CompostNet: An Image Classifier for Meal Waste

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***Abstract*—It can be confusing to know what pieces of waste go in which bin. Many businesses, cafes, and outdoor spaces provide trash, recycling, and composting bins, requiring consumers to decipher instructional text, icons, or images in order to sort their waste accurately. Moreover, different locations may have different rules for how to separate waste, and often people inadvertently throw their trash in the wrong bin. Machine learning solutions can help us more quickly and accurately choose the proper receptacle for our waste by classifying a photograph of the waste. This paper presents a novel image classification model that categorizes the types of waste produced after eating a meal, which could be used in applications that encourage patrons to correctly sort waste in locations where these solutions are implemented. Building on recent work in deep learning and waste classification, we introduce CompostNet, a convolutional neural network that classifies images according to how they should be appropriately discarded. We provide details about the design and development of CompostNet, along with an evaluation of its effectiveness in classifying images of waste. Further, we discuss two different approaches to the design of our system, one using a custom network and the other augmenting a pre-trained image classification network (MobileNet) through transfer learning, and finding greater success with the transfer learning approach. To the best of our knowledge, CompostNet is the first waste classification system that uses a deep learning network to identify compostable, recyclable, and landfill materials. CompostNet is an application of machine learning for social good, and supports United Nations Sustainable Development Goal 12: Responsible Consumption and Production [1].**

***Index Terms*—image classification, neural networks, waste management**

I. Introduction

A. Problem Definition

Junk, waste, detritus, garbage, trash. Whatever its called, humans produce a lot of it. The United States generates 624,700 metric tons of solid waste each day [2]. Recycling and composting programs exist (see Figure 1) but are not perfect. 1 in 4 items placed in a recycling container is not actually recyclable [2], which can further contaminate the surrounding recyclable materials. When individuals sort their waste after a meal, they may not know what is recyclable, what is trash, and what is compostable. When people are unsure about how to sort their waste, more of it will be misplaced, and probably end up in landfills.

B. Motivation

This work is motivated by a general concern about trash. Waste management and organization is a growing concern for many groups. For example, Goal 12 of the United Nations Sustainable Development Goals is "Responsible Consumption and Production" [1]. Specifically, target 12.5 is to "Substantially reduce waste generation through prevention, reduction, recycling and reuse" [1]. The European Commission has an environmental policy that sets several priority objectives for waste policy [3]. Extensive research has been done to study waste management across the globe [4], [5], [6], [7] and a Google Scholar search of "household waste classification" returns 277,000 results. We use machine learning to address this problem, as it can be used to classify objects with a high rate of accuracy. Although efforts to improve waste sorting accuracy must be multifaceted, this system can be used at the first point of differentiating different types of waste and will help people learn how to sort their waste.

Fig. 1. A set of waste receptacles in the cafeteria of a technology company in San Mateo, California.

C. Terminology

In this paper, we use the term 'waste' to refer to all material that is discarded. This term encompasses all of the materials that we are classifying. We use the labels 'landfill', 'recyclable', and 'compostable' to refer to the locations or processes that these materials will go to or undergo after they are thrown into the correct waste bin. We also use the term 'trash' as a synonym to 'landfill'.

There are different guidelines for recyclable and compostable materials, based on the recycling and composting facilities for a municipality. We use the San Francisco Recology guidelines [8]. Recology is an integrated resource recovery company headquartered in San Francisco, California. Recology processes compostable waste in an industrial composting facility. Industrial composting facilities can process Bioplastics, meat, and dairy products, unlike backyard composting facilities which cannot break down fish, meat, dairy products, and bio-plastics [9]. In addition, some recycling facilities will not recycle plastic utensils, while Recology will accept plastic utensils [9].

D. Overview

We situate our work in the field of machine learning and image classification, and discuss recent work done to classify waste materials in section II. We then describe our methodology in section III, starting with our data collection practices. We begin with the TrashNet dataset [10], which we modify and augment to include compostable products. We then discuss our neural network architectures used in the paper to conduct supervised learning and train two models, one of which is an example of transfer learning. Finally, in section V, we present designs for a waste sorting system, which can be built with a Raspberry Pi 3 running TensorFlow and a Google Cloud server.

II. Related Work

A. Image Classification

Image classification is a major learning problem in artificial intelligence. Recent image classification models often rely on deep neural networks, specifically Convolutional Neural Networks (CNNs). CNNs [11] are variants that learn by performing convolutions and have shown stellar performance on image classification tasks. Image recognition relies on supervised learning which involves labeling data to train networks. After the network is trained, it can classify images into discrete classes [11]. Using image recognition, the networks can answer questions like “What objects or shapes are in the image?” [12].

B. Waste Classification

There are many ways waste classification can be addressed - from educating individuals about sorting household trash [5] to using a hyperspectral imaging system to analyze attributes of waste products at compost or recycling facilities [7]. Few researchers have studied the use of CNNs to develop image recognition models for classifying waste. In [10], Gary Thung and Mindy Yang build the CNN “TrashNet” to classify waste into 5 classes of recyclable content and trash [10]. SpotGarbage [13] is a mobile application designed by researchers at the Indian Institute of Technology. This app allows users to identify garbage in the street around Indias urban centers. SpotGarbage uses a CNN called GarbNet, which has been trained on an annotated dataset called Garbage In Images. Both of these projects do not classify food waste separately.

III. Technical Structure

A. Dataset

We began with the data collected by Thung and Yang. Their dataset consists of 2527 images in 6 hand-labeled classes: glass, plastic, cardboard, metal, paper, and trash [10]. We wanted to be able to train our models on images of compostable content, in addition to recyclable and landfill content. We kept the subcategories of recyclables to make it easier to train the models, but we were more concerned with the three categories of ‘trash’, ‘recyclable’, and ‘compostable’. We augmented their dataset by adding 175 photos of food waste and 49 photos of landfill waste. Three example images are seen in Figure 2. We moved 2 photos of an apple core from the class ”trash” to the ”compostable” class, bringing the total image count to 177. We followed the methods for data collection that Thung and Yang outline in their project. We took photos of the waste against a white poster board and used natural or overhead lights. We also focused on 1 piece of waste in each photo. Although Thung and Yang resized their images to 512×384 pixels, we resized our images to 400×300 pixels for the Version B model. The Version A model required images to be resized to 224×224 pixels.

Fig. 2. Three images from our compostable class.

B. Models

1. CompostNet - Version A

MobileNet is a lightweight mobile-first convolutional neural network trained on the ImageNet database [14]. We chose MobileNet because it balances efficiency and accuracy. We trained CompostNet - Version A on Tensorflow v. 1.7. CompostNet is 50% smaller than a full MobileNet, which we chose to avoid overfitting to our data. Overfitting refers to the image classification model being too trained on the dataset. The networks has memorized the training data but cannot extrapolate the learning to new data [15]. The base MobileNet model has 87 layers [14]. This pre-trained model serves as the first layer in our model. After the MobileNet model layer we have 4 layers which have been trained on our dataset. The last dense layer has a softmax function to present us with the 7 outputs corresponding to the waste classes. The system architecture, including the MobileNet layer and our retrained layers, is shown in Figure 3.

2. CompostNet - Version B

CompostNet - Version B contains 3 convolutional layers. Our first layer breaks down the input image into 32 output matrices. It then goes through a max pooling layer with a 2x2

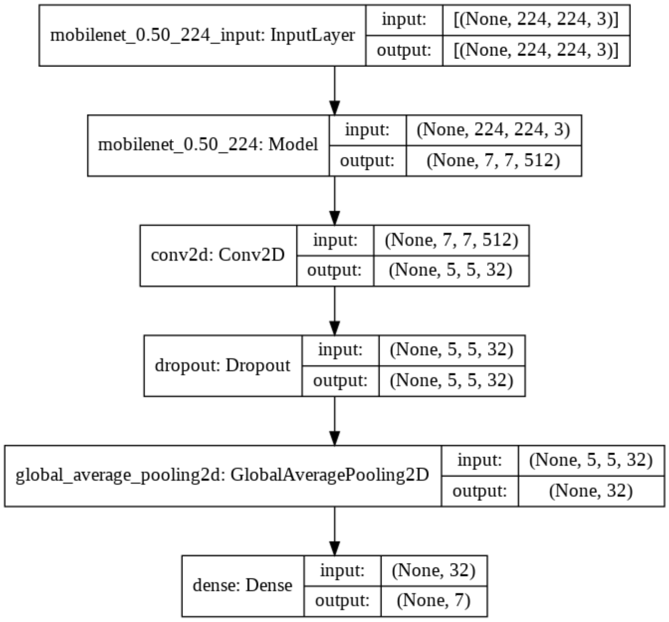

Fig. 3. Architecture for CompostNet - Version A. [14]

filter, which halves the dimensionality of the output matrices, reducing computation costs and helping us avoid overfitting. We apply a dropout rate of 30% after this step as an additional step to avoid overfitting. In our testing, we found that this rate was most effective in improving the accuracy of this model. These 3 layers are replicated twice, with output matrices the size of 64 and 128, respectively. Finally, we flattened the output and passed it through a densely-connected neural network layer. The network architecture is viewable on our GitHub repository.

IV. Results and Evaluation

Thung and Yang achieved an accuracy of 75% using their CNN 'TrashNet'. We treated that as our baseline and aimed to exceed that level of accuracy.

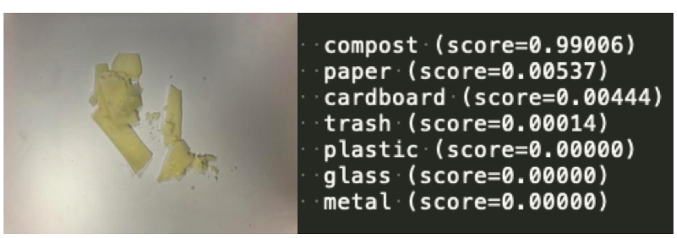

Fig. 4. Compost99.jpg from our test set, and the confidence scores returned by Version A model.

A. CompostNet - Version A

Our train-test split was 97.5/2.5. We split the dataset into 2 groups, 97.5% of images went to train the network, and 2.5% of the images were excluded from training to test the network after it had finished training. This is a small amount of test data, but because our dataset is small, we chose to maximize the training dataset. We ran 150 epochs, with a batch set of 100. We then tested the accuracy of the model on classifying the images in the test set. Our network returned confidence scores for each of our 7 classes. These values add up to 1, and demonstrate how the model has classified the object. Once the network has been trained, it can classify images in approximately 2 seconds. An example test photo and the network output scores is shown in Figure 4. The model was less certain about categorizing certain images. For instance, Metal91.jpg contains a piece of waste that could be mistaken as glass. Figure 5 shows the image and the scores returned by the model. The model is 88% confident that it is metal, but 5% confident that it is glass. It is clear that the dataset must be expanded because of the amount of items that will need to be classified if a hardware system is deployed with this model.

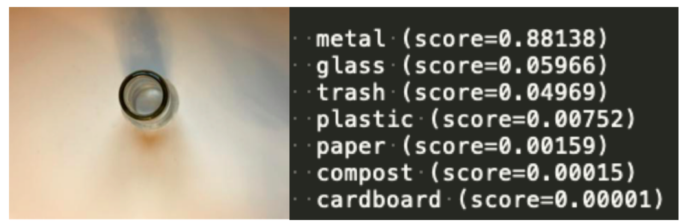

Fig. 5. Metal91.jpg from our test set, and the confidence scores returned by Version A model.

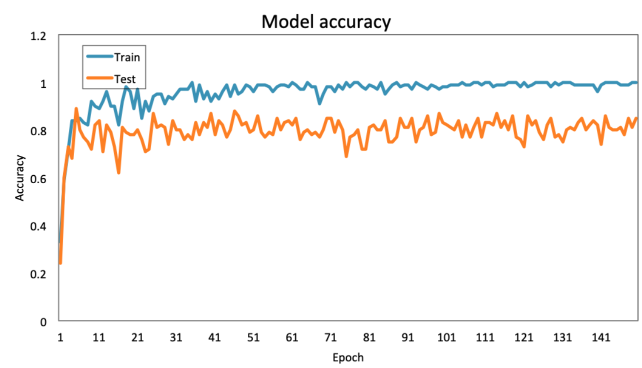

Fig. 6. Test and train accuracy for CompostNet - Version A over 150 epochs.

After achieving a high training and validation accuracy, the test accuracy was 82.1%, as shown in Figure 6. Overall, the Version A model accurately identified the correct class.

B. CompostNet - Version B

Our train-test split was 80/20. We ran the model for 20 epochs, with a batch size of 8. The model's test accuracy was 22.695%, see Figure 7.

Version A had an accuracy of 82.1% while Version B had an accuracy of 22.695%. This difference is not surprising. Version A has 91 layers and has been trained on the ImageNet dataset, which has over 1.3 million images [16]. Version B is less robust. If we can expand our dataset, Version B might return

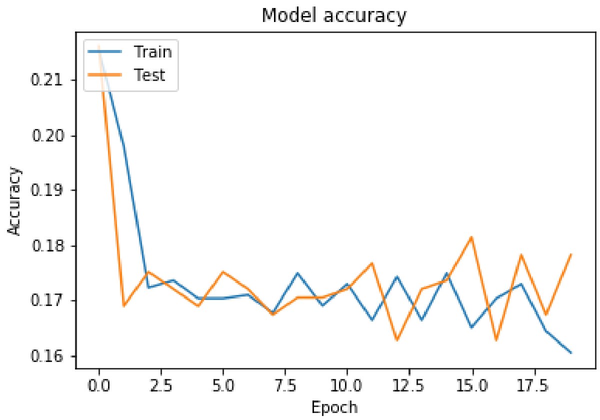

Fig. 7. Test and train accuracy for CompostNet - Version B over 20 epochs.

better results. Adjusting the hyperparameters of the model may also improve the accuracy.

V. Conclusion and Future Work

A. Deployment Framework

We have validated that our system classifies images with an accuracy above 75%, which was our baseline. To fully implement this project, we propose a hardware system that will sit by the waste receptacles in a cafeteria or restaurant. We are inspired by hardware developed by Makoto Koike [17]. We will use a Raspberry Pi 3 to take a photo of a piece of waste presented by the user and send the photo to a Google cloud server to categorize and store the data, and send a signal back to the Raspberry Pi. LEDs on the Raspberry Pi will direct the user to place the item in the correct bin.

B. Future Work

We would like to expand the types of compostable materials (bio-plastic, paper plates, bamboo utensils, etc.) in our dataset to improve the accuracy of the CompostNet model. The Office of Sustainability at the University of California, Santa Cruz has expressed interest in this project as it aligns with the University of California sustainability goal of 90% of waste diverted from landfill by 2020 [18]. In an email sent to the UCSC community, Associate Chancellor Ashish Sahni wrote to students: “Campus recycling is temporarily being landfilled due to high rates of contamination, with the highest rates in our residential and dining halls . . . If you are unsure if something is recyclable, it is better to throw it into the landfill bin!” [19]. Our CompostNet system can help educate students about what can be recycled and composted at the end of a meal so that waste is sorted correctly.

C. Conclusion

We have analyzed two models for image recognition for three categories of waste - landfill, recyclable, and compostable. We demonstrate that with a small dataset, a model based on transfer learning returns good results for recognizing images of waste. The issue of the growing amount of waste sent to landfills is addressed by the United Nations Sustainable Development Goal 12.5, as well as other countries and organizations. It is incumbent upon all of us to divert waste from landfills, and reduce the amount of waste we create.

Our dataset and code are available for download at https://github.com/sarahmfrost/compostnet.

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