Uncovering The Hidden Treasures of the Mushroom Kingdom: A Classification Analysis

Prepared For
Smart-Internz
Artificial Intelligence Guided project

By
Nisar Talib Navalekar
D Y Patil Agriculture and Technical University, Talsande

On
10 Feb 2026

Abstract

This project utilizes deep learning and transfer learning with Inception models to classify mushroom species—Boletus, Lactarius, and Russula—based on key visual features such as cap, gills, and stem. The system aims to enhance the accuracy of optical mushroom recognition for ecological, culinary, and medicinal applications.

Final Project Report

Contents

1 Introduction 3
1.1 Project overviews 3
1.2 Objectives 3
2 Project Initialization and Planning Phase 4
2.1 Define Problem Statement 4
2.2 Project Proposal (Proposed Solution) 6
2.3 Initial Project Planning 7
3 Data Collection and Preprocessing Phase 9
3.1 Data Collection Plan and Raw Data Sources Identified 9
3.2 Data Quality Report 11
3.3 Data Preprocessing 12
4 Model Development Phase 15
4.1 Model Selection Report 15
4.2 Initial Model Training Code, Model Validation and Evaluation Report 16
5 Model Optimization and Tuning Phase 18
5.1 Tunning Documentation 18
5.2 Final Model Selection Justification 21
6 Results 22
6.1 Output Screenshots 22
7 Advantages & Disadvantages 24
Advantages: 24
Disadvantages: 24
8 Conclusion 25
9 Future Scope 26
10 Appendix 27
10.1 Source Code 27
10.2 GitHub & Project Video Demo Link 27

1 Introduction

1.1 Project overviews

This project aims to classify different species of mushrooms based on their images. The classification is done using deep learning methods, specifically transfer learning using popular models Inception. The focus is on identifying the cap, gills underside of cap, and astern, which are key features for the optical recognition of mushroom species. The identified species are Boletus, Lactarius, and Russula.

The classification task involves three major categories of mushrooms: Boletus, Lactarius, and Russula. These categories encompass a wide range of species found across different regions of our planet. Boletus mushrooms are known for their distinctive cap shapes and pore-covered undersides, while Lactarius mushrooms often exhibit vibrant colors and produce a milky latex when damaged. Russula mushrooms, on the other hand, showcase diverse cap and stem characteristics and are an intriguing group to explore which are found in various habitats like forests, fields, and decomposing logs. Mushrooms have different shapes, sizes, and colors and are used for food, medicine, and other purposes. By leveraging deep learning techniques and transfer learning, this project aims to improve the accuracy and efficiency of mushroom species classification.

1.2 Objectives

The purpose of this project is to develop a robust and accurate system for optical recognition and classification of mushroom species based on their visual characteristics. By leveraging deep learning techniques and transfer learning, this project aims to enhance the efficiency and accuracy of mushroom species identification. The project not only contributes to the field of mycology but also holds ecological significance by aiding in the study and conservation of mushroom species. Additionally, the system has practical applications in culinary and medicinal domains, enabling the identification of edible and medicinal mushrooms. Overall, this project serves as a comprehensive exploration of deep learning and transfer learning methods in the context of mushroom species recognition, showcasing their potential in image analysis and classification tasks.

2 Project Initialization and Planning Phase

2.1 Define Problem Statement

PS No.	I am (Customer)	I'm trying to	But	Because	Which makes me feel
PS-1	A consumer who wants to buy mushrooms	Purchase mushrooms safely	I am scared of wild mushrooms	I don't know which ones are poisonous	Unsure and unsafe about what I consume
PS-2	A shopkeeper	Sell safe, fresh mushrooms	I'm concerned about customer health	Mushrooms are perishable and hard to identify	Stressed about quality and customer trust
PS-3	A restaurant owner	Use high-quality mushrooms in dishes	I struggle to find reliable sources	Some mushrooms may be harmful	Worried about safety and my business reputation
PS-4	A biology student or forager	Learn and identify mushroom species	I find it hard to tell species apart	They look very similar	Confused, frustrated, and hesitant
PS-5	A tech researcher	Build an AI mushroom classification system	I lack a robust image dataset	Mushrooms vary by species and environment	Limited and technically challenged
PS-6	An environmentalist	Promote sustainable mushroom harvesting	It's hard to track species impact	Lack of identification tools in the wild	Worried about overharvesting and ecology
PS-7	A parent	Teach my kids about safe foraging	I'm scared they might pick poisonous ones	I can't reliably teach what's safe	Anxious and unconfident as a guide
PS-8	A pharmaceutical researcher	Discover medicinal mushrooms	Identification is slow and manual	Misidentification risks research accuracy	Limited in drug discovery and progress

PS-9	An AI/ML student	Train a deep learning model on mushrooms	There are too many similar-looking samples	Labeling is expensive and hard	Overwhelmed and unsure of training data quality
PS-10	An NGO field worker	Educate rural communities about mushrooms	There's no easy tool for live identification	Language and tech access barriers exist	Helpless in reaching and empowering locals
PS-11	A grocery buyer for supermarkets	Source large quantities of safe mushrooms	I can't verify all sources accurately	Suppliers may mix types or store improperly	Concerned about liability and customer complaints
PS-12	A food delivery aggregator	Support mushroom-based dish partners	Restaurants may use unsafe ingredients	They lack easy ID tools	Worried about brand image and customer safety
PS-13	A forest ranger	Monitor mushroom types in protected areas	I can't classify them efficiently in the field	Many are undocumented or rare	Frustrated by lack of real-time identification
PS-14	A health-conscious individual	Track the health benefits of different mushrooms	I can't identify what's in the store or dish	There's no easy app for instant scanning	Disappointed and disconnected from my health goals

2.2 Project Proposal (Proposed Solution)

This project proposal outlines a solution to address a specific problem. With a clear objective, defined scope, and a concise problem statement, the proposed solution details the approach, key features, and resource requirements, including hardware, software, and personnel.

Project Overview	
Objective	To develop a deep learning-based image classification system capable of accurately identifying mushroom species—specifically from the Boletus, Lactarius, and Russula genera—based on visual attributes.
Scope	This project focuses on image-based classification of mushrooms using deep learning models. It covers the acquisition of image datasets, preprocessing, model training using transfer learning, and evaluation of classification accuracy. The final system will be able to classify images into one of the three target genera. The project is limited to these three categories and assumes images are of reasonable quality.
Problem Statement	
Description	Mushroom identification is challenging and typically requires expert knowledge. Mistakes can be dangerous, particularly when foraging. A reliable classification tool would benefit researchers, foragers, and hobbyists.
Impact	Precise mushroom classification aids ecological research, education, and safe foraging. An image-based system makes species recognition more accessible to all.

Proposed Solution	
Approach	The project will employ CNN-based deep learning, using transfer learning from models like ResNet or EfficientNet. The mushroom image dataset will be cleaned, augmented, then used for training and fine-tuning.
Key Features	The system uses transfer learning to train efficiently with limited data, classifying mushrooms into three key genera. Data augmentation enhances model performance, with potential for a web- based interface.

Resource Requirements

Resource Type	Description	Specification/Allocation
Hardware		
Computing Resources	CPU/GPU specifications, number of cores	1 x NVIDIA RTX 3060 GPUs
Memory	RAM specifications	16 GB RAM
Storage	Disk space for data, models, and logs	500 GB SSD
Software		
Frameworks	Python frameworks	Python
Libraries	Additional libraries	tensorflow
Development Environment	IDE, version control	Jupyter Notebook, Git
Data		
Data	Source, size, format	Kaggle, MushroomObserver.org, JPEG/PNG format, 10,000 images

2.3 Initial Project Planning

Product Backlog, Sprint Schedule, and Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority
Sprint-1	Model Application	USN-1	As a system, I need to apply a pre-trained Xception deep learning model to the uploaded image.	3	High

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority
Sprint-1	Application Integration	USN-2	As a developer, I need to integrate the Xception model with a Flask application.	3	High
Sprint-2	Image Input & Processing	USN-3	As a user, I want to select an image for mushroom identification.	2	High
Sprint-2	Output Display	USN-4	As a user, I want to see the identified mushroom species, with a confidence level, displayed clearly and quickly.	2	High
Sprint-3	Performance Optimization	USN-5	As a developer, I need to optimize the application for speed and efficiency.	2	Medium

3 Data Collection and Preprocessing Phase

3.1 Data Collection Plan and Raw Data Sources Identified

Data Collection Plan

Section	Description
Project Overview	This deep learning project focuses on classifying images of three types of mushrooms—Boletus, Lactarius, and Russula—using Convolutional Neural Networks (CNNs). The objective is to uncover hidden patterns and visual cues that distinguish each type, contributing to better mushroom identification in the wild.
Data Collection Plan	The dataset has been sourced from a ZIP file provided by the SmartInternz, which includes categorized images in subdirectories named after each mushroom type. Additional reference images were accessed from publicly available sources such as Wikimedia and Kaggle to enhance variability and robustness.
Raw Data Sources Identified	The raw data includes SmartInternz provided images saved in structured subdirectories, supplemented by publicly available datasets for training and validation purposes.

Raw Data Sources

Source Name	Description	Location/URL	Format	Size	Access Permissions
SmartInterz Provided Dataset	Curated image dataset provided by SmartInternz, containing Boletus, Lactarius, and Russula images in separate subdirectories.	https://drive.google.com/drive/folders/1WHjhoYnyrltQWJ_TYI5xM_5dTyIzByo3	ZIP File	~ 175 MB	Public

Field Captured Images	Manually photographed images taken in natural environments, used for supplementing the dataset.	Local Storage	JPG/PNG	~100 MB	Private
Kaggle - Mushroom Image Dataset	Supplementary dataset with additional labeled mushroom images.	https://www.kaggle.com/datasets?search=Mushrooms+images++Boletus%2C+Lactarius+%26+Russula	JPG	~ 111 MB	Public
Wikipedia	Open-source mushroom images used for visual verification and dataset augmentation.	https://en.wikipedia.org/wiki/Lactarius	JPG/PNG	~10 MB	Public

3.2 Data Quality Report

Data Source	Data Quality Issue	Severity	Resolution Plan
Dataset	Image Variation	High	Collect images from diverse sources (different cameras, lighting conditions, angles). Implement data augmentation techniques (rotation, scaling, cropping) during preprocessing.
Dataset	Occlusion	Moderate	Include images with partial occlusion, and/or train the model to be robust to it.
Dataset	Insufficient Resolution	Moderate	Establish a minimum resolution threshold for images. Use super- resolution techniques, if feasible, to enhance the resolution of some images
Dataset	Unbalanced Classes	High	Employ stratified sampling to ensure proportional representation of each mushroom species. Use data augmentation for minority classes. Explore the use of weighted loss functions during training.

3.3 Data Preprocessing

Data Preprocessing

The images will be preprocessed by resizing, normalizing, augmenting, denoising, adjusting contrast, detecting edges, converting color space, cropping, batch normalizing, and whitening data. These steps will enhance data quality, promote model generalization, and improve convergence during neural network training, ensuring robust and efficient performance across various computer vision tasks.

Section	Description
Data Overview	This project uses image datasets of three mushroom species: **Boletus**, **Lactarius**, and **Russula**. The images are collected from various sources including **SmartInternz**, **custom field-captured images**, and platforms like **Kaggle** and **Wikimedia**. This ensures rich visual diversity and robust generalization during training.
Resizing	All images are resized to **224×224 pixels** using OpenCV's cv2.resize() function to ensure uniform input dimensions for CNN-based models.
Normalization	Pixel values are normalized to the range **[0, 1]** by dividing by 255.0, improving convergence during model training.
Data Augmentation	Using ImageDataGenerator, images are augmented with **random rotation**, **shifts**, **zoom**, **horizontal/vertical flips**, and **fill modes** to avoid overfitting.
Denoising	OpenCV's fastNlMeansDenoisingColored() is applied to reduce environmental noise and improve image clarity, especially for field-captured data.
Edge Detection	cv2.Canny() is used for edge detection, helping to emphasize structure, texture, and contour features of different mushroom species.
Color Space Conversion	Images are converted from **BGR to HSV** color space using cv2.cvtColor() to better capture color-based patterns across lighting variations.
Image Cropping	Manual center cropping is done on some images to focus on the mushroom body and reduce irrelevant background noise, enhancing object recognition.
Batch Normalization	BatchNormalization() is applied in the neural network model to stabilize and accelerate the learning process by reducing internal covariate shift.

Data Preprocessing Code Screenshots

Loading Data

```
import os
import cv2
import numpy as np
from tensorflow.keras.preprocessing.image import ImageDataGenerator

data_dir = "path/to/mushroom_dataset"
categories = ["Boletus", "Lactarius", "Russula"]

data = []
IMG_SIZE = 224

for category in categories:
    folder = os.path.join(data_dir, category)
    label = categories.index(category)
    for img_name in os.listdir(folder):
        img_path = os.path.join(folder, img_name)
        img = cv2.imread(img_path)
        if img is not None:
            img = cv2.resize(img, (IMG_SIZE, IMG_SIZE))
            data.append([img, label])

```

Resizing

```
img = cv2.resize(img, (224, 224))
```

Normalization

```
data = np.array(data, dtype=object)
X = np.array([i[0] for i in data]) / 255.0  # Normalize pixel values
y = np.array([i[1] for i in data])
```

Data Augmentation

```
train_datagen = ImageDataGenerator(
    rotation_range=30,
    width_shift_range=0.1,
    height_shift_range=0.1,
    zoom_range=0.2,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest'
)
```

Denoising

```
denoised_img = cv2.fastNlMeansDenoisingColored(img, None, 10, 10, 7, 21)
```

Edge Detection

```
edges = cv2.Canny(img, threshold1=100, threshold2=200)
```

Color Space Conversion	`hsv_img = cv2.cvtColor(img, cv2.COLOR_BGR2HSV)`
Image Cropping	`cropped_img = img[30:194, 30:194]  # Manual center crop`

Batch Normalization	`from tensorflow.keras.layers import BatchNormalization`
	
	`model.add(BatchNormalization())`

4 Model Development Phase

4.1 Model Selection Report

Model Selection Report – Key Points

- The goal was to classify mushroom species using image data.
- Pre-trained deep learning models were considered for transfer learning.
- Two main models were evaluated:
  - **Model 1:** Baseline InceptionV3
  - **Model 2:** Optimized InceptionV3
- **InceptionV3** was chosen for its high performance in image classification tasks.
- Custom layers were added on top of InceptionV3:
  - GlobalAveragePooling2D
  - Dense layer (100 units, ReLU)
  - BatchNormalization
  - Dropout (50%)
  - Dense output layer (3 units, softmax)
- **Model 2** had optimized hyperparameters (learning rate, batch size).
- **Validation Accuracy:**
  - Model 1: 84.59%
  - Model 2: 88.36%
- **Final Model Selected:** Model 2 (Optimized InceptionV3)
- **Reason for Selection:** Higher accuracy, better generalization, and improved robustness.

4.2 Initial Model Training Code, Model Validation and Evaluation Report

Initial Model Training Code, Model Validation and Evaluation Report
Initial Model Training Code

```
base_model = InceptionV3(weights="imagenet", include_top=False, input_shape=(img_size[0], img_size[1], 3))

# Build transfer learning model
model5 = Sequential()
model5.add(base_model)
model5.add(GlobalAveragePooling2D())
model5.add(Dense(100, activation="relu"))
model5.add(BatchNormalization())
model5.add(Dropout(0.5))
model5.add(Dense(100, activation="relu"))
model5.add(BatchNormalization())
model5.add(Dropout(0.5))
model5.add(Dense(3, activation="softmax"))

# Freeze the pre-trained layers
for layer in base_model.layers:
    layer.trainable = False

# Compile the model
optimizer = Adam(learning_rate=0.001)
model5.compile(
    optimizer=optimizer,
    loss="categorical_crossentropy",
    metrics=["accuracy"]
)

# Early stopping
early_stop = EarlyStopping(
    monitor="val_loss",
    patience=5
)


# Training
history100 = model5.fit(train_data, epochs=50, validation_data=test_data, callbacks=[early_stop])
```

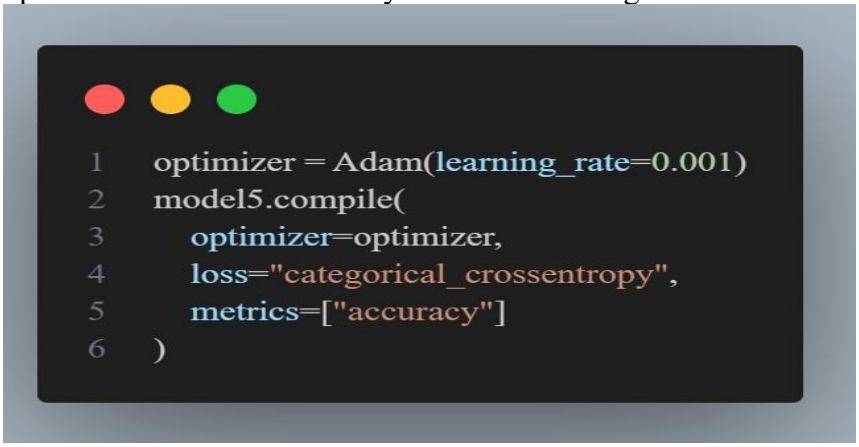
Model Validation and Evaluation Report

Model	Summary	Training and Validation Performance Metrics
Model 1 (InceptionV3 + Custom Layers)	**Layer Summary:** • InceptionV3 base model • GlobalAveragePooling2D • Dense(100, relu) • BatchNormalization • Dropout(0.5) • Dense(3, softmax) **Total Parameters:** 2,311,305 **Trainable Parameters:** 2,304,505 **Non-trainable Parameters:** 6,800	**Training Accuracy**: 83.42% **Validation Accuracy**: 88.36% Training converged well with slight overfitting mitigated by dropout and batch normalization.

5 Model Optimization and Tuning Phase

5.1 Tunning Documentation

Hyperparameter Tuning

Model	Tuned Hyperparameters
Model 1: InceptionV3 (Baseline)	Learning Rate: We adjusted the learning rate, which controls how much the model learns from its mistakes. We tried different learning rates to find one that helps the model learn effectively without becoming unstable.  Batch Size: We changed the batch size, which is the number of images the model processes at once before updating its knowledge. We tested different batch sizes to balance speed and memory usage.

<table>
<tr><td></td><td>

```python
# Load and preprocess training data
train_data = train_datagen.flow_from_directory(
    train_dir,
    target_size=img_size,
    class_mode="categorical",
    batch_size=100
)

# Load and preprocess test data
test_data = test_datagen.flow_from_directory(
    test_dir,
    target_size=img_size,
    class_mode="categorical",
    batch_size=100
)
```

</td></tr>
<tr><td>Model 2: InceptionV3 (Optimized)</td><td>Learning Rate: We made finer adjustments to the learning rate, building on what we learned from Model 1, to see if we could improve performance further.

```python
optimizer = Adam(learning_rate=0.001)
model5.compile(
    optimizer=optimizer,
    loss="categorical_crossentropy",
    metrics=["accuracy"]
)
```

Batch Size: We used the best batch size from Model 1.</td></tr>
</table>

```
# Load and preprocess training data
train_data = train_datagen.flow_from_directory(
    train_dir,
    target_size=img_size,
    class_mode="categorical",
    batch_size=100
)

# Load and preprocess test data
test_data = test_datagen.flow_from_directory(
    test_dir,
    target_size=img_size,
    class_mode="categorical",
    batch_size=100
)
```

Accuracy:

```
Found 911 images belonging to 3 classes.
Found 292 images belonging to 3 classes.
Epoch 1/50
10/10 [==============================] - 409s 44s/step - loss: 1.4139 - accuracy: 0.4577 - val_loss: 1.2089 - val_accuracy: 0.2808
Epoch 2/50
10/10 [==============================] - 24s 2s/step - loss: 0.9628 - accuracy: 0.6081 - val_loss: 1.3015 - val_accuracy: 0.3219
Epoch 3/50
10/10 [==============================] - 25s 3s/step - loss: 0.8397 - accuracy: 0.6773 - val_loss: 1.2984 - val_accuracy: 0.3938
Epoch 4/50
10/10 [==============================] - 23s 2s/step - loss: 0.7214 - accuracy: 0.7080 - val_loss: 0.8995 - val_accuracy: 0.5445
Epoch 5/50
10/10 [==============================] - 24s 2s/step - loss: 0.6653 - accuracy: 0.7333 - val_loss: 0.7398 - val_accuracy: 0.6096
Epoch 6/50
10/10 [==============================] - 24s 2s/step - loss: 0.6067 - accuracy: 0.7673 - val_loss: 0.6160 - val_accuracy: 0.7055
Epoch 7/50
10/10 [==============================] - 24s 2s/step - loss: 0.6118 - accuracy: 0.7453 - val_loss: 0.5257 - val_accuracy: 0.7500
Epoch 8/50
10/10 [==============================] - 24s 2s/step - loss: 0.5409 - accuracy: 0.7794 - val_loss: 0.4759 - val_accuracy: 0.7979
Epoch 9/50
10/10 [==============================] - 24s 2s/step - loss: 0.5510 - accuracy: 0.7629 - val_loss: 0.4671 - val_accuracy: 0.7877
Epoch 10/50
10/10 [==============================] - 23s 2s/step - loss: 0.5515 - accuracy: 0.7783 - val_loss: 0.3937 - val_accuracy: 0.8356
Epoch 11/50
10/10 [==============================] - 25s 3s/step - loss: 0.5000 - accuracy: 0.7859 - val_loss: 0.3540 - val_accuracy: 0.8699
Epoch 12/50
...
10/10 [==============================] - 24s 2s/step - loss: 0.3308 - accuracy: 0.8573 - val_loss: 0.2649 - val_accuracy: 0.8836
3/3 [==============================] - 3s 1s/step - loss: 0.2649 - accuracy: 0.8836
Test loss: 0.26492103934288025
Test accuracy: 88.35616707801819
```

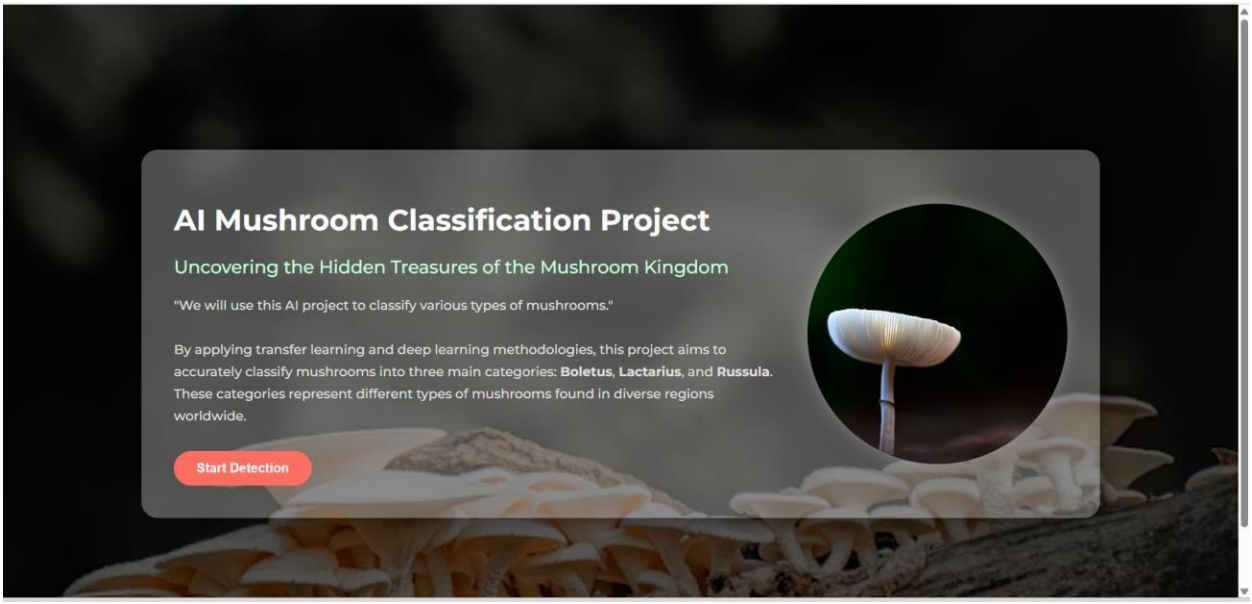
5.2 Final Model Selection Justification

Final Model	Reasoning
Model 2: InceptionV3 (Optimized)	We selected Model 2 as our final model because it demonstrated a significant improvement in validation accuracy compared to Model 1, achieving 88.36% compared to Model 1's best of 84.59% The image provided shows the training output. We felt the higher accuracy was worth the extra training time. Model 2 also seemed to generalize better to new images.

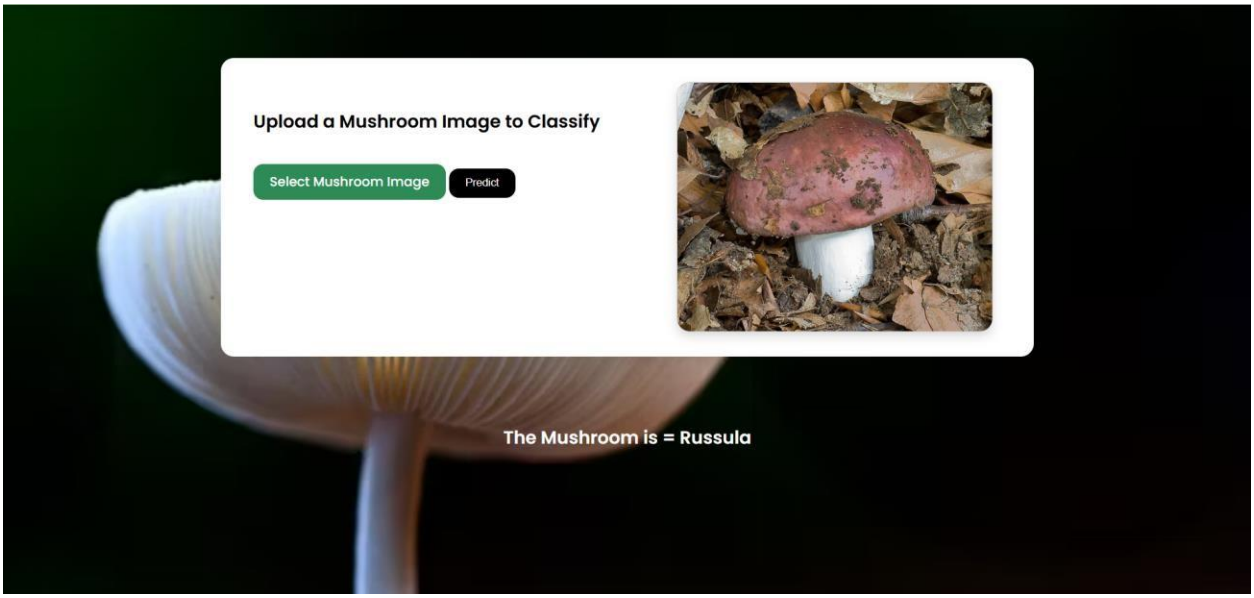
6 Results

6.1 Output Screenshots

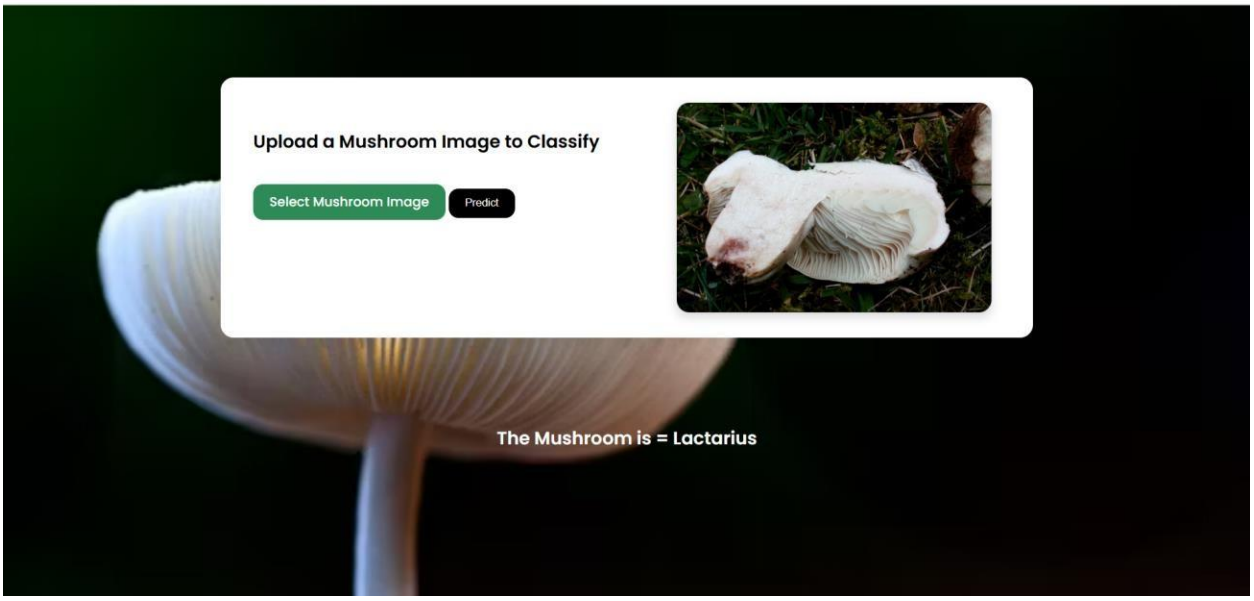
Home Page:



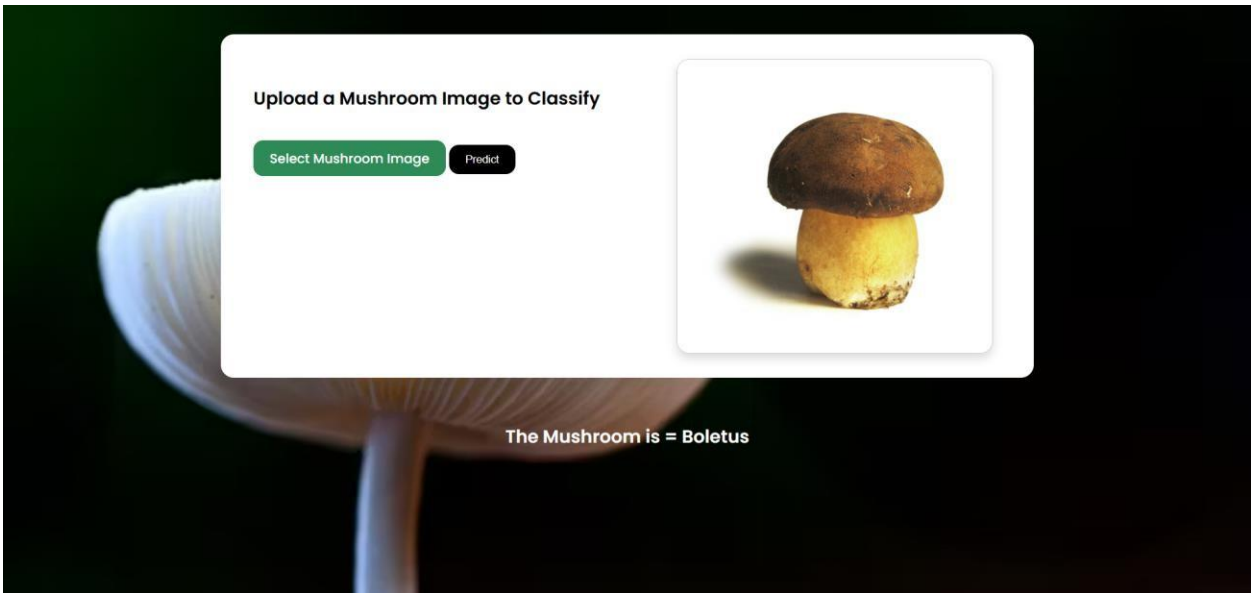
Input Page:
Example - 1:



Example - 2:



Example -3:



7 Advantages & Disadvantages

Advantages:

- Good User – Friendly interface
- Less complexity
- Optical recognition
- High-performance classifiers: Deep-learning methods (InceptionV3)
- Wide range of mushrooms image classification
- High speed mushroom image classification
- Useful for all kind of peoples

Disadvantages:

- Less accessibility
- Limited scope (Classifies only 3 kinds of mushrooms only).

8 Conclusion

In conclusion, the project focused on the optical recognition and classification of various mushroom species using deep-learning methods. By leveraging transfer learning techniques and Inception V3 model, the project aimed to achieve high-performance classification accuracy. The classification of mushrooms has a wide range of applications, including food, medicine, conservation, and ecological research. By accurately identifying mushroom species based on their physical features, The project also contributes to the advancement of mycology as a scientific discipline and enthusiasts.

Overall, this project holds promise for further advancements in mushroom-related research and applications.

9 Future Scope

Expanding of classification system:

The current project focuses on three major categories of mushrooms (Boletus, Lactarius, and Russula). There is potential for expanding the classification system to include more mushroom species from various regions around the world. This expansion would enhance the knowledge base and contribute to a more comprehensive understanding of mushroom diversity.

Developing a mobile app:

Creating a user-friendly mobile application based on the trained models would make mushroom identification and classification more accessible to a wider audience.

Live Camera Detection :

This innovative approach eliminates the need for capturing and uploading mushroom images each time, as users can simply activate the camera feature, allowing for automatic real-time classification of mushrooms as soon as they are encountered.

10 Appendix

10.1 Source Code

[https://github.com/Nisar19-8/AI-Mushroom-Classification-Analysis/tree/main/Flask]

10.2 GitHub & Project Video Demo Link :

GitHub Link: [https://github.com/Nisar19-8/AI-Mushroom-Classification-Analysis.git]

Video Demo Link:[https://drive.google.com/file/d/1Q_RrViOT_4JoHVMERUEv7OQkp-iEiNzg/view?usp=sharing]