

ENHANCED EDIBILITY DETECTION IN MUSHROOM USING DEEP LEARNING ALGORITHMS

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ABSTRACT

This paper introduces a novel approach to classify mushrooms as either edible or poisonous by using a deep learning framework rooted in the Residual Network (ResNet) architecture. By utilizing convolutional neural networks (CNNs) along with a specially labeled dataset, Our approach is able to precisely determine mushroom species. The ResNet framework, renowned for managing deep networks effectively, significantly boosts prediction accuracy and performance. We've designed the application with a user-friendly graphical user interface (GUI) created in Tkinter, ensuring it's accessible even to those without technical backgrounds. This tool is geared towards helping foragers, hobbyists, and consumers safely determine the edibility of mushrooms they encounter.

Keywords: Mushroom Classification, Deep Learning, Resnet Architecture, Edible Mushrooms, Poisonous Mushrooms, Image Processing, Tkinter GUI.

I. INTRODUCTION

Mushrooms are essential components of ecosystems, contributing to biodiversity and playing significant roles in nutrient cycling. Beyond their ecological importance, mushrooms hold cultural, culinary, and medicinal value worldwide. They are consumed as food and utilized in traditional medicine practices due to their nutritional benefits and potential medicinal properties. However, distinguishing between edible and poisonous mushrooms is crucial for safety, as consuming toxic varieties can pose serious health hazards [1].

Recent advancements in artificial intelligence (AI), particularly in deep learning, have transformed the area of image recognition. Convolutional Neural Networks (CNNs), inspired by how the brain processes visual information, have proven highly effective in analyzing images, including those of mushrooms. One notable innovation in deep learning is the Residual Network (ResNet), introduced by He et al. 2015 [2]. ResNet's architecture enhances the training of deep neural networks by introducing residual connections that facilitate better learning efficiency.

In mushroom classification, AI models leverage these advanced neural networks to classify mushroom images accurately. These models are trained on extensive datasets containing labeled images of various mushroom species and environmental conditions. Preprocessing methods, like resizing and normalization, ensure that the models perform well across diverse scenarios [3].

To make mushroom identification more accessible, AI-driven systems often incorporate user-friendly applications with graphical interfaces (GUIs). These interfaces allow users to upload mushroom photos effortlessly and receive immediate classification results. By empowering users with the capacity for make informed decisions about mushroom edibility, these applications promote safety and confidence in mushroom-related activities [4].

This study introduces an innovative method for mushroom classification using a ResNet-based deep learning model included into a Tkinter GUI. Mushroom classification is a need for a range of uses, such as food safety and ecological studies. We conducted a comparative study among VGG19, Inception, ResNet, and a baseline CNN, selecting ResNet for its superior performance in capturing intricate mushroom features [1]. Our approach aims to automate and improve the accuracy of mushroom species identification, making it accessible to both researchers and enthusiasts through an intuitive graphical interface.

II. METHODOLOGY

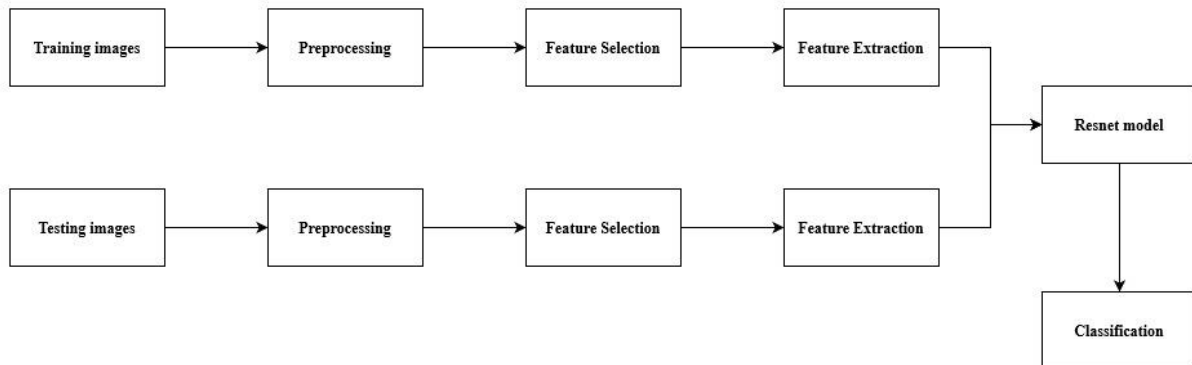


Figure 1: System Design

It has several sequential steps

- **Training Images Collection:** The first step involves collecting a comprehensive set of training images representing various classes of mushrooms. These images form the basis for training the deep learning model.
- **Preprocessing:** The collected training images undergo a preprocessing phase to standardize them for the model. This involves resizing, normalization, and possibly data augmentation to improve the model's robustness.
- **Feature Selection:** Following preprocessing, feature selection techniques are applied to identify the most relevant features from the images that contribute to distinguishing between different mushroom classes.
- **Feature Extraction:** In this step, the selected features are extracted from the preprocessed images. Feature extraction helps in transforming the input images into a format suitable for feeding into the ResNet model.
- **Training the ResNet Model:** The extracted features from the training images are then given to the ResNet model. The model is trained to learn the patterns and characteristics that differentiate various mushroom classes.
- **Testing Images Collection:** A separate set of testing images is collected to evaluate the performance of the trained model. These images are independent of the training set to ensure an unbiased assessment of the model.
- **Preprocessing of Testing Images:** Same as training images, the testing images undergo preprocessing to standardize them before feature extraction.
- **Feature Selection and Extraction for Testing Images:** The same feature selection and extraction processes applied to the training images are also applied to the testing images.
- **Classification:** Finally, the features extracted from the testing images are input into the trained ResNet model, which performs the classification of the mushrooms. The model's predictions are then evaluated to provide accuracy and effectiveness.

III. ALGORITHMS USED

Resnet101v2 architecture

ResNet101v2 is a deep convolutional neural network architecture designed to tackle complex image classification and various computer vision tasks. It builds upon the theory of residual learning, introducing shortcut connections that allow the network to learn residual functions, thus mitigating the vanishing gradient problem and facilitating the training of very deep networks.

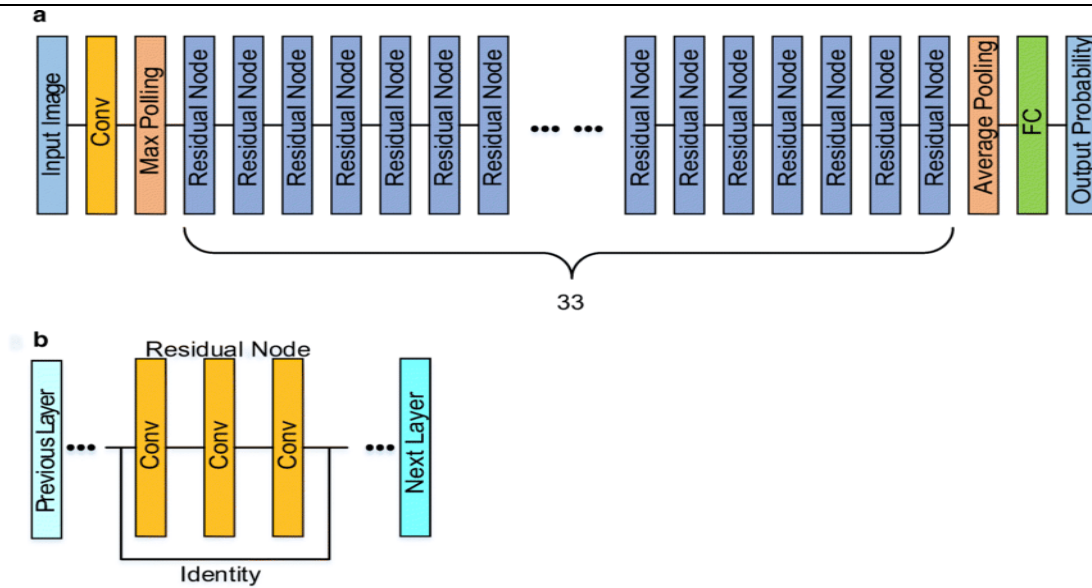


Figure 2: Resnet101v2 architecture

The usage of bottleneck blocks, which are made up of three convolutional layers each—a 1x1 layer for dimension reduction, a 3x3 layer for dimension restoration, and another 1x1 layer for dimension reduction—is what distinguishes the architecture. In contrast to ResNet v1, ResNet v2 improves training stability and speeds up convergence by applying batch normalization prior to the activation functions (ReLU). Three blocks make up the first stage, four make up the second, twenty-three make up the third, and three make up the last stage of residual blocks in the network's structure. The number of blocks increases in deeper tiers. The final layer in this design is a fully linked dense layer with a softmax activation function for classification, which is followed by a global average pooling layer. With about 44.5 layers overall and 101 layers in total

IV. RESULTS AND DISCUSSION

To determine the most effective model for mushroom classification, we evaluated several deep learning architectures, including ResNet, VGG19, Inception, and a traditional Convolutional Neural Network (CNN). Each model was trained and tested on the same dataset, and their performance was compared using accuracy as the primary metric. The following table summarizes the accuracy of each model, highlighting their respective strengths and weaknesses in this classification task.

Comparison of Models

Model	Accuracy
VGG19	77%
ResNet	81%
Inception	63%
CNN	49%

Based on the comparison, the ResNet model is the best choice for classifying mushrooms in this study. It performs well because of its advanced design, which includes special connections that help it learn better. It also extracts important features from the images effectively and performs consistently well across different types of mushrooms.

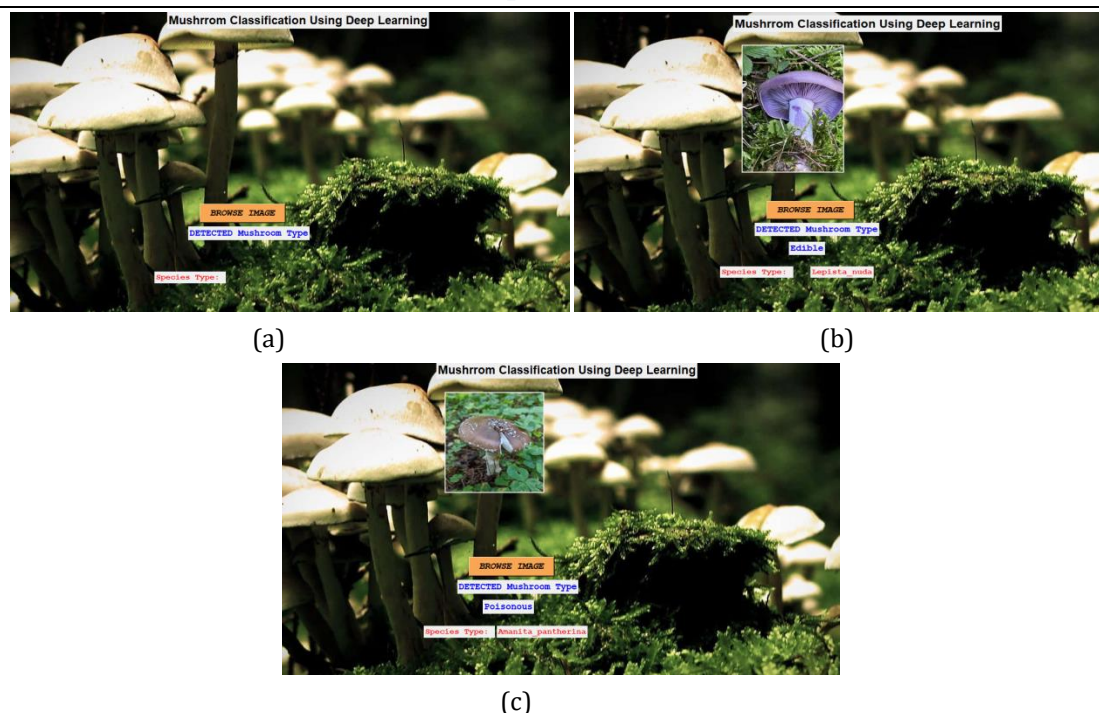


Fig (a) User Inter Face, **Fig (b)** Predicting the mushroom is edible, **Fig (c)** Predicting the mushroom is poisonous

V. CONCLUSION

In this study, we found that the ResNet model was the best at identifying different types of mushrooms, with an accuracy of 81%. It performed better than other models we tested, such as VGG19 (77%), Inception (63%), and a simpler CNN (49%). ResNet's design allows it to learn complex features well, which helped it maintain consistent performance across various mushroom types. While VGG19 also did well, it didn't match ResNet's effectiveness. To improve ResNet further, future work could focus on adjusting its settings and using a broader range of training data. These steps could boost its accuracy and reliability even more.

VI. REFERENCES

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