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Category-aware Recycle Classification using Convolutional Neural Networks

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ABSTRACT

Generally, the filtration of non-recyclable garbage is conducted in order to make a material recycling process efficient. However, this filtration task is very time-consuming and costly, since it is generally done manually. Thus, it is significantly considered that an automation technique is necessary in solving this problem. There have been a number of attempts to resolve this problem. The previous methods used the shallow convolutional neural network to compose their network. However, these methods tend to display poor accuracy, which makes it impossible to be applied in real-life situations. To solve this problem, I propose a novel category-aware recycle classification system. The proposed system is composed of three models, which are garbage feature extractor, garbage classifier, and recycle classifier. The input image is fed to the garbage feature extractor and then converted into feature maps. The feature maps are then fed to each the garbage classifier and the recycle classifier. The garbage classifier predicts the category of the input garbage image while the recycle classifier determines if the input is recyclable or not. Through experiments, the proposed method outperforms the other state-of-the-art methods by a maximum 20.2% difference in accuracy on Garbage Classification and Industrial and Residential Waste datasets.

1. Introduction

In recent research and surveys, scientists and environmentalists have found out that most of the environmental pollution is caused by garbage that is not recycled [1]. The un-recycled garbage is usually burnt or buried underground, which causes severe contamination and destruction of the ozone layer [2]. Due to ignorance about what can be recycled or not, the amount of garbage that is not being recycled is increasing dramatically causing the pollution rate to escalate. Therefore, the residential waste managing project is significant, considering that it will have a positive impact on the pollution going on.

To address this problem, numerous numbers of studies have been proposed. Meng et al. proposed a garbage classification system using CNN (Convolutional Neural Network) [3]. However, their method tends to be sensitive against noisy input samples since their method was implemented using a shallow CNN. To address this problem, Azis et al. proposed deeper CNN to develop a garbage classification system [4]. Their architecture consists of numerous layers, which makes the network have a higher computational cost, making the system operate slower. This problem disables their method to be put in real-life situations. Thus, these previous methods proposed by Meng et al. and Azis et al. are considered substandard.

To solve this problem, I propose a category-aware recycle classification system. The proposed system is composed of a garbage feature extractor, a garbage classifier, and a recycle classifier. First, the garbage feature extractor takes the garbage image as input and outputs the feature map which has garbage-related representations. The extracted feature map is fed to the garbage classifier and the recycle classifier. Then, the garbage classifier and the recycle classifier each generates scores on the input image. After the two final scores are extricated from each of the classifiers, the network determines which type of waste the fed image is closest to based on the scores pulled out by the garbage classifier, and the recycle classifier determines if the image can be recycled or not based on the scores that are on the recycle classifier.

The main contributions of this paper are as follows: The proposed system not only estimates if the trash can be recycled or not, but also determines the category of the waste, which allows the trained system to outperform the existing state-of-the-arm methods without having additional computations. The proposed method enables the network to have high accuracy and conciseness at the same time. Moreover, through the experiments, it is shown that the proposed method can be operated on a computer with low-specification. Thus, I expect the proposed method to be easily expanded to real-life situations, which is a clear contribution.

2. Method

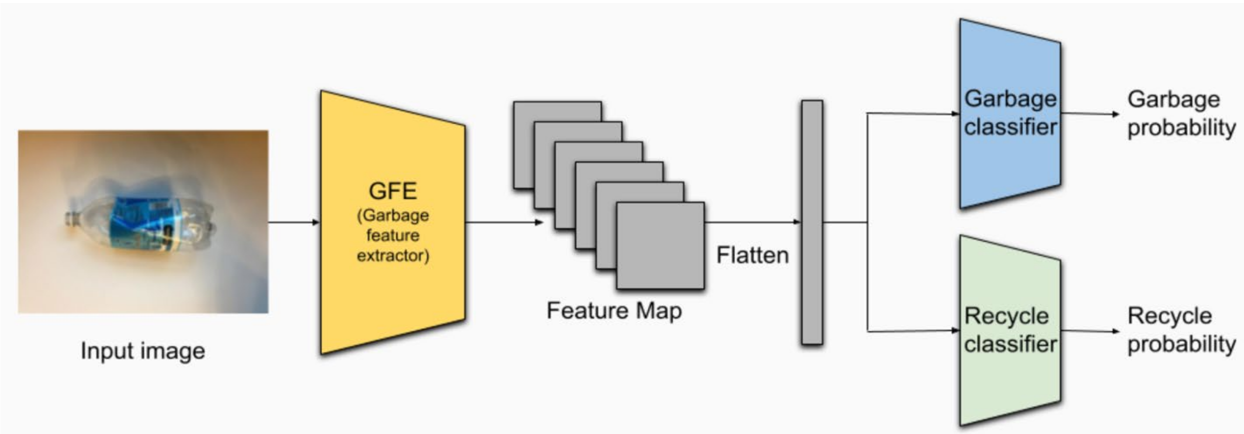

Figure 1. The overall architecture of the proposed system

Figure 1 shows the overall architecture of the proposed garbage classification system. The system is composed of GFE (Garbage Feature Extractor), garbage classifier and recycle classifier. First of all, the GFE receives a garbage image as input, then generates a feature map including image characteristics such as the overall shape, color, and textile information. These features are often entangled but it is important to extract shape-related and texture-related features in order to achieve precise predictions. To implement aforementioned feature extraction, the feature map extracted from the garbage feature extractor is fed to both garbage classifier and recycle classifier. As the extracted features are fed to both garbage classifier and recycle classifier, the GFE can disentangles the shape and texture related features. This unique joint training strategy allows the trained GFE to focus on extracting shape and texture related features. After the feature map is fed to the garbage classifier and the recycle classifier, each classifier determines the type of the input and if the waste can be recycled, respectively. Garbage classifier is developed to classify the category of each input garbage image.

For the architecture, I exploit Mobilenetv2 [5] to implement the GFE. Mobilenetv2 shows relatively fast inference time and has a comparable accuracy when compared to other CNNs (Convolutional Neural Network) architectures such as ResNet [6], VGG [7] or HRNet [8]. For the garbage classifier and recycle classifier, I developed a two-layer neural network. Through the extensive experiments, I have found that the depth of the networks are deep enough to have non-linearity to achieve accurate results.

To train the proposed system, I use the cross entropy loss function [9] which is generally used to train the classification models. The cross entropy loss function takes predicted probabilities of the ground truth category as inputs and calculates the loss. The mathematical form of the cross entropy loss function is defined as Equation 1.

Equation 1: cross entropy loss function

$$L_{CE} = -ln\hat{y}$$

Here, $\hat{y}$ denotes the predicted probability of the model, and it is fed to the function to output the loss. The value of the function, which is the loss, would be 0 when the $\hat{y}$ (the probability) is 1, and rises to infinity until the probability reaches 0. The function is applied to both models recycle classifier and garbage classifier.

Data augmentation is a method that can increase the amount of the substantial dataset samples by augmenting the original samples. This process is usually done by changing the color of the image or by changing geometric features such as rotation. The reason why data augmentation is used is because it can effectively make the model more robust and accurate by providing a wide range of dataset samples to the trained model.

In this research, I use random perspective, color jitter, and horizontal flip for augmentation methods. Random perspective randomly changes the original data into another image that is looked at from a different angle. Color jitter changes the color, hue, and saturation of the image with the randomly chosen modification strengthness. Finally, horizontal flip is an augmentation technique that flips the image horizontally. I have found that vertical flip does not lead to any performance increase as the garbash images normally lie upright, thus chose not to include the vertical flip in one of my augmentation methods.

Original	Random Perspective	Color Jitter	Horizontal Flip
(a)	(b)	(c)	(d)

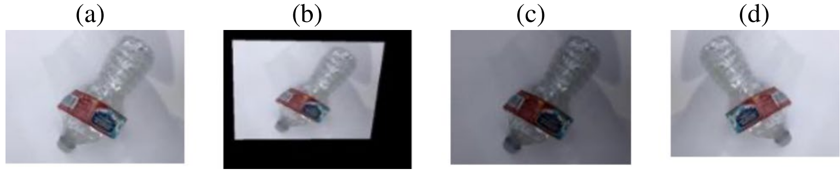

Figure 2. Example of the data augmentation technique used in this paper

Figure 2. shows the images generated by each augmentation method explained above. Fig 2. (a) represents the original image, and (b) is an image of random perspective, which is an original image looked at from a different angle. (c) is the color jittered sample, which changed the color of the original image. (d) is an image that went through horizontal flip, and it has a reversed right and left from the original image. For the optimizer algorithm, I use Adam [10] to train the proposed method. The model is trained for 50 epochs with a learning rate of 0.0001, and a batch size of 128.

3. Expermental Result

In this chapter, how the proposed method is trained and evaluated is explained in detail. To train the proposed method, I use Garbage Classification [11] and Industrial and Residential Waste [12], [13] dataset which are publicly available online. First, Garbage Classification Data [11] was used in training the model, which contains 2,529 samples of garbage images. The total samples are categorized into 6 types, which are cardboard, glass, metal, paper, plastic, and regular trash.

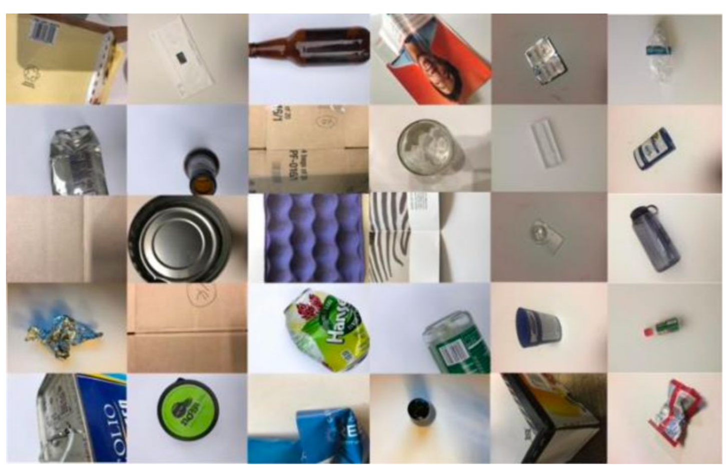

Figure 3. Snippet of Garbage Classification Dataset [11]

As shown in Figure 3, the dataset contains a variety of images that have different environments, lighting, and other external factors. Thus, this made the classification task a lot more demanding.

I also used another dataset to train the proposed model which is household and industrial waste. Two dataset combined has 350,000 samples of garbage, and in total there are 20 categories which are paper, plastic, glass, can, steel, clothes, electronic products, styrofoam, vinyl, furniture, bicycle, lamp, pet bottle, wood, concrete, synthetic resin, fiber, brick, and tires.

Figure 4. Snippet of industrial waste and residential waste[12],[13]

For the evaluation metric, I choose precision, since it is commonly used to rate classification models. The accuracy of the program is computed by dividing the amount of right answers with the number of samples, which will give a value between 0 and 1. I conduct comparison experiments to verify the superiority of the proposed method. I compare the accuracy of the proposed model with the one of existing state-of-the-art methods on the aforementioned two garbage datasets. I choose five different methods AlexNet [14], Meng et al. [3], Mao et al. [15], VGG [7], and Resnet [6] which show comparable accuracy on image classification.

3.1 Comparison with State of The Art Method

Table 1. Accuracy comparison with the state-of-the-art method

Method	Accuracy
AlexNet[14]	71.5%
Meng et al. [3]	73.7%
Mao et al. [15]	81.9%
VGG16[7]	83.1
Resnet18[6]	87.5%
Proposed Network	91.7%

Table 1 compares the accuracy of the proposed model to previous state-of-the-art methods that have comparable performances among the off shelf networks. The proposed model achieves an accuracy value of 91.7%. The first two methods, AlexNet and Meng et al. and AlexNet, show a poor performance having a shallow network. The accuracy differs by 20.2% and 18.9% with the proposed model. The next three models show relatively deeper networks.

Compared to AlexNet, Meng et al., Mao et al., VGG16, and Resnet18, the proposed model shows greater accuracy by 20.2%,18%, 9.8%, 8.6%, and 4.2%, respectively. The first two networks, AlexNet and Mao et al., show extremely low accuracy due to the shallowness of their network, showing 71.5% and 73.7% for the accuracy. The next 3 models have relatively deeper networks showing better accuracy than the previous models, but still has a lower accuracy than the proposed model. Since AlexNet and Meng et al. 's networks have shallow depth, they tend to have poor accuracy. Mao et al.'s network and VGG16 has a relatively deeper layer depth, but their performance is inferior compared to the proposed model. Resnet18 shows the greatest accuracy among the comparison state-of-the-art methods. However, this method also produces poor results compared to the proposed model, showing a performance gap of 5.3% with the proposed model.

3.2 Why the Proposed Model Works Better?

We can deduce that the accuracy of the proposed model is superior to the previous state-of-the-art methods, because the proposed model uses a waste classification to determine the availability of recycling, which is classifying the wastes. This modification allows the trained model to extract more rich features compared to the other methods that are trained without an auxiliary garbage classifier.

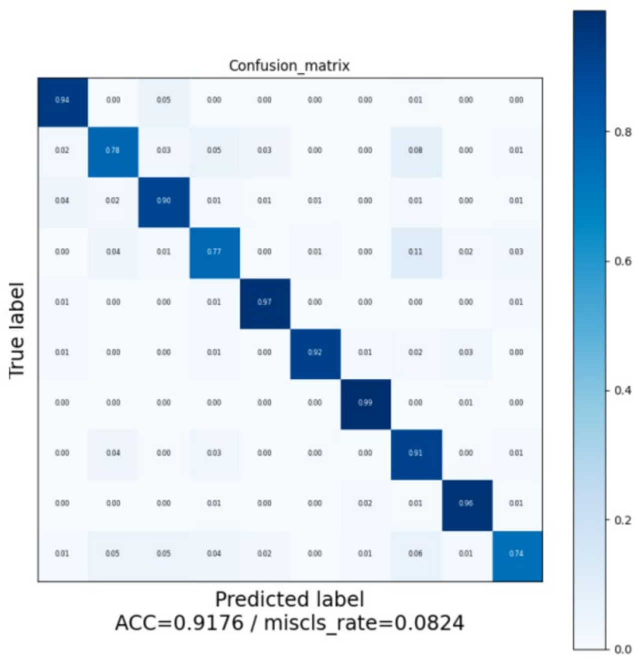

Figure 5. Confusion matrix of the proposed method

Figure 5 is the confusion matrix of the proposed method. The confusion network shows how each category was accurately predicted, giving a score out of 1. The matrix enables a deeper analysis on the proposed network, showing the category-wise information of the trained model. The category-wise information is considered as significant data, since it provides specific information about the accuracy of each column. Moreover, the diagonal line of the matrix is also significant in analyzing the data. The diagonal line shows the accuracy for each column. As the value on the diagonal line is higher, the system is considered accurate and precise.

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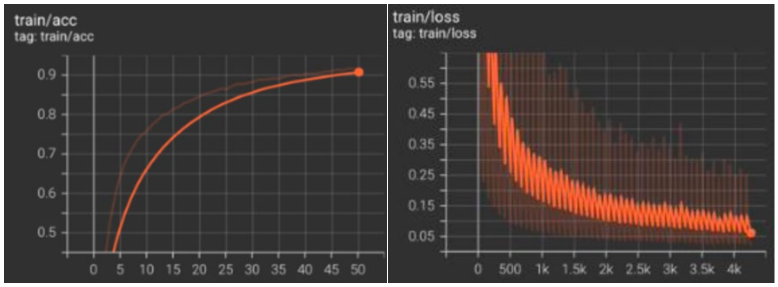

(a) **(b)**

Figure 6. Accuracy development graph Loss reduction graph

The graphs on the top each show the accuracy change, and the loss change throughout the development of the model. Graph (a) is the accuracy of the model. The accuracy of the system starts at a low value and increases exponentially at first and at a slow rate later, ultimately reaching the value of 0.9176. As the training is occurring, the accuracy value rising without stop, implicating that the model was trained successfully. Graph (b) shows the change in loss in the process of developing the model. The loss starts at a high value, and decreases as the training is executed. The rate of decreasing is not considered rapid, but the fact that the loss dropped down to about 0.05% makes the training successful.

3.3 Application

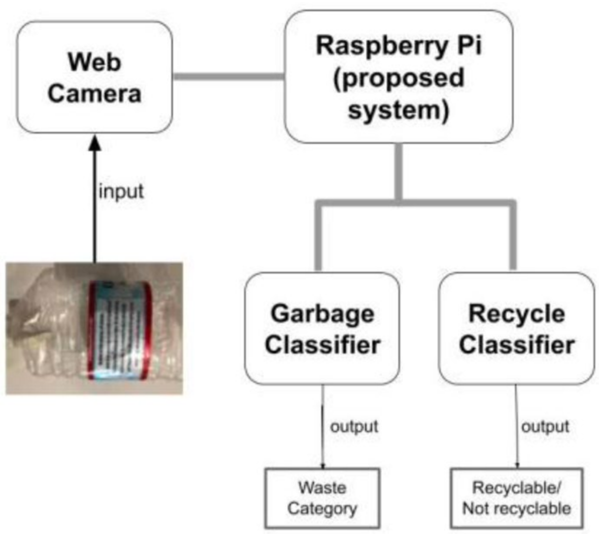

Figure 5. Confusion matrix of the proposed method

In order to expand the proposed model to the real world, we developed a practical application. The application is an informative system that gives feedback of whether the input image is recyclable or not. As shown in Figure 7, the application is developed on the edge device which is raspberry Pi and web camera. Given input garbage image is fed to raspberry Pi, and raspberry Pi runs the proposed model on the input, outputting the category of the waste from the garbage classifier and the recyclability from the recycle classifier.

The setup of the model shows how the camera and the computer are connected. The camera gets visual information and takes a photo of the garbage. Then the photo is sent to the computer, and the program starts. The visual information of the image goes through the program which is run by the computer, and the final decision of the program is displayed. The figure also shows the full computer body, showing that it can be put in small places and can be accessed easily by residents.

4. Conclusion

In this research, I proposed a category-aware recycle classification system. The proposed system is constructed by three modules which are garbage feature extractor, garbage classifier, and recycle classifier. The input garbage image is processed through the garbage feature extractor, which produces a feature map. The feature map is then afterwards fed to the garbage classifier and the recycle classifier, which predicts the category of the garbage and the recyclability of the garbage, respectively. The proposed method achieved an accuracy of 91.7% on Garbage Classification Dataset and Industrial Waste and Residential Waste Dataset. It is shown that the proposed method is superior to the existing state-of-the-art methods by achieving higher accuracy than the comparison methods. The proposed method showed a noticeable performance gap which is up to 20.2%. I also conducted an ablation study to investigate how each proposed idea in the proposed method incremented the performance of the final model. The method used in the proposed model, which classifies the category of the image with determining the recyclability, contributed in increasing the accuracy significantly, since it was clear if the garbage is recyclable or not with the type is decided. This unique process of training is considered to have a huge contribution to the development of the model, as it significantly increased the accuracy. Furthermore, the implementation of two classifiers enforced the feature extractor to extract more rich features. In the future, I plan on expanding the technology to real-life situations such as residential dumpsters. In order to do this, the proposed model has to operate on low-quality computers that are cheaper than Raspberry Pi. Since the current model is too concentrated and heavy to work in computers with lower quality, making the model lighter is a necessity.

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