Municipal Solid Waste Segregation with CNN

Chutimet Srinilta
Department of Computer Engineering
Faculty of Engineering, KMITL
Bangkok, Thailand
chutimet.sr@kmitl.ac.th

Sivakorn Kanharattanachai
Department of Computer Engineering
Faculty of Engineering, KMITL
Bangkok, Thailand
59601341@kmitl.ac.th

***Abstract*—Pollution from municipal solid waste has been a problem in Thailand for a long time. People generate waste in every minute. Ineffective waste segregation does increase difficulties in solid waste management. The Pollution Control Department of Thailand provides segregation guideline for municipal solid waste. Household wastes should be separated into four types—general waste, compostable waste, recyclable waste and hazardous waste. This paper explored performance of CNN-based waste-type classifiers (VGG-16, ResNet-50, MobileNet V2 and DenseNet-121) in classifying waste types of 9,200 municipal solid waste images. Waste type can be identified directly from waste-type classifier or derived from waste-item class. Derived classifiers outperformed their corresponding direct classifiers in the experiment. The highest waste-type classification accuracy was 94.86% from the derived ResNet-50 classifier.**

Keywords—Convolutional Neural Networks, waste classification, image classification, transfer learning

I. INTRODUCTION

In Thailand, a waste issue has been brought into serious attention just recently. A patch of garbage, almost 10 kilometers long, was seen floating in the Gulf of Thailand in February 2017. Plastic and hazardous waste smugglings were raided and cracked down in May 2018. Tons of plastic waste had been imported to Thailand from countries around the world. Not long after that, in June 2018, a pilot whale was found dead in southern Thailand with 80 plastic bags inside its stomach. These sad pieces of news were quite shocking to all Thais and the world. They have raised public awareness about the growing marine plastic pollution and the waste management problems in Thailand.

Thailand is among the five biggest contributors of ocean waste. Thailand is soon to be a “garbage bin of the world”. In order to attack these problems, Thai people need to start from changing their behavior. The 3Rs—Reuse, Reduce and Recycle—must be employed in daily activities.

According to the Pollution Control Department, Thailand produced 27.82 million tons of Municipal Solid Waste (MSW) in 2018 which was 1.64% higher than the previous year. 34% of municipal solid wastes were segregated at their sources and re-utilized. The number was increased from that of the year 2017 by 13%. This improvement was mainly because of the government policy on pursuing the 3R scheme. Also, everyone was alarmed by the shocking news and acted on the problem together. However, there still were 7.36 million tons (27%) of solid waste that were not disposed properly [1]. Now that Thai people are concerned about the problems and willing to take actions, Thailand is hopeful that waste management situation will keep on getting better each year.

The Pollution Control Department of Thailand gives guideline to classify MSW into four types according to the way the wastes are treated. These four waste types are general waste, compostable waste, recyclable waste and hazardous waste [2]. In a four-bin system, waste bins come in four different colors. Blue bins are for general wastes. Green bins are for compostable wastes. Yellow bins are for recyclable wastes. Red bins are for hazardous wastes. However, it is quite common to find only general-waste and recyclable-waste bins at public places like bus stops, parks and shopping malls. In that situation, recyclable items should go in recyclable-waste bin while all other items go in general-waste bin.

Waste segregation is an important step in waste management process. Wastes that go in a wrong bin can lead other wastes to a wrong place. For example, recyclable wastes in recyclable-waste bin may end up being sent to landfill if many non-recyclable wastes are found in the same bin. It is best to segregate MSW at the place where it is generated. Waste segregation can be more difficult than it sounds. At present, public places provide waste bins labeled for segregation and end up with mixed wastes in every bin. At Wongpanit, Thailand’s biggest full-loop recycling facility, solid wastes are segregated mainly by human [3].

We believe that computer vision can make waste segregation easier and more effective. This will certainly help reduce pollution from waste that our country, Thailand, is currently facing. We studied transfer learning waste classification models. The main objective of our study was to explore performance of four CNN architectures in classifying wastes according to the four-bin system.

The rest of the paper is organized as follows. Related works are discussed in Section II. Section III talks about methods. Experimental framework is described in section IV. Result and discussion are in Section V. Section VI concludes the paper.

II. RELATED WORKS

Convolutional Neural Networks (ConvNet or CNN) have been around for computer vision problems such as object detection, object segmentation, motion tracking, object recognition, object classification and semantic segmentation. Reference [4] found that classification performance was significantly improved when CNN models were employed to classify 1.2 million images in ImageNet dataset. There are a number of CNN architectures pre-trained on ImageNet dataset. Reference [5] studied an optimization of deep residual networks for images recognition. ImageNet and CIFAR-10 datasets were used in their study. CNN architectures from ResNet family were took into consideration.

The following research works are related to using CNN models to classify waste images. Reference [6] compared two waste classification models: CNN AlexNet and support vector machine (SVM). Waste images were to be sorted into three classes: plastic, paper and metal. SVM classifier could reach 94.8% accuracy while CNN classifier achieved only 83%. A

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deep neural network classification model called "RecycleNet" was proposed in [7]. RecycleNet classified recyclable objects into six classes: paper, glass, plastic, metal, cardboard and trash. DenseNet121 architecture was chosen for RecycleNet model. Connection patterns of the skip connections inside dense blocks were altered to obtain faster prediction time. RecycleNet model was trained and tested on Trashnet dataset. RecycleNet was 81% accurate on the test data. Reference [8] used an OverFeat-GoogLeNet model to localize and classify wastes on streets. Waste images were collected by a high-resolution camera attached to a vehicle running on streets. Most of wastes found were leaves and cigarette butts. Reference [9] compared waste classification performance of CNN-based (VGG-16 and AlexNet) and traditional machine learning classifiers (KNN, SVM and RF). CNN-based classifiers outperformed traditional ones. The highest accuracy achieved was 93% from VGG-16 model. Trashnet dataset was used in their experiments. Reference [10] proposed a multilayer hybrid deep-learning system that could determine whether a certain waste was recyclable. AlexNet together with multilayer perceptrons were employed in their system.

III. METHODS

A. Data Collection

MSW are wastes from households. Images in our dataset are household items selected from the following sources.

- Food-101 dataset [11]
- Cola bottle identification dataset [12]
- Home Objects dataset [13]
- Flickr Material Database (FMD) [14]
- Glassense-Vision dataset [15]
- Glasses and bottles [16]
- Waste images scraped through Google search

Distribution of images in our dataset is shown in Table I.

TABLE I. MUNICIPAL SOLID WASTE DATASETS

Waste Type	Waste Items	Number of Images
General waste	foam containers	460
	snack foil packages	460
	rubbers	460
	instant noodle cups	460
	plastic straws	460
	Total	2,300
Compostable waste	left over food	460
	leaves	460
	fruits	460
	egg shells	460
	rice straws	460
	Total	2,300
Recyclable waste	papers	460
	UHT cartons	460
	glasses	460
	PET water bottles	460
	soda cans	460
	Total	2,300
Hazardous waste	light bulbs	460
	electronic wastes	460
	batteries	460
	thinner & oil bottles	460
	aerosol spray cans	460
	Total	2,300

Most of the images in our MSW dataset have single color background. Waste object is positioned in the center area of the image. There can be multiple objects of the same item class in any given image. Fig. 1 shows sample images in the dataset.

Fig. 1. Sample of waste images in our MSW dataset

B. Classification Models

Four well-known CNN architectures were employed in our experiments. They were VGG-16, RestNet-50, MobileNet and DenseNet-121. All have been pre-trained on the ImageNet dataset.

VGG-16 : VGG network architecture has been known for its simplicity. Multiple 3x3 convolution filters are stacked on top of each other increasing depth of the network. There are 16 convolutional layers in VGG-16.

ResNet-50 : ResNet family of architecture comes from residual learning concept. ResNets learn the residuals in order to do the prediction. ResNet architecture is a stack of residual blocks. Each block is composed of three convolutional layers and a ReLU. Batch normalization is performed between residual blocks. ResNet architecture can be as deep as 152 layers. ResNet-50 has 50 layers. RestNet-50 has been widely used in recent computer vision solutions.

MobileNet V2 : MobileNet architecture is relatively new. MobileNets are light weight deep neural networks designed to achieve high accuracy in limited resource operating environment. Depth-wise separable convolution is performed after full convolution operation. Model size and complexity is small. MobileNets are suitable for mobile and embedded vision applications.

DenseNet-121 : DenseNet architecture is also new. It simplifies the connectivity pattern between layers. In DenseNets, convolutional layers are followed by several dense blocks. Transition layers are between adjacent dense blocks. There are a number of dense layers in a dense block. DenseNets connect each layer to every other layer in a feed-forward fashion. DenseNets achieved significant improvements over most of previous architectures.

We used transfer learning approach. Eight transfer learning classifiers were created from the above four CNN architectures. Four of them were waste-item classifiers and the other four were waste-type classifiers.

C. Model Evaluation

Cross-validation technique has been known for error estimation and model selection. Our waste classification models were evaluated by 10-fold cross-validation.

Evaluation metrics were

- Classification accuracy
- Classification confusion matrix

If a given waste is classified as paper, it is a recyclable waste. If a waste is a light bulb, then it is a hazardous waste. Thus, waste type can be derived from waste-item class. In addition to using waste-type classifier directly, we can use output from waste-item classifier to identify waste type as well.

There are 20 waste-item classes and four waste-type classes in our dataset. When classification is made at waste-item level, confusion matrix of size 20x20 is obtained. Waste-item classes are organized in such a way that classes of the same waste type are next to each other. Therefore, waste-type confusion matrix (4x4) can be derived from waste-item confusion matrix (20x20). Waste-item matrix cells are summed according to their actual and predicted waste-type classes (Fig. 2).

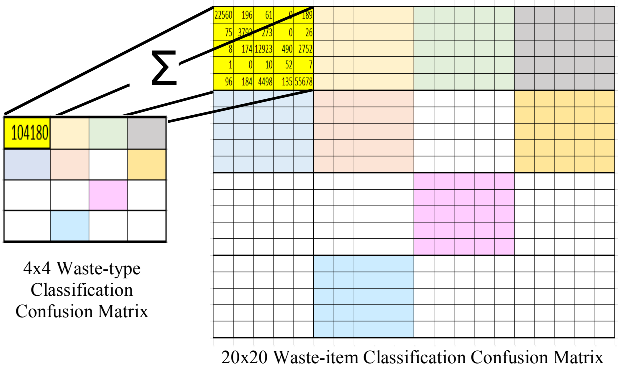

Fig. 2. Derivation of waste-type confusion matrix from waste-item confusion matrix

After the derived waste-type confusion matrix was constructed, performance of a waste-type classifier was then calculated the matrix accordingly.

Our dataset was balance at both waste-item and waste-type levels. Model accuracies were macro average values of all classes classified by the model.

IV. Experimental Framework

A. Objectives

Objectives of the experiment were

1. To use CNN-based models to classify waste types from their images according to the four-bin system.
2. To compare classification performance of CNN-based classifiers.

B. Experiment Settings

Data :

Balanced dataset of 9,200 MSW images (20 waste-item classes, 4 waste-type classes). Training:testing ratio was 70:30, stratified across all classes. All images were resized to 224x224 pixels in data-preprocessing process. This size is default input size for all classifiers under consideration.

Classifiers :

Waste-item classifiers (direct) : VGG-16, ResNet-50, MobileNet V2 and DenseNet-121. ImageNet pre-trained weights. 10-fold cross-validation. 30 epochs.

Waste-type classifiers (direct and derived) : VGG-16, ResNet-50, MobileNet V2 and DenseNet-121. ImageNet pre-trained weights. 10-fold cross-validation. 30 epochs.

V. Results and Discussion

Waste classification accuracies are shown in Fig. 3. Accuracies are grouped by classifier's network architecture—VGG-16, ResNet-50, MobileNet V2 and DenseNet-121. Striped bars show accuracies of waste-item classifiers. Dotted bars depict accuracies of derived waste-type classifiers. Checkered bars are accuracies of direct waste-type classifiers.

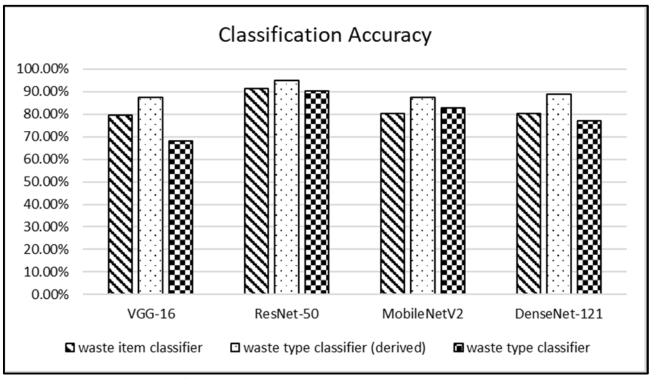

Fig. 3. Waste classification accuracy

In classifying waste items, all four architectures achieved more than 80% accuracy (striped bars). We can say that all four architectures are good candidates for segregating waste items.

There was virtually no difference, in terms of classification accuracy, among VGG-16, MobileNet V2 and DenseNet-121 classifiers. They all came up with approximately 80% accuracy. ResNet-50 classifier was the only leader with accuracy of 91.30%.

The four-bin system groups wastes according to the way they are to be processed after waste collection. Waste items that look different belong to the same group if they are to be processed the same way. For example, glass and paper both belong to recyclable group, light bulb and battery are in hazardous group. According to this grouping criterion, each group can contain items that do not have similar physical appearance. Thus, identifying type of waste from the way it looks alone may not be as effective. All CNN architectures were pre-trained to classify objects from their appearance; therefore, they may not do well under the four-bin circumstance where appearance alone might not be enough to make a cut.

This observation is seen in our experiment. In all architectures, except MobileNet V2, waste-item classifiers (striped bars) were doing better than their corresponding waste-type classifiers (checkered bars). The difference was more noticeable in VGG-16 network. VGG-16 waste-item classifier gave 79.68% classification accuracy while VGG-16 waste-type classifier could reach only 67.93%.

All four derived waste-type classifiers (dotted bars) performed better than the corresponding direct ones (checkered bars). Classification accuracies of derived waste-type classifiers were ranging from 87.36% to 94.86%. Derived classifiers worked well because CNN models were good at classifying objects. Waste-item classification was highly accurate on every CNN architecture employed in our experiment. Derived classifiers took it from there. They considered post-collection information of each waste item and assign it to a proper waste-type class. It was difficult to convey post-collection information visually. As a result, the derived waste-type classifiers could achieve higher classification accuracies.

However, we believe that all direct waste-type classifiers would have performed better if they were trained with a larger MSW dataset. Also, fine-tuning could have been done to obtain better performance. Room for improvement can be taken from Table II below. VGG-16 classifier did not handle recyclable items well. DenseNet-121 did poorly with hazardous wastes.

TABLE II. CLASSES HAVING MINIMUM CLASSIFICATION ACCURACY

Waste-type Classifier		Minimum Accuracy	
		Value (%)	Waste Type
VGG-16	derived	81.98	recyclable
	direct	52.95	recyclable
ResNet-50	derived	92.84	general
	direct	87.41	general
MobileNet V2	derived	81.03	hazardous
	direct	75.46	recyclable
DenseNet-121	derived	80.78	hazardous
	direct	58.77	hazardous

Highest waste-type classification accuracies are shown in Table III. They lay between 95.36% and 98.72%. They all were for compostable wastes.

TABLE III. CLASSES HAVING MAXIMUM CLASSIFICATION ACCURACY

Waste-type Classifier		Maximum Accuracy	
		Value (%)	Waste Type
VGG-16	derived	95.36	compostable
	direct	95.86	compostable
ResNet-50	derived	97.83	compostable
	direct	98.34	compostable
MobileNet V2	derived	98.72	compostable
	direct	98.07	compostable
DenseNet-121	derived	98.36	compostable
	direct	96.53	compostable

VI. CONCLUSION

Municipal waste management has been an important problem in Thailand. This problem cannot be solved without an effective waste segregation process. Our experiment shows the potential of using CNN with waste segregation. All four CNN-based classification models (VGG-16, ResNet-50, MobileNet V2 and DenseNet-121) could separate wastes into four classes—general waste, compostable waste, recyclable waste, and hazardous waste. Waste types can be classified directly using a waste-type classifier or derived from the output of a waste-item classifier. In the case when training dataset is limited, derived classification can be an interesting choice. Derived classifiers outperformed the rest in our experiment. ResNet-50 classifiers performed equally well in classifying waste items and waste types.

REFERENCES

[1] Pollution Control Department, Booklet on Thailand State of Pollution 2018. Bangkok: S.Mongkon Press Limited Partnership, 2019.

[2] Pollution Control Department, Public Guide on Waste Seggregation. Bangkok: He's Company Limited, 2016.

[3] Project Energica. "Wongpanit's Waste Sorting Machine," *YouTube*, Oct. 14, 2015 [Video file]. Available: https://www.youtube.com/watch?v=gRsEroyc6bg. [Accessed: 5 Mar. 2019].

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," Advances in neural information processing systems, pp. 1097-1105, January 2012.

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep resudial learning for image recognition." 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

[6] G. E. Sakr, M. Mokbel, A. Darwich, M. N. Khneisser, and A. Hadi, "Comparing deep learning and support vector machines for autonomous waste sorting," 2016 IEEE International Multidisciplinary Conference on Engineering Technology (IMCET), November 2016.

[7] C. Bircanoğlu, M. Atay, F. Beşer, Ö. Genç, and M. A. Kızrak, "RecycleNet: Intelligent waste sorting using deep neural networks," Innovations in Intelligent Systems and Applications (INISTA), July 2018.

[8] M. S. Rad, A. V. Kaenel, A. Droux et al., "A computer vision system to localize and classify wastes on the streets," in *Computer Vision Systems*, pp 195-204, Spring, Cham, 2017.

[9] B. S. Costa, A. C. S. Bernardes, J. V. A. Pereira et al., "Artificial intelligence in automated sorting in trash recycling," The Encontro Nacional de Inteligência Artificial e Computacional (ENIAC), October 2018.

[10] Y. Chu, C. Huang, X. Xie, B. Tan et al, "Multilayer hybrid deep-learning method for waste clssificastion and recycling," Computational Inttelligence and Neuroscience, 2018.

[11] L. Bossard, M. Guillaumin and L. V. Gool, "Food-101 — Mining Discriminative Components with Random Forests," European Conference on Computer Vision (ECCV), pp. 446-461, 2014.

[12] Rohit Verma, 'Cola Bottle Identification', 2018. [Online]. Available: https://www.kaggle.com/deadskull7/cola-bottle-identification. [Accessed: 5 Mar. 2019]

[13] Vision.caltech.edu, 'Home Objects Dataset', 2006. [Online]. Available: http://www.vision.caltech.edu/pmoreels/Datasets/Home_Objects_06/. [Accessed: 5 Mar. 2019]

[14] L. Sharan, R. Rosenholtz, and E. Adelson, "Material perception: what can you see in a brief glance?," Journal of Vision, vol. 9, no. 8, p. 784, 2009.

[15] J. Sosa-Garcia and F. Odone, "Hands on recognition: adding a vision touch to tactile and sound perception for visually impaired users," submitted to IEEE Transactions on Human-Machine Systems.

[16] Nishant Kumar, 'Image-Classifier-using-TensorFlow', 2017. [Online]. Available: https://github.com/nish10/Image-Classifier-using-TensorFlow/tree/master/data. [Accessed: 5 Mar. 2019]