

DEEP LEARNING APPROACH TO MUSHROOM SPECIES CLASSIFICATION

Yanni Alan Alevras

Student# 1009330706

yanni.alevras@mail.utoronto.ca

Nicholas Biancolin

Student# 1009197726

n.biancolin@mail.utoronto.ca

Eric Liu

Student# 1009098450

ey.liu@mail.utoronto.ca

Jason Ruixuan Zhang

Student# 1008997631

jasonrx.zhang@mail.utoronto.ca

1 PROJECT DESCRIPTION

- motivations behind project - 87- mushrooms are a common type of plant that are difficult to identify, especially since some are edible and some are poisonous
- goal of project - Create a deep learning model that can classify mushrooms into their respective species
- why deep learning is a reasonable approach - mushrooms have a lot of visual features that can be used to classify them - deep learning models have been shown to be effective at image classification tasks

2 INDIVIDUAL CONTRIBUTIONS AND RESPONSIBILITIES

- How team is working together
- project management software used to communicate/track results
- detailed list of what everyone has worked on, and what they will be working on

Jason:

Set up python environment for the group to work with. Genus grouping to reduce size of dataset. Random forest baseline model with accuracy, precision, recall, F1, and support reports. Baseline Model section of the report..

Yanni:

Researching which forms of data augmentation are most relevant to the project. Data augmentation additions to the dataset. Data Processing and Individual Contributions and Responsibilities sections of the report.

Eric:

Rough Draft for Primary Model section of the report. handdrawn diagram of structure. Data Separation and Apply Transfer Learning: alexNet. Class Structure, Training Function, Accuracy function. Validation Loss and Graphs.

Yanni	Nick	Eric	Jason
-------	------	------	-------

Project Progress Report	Eric Liu	Jason Zhang	Nicholas Biancolin	Yanni Alevras
Brief Project Description (June 30th, 11:59 pm)			W	
Individual Contributions and Responsibilities (June 30th, 11:59 pm)			W	W
Contributions - Data Processing (June 30th, 11:59 pm)				W
Contributions - Baseline Model (June 30th, 11:59 pm)		W		
Contributions - Primary Model (June 30th, 11:59 pm)	W			
Illustrations (July 1st, 11:59 pm)	W			W
Latex format (July 2nd, 11:59 pm)	W	W	W	W
Editing (July 3rd, 11:59 pm)	ED	ED	ED	ED
Final Proofread (July 4th, 6:00 pm)	W	W	W	W

Table 1: Project Progress Report Task Breakdown

Project - Training and Testing	Eric Liu	Jason Zhang	Nicholas Biancolin	Yanni Alevras
In charge of code connection/solving merge conflicts (August 10th, 11:59pm)	W	W	ED	
Data Cleaning (June 16th, 11:59pm)	W	W		ED
Image Grouping (June 16th, 11:59pm)	ED		W	ED
Transfer data to training format (June 16th, 11:59pm)	ED	ED	W	
Data annotations, splitting (June 16th, 11:59pm)	W			ED
Model implementation (June 19th, 11:59pm)		W		ED
CNN architecture (June 19th, 11:59pm)		ED		W
Training Loop (June 19th, 11:59pm)	W	W	ED	ED
Hyperparameter adjustments (July 15th, 11:59pm)	W	ED		W
Training (July 15th, 11:59pm)	W ED	W ED	W	W
Validation (July 15th, 11:59pm)		W		ED
Testing (August 10th, 11:59pm)	W	ED	W	
Iterative (if needed) (August 10th, 11:59pm)		ED		W
Evaluation (August 10th, 11:59pm)	W	W	W ED	W
Documentation (August 10th, 11:59pm)	W	W	ED	
Resource management (August 3rd, 11:59pm)			W	ED
Analyze Result for Presentation and Project (August 3rd, 11:59pm)	W	W	W	W

Table 2: Project Training and Testing Task Breakdown

Presentation	Eric Liu	Jason Zhang	Nicholas Biancolin	Yanni Alevras
Presentation Brainstorm (August 5th, 11:59pm)	W	W	W	W
Problem - slides (August 5th, 11:59pm)		ED	W	
Data Processing - slides (August 5th, 11:59pm)	W			ED
Model - slides (August 5th, 11:59pm)		W	ED	
Result - slides (August 5th, 11:59pm)	ED			W
Slides Editing (August 5th, 11:59pm)	ED	ED		
Individual Practice (August 7th, 11:59pm)	W	W	W	W
Group Practice (August 7th, 11:59pm)	W	W	W	W
Record Presentation (August 7th, 11:59pm)	W	W	W	W
Editing (August 10th, 11:59pm)			W	ED

Table 3: Presentation Task Breakdown

Project Final Report	Eric Liu	Jason Zhang	Nicholas Biancolin	Yanni Alevras
Latex Formatting (August 12th, 11:59pm)	W	W	ED	
Introduction (August 7th, 11:59pm)		ED	W	W
Illustration (August 7th, 11:59pm)	W	ED		
Background and Related Work (August 7th, 11:59pm)		W	ED	ED
Data Processing (August 7th, 11:59pm)		W		ED
Architecture (August 7th, 11:59pm)	ED		W	
Baseline Model (August 7th, 11:59pm)	ED	ED		W
Qualitative Results (August 7th, 11:59pm)	W	ED		
Quantitative Results (August 7th, 11:59pm)		W		ED
Evaluation of Model (August 7th, 11:59pm)	W		W ED	ED
Discussion (August 7th, 11:59pm)	ED	W		W
Ethical Considerations (August 7th, 11:59pm)		W		ED
Project Difficulty (August 7th, 11:59pm)	W	ED		
Editing (August 12th, 11:59pm)	ED		ED	W
Final Proofread (August 14th, 11:59pm)	W	W	W	W

Table 4: Project Final Report Task Breakdown

3 NOTABLE CONTRIBUTION

Data Processing

The dataset contains 509 species. Stated in our project proposal, due to some low amount of sample imaging for some species we decided to group by genus, and keep the top 15 genera with the largest datasets. This genus grouping was done through iterating all of the species in the dataset, and moving all of the data into a new directory for that genus. These directories were then ordered by size, and the top 15 were kept.

To artificially increase the amount of data in our dataset, we used data augmentation, creating a copy of each sample with a horizontal flip, 90 degree rotation, 180 degree rotation, 270 degree rotation, gaussian noise, and random erasing (small black rectangles). These methods were preferred over others such as kernel filters, lowering the quality of an image. Since these mushrooms can be identified based on specific visual traits found within their genus, high detail in the training images are necessary to allow for differentiation between the different genera. Due to this, prioritizing the quality of the image was necessary. In addition, our model is colour agnostic, so having a method like color space transformations are not necessary, and would allow for too many almost duplicate images in the dataset. Some simple methods were the flip and rotations, which kept the same image, but just made the model look at it a different way. Gaussian noise was added as a technique to allow the model to draw attention towards the most robust features of the image, relevant to the nature of this dataset where many genera are similar in shape and very based on texture or pattern. Random erasing is important for training with data that varies in resolution. This dataset has mostly high quality images, but some are lower resolution. This method was added for a similar reason as gaussian noise, but instead to train the model to identify more distinct features of one genus to another (Shorten et al., 2019).

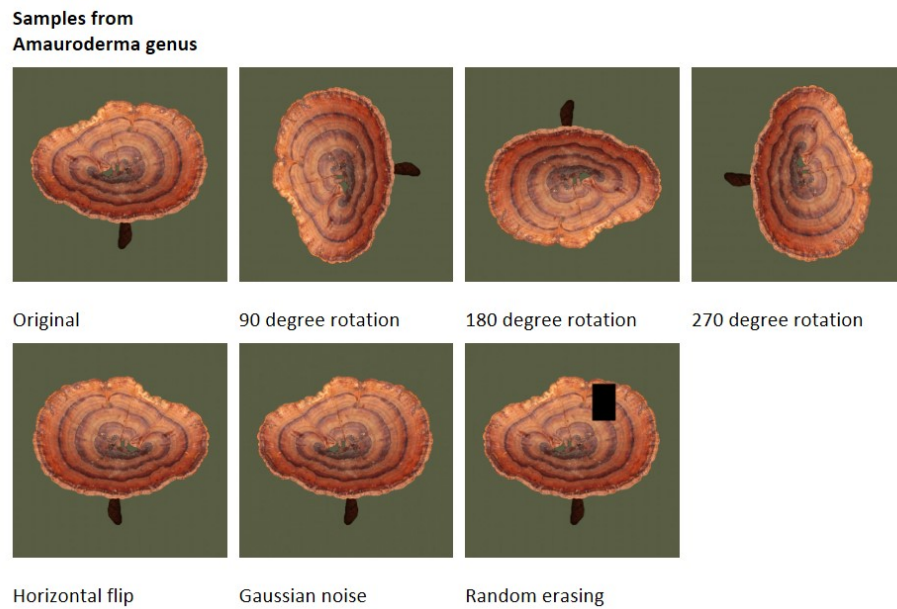


Figure 1: Data Augmentation Examples

To test this data, it is split into % training, % validation and % testing. Our evaluation metrics consist of accuracy, precision, recall, F1 and support. This is to provide a wider view on the performance of the model, including underrepresented classes.

The biggest challenge for the data processing, was figuring out how much original data we would need, and how much we want to use data processing to increase the amount of data. Including what types of data augmentation we would see fit, explained above. Overall the top 15 genera have around 200-1000 images each, with data augmentation multiplying that by seven.

Primary Model

Baseline Model

Primary Model

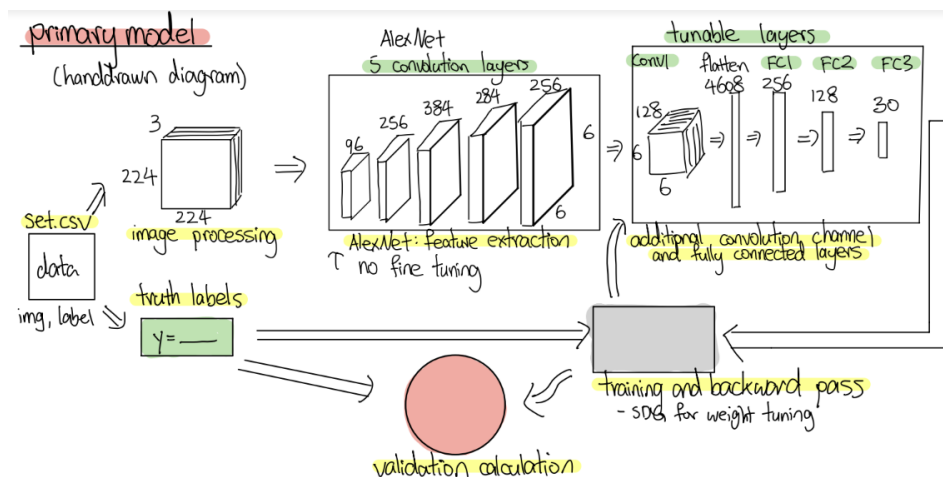


Figure 2: Model Structure and Tensor Sizes

Our CNN model consists of two main sections: a non-tunable transfer learning part and a tunable convolution and fully connected layers section.

NON-TUNABLE SECTION

The team uses AlexNet for its high-level feature extraction. AlexNet processes a $3 \times 224 \times 224$ input image and the feature extraction outputs a $256 \times 6 \times 6$ tensor. There are five convolutional layers and three pooling layers, the order of the layers is shown on the hand-drawn diagram above. Since the model needs to differentiate between mushrooms with very similar appearances, AlexNet excels in extracting the fine features that set them apart.

TUNABLE SECTION

To make the model specific to the team's project, the team uses one additional convolutional layer, outputting a $128 \times 6 \times 6$ tensor. After the additional convolutional layer, the output gets flattened and passed through three fully connected layers with ReLU activation functions in between. The fully connected layers turned the size from 4608 to 256, then to 128, and lastly to 30, matching the number of output classes the team decided for the model.

In total, there are $5 + 3$ layers in the non-tunable section and $1 + 3$ layers in the tunable section, making our class structure 12 layers in total.

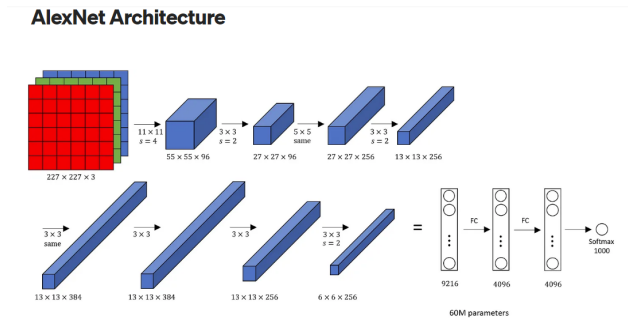


Figure 3: Class Structure: AlexNet ?

CALCULATION OF PARAMETERS

NUMBER OF PARAMETERS FOR THE ALEXNET STRUCTURE:

$$\begin{aligned}
 \text{Conv1} &= 3 \times 11 \times 11 \times (96 + 1) = 35,271 \\
 \text{Conv2} &= 96 \times 5 \times 5 \times (256 + 1) = 616,800 \\
 \text{Conv3} &= 256 \times 3 \times 3 \times (384 + 1) = 886,080 \\
 \text{Conv4} &= 384 \times 3 \times 3 \times (384 + 1) = 1,310,720 \\
 \text{Conv5} &= 384 \times 3 \times 3 \times (256 + 1) = 887,232
 \end{aligned}$$

NUMBER OF PARAMETERS FOR THE TUNABLE SECTION:

$$\text{Conv1} = 256 \times 3 \times 3 \times (128 + 1) = 297,216$$

$$\text{Fc1} = 4608 \times (256 + 1) = 1,183,296$$

$$\text{Fc2} = 256 \times (128 + 1) = 33,024$$

$$\text{Fc3} = 128 \times (30 + 1) = 3,968$$

The total number of parameters is 5,273,927, the number of trainable parameters is only 1,517,504. This ensures the training time for our models is feasible, allowing the team to focus on more epochs and more variations using data augmentations in the future.

At the start, the team pushed all images into the feature extraction part of AlexNet, converting data into tensors. We randomly split the data into a 75%, 15%, and 10% ratio for training, validation, and testing.

For our current best result, we used a batch size of 36, learning rate of 0.007, and 15 epochs. We chose Cross Entropy Loss for the loss function as we want the model to classify the image into one of the 30 classes. For the optimizer, the group decided on Stochastic Gradient Descent (SGD).

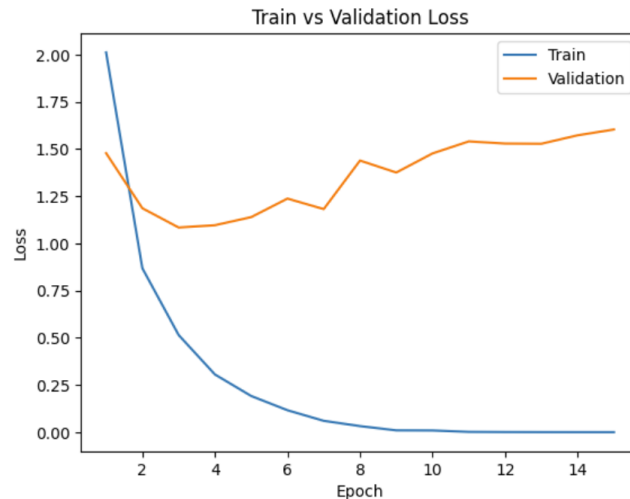


Figure 4: Validation Loss

The team's training graph with the specified hyper-parameters is shown above. It indicates that the model is overfitted quickly, to tackle this issue, the team aims to implement regularization and drop off in the future.

Testing Accuracy:

- Epoch 4: Test Classification Accuracy: 64.01%
- Epoch 8: Test Classification Accuracy: 65.12%

From the above graph, the team chose epochs 4 and epoch 8 and did accuracy testing, using the testing data. The testing accuracy is at a good starting point considering the model must classify an image into one of thirty classes. The accuracy can be improved using various techniques:

- The current data used in the training is not augmented. The data augmentation functions are completed, but not used currently to save runtime for the training loop. The team will add the augmented data as part of training in the future.
- Further hyperparameters fine tuning.
- Implementing regularization and drop off to reduce the quick overfitting seen in the validation graph.