Binary Image Classification: Edible vs. Poisonous Mushrooms using FastAi's Pre-Trained Residual Networks

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Introduction - Importance & Risks

Public Health: Accurate classification ensures safety, preventing severe health complications from consuming toxic mushrooms.

Resource Conservation: Mislabeling edible mushrooms as poisonous can lead to unnecessary waste of valuable food sources.

Serious Consequences: Mistakenly identifying poisonous mushrooms as edible can result in hospitalizations or fatalities, emphasizing the need for precise models.

From the 2021 39th Annual Report by the American Association of Poison Control Centers' National Poison Data System:

- 7,514 documented cases of mushroom-induced poisonings in humans.
- 2 human fatalities linked to mushrooms, including the identified species Amanita Phalloides and another unidentified species.
- 2 human deaths associated with mushrooms and other substances, involving a psilocybin species and an unidentified species.

See link for full report: https://piper.filecamp.com/uniq/foxfmW1ZMgxnjQTH.pdf

Problem Statement

Objective: Classify mushroom images into two categories: "edible" or "poisonous".

Input: Digital images spanning diverse mushroom species, with inedible, poisonous, and hallucinogenic types all categorized under the "poisonous" class.

Output: A label denoting either "edible" or "poisonous".

Significance: Ensuring public safety by preventing consumption of toxic mushrooms.

Challenges: Vast variety in mushroom appearance, subtle differences between some species, and varying image conditions (lighting, angle, background).

Problem Statement Continued

Concerns with Human-Led Mushroom Foraging:

Similar Features: Many edible and poisonous mushrooms have closely resembling features, making manual identification prone to errors.

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Jack O'lantern **Poisonous**

Golden Chanterelle **Edible**

Problem Statement Continued

Human Expertise Limitation: Even seasoned mycologists can sometimes be uncertain, especially with lesser-known species.

As cited in "Biodiversity" by The Navigator Company, from the approximated 3.8 million global fungal species, a mere 148,000 have been recognized, constituting only 3.9%.

Time-Consuming: Manual identification is time-intensive, especially when dealing with large quantities.

Variable Image Conditions: Traditional methods might struggle with variations in image quality, lighting, and backgrounds.

See link for full article: biodiversity.com.pt

Problem Statement Continued

Why machine learning?

Automated Processing: Machine learning models can process vast numbers of images quickly.

Learning from Data: The ability to learn and adapt from a large dataset of labeled mushroom images.

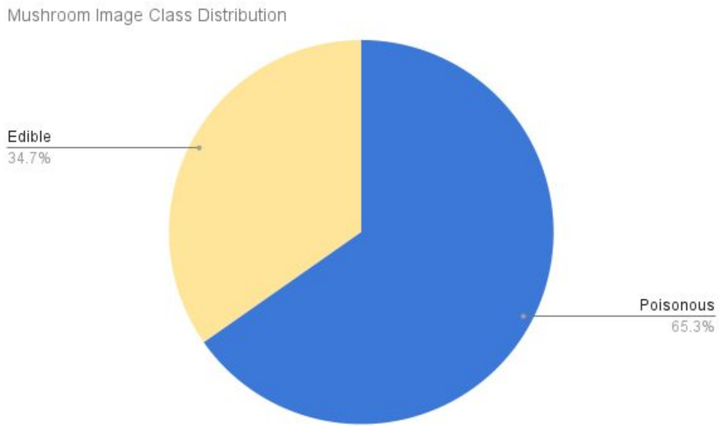
Accuracy: With proper training, machine learning models can achieve high accuracy, even in challenging cases.

Continuous Improvement: As more data becomes available, models can be further trained to improve accuracy.

Consistency: Unlike humans, a well-trained model will provide consistent evaluations without fatigue or subjective biases.

Data Overview

- Total of 3,400 images: 1,181 categorized as edible mushrooms and 2,219 as poisonous mushrooms.



- Utilizing Marcos Volpato's dataset titled 'edible and poisonous fungi' available on Kaggle.com.

See link for dataset: https://www.kaggle.com/datasets/marcosvolpato/edible-and-poisonous-fungi

Data Overview Continued

Sample edible and poisonous mushroom images:

Boletus **Edible**

Death Cap **Poisonous**

Methodology

Introduction to Deep Learning and CNNs:

Deep Learning: A specialized branch of machine learning that utilizes multi-layered neural networks.

CNNs (Convolutional Neural Networks): Specialized deep learning architecture for image-related tasks.

Importance: CNNs excel at automatically extracting hierarchical features from images, from edges to complex patterns.

Residual Networks (ResNets) in CNNs: Convolutional structures that integrate "skip connections" to bypass certain layers, optimizing deep network training and addressing challenges of depth in CNNs.

Methodology Continued

Why I used FastAi’s Python library:

Integration with FastAi: ResNets are seamlessly integrated into the FastAi library, offering optimized pre-trained models for various tasks.

Depth Flexibility: ResNets offer several layer configurations to cater to different experimentation needs.

Advantages with FastAi: Utilizing ResNets with FastAi provides easy access to transfer learning, fine-tuning, and other advanced training techniques optimized for these architectures.

Data Pre-processing & Augmentation

Data Preprocessing Steps:

I constructed a dataframe containing features that encompass image filepaths, along with their corresponding class labels ("edible" or "poisonous"). The class labels were derived by extracting the initial word from the subdirectory's label.

Integrity Check: Review all images in each folder for corruption or incompletion.

- If an image is identified as corrupted, its path is printed for closer inspection.
- Total and report the number of such files.

File Type Conversion: Transform non-jpg (png, jpeg) image files into jpg format.

PNG Adjustments: PNGs with RGBA and index-based modes are first converted to RGB mode before transitioning to jpg.

Data Pre-processing & Augmentation

Spot-Checking Discovery: Some images in the dataset contain watermarks or banners displaying an image database name.

Annotation Removal: Attempted multiple methods to erase these annotations:

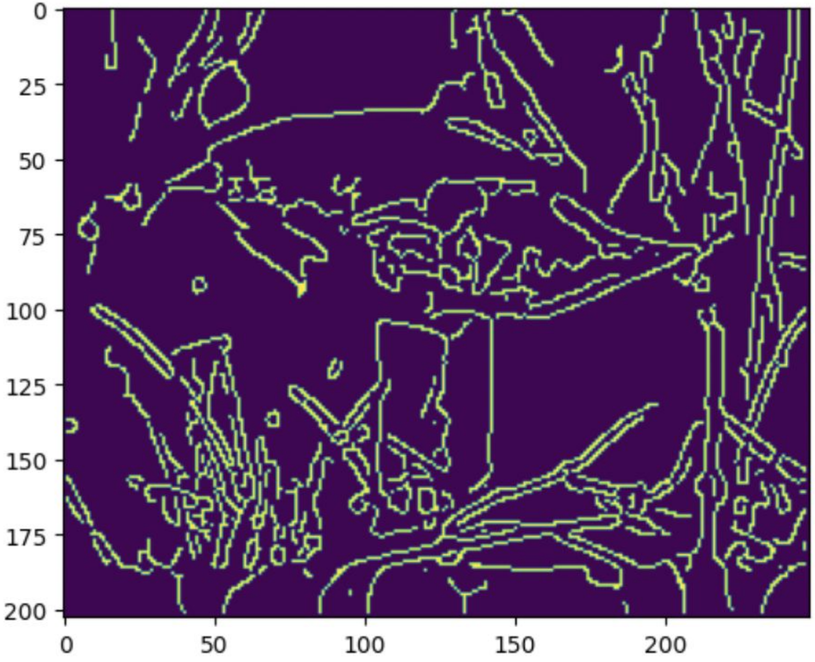
Biharmonic inpainting:

Data Pre-processing & Augmentation

Denoise:

Data Pre-processing & Augmentation

Canny edge detector:

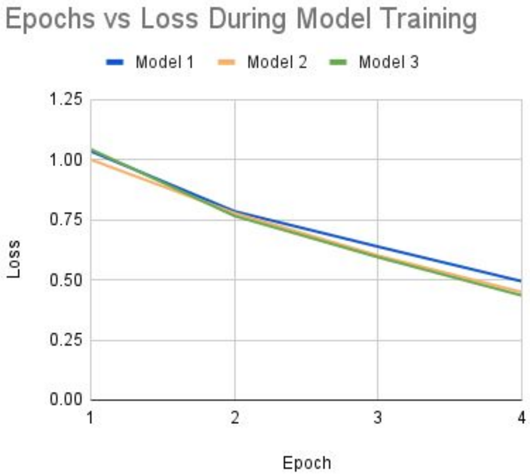


Model Training

Dataset Splitting: Segregated my image dataset into 64% for training, 16% for validation, and 20% for testing to achieve a balanced representation and thorough assessment.

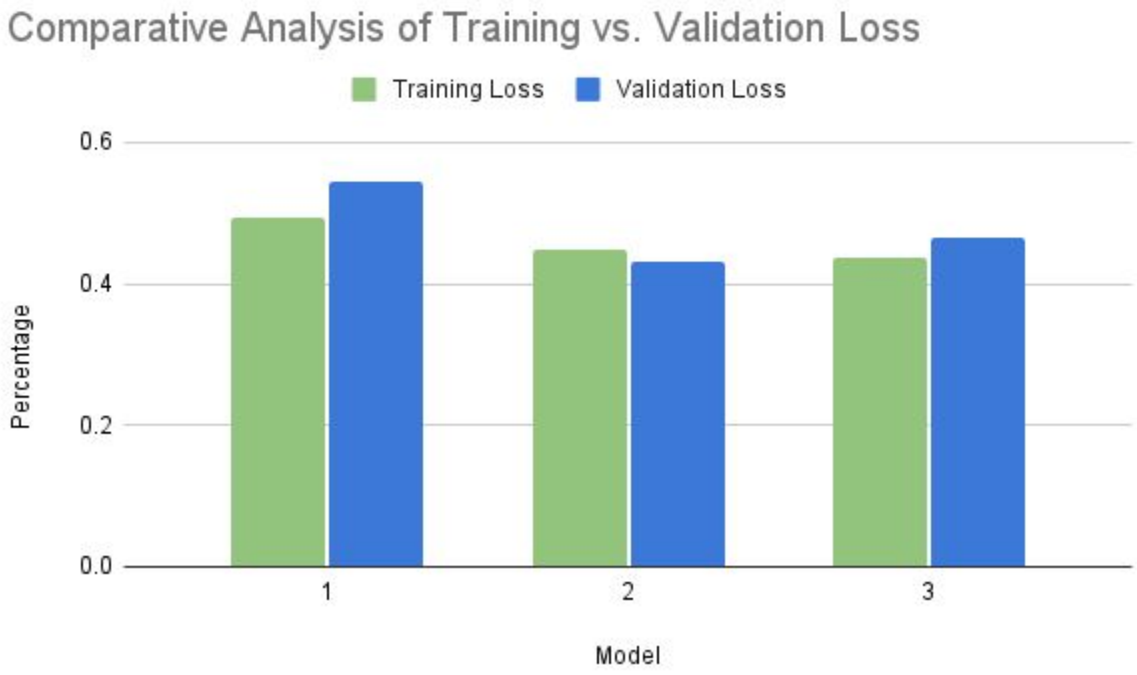
Model Design: Utilized both ResNet34 and ResNet50 architectures, experimented with image resizing, and trained each for 4 epochs.

Performance Visualization: Epochs mapped on the x-axis with corresponding loss on the y-axis.



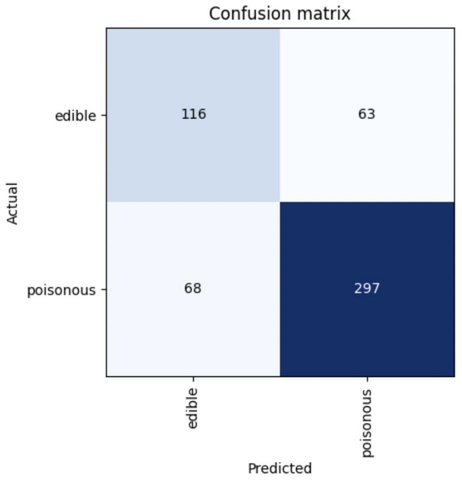
Model Training Continued

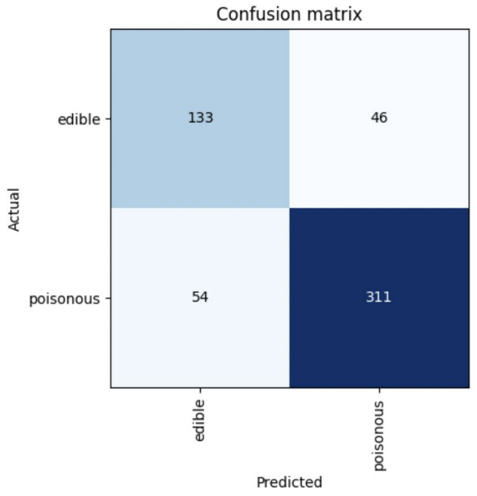
Loss Trend Analysis: Closeness between training and validation loss indicates minimal overfitting.

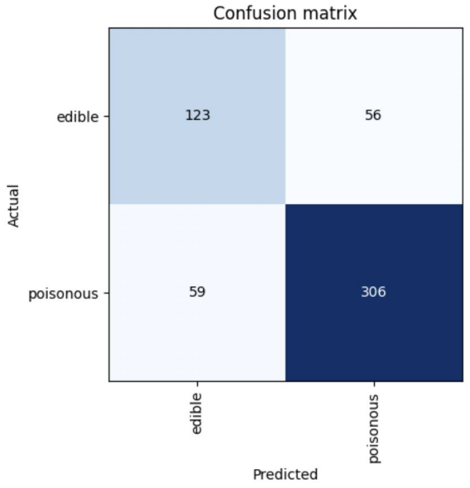


Model Performance

Confusion Matrix Analysis: Comparative breakdown of classification results for our three distinct models.

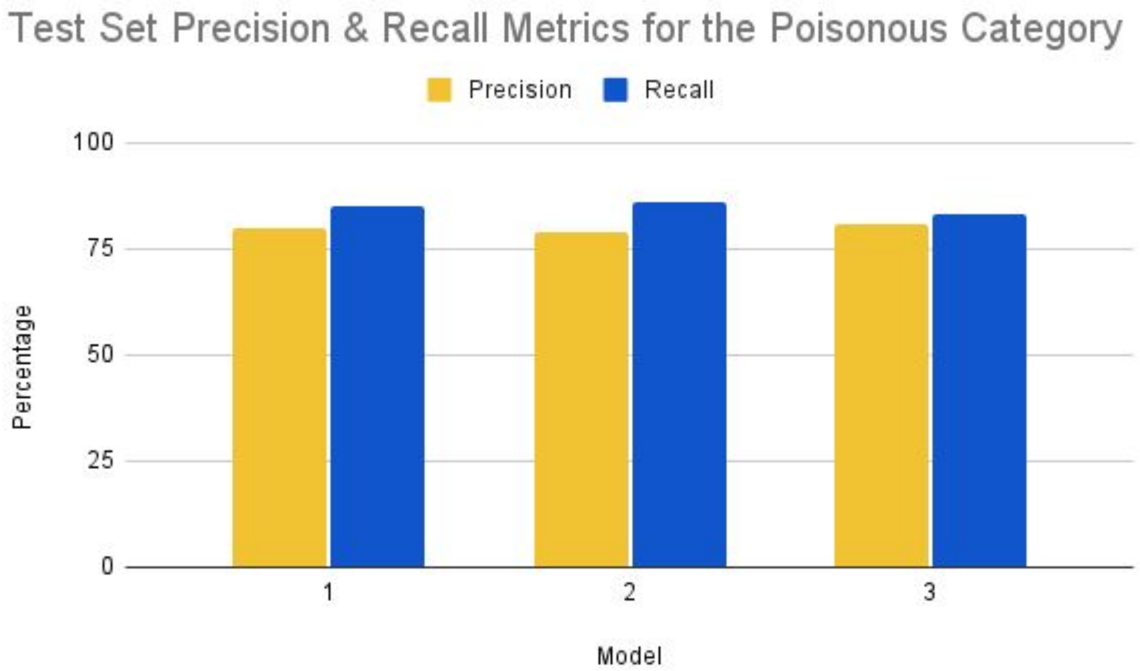






Model Performance Continued

Stressing high recall for the poisonous category: Essential to prevent severe risks associated with mistakenly identifying toxic mushrooms as edible.



Sample Predictions from Model 2

Highlighting accurate predictions for each class (edible, poisonous):

Highlighting inaccurate predictions for each class (poisonous as edible, edible as poisonous):

Future Work & Improvements

Enhancing Model Performance with Quality Data

- Prioritize the addition of high-quality images for accuracy.

- Accurate labeling: "Poisonous" or "Edible".

- Image attributes:
  - ➔ High resolution.
  - ➔ Captures top of the cap, underside, and stem.
  - ➔ Background vital for insights into habitat.

Future Work & Improvements Continued

Advanced Hardware and Dataset Refinements:

- Consider GPU system capable of managing Resnet50 and 224-pixel images.

- Address watermark issues in dataset:
  - ➔ Explore more thresholding and biharmonic inpainting augmentation.
  - ➔ Preserve crucial image features when removing markups.

Model Integration & Practical Applications:

- Develop a mobile app tailored for mushroom foragers.
- Real-time edible vs. poisonous classification.
- Enhance safety and knowledge in the field.
- Potential to integrate with GPS for location-specific insights.

Questions and Discussion Opportunity

Thank you Ricardo Alanis for your guidance during my Springboard Data Science Career Track enrollment!