

DEEP LEARNING APPROACH TO MUSHROOM SPECIES CLASSIFICATION

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1 INTRODUCTION

The format for the submissions is a variant of the ICLR 2022 format. Please read carefully the instructions below, and follow them faithfully. There is a **9 page** limit for the main text. References do not have any limitation. This is also ICLR’s standard length for a paper submission. If your main text goes to page 10, a -20% penalty would be applied. If your main text goes to page 11, you will not receive any grade for your submission.

We propose the use of the MIND.Funga dataset (Drechsler-Santos et al., 2023), which has approximately 17 000 images of nearly 500 species of fungi. This dataset is well-suited for our project, as it is built primarily for use in deep classification models. Images are also curated to be of a high quality and are labelled by species.

Our code can be found at this GitHub repository.

2 BACKGROUND & RELATED WORK

One key application of a fungi identification model is food safety and satisfaction.

In Bangladesh, a country with a large mushroom production, a farming method was developed by Rahman et al. (2022) using machine learning to classify which mushrooms are being harvested. This system intended to remove toxic species that may have grown in the same area as the target mushroom. Wang et al. (2018) created an algorithm to identify disease, discolouration, freshness, as well as other factors contributing to the commercial quality of a white button mushroom.

Our software would sort these mushrooms into genera, which would assist in identifying different types of mushrooms instead of certain physical features. Keeping with the theme of food quality, in Taiwan, Lu et al. (2019) developed a system to determine how much a mushroom has grown using an image recognition model, which produces an estimate based on images from different times. This used a convolutional neural network (CNN) to provide these results, which will be similar to our model’s architecture. In the Chinese province of Yunnan, H. Zhao et al. (2021) created a wild mushroom identification model that used a CNN to identify edible and medicinal mushrooms due to increasing popular interest in mushrooms.

Other field work includes smartphone applications for recreational use, like ShroomID, which details mushroom species, while providing a heatmap of its location and seasonality. This educational tool provides useful information about a mushroom, after it has been identified using a classification model (Sh, 2023).

3 DATA PROCESSING

Many species in the dataset have a relatively small amount of images associated with them (< 30 images), which may be detrimental when training, testing, and validating our model. To mitigate this, we intend to group images into larger “buckets” corresponding to a higher level of taxonomic classification, i.e., grouping by genus instead of by species. This is a simple way to reduce the number of classes our model must be trained on, and to increase the amount of data to a sufficient amount that model features can be reasonably trained. Genera form an ideal way to group images together — biologically species of the same genus share many physical characteristics, and they share a root name (the first word in the species name), which enhances ease of processing. Existing literature (Hollister et al., 2023) also suggests that models trained to classify genera tend to have better accuracy and are less difficult to train than species-level classification.

Once we have performed this combination, any genera with less than 75 images will be discarded from the dataset. This matches the lower threshold of published ecological classifiers, like iNaturalist (Shepard, 2022) or models trained on the ETHZ human dataset (Schneider et al., 2019). It also matches what is considered by Farley et al. (2024) to be the lower end of images per class to train a model without overfitting.

4 ARCHITECTURE

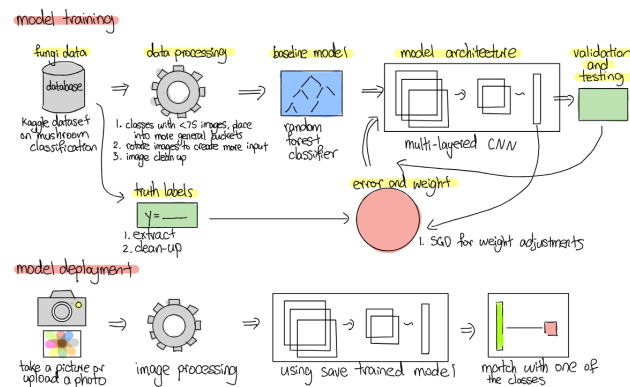


Figure 1: Proposed model training and deployment pipeline

5 BASELINE MODEL

For the baseline model we are comparing our model against, we selected a random forest classifier model. Our goal is to identify several hundred species of macrofungi, making this a multiclass classification problem. Decision trees like random forest are generally suited for multiclass problems (Breiman & Cutler, 2004). Other methods, like support vector machines, are generally suitable primarily for binary classification problems (James et al., 2023).

6 PROJECT PLAN

Task Breakdown and Responsibilities (Green = completed, Yellow = in progress, Red = not started)
W = wrote/coded/drawn, ED = edited, MR = major revision, FP = Final section proofread

Project Proposal	Eric Liu	Jason Zhang	Nicholas Biancolin	Yanni Alevra
Introduction (June 4th, 11:59pm)	W	W	W	W
Illustration/Figure (June 5th 11:59pm)	W			
Background and Related Work (June 5th 11:59pm)				
Data Processing (June 5th 11:59pm)				
Architecture (June 5th 11:59pm)				
Baseline Model (June 5th 11:59pm)	W			
Ethical Considerations (June 5th 11:59pm)	W			
Project Plan (June 5th 11:59pm)	W			
Task research and distribution (June 5th 11:59pm)	W			
Risk Register (June 5th 11:59pm)	W			
Github, References (June 5th 11:59pm)	W			
Structure, Grammar and Mechanics (June 5th 11:59pm)	W			
Document in LaTeX (June 5th 11:59pm)				
Editing (June 6th 11:59pm)				
Final Document Proofread (June 6th 11:59pm)				

Table 1: Project Proposal Task Breakdown

Project Progress Report	Eric Liu	Jason Zhang	Nicholas Biancolin	Y
Brief Project Description (June 30th, 11:59 pm)				
Individual Contributions and Responsibilities (June 30th, 11:59 pm)				

Table 2: Project Progress Report Task Breakdown

PROJECT PROGRESS REPORT

7 RISK REGISTER

As with any large scale project, there are many associated risks:

- What if a team member elects to drop the course?
- What if the model isn't training properly?
- What happens if there's scope creep?
- What happens during time crunches?

We are privileged to have been friends for over a year. We have respect for and have worked with each other in the past. We recognise that a group member dropping the course, while far from ideal, is a choice that is made for a reason. Should such a case occur, we will meet and discuss how extra work will be divided and make a plan to ensure the project continues as planned with an extra workload.

We intend to avoid quality issues with the model by setting a timeline that leaves time for multiple rounds of iteration, further training, and debugging. If the model's performance is subpar, we intend to first make changes to the data processing and architecture. With a relatively small amount of data per class, deliberate improvements to both areas may be able to immediately improve performance.

As with many projects, this proposal was written with the understanding that circumstances may change as the semester continues. If left unchecked, project requirements can change drastically from the original proposal. We will keep this in mind as we discuss and work on the project to avoid any misconceptions.

Finally, we have experienced many short time constraints in previous projects and understand how they may affect the quality of the final product. The timeline we intend to set leaves extra room for unexpected issues. Should a time crunch occur, we will evaluate our responsibilities and progress and work according to a priority queue.

Contributions - Data Processing (June 30th, 11:59 pm)				
Contributions - Baseline Model (June 30th, 11:59 pm)				
Contributions - Primary Model (June 30th, 11:59 pm)				
Illustrations (July 1st, 11:59 pm)				
Latex format (July 2nd, 11:59 pm)				
Editing (July 3rd, 11:59 pm)				
Final Proofread (July 4th, 6:00 pm)				

Table 3: Project Progress Report Task Breakdown

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