WASTE CLASSIFICATION

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ABSTRACT

Waste sorting is a major environmental problem. Many have a hard time determining whether waste is organic, meaning food or natural material. Versus recyclable, which are able to be processed and used again. Computer Vision may be used to combat this problem. Our idea is to build and utilize a Convolutional Neural Network (CNN) to classify recyclable and organic waste. We use the Pytorch Machine Learning Library in our CNN. The model uses a simple CNN model with binary cross entropy to classify through images from our dataset as recyclable (R) or organic (O). The model is about 80-90% successful in its final state. In the majority of cases, it can quickly and successfully determine if an object is recyclable or organic.

Keywords Computer Vision · Convolutional Neural Networks · Waste Classification

1 Introduction

With the rise of use-and-throw materials in our society, plastics have become prevalent, with over 25.8 million tons of plastic waste ending up in waste streams in 2014 [1]. However, much of these plastics and other wastes can be recycled, but fail to do so. In 2014, 69.2% made it through recycling processes, but 30.8% was left in landfills. In our society, waste classification has become an important problem, and as such, it is important that landfills and other waste classification sites are able to properly classify recyclable wastes such as plastics, from non-recyclable wastes such as organic materials, so that as much recyclable materials can be reused. When waste is sorted properly, a higher percentage of recyclable materials are correctly identified, which can lead to many benefits for the environment, as materials such as plastics can take decades to properly be broken down.

Unfortunately, in the status quo, many recyclable materials are being contaminated with other non-recyclable materials, leading to them being simply discarded rather than broken down properly. According to the Columbia Climate School, In 2016, China received millions of tons of "recyclable" materials from the United States [2]. However, 30% of these "recyclable materials" were never recycled, because they were contaminated by other wastes that were non-recyclable. These situations are non-unique, and many unrecycled plastics contribute to patches of garbage that float around in the oceans, such as the Great Pacific Garbage patch, which is an accumulation zone of plastics that occupies the Pacific Ocean [3].

To mitigate the effects of recyclable waste being discarded and not recycled, many cities and states have adopted new technologies to quantify and assess waste at waste sorting centers. An approach that some centers have begun to adopt involves computer vision, involving machine learning to recognize and differentiate recyclable wastes and nonrecyclable wastes in the initial stage so that recyclable wastes are not contaminated, and are instead sorted and recycled properly.

In this paper, we propose an approach to classify wastes through Computer Vision, and use a machine learning classification model. Using a convolutional neural network, we trained our model to classify organic materials (O) from recyclable materials (R). This approach allows us to differentiate between recyclable wastes and non-recyclable wastes to prevent waste contamination.

Layout This paper is organized as such: Section 1 examines previous work in waste classification. Section 2 provides a deep analysis of the classification model. Section 3 examines the results of the model. Section 4 provides a final conclusion of our study and its further applications.

2 Previous Work

Previous approaches involve using a Convolutional Neural Network (CNN), a deep learning algorithm which involves multiple node layers, involving an input layer, hidden layers, and an output layer. Using matrix multiplication, CNNs provide a highly effective solution to Computer Vision by analyzing patterns in visual data for classification tasks. CNNs were popularized by AlexNet, a Convolutional Neural Network that was developed to classify the ImageNet dataset.

2.1 Automatic Image-Based Waste Classification

Many current approaches to waste classification utilize the CNN model for computer vision, including the Automatic Image-Based Waste Classification system [4]. Using the TrashNet dataset, researchers trained multiple CNN architectures, including Inception, ResNet, and VGG, finding that a combined model involving both the ResNet and VGG models achieved the highest accuracy of 88.6%. These previous works involve similar steps in training a model for image classification, something we utilized in building the framework of our model.

2.1.1 Steps Utilized

- *Data Cleaning*- First, images needed to be analyzed by the model must be pre-processed to be in a uniform dimension and the data must be pre-labeled. For the "Automatic Image-Based Waste Classification System", transformations were randomly applied on the data to generate additional images, and the images were resized to be standard. Additionally, the researchers normalized the brightness values of the images to be between 0 and 1.
- *Learning and Classifying*- As detailed by the previous research analyzed in this section, deep learning models are trained after features are extracted. Many different machine learning models can be used, but the models from the previous papers follow the example of a Convolutional Neural Network, such as AlexNet.
- *Analysis*- After the model is trained, a final testing set is used to evaluate the overall accuracy of the model.This approach involves using a Convolutional Neural Network (CNN), a deep learning algorithm which involves multiple node layers, involving an input layer, hidden layers, and an output layer. Using matrix multiplication, CNNs provide a highly effective solution to Computer Vision by analyzing patterns in visual data for classification tasks. CNNs were popularized by AlexNet, a Convolutional Neural Network that was developed to classify the ImageNet dataset.

2.2 ImageNet Classification with Deep Convolutional Neural Networks

The foundation for the convolutional neural network style of the machine learning model was popularized by the paper "ImageNet Classification with Deep Convolutional Neural Networks", which outlined in greater detail the steps required to build a machine learning model for image classification using a CNN [5]. This research outlines the steps required to build such a framework, detailing overcoming issues such as the model "overfitting"- meaning it overcompensated accuracy to match the training data, performing worse on the testing data. To combat this, the researchers implemented "dropout", which is a regularization pattern. Our team found this very helpful and implemented similar methods when combating the issues of overfitting with our waste classification model. This research showed that CNN models were highly efficient in solving image classification tasks with complex datasets, something that prompted our research into using a CNN based framework for building our waste classification model.

Conclusion Paragraph This concludes the previous works review. Our research utilized many of the same steps used in order to build a computer vision framework, but we also changed steps in order to fit our purposes of waste classification, such as using a different optimization setting, a different dataset than the studies described, and a different structure of the neural network.

3 The Model

3.1 Initial Stages

Notable import statements for our model included `numpy`, `matplotlib`, and `torch` (Pytorch). Our dataset (25,079 images) is from Kaggle. The specific dataset may be found at

`https://www.kaggle.com/techsash/waste-classification-data`

The dataset was moved to Google Drive and mounted onto a Google Colab. Below and left is an example of a random sample; below and right is an example of a random batch of 128 samples. See Figure 1 and Figure 2.

Training and testing data was split 80% and 20%, respective. Batch size was 128. Our image classification base model used cross entropy as well as calculated predictions and predicted loss. At the end of each epoch, the base model gave training loss, validation loss, and validation accuracy. See Figure 3.

3.2 Our CNN model's layers

Layers in our model included: Conv2d, ReLU, MaxPool2d, Dropout, Flatten, Linear, and BatchNorm1d. Our Conv2d layers created convolutional kernels of size 3 with a final number of 512 output filters. These kernels would "scan" through the full image. We used the ReLU linear activation function for our neural network. Our MaxPool2d layers chose the maximum value in our matrix, which was sized 2x2. It reduces the dimensions of the outputs from the Conv2d layer. Towards the end, our model included flattening layers to convert the data into even smaller arrays, which were then input into the linear layers. Lastly, we included BatchNorm1d to normalize the inputs for each layer during training and dropout to reduce overfitting.

3.3 Closing

Overall, our model had 30 layers. We used the Adam optimizer, set learning rate to 0.001, and trained for anything between 5 to 50 epochs during the testing phase of our model. Finally, we fit the model and plotted its loss and accuracy per epoch, as well as accuracy on each epoch. Ultimately the model was loaded onto the final function `predict_image`, which was then used to test on a random sample and generate a prediction on whether an image was Organic or Recyclable.

3.4 Figures

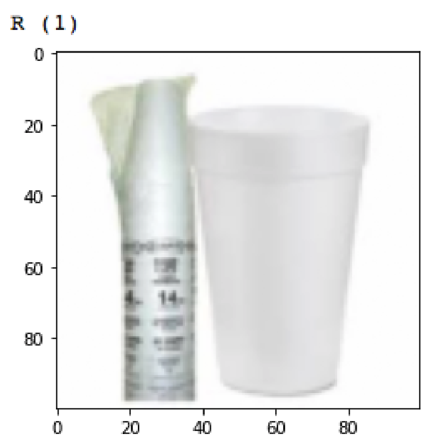


Figure 1: Random Sample from Dataset

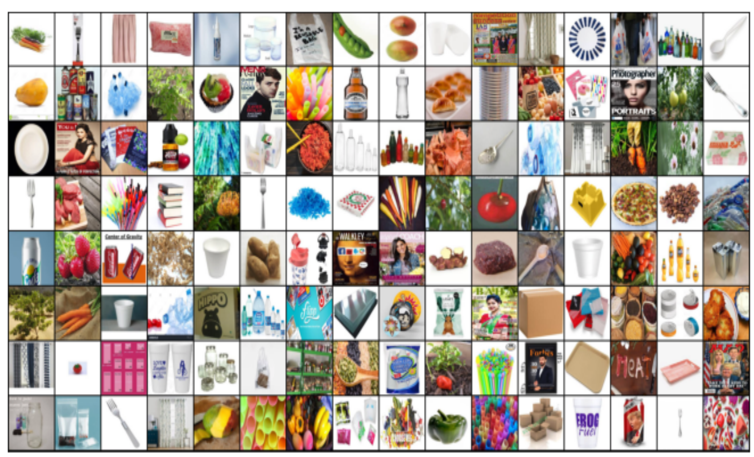


Figure 2: Random Batch of 128 from Dataset

```
Epoch [0], train_loss: 0.4741, val_loss: 0.3350, val_acc: 0.8549
Epoch [1], train_loss: 0.3499, val_loss: 0.3273, val_acc: 0.8664
Epoch [2], train_loss: 0.3205, val_loss: 0.3028, val_acc: 0.8790
```

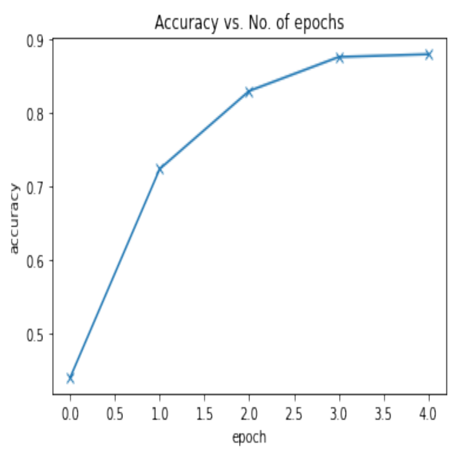
Figure 3: Epochs, Training Loss, Validation Loss and Accuracy

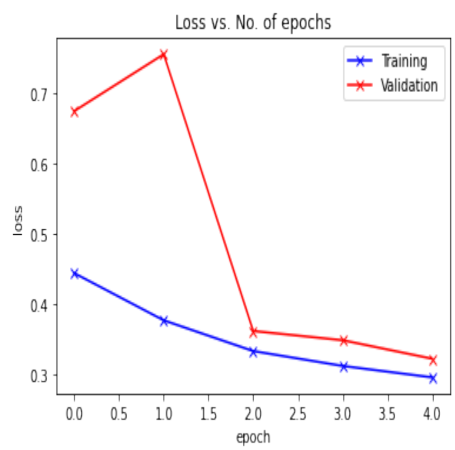
4 Results

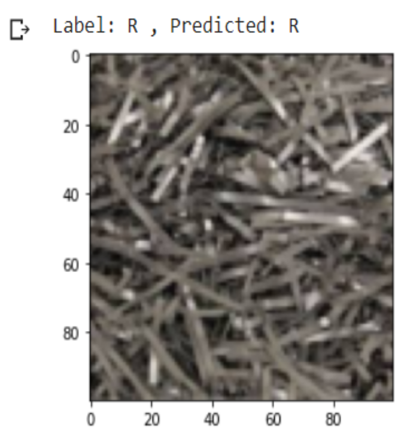
Our first model used Binary cross entropy, (uses target of 0 or 1 for example) and was not accurate. It had an accuracy of about 30-40%. Using Cross entropy made our model able to have an accuracy between 80-90%. This is because the Binary cross entropy does not use multi variable classification unlike cross entropy. Using multi variable classification seemed to have a much lower loss than not having when using Binary cross entropy, which allowed for a higher accuracy. Our next model ran into an overfitting problem. The model would get 90% accuracy for all the training sets; however, for the test sets, the model would get 40% accuracy for all the test sets. This might have happened due to the model having far too many layers. Having too many layers in a model is an easy way for an ML model to overfit. Changing our model to have less layers and softmax to make the losses closer together helped prevent the model from overfitting. See table 1 for models and accuracies.

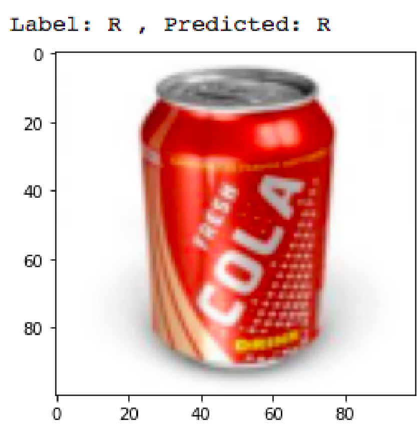
Table 1: Model Number and Accuracy

Model Number	Details	Accuracy (%)
1	Initial model; few epochs, few layers	80
2	Revised model; More epochs, more layers	90
3	Added batchNorm and droupout	92









5 Conclusion

After conducting our final testing, our model achieved a result of 92% accuracy. This image-based classification of waste through a CNN is something we hope will allow for greater accuracy in waste-sorting center; by implementing our model in them, with our accuracy rate we can ensure that a greater percentage of waste is properly classified, thus mitigating the issue of waste contamination and allowing more to be recycled. We hope to increase the accuracy of the model in future installments. In addition, this model can also be utilized by civilians, who can view whether their household waste is recyclable or not. This can be achieved by incorporating our machine learning model into a mobile application.

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