Brief Report

Using Deep Learning for Prediction of Edible and Poisonous Mushrooms

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Posted Date: 4 April 2025

doi: 10.20944/preprints202504.0386.v1

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Using Deep Learning for Prediction of Edible and Poisonous Mushrooms

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Abstract: This article presents an CNN based model to predict edible and poisonous mushrooms from image data. We have used dataset — Danish Fungi 2018 (DF18) with several unique characteristics: species-level labels, a small number of errors, and rich observation metadata. An advanced CNN model U2Net was implemented to build the model for prediction. While validating on a test data, the model could predict edible mushrooms with an accuracy of 62.5% and poisonous mushrooms with 85.45% respectively. The model has been finally deployed into a real-time mobile application front-end, to increase public interest in fungi in detecting edible and poisonous mushrooms.

Keywords: mushrooms; deep learning; CNN; U2net; android

1. Introduction

Ingestion of poisonous mushroom species can cause severe life-threatening failure of organs in humans. Every year numerous food poisoning cases come up due to misidentification of mushrooms around the world. This issue is also prevalent to certain regions of India like Jammu & Kashmir, Himachal Pradesh, Uttarakhand, and Northeastern states. Also, wild mushrooms are part of diet of tribal and ethnic groups of India residing in hilly areas of India. 53 patients with mushroom poisoning were admitted to Meghalaya over the five-year study period (2014–2019) [1]. In recent years it is reported that in the tribal region of Central India, 209 cases of mushroom food poisoning were registered. Most cases (171 out of 81.81%) came from rural areas, while 86% of cases belonged to lower socioeconomic classes. The winter season accounted for 109 (52.15%) of these cases, with summer coming in second at 69 (33.11%) and rainy season at 31, 14.83 percent [2].

To mitigate the issue of misdetection of Mushrooms, many researchers have come up with Image Based CNN for predicting the edibility of Mushrooms [3,4]. However, no such smartphone applications are available In India till now. Therefore, an approach has been made to develop an application for the prediction of poisonous and edible mushroom from images. The current study uses CNN algorithm for building the predictive models and then deploy into a smartphone application to predict the edibility of Mushrooms from its image.

2. Methodology

Data Collection

The dataset used for training CNN model was downloaded from GitHub provided by the Danish Svampe Atlas for 2018 Fungi Classification [5,6] for research purposes. Dataset contains over 100,000 fungi images of nearly 1,500 wild mushrooms species.

Categorization of Mushrooms into Poisonous and Edible Mushrooms

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The information of Poisonous and Edible Mushroom species was collected from mainly three web portals – First nature [7], Monaco nature encyclopedia [8] and MyKoweb [9]. These web portals contain extensive and detailed information regarding shape, color, size, smell, distinctive features and also its edibility. In these portals, edibility for only 122 mushrooms could be found. Out of 122 species, 57 species were found out to be edible and 65 species were poisonous.

Removal of Unwanted Background from Mushroom Images Using U² Net Image Segmentation Model

The images present in the collected dataset often contains unwanted objects. Training a CNN model with such images or images having objects not related to output label might confuse the deep learning model. To remove such objects from the images, a python library named **rembg** was used. This library uses an image segmentation CNN model called U²Net [10] that recognizes the edge or boundary of an object and extracts it into a new image.

Manual Extraction of Region of Interest or Mushrooms Using OpenCV

After removal of unwanted objects or noise, OpenCV [11,12] was used to extract out multiple mushroom images in square shape. OpenCV operations like dilation, erosion, detecting contours were used to achieve or get the images in desired format. For every species, 32 images were obtained where half of these images were top view of the mushroom and other half was bottom view of the mushrooms.

Selection of Mushroom Species for Model Training While Maintaining Data Balance

A total of 14 mushroom species was selected for training where 7 species belonged to poisonous species and other 7 species belonged to edible mushroom species. These were selected such that equal number of both poisonous and edible species was taken having same genus.

Data Augmentation

To increase size or number of images, data augmentation was performed by rotating images, increasing and decreasing brightness and adding small amount of blurring.

For every mushroom image, a total of 5 augmented images were created.

No of image for each species = 32

No of images after augmentation = 32 x 5 + 32= 192

Therefore, total poisonous mushroom images = 192 x 7 = 1344

Total edible mushroom images = 192 x 7 =1344

3. Model Development on Top of InceptionV3 Pretrained on ImageNet Dataset

InceptionV3 pretrained on ImageNet dataset was used as the based model for the CNN model. InceptionV3 is a 48 layers CNN model consisting of 27 convolutional layers, 13 pooling layers, and 8 fully connected layers. The last layer is a Global average pooling layer followed by a Dense layer with 1000 neurons.

For training it on Mushroom images, the last layer of Inceptionv3 was removed and a layer of 128 neurons was attached followed by a single layer of 1 sigmoid neuron. And the model accepts an image with input shape of 299 x 299 x 3.

4. Model Evaluation

For training the CNN, SGD optimizer was used which resulted in lower training time and better prediction accuracy. To test or evaluate the trained model, a minimum of 16 mushroom images for each species was kept separated and not used in the training set. Below is the model's performance on both edible and poisonous species in Table 1 and Table 2 respectively. From Table 1, it can be seen

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that considering all the species, the overall accuracy for predicting edible mushroom is ≈ 62.5 %. Similarly, from Table 2, the predictive accuracy of the model for poisonous mushroom is 85.45%.

Table 1. Performance of CNN model in predicting edible mushroom species.

Species name	Image Count	Predictions	Accuracy (%)
Agaricus augustus	16	Edible=11 Poisonous=5	68.75
Amanita fulva	16	Edible=14 Poisonous=2	87.5
Amanita rubescens	16	Edible=9 Poisonous=7	56.25
Lactarius deliciosus	16	Edible=12 Poisonous=4	75
Lactarius detterimus	16	Edible=7 Poisonous=9	43.75
Russula cyanoxantha	16	Edible=8 Poisonous=8	50
Russula vesca	16	Edible=9 Poisonous=7	56.25

5. Deployment of Model into Android App

After exporting the trained model to h5 file format, the file has been converted to *tflite* model to integrate it into an Android App. The development of the application was done on Android Studio using java programming language. The application has the functionality to either capture an image of a mushroom or pick from gallery of the device for prediction of the edibility of the mushroom. The detailed methodology followed in this study has been depicted in Figure 1.

Table 2. Performance of CNN model in predicting poisonous mushroom species.

Species name	Image Count	Predictions	Accuracy (%)
Agaricus xanthodermus	16	Edible=3 Poisonous=13	81.25
Amanita muscaria	16	Edible=0 Poisonous=16	100
Amanita pantherina	16	Edible=2 Poisonous=14	87.5
Lactarius terminosus	16	Edible=6 Poisonous=10	62.5
Lactarius helvus	16	Edible=1 Poisonous=15	93.75
Russula emetica	14	Edible=0 Poisonous=14	100
Russula grata	16	Edible=4 Poisonous=12	75

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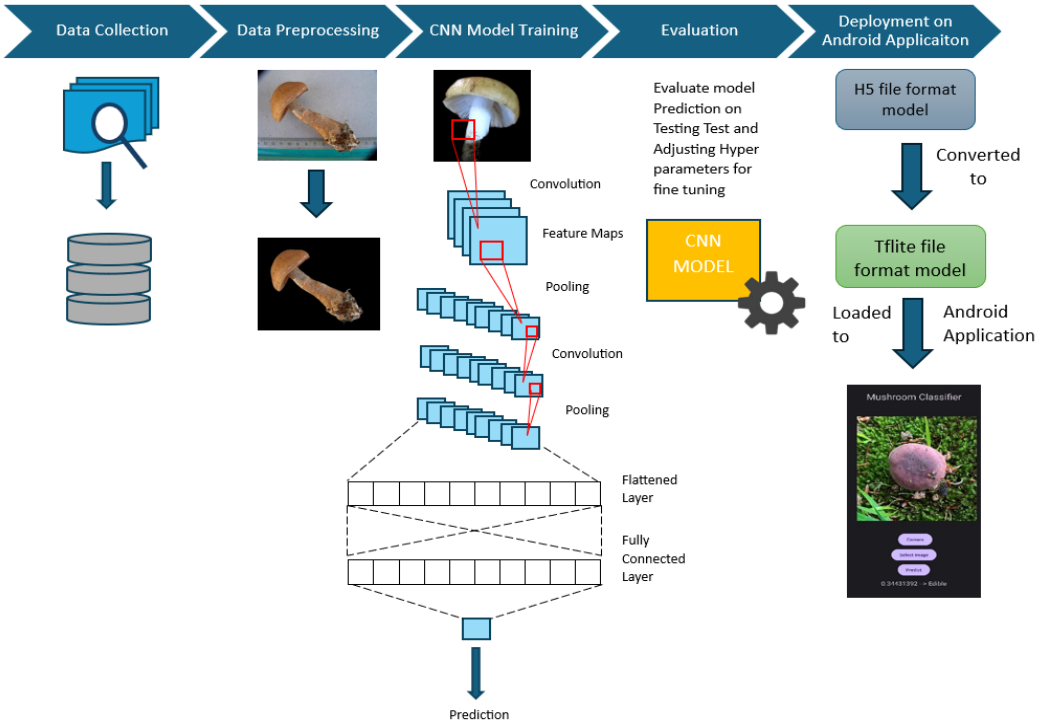

Figure 1. Detailed methodology for development of CNN based model for predicting edible and poisonous mushrooms.

Conclusion

It is evident that the accuracy of the Deep learning CNN model is not quite good due to low number of training images of Mushroom. Enhanced training dataset can significantly improve the accuracy of the Model. Alternative approaches like dual or multibranch CNN can be used to train on both top view and bottom view of mushroom images at once. This can significantly help the model to identify and distinguish between a poisonous and edible mushroom species.

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