Artificial Intelligence & Machine Learning

Project Documentation

1. Introduction

1.1 Project Title

Smart Sorting: Transfer Learning for Identifying Rotten Fruits and Vegetables

2. Project Overview

2.1 Purpose:

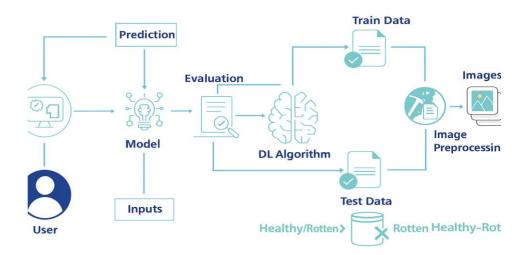
To develop an AI-powered web application that classifies uploaded images of fruits or vegetables into Healthy or Rotten categories, using Transfer Learning with VGG16, and provides:

- 1. A confidence score
- 2. A recommendation: "Good to Eat" or "Don't Eat"

2.2 Features:

- 1. Image upload with real-time classification
- 2. Real-time inference using VGG16 (Transfer Learning)
- 3. Confidence score display
- 4. "Good to Eat"/"Don't Eat" recommendation
- 5. Multi-class support (28 classes from real-world dataset)
- 6. Lightweight and optimized predictions
- 7. Feedback system for continuous learning
- **8.** Error handling (invalid input, corrupt files, etc.)

3. Architecture



3.1 Backend (Flask)

- **Framework:** Flask (Python 3.9)
- **Model:** fruit_veg_disease_model.keras trained using VGG16 with Transfer Learning
- Preprocessing:
 - o Image resizing, scaling, normalization
 - Data augmentation applied during training phase
- Modules:
 - o **app.py:** Flask routes for prediction and feedback
 - o class_names.json: JSON labels for 28 fruit/veg classes
 - o **feedback data:** Stores feedback in .json format

3.2 Frontend

- Built using HTML, Internal CSS & Jinja Templates
- Pages:
 - o index.html Upload interface
 - o **result.html** Prediction results with score and recommendation
 - o **feedback.html** Collects feedback

3.3 Model

- Model: VGG16 pretrained on ImageNet, fine-tuned with 28-class dataset
- Libraries:
 - o Keras 2.10
 - o TensorFlow 2.10
- **Optimizer:** Adam
- Loss: Categorical Crossentropy
- Evaluation:
 - o Accuracy
 - o F1 Score
- Multiple versions:
 - best_model.keras
 - o final_model.keras
 - o model_checkpoint.h5
 - o model_checkpoint.keras
 - o fruit_veg_disease_model.h5
 - healthy_vs_rotten_model.keras

3.4 Dataset

- Source: Kaggle Fruit and Vegetable Disease Dataset
- Structure:
 - o train: Healthy & Rotten classes
 - o **validation:** For evaluation
- Preprocessing Techniques Used:
 - o Image resizing & normalization
 - Data augmentation
 - o One-hot encoding for labels
 - Feature scaling

4. Setup Instructions

4.1 Prerequisites:

- Python 3.9+
- Flask 2.2.5
- TensorFlow 2.10.0
- Keras 2.10.0
- Other Python libraries (see requirements.txt)

4.2 Installation:

Step-by-step guide to clone, install dependencies, and set up the environment variables.

1. Create a virtual environment:

- 1. conda create -n smart-sorting python=3.9
- 2. conda activate smart-sorting

2. Install dependencies:

1. pip install -r backend/requirements.txt

3. Run the Flask server:

1. python backend/app.py

5. Folder Structure

• Client: Describe the structure of the HTML, With Internal CSS frontend.

• Server: Explain the organization of the Flask backend.

6. Running the Application

• Start Flask server: python backend/app.py

7. API Documentation

Route	Method	Description
/	GET	Load upload form
/predict	POST	Handle image upload & return prediction
/feedback	POST	Save user feedback to local JSON

8. Authentication

- Not implemented.
- Future Scope: Added admin panel to review feedback and retrain models.

9. User Interface

9.1 By index.html code

• Starting page



Content Page

Project: Smart Sorting

Smart Sorting is an Al-driven image classification system designed to detect whether fruits and vegetables are fresh or rotten using deep learning.

Sorting fruits and vegetables manually is time-consuming, inconsistent, and often inaccurate. Rotten items may go unnoticed, leading to customer dissatisfaction and increased waste. There is a growing need for an automated, scalable, and cost-effective solution that can reliably classify produce quality.

We propose a smart, deep learning-based solution that utilizes **transfer learning** with the **VGG16** architecture. By training on a labeled dataset of fresh and rotten produce across 28 categories, the model learns to differentiate between subtle patterns of decay, discoloration, and texture change.

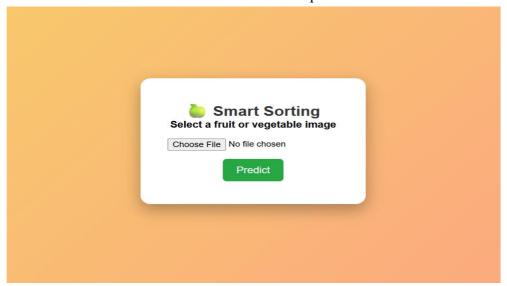
Transfer learning allows us to leverage pre-trained models like **VGG16**, which have already learned powerful feature representations from millions of general images. Instead of training a model from scratch—which requires vast amounts of labeled data and computational resources—we fine-tune the last few layers of a pre-trained model on our smaller dataset of fruit and vegetable images.

This is especially useful in detecting rot or spoilage, where the visual differences (like subtle color changes, mold, or texture distortions) can be difficult to classify with traditional image processing. Transfer learning enables high accuracy even with limited training data, speeds up development, and improves generalization.

In short, transfer learning brings deep visual underst Next I ur model—without needing to reinvent the wheel.

9.2 By result.html

• Choose a file from the trained dataset to predict Rotten or Health



• Predicted Healthy – Good to Eat

Prediction Result

Predicted Class: Bellpepper_Healthy

Confidence: 99.07%

Result: Good to Eat



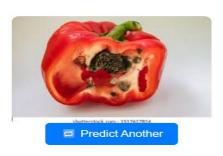
• Predicted Rotten – Don't Eat

Prediction Result

Predicted Class: Bellpepper__Rotten

Confidence: 99.89%

Result: X Don't Eat



9.3 By Feedback.html

• Feedback Form – Form Clients

	Feedback Form	
Your Name (optional):		
John Doe		
Your Email (optional):		
john@example.com		
Was the prediction acc	urate?	
0		
Yes		
0		
No		
If not, what was the cor	rect label?	
Select Correct Label		•
Additional Comments of	or Suggestions:	
Write your suggestions	or issues	

10. Testing

10.1 Data Preparation & Sample Validation

- Performed by: Mallela Suguna
- Responsibilities:
 - Cleaned and structured dataset from Kaggle
 - Organized class-wise folders for healthy/rotten images
 - o Manually checked 28-class image distribution for balance

• Validation:

- Verified preprocessed images
- o Helped ensure training/validation split had proper class representation

10.2 Model Testing

- Performed by: Durga Challa
- Responsibilities:
 - o Validated model performance on validation data
 - o Measured accuracy, confidence score, and class prediction reliability

• Results:

- o Training Accuracy: 88.49%
- Validation Accuracy: 88.26%

• Tools & Libraries:

- o TensorFlow 2.10,
- o Keras 2.10,
- o Scikit-learn

• Techniques Used:

- Confusion matrix
- o Precision, Recall, F1 Score
- Manual verification using test images

10.3 Flask & UI Integration Testing

- **Performed by**: *M M Bhavesh H R K*
- Responsibilities:
 - o Integrated Flask with HTML templates
 - o Ensured routing between /, /predict, and /feedback
 - o Handled static assets (uploaded images, result images)
- Tools Used:
 - Flask debug server
 - o Browser-based testing with real-time uploads

10.4 Web Application Testing & Feedback

- **Performed by**: *Poornima D C*
- Responsibilities:
 - o Functional testing of the entire prediction and feedback flow
 - o Validated UI pages and error handling
- Test Cases:
 - Upload valid/invalid image formats
 - Verify result and feedback routing
 - o Test data storage in feedback data/ (folder)

11. Demo

 $\underline{https://drive.google.com/file/d/1quqM_IQEYPyNyhenzheFxCVefvk2eQg1/view?usp=driv} \\ \underline{e \ link}$

12. Known Issues

• By split and copied the all the trained images and finally, I have fixed the issues.

```
Apple__Healthy: 1950 train, 488 validation
Apple__Rotten: 2340 train, 585 validation
☑ Banana_Healthy: 1599 train, 400 validation
☑ Banana__Rotten: 2237 train, 560 validation
☑ Bellpepper__Healthy: 488 train, 123 validation
☑ Bellpepper__Rotten: 472 train, 119 validation
Carrot_Healthy: 495 train, 124 validation
Carrot__Rotten: 463 train, 116 validation
Cucumber_Healthy: 486 train, 122 validation
Cucumber__Rotten: 474 train, 119 validation
Grape__Healthy: 160 train, 40 validation
☑ Grape__Rotten: 160 train, 40 validation
Guava_Healthy: 160 train, 40 validation
Guava Rotten: 160 train, 40 validation
☑ Jujube__Healthy: 160 train, 40 validation
Jujube__Rotten: 160 train, 40 validation
Mango__Healthy: 1450 train, 363 validation
Mango__Rotten: 1797 train, 450 validation
Orange__Healthy: 1660 train, 415 validation
☑ Orange__Rotten: 1748 train, 438 validation
Pomegranate__Healthy: 160 train, 40 validation
Pomegranate__Rotten: 160 train, 40 validation
Potato__Healthy: 491 train, 123 validation

✓ Potato__Rotten: 467 train, 117 validation

Strawberry_Healthy: 1282 train, 321 validation
Strawberry__Rotten: 1276 train, 320 validation
  Tomato__Healthy: 483 train, 121 validation
Tomato__Rotten: 476 train, 119 validation
```

All classes split and copied successfully!

• At last, all the trained dataset images are saved Successfully

```
Found 23417 images belonging to 29 classes.
 Found 5867 images belonging to 29 classes.
C:\ProgramData\anaconda3\tib\site-packages\keras\src\layers\convolutional\base_conv.py:113: UserWarning: Do not pass an 'input_shape'/'input_dim' argument to a layer. When using Sequential models, prefer using an 'Input(shape)' object as the first layer in the model instead.

super().__init__(activity_regularizer-activity_regularizer, "*kwargs)

C:\ProgramData\anaconda3\tib\site-packages\keras\src\trainers\data_adapters\py_dataset_adapter.py:121: UserWarning: Your 'PyDataset' class should ca

11 'super().__init__(**kwargs') in its constructor. '**kwargs' can include 'workers', 'use_multiprocessing', 'max_queue_size'. Do not pass these arg

uments to 'fit()', as they will be ignored.
 self._warn_if_super_not_called()
Epoch 1/10
 301/732 -
                                     - 9:32 1s/step - accuracy: 0.2145 - loss: 2.7656
C:\ProgramOata\anaconda3\Lib\site-packages\PIL\Image.py:1856: UserWarning: Palette images with Transparency expressed in bytes should be converted t
   warnings.warn(
 732/732
                                    - 1148s 2s/step - accuracy: 0.3190 - loss: 2.3590 - val_accuracy: 0.6934 - val_loss: 1.0414
 Epoch 2/10
 732/732 -
                                  — 851s 1s/step - accuracy: 0.6298 - loss: 1.2333 - val accuracy: 0.7825 - val loss: 0.7461
 Epoch 3/10
 732/732 -
                                 Epoch 4/10
 732/732 -
                                   - 766s 1s/step - accuracy: 0.7562 - loss: 0.7607 - val_accuracy: 0.8120 - val_loss: 0.6214
 Epoch 5/10
 732/732 -
                                  -- 731s 999ms/step - accuracy: 0.7931 - loss: 0.6454 - val_accuracy: 0.8478 - val_loss: 0.5084
 732/732 -
                                  --- 730s 997ms/step - accuracy: 0.8185 - loss: 0.5370 - val_accuracy: 0.8483 - val_loss: 0.5076
                                  --- 730s 998ms/step - accuracy: 0.8449 - loss: 0.4634 - val accuracy: 0.8596 - val loss: 0.5148
 732/732 -
 732/732 -

    723s 988ms/step - accuracy: 0.8626 - loss: 0.4120 - val accuracy: 0.8587 - val loss: 0.4980

                                  -- 793s 1s/step - accuracy: 0.8652 - loss: 0.3868 - val accuracy: 0.8749 - val loss: 0.4561
 732/732 -
                                    - 803s 1s/step - accuracy: 0.8849 - loss: 0.3402 - val accuracy: 0.8826 - val loss: 0.4252
 732/732 -
```

13. Future Enhancements

- Responsive frontend using React.js
- Admin dashboard to review feedback
- Feedback-based model retraining
- Real-time camera integration
- Model compression for mobile support