AI-Based Image Classification Used to Accurately Distinguish Recyclable Material Versus Non-Recyclable Material

By: Katarina Avlijas

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Abstract

In today's world, pollution is increasing as plastics and other materials are not recycled properly, resulting in landfills. One cause of this improper disposal of materials is that it can be difficult to tell if a material is able to be recycled. In response, I created a machine learning model that can distinguish recyclable materials from trash through image classification. For my model, I used a dataset called trash-net. I first extracted the contents of the data and resized the dataset in order to have better organization. There are six categories within the dataset: cardboard, glass, metal, paper, plastic, and trash, that the images are organized in. I used resnet34 which is a pre-trained convolutional neural network (CNN) in order to perform the image classification. Afterwards, I trained my model by running the program repeatedly and then tested it by seeing if it accurately predicted if a material was recyclable or not. Lastly, I used matplotlib to visualize the results. The accuracy of the model ended up being about 88%. Generally, if the accuracy of a machine-learning model is higher than 50% then it performs relatively well. With more training and a greater number of images, the program could potentially increase in accuracy. In conclusion, I think my model would help as it could generally classify if a material was recyclable or not. However, an application in which the user directly scans an item would be more useful. Nevertheless, my model performed well and enabled me to learn more about the use of artificial intelligence.

1. Introduction

In the world today, about half of all plastic materials end up in landfills and only 9% of used plastic ends up getting recycled sufficiently. It is critical to understand that recycling helps as it reuses and repurposes materials in order to help build a more sustainable environment. However, it can be difficult to tell if a material is recyclable and so in response, people automatically throw it into the waste bin. Throwing away materials into the recycling which are not recyclable is also harmful as it creates issues when sorting the materials in the facility and ultimately ends up in the landfill. In response, I decided to build an AI-based classifier that can distinguish recyclables as it would be a useful resource in order to help others when unsure about where to dispose of their materials. In this case, using image classification would prove to be the most useful as the dataset I had used by Gary Thung called Trash-net had contained six different categories of images: cardboard, glass, metal, paper, plastic, and trash. Later when training the model, I used labeled images as the input in order for the model to be able to distinguish materials when it was later given unlabeled data to test it and sort the materials into the appropriate categories accurately. Overall, I had wanted to create a model that would be able to classify different materials, recyclable and non recyclable, to help others in their own sorting disposal at home.

2. Background

Reducing the amount of pollution that results each year is not a simple task to find a solution for, especially because of the large surface area trash can cover, making it more difficult to clean. One example of a project done to help this issue was by the organization called Go Green Cambodia. Along with help from different foundations and corporations in Germany, the main focus had been on detecting areas with high quantities of trash using satellite images in order to allow for better clean up management. Similarly, they had also used image data in their project, but had also utilized Planetscope, a tool used to obtain high quality imaging from satellites. While the project did have a well-planned approach and execution, it did contain a few limitations. The data had contained unequal amounts of images for each material which had resulted in a higher accuracy because the model had different levels of training based on the kind of material. Second, only plastic and other polluting materials could be detected if they were on the surface of an area, not underwater. The model would also sometimes mix up materials depending on if they looked similar. Despite these limitations, the model was able to achieve a final accuracy score of 83%. Even though this model would improve the level of clean management, there would still continue to be an increase in pollution because plastics and other materials are not biodegradable. Packaging materials can cause a significant amount of damage to the environment because they are not able to decompose in a faster time period and most of the time are single use. However, there is a biopolymer called PLA that is made from renewable resources and is also biodegradable. With more of its use in plastics, it could greatly improve the surrounding environment by making it more sustainable. However, it has low heat resistance, so it cannot be used for products that undergo high temperatures. Nevertheless, it could still be a useful resource to incorporate as it would allow for materials to be reused to benefit the environment.

3. Dataset

For this project, I used image data as it would be the most useful for making an image classification model. I had used Trash-net, a dataset composed of 482 plastic items, 137 trash items, 501 glass items, 410 metal items, and 594 paper items. All of the images were already organized into their appropriate categories of plastic, trash, glass, metal, cardboard, and paper within the dataset. However, some of the images contained a fullscreen of the material while some only had an object on a white background, affecting the accuracy depending on which type of image was easier for the model to classify. Some of the images also had a glare from a light that could make them more difficult to distinguish for the model. Figure 1 and 2 show examples of two different images from the cardboard category.

Figure 1: cardboard5.jpg **Figure 2**: cardboard134.jpg

Each of the images had been renamed in order to be labeled with the category name as well as the image number so that the model could be able to train on that data and later be tested on it. In the data preprocessing, the dataset had to be unzipped in order to extract its contents. Afterwards, all of the images had to be resized to the dimensions of 3264 x 2448 in order to decrease the run time, the amount of time the computer's algorithm needs to run the code, and storage size. The data was then split into a 50-25-25 split among training, validating, and testing.

4. Methodology / Models

5.1: Mounting to Google Drive

I first needed to mount the dataset to my google drive in order to be able to access it through Google CoLab. I had then done a process called unzipping in order to be able to access the image files within Trash-net.

5.2: Resizing and Renaming Images

Then, I needed to rename the images in order to have all of the pictures be named with their category name and number. Afterwards, I had resized all of the images in order for them all to have the same dimensions. In order to do this task, I had to find the minimum dimensions of all the images and resize all of them to that value. This value was 3264 x 2448. I had then checked my image files through the function **os.listdir(os.path.join(os.getcwd(),"dataset-resized"))** in order to make sure all of the files were extracted from the dataset.

5.3: Train, Validate, and Test

After extracting the contents of the dataset of the resized dataset, I had separated the data into a 50-25-25 split among training, validating, and testing. I did not have a designated category for train, validate, and test in the dataset, but rather had selected the images randomly. Figure 3 shows an example of how one set of images would look like that the model would be tested on.

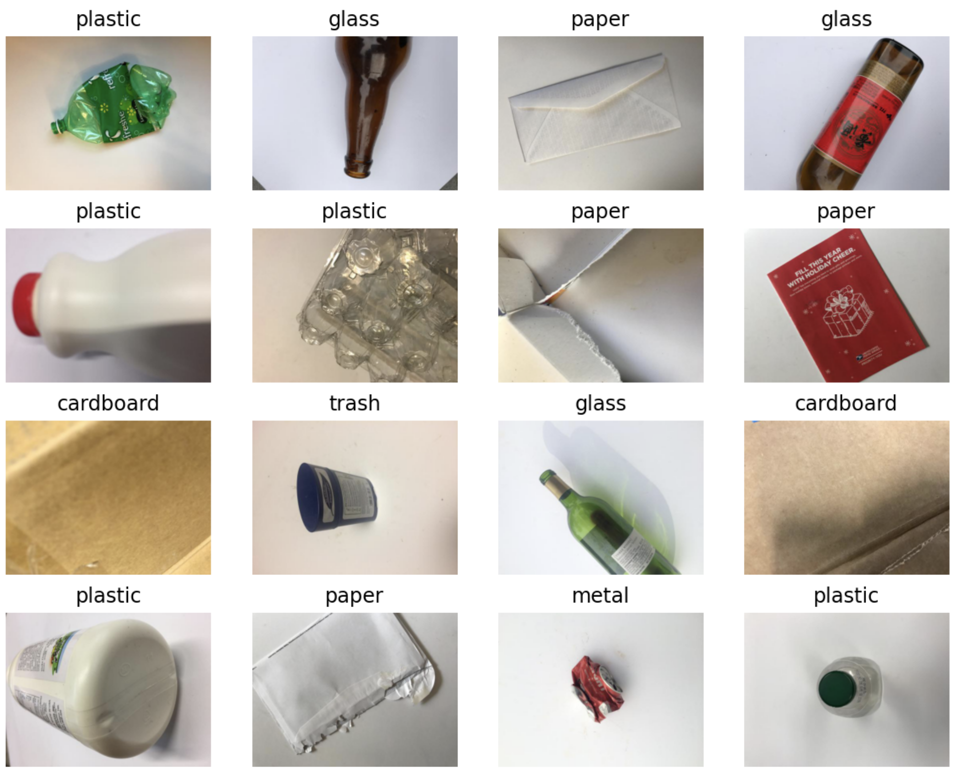

Figure 3: Example set

5.4: Using a Pre-trained CNN Resnet34

I then loaded a pre-trained convolutional neural network called resnet34 in order to perform the image classification for the model. Resnet34 has 34 layers and it has been pre trained on the ImageNet database, therefore it will improve the performance of my model.

5.5: Learning Rate

I got the learning rate of the model and fine-tuned it with different rate values in order to improve performance. Figure 4 is an image of the learning rate.

```
learn.lr_find()
```

```
SuggestedLRs(valley=0.0008317637839354575)
```

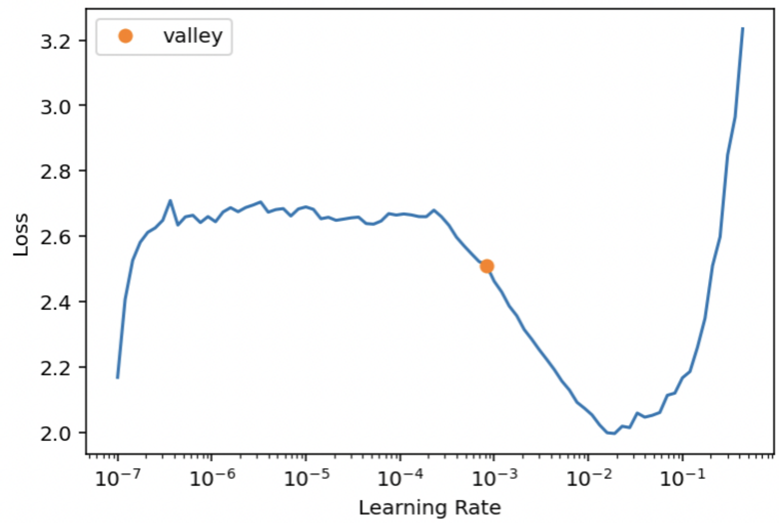

Figure 4: The learning rate of the model with a 2.5 loss.

5.6: Visualizing Results and Finding Accuracy

I kept repeating step 5 and testing the prediction of the model to check if the model was accurately predicting which materials were recyclable and which were not. Afterwards, I visualized the results through matplotlib and found the accuracy.

5. Results and Discussion

After training and testing the model, the final accuracy of the model was able to reach 88%. Generally, if the accuracy of a model is greater than 50% then the model performs relatively well. However, after visualizing the results in matplotlib, I noticed that there was not an equal amount of images sorted into each category as there were 137 paper items while only 28 trash items. The boxes colored in a darker shade of blue emphasize the amount of items correctly sorted into their appropriate category. I concluded that this number was not equal for each category because of errors the model made, but also because there was an unequal amount of images within each category in the dataset. This would affect the results because the model would not have the same level training and testing on each category, similarly to the Go Green Cambodia project in their limitations as they also had this issue. In terms of which category had the most classification errors, it would be the glass as it had mistaken ten images for plastic. See Figure 5 for the graph of the results.

```
interp.plot_confusion_matrix(figsize=(7,7))
```

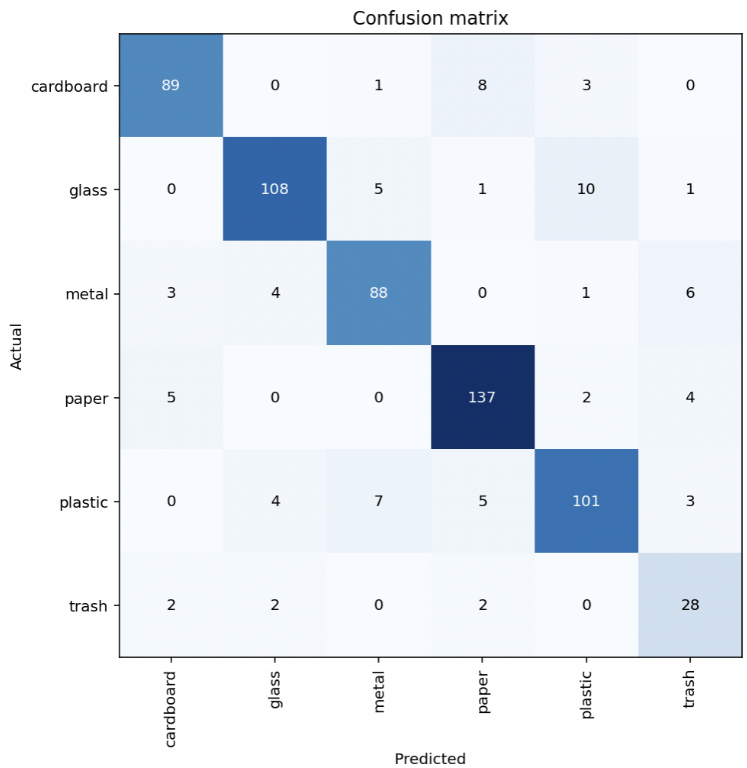

Figure 5: Matplotlib confusion matrix showing visual results between actual and predicted.

Within the results, I was also able to find the prediction, actual, loss, and probability of the top losses of the model, which are images with mistakes. The prediction was the category the model had classified the material in versus the actual category, while the loss and the probability were numerical values. For example, in Figure 6, the material was cardboard, but the model classified it as paper and it had a 6.23 loss value with 98% probability. The main mistakes the model made when classifying were from the category of plastic along with some error with the cardboard category. Some of the materials were unexpectedly classified wrong, such as when the material was plastic but the model classified it as metal. Others, such as when the material was plastic but the model classified it as glass, were understandable as they could look very similar. Some of these results could also have occurred from an unclear image and a difference in lighting.

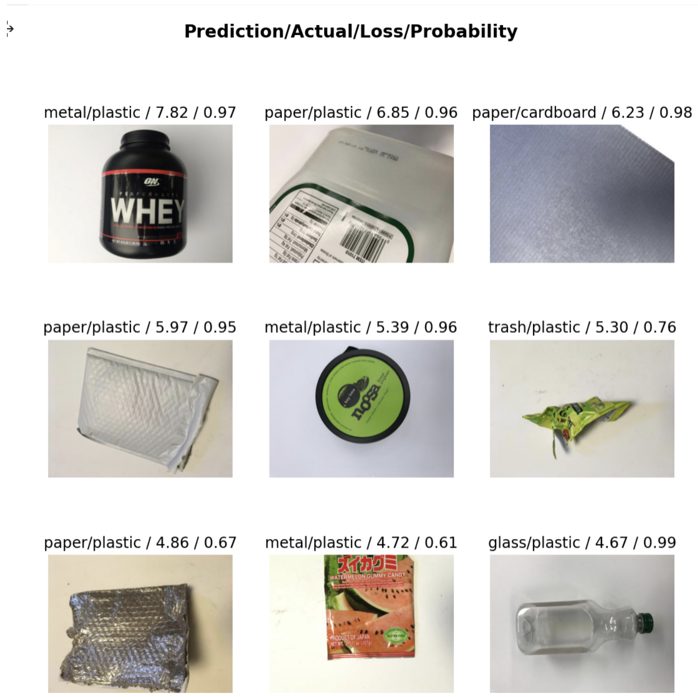

Figure 6: A visual representation of the prediction, actual, loss and probability of the top losses

Another way of representing the results was showing, within a testing set, the category of the material the model predicted versus the actual one with a colored representation. Figure 7 shows the visual result and had colored the writing above the image in green if the model had correctly classified the image and in red if the prediction was incorrect.

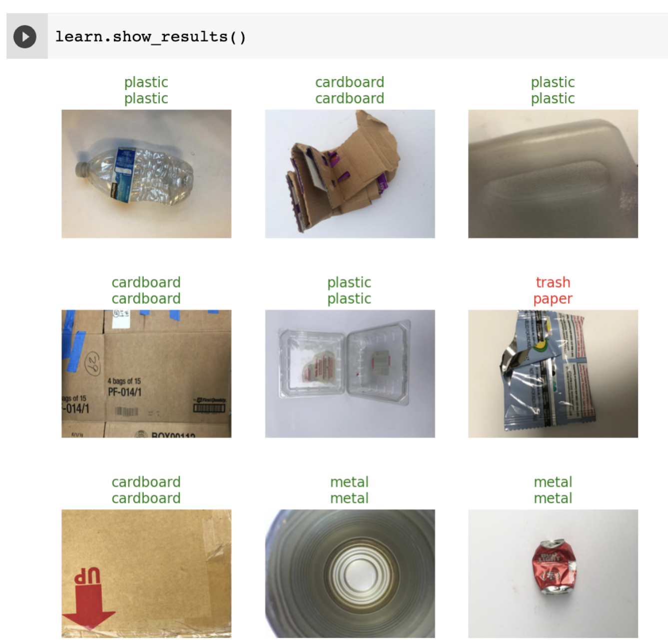

Figure 7: Visual results of correct and incorrect predictions of the model within one testing set.

6. Conclusions

In this project, I went through the process of organizing the dataset by resizing and renaming images along with training, testing, and validating as well as integrating a pretrained CNN and then observing the learning rate and results of the model. For this being my first in depth AI and machine-learning project, I believe my model performed relatively well as it was able to reach a high accuracy. Even though I was not able to make an application in which a user could scan an item and it would say if it was recyclable or not, I was able to create a demonstration in which I input my own image into the system and the output would be the category of that the model would classify it in which was still interesting to see. Despite reaching a high accuracy, my model could still be improved. First, I would add more images to the dataset in order for each category to have the same number and so that the model would not have varied levels of training and testing depending on the material. I would also make sure that images did not contain any glare or change in lighting in order for the accuracy to not be impacted. A more advanced CNN could also help my model improve. Furthermore, I would attempt to make an application, using this model, that could help people in their waste sorting at home and could potentially result in less materials ending up in the wrong place. Nevertheless, I still enjoyed doing this project and hope to continue researching environmental issues.

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Reference Acknowledgement Jupyter Notebook: https://nbviewer.org/github/collindching/Waste-Sorter/blob/master/Waste%20sorter.ipynb

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Dataset: https://github.com/garythung/trashnet/blob/master/data/dataset-resized.zip