Classification of Mushroom Species Using Transfer Learning

Harshal Geete[1]

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Abstract

A convolutional neural network (CNN) model was employed to classify images of mushrooms by species using transfer learning. ResNet-50 provided the base model, chosen because of its proven reliability for image classification problems and base data set that included images similar to the ones used in this task. The data set used to train the model was comprised of approximately 9,500 images of mushrooms, with the goal of ultimately being able to identify edible species. The pretrained ResNet-50 model achieved an identification accuracy rate of 82%.

Introduction

Foraging for edible wild mushrooms – mushroom hunting – has become a popular pastime for hikers, gourmands, and the curious alike. There are, however, thousands of species of mushrooms and only a small number of them are safe to eat [1]. As such, it is essential – particularly for novice foragers – to properly identify any mushrooms prior to handling them and, most especially, prior to eating them. This is not an easy task: There is no single characteristic that is common to all safe mushrooms, and vice versa. Moreover, a number of poisonous varieties look nearly identical to their edible counterparts, and others are safe to eat when they are young but not when they are older [1]. Identifying an edible mushroom, then, can be challenging even for experienced foragers. A mobile app built around a program that identifies and classifies mushrooms as edible or poisonous based on an image would provide a user-friendly solution to this problem.

Reliable methods of identifying mushrooms, preferably while foragers are still in the field, is key to safely enjoying this burgeoning hobby. The risk associated with a misidentification is substantial, potentially even deadly, so creating a model that avoids false identifications is crucial and adds a layer of required accuracy to such an undertaking. For purposes of training the

[1] MS student, Northeastern University Khoury College of Computer Science, Data Science

model presented here, a data set with a limited number of images and mushroom species was used: roughly 9,500 images of mushrooms belonging to 12 distinct mushroom species [2]. The developed framework, however, could be expanded to include potentially thousands of species.

For this image classification problem, a convolutional neural network (CNN) with transfer learning was used. ResNet-50, a pre-trained model, provided the foundation. The model was retrained with the new data set using fine-tuning, with the end result being a classification of mushroom species based on an image input. Competing methods, such as regression and forests, were also considered; these methods were deemed less advantageous because they could lead to unreasonable training times, may not be as accurate, and might result in overfitting/underfitting.

Key components of this approach include preprocessing and validation. Preprocessing the image data made it possible to train the CNN model using a subset of the original image inventory (the training set). Validation of the resulting CNN model was carried out using the remaining images (the test set). Here, an essential component of the results is the accuracy of the model predictions. The error rate of the model is important to evaluate because, for this problem in particular, the risk associated with a false identification may be substantial.

Preliminaries

Transfer Learning

It was concluded that employing a CNN model with transfer learning would be the best and most efficient method to approach this problem. Transfer learning is ideal when only relatively smaller data sets are available for specific training purposes. Training limitations due to the size of such data sets can be compensated for by taking advantage of the vast data sets upon which a base model has been trained. Feature identification from the pretrained model can be applied to the new data set – in effect, transferring the prior learning that is part of the base model to the new model.

A number of pretrained models are being continually refined and made available; from among them, ResNet-50 was selected for purposes of this project for several reasons. ResNet models have demonstrated excellent generalization accuracy and a low error rate [3]. They enhance the performance of neural networks with deep layers, and the skip connections in ResNet solve the problem of vanishing gradient in deep neural networks by allowing this alternate shortcut path for the gradient to flow through [3]. The are a number of ResNet models from which to choose.

ResNet-50 is a 50-layer CNN and is trained on a million images belonging to 1,000 categories from the ImageNet database [3]. ImageNet categories include many that are helpful to the training required for this project (*e.g*., broccoli, cauliflower, coral fungus) and, specifically, mushrooms [4]. This makes ResNet-50 an ideal candidate for transfer learning since a portion of the base task is similar to the task at hand.

Data Set

The data set for this project contained images belonging to 12 different mushroom species: Agaricus, Amanita, Boletus, Cortinarius, Entoloma, Exidia, Hygrocybe, Inocybe, Lactarius, Pluteus, Russula, and Suillus. A total of 9,473 images of mushrooms were used, with the number of images in the train, test, and validation sets at 6684, 1836, and 953, respectively.

Initially, the goal was to find a data set that had mushroom images separated into edible, non-edible or poisonous, and conditionally edible categories. This would have allowed for identification of both species and safety level, a necessary component if the model was to be assessed based on the rate of false identification associated with a species being labeled edible when it is actually poisonous. Finding a data set that contained images of various mushroom species along with their safety categories proved to be difficult, however, so the methodology here was developed solely for species identification.

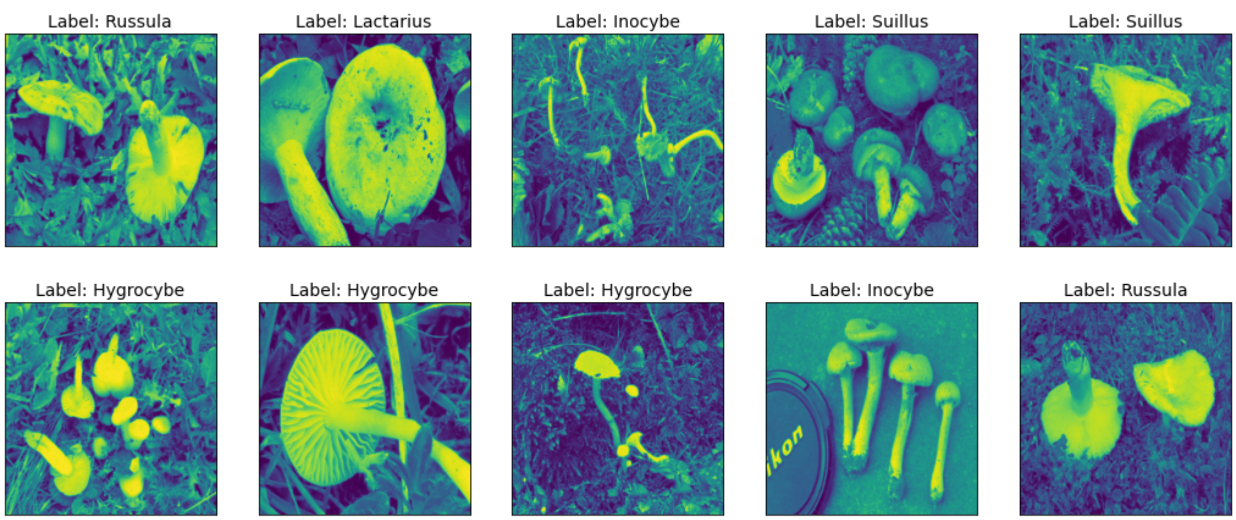

Figure 1: Examples of mushroom image input and their species label

Methodology

For the pretrained CNN with transfer learning, the ResNet-50 model was modified to meet the demands of the project, redefining the input and output layer sizes to correspond with the data set being used. Inputs consisted of the 9,473 mushroom images, which were reshaped to have size 3, 244, 244. Problems have an output layer of size 12, corresponding to the 12 mushroom species contained within the data set. Input, output, and parameter data is summarized in Table 1. The model was retrained using the images in the training set (fine-tuning), and the learning rate used was 0.001.

Table 1: Summary of input and output convolutional layers, activation function layers, and number of parameters of transfer learning model

Layer (Type)	Output Shape	Parameter #
Conv2d-1	[-1, 64, 112, 112]	9,408
BatchNorm2d-2	[-1, 64, 112, 112]	128
ReLu-3	[-1, 64, 112, 112]	0
Bottlenech-172	[-1, 2048, 7, 7]	0
AdaptiveAvgPool2d-173	[-1, 2048, 7, 7]	0
Linear-174	[-1, 12]	24,588
Total parameters: 23,532,620 Trainable parameters: 23,532,620 Non-trainable parameters: 0		
Input size (MB): 0.57 Forward/backward pass size (MB): 286.55 Parameter size (89.77) Estimated Total Size (MB): 376.89		

Results

The rate of false species identification was analyzed. The results derived from the ResNet-50 model using transfer learning are shown in Figures 2 and 3. Because there was a threshold after which the more epochs that were used to retrain the model did not increase the training accuracy significantly, the number of epochs used here was capped at 20. Because the validation accuracy began to decrease with more epochs past this point, this cap also served to limit overfitting.

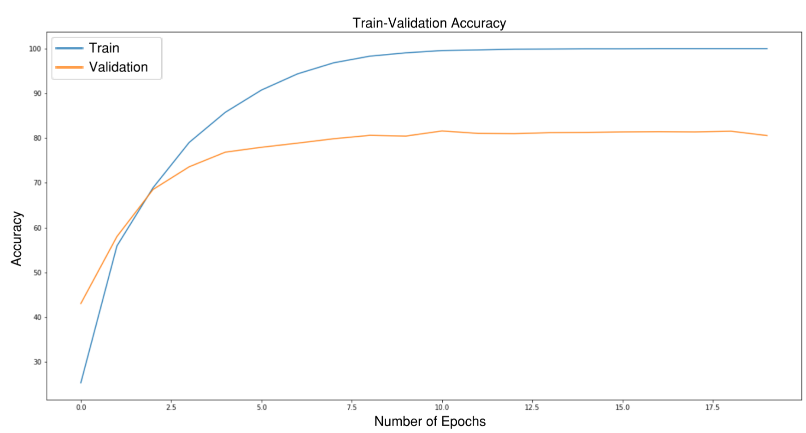

Figure 2: Model mushroom identification training and validation accuracy

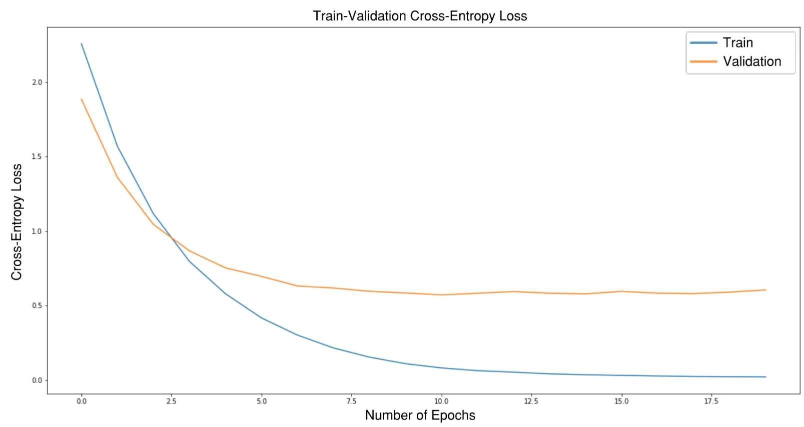

Figure 3: Model mushroom identification training and validation cross-entropy loss

The final training accuracy was 99.99%, with a validation accuracy of 81.54%. An example of the output for a sample of mushroom images (which include two miss-classifications) is provided in Figure 4.

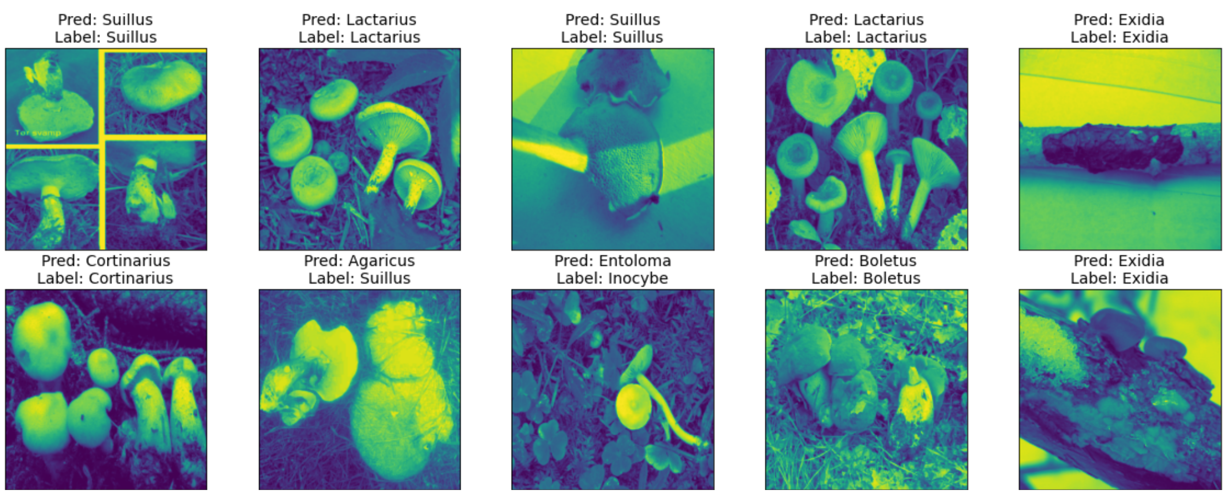

Figure 4: Example of model output for mushroom images – predicted class and label

Discussion

It was expected that the validation accuracy would be lower than the training accuracy, which was the case. Given the limitations of this model, a validation accuracy of 82% was deemed acceptable.

The model was limited by the small amount of data available for training. In order to retrain a CNN model more thoroughly, more data than was available in the present mushroom image inventory would be required. Additionally, the 12 mushroom species in this data set had a wide range of characteristics, with subspecies in each that ranged from edible to poisonous. If the data was organized further (into subsets of mushroom species) based on safety level, this would be helpful for both the task's interpretability and for creating classes containing mushrooms with more distinct characteristics from each other. Both of these factors could help to improve the model's efficacy.

Another limitation of the ResNet-50 model is that it is able to make classifications based only on the mushroom species that were included in the training data. This data set is by no means close to the number of mushroom species that exist in the wild. Access to a data set that was substantially larger – or even complete, if a photographic catalog containing all known mushroom species was available – could resolve this limitation (and provide ample data for both retraining an existing model or training a new one).

For this high-stakes image classification, a model that is well-trained and incredibly accurate would be needed for use in an app that is available to the public. In future, the model could be expanded to include more species of mushrooms than the 12 that were available in this data set. The error rate for the model could be reduced with additional training, particularly if given a larger data set. Other opportunities for improvement and further development include comparing more than one base model for transfer learning (*e.g.*, AlexNet, MobileNetV2, VGG-16, other ResNet models), employing feature extraction rather than finetuning, and building a new CNN model to classify the images if an expanded data set was available.

Conclusion

A limited data set consisting of images of mushrooms was classified using a convolutional neural network (CNN) model that utilized transfer learning. ResNet-50 was used as the pretrained model, which allowed for the training that had been done using a much larger data set to be taken advantage of while retraining using the small data set. This model's results were analyzed in the context of the mushroom identification task and the needs of a potential mushroom foraging mobile app. It was demonstrated that the accuracy of identification was reasonable given the limitations of the data set but would need to be enhanced for future implementation.

References

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