AI Mushroom Identification: Pacific Northwest Mushroom Classification through Image Recognition with Convolutional Neural Networks

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Abstract. Wild mushroom identification is notoriously difficult and usually reserved for mushroom experts or mycologists. However, with the help of artificial intelligence (AI) such as deep learning, the problem may be simplified tremendously. We have collected a dataset of nearly 11000 images for fifteen different mushroom species, and the deep learning technique Convolutional Neural Network (CNN) was created to classify these fifteen different species of mushrooms by being fed a randomized set of preprocessed images converted to grayscale. Methods of preprocessing were explored in their relation to accuracy rates as well as manipulating layer size, batch size, and number of epochs. The study concluded that preprocessing of images for comparison is an extremely important step in creating a CNN network especially when not doing a linear comparison but a comparison amongst fifteen different species. We also attempted to explore the number of epochs as well as manipulating the number of layers of a CNN network, but it did not have a significant effect on retrieving a higher accuracy rate from the network. The experiment ended with a ~11% accuracy rate when comparing fifteen different species of mushrooms and ~70% accuracy rate when comparing two distinct species of mushrooms. The code is available on Github: https://github.com/aestheticCoder/MushAI

Keywords: artificial intelligence, image recognition, convolutional neural networks, classification, mushroom identification, mushrooms, deep learning, machine learning.

1 Introduction

Mushrooms and the fungi that produce them are some of the most fascinating and diverse organisms on our planet and the mushroom, the fruiting body of the fungus, can also be a tasty addition into any dish. There are thousands of species of mushroom producing fungi, but not all are edible. Even with the variability in toxicity, there are several mushrooms that are poisonous enough to kill a healthy adult. For example, the mushroom nicknamed "destroying angel" (*Amanita ocreata*), consuming even half of the mushroom-cap can be fatal [1]. Being able to identify what is edible from what can kill is essential to any amateur mushroom hunter. Proper identification of edible species of mushrooms usually requires extensive background knowledge in mycology. However, with the new advances of Artificial Intelligence technology in the area of image recognition, even an amateur may soon be able to accurately identify whether a wild mushroom is edible with just an image [2]. This study aims to create a reasonably accurate mushroom identifier using neural network image recognition techniques. The focus for our image recognition AI is on the fifteen most common edible and poisonous mushrooms of the Pacific Northwest. In order for us to achieve our goal, there were several technological problems we had to overcome. Several mushrooms are so similar, it may be almost impossible to identify with a high degree of accuracy without taking physical samples (spore, scent, etc). Currently applications for mushroom identification exist under both iOS and Android. For example, iFunch is an iOS app that is $3.99 and encompasses an identification method as well as an AI recognition feature, and Mushroom Identification is an Android app that is $4.99 and has a database which is “supported by scientists and collaborators". None of them are free and some of them are not fully automated, but our method is open-source and fully automated.

2 Literature Review

2.1 The Image Identification Problem, A Mycological Perspective

A mushroom is the “fruiting body” of a fungus, that is, the structure that bears the microscopic spores that reproduce the fungus. A mushroom is therefore similar to an apple on a tree — the apple bears small seeds which ultimately reproduce the tree [3]. Mushroom producing fungi are so diverse that there are thousands of species just in the Pacific Northwest of the United States, and many mycologists believe that only two - thirds of all mushrooms in North America have been identified and described by science [4]. However, the immense diversity of mushroom producing fungi quickly demonstrates the difficulty of properly identifying the desirable edible species from the deadly poisonous species, when there are so many possibilities that any one mushroom could be, just in the Pacific Northwest. To add to the difficulty, many poisonous species of mushrooms appear nearly identical to edible species, so to an untrained collector a simple mixup could be a fatal mistake.

Mycologists have created a complex identification and classification system based on the features that a mushroom may exhibit, usually referred to as a dichotomous key. The key, when properly followed, allows for an accurate identification of a given unknown mushroom specimen [5]. However, this feature system highlights the problem of accurate mushroom identification and classification purely by image, as there are important identification features that an image can never contain. This information may be necessary to confirm a proposed mushroom identification, such as location, specific habitat and season information. As Table 1 illustrates, an image can contain many important features key to identification, yet there may be important identification information it can miss. This missing information could potentially cause a false positive result and an inaccurate identification even when an image recognition AI "gets" it right, as it is simply missing the data that it needs to make an accurate identification. In the worst case, this feature data, if not properly considered by the AI, could unintentionally harm someone who uses and accepts the AI's correct but inaccurate identification and goes on to consume a poisonous look alike. Therefore, ensuring that we can account for some of the most important features is important to have an accurate and reasonably safe mushroom identification AI.

Even so with an AI that accounts for these extra features it can still make a mistake just like a professional mycologist can, so we must formally state that the user must assume the risks of consuming any wild mushrooms they find, and that we can not take responsibility for any mistakes that may happen and their consequences. As one should always remember that with any wild mushrooms, the cardinal rule is never to eat one that you are not certain is edible.

Table 1. Visual vs Non-visual feature comparison..

Identification Features present in an Image	Identification Features not present in an Image
Overall Shape	Geographic Location
Cap/Stem Color	Specific Habitat
Cap Texture	Season found
Gill Presence/Color	Relative Size
Ring Presence/Structure on Stalk	Growth Stage
Veil Presence and Color	Spore color (obtained from a spore print)
Grouping Density	Gill Shape/Structure
General Habitat	Stalk surface Texture
Foot Presence (specimen must be dug up)	Order and Taste
Bruising Color (specimen must have visual bruising)	Rarity

Even so, if you do decide to consume a mushroom you are confident is edible and safe, it is always a good idea to save an uncooked sample form the mushroom species you collected in the refrigerator, should you develop any nasty symptoms, you will be able to provide it as evidence to a medical professional so they can help you with the appropriate care[4].

2.2 Deep learning and its application

Deep learning is a class of machine learning algorithm that is designed to use multiple layers to progressively extract higher level features from raw input given[6]. To put in layman's terms it is best to describe the class of machine learning as a function in which it takes a variety of unknown inputs and outputs a desired result or value. Deep learning networks have been successfully applied to unsupervised feature learning for single modalities(e.g. Text, images, or audio)[7]. For the purpose of our research to identify different mushroom species, deep learning methods would be the most practical approach to our problem due to the wide variety of applications that the deep learning approach has been tested on. In comparison to traditional machine learning it builds neural networks that simulate the mechanisms of the human brain whereas in traditional machine learning, data is taken and pushed through a series of algorithms and then used to make a prediction. Traditional machine learning such as the Bayesian model selection framework has achieved relative success in image quantification and prediction of growth patterns of various filamentous fungi [8]. Yet conversely, in a study on visual features of leaves in plant identification using various artificial intelligence techniques including in naive bayes algorithm as well as deep learning techniques; the study concluded that out of 6 techniques that were tested the SVM(Support Vector Machines) model was the most accurate with an accuracy of 92.91% [9]. This leads us to believe that SVMs would possibly be another route into solving the problem of being able to identify different species of mushrooms. Though it is not a deep learning method and may not directly solve our task of defining different species; however it may be helpful as a possible preprocessing method for our image set, later being fed to a neural network for the classification.

2.3 Convolutional Neural Networks

Deep learning in the AI field has been widely and successfully applied to solve problems in different fields[6, 10–13]. Convolutional Neural Networks (CNN) are deep learning networks that implement many layers called convolutional layers. A convolutional layer is a hidden layer of neurons that have a field of view and can be thought of as the expression of a mathematical operation on two functions. [14] An example of this would be using some portion of an image as the first input (field of view), and a filter as the second. The result is a convolutional layer that could then be used as input for an additional convolutional layer, or input for a pooling layer. These convolutional layers are what distinguish CNNs from other neural networks. An important distinction between CNNs and other forms of Neural Networks is that the neurons in each convolutional layer, are not connected to every other neuron in the previous layer such as in a Multi-Layer Perceptron[15]. By focusing on just a local representative field, computational costs are greatly reduced for each neuron. This benefit becomes exponential as the number of pixels in an image increases.. This process of convolution makes CNN extremely powerful when used for pattern matching or image recognition.

A lot of that power comes from how CNNs use their filters. The type of filter used in each convolutional layer is critical and plays a major role in the final output. These filters are called Kernels and are designed to exaggerate features or patterns within an image, then pass that result to another layer. Kernels are designed for many purposes but the most prolific kernels are edge detecting (vertical, horizontal and angled) and shape/corner detecting. By layering many of these convolutions or outputs, convnets (Convolutional Neural Networks) are accurately able to extract features from an image[16]. For instance, we can see this more pronouncedly if we overlay similar vertical edge filters after passing an image. The result would be an enhanced image along all vertical lines, with blurriness everywhere else. Combine this with a horizontal edge filter and shapes such as crosses start to materialize[17].

In conjunction with the use of these kernels, max (or min/avg) pooling is another strategy used to reduce the magnitude of the input data[18]. By taking the maximum value in a given pool (some areas of the image), we are able to extract features with minimal computing cost. In the commonly used max pooling, the largest value in a local field would continue to be used as input into the next hidden layer until a larger value is compared to it or the pooling layers cease. As the cost of computational power has decreased dramatically over the years, pooling as a strategy to reduce dimensionality or space complexity is becoming less popular.

3 Methods

Using artificial intelligence technology and deep learning techniques we developed a convolutional neural network or CNN to predict what a mushroom species was in a given random image from our dataset. The team created a CNN model which was fed our dataset of over 9,000 images which spanned profiles of a total of fifteen different species of mushrooms. See Table 2 for a complete reference to the species that made up our dataset. The dataset was shuffled and 10% (~928) of the images were used as the testing set while the remaining 90% of the images were used as a training set. Images were of variable dimensions and had to be normalized to 50 x 50 px in a preprocessing step and assigned labels before being fed into the CNN. In the preprocessing step the images were also converted to gray scale to reduce background noise in the pictures. The CNN was a multilayer neural network consisting of a total of three 2-dimensional layers performing 32, 64, and 128 different convolutions respectively. Reshaping functions and max pooling were implemented. In addition we used a Rectified Linear Unit (ReLu) as our activation function several different learning rates, ranging from .5 to .0001. The most optimal batch sizes we found were between 100-200 and and the best results came from between 3-5 training Epochs.

Table 2. Different mushroom for training

Mushroom species	Size of Training Image Set (number of images)	Size of Test Image Set (number of images)	Total (number of images)
Amanita muscaria	849	212	1061
Amanita pantherina	583	146	735
Amanita phalloides	962	246	1208
Amanita virosa	574	143	697
Conocybe	498	123	621
Coprinopsis atramentaria	552	137	689
Cortinarius violaceus	485	122	607
Galerina marginata	926	232	1158
Gyromita esculenta	594	152	746
Helvella vespertina	453	114	567
Laetiporus conifericola	481	121	602
Panaeolina foenisecii	628	157	782
Paxillus involutus	416	104	520
Psilocybe cyanescens	520	129	649
Turbinellus floccosus	752	185	937

4 Results and Discussion

Initial runs of our CNN returned an accuracy rate near 70% (0.692) as this accuracy rate was the result of only initial test runs for which the team limited the number of possibilities to only two distinct species of mushrooms *Amanita Muscaria* and *Cortinarius Violaceus.* As development of our CNN model continued the team worked to add all fifteen of the mushroom species that comprised our dataset into our CNN model. Initial results showed an accuracy rate of 6%, which is about the accuracy that could be expected by random guessing. With adjustments to the learning rate, the amount of hidden layers, how many features and batch size, we were able to increase our accuracy to over 11% (0.113). Although still disappointing, this is an important step forward, as it is better than would be expected by random chance. Attempts at being able to distinguish by color proved to be neither reliable nor helpful towards achieving a higher accuracy rate, hence images were converted to grayscale in the preprocessing step. There are several possible reasons for our low accuracy rate. Some of them resulting from preprocessing techniques that converted the image to grayscale as well as decreasing the size of images too greatly, which may have also caused some distortion in the image. Additionally we suspected imbalancing issues in our dataset were causing a severe skew in our results so we attempted to adjust for that. We trained our AI on 20 epochs with a maximum image count of 500. The variability in image count originally ranged from 400 to 1000. To prevent our AI from learning the features of one specific type of mushroom (the one with the largest data set) and building a bias into its prediction we selected a maximum of 500 random images from each species. Unfortunately this did not improve accuracy as the result was still roughly 6%. This tells us imbalance did not play a major factor in lowering our results. To help locate one reason for our poor accuracy we used a plotting library to help visualize what the AI "sees", which is shown in Figure 1.

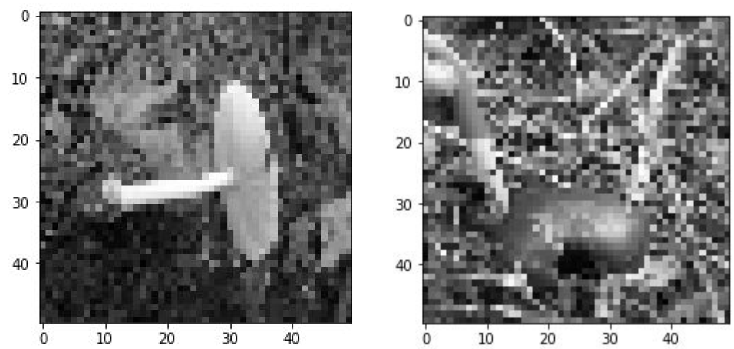

Figure 1. Examples of the images after preprocessing.

We noticed significant degradation in the quality of many of our images. The reduction into a 50x50 image proved to be too small a size to clearly distinguish critical features for many of our images. One issue we encountered with our AI was around generalization. In machine learning a powerful strategy is to train your neural network on as many generalizations as possible. This strategy had its pitfalls and at times became a detriment to us. When we trained our network on two mushrooms, it became fair at distinguishing between two fairly non-similar species. Even with poor image quality, we were able to generate results of 70% accuracy between two species. The principle of generalizations hurt our results when we increased the number of species to 15 but left the image quality the same. The differences between several mushrooms became too difficult to distinguish and accurately predict. Going forward we would like to increase the input size of the data our CNN trains on, as well as filter the images to only contain mushrooms and as little background noise as possible. Having larger, sharper images with less noise would be ideal to train our AI on. This would allow our network to be able to discern small features that we lost during our image transformations.

5 Conclusion

This study through the process of a combination of literature review and first hand implementation of a convolutional neural network or CNN, was able to illustrate the inherent difficulty involved with creation of an accurate wild mushroom classifier. Not only did we determine the inherent difficulties with both mushroom identification in general and through images alone, we also determined the inherent difficulties involved with deep learning and neural networks from both literature review and actual implementation.

Methods of improvement mainly reside in the preprocessing stage of our CNN network. One of the biggest issues that resulted out of our research was the normalization step of images to be fed into our CNN network. When normalizing our images to a 50x50 grayscale image we had sacrificed the accuracy of our CNN because in normalizing them to a smaller pixel size generalized the image so much to the point of it being indistinguishable for our AI to determine the difference between two different species of mushroom. This was especially prevalent in species that already looked the same initially and shrinking their images made finding features an extremely difficult task for our CNN to handle. In order to fix this problem our group hypothesized trying to increase the normalization to a 100x100 size image so when converted to grayscale features would still be able to be pulled by our CNN.

Choosing another AI technique would have been another possible path to increased accuracy. Possibly an SVM or random-forest network would have been more equipped to handle a dataset this large with so many similar training data sets, especially with the use of a kernel that would have better linearized the data to be categorized better when tested on. We recommend that aside from maximizing the preprocessing efficiency step of our image data set that any group that would like to reproduce our work would try to use an SVM or random forest model to compare the accuracy rates to the CNN and see if that would be a more bountiful route to explore.

There was also discussion on whether or not CNN would have more luck finding features of our training data if it was looking on the basis of color and not grayscale. Yet that brings up a strong counterargument that the background noise of each image would severely swerve the accuracy rates due to them being taken into consideration as well. Possibly a solution to this would be to construct an object detection step that would take out solely each mushroom that we were looking at and eliminate the background around it to the point where the only color features that would be extracted would be those that came directly from the mushroom and not the background.

This experiment proved to be a daunting task due to our dataset not being numbers but actual images in which we were trying to build an AI model to work with. The construction of a CNN was not the most difficult part for our group but the preprocessing of images; this proved to be a crippling factor in our accuracy and is the reason why we were not able to obtain as high an accuracy as we wanted to and will be the first problem that should be tackled in future research.

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