Computer Vision Project

TrashSorting - A Classification Model

Group 20

Kasey Le 301479381

Grace Kim 301321070

Github Repository: https://github.com/lmtkhanh/IAT481-CV-Project

IAT 481 - Spring 2024

Instructor: Dr. O.Nilay Yalcin

TA: Maryiam Zahoor

Introduction

The main objective of **TrashSorting** is to develop a classification model that helps people sort waste into the right recycling categories. **TrashSorting** tackles the challenge of improper waste segregation which impacts recycling efficiency and environmental sustainability. Our model uses supervised learning and is intended for integration into a user-friendly mobile application to be conveniently used in both private properties and public areas including offices. Our group utilized three recycling categories as assigned: glass, plastic, and food organics.

Dataset Report

Firstly, our dataset is created using 2 main sources:

- Images from an existing dataset: We used a part of RealWaste Image Classification found on Kaggle, specifically extracting the three folders that matched the *three waste categories* that we planned to tackle: Food Organics (411 files), Plastic (921 files), and Glass (420 files), totalling a *1752* image files. The images in this dataset are named with the following convention: [Category]_[Index]
- Additional images collected by the team: We then searched online for images for these *three categories*. Each of us added 10 images into each category, totalling 60 images, 20 more for every category. We directly added these images into aforementioned Kaggle dataset folders and named them sequentially according to the format, starting from the index of the last image in each set. For example:

Examples of our dataset and the new images we added, along with how they were named:

- In the Food Organic folder:

Existing images

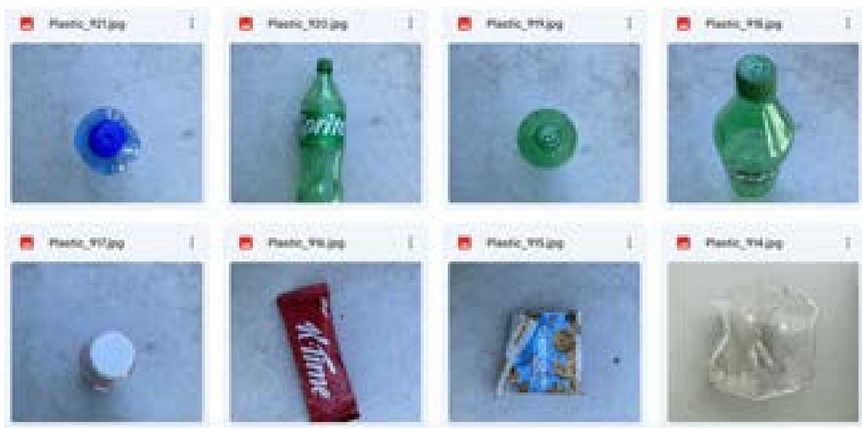
Our added data

- In the Glass folder:

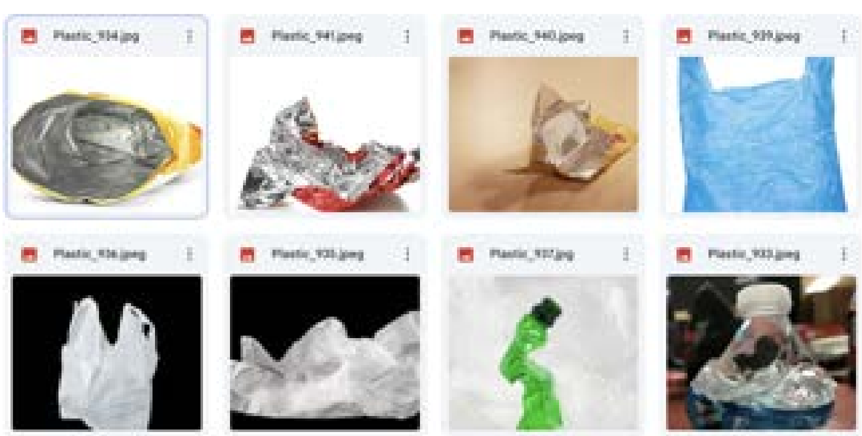
Existing images

Our added data

- In the Plastic folder:



Existing images



Our added data

In total, we have three categories with a total of 1812 images, specifically: 431 images for Food Organics, images for 941 Plastic, and 440 images for Glass.

Then, we used code to organize and split our image dataset into a structure that is accepted by the YOLO framework, which are as followed:

Root Folder:

- Train: (80% of dataset)
    + Food Organics
    + Plastic
    + Glass
- Test: (20% of dataset)
    + Food Organics
    + Plastic
    + Glass

In order to do this, we used the following code to create new directories that match the structure above:

```
directories = [
    '/content/drive/MyDrive/IAT 481/CV-Project/DATA/train',
    '/content/drive/MyDrive/IAT 481/CV-Project/DATA/test',
    '/content/drive/MyDrive/IAT 481/CV-Project/DATA/train/glass',
    '/content/drive/MyDrive/IAT 481/CV-Project/DATA/train/plastic',
    '/content/drive/MyDrive/IAT 481/CV-Project/DATA/train/organics',
    '/content/drive/MyDrive/IAT 481/CV-Project/DATA/test/glass',
    '/content/drive/MyDrive/IAT 481/CV-Project/DATA/test/plastic',
    '/content/drive/MyDrive/IAT 481/CV-Project/DATA/test/organics'
]

# Loop through the directory paths and create them if they don't exist
for directory in directories:
    os.makedirs(directory, exist_ok=True)
```

We then defined a function to take images from a source directory where our dataset is located and move them to the newly created test and train folders according to their category. We also split this data using train_test_split with a ratio of 80-20:

```
from sklearn.model_selection import train_test_split
def organize_file(source_dir, train_dir, test_dir):
  files = []
  for f in os.listdir(source_dir):
    files.append(f)

  train_files, test_files = train_test_split(files, test_size=0.2, random_state=42)
  for file in train_files:
        file_path = os.path.join(source_dir, file)
        # Open, convert and save the image in the destination directory
        image = Image.open(file_path)
        image = image.convert("RGB")
        image.save(os.path.join(train_dir, file), "JPEG")

  for file in test_files:
        file_path = os.path.join(source_dir, file)
        # Open, convert and save the image in the destination directory
        image = Image.open(file_path)
        image = image.convert("RGB")
        image.save(os.path.join(test_dir, file), "JPEG")
```

We then defined the source directories for each category as well as directories for where they should be organized:

```
#Importing Glass images
glass_source = '/content/drive/MyDrive/IAT 481/WasteData/Glass'
glass_train = '/content/drive/MyDrive/IAT 481/CV-Project/DATA/train/glass'
glass_test ='/content/drive/MyDrive/IAT 481/CV-Project/DATA/test/glass'

#Importing Food Organics images
organics_source = '/content/drive/MyDrive/IAT 481/WasteData/Food Organics'
organics_train = '/content/drive/MyDrive/IAT 481/CV-Project/DATA/train/organics'
organics_test = '/content/drive/MyDrive/IAT 481/CV-Project/DATA/test/organics'

#Importing Plastic images
plastic_source = '/content/drive/MyDrive/IAT 481/WasteData/Plastic'
plastic_train = '/content/drive/MyDrive/IAT 481/CV-Project/DATA/train/plastic'
plastic_test = '/content/drive/MyDrive/IAT 481/CV-Project/DATA/test/plastic'
```

Then we called the function and passed to the suitable directories:

```
organize_file(glass_source, glass_train, glass_test)
```

```
organize_file(plastic_source, plastic_train, plastic_test)
```

```
organize_file(organics_source, organics_train, organics_test)
```

Our dataset is now ready to be trained using the YOLO framework. However, there is a possible bias with how our dataset was created that we need to take into consideration. A significant portion of our images came from an existing online dataset, which we carefully examined beforehand. This might have led us to subconsciously select similar types of trash objects like those presented in the dataset during our online search. This could limit the diversity of our dataset and potentially affect our model's ability to generalize to new, unseen examples. To mitigate this, we could have added our own data into the dataset before incorporating an existing dataset to avoid having a preexisting preference for the types of objects included. Or, we could have deliberately searched for images that are underrepresented or differ significantly from those in the existing dataset.

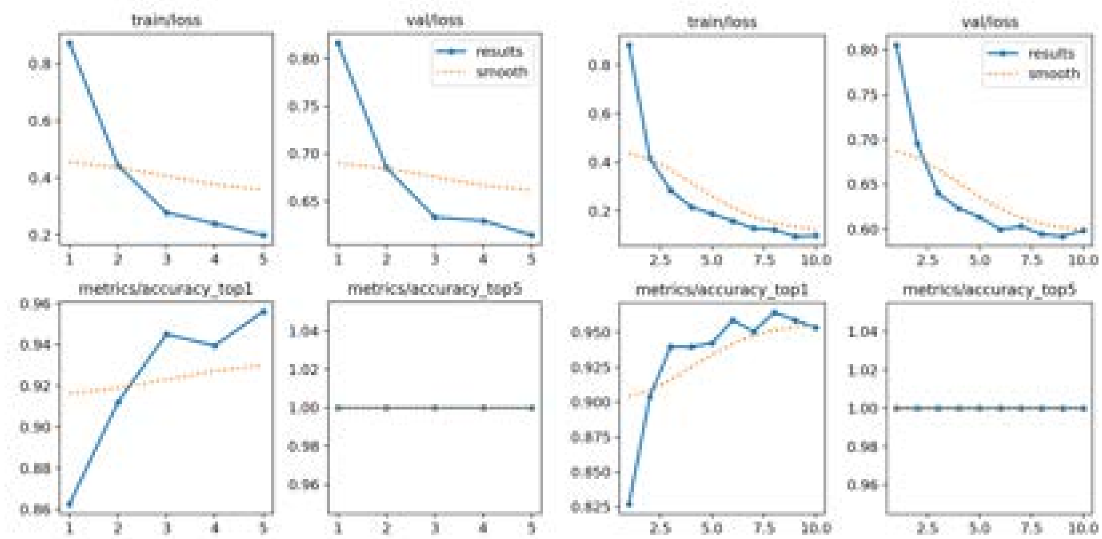
Training Report

Evaluation Metrics: Top 1 Accuracy

The two evaluation metrics available for our classification model were Top 1 Accuracy and Top 5 Accuracy. Top 5 Accuracy indicates the percentage of test samples for which the true label is among top 5 predictions made by the model. However, this metric only works best when we have a lot of classes for our model, at least more than 5. In our case, we only have three classes and thus making it unsuitable as an evaluation metrics.

Data Augmentation

For hyperparameter tuning, our team modified the number of times the dataset is passed through (epoch). Firstly we configured two models with the same YOLO architecture. The intent was to compare two different hyperparameters in order to find the appropriate weight with an awareness of potential underfitting/overfitting issues that ultimately improve performance.



Loss Metrics: The decline in both training and validation loss across epochs for both models signifies effective learning. However, model_2 benefits from the extended training, likely achieving a more refined fit to the data, as suggested by its steady performance improvement.

Model_1 achieves a top-1 accuracy of 95.6% by the end of its 5 epochs, showcasing a strong capability to accurately classify images. The steady decrease in loss across epochs indicates effective learning and model improvement over time.

Model_2, with a longer training duration of 10 epochs, further refined its classification performance, achieving a slightly higher top-1 accuracy of 96.4%. This model's extended training allows for more nuanced learning and adaptation to the dataset, reflected in its marginally higher accuracy and fitness score.

Evaluating better model: The Second Model ‘model_2’ with 10 epochs

1. **Accuracy**

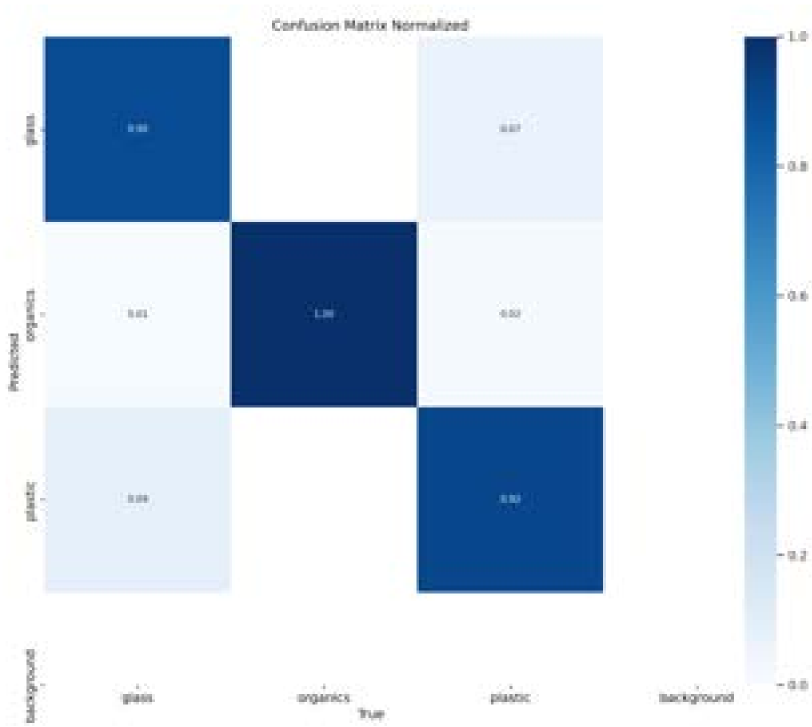
epoch	train/loss	metrics/accuracy_top1	metrics/accuracy_top5	val/loss	lr/pg0	lr/pg1	lr/pg2
1	0.88204	0.82692	1	0.80582	0.00023538	0.00023538	0.00023538
2	0.41477	0.90385	1	0.69535	0.00042652	0.00042652	0.00042652
3	0.28396	0.93956	1	0.64014	0.00057053	0.00057053	0.00057053
4	0.21625	0.93956	1	0.6231	0.00050194	0.00050194	0.00050194
5	0.18839	0.94231	1	0.61368	0.00050194	0.00050194	0.00050194
6	0.15742	0.95879	1	0.59971	0.00043126	0.00043126	0.00043126
7	0.12847	0.95055	1	0.60311	0.00036057	0.00036057	0.00036057
8	0.12235	0.96429	1	0.59438	0.00028988	0.00028988	0.00028988
9	0.09479	0.95879	1	0.59196	0.0002192	0.0002192	0.0002192
10	0.09814	0.9533	1	0.59847	0.00014851	0.00014851	0.00014851

The accuracy for our model had an increase from 82.6% to 95.8% from epoch 1 to epoch 6, then slightly decreased to 95% at epoch 7 and increased again at epoch 8, *peaking at 96.4%*. It later slightly decreased once again to 95.8% and then ending up at 95.3% during the last 2 epochs. The model's performance is highly impressive with a high accuracy, meaning that it is effectively learning from the data.

For the validation data, the model reported an *accuracy of 98.1%* on the validation data. There are no clear indications of overfitting or underfitting. The model exhibits somewhat consistent performance, only with a difference of ~2% in accuracy, in both training and validation, with no significant deviations that would suggest overfitting or underfitting.

2. Confusion Matrix

Considering the purpose of the model, which is to identify items correctly, the most crucial values are true positives and false negatives. We aim to maximize true positives while minimizing false negatives in order to increase the accuracy of item identification and avoid missing items that should have been identified.



<u>Glass:</u>

- True Positive: 90% of the actual Glass instances were correctly identified.
- False Negative: 9% of actual Glass were wrongly identified as Plastic and 1% of it were wrongly identified as Organics.

<u>Organic:</u>

- True Positive: 100% of Organic instances were correctly identified, indicating perfect sensitivity for this class.
- False Negative: None of the Organic instances were mistakenly identified as other materials.

<u>Plastic:</u>

- True Positive: 92% of Plastic instances were correctly identified, showing a high sensitivity for this class.
- False Negative: 7% of actual Plastic were wrongly identified as Glass and 2% of it were wrongly identified as Organics.

Interpretation and Implications: The model performs exceptionally well at identifying Organic materials, with a negligible rate of confusion with Plastic and Glass occasionally gets identified as Organics. The model shows high accuracy in identifying Glass and Plastic but still misclassify and confuse between the two.

3. **Batch Prediction based on Labels**

Examining the performance of our model during the validation process using 3 batches of 16 images each to see if our model can correctly identify the true labels.

First Batch:

The model incorrectly identified 1 out of 16 objects, specifically misclassifying a glass object as plastic (last row first image).

Labels (left) and Predictions (right)

Second Batch:

The model incorrectly identified 3 out of 16 objects, specifically misclassifying two plastic objects as glass (first row last two images) and one glass object as plastic (third row last image).

Labels (left) and Predictions (right)

<u>Third Batch:</u>

The model incorrectly identified 2 out of 16 objects, specifically misclassifying one plastic object as glass (last row first image) and one glass object as plastic (second row last image).

Labels (left) and Predictions (right)

<u>Interpretation and Implication:</u> With a similar pattern as the previous evaluation using confusion matrix, our model exhibited a consistent challenge in distinguishing between glass and plastic objects across three batches, with a total of 6 misclassifications out of 48 images. This suggests a need for model refinement to better capture and differentiate the features of glass and plastic items.

Prediction (Testing Images outside of the Dataset)

1. **Food Organics - Model correctly predict test images**

The model is highly effective in identifying food organics images, correctly predicting them three times out of three, with a nearly perfect confident rate (From left to right, the confident rate is: 99% - 100% - 100%).



2. **Plastics - Model sometimes incorrectly predict test images**

The model correctly identified plastic items in two out of three cases (~67% Accuracy), showing a moderate level of performance for this category. While not perfect, this indicates that the model has learned some relevant features for identifying plastics, although still confusing them with other materials. (From left to right, confident rate is: 98% - 89% - 5%)

3. **Glass - Model incorrectly predict test images**

The model failed to correctly identify any of the glass items across three test attempts (0% Accuracy), indicating a significant challenge in accurately classifying this category. This performance suggests that the model struggles to distinguish glass from other materials, especially from plastic objects. (From left to right, confident rate is: 9% - 2% - 38%)

Potential Reasons Behind Model’s Shortcomings

Through our validation and evaluation process, we noticed that the model frequently failed to distinguish between Glass and Plastic objects. This might be attributed to the few following reasons:

- <u>Lack of distinctive features learned:</u> We noticed that Glass and Plastic objects share a lot of visual characteristics, usually having a bottle-like shape, similar transparency, or reflectiveness. Without sufficient data, the model might be unable to capture the subtle differences. This makes sense considering that the food organics category was trained better than these two categories, maybe due to its distinctive features.
- <u>Limited and Biased Data:</u> If the training dataset is limited in diversity or biased towards certain characteristics, the model's representation of each class will be skewed. For example, if the majority of glass images in the training data are of clear glass bottles and the plastic images are predominantly of opaque containers, the model might learn to associate transparency with glass and opacity with plastic. Consequently, when presented with a transparent plastic item, the model might incorrectly classify it as glass due to these learned associations.
- <u>Class imbalance:</u> Plastic class is almost double in size compared to the other two classes. This imbalance can cause the model to develop a bias towards the majority classes, as it "sees" more examples of these classes during training and becomes better at recognizing them.

Challenges

The biggest challenge we had on the previous steps mostly pertains to technical issues while running ColabNotebook and importing our dataset since we are working online asynchronously and having difficulty to picking up where the other person left off due to the inability to sync where we store our dataset. This caused us having to run our code multiple times and creating many classify folders, causing it hard to navigate through the files while doing evaluation.

Reference List

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