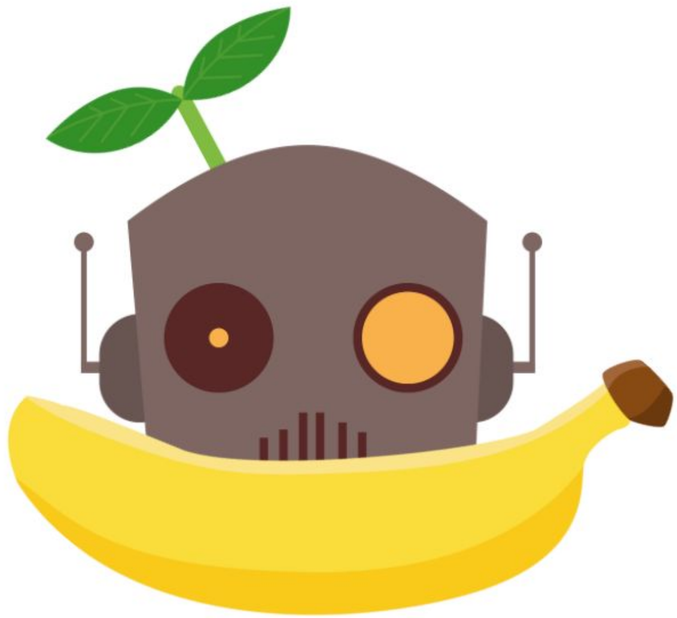
BANANA BOT FINAL PROJECT

AN AI COMPOST SORTER



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INTRODUCTION:

The goal of our final project was to create computer vision software for an AI compost sorting robot, BananaBot, that would distinguish compostable items from non-compostable items. The US is currently the global leader of food waste, producing 80 billion pounds of food annually with 95% of that waste ending up in landfills. When compost is decomposed in landfills, there is not enough oxygen for it to decompose aerobically, so it ends up producing an excess of methane gas. Methane is a potent greenhouse gas, and 20% of global warming can be attributed to methane concentrations. With BananaBot, we are hoping to limit the amount of compost in landfills and help combat climate change by separating compostable items from non-compostable items at landfills.

This problem is challenging because there are countless items that get thrown away, meaning the necessary dataset for a neural network to reliably separate compost from trash would be extremely large. As predicted in the project proposal, creating the dataset and respecting the given time constraints were the biggest challenges in this project. Creating a reliable dataset takes time, and we had to create a large portion of the dataset ourselves because we were not able to find any available datasets of compostable items. Since we didn't want to spend all of our allotted time for this project creating a dataset, we augmented our dataset by flipping each image horizontally and vertically. In order to create the BananaBot, we created a convolutional neural network with Keras and trained it on 80% of our dataset, with the other 20% set aside for testing and validation sets. We were able to achieve nearly 70% categorical accuracy and over 97% accuracy in sorting compostable items from non-compostable items.

BACKGROUND

There currently exists a multitude of trash and recycling AI robots. However, we knew it would be helpful to create a compost sorting robot to alleviate the pressure that food waste puts on landfill capacity and overall greenhouse gas production.

Previous approaches to trash sorting include SamurAI, an AI recycling bot that is implemented at landfills and put above conveyor belts to rapidly sort out recycling from trash, and MIT's recycling bot that can determine if something is recyclable based on touch. Many of the existing technologies that do sort compost are smart trash cans, such as Oscar the AI Trash robot, which utilizes a big display and camera that will recognize what is in your hand and tell you the correct bin to put it in. A very similar project to ours would be the trash sorting robot that Alphabet is currently developing testing robots in their offices that can sort trash, compost, and recycling. There do not seem to be many robots dedicated to solely sorting compost, especially at a sorting site on a conveyor belt. Most of the robots that handle compost are smart trash cans that will tell you where to put your assorted trash. The use of computer vision and AI is pretty constant between all the robots we came across, with the exception of MIT additionally using a touch sensor!

DATA AND METHODS

For this project, we decided to keep the scope of our project small. We chose to compose our compostable category of bananas, persimmons, and strawberries because these were the fruits we ate most commonly. This decision was ultimately made because of the short time span of this project. If we had more time we would have liked to include more classes of food scraps, green waste such as lawn clippings or twigs, and items that might pass as recycling but are compostable like pizza boxes or compostable to-go boxes with food stains. Our dataset consisted of images we had taken ourselves, images pulled from Google Image searches, and from items in the TrashNet dataset.

As we are not very experienced in this field, we had initially planned to write our convolutional neural network such that if the testing accuracy for an image was less than a certain threshold and did not fit into any class, the item would be labeled as "non-compostable." However, after discussing with Dr. Ventura, we found that this approach was called "open-set recognition" which is an open area of research, so we instead opted to add multiple non-compostable classes from the TrashNet dataset. We ended up with 14 classes in total: singleBananas, bananaBunches, bananaPeels, strawberries, persimmonLeaves, persimmonTops, persimmonPeels, wholePersimmons, trash, plastic, paper, metal, glass, and cardboard. The first 8 classes were categorized as compostable, and the latter 6 were categorized as non-compostable.

Since fruit can be sent to a landfill as either scraps, or as a whole with varying degrees of ripeness, we decided to separate each fruit further into subclasses such as peels, tops, or leaves. The combination of all of those classes make up the compostable category. With all of our compostable and non-compostable images combined, our dataset was 3061 images. Later on in the project however, we decided to implement data augmentation, which entailed flipping each image in the training set vertically and horizontally to increase our dataset to 7,979 images.

We used Google Collab so we could all easily access the project and inspire team collaboration. To store our dataset, we utilized Google Cloud Storage, and had the images separated in zip files by their class. We had issues in the beginning of our project downloading images from Google Drive, and were much more successful with storing a zip file of JPG images that we could download with Keras's `get_file` function.

The way that we classified each class as either compostable or not was dependent on the order that it was downloaded in; we stored the index and label of each class, and if the index was before the wholePersimmons class (which was the last compostable class downloaded), then it was classified as compostable, and non-compostable otherwise. After categorizing each class, we added padding to make the image square if it wasn't already, and resized all the images to be 96x96 pixels. We then separated the dataset, saving 80% for the training of the convolutional neural network, 10% for testing, and 10% for validation. Then, we augmented the training set by adding a flipped and mirrored version of each image. We used Keras to build the convolutional neural network with 4 convolutions each with 32 channels, 5 Dense layers, and a final softmax activation.

EVALUATION

To evaluate our convolutional neural network, we pulled out 10% of the images out of the dataset for testing, and 10% for validation *before* we augmented the data. At first, we made the mistake of separating the data after augmenting it. While we were very pleased with the results, we realized that the CNN was essentially cheating. When we made small changes such as an image flip, and *then* split the dataset into test, validation, and training sets, we were training on images that were very similar to the test images, thus exposing the test set during the training phase. After fixing this issue, we were able to correctly determine the accuracy of our neural network.

After our first few corrected test runs, we realized that there were many misclassifications. When looking closely at the inaccuracies in classification, we found many misclassifications were among a specific fruit, but misclassified as one of the fruit's subclasses. For example, a banana peel might be misclassified as a single banana (banana classes included singleBananas, bananaBunches, and bananaPeels). We then took a step back and realized our original goal was to create a compost sorter, not a fruit classifier. So, we separated the classes into two overarching categories: compostable and non-compostable. We then counted misclassifications among subclasses as *correct* classifications as long as the misclassification was in the same category (compostable or non-compostable) as the true classification. We deemed this metric as the "compostability accuracy."

During the training phase, we used our validation set results to guide the design of our network. The validation set was critical in choosing an appropriate amount of epochs and other specifics related to the number and type of convolutions comprising the network. This ultimately led to us getting around 1.8 million trainable parameters and 30 epochs with a batch size of 256. We arrived at this decision by trying many different setups and techniques, logging each result, and choosing the best and final configuration.

Our ultimate reach goal in terms of accuracy percentages came from a notable and similar project, "Deep Learning for Classifying Food Waste." This project had access to a dataset totalling about half a million hand-annotated images, and was able to achieve a categorical accuracy of 83.5%. This goal was not our baseline target of 70%, but rather was a reach due to the authors' combined experience and expertise in the field as well as their phenomenally large dataset. However, given our group's limited experience and relatively small, self-procured dataset, we are very happy with the results we were able to achieve.

RESULTS

The results of the evaluation on our very first iteration of the project were not very good. With a training accuracy of 88.49%, and a testing accuracy of 54.82%, we noticed that there were many misclassifications. We decided that there were two major improvements that we could make in order to remedy our low accuracy: to get more data, and to analyze our compostability accuracy. In order to create a larger dataset without using more time to take more pictures, we decided to augment the data. We included a horizontally flipped and vertically flipped version of every training image. Another fundamental improvement was ensuring our CNN was not "cheating" by separating the testing and validation data before augmenting it. With all these improvements, we were able to bring our testing accuracy up to 69.4%. Once we differentiated by category (compostable vs. non-compostable), we achieved a compostability accuracy of 97.7%. What this means is some things were misclassified, but these misclassifications could be ignored when the true classification was in the same category as the misclassification.

OUTLOOK

We did not expect our convolutional neural network to be very accurate, because we still had a relatively small and undeveloped dataset. However, our final results were surprising, especially when we analyzed the compostability accuracy. Despite our missed baseline – and somewhat arbitrary – goal of 70% categorical accuracy, our compostability accuracy blew away our expectations. Given our lack of experience and small dataset, we are hopeful that future groups will be able to produce an even better system.

For this project, we were slightly too ambitious and ended up not being able to complete as much as we had initially anticipated. While we were able to very accurately determine whether an item was compostable or not, we thought that our compost dataset would have included a lot more categories. We had not truly realized how much time it would take to photograph a food in all of its various forms and states. Although the quarter is over, if we were to continue working on this project in the future, the first thing we would want to expand upon would be the dataset. We really wanted a bigger range of food scraps, leftovers, green waste, and items that look recyclable but aren't, such as pizza boxes with food stains, or biodegradable to-go containers. Additionally, we would like to implement open set recognition to be able to classify items as non-compostable if they did not match any existing class in the compostable category. Currently both of our categories in the datasets are underdeveloped, and removing the need for a trash class would allow us to spend more time adding more classes to our compostable class. Finally, if we were to continue with this project, we would want to figure out how to use our dataset to accurately recognize items from a zoomed-out view of multiple items on a conveyor belt. Currently, the images in our dataset have the item cropped relatively well and centered in the image, but in reality, when food is going down a conveyor belt, the item will be layered, offcentered, and poorly cropped in most frames of the video.

Through this project we were all able to learn a great deal. We learned how to add padding to an image and center it on a page, and how to create a successful dataset and grow it without taking more pictures. While this led to our infamous mistraining runs where our network cheated, we learned the hard way that data augmentation is a powerful tool. This technique saved us countless hours of gathering more images. In the end, we were impressed with our BananaBot and were very proud of its impactful results.

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