HIDING IN PLAIN SIGHT: HARNESSING DEEP LEARNING TO DETECT MORELS IN NATURAL SETTINGS

INTRODUCTION

Have you ever tried foraging for wild foods? If yes, you are probably familiar with the infamous Morel. These mushrooms are well known amongst foragers of all skill levels. The cap of a morel features a distinct honeycomb pattern that makes confident identification relatively simple but also makes them notoriously difficult to find.
This characteristic presents an interesting problem for a computer vision model to solve. Consider that a novice forager will often have trouble seeing morels without the guidance of an expert, but once the novice completes a few successful hunts, spotting them becomes much more natural. It would appear to be a simple matter of training the eye to recognize the pattern. Can a CNN learn to be an expert forager too?

Author

Elaina Rohlfing

Affiliations

University of Missouri, St. Louis
Deep Learning, Spring 2024
Professor Badri Adhikari

01 OBJECTIVE

Create a high-quality dataset and analyze the performance of CNN architectures, transfer learning, and off-the-shelf tools to determine whether a CNN can classify images of Morels in the wild.

Expert or novice?


fig 1. A few samples from the training set.

05 CONCLUSION

I believe that creating a more comprehensive data set that has classes to represent a greater diversity of the wildlife present in a morel's habitat could allow a model to provide more reliable predictions. Of course, spending more time working with a large model, such as MobileNet may ultimately lead to similar improvements.
It is worth noting that there is a field of study; Camoflauged Object Detection is centered around how to best train a model to detect hidden and obscured objects. If I had a bit more time I would have liked to explore some of that research for this protect, I think it would provide some interesting insight.

06 CHALLENGES AND FUTURE WORK

The biggest challenge I faced in ths project was image sampling. I ultimately created two fully independent datasets for this project, which ultimately ate up a significant portion of my time. The second iteration of the dataset did in fact show huge performance increases, so the time spent seems to have been worth while.
In the future I hope to expand on this idea. I am interested in the intersection of Artificial Intelligence and how it can be leveraged to educate and inspire users about the natural world around them.
I believe this project could be extended to a much broader use tool that would educate users in the process of identification. Similar to tools such as iNaturalist, but with the goal to engage the user in learning about the wildlife in front of them rather than only leveraging computer vision as a (powerful) search engine.

02 METHODOLOGY

A significant portion of this project focused on curating a high-quality dataset from scratch. The goal was to collect samples representative of a typical forager's viewpoint. Samples should include images where the mushrooms may not be obvious or even partially obscured.

- Dataset creation
  - Images were collected in batches and then filtered to ensure quality and representativeness.
    - Google image search (roughly 10% of the dataset)
    - Facebook Morel and foraging communities with publicly available media
  - The remaining 398 images were manually sampled to create the "morel" and "none" classes
  - The final dataset contains 792 samples with two evenly split classes

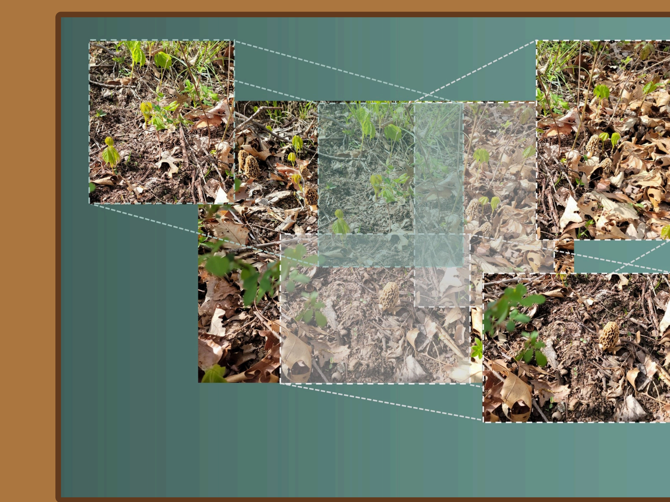
fig 2. The image sampling process

- Model Building
  - CNN architecture was explored with the following workflow:
    - Overfit a small model
    - Systematically test each hyperparameter to find an ideal model
    - Apply data augmentation and regularization to improve accuracy and reduce overfitting
  - Transfer Learning with MobileNetV2
    - Followed a basic tutorial for transfer learning from tensorflow.org
    - MobileNetV2 was selected because there is potential to provide real-time assistance to foragers.
    - Given more time, I would have liked to explore this further.
- Teachable Machines
  - An off-the-shelf tool trained simply by uploading my dataset and a significant reduction in the learning rate.
  - I was able to produce a model with very high accuracy and capabilities to be deployed to a mobile app, but due to time constraints, I was not able to pursue this.

03 ANALYSIS

With the final dataset I was able to get reasonably good results in each stage of development. Due to space constraints I am not able to share all results here, but these results show how successful the model was at overfitting, even on a model of only 1049 parameters. Interestingly, augmentation noticeably stunts the model's ability to converge. Some more experimentation here may eventually provide some more positive results. It is possible the model may still be a bit too small.

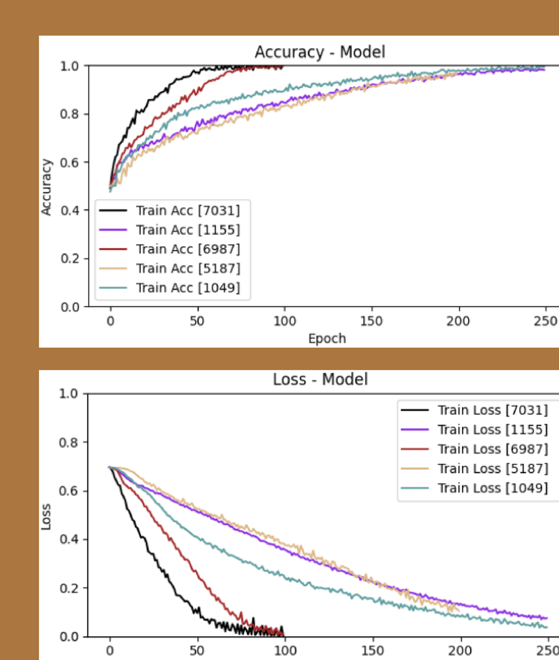

fig 3. Overfitting

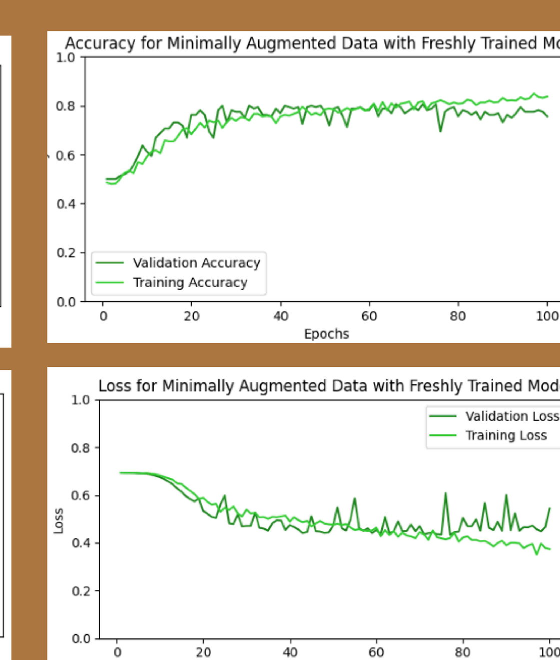

fig 4. Impact of augmentation

This is a screenshot to highlight the results I gathered from the Teachable Machine. The model clearly performs well, but the real insights were gained from interacting with the live camera. The dataset may be may be stunting model performance due to its narrow scope.

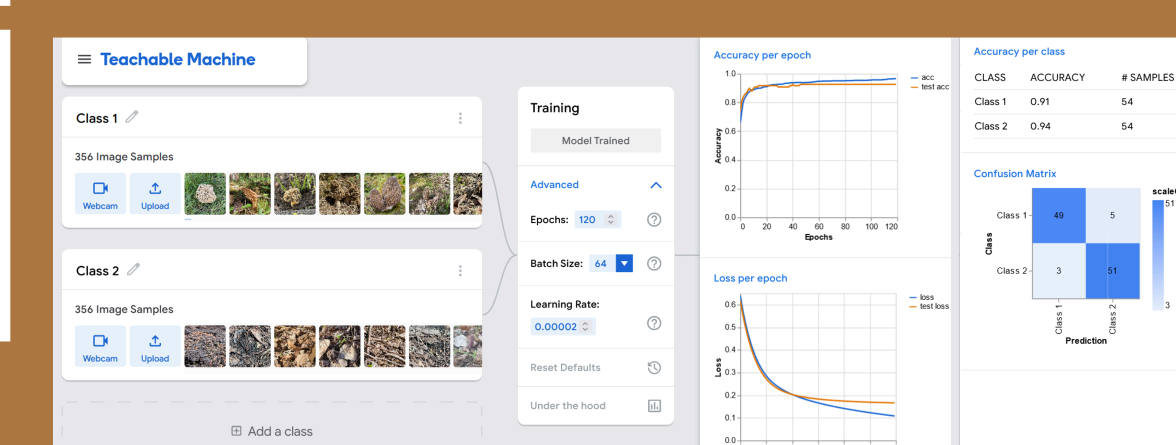

fig 5. Teachable Machine

04 RESULTS/FINDINGS

Results suggest that, yes, a convolutional neural network has the potential to learn how to reliably spot morels hidden in the natural landscape. However, after exploring predictive power with the Teachable machine, I do not feel that this is something I am able to prove with my current dataset. Despite the models' showcasing high validation accuracy in several iterations, they are only being evaluated with morel-specific data. In a real-world dataset, when the images encompass a full range of plant, fungi, and animal matter, the model is ill-equipped to understand the nuances between a tree stump and a morel. It is clear that further research and a more robust dataset is required.