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DjunkGo: A Mobile Application for Trash Classification with VGG16 Algorithm

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Abstract

Garbage is one of the big problems in many countries including Indonesia. A bad waste management and low awareness of people participating in sorting the trash are 2 obstacles that we face in daily life. However, if we can ask them to sort the trash properly, they will not only help the waste collector, but also improve the waste management in the country. That encourages us to develop a mobile application that helps people to identify the type of the trash they have so that they can sort it by themselves. This application applies image processing and VGG16 algorithm to identify the trash with accuracy 90%. Furthermore, this application also links them to an appropriate agency that can recycle their trash based on its type. Therefore, the waste sorting process will be easier and recycling is also faster.

Keywords: waste management; VGG16; image classification

1. Introduction

A bad waste management is still a big issue in Indonesia. The latest research by Sustainable Waste Indonesia (SWI) revealed that about 24% of waste in Indonesia is still not managed well. It means, around 15 million of 65 million tons of waste produced per day has polluted the ecosystem and the environment in Indonesia. Furthermore, only 7% of the waste is successfully recycled every day. The rest of it ends up in Final Disposal Sites (TPA). In addition, based on this research we found that most of the garbage on TPA is organic waste (60%), followed by plastic (14%), paper(9%), and other materials (Badan Penelitian dan Pengembangan Kementerian Dalam Negeri, 2018). Actually, organic waste is the easiest to recycle. However, the low awareness of people participating in sorting the trash makes this problem harder.

Based on the Government Regulation Number 81 (2012) concerning Management of Household Waste and Types of Household Waste, article 17 (1) it is stated that the sorting is carried out by everyone at the source. However, even if someone sorts the trash at home, sometimes the garbage collector will take all the trash in one container so that the trash sorting at home will be useless. It motivates us to make a technology that can link people to an appropriate agency that can recycle their trash based on its type. Furthermore, we also want to encourage people to be aware of the importance of shorting the trash. Therefore, we implement machine learning to help people to identify the type of garbage so that the sorting will be easier. Then, we plan to manage a system so that people who do sorting can get money from the agency. Hence, the sorting process will not only be easier but also bring benefit to both people and agency.

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2. Materials and Method

2.1. Deep Learning

In traditional machine learning, features are selected by humans and feature engineering plays a significant role to get a high accuracy of model. On the contrary, in deep learning, the model may get a high accuracy easily without human's contribution in selecting features. Deep learning originated from an artificial neural network which uses a complex structure of algorithms modeled on the human brain (LeCun et al., 2015). Since the feature selection occurs on the system, deep learning is still not interpretable. However, in some cases, we do not need to know the specific feature used in the model as long as it can predict very well.

There are many kinds of structures in deep learning. In Costa, B. S. et al (2018), the authors tried to classify the garbage into 4 classes. They compared 5 algorithms; VGG-16, AlexNet, K-Nearest Neighbor, Support Vector Machine, and Random Forests. Here VGG-16 outperformed the other model with accuracy 93% followed by AlexNet with accuracy 91%. Kumar, A. P. S. et al also compared VGG-16 with standard structure of Convolutional Neural Network (CNN) and found VGG-16 was better than CNN with accuracy 84% (Kumar et al, 2021). In Ozkaya and Seyfi (2019) compared VGG-16 with other pre-trained models and found VGG-16 is better than others when the classifier is softmax with accuracy 90% and GoogleNet is better than others when the classifier is SVM with accuracy 97.86% followed by VGG-16 with accuracy 97.46%. Therefore, we decided to use VGG-16 since it shows better performance than the other algorithms.

2.2. Dataset

Since our goal is helping people to sort the trash from home, we focus more on the image of household waste. Here we did a scraping technique to get images from google and kaggle. Totally, we collected 7100 images that will be divided into 8 classes. These classes are determined based on our interview with some waste collectors in Indonesia; they are Organic, Cardboard, Plastic Bottle, Glass Bottle, Plastic, Paper, Plate, and Metal with number of image are 2798, 712, 744, 658, 290, 658, 367, and 690 respectively. The image size is 224 x 224 x 3 with Red, Green, Blue (RGB) channels.

2.3. Proposed Method

VGG-16 is a special structure of convolutional neural network proposed by Sinyoman and Zisserman in 2014. This network consists of 16 layers including 5 Max-Pooling Layers and 3 Fully-Connected Layers. In order to prevent overfitting, we add a dropout layer before going to the classifier function, Softmax (Srivastava et al. 2014). Moreover, this layer can be useful to avoid noise in the background of the image (Srivastava et al. 2014),. For optimizer, we choose RMSprop since it performs very well based on the review of Zaheer and Shaziya (2019). Furthermore, we use learning rate = 0.0001 with categorical cross entropy as loss function, and accuracy for evaluation metrics. In addition, we also use batch size = 256 and epoch =15 in this experiment. The complete structure of the neural network implemented is provided in Figure 1.

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Model: "sequential"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14714688
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 1024)	25691136
dropout (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 8)	8200

Total params: 40,414,024
Trainable params: 30,418,952
Non-trainable params: 9,995,072

Figure 1. Structure of neural network

3. Results and Discussion

3.1. Image preprocessing

Before training the model, we did normalization to the image. We did it to make computation easier and faster since we plan to deploy this model to a mobile application. Here we did rescale 1./255 that transforms every pixel of image from [0, 255] to [0, 1]. Then, to make the image more diverse, we make some image augmentation with zoom and rotation. Then, we divide our dataset into 80% for training, 10% for validation, and 10% for testing.

3.2. Model Evaluation

After preprocessing the image, we trained the model and evaluated it by accuracy and loss graph. After 15 iterations, accuracy of both training and validation are high. Accuracy of training reaches 90% and accuracy of validation is 88%. The graph shows there is no overfitting on this model (Figure 2). Furthermore, we need to check whether the model can identify the class of image correctly for each class. Therefore, we used the ROC Curve and gained a high true positive rate for each class. All in all, we conclude that this model is good enough and ready to be deployed.

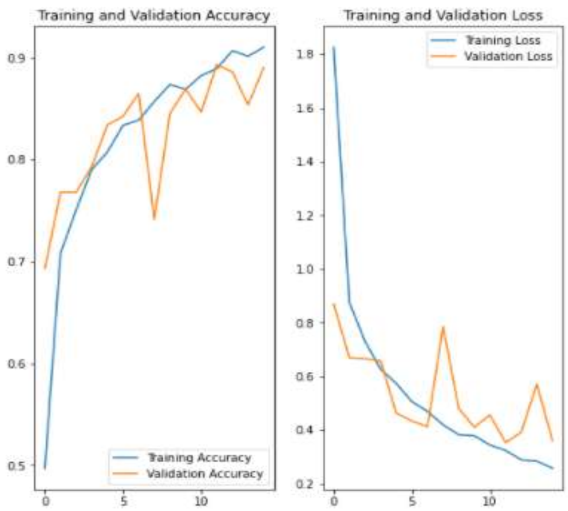

Figure 2. Accuracy and Loss Function Graph after 15 iterations

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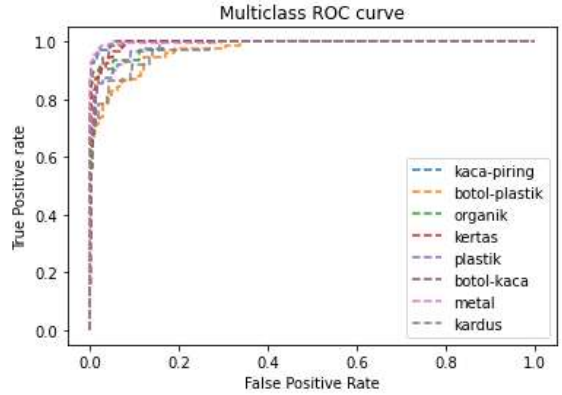

Figure 3. Multiclass ROC Curve

3.3. Model Deployment

The model is deployed in an android mobile application called “DjunkGo” to predict the class of the trash image given by the user. After successfully predicting the image, the user may save it to the list. Then, they may sort the trash and give it to the waste collector. Here we try to test our application using the testing dataset. The result shows the application can predict the image correctly (Figure 4). The design of this application is provided in Figure 5

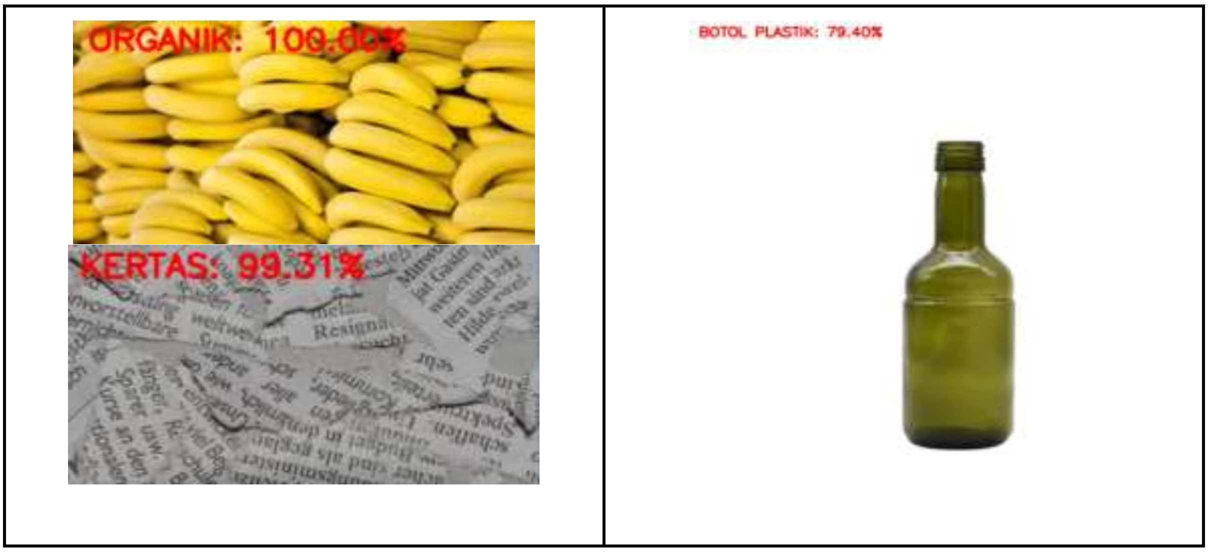

Figure 4. Testing the model

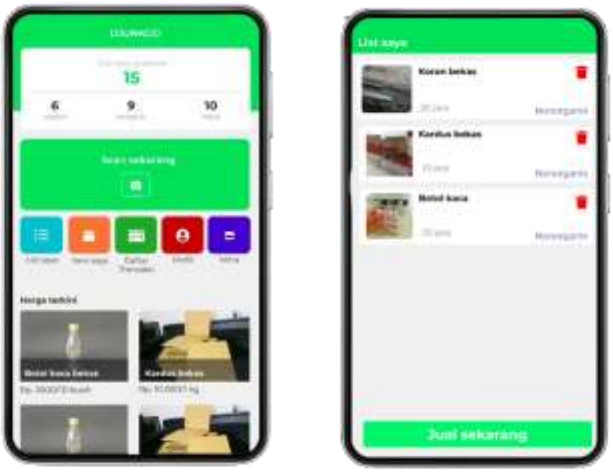

Figure 5. Design of application, scan and save the trash.

4. Conclusion and Future Work

Artificial intelligence can be the solution to improve waste management in Indonesia. In this experiment, we implement VGG-16 to classify the trash image and reach a high accuracy. Furthermore, it can run in an android mobile application so users can sort their household trash easily. However, to make this application really helpful, we need to find proper waste collectors that want to link with this application. In addition, we also have to manage a scenario to improve the model after getting new images from the user. Therefore, for future work we plan to add more images to make a better model and establish cooperation with many agencies of waste collectors in each region in Indonesia.

5. Acknowledgements

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