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Implementation of Deep Learning Model for Classification of Household Trash Image

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Abstract: The problem of household waste management is a very important issue today, where the rapid urbanization, consumptive culture, and the tendency to dispose of waste without sorting it first from home, makes the volume of waste in landfills increase. Therefore, household waste management needs to be managed quickly and appropriately, so as not to have a major impact on environmental, hygiene, and health problems. Although some environmental communities and local governments have made efforts to manage waste through recycling systems, the long-term use of human labor is inefficient, expensive, and harmful to workers' health. Therefore, utilizing artificial intelligence technology is the best solution to classify waste types quickly and accurately. This research tries to test several pre-trained convolutional neural network (CNN) models to perform classification. The results of testing pre-trained CNN models, such as AlexNet, VGG16, VGG19, ResNet50, and ResNeXt50, found that the pre-trained model ResNext50 is better with 100% accuracy, while the training loss and validation loss are 0.0414 and 0.0304, respectively. Then the second best model is the pre-trained ResNet50 model with 100% accuracy with training loss and validation loss of 0.0832 and 0.1077, respectively.

Keywords: Trash; Classification; CNN; Pre-trained Model; ResNeXt

INTRODUCTION

According to data from the Sistem Informasi Pengelolaan Sampah Nasional (SIPSN) of the Ministry of Environment and Forestry Indonesia in 2023, the national waste generation reached 35.7 million tons/year, where the total national waste production can be managed at around 62.85%, while the remaining 37.15% is still not well managed. Likewise, based on Ministry of Environment and Forestry data in 2023, the largest waste composition comes from household trash, which reaches 51.1% (sipsn.menlhk.go.id, 2023). This happens because most people do not sort household trash at home (Hidayat Salam, 2023), so some landfills in some regions of Indonesia experience a waste management crisis that raises environmental, hygiene, and health problems (Indraswari, 2023).

Therefore, a trash management system at the local level is necessary to ensure efficient resource utilization. One of the most effective methods of protecting the environment is recycling (Beardsley, 1985). However, the long-term use of human labor can in some aspects reduce efficiency, increase costs, and harm workers' health (Kaya et al., 2023).

To overcome these problems, currently, artificial intelligence-based technology to classify image-based objects has been widely applied in various fields. Several studies such as research on classifying road types: normal, cracked, and potholes using the LGBM Classifier machine learning algorithm to monitor and maintain roads. The results of the study achieved an accuracy of 90% (Robet et al., 2022).

Other research, applied Convolutional Neural Network (CNN) architecture to model the classification of traffic signs with the aim of the model being used in self-driving car systems to identify each traffic sign accurately. The results of the research model from CNN TrafficSign can achieve 95.8% accuracy (Pothineni et al., 2023).

The used deep learning models such as AlexNet, MobileNet, and ResNet50 to perform feature extraction while classifying people who used masks during the COVID-19 Pandemic was also carried out (Sethi et al., 2021). The results of the three models show that the ResNet50 model has a better performance by achieving an accuracy of 98.2%. Likewise, the application of artificial intelligence models in the identification of household trash has been widely studied by previous researchers. In 2019, a study on trash classification using pre-trained CNN InceptionV1 was conducted (Tiyajamorn et al., 2019), and obtained 94% accuracy with a classification time of 4.2 seconds. Meanwhile, Chen (Chen et al., 2021) proposed InceptionV3, and got 93.125% accuracy.

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The use of ResNet-34 model is also done (Kang et al., 2020) which was optimized through three approaches: 1) multi-feature-fusion, 2) feature-reuse of residual units, 3) designing a new activation function, and obtained 99% accuracy, with a classification time of 0.95 seconds. Meanwhile, Zhang (Q. Zhang, Zhang, et al., 2021) improvised ResNet-18, and obtained an accuracy of 95.87%. Rahman (Rahman et al., 2022) used ResNet-34, and obtained a result of 95.3125%.

In 2020 Yujie (Yujie He et al., 2020) used TrashNet data (Thung, 2017), modified AlexNet on parameters, and performed data augmentation. Then perform classification with a Support Vector Machine (SVM) and obtain 79.94% accuracy. The use of AlexNet for feature extraction was also carried out (H. Zhang et al., 2023), where information from the extraction was classified using the Deep Belief Network (DBN) and hyperparameter optimization using Optuna. Another approach is to optimize the DenseNet121 model with data augmentation and apply the Genetic Algorithm (GA) to the fully connected layer to improve accuracy (Mao et al., 2021). The proposed model results reached 99.6%.

Research using DenseNet169 based on transfer learning was also conducted (Q. Zhang, Yang, et al., 2021) and obtained an accuracy above 82%. Shi (Shi et al., 2021) proposed a Multilayer Hybrid-CNN (MLH-CNN) which has the same structure as VGGNet but is simpler. By changing the number of network modules and channels in the model, the evaluation results can outperform other models such as AlexNet, ResNet50, and VGG16 with an accuracy value of 92.6%.

The use of MLH-CNN was also conducted (Yang et al., 2022) but the researchers preprocessed the data with an adaptive image-brightening algorithm on the background and a threshold method to reduce noise from shadows. The model can achieve 96.77% on its test dataset, and 93.72% on TrashNet. The use of Unmanned Aerial Vehicles (UAVs) to classify clean locations and litter locations was also carried out (Verma et al., 2022) by designed CNN models with 10, and 14 layers. Where each model consists of 3 convolution layers and 5 convolution layers with maxpool. The comparison results show that the first model is superior by 94%.

Recently, Hossen (Hossen et al., 2024) proposed GCDN-Net which has two tasks, namely 1) the classification of litter and non-litter images, and 2) the classification of litter types. The test result reached 95.77%. A comparison of DensNet-201, Inception-V3, MobileNet-V2, and ResNet-50 models for plastic trash separation (Pučnik et al., 2024) resulted in the conclusion that the Inception-V3 was superior by an average of 78.34% in separating packaging materials based on their composition, size, cleanliness, and appearance.

Based on the above study, the utilization of pre-trained convolutional neural network architecture from ImageNet in image classification (Krizhevsky et al., 2012) is a model that is widely used by researchers to save computing time, and can also achieve better accuracy. Therefore, in this study, researchers compared several pre-trained convolutional neural network models in classifying household trash types to evaluate accuracy.

LITERATURE REVIEW

Deep learning, particularly Convolutional Neural Networks (CNN), has yielded significant improvements in accuracy and performance by automatically learning feature representations from raw images compared to traditional machine learning methods (e.g., Support Vector Machine (SVM), Decision Trees) that have had limited success in image classification, especially for large and complex datasets. There are several main architectural developments in image classification, namely:

AlexNet

AlexNet, which won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), was the first deep CNN to achieve a substantial improvement in classification performance, popularizing the use of deep learning in computer vision. The excellent of the model is where the use of ReLU activations, dropout, data augmentation, and GPU training allows AlexNet to handle large datasets effectively (Krizhevsky et al., 2012).

VGG-Net

VGGNet is a type of Convolutional Neural Network (CNN) architecture developed by the Visual Geometry Group (VGG) at the University of Oxford. VGGNet gained popularity due to its outstanding performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014. VGGNet is particularly known for introducing a simple but deeper network (up to 19 layers) with 3x3 convolutional filters, achieving state-of-the-art performance by demonstrating the importance of network depth for feature extraction (Simonyan & Zisserman, 2015).

ResNet

ResNet, or Residual Network, is a deep Convolutional Neural Network architecture introduced by researchers at Microsoft Research in 2015. It's highly influential due to its innovative use of residual connections, which allowed for the successful training of very deep networks without the problems of vanishing and exploding gradients. ResNet achieved groundbreaking performance in the ImageNet competition, winning the 2015 ILSVRC with a 152-layer version. The main idea behind ResNet is the residual block, where the input is passed directly to the output of a layer after some intermediate operations (like convolutions and ReLU activation) (He et al., 2016).

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ResNeXt

ResNeXt is an extension of the ResNet architecture, proposed by researchers at Facebook AI Research. It builds upon the strengths of ResNet, specifically the use of residual connections, but introduces an additional concept called "cardinality" or the number of parallel paths in each residual block. This design improves the network's representational power while keeping computational costs relatively low, making ResNeXt highly efficient and effective for tasks like image classification and object detection (Xie et al., 2017).

Pre-Trained Model

A pre-trained model is a neural network model that has already been trained on a large dataset and has learned useful features from that data. These models are valuable in many machine learning tasks because they save time and computational resources and often achieve better results than training a new model from scratch, especially if the available data is limited (Han et al., 2021).

METHOD

In this section, the research method proposed in this study consists of several stages which are illustrated in Fig. 1.

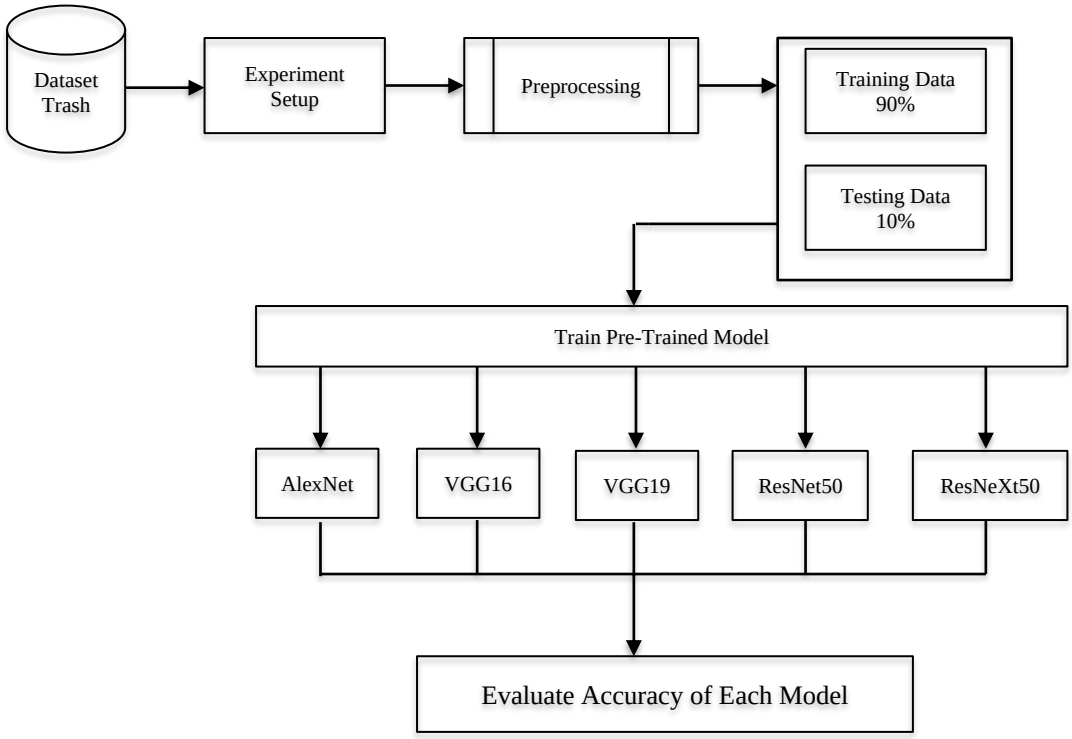

Fig. 1 Research Stages

Dataset

Our research dataset was collected from publicly published datasets accessible through https://www.kaggle.com/datasets/feyzazkefe/trashnet. The dataset were divided into six categories: cardboard, glass, metal, paper, plastic, and trash. The total number of images is 2527, with 403 in the cardboard category, 501 in the glass category, 410 in the metal category, 594 in the paper category, 482 in the plastic category, and 137 in the trash category. The images in the dataset are 512x384 pixels in size. The dataset is 47 MB large. Fig. 2 depicts some examples from the dataset.

*name of corresponding author

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Fig. 2 Sample of Dataset
(Source : https://www.kaggle.com/datasets/feyzazkefe/trashnet)

Experiment Setup
The software, and hardware specifications used in the study are shown in Table 1 below.

Table 1. Experiment Setup

Hardware/Software	Description
Google Colab	Software Spesification
Jupyter Notebook	Virtual Environment for Python code
Google Drive	Dataset Storage
Pytorch 2.4.0 dan Scikit-Learn	Open-source software for training and testing the images

Data Preprocessing
The dataset of trash images obtained consists of six folders with each category of waste types that have been determined. Then, before the model training process is carried out, the images from each waste category folder are divided into 90% for the training folder and 10% for the testing folder. After the dataset division is done, the next step is to resize the original image from 512x384 to 128x128 and normalize the data. The purpose of resizing the image and normalizing the data is to speed up computation time.

Train Model
We conducted experiments on several CNN models from the Pre-trained model, namely: AlexNet, VGG16, VGG19, ResNet50, and ResNext50. Based on several previous literature reviews, it is stated that the ResNeXt model has better performance. Therefore, we try to do a comparison of some of these models by configuring the parameters as follows: learning rate = 0.001, batch_size =32, epochs = 50, for the optimizer, we chose the AdaDelta (Zeiler, 2012), because this method in its research for classification on MNIST data was able to surpass the SGD, Momentum, and Adagrad methods.

Evaluation Model
Some of the measurement metrics used in the training and validation process are accuracy, loss, and confusion matrix. Accuracy is a basic metric that measures the extent to which the model can predict correctly, while loss is a function used to calculate the difference between the output created by the current algorithm and the expected output. The accuracy and loss equations can be seen below.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Prediction}} \text{x}100\% \quad (1)$$

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$$\text{CrossEntropyLoss} = -\frac{1}{N}\sum_{i=1}^{N}\log\left(\frac{e^{Zyi}}{\sum_j e^{Zj}}\right) \quad (2)$$

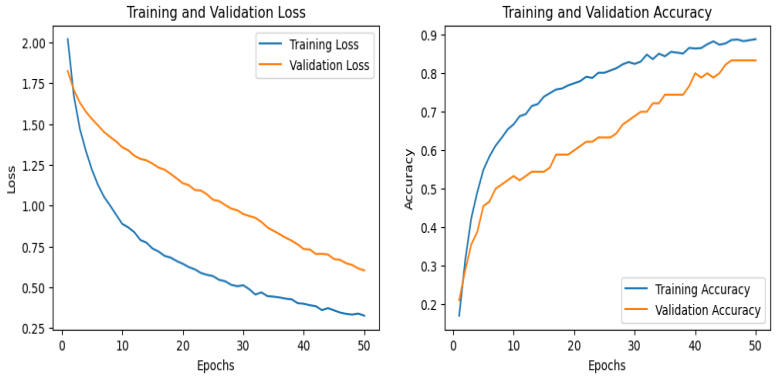
RESULT

In this section, we will explain the research results obtained. In the first stage, the pre-trained AlexNet model was used for training the trash dataset with the parameters that had been determined at the beginning. Then proceed with training on the models VGG16, VGG19, ResNet50, and finally ResNeXt50 model. The results of the model comparison above can be seen in Table 2, which denotes the level of accuracy, as well as training loss and validation loss.

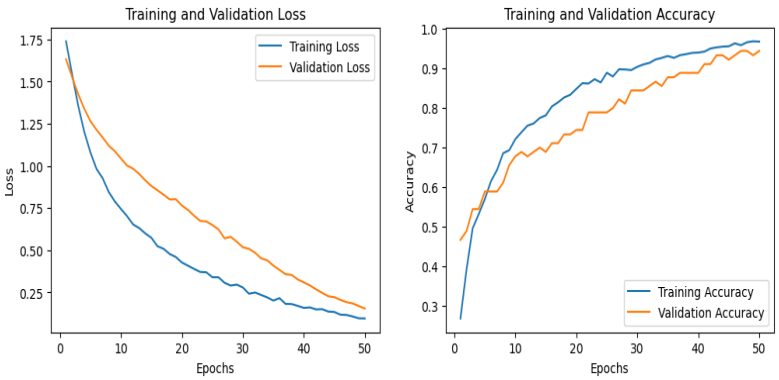
Table 2. Comparison of CNN Model in Classification

No	Pre-Trained Model	Accuracy	50 Epochs	
			Train Loss	Val Loss
1	AlexNet	83.33%	0.3261	0.6034
2	VGG16	94.44%	0.0961	0.1551
3	VGG19	96.67%	0.0773	0.1176
4	ResNet50	**100%**	0.0832	0.1077
5	**ResNeXt50**	**100%**	**0.0414**	**0.0304**

Pre-Trained AlexNet



Pre-Trained VGG16



*name of corresponding author

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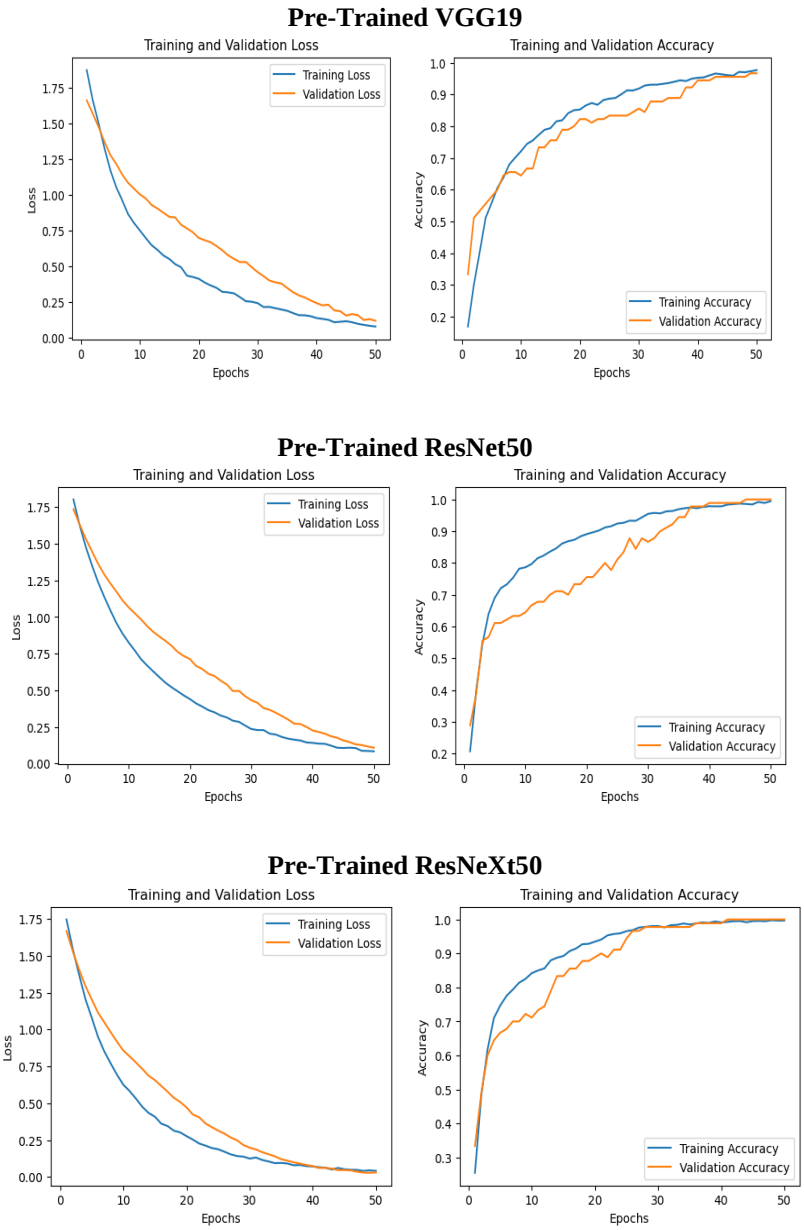

Fig. 3 Results of Five Pre-Trained Models in the Training Phase

Fig.3 denote the graphical result of AlexNet, VGG16, VGG19, ResNet50, and ResNext. In this comparison with a relatively small amount of data, the ResNeXt50 model was able to outperform other models at the 50th epoch with an accuracy value of 100%, and with training loss and validation loss values of 0.0414, and 0.0304, respectively.

DISCUSSIONS

To determine the performance of the five models that have been trained, the researchers also conducted an evaluation using confusion metrics to see the accuracy of each model shown in Fig. 4. In the test data of 15 images from each trash category, the types of plastic and trash are more difficult to classify by the AlexNet, VGG16, and VGG19 models. However, both ResNeXt50 and ResNet50 models can be classified well.

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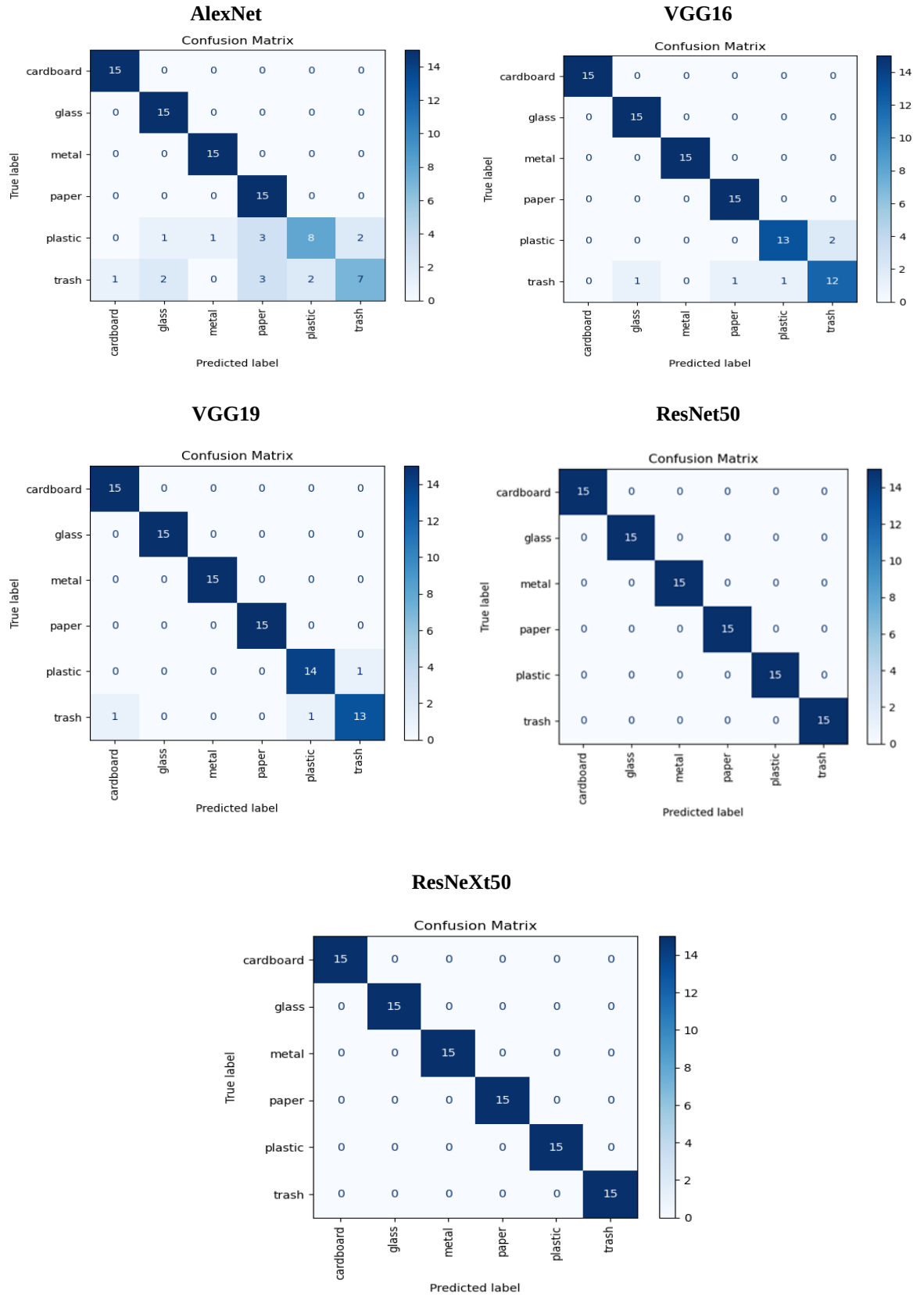

Fig. 4 Confusion Matrix Each Pre-Trained Model

CONCLUSION

Household trash is a major problem in many countries around the world. Recycling is considered the most effective method to reduce household trash, but it is inefficient, and can adversely affect the health of workers.

*name of corresponding author

This research aims to improve the effectiveness of household trash classification by comparing several pre-trained CNN models such as AlexNet, VGG16, VGG19, ResNet, and ResNeXt. In this research, pre-trained ResNeXt model architecture for trash classification in six categories using the TrashNet dataset has better performance with 100% accuracy and then the second-best model is the ResNet50 pre-trained model. This research is expected to help municipalities and recycling facilities classify trash and create an efficient waste management system. In addition, reducing the need for manual labor in recycling will contribute to maintaining the health of individuals involved in this sector.

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