Agaricus Mushroom Identification

Using Neural Networks

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Abstract

Mushroom classification is an old and well-explored problem in mycology. Many mushrooms are extremely deadly, while others are remarkably delicious. Explorers need to reliably identify mushrooms in order to tell the difference. The idea of this project is to form the basis of an easy-to-use app that could help survivalists identify mushrooms they find in the wild. To address this problem, I used a collection

of photographs of the Agaricus genus as well as a database of mushrooms labeled as poisonous or edible and identified by certain characteristics. The initial conceit of the problem - identifying mushrooms based on a list of characteristics - was a success. Photo recognition remains unreliable, however.

I. Introduction

Reliable mushroom identification can aid wilderness explorers and mycologists. Developing an AI to aid in the process can save lives. Unfortunately, there is a lack of widely available photo banks of mushrooms labeled by edibility. To compensate for this, the output of a simpler AI was used to train a more sophisticated one.

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II. Problem Formulation

The first AI takes a table of mushrooms and their characteristics [1]. The data included is as follows: **poisonous, cap-shape, cap-surface, cap-color, bruises, odor, gill-attachment, gill-spacing, gill-size, gill-color, stalk-shape, stalk-root, stalk-surface-above-ring, stalk-surface-below-ring, stalk-color-above-ring, stalk-color-below-ring, veil-type, veil-color, ring-number, ring-type, spore-print-color, population,** and **habitat.** This data was encoded and normalized. Any missing data was replaced with the mean, to approximate the most common types of mushrooms.

The second AI takes a database of photographs and identifies its edibility. There is a databank of photos of mushrooms, but it is labeled by genus, not edibility. To bridge the gap between the two datasets, I identified the characteristics of the mushrooms myself, based on the 7 most significant characteristics from the first AI: **cap surface, bruises, gill attachment, gill spacing, gill size, gill color,** and **stalk shape**. Contributing to some of the entropy of this project, I am not a mycologist. Fortunately I do not have to identify whether the mushrooms are poisonous or not, just describe their characteristics. I used the University of Saskatchewan [2] guide for this process.

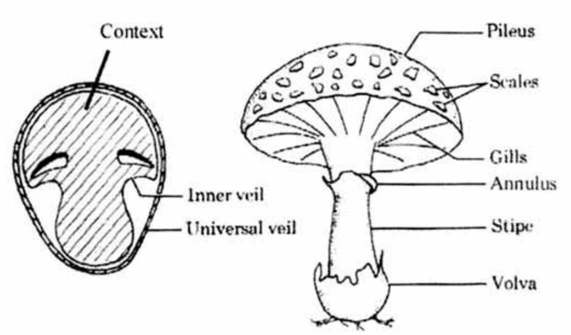

Figure 1: A small part of mushroom anatomy

III. System Design

III.i. Design

First, I used a dataset of mushrooms labeled by edibility containing characteristics such as gill size, cap color, habitat, odor, etc. This is used to train a fully-connected neural network (FCNN). Once this AI was trained, it was used to predict the edibility of the set of photographs. Then, the FCNN predicts the edibility of the photographs in the second set of mushrooms using the classifications done by myself. Once this data was generated, it serves as the y values for the CNN set up to classify the photographs.

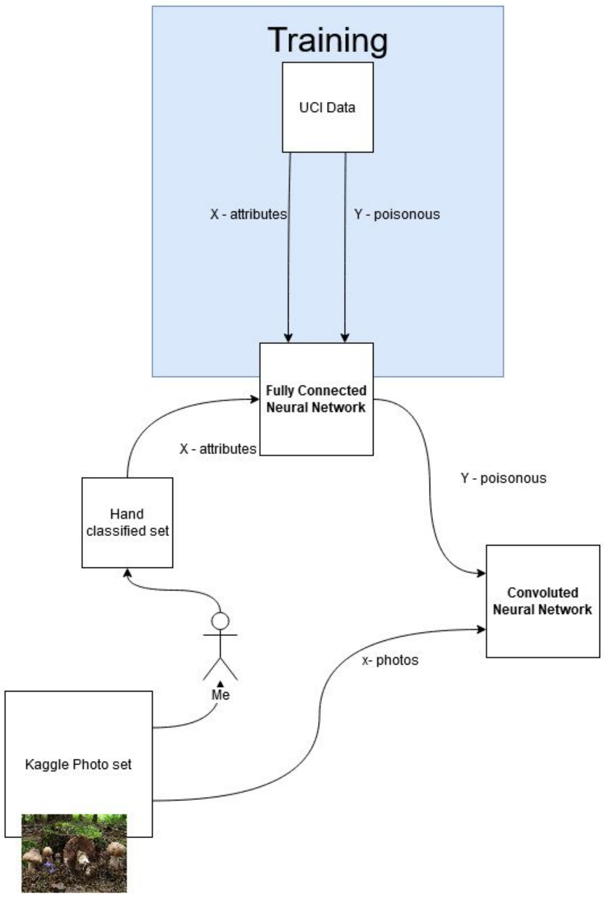

Figure 2: Visualization of overall design of project

III.ii. Classification FCNN

The FCNN used to identify mushrooms uses **relu** activation, three Dense layers, and **Adam** optimization**.** Early stopping was used, in conjunction with train/test split data. Feature importance was then used to select for the most important characteristics. Some characteristics cannot be identified from a photograph, such as odor, habitat, or population. A new model was made, based on the most important characteristics as well as the ability to identify a given characteristic from a photograph. The resulting dataframe is only eight columns wide instead of twenty-three.

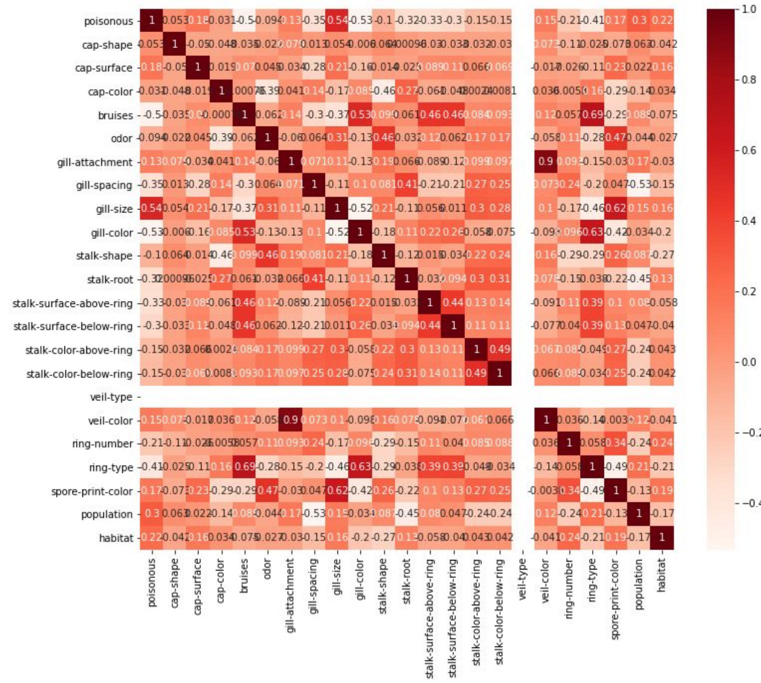

Figure 3: Feature importance table. Higher resolution available on request.

III.iii. Photo Recognition CNN

Input images from Kaggle [3] were resized into 64x64 and normalized. These photos were identified by me and then fed into the FCNN to determine edibility. The resulting prediction list serves as the y list for the CNN to be trained on in conjunction with the photo bank. Because only a small fraction of the given photo set appears to be poisonous, the dataset was upsampled to compensate, bringing the ratio of poisonous/edible from approximately 10% to approximately 30%.

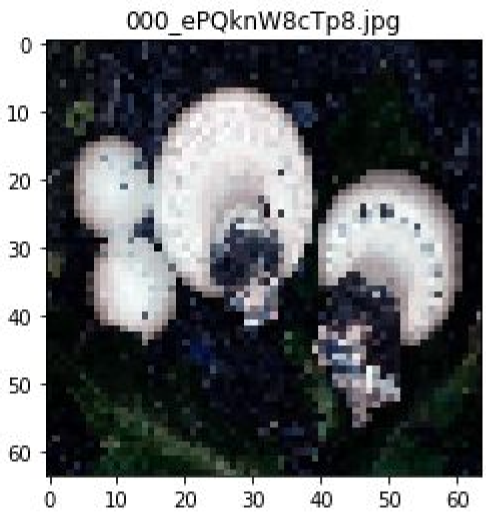

Figure 4: Mushroom photos uniformly resized before used as dataset.

A convoluted neural network was built with a kernel size of 3x3 and two convulution layers, each followed by a max pooling layer. Then a flatten layer was added, followed by a dropout of 0.7 and a **Relu** activation layer. This is the layer combination that had the best accuracy in experimentation. Three dense layers are added on top of this, including a final **softmax** dense layer. The model is trained with a train/test split of 20% given the small data size.

IV. Experimental Evaluation

IV.i. Methodology

Models were compared based on their F-measure, precision, accuracy, and recall scores. ROC curves and confustion matrices were examined. The outcomes were also compared to common mushroom identification heuristics.

IV.ii. Results

The first AI was very successful. Before feature importance was incorporated, results were as accurate as 1 error in 1600. Average precision, recall, and f1 are 1.00. This outperforms common heuristics, which are accurate up to 98.5% of the time. [1].

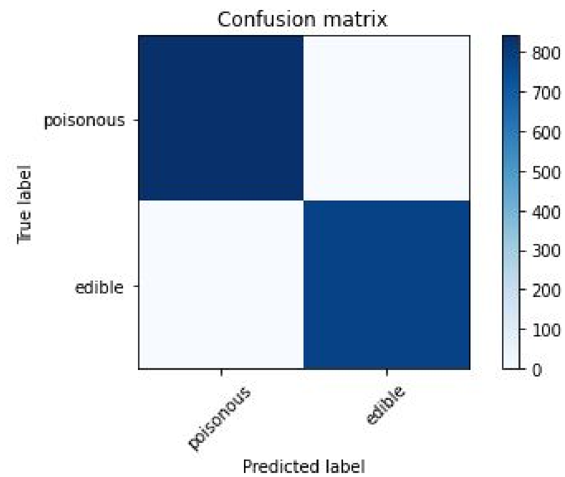

Figure 5: first AI has F1 score of 1.00

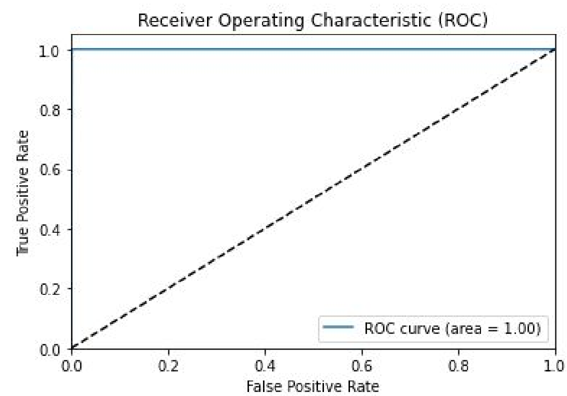

Figure 6: first AI has ROC score of 1.00

Once feature importance is incorporated the first model's accuracy drops to an f1 score of 98.

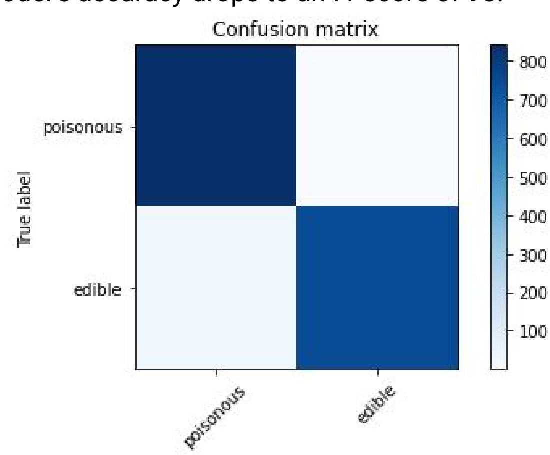

Figure 7: confusion matrix after feature importance used to drop all but eight columns

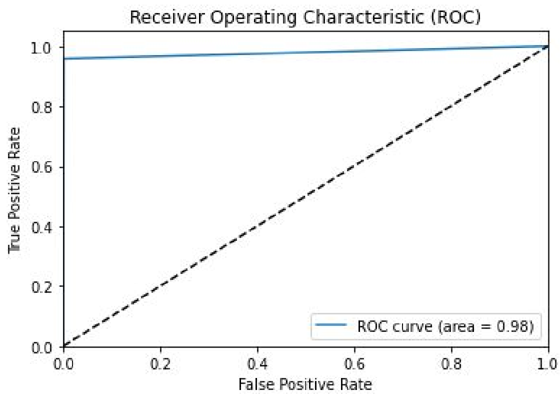

Figure 9: ROC curve after feature importance considerations

The photo recognition AI is less successful. It frequently labels the entire sample as poisonous. The average precision is somewhere around 0.30-0.50 and the average recal is around 0.5-0.75 depending on the accuracy of the run. The f1-score is around 0.40-0.60 while the accuracy is around 0.70.

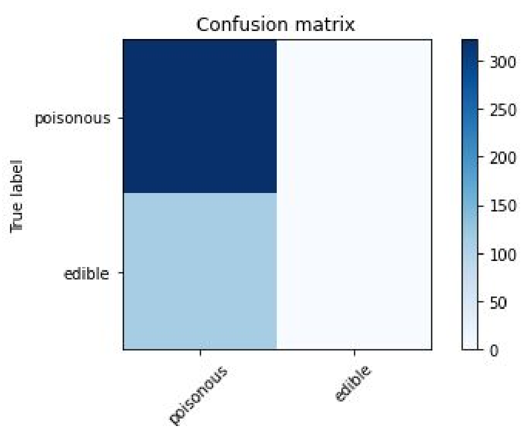

Figure 10: confusion matrix of photo recognition CNN.

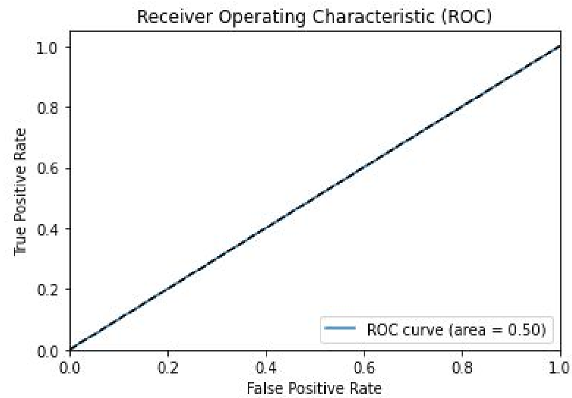

Figure 11: ROC score of 0.5 for photo recognition CNN

V. Related Work

On Kaggle [3] there exist other works related to the photo dataset. This work identifies mushrooms by their family, however, not edibility. It utelizes Pytorch instead of Tensorflow. The model succeeds in its aim of classifying mushrooms by genus.

VI. Conclusion

The first AI worked perfectly without a hitch. I would say it can safely be used to identify whether a mushroom is poisonous, assuming its input is clean and correct. A mycologist or wilderness expert could use this and expect to receive good outcomes 99% of the time.
The second AI was less successful. There are numerous reasons why this might be the case. The sample size is relatively small and uniform as they are all members of the *Agaricus* family. Only small percentage of the samples are poisonous (if the output of the first AI is to be believed.) Additionally, the classification data fed to this AI was not done by an expert, but an amateur. It’s also possible that we are not yet capable of using photo recognition to reliably identify poisonous mushrooms, but I do not think it is time to give up yet. I would not trust this AI to tell me if a mushroom is edible. (a moot point, since it labels everything poisonous… so at least it is safe)

It is always advisable not to eat any mushrooms you find growing wild, even with the help of an AI.

VII. Work Division

This project was done with Ace English. I did not have any peers in my group.

VIII. Learning Experience

Aside from the fascinating information I have gained about how to identify mushrooms by hand, I gained valuable experience in designing AI. Feeding output from one AI to another is not something I thought would be possible or reliable. I also have a greater understanding of Python and its many tools related to data science. Machine learning is a powerful tool that can be applied to infinite areas of study.

IX. References

[1] J Schlimmer (1981). Mushroom Data Set, https://archive.ics.uci.edu/ml/datasets/mushroom

[2] EF Bossenmaier (2014). Fungi of Saskatchewan, https://www.usask.ca/biology/fungi/

[3] M See (2019). Mushrooms classification - Common genus's images, https://www.kaggle.com/maysee/mushrooms-classification-common-genuss-images