



Mushroom Toxicity Classification

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TABLE OF CONTENTS

01 INTRODUCTION

Our Problem & Hypothesis

03 DATA PROCESSING #1

Resnet 50: EDA, Modeling & Analysis,
And Our Setup

05 DATA COMPARISON

Comparing Our Data From Both
Models

02 DATASET OVERVIEW

What Dataset Did We Use?

04 DATA PROCESSING #2

YOLOV8: EDA, Modeling & Analysis,
And Our Setup

06 CONCLUSION

Final Comparison In Relation To
Real World

INTRODUCTION

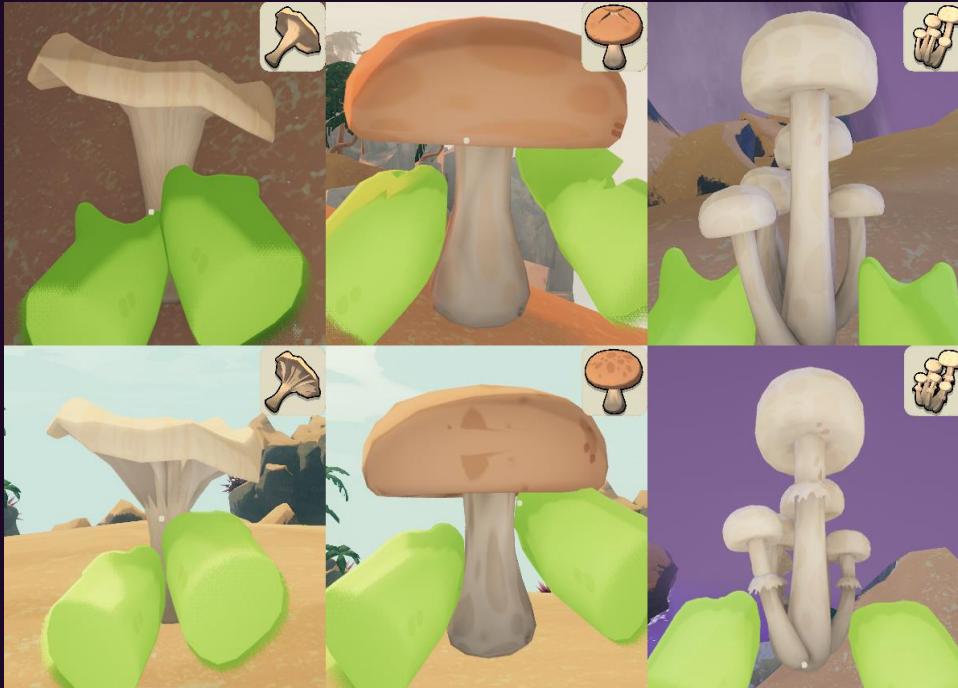
When You're Out In The Wild, You'll Come Across All Kinds of Plants (Bushes, Flowers, Berries). But, Mushrooms Are Often The Most Eye-Catching Of The All.

WE LOVE MUSHROOMS



- But, While Some Mushrooms May Look Pretty, We Have To Remember That They're Also A Major Safety Concern. Many Poisonous Mushrooms Can Resemble Edible Species, Making Visual Identification Challenging.

OUR HYPOTHESIS



Visual features in mushroom images cannot be used to accurately predict whether a mushroom is poisonous or non-poisonous.

02

DATASET OVERVIEW

Our Metrics & Dataset Breakdown

OUR DATASET

Dataset Name: Mushrooms
Images Classification 215

Data Split:

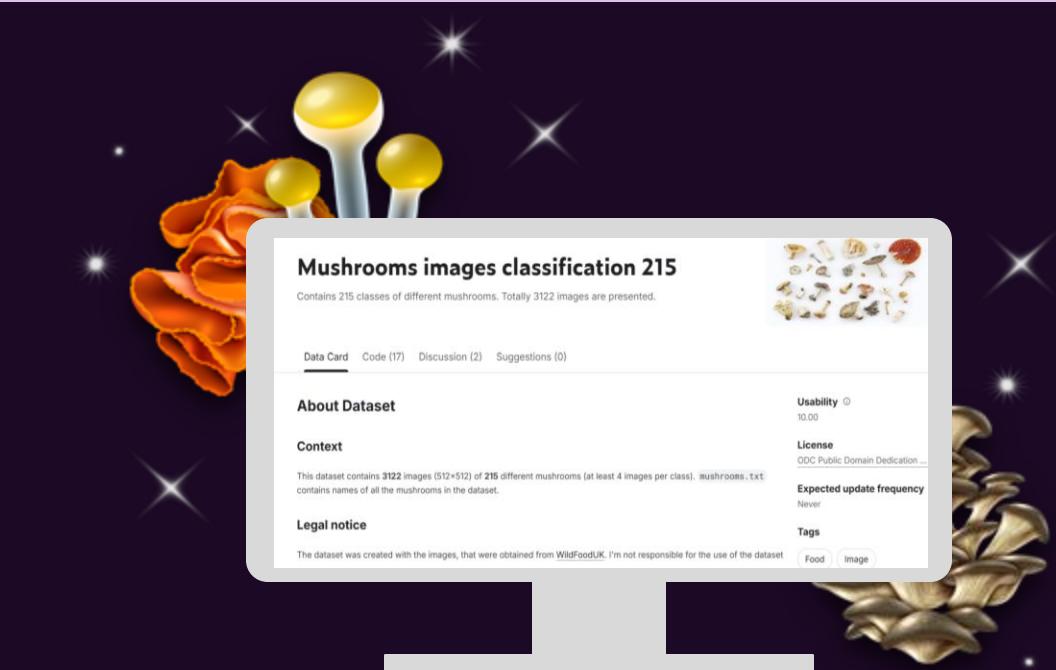
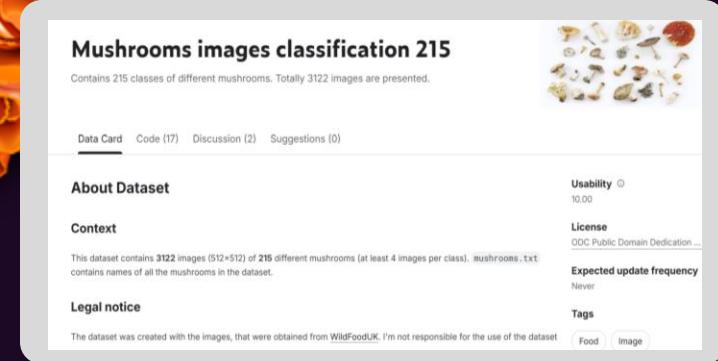
- 3122 Images Of 215
Mushrooms

Why We Chose This Dataset:

- Large Variety Of
Mushroom Species
- Semi-Balanced
Sample Size

Dataset cleaning:

- Many had only 1–5 images causing unstable training
- Filtering these we get 3,085 images across 210 species
- Created a pandas DataFrame, mapping each image to its species, then converted species names into numeric labels using LabelEncoder.
- Created stratified train/validation/test splits (60/20/20)



METRICS USED



Good Overall Measure
Of Model Correctness

ACCURACY

Prevents False
Alarms

PRECISION



MAGIC MUSHROOMS METRICS



RECALL

Measure Of Our Poisonous
Mushrooms Labeled As Non-
Poisonous

F1 SCORE

How Accurate Our
Poisonous Mushrooms
Were Tracked





03

DATA PROCESSING #1

Our Resnet 50 Model





ResNet-50



ResNet50 is a deep convolutional neural network with fifty layers that is widely used for image classification tasks. It was originally trained on the ImageNet dataset, which contains millions of images, allowing it to learn strong representations of shapes, textures, and visual patterns. The model uses residual connections that help information flow through the network more efficiently, making it easier to train and more accurate on challenging visual problems. In this project, ResNet50 serves as the backbone that extracts detailed features from mushroom images, such as cap structure, gill patterns, and surface texture.

Resnet-50

- The code builds a complete pipeline that loads mushroom images from disk, cleans the dataset, and prepares it for training a deep learning model. Image file paths are collected and labeled by species, rare classes with very few examples are removed, and the remaining data is split into training, validation, and test sets using a stratified method so that each species is fairly represented.
- A TensorFlow data pipeline then reads each image, resizes it to the required input size for ResNet fifty, applies data augmentation such as flips, rotations, zoom, and contrast changes, and converts labels into one hot vectors.
- The model is first trained with the base network frozen and then fine tuned by unfreezing the upper layers so that it can better adapt to mushroom specific visual patterns. Class weights are used to reduce the effect of class imbalance



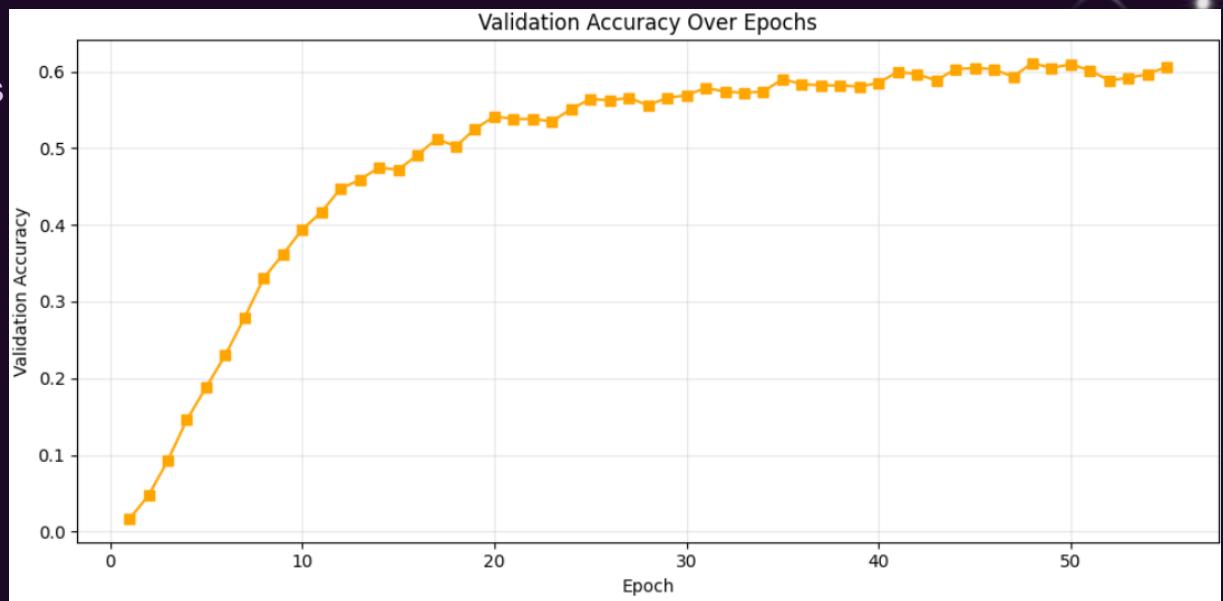
PERFORMANCE & METRICS

ACCURACY	58%
RECALL	0.58
PRECISION	0.6
F1-Score	0.56

The model achieves about fifty eight percent accuracy when predicting the top fifteen most common mushroom species. Precision and recall values near sixty percent show that the model is able to correctly identify many species and retrieve most of their true examples. Some rare species remain difficult to classify due to very small sample sizes and strong visual similarity to other mushrooms, which results in zero precision or zero recall for those classes.

Validation Accuracy Curve

- The graph measures the model's generalization ability with mushrooms
- Fast improvement with in first 10-15 epochs from pretrained ResNet50
- Slower gains after unfreezing upper layers for fine tuning from around 45% to 60%
- The curve then stabilizes demonstrating that the model has learned all it could from the dataset



Demonstrates difficulty of image only toxicity prediction is somewhat unreliable



04

DATA PROCESSING #2

Our YOLOV8 Model



★ YOLOV8 MODEL OVERVIEW



WHAT IT DOES

Yolov8 Is A Good Model
For Object Detection &
Image Classification



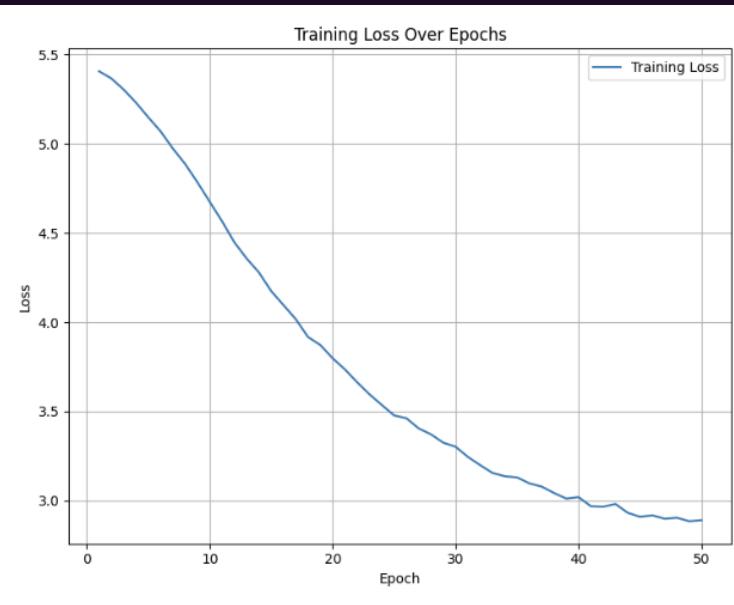
WHAT WE DID

We Used It To Identify
Visual Patterns Like Cap,
Shape, Color and Texture



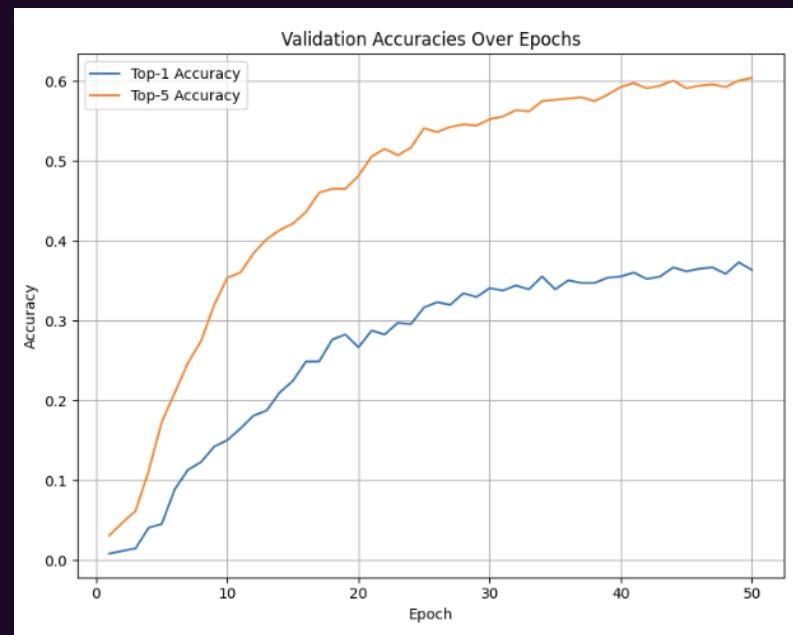
BECAUSE

We Did This Because It
Performs Strongly On
Visual Tasks



The Training Loss Steadily Decreased Across 50 Epochs, Showing That The Model Was Learning Effectively.

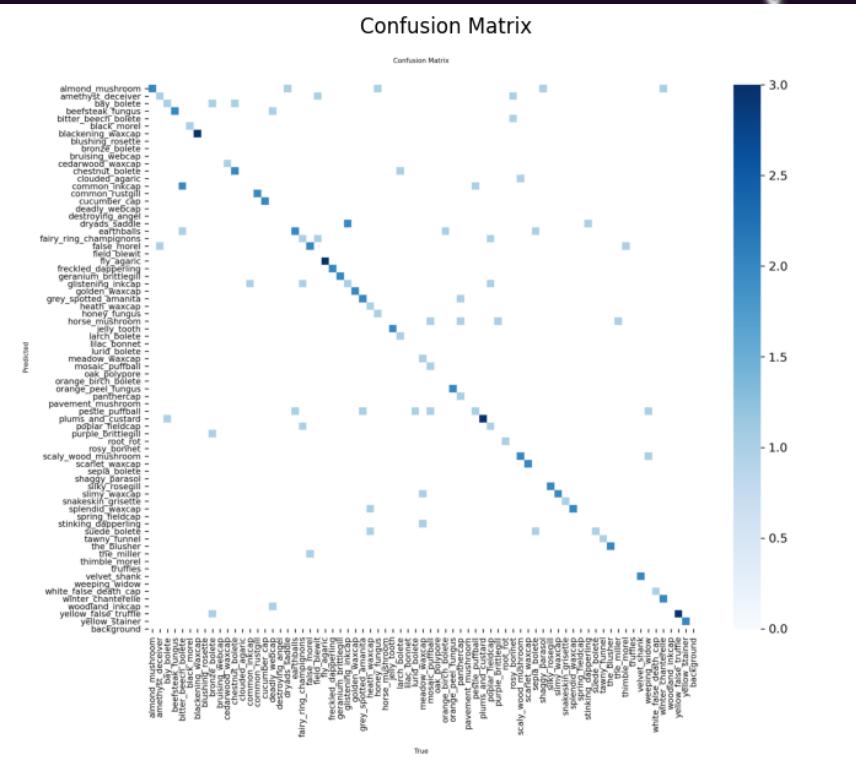
Top-1 Accuracy Peaked Around 35%, While Top-5 Accuracy Reached About 60%, Indicating That While The Model Struggled To Pinpoint The Exact Species, It Often Narrowed Down The Correct category Within Its Top Predictions.



PERFORMANCE & METRICS

ACCURACY	~50-70%
RECALL	Moderate
PRECISION	Moderate
F1-Score	Mid-Range

YOLOV8 Had Difficulty Distinguishing Poisonous vs Non-Poisonous Mushroom Due To Visual Similarity And Subtle Features, Resulting In Mid-Range Performance



05

DATA COMPARISON

Comparing Our Findings In Both Models

Accuracy Scores

-Both models learned important mushroom features as ResNet50 and YOLOv8 perform far above random guessing (0.48% for 210 species)

-ResNet50 is more stable but lower in top accuracy as it has strong generalization but limited fine grained separation

-YOLOv8 shows higher peak accuracy but more variability since it often identifies the correct species *among the top few guesses*

- top-1 accuracy is ~35%
- top-5 accuracy is ~60%

MODELS	MODEL 1: RESNET 50	MODEL 2: YOLOv8
ACCURACY SCORES	58%	50% & 70%

-Both struggle among visually similar species, confirming that appearance alone is not enough to distinguish mushrooms

-This is the limitation that the models have but still resulted in some accurate data

We used two models to confirm whether the limitation was due to the model or the dataset.



06 CONCLUSION

SO WHAT DOES THIS MEAN?

Based On Our Accuracies. .

. . . We Can Conclude That Mid-Range Performance Indicates This Dataset Alone Isn't Sufficient Enough To Determine Whether A Mushroom's Appearance Can Predict The Type & Toxicity



This Can Relate To The Real World. .

Because Identifying Mushrooms Based On Appearance Alone Is Often Unreliable. Many Poisonous and Non-Poisonous Mushrooms Look Extremely Similar, Making A Visual Classification Difficult For Both Human & Machines

CLASSIFICATION IN THE REAL WORLD



MUSHROOM CLASSIFICATION

PHYSICAL

Their Form, Cap, Size, Color, Any Extra Spores They May Have

HABITAT

Based On The Environment And The Other Plants It's Growing Nearby

ODOR

What Odors Do They Release? (DO NOT TEST THIS IRL!! THIS CAN BE VERY DANGEROUS)

RELATING BACK TO OUR HYPOTHESIS

THE WHOLE MUSHROOM

Visual features in mushroom images cannot be used to accurately predict whether a mushroom is poisonous or non-poisonous.

PARTS OF THE MUSHROOM	Appearance	Habitat	Odor	Extras
APPEARANCE ALONE DOESN'T IDENTIFY A MUSHROOM				

APPEARANCE
ALONE DOESN'T
IDENTIFY A
MUSHROOM

WHICH SUPPORTS
OUR INITIAL
HYPOTHESIS!! :)

THANKS!

DO YOU HAVE ANY QUESTIONS?

Links For Our Colabs:

YOLOV8:

<https://colab.research.google.com/drive/10MQyKB5liePDgMPJFvvIL7xE2N8LsW6b?usp=sharing>

RESNET50:

<https://colab.research.google.com/drive/1TMCXhsNLp6QOe9xnkCRIuMtVSwz1b03z?usp=sharing>

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