Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 10, No. 4, November, Pp. 499-510

Transfer learning approaches for non-organic waste classification: experiments using MobileNet and VGG-16

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Article Info

Keywords:
Machine Learning, MobileNet, Non-Organic Waste, VGG-16, Waste Management

Article history:
Received: April 28, 2025
Accepted: July 25, 2025
Published: November 01, 2025

Cite:
Z. Sari and S. Basuki, "Transfer Learning Approaches for Non-Organic Waste Classification: Experiments Using MobileNet and VGG-16", *KINETIK*, vol. 10, no. 4, Nov. 2025.
https://doi.org/10.22219/kinetik.v10i4.2319

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Abstract

This paper develops machine learning (ML) models for classifying non-organic waste automatically. The goal is to support more effective waste management by increasing recycling rates, reducing landfill use, and minimizing environmental impact. The ML models proposed in this paper classify 20 types of non-organic waste collected from the internet, which consists of 2,552 instances. Our experiments reveal several key findings. First, MobileNet, which achieved 86% accuracy, outperforms VGG-16, which reaches only 72% accuracy. Second, both models show good classification performances in classifying glass bottles, toothbrushes, and cigarette butts. Third, both models suffer from misclassification in visually similar categories, especially when it comes to paper-based waste like books, cardboard, foam packaging, and carton packaging. Fourth, MobileNet has difficulty detecting plastic packaging, carton packaging, and books, while VGG-16 exhibits higher misclassification rates for foam packaging, cardboard, and newspapers. These results pose a further critical development of the model to classify non-organic waste with similar textures and shapes. Moreover, it presents the urgency of improving the model to distinguish visually similar waste materials. Considering the number of labels used in this paper compared with existing studies, the findings demonstrate the competitiveness of our models for non-organic waste classification.

1. Introduction

Waste management, consisting of collection, transportation, processing, and disposal, plays an important role in environmental sustainability [1]. Urbanization and industrialization have made traditional waste management methods ineffective [2], [3]. This can result in serious environmental pollution due to the inability of landfills to both process and accommodate it. Non-organic waste, such as plastic, metal, glass, textiles, and their derivatives, is a type of dangerous waste because it does not decompose easily and can cause potential long-term pollution [4], [5], [6], [7], [8]. This condition is exacerbated by the fact that only 16% of waste globally ends up being recycled, and the rest still pollutes the environment [9]. The recycling process, as a potential solution to this issue, can be implemented effectively only if non-organic waste is sorted by type from the beginning. Therefore, an intelligent system capable of classifying this type of waste automatically and accurately is required.

Artificial intelligence (AI), especially machine learning (ML), has been widely adopted as a solution in various fields, including in the field of waste management. Waste management research has been widely carried out with emphasis on three aspects, namely the use of pre-trained models, dataset benchmarking, and practical integration. This paper has identified several works on adopting pre-trained models (transfer learning), as in [10], [11] which use VGG16 and compare multiple pre-trained models such as InceptionV3, ResNet, and MobileNet. Additionally, research [12], [13] compare the performance of DenseNet, MobileNet, ResNet, and InceptionV3. Several works focus on building and using public waste datasets TrashNet, WaDaBa, and RealWaste for standardized evaluations, as in [13], [14], [15], and a dataset consisting of real and synthetic data called Re-Sort-IT for robotic waste sorting purposes [16]. Waste detection systems for practical purposes can be found in IoT-based smart bins and robotic sorting systems [15], [16]. More practical areas are also accommodated by [15], [17] using MobileNet deployed on Raspberry Pi, [12], [18] as well as NASNet and MobileNet for IoT and mobile devices. Following this, research focusing on the use of waste data on mobile devices without developing the ML model has been developed by [19]. However, existing research poses several issues, such as limited number of labels in public datasets and the use of single-image (sorted) waste samples rather than a collection of similar images, which has the potential to obscure the detection process. Thus, there is an urgency to develop research that addresses this gap.

This research aims to build an ML model to classify non-organic waste that contributes to three aspects, namely (i) building a dataset with more labels, in accordance with the most commonly encountered non-organic waste in everyday life, (ii) using more instances in each label, and (iii) conducting a comprehensive evaluation to determine model performance and determine which groups of waste are easy/difficult to classify. This paper uses a transfer learning approach using the MobileNet model [20] and Visual Geometry Group (VGG)-16 [21], to fine-tune the collected waste image data. Evaluation is conducted using standard metrics such as accuracy, precision, recall, and F1 score. Apart from that, it is important to carry out error analysis manually to gain visual insight into the model's strengths and weaknesses. The output of this research provides not only numerical evaluation of model performance but also insight into techniques for grouping non-organic waste to support model performance. This research helps advance waste management technologies by identifying which types of non-organic waste are the most difficult to sort. It also supports AI-powered waste handling systems that can be beneficial for the environment.

This paper delivers several contributions as follows:

- A dataset of non-organic waste consisting of 20 categories and 2,552 instances has been developed.
- The MobileNet model, achieving 86% accuracy, outperforms the VGG-16 model which reaches an accuracy of 72%.
- Both models are effective in predicting distinguishable categories such as cigarette butts, chopsticks, tires, toothbrushes, and glass bottles.
- Both models are less effective in predicting paper-based waste, such as cardboard, carton packaging, books, and foam packaging.

2. Method

This section explains the proposed method for non-organic waste prediction. There are three sub-chapters in this section, namely waste dataset development, machine learning model development, and model evaluation with error analysis of misclassified instances. All stages are presented in Figure 1.

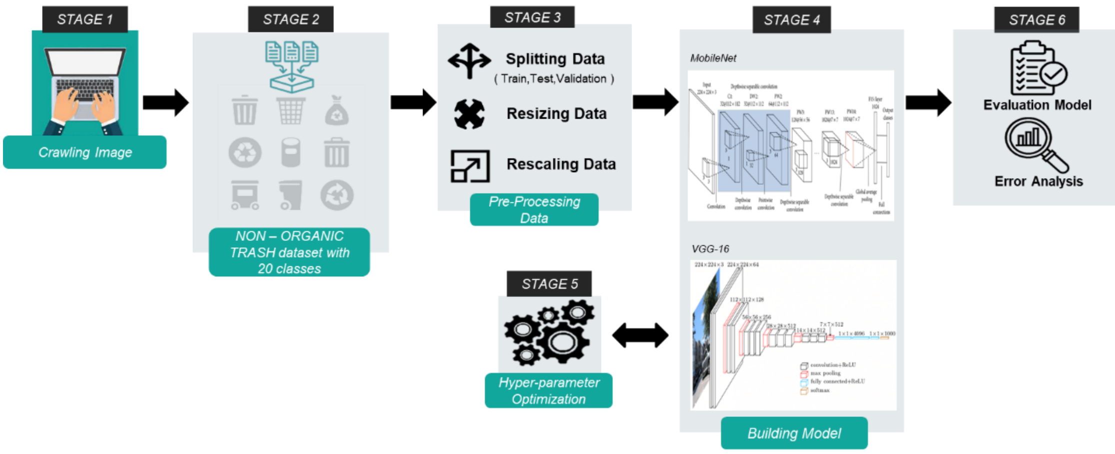


Figure 1. The Process Flow to Develop a Machine Learning Model for Non-organic Waste

2.1 The Development of Non-organic Waste Dataset

The non-organic waste dataset was collected from various internet sources, including Open Datasets, Google Images, and Flickr. In this stage, ensuring diversity in image conditions such as angles, background, lighting, resolution, and object occlusion is essential for achieving better model generalization. The waste categories were identified based on the types of non-organic waste commonly found in daily life, using direct observations and reviews of waste classification systems that use machine learning. To achieve this, general keywords such as "non-organic waste" and category-specific terms like "book," "textile," and "tire" are used. As a result, the dataset consists of 20 main categories, covering various forms of plastic, glass, paper, and metal waste. To improve data quality and consistency, the image preprocessing (filtering, cleaning, duplicate removal, etc.) is required.

2.2 Building Machine Learning Model

Non-organic waste classification is performed using a dataset obtained in the previous stage and pre-processed. This paper uses two popular pre-trained models: MobileNet and Visual Geometry Group (VGG)-16. The section below presents how the classification process is carried out.

2.2.1 MobileNet

The MobileNet model is designed to be very compact and effective, making it suitable for use on mobile or embedded devices. MobileNet uses a special convolutional layer called depthwise separable convolution, which functions to reduce the number of parameters and computational resources [20]. This model has shown excellent performance on ImageNet classification [22], [23], [24]. The components of the MobileNet model are presented in Table 1 below.

Table 1. The Component of MobileNet Model

Component	Description
Input	Fixed-size 224x224 RGB image.
Depthwise Separable Convolutions	Depthwise Convolution: Utilizes one filter for each input channel.
	Pointwise Convolution: Employs 1x1 convolutions to amalgamate depthwise outputs.
Architecture	• 28 layers: 13 depthwise separable convolutions, one fully linked layer, and a softmax output. • Each convolution is succeeded by batch normalization and ReLU activation.
Width Multiplier	Decreases the quantity of filters in each layer to regulate model dimensions and computational requirements.
Resolution Multiplier	Decreases the resolution of the input image to further lower computing expenses.
Output	Probability distribution over 1000 ImageNet classes.

2.2.2 Visual Geometry Group (VGG)-16
The VGG-16 model is composed of 16 layers, of which 13 are convolutional layers and the remaining 3 are fully connected layers [25]. The working principle of VGG-16 is a small receptive convolutional filter measuring 3x3 and arranged in several layers. This composition is considered capable of maintaining network depth while keeping computational complexity manageable [21]. The components of VGG-16 are presented in Table 2.

Table 2. The Component of VGG-16 Model

Key Component	Explanation
Input	RGB image with a fixed dimension of 224x224 pixels.
Convolutional Layers	• Thirteen layers utilizing 3x3 filters, with a stride of one and padding to preserve spatial resolution. • ReLU activation applied after each convolution. • Max-pooling (2x2 window, stride 2) used after some convolutional layers for downsampling.
Depth and Feature Maps	Number of feature maps increases progressively: 64 → 128 → 256 → 512.
Fully Connected Layers	• Three fully connected layers. • The initial two layers consist of 4096 units each, with ReLU activation and a dropout rate of 0.5 for regularization purposes. • The last layer: 1000 units (for ImageNet classes) with softmax activation.
Output	Probability distribution over 1000 ImageNet classes.

2.3 Model Evaluation and Error Analysis
The machine learning model from the previous stage is evaluated to determine the performance of each model and scenario used. The performance indicators used in this paper, namely recall, accuracy, precision, and F1 score are shown in Equations 1–4, and were derived from the confusion matrix in Table 3.

$$\mathrm{Accuracy} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \tag{1}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{2}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{3}$$

$$\text{F1 Score} = 2 \text{ x } \frac{\text{Precision x Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Table 3. Confusion Matrix

	Positive (P)	Negative (N)
Positive (P)	TP (True Positive)	FN (False Negative)
Negative (N)	FP (False Positive)	TN (True Negative)

During the model evaluation phase, an analysis of correct and incorrect classifications (error analysis) is performed. This is crucial for gaining visual insight into the model's strengths and weaknesses. The results of this analysis are useful not only for improving model performance but also for revising the non-organized waste categorization if necessary. More specifically, this process involves identifying the true labels of instances that failed to be classified.

3. Results and Discussion

This section describes the experiment results that have been conducted in this paper, which consists of three parts, namely the dataset, prediction results, and error analysis.

3.1 Dataset of non-organic waste

This paper has identified 20 categories of non-organic waste commonly found in public areas. In our dataset, each waste instance contains a collection of waste items from the same category. This is caused by the data-gathering process, which relies on internet searches, making it impossible to separate individual waste objects beforehand. Figure 2 presents the waste sample, while Figure 3 displays the overall distribution.

(1) book (2) bulb (3) can (4) cardboard
(5) carton box drink (6) carton packaging (7) chopstick (8) cigarette butts
(9) foam packaging (10) glass bottle (11) newspaper (12) paper
(13) plastic bag (14) plastic bottle (15) plastic packaging (16) spray can
(17) texstil (18) tire (19) toothbrush (20) toothpick

Figure 2. Sample of Instances of Non-organnic Waste in the Dataset

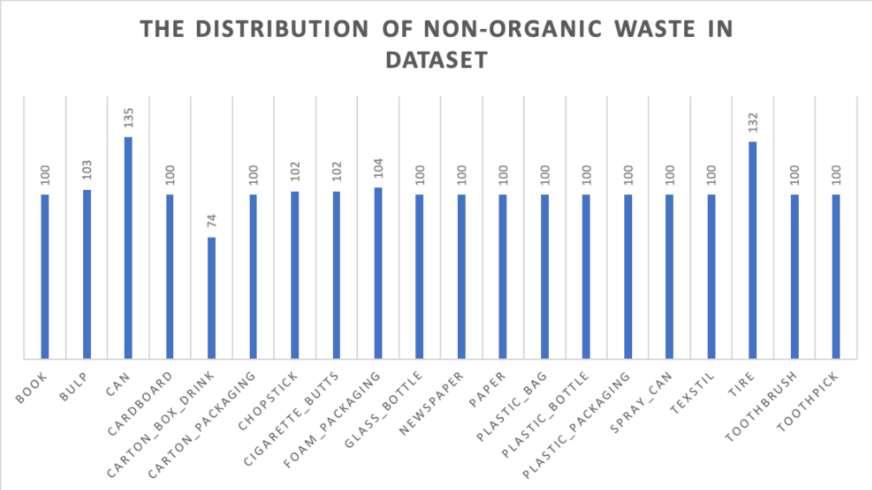


Figure 3. The Distribution of the Instances of Non-organic Waste in the Dataset

3.2 Classification results of non-organic waste

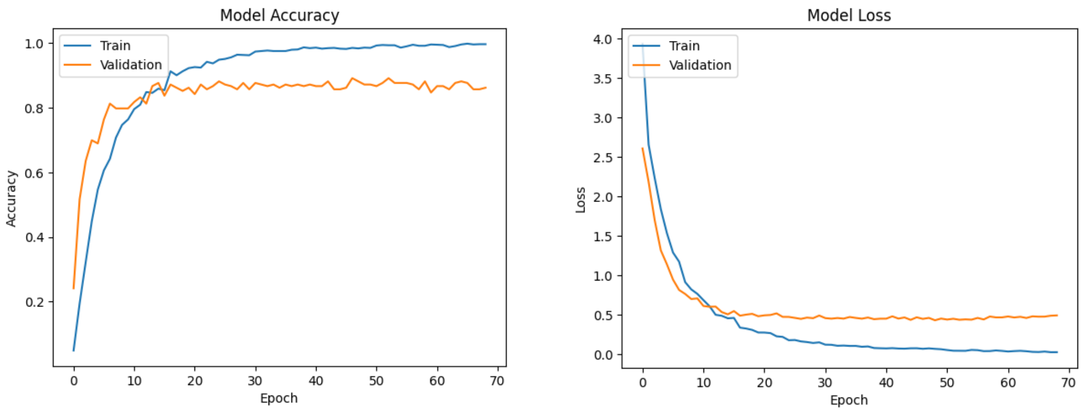
The experiment results are presented in Table 4. In general, MobileNet achieved a classification accuracy of 0.86, outperforming VGG-16, which achieved an accuracy of 0.72. Looking further into MobileNet's performance, five categories achieved the best results based on precision, recall, and F1-score: toothbrush, tire, cigarette butts, chopsticks, and plastic bags. Interestingly, the VGG-16 model produced competitive scores in nearly the same categories as MobileNet, including cigarette butts, chopsticks, tires, toothbrushes, and glass bottles. This evidence indicates that both pre-trained models are effective in detecting these five types of non-organic waste. However, both models showed less competitive performance in paper-based and packaging waste categories.

Table 4. The Performance Comparison of MobileNet and VGG-16 for Predicting the Non-organic Waste

Pre-Trained Model	Non-organic waste category	Precision	Recall	F1-score	Accuracy
MobileNet	book	0.88	0.77	0.82	0.86
	bulb	0.88	0.91	0.89	
	can	0.85	0.95	0.89	
	cardboard	0.77	0.8	0.79	
	carton_box_drink	0.88	0.91	0.89	
	carton_packaging	0.78	0.7	0.74	
	chopstick	0.91	0.91	0.92	
	cigarette_butts	0.91	0.97	0.94	
	foam_packaging	0.87	0.84	0.86	
	glass_bottle	0.96	0.83	0.89	
	newspaper	0.79	0.9	0.84	
	paper	0.83	0.8	0.81	
	plastic_bag	0.9	0.93	0.92	
	plastic_bottle	0.82	0.9	0.86	
	plastic_packaging	0.79	0.73	0.76	
	spray_can	0.78	0.83	0.81	
	texstil	0.92	0.88	0.86	
	tire	0.97	0.95	0.96	
	toothbrush	1	0.77	0.87	
	toothpick	0.78	0.93	0.85	
VGG-16	book	0.73	0.63	0.68	0.72
	bulb	0.93	0.78	0.85	
	can	0.83	0.71	0.76	
	cardboard	0.59	0.43	0.5	
	carton_box_drink	0.71	0.74	0.72	

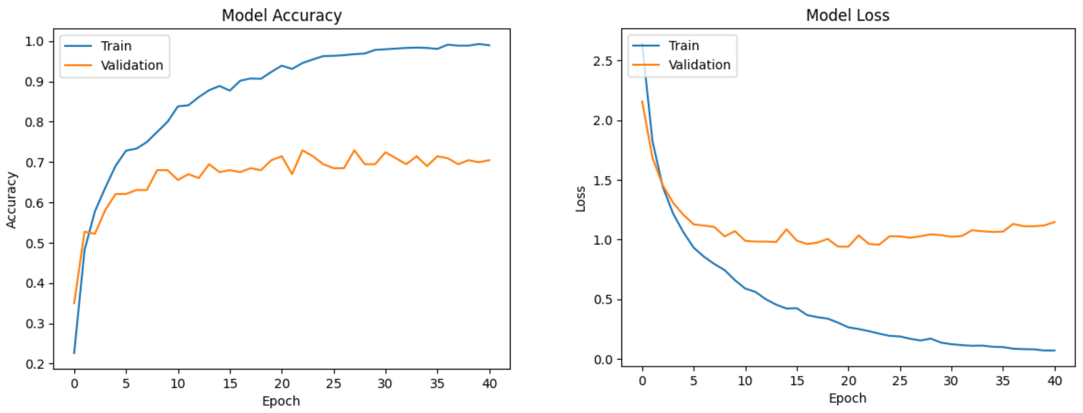
carton_packaging	0.46	0.73	0.56
chopstick	0.78	0.94	0.85
cigarette_butts	0.86	0.97	0.91
foam_packaging	0.71	0.38	0.49
glass_bottle	0.87	0.87	0.87
newspaper	0.53	0.6	0.56
paper	0.56	0.67	0.61
plastic_bag	0.75	0.8	0.77
plastic_bottle	0.79	0.63	0.7
plastic_packaging	0.76	0.73	0.75
spray_can	0.67	0.6	0.63
texstil	0.74	0.77	0.75
tire	0.8	0.9	0.85
toothbrush	0.83	0.83	0.83
toothpick	0.77	0.8	0.79

The superiority of the MobileNet model to predict the waste category is also represented by the curve of accuracy and loss during training stages. Figure 4 shows that MobileNet is superior as it achieves higher validation accuracy with better generalization. While overfitting exists, it is not as severe as in the VGG-16 model. Both models have overfitting, but it is worse in the VGG-16 model because the larger gap between training and validation accuracy shows that this model is memorizing the training data rather than learning general patterns. The model's loss presents the same trend as the MobileNet model, which is better at reducing losses during training compared with the VGG-16 model. The hyperparameter setting of these results is presented in Figure 5.



(a) Model Accuracy and Loss on MobileNet

(b)



(b) Model Accuracy and Loss on VGG-16

Figure 4. The Learning Curve during Training Stage Using MobileNet and VGG-16

MobileNet HyperParameter using RandomSearch

Parameter	Value
dense_unit	320
dropout	0.7000000000000001
learning_rate	0.0004935568202244433

(a) MobileNet

VGG-16 HyperParameter using RandomSearch

Parameter	Value
dense_unit	192
dropout	0.1
learning_rate	0.002564987986358073

(b) VGG-16

Figure 5. Hyperparameter Setting of (a) MobileNet and (b) VGG-16

3.3 Error Analysis

Error analysis is used to analyze the error in predicting the type of waste. This stage is important to improve the model in further research. The recap of error analysis is presented in Table 6. The error analysis of MobileNet-based classification model reveals interesting phenomena, especially among waste that is visually or texturally similar. Book was misclassified seven times, being predicted as foam packaging, paper, newspaper, cardboard (twice), plastic packaging, and toothpick, indicating the model has difficulty to differentiate among similar fibrous textures. There were six misclassifications for cardboard, with the model frequently confused it with textile, plastic bottle, book, and carton packaging (three times), indicating challenges in distinguishing between paper-based waste. Carton packaging, with nine misclassified instances, was often mistaken for foam packaging (twice), pulp, newspaper, cardboard (three times), plastic packaging, and carton box drinks. Paper was misclassified six times as cigarette butts, textiles, newspapers (twice), toothpicks, and plastic bags. Meanwhile, plastic packaging, with 8 misclassifications, was confused with foam packaging, carton packaging, cans (three times), bulbs, and plastic bags (twice). Textile, with six misclassifications, was predicted as paper (twice), newspaper (twice), and cardboard (twice). Toothbrush was misclassified seven times as cigarette butts, spray can, carton packaging, and toothpick (four times), which shows difficulties in distinguishing elongated objects.

Table 6. The Analysis of Miss-classified Instances on Both MobileNet dan VGG-16 Models

Model	Categories	Number of Wrongly Predicted as	Number of Missclassified Instances	Sample Instances	Cause of Error
MobileNet	**Book**	foam_packaging (1), paper (1), newspaper (1), cardboard (2), plastic_packaging (1), toothpick (1)	7		The error occurred because all the book covers in the image were brown and looked like cardboard.
	Cardboard	textil (1), plastic_bottle (1), book (1), carton_packaging (3)	6		The error occurs because the shape of the cardboard is like the shape of carton packaging when observed from above.
	Carton packaging	foam_packaging (2), bulb (1), newspaper (1), cardboard (3), plastic_packaging (1),	9		The error occurs because the shape of the carton packaging is

		carton_box_drink (1)			similar to cardboard.
	Paper	cigarette_butts (1), texstil (1), newspaper (2), plastic_bag (1), toothpick (1)	6		The error occurs because the shape and color of the paper looks like a pile of used newspapers.
	Plastic packaging	foam_packaging (1), carton_packaging (1), can (3), bulb (1), plastic_bag (2)	8		The error occurs because the striking shape and color of the plastic packaging is like the shape and color of most can images.
	Textile	paper (2), newspaper (2), cardboard (2)	6		The error occurs because the textile looks stiff and similar to paper.
	Toothbrush	cigarette_butts (1), spray_can (1), carton_packaging (1), toothpick (4)	7		The error occurs because the shape and color of the toothbrush image are similar to the toothpick image.
VGG-16	**Book**	foam_packaging (1), paper (1), newspaper (4), cardboard (2), plastic_packaging (1), texstil (1), spray_can (1)	11		The mistake occurred because the pile of faded gray-brown books looked like a pile of used newspapers.
	Can	spray_can (5), carton_box_drink (2), carton_packaging (1), glass_bottle (1), bulb (1), cigarette_butts (1), toothbrush (1)	12		The error occurred because the shape of the collection of cans looked like a pile of used cans

				without sprays.
Cardboard	paper (3), newspaper (5), book (2), carton_packaging (5), chopstick (1), toothpick (1)	17		The error occurs because the cardboard looks like used carton packaging that is neat and has folds.
Foam packaging	paper (3), carton_packaging (6), plastic_packaging (2), tire (3), newspaper (1), cigarette_butts (1), can (1), toothbrush (1), bulb (1), cardboard (1)	20		The error occurred because the shape of the foam packaging resembled torn used paper.
Newspaper	book (3), cardboard (4), texstil (4), chopstick (1)	12		The error occurs because the shape of the stack of newspapers is similar to the position of the stack of cardboard.
Plastic bottle	carton_packaging (1), tire (3), plastic_bag (2), book (1), cigarette_butts (1), carton_box_drink (1), texstil (1), can (1)	11		The error occurs because the texture of the plastic bottle has circular lines that resemble tires.
Spray can	plastic_bottle (2), can (3), glass_bottle (3), plastic_packaging (1), carton_box_drink (2), carton_packaging (1)	12		The error occurs because the shape of the spray can without the spray looks like a regular can.

This paper found interesting patterns in analyzing all instances that VGG-16 failed to predict. First, foam packaging was the category that has the most instances of error to be classified. Errors occurred when foam packaging was predicted as paper, carton packaging, plastic packaging, tires, newspapers, etc. In this context, the model struggled to distinguish between various types of packaging. Second, cardboard has the second most classification errors. This type of waste was often predicted as paper, newspaper, books, carton packaging, etc. This indicated that the model struggled to distinguish paper-based waste. Next, the model failed to distinguish between the spray category and various types of packaging objects with similar shapes, such as glass bottles, plastic bottles, drink carton boxes, etc.

Fourth, misclassifications occurred in the categories of book, plastic bottle, and newspaper, which were often driven by visually similar visuals, textures, and shapes.

Observing these failed instances led to model improvements, particularly in distinguishing paper-based waste such as cardboard, carton, book, and foam. These types of waste generally have identical visuals. Furthermore, the developed model can be deployed on sorting hardware to sort waste types according to their processing methods. This hardware needs to be compatible with Indonesia's waste management landscape, where waste sorting at the source is not a common practice.

4. Conclusion

This paper has developed machine learning models to classify non-organic waste. This study constructed a dataset that included 20 waste categories and 2,552 instances. The experiment indicates that the MobileNet achieved a more competitive result, reaching 86% accuracy compared to VGG-16, which achieved 72%. The analysis of misclassified instances reveals that both models show their effectiveness in predicting categories such as cigarette butts, chopsticks, tires, toothbrushes, and glass bottles. On the other hand, both models are less effective in predicting paper-based categories such as cardboard, carton packaging, books, and foam packaging. The determining factor for a model's success or failure in predicting waste types is the visual similarity in shape, color, and texture.

In future research, we aim to enhance model performance by incorporating more diverse data and augmenting the dataset, as well as employing explainability models such as Local Interpretable Model-Agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), or Gradient-weighted Class Activation Mapping (Grad-CAM) for diagnostic purposes.

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