Waste Classification using Convolutional Neural Network

Fatin Amanina Azis
Faculty of Integrated Technologies
Universiti Brunei Darussalam
16b4006@ubd.edu.bn

Hazwani Suhaimi
Faculty of Integrated Technologies
Universiti Brunei Darussalam
hazwani.suhaimi@ubd.edu.bn

Pg Emeroylariffion Abas
Faculty of Integrated Technologies
Universiti Brunei Darussalam
emeroylariffion.abas@ubd.edu.bn

ABSTRACT

Recycling of waste from households and industries, is one of the methods that has been proposed to reduce the ever-increasing pressure on landfills. Different types of waste types warrant different management techniques and hence, proper waste segregation according to its types is essential to facilitate proper recycling. Current existing segregation method still relies on manual hand-picking process. In this paper, a method; based on deep learning and computer vision concepts, to classify wastes using their images into six different waste types (glass, metal, paper, plastic, cardboard and others) has been proposed. Multiple-layered Convolutional Neural Network (CNN) model, specifically the well-known Inception-v3 model has been used for classification of waste, with trained dataset obtained from online sources. High classification accuracy of 92.5% is achievable using the proposed method. It is envisaged that the proposed waste classification method would pave the way for the automation of waste segregation with reduced human involvement and therefore, helps with the waste recycling efforts.

CCS Concepts

• **Applied computing → Physical sciences and engineering → Engineering → Computer-aided design**

Keywords

Waste Segregation; Recycling; Convolutional Neural Network; Image processing; Inception-v3.

1. INTRODUCTION

The production and accumulation of waste across the globe has reached billions of tonnes annually [1]. This can be attributed to the increased trend of urbanisation; as more people are now living in big cities, producing an ever-increasing amount of waste from domestic, commercial and industrial activities. Waste management is a global problem that has numerous environmental concerns related to it [2]. Some of these wastes end up in landfills, where they are buried to allow for slow decompositions and some, incinerated due to pressure from the huge amount of waste on the limited landfills. Some of these wastes are disposed in soil, oceans and rivers, especially in less developed countries where waste management is less mature. All of these, inevitably, contribute to environmental pollution, and consequently, health and economic problems [2].

Recycling of waste into other useful products has been lauded as one of the most useful and powerful methods that needs to be implemented in order to reduce the pressure on landfills and for proper waste management. Indeed, numerous efforts have been implemented by different government agencies and industries to promote recycling through various incentives and policies [3]. In the first instance, the commonly-mixed waste from different activities requires proper segregation according to its types, before it can be recycled accordingly. Waste segregation may be done by household or industries before it is collected by recycling companies, or it can be done by the recycling companies themselves. With the exception of big recycling companies who may have material recovery facilities to automatically segregate their collected waste, small recycling companies; especially in the developing countries, as well as segregation on a household, community or company level, may still resort to manual segregation, which can be labour intensive and requires a lot of time. As such, some researchers have put effort on finding efficient and affordable alternative solutions to manual segregation [2] [4].

On a fundamental level, waste segregation may be divided into two distinct processes [4]: 1) classification, and 2) segregation, of the different waste types. The classification process is imperative as it is the first step towards the overall waste segregation. This may be performed effectively by relying on different machine learning and image processing techniques [4] [5].

Different machine learning and image processing techniques [6] [7][8] have been proposed in the literature for the classification of different images and objects. One of the most frequently used deep learning methods for image classification is the Convolutional Neural Network (CNN) [4][9]; which performs well in classifying image datasets [9] as well as for real-time image recognition applications [10] . Reference [11] provides an extensive review on the different CNN architectures that are available in the literature; including the earliest LeNet architecture that had been originally proposed by LeCuN in 1998 for hand-written digit recognition application. Consequently, AlexNet was proposed by Krizhevesky et al. [12] as part of ImageNet Large Scale Visual Recognition Challenge in 2012, by making the architecture deeper with a number of parameter optimizations strategies. However, the architecture suffers from overfitting due to its increase depth [11]. Despite this, the AlexNet architecture has been successfully applied to numerous computer vision applications, such as object detection, object tracking, video classification, etc. [13]. Since then, numerous CNN architectures have been proposed; including the different versions of the Inception architectures, from Inception-v1 (also referred to as GoogleNet), Inception-v2, Inception-v3 and Inception-v4 [13]. Although they present similar general architectural layout, different Inception's versions have distinct computational costs due to their different depth. The Inception architectures are widely used due to their simplicity and cost-effectiveness, whilst providing respectable accuracies [11]. Due to

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their wide usage, these different versions of Inceptions architecture are widely made available in numerous open source neural network libraries, most notably Keras Applications [9], to allow quick deployment of the architectures for numerous image processing applications.

In this paper, Convolutional Neural Network (CNN) is proposed for classification of common wastes into six different waste types: cardboard, glass, metal, paper, plastic and others. It is envisaged that the proposed classification method based on image of the waste, shall pave way for automated segregation of waste and replace the current manual segregation method. The following section discusses the proposed method for waste classification; subdivided into training and testing, whereby Inception v3 model is chosen as the classification model. Results from the chosen classification method is presented and discussed in the results and discussion section. The final section concludes the paper.

2. Proposed Classification Method

Convolutional Neural Network (CNN) is a widespread techniques used for image classification in deep learning, by extracting some features from image dataset, clustering the dataset and then, using the information to classify unknown images appropriately. It consists of multiple layers, as depicted in Figure 1. 1) Convolutional layer, 2) activation and pooling layers, and 3) fully-connected layer, form the main layers of a CNN.

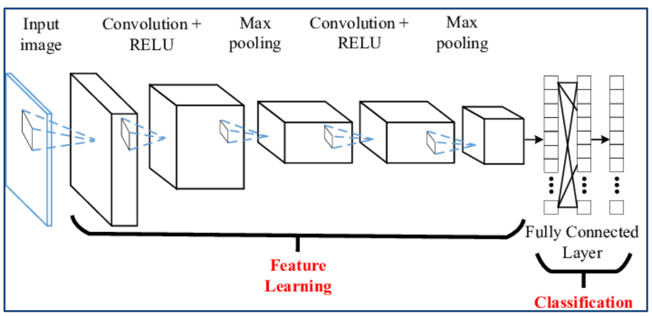

Figure 1. Convolutional Neural Network architecture [14]

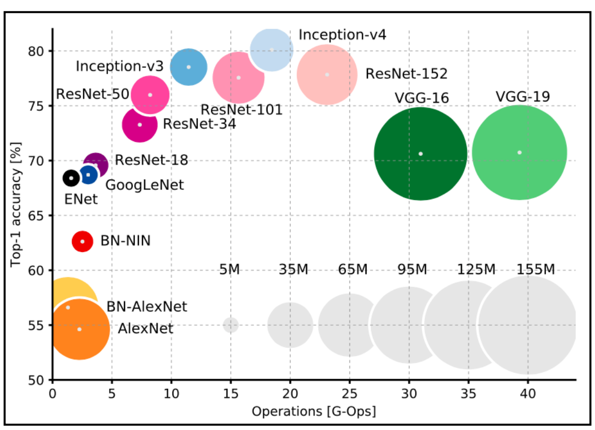

Figure 2. Performance comparison of different ImageNet Models [15]

Reference [16] provides in-depth analysis on different deep neural networks for image recognition, with performance comparisons of the different models, in terms of operations required for processing against accuracy obtained using the ImageNet dataset [15] given in Figure 2.

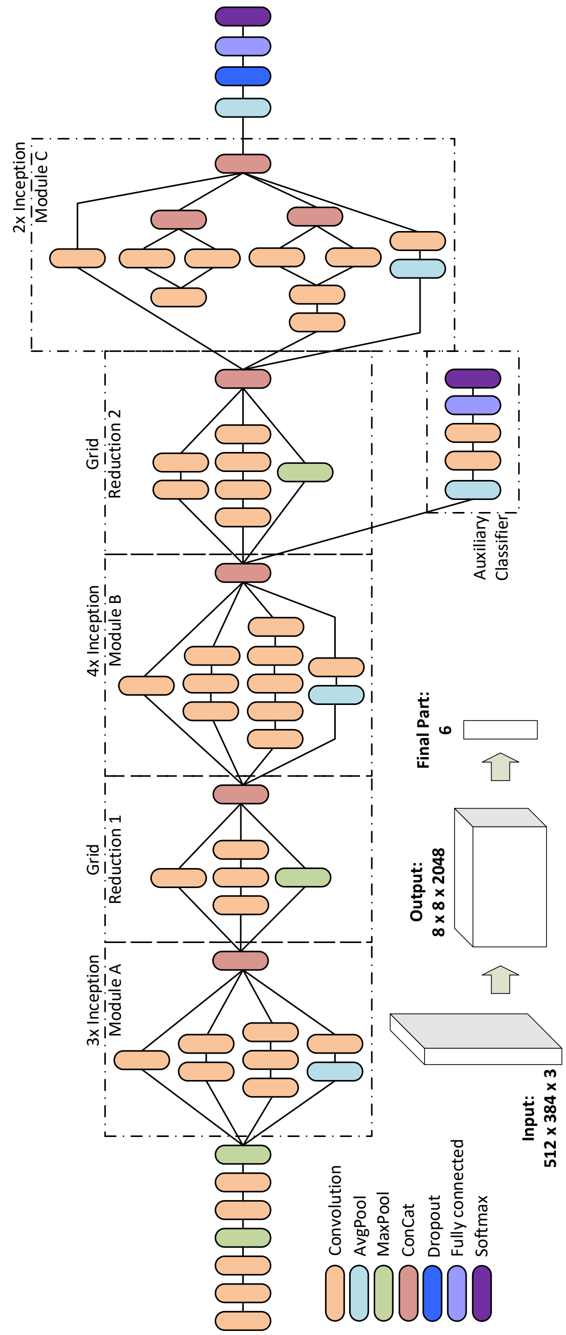

Figure 3. Architecture of the Inception-v3 model [14]

Inception-v3 model has been selected for the waste classification model in this paper; due to a compromise between accuracy and amount of processing required. The model has been used extensively for the classification of objects, and is one of the variations of the original GoogLeNet version. It is supported by Keras; an open-source neural-network library. Although Inception-v3 is 42 layers deep as opposed to GoogLeNet with 22 layers, its computation is only about 2.5 higher than that of GoogLeNet and more efficient than other established methods, but yet, producing better accuracy [13]. In fact, it can be seen from Figure 2 that Inception-v3 model is able to achieve accuracy of above 75% and despite having 24 million parameters, the model only needs about 11 G-Ops; much lower as compared to other models considered in the comparison, particularly Inception-v4, which although achieves a slightly higher accuracy but requires more operations. Consequently, this allows Raspberry Pi 3B; a portable and cheap processor, to be used for both training and testing. This is significantly important as it can be further developed as part of an affordable waste segregation system.

Figure 3 provides the overall view of the Inception-v3 architecture [13], [17]; consisting of Convolution, Average Pool, Max Pool, Concatenation, Dropout, Fully connected and Softmax activation layer. The different layers are classified into Inception Modules A, B and C, Auxiliary classifier and grid size reduction modules, for ease of representation. The input image size to the model is changed to 512 x 384; from the 299 x 299 dimension of the original Inception-v3 model, to coincide with the default image dimension of Raspberry Pi 5MP camera. Increasing the dimension coincidentally improves the performance of the model. RGB matrix of the input image is used, increasing the input image data 3 times i.e. to 512 x 384 x 3. Output from the model is the probability of the input data corresponding to any of the six waste types under consideration.

For the purpose of this paper, the methodology to classify an image for the purpose of waste classification is divided into training and testing phase, as shown in Figure 4. Image data, obtained from an online database, are split into training and testing image datasets. As CNN falls under supervised learning category, in the training phase, the training image data are first labelled accordingly into six (6) waste types: glass, metal, paper, plastic, cardboard and others. These training image data are used to trained the chosen model; with the data forward and backward propagating several times to find the best trained model.

Once the model has been trained, accuracy of the already trained model can then be determined from testing image data. The trained Inception-v3 model gives the probability of an input image data belonging to each of the six waste types; with the waste type with the highest probability representing the classification of the input image data from the model.

The steps taken to classify the waste categories using the deep learning model is given in Figure 4.

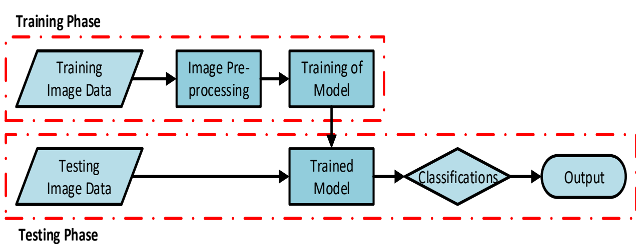

Figure 4. Simplified methodology for the Training and Testing Phases

3. RESULTS AND DISCUSSION

Around 2,400 input image data were obtained from a Plastic Detection Model library in GitHub, to be used for training and testing of the classification model. These image data are composed of data images for cardboard, glass, metal, paper, plastic and other waste types; with equal proportions. A single board computer, Raspberry Pi 3B, with Quad Core 1.2 GHz 64bit CPU and 1GB RAM, was used for the training and testing phases. Tensorflow platform was used, with Keras library to build the Inception-v3 model [9]. As the Inception-v3 model has already been pre-trained using the huge database of images from ImageNet dataset, transfer learning was taken advantage of to accelerate the training phase, by using the pre-trained parameters as initial starting parameters for the training phase.

Figure 5 depicts samples of different types of wastes from the image dataset. 90% of the input image dataset were used for training the Inception-v3 model; with 10% utilized for validation to prevent overfitting of the model to the input training dataset. Approximately 10% of the remaining input image dataset were used for testing the trained Inception-v3 model.

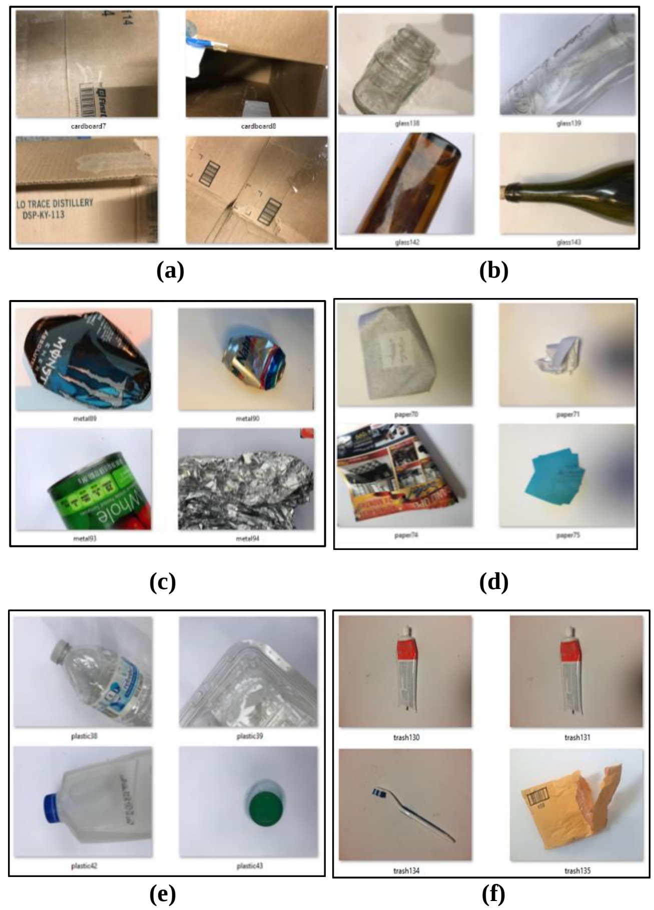

Figure 5. Selected samples from different waste types, a) Cardboards, b) Glasses, c) Metals, d) Papers, e) Plastics and other waste

Table 1. Important parameters used for training

No.	Parameters	Values
1	Learning rate	0.01
2	Testing percentage	10%
3	Validation percentage	10%
4	Training cycles	4000
5	Train batch size	100
6	Validation batch size	100
7	Input image	512 x 384

Important parameters from the training phase are given in Table 1, with Figure 6 depicting accuracies of the training dataset and validation dataset against the training cycles. It can be observed that accuracies of both training and validation datasets converge to some optimal values. 99% and 92% accuracies were achieved from the training and validation datasets, respectively. Cross entropy from the training and validation datasets are given in Figure 7;

again showing convergence for both datasets but to some minimal values. Cross-entropy, l is calculated using:

$$l = -\sum_{k=1}^{6} log(p(k)).q(k) \quad (1)$$

where $p(k)$ and $q(k)$ are the actual probability and approximated probability (from the current model) of classifying waste type k, respectively. Cross-entropy for training dataset was at 0.132 and 0.325 for the validation dataset. Both figures show that the trained model fits well to the input image dataset without overfitting.

Figure 6. Accuracies of training and validation image datasets against training cycles

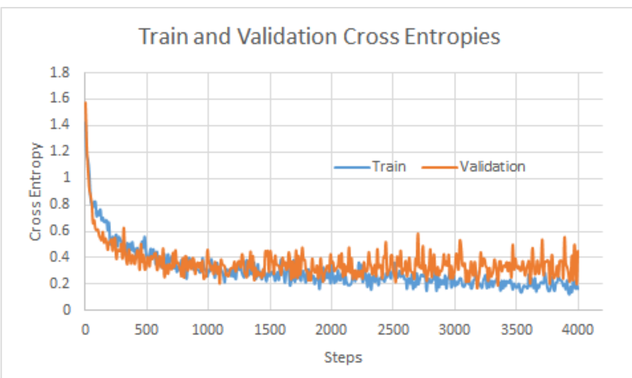

Figure 7. Cross entropies of training and validation image datasets against training cycles

Accuracy of the trained model was then tested using the testing image dataset, which consists of 240 image data with equal proportions of waste types. This is defined as the ratio of the number of correct classification prediction of image data using the trained model to the total number of image data, either for the specific waste types or for the total waste considered. Results from the test are tabulated in the form of a confusion matrix and given in Table 2.

From the results shown in Table 2, it can be seen that from a total of 40 image data for each waste types, 37 image data (92.5%) were correctly classified for cardboard, 38 image data (95%) for metal, 36 image data (90%) for plastic, 37 image data (92.5%) for glass, 38 image data (95%) for paper and 36 (90%) for other waste are correctly classified. Overall accuracy of the trained classification model during testing stands at 92.5%.

Metal and paper provide the highest accuracy of 95%, whilst plastic and other waste provide the lowest accuracy of 90%. It is interesting to note that plastic has 10% chances to be confused with glass. To improve accuracy even further, other classification methods may need to be considered.

Table 2. Confusion Matrix for the testing phase

		Actual						
		Card-board	**Metal**	**Plastic**	**Glass**	**Paper**	**Other**	**Total**
Predicted	**Card board**	37	0	0	0	3	0	**40**
	Metal	0	38	2	0	0	0	**40**
	Plastic	0	0	36	4	0	0	**40**
	Glass	0	0	2	37	1	0	**40**
	Paper	1	0	1	0	38	0	**40**
	Other	0	0	2	0	2	36	**40**
Total		**38**	**38**	**41**	**41**	**44**	**36**	**240**

4. CONCLUSIONS

Waste segregation requires two distinct steps: waste classification and the actual segregation. In this paper, convolutional neural network (CNN), and specifically, the Inception-v3 architecture has been proposed for general waste classification into six categories: cardboard, metal, plastic, glass, paper and other waste. This has been done by pre-training the Inception-v3 model using online image dataset, using affordable Raspberry Pi 3B for the training and testing phases. It has been shown that the model is able to achieve 92.5% accuracy in identifying the correct waste types. To increase the accuracy even further, other classification methods may be considered. Additionally, images of commonly found waste may be collected and used to train the model, which would help to improve the accuracy of the model.

The results shown are very encouraging, as not only high accuracy is achieved, minimal computational requirement is needed for the training and testing of the model. This may pave the way for an affordable and effective automated waste recycling bin which is expected to reduce, if not eliminate, the need for manual waste segregation.

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