May A.I. *sa Basura*: Garbage Classification Using Convolutional Neural Networks

Jeffrey L. Go,[1*] Ma. Angela Legaspi,[1*] Accever Mendoza,[1*] and Van Arloe M. Yu[1*]
[1]*Aboitiz School of Innovation, Technology, and Entrepreneurship*
Asian Institute of Management Paseo de Roxas, Makati City
*Corresponding author: jlgo@aim.edu, mlegaspi@aim.edu, amendoza@aim.edu, vayu@aim.edu

Abstract

In the Philippines, tons of garbage is generated every single day and are steadily increasing every year. This paper aims to use artificial intelligence to create a model to classify different types of garbage using convolutional neural network. The data from Kaggle contains metal, paper, cardboard, trash, glass, and plastic. The authors added sachet because it is one of the most common types of garbage in the Philippines. The baseline to beat is 21% which is 1.25 x PCC and also 77% from the submission in Kaggle. The Xception model, a pretrained Convolutional Neural Network (CNN), was used as a base for the classifier model. The resulting accuracy was 83% which outperformed the baseline. This can help automate waste segregation facilities in the country. The results could further be improved by adding more data for each class and be more representative by adding more classes of wastes.

Keywords: Waste Segregation, Xception, Transfer Learning, Convolutional Neural Network, Machine Learning, Deep Learning, Artificial Intelligence

1 Introduction

The Philippines generates an estimated 43,684 tons of garbage daily, including 4,609 tons of plastic waste (Romulo, 2019). Currently, Metro Manila alone generates 12,500 tons of waste which put the city among the top five most severe waste-ridden cities in the world (Masigan, 2019). This is brought about by the increase in population, enhanced standard of living and development of both the urban and rural areas. The projected solid waste production is expected to be 77,776 tons throughout the country by 2025 (SEPO, 2017). There are many programs implemented both in the local and national to properly manage wastes, but what the country needs is a sustainable solution. This paper aims to use artificial intelligence (AI) to develop a model for garbage classification using convolutional neural networks. This research aims to include the Philippine context to address the generated 164 million sachet waste daily (Cabico, 2019).

2 Review of Related Literature

2.1 Waste Segregation in the Philippines

The Philippines creates more solid waste as population increases, living standards are upgraded, and urban and rural areas are industrialized. According to government data, the Philippines generates an estimated 43,684 tons of garbage daily, including 4,609 tons of plastic waste (Romulo, 2019). Despite the introduction of the Ecological Solid Waste Management Act almost two decades ago, the Philippines remains one of the leading marine plastic polluters. Due to the lack of proper disposal facilities and indiscipline of the public, garbage accumulates makes their way to bodies of water and eventually sucked up by ocean currents to form massive garbage patches. Most of the waste generated by the Philippines consists of single-use plastics – a product of our “sachet” or “tingi” culture (Vila, 2018). Filipinos generate almost 164 million sachet waste daily (Cabico, 2019). Shampoo, bath soap, toothpaste, cooking oil, soy sauce, vinegar, and many other low-cost consumer products come in small, single-use plastic packages that are affordable for the country’s bulk of poor and middle-income families.

The national government claims it’s done all it can, and that the responsibility is on local government units (LGUs) to get their trash in order and on the Filipino people to dispose of their garbage more responsibly. The majority of the problem arises from poor segregation of reusable, recyclable and compostable waste by households, compounded by inefficient waste collection. Thus, there is a need for LGUs to be creative to promote waste segregation at source, at the household level (ADB, 2015).

2.2 Technologies in Waste Segregation

More time and additional manpower are needed to sort waste manually by handpicking (Flores et al, 2018). Sorting waste can be done now in various methods and forms. A computer vision approach to classify trash could be an efficient way to segregate waste (Costa et al, 2018). Their project aims to take images of garbage and classify them into four classes: glass, paper, metal and plastic using pre-trained models VGG-16, AlexNet, Support Vector Machine, K-Nearest Neighbor and, Random Forest. In another study, (Torres-Garcia et al, 2017) an Intelligent Waste Separator (IWS) was proposed which is a device that receives the incoming waste and places it automatically in different containers by using a multimedia embedded processor, image processing, and machine learning to select and separate waste. Sathe et al, 2019 have implemented a convolutional neural network system such that when the waste is to be dumped in the garbage bin, the system will identify the type of waste and will open the dustbin of that category accordingly (Sathe et al, 2019). Using these systems, it becomes easier to segregate waste at the household level.

The new era of Internet of Things (IoT) paradigm is being enabled by the proliferation of various devices like RFIDs and sensors which are embedded in the environment to monitor and collect ambient information (Anagnostopoulos et al, 2017). In a city, this leads to Smart City frameworks. A typical example of services offered in the framework of Smart Cities is IoT-enabled waste management. Intelligent trashcan equipped with IoT sensors and AI programs is an example of smart recycling. The sensors present on the can measure the waste content of the garbage thrown inside them and send information to the main disposal system for processing. The system differentiates the data based on the quantity of waste, type of garbage, and waste disposal methods.

These technologies can be a means to convert a person’s trash to another person’s treasure. Some local government units have demonstrated that effective waste segregation can help the Filipino people to put food on the table. In Barangay Bayanan, Muntinlupa City, households can hand over segregated plastic trash in return for rice (Reuters, 2019). The exchange rate is 2:1 – 2 kilograms of plastic trash gets you 1 kilogram of rice. With the aid of technology and right community programs, it is possible to reframe the waste management problem in the country.

2.3 Transfer Deep Learning

Traditional machine learning is achieved by training and testing a model from data that is within the same data distribution. Using data from a different distribution can decrease the performance of the model which makes it difficult to collect training data. For use cases like image recognition and object detection, collecting data and training a model can be computationally expensive. Transfer learning can be used to improve a model’s performance in a certain domain by using information from other domains (Weiss, 2016).

Recent domain specific research involving image recognition use transfer learning to decrease data requirements, speed up training, and achieve a higher accuracy. One of the popular transfer learning models today is Xception, which was developed by Google and outperformed VGG-16, ResNet-152, and Inception V3 on the ImageNet dataset (Chollet, 2017). In another example, the Xception model outperformed the VGG-16 when applied to a malware classification model (Lo et al, 2019).

3 Data and Methodology

3.1 Data

Data was obtained from a student in Wuhan University and was extracted from Kaggle (Garbage Classification, 2018). To augment the data and make it relevant here in the Philippines, we add one of the more common types of garbage: sachet. Different types of sachet were acquired, and their images are taken.

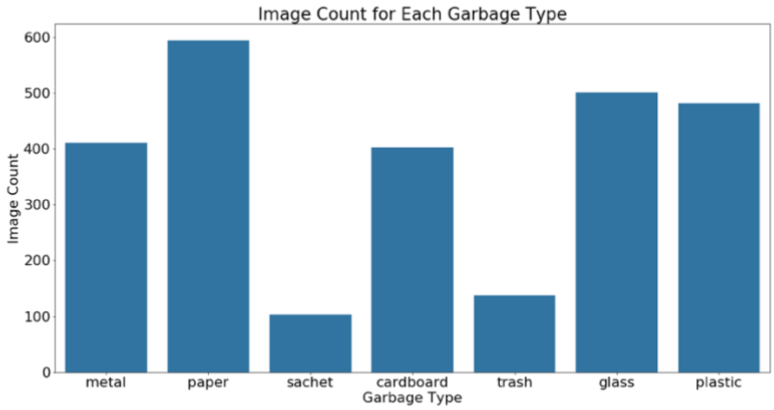

Figure 1: Image Count for each type of garbage. Paper is the most common class.

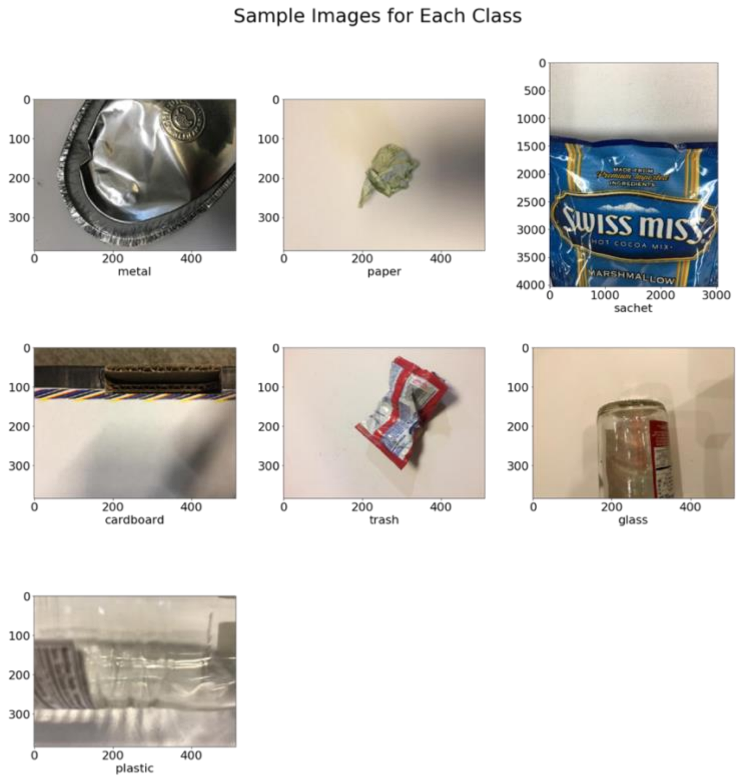

Figure 2: Sample images for each class of garbage. Sachet images will be resized later.

We have a total of seven classes, namely metal, paper, sachet, cardboard, trash, glass and plastic. The image count may be seen in Figure 1. Paper has the most images with 594, and sachets have the least with 103. In Figure 2, we show some examples of the images taken.

3.2 Methodology

3.2.1 ImageNet

Developed by Fei-Fei Li, the ImageNet project is a large visual database for use in visual object recognition software research. This database contains more than 14 million images with more than 20,000 categories and is widely used as a benchmark for image classification algorithms. In Figure 3, we see example images from the dataset.

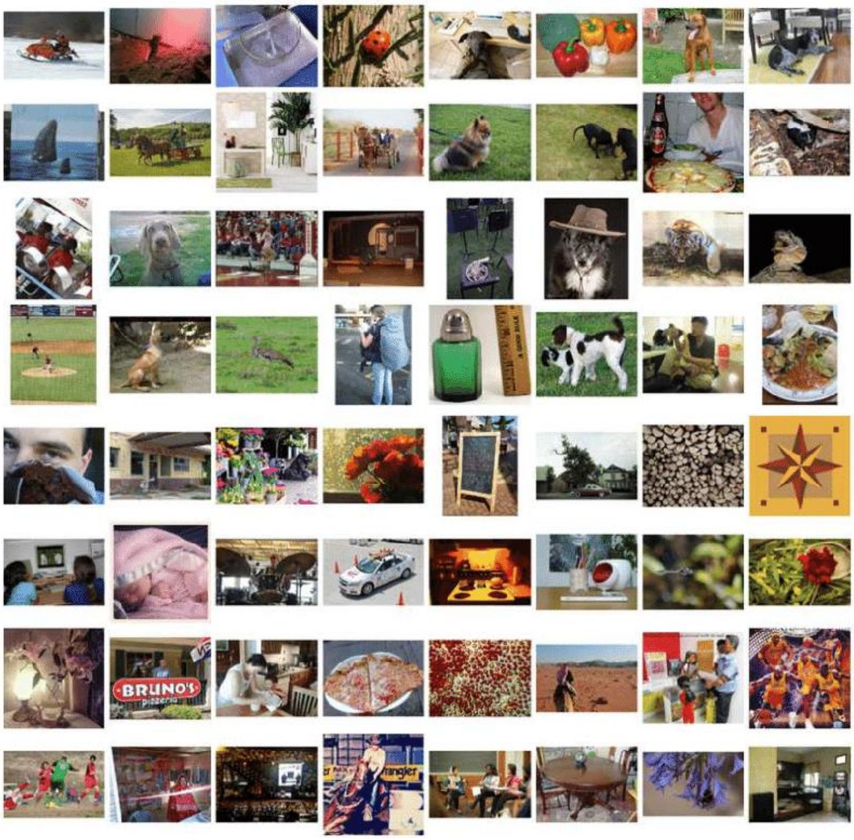

Figure 3: Sample images from the ImageNet dataset

History has shown that convolutional neural networks (CNN) provide the best results when classifying images. In 2012, a CNN called AlexNet achieved a top-5 error of 15.3% in the ImageNet 2012 Challenge, which is more than 10.8% lower than the runner up. Since then, multiple CNNs have been used on this dataset, which includes Xception, VGG16, VGG19, ResNet, and InceptionV3. On November 11, 2019, Xie et al published the Noisy Student method, which is based on the EfficientNet model to achieve the state top-1 accuracy of 87.4%.

3.2.2 Xception

In this paper, we use the Xception model as a base for our classifier. This is due to ease of access, with weights that are trained for ImageNet available in Keras and good performance, with a top-1 accuracy of 79% and top-5 accuracy of 94.5%. We now discuss the architecture of the Xception model.

3.2.2.1 Modified Separable Convolution

The layers on the Xception model are similar to those found in other CNNs. These include multiple 2D convolution layers, together with max pooling. Where Xception differs is in the additional modified separable convolution. A visualization of the separable convolution may be seen in Figure 4.

The modified separable convolution has two major operations, the pointwise convolution and the depthwise convolution. A pointwise convolution is just a 1×1 convolution with a channel for each filter in the previous layer. A depthwise convolution, on the other hand, separates each filter from the previous layer and applies a $n\times n$ convolution separately. The original separable convolution first applies a depthwise convolution, before applying a pointwise convolution. Xception, on the other hand, modifies this operation by first applying pointwise convolution before the depthwise convolution.

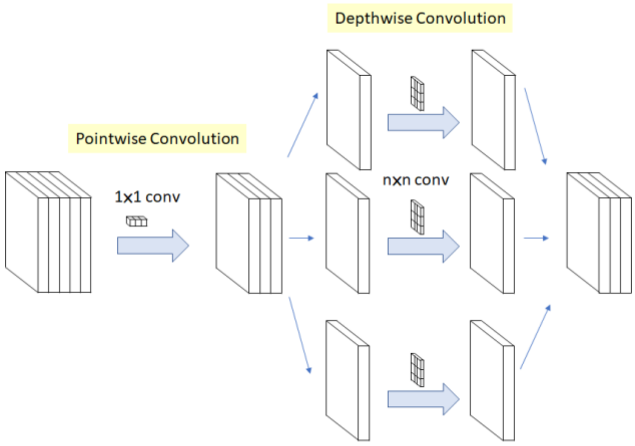

Figure 4: A modified separable convolution applies a pointwise convolution before a depthwise convolution.

3.2.2.2 Xception Model

The layers used for the Xception model may be seen in Figure 5. In our application, we use the weights trained on the ImageNet dataset except for the optional fully connected layers and the output layer. This provides us with 20M trained parameters. We train our own fully connected layer with 256 units and a Dropout layer with a rate of 0.5. Instead of a dense output layer with a logistic regression activation function, we use softmax instead. This provides us with a total of 100M trainable parameters.

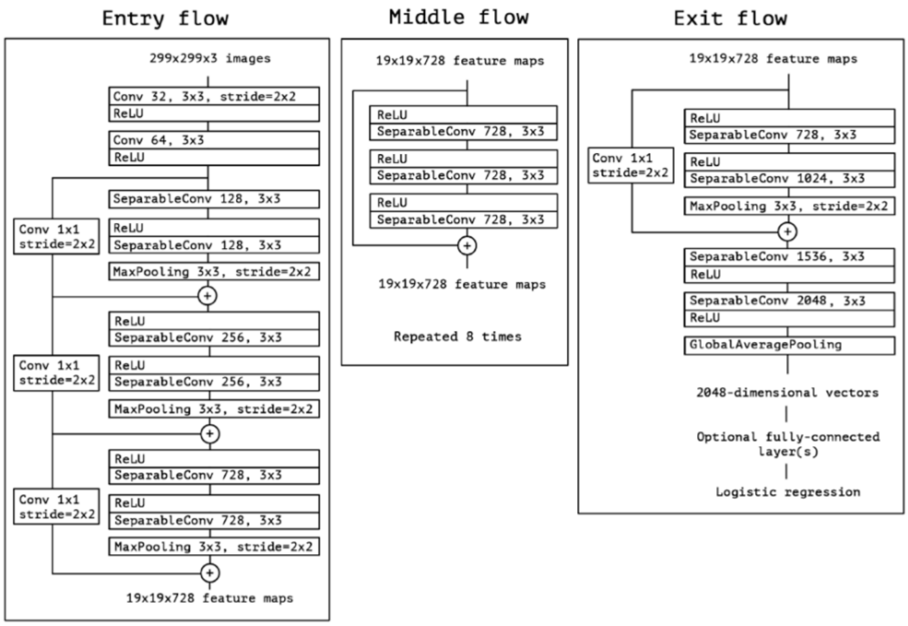

Figure 5: The architecture of the Xception model includes convolutions, separable convolutions and fully connected layers.

3.2.3 Feed Forward

The next step is to take images from the dataset and feed it forward to the pretrained Xception base. Sachet images have a different image size, so it is resized to 512 by 384 pixels to make it uniform to the other classes. To keep within memory limits, we only take 1000 out of 2630 data points.

We split our data into train, validation, and test splits by taking the first 600 as train, next 200 as validation and last 200 as the test set. The sampling is stratified so that the proportion of each class in each split is close to the original distribution. We compute for the PCC based on the 1000 images extracted. We obtain PCC = 0.1695 so the accuracy to beat is 1.25PCC = 0.2119.

3.2.4 Fully Connected Layers

As discussed earlier, after the feed-forward process on the convolutional base, we pass the results through a fully connected layer with 256 units and add a dropout layer with a rate of 0.2. We then use a fully connected network as an output layer with 7 units, one for each class. All in all, we have 100M parameters. The activation function for the first dense layer is relu, while the activation function for the output layer is softmax.

We compile the model using the Adam optimizer and categorical cross-entropy function. We also save the model with the best validation accuracy for use in the test dataset. The summary of the model may be seen in Figure 6.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_4 (Dense)              (None, 256)               100663552 
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_5 (Dense)              (None, 7)                 1799      
=================================================================
Total params: 100,665,351
Trainable params: 100,665,351
Non-trainable params: 0
_________________________________________________________________
```

Figure 6: Architecture of the fully connected layers

4 Results and Analysis

After fitting the model for 30 epochs with batch size 20, we obtained the best train accuracy of 0.9948 and a validation accuracy of 0.82. From Figure 7, we see that there are no substantial improvements in the performance of the model after 10 epochs.

Loading the model with the best validation score we obtain 0.83 accuracy, which is similar to the validation accuracy. The accuracy we obtained is four times greater than the PCC so the performance of this model is very good.

To have a deeper insight into the model, we plot its confusion matrix in Figure 8. Here, we see that the model best classify paper, cardboard, sachets, and glass. On the other hand, it often misclassifies metal and plastic as glass, while trash is misclassified as metal or paper.

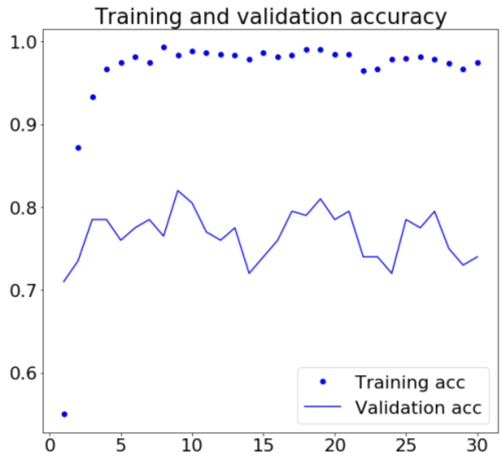

Figure 7: Accuracy of the model with respect to epochs

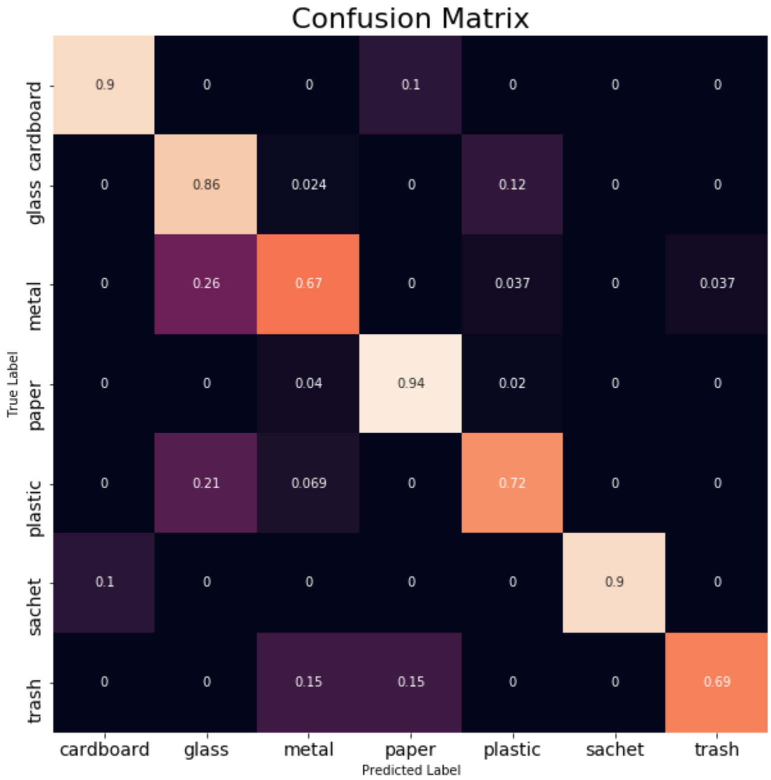

Figure 8: Confusion matrix from the model predictions

To have a better understanding of the performance of the model, we look at some examples of misclassifications. In **Error! Reference source not found.**, we have a prediction of glass when the actual class is plastic. We see that the problem of classifying both cases is that the images involve a large transparent area with possible label stickers. We may improve the performance of the model by adding more examples and augmenting the images but currently are not able to do so due to hardware limitations. This process may capture the subtle differences between the two classes.

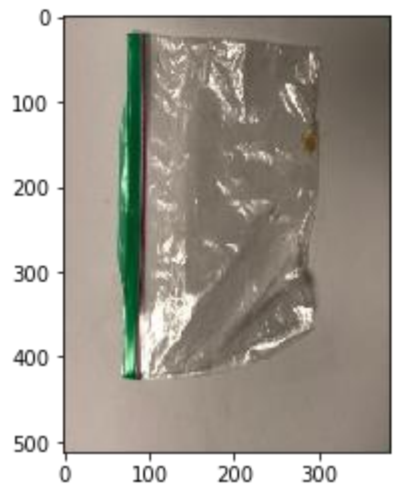

Figure 9: Plastic garbage misclassified as paper

In Figure 9, we classified trash as paper. By looking at other examples of trash, this class is the hardest to classify since it includes a diverse type of image. This includes nonrecyclable products like the apple core. Here, we also believe that there are still potential gains to be had with more images and augmentations.

5 Conclusions and Recommendations

This paper presented a framework for garbage classification using convolutional neural networks. We used transfer learning using the Xception model by Google that was pre-trained on the ImageNet dataset. We were able to consider the Philippine context by augmenting the original dataset with sachets which is a product of our "sachet culture." Our model was able to classify garbage in seven classes, namely, metal, paper, cardboard, trash, glass, plastic, and sachet. The model was able to classify garbage images at an 83% accuracy beating the 1.25*PCC and Kaggle baseline.

The model developed in this research generalizes garbage in only limited to seven classes. The model can be further improved by adding classes that require a separate waste processing purpose. Currently, the model is only able to classify one class of garbage in an image at a time. To adapt to real-world applications where garbage is bunched together, the model should be scaled up to an object detection model where it can classify multiple objects in an image using bounding boxes. This will enable the model to process satellite or drone images.

This research can be used as a reference when planning the Philippine AI roadmap. It can help augment and automate waste segregation facilities using IoT powered robots and increase throughput. Automation can increase the morale of our fellow Filipino people since we can now leave waste segregation jobs to AI so that we can upskill our workforce.

This research can help in educating both the youth and adults on waste segregation through a mobile application with a built-in garbage classifier. This will help address the remaining gap in the understanding of waste segregation. The app will just be a simple point and shoot camera that outputs details on the recycling and disposal of any garbage.

This research can help in policymaking for monitoring the footprint of FMCG companies. A similar model can be developed using convolutional neural networks to classify what the company manufactured certain garbage. In the case of sachets, a model can be developed to detect the brand name in the sachets. This can help our government to quantify and attribute waste to companies. This can help in creating policies focused on penalizing and managing companies to decrease their waste footprint.

Acknowledgements

We would like to acknowledge our professors for the course Machine Learning 2.0 at the Asian Institute of Management Dr. Christopher Monterola, Dr. Erika Legara, Dr. Christian Alis, and Prof. Eduardo David. We would also like to thank Amazon Web Services and Acer for providing us with the computing resources for this project.

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