer Science Research*, vol. 3, no. 1, 2022, doi: 10.47065/bulletincsr.v3i1.198.

[16] C. Shi, C. Tan, T. Wang, and L. Wang, "A waste classification method based on a multilayer hybrid convolution neural network," *Applied Sciences (Switzerland)*, vol. 11, no. 18, 2021, doi: 10.3390/app11188572.

[17] Y. Zhao, H. Huang, Z. Li, H. Yiwang, and M. Lu, "Intelligent garbage classification system based on improve MobileNetV3-Large," *Conn Sci*, vol. 34, no. 1, pp. 1299–1321, 2022, doi: 10.1080/09540091.2022.2067127.

[18] A. Reza Fahcruroji *et al.*, "IMPLEMENTASI ALGORITMA CNN MOBILENET UNTUK KLASIFIKASI GAMBAR SAMPAH DI BANK SAMPAH".

[19] A. Ibnul Rasidi, Y. A. H. Pasaribu, A. Ziqri, and F. D. Adhinata, "Klasifikasi Sampah Organik dan Non-Organik Menggunakan Convolutional Neural Network," *Jurnal Teknik Informatika dan Sistem Informasi*, vol. 8, no. 1, Apr. 2022, doi: 10.28932/jutisi.v8i1.4314.

[20] Kartiko, A. Prima Yudha, N. Dimas Aryanto, and M. Arya Farabi, "Klasifikasi Sampah di Saluran Air Menggunakan Algortima CNN," *Indonesian Journal of Data and Science*, vol. 3, no. 2, 2022, doi: 10.56705/ijodas.v3i2.33.

[21] L. Yong, L. Ma, D. Sun, and L. Du, "Application of MobileNetV2 to waste classification," *PLoS One*, vol. 18, no. 3 March, 2023, doi: 10.1371/journal.pone.0282336.

[22] H. Oktafiandi, "Implementasi Algoritma Convolution Neural Network pada Klasifikasi Limbah dengan Arsitektur MobileNet," 2023. [Online]. Available: https://winco.cilacapkab.go.id

[23] Z. Md, A. Amin, N. Sami, and R. Hassan, "An Approach of Classifying Waste Using Transfer Learning Method," 2021.

[24] R. A. Firmansah, H. Santoso, and A. Anwar, "TRANSFER LEARNING IMPLEMENTATION ON IMAGE RECOGNITION OF INDONESIAN TRADITIONAL HOUSES," *Jurnal Teknik Informatika (Jutif)*, vol. 4, no. 6, pp. 1469–1478, Dec. 2023, doi: 10.52436/1.jutif.2023.4.6.767.

[25] K. Maharana, S. Mondal, and B. Nemade, "A review: Data pre-processing and data augmentation techniques," *Global Transitions Proceedings*, vol. 3, no. 1, 2022, doi: 10.1016/j.gltp.2022.04.020.

[26] L. W. Qin *et al.*, "Precision Measurement for Industry 4.0 Standards towards Solid Waste Classification through Enhanced Imaging Sensors and Deep Learning Model," *Wirel Commun Mob Comput*, vol. 2021, 2021, doi: 10.1155/2021/9963999.

[27] X. Sang, C. Li, H. Li, R. Yang, Z. Liu, and R. Article, "A Real-time and High-Performance MobileNet Accelerator based on adaptive dataaow scheduling for Image Classiication," 2023, doi: 10.21203/rs.3.rs-3132056/v1.

[28] Mark Sandler, A. Howard, M. Zhu, A. Zhmoginov, and Liang-Chieh Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks Mark," *Convolutional Neural Networks with Swift for Tensorflow*, 2019.

[29] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2018. doi: 10.1109/CVPR.2018.00474.

[30] J. Srilatha, T. S. Subashini, and K. Vaidehi, "Plastic and non-plastic separation from trash using SSD mobilenet based object detector," 2022.

[31] D. Surender Dhiman, K. Srivatsan, and A. Jain, "Waste Classification using Transfer Learning with Convolutional Neural Networks," in *IOP Conference Series: Earth and Environmental Science*, 2021. doi: 10.1088/1755-1315/775/1/012010.