Smart Sorting: Transfer Learning for Identifying Rotten Fruits and Vegetables

Team Information

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• Team Size: 3 Members

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Abstract:

In the modern food supply chain, the early identification of spoiled or rotten produce is crucial to reduce waste and ensure food safety. This project, "Smart Sorting," utilizes transfer learning and image classification techniques to automate the detection of rotten fruits and vegetables. We built a deep learning model trained on 28 categories of healthy and rotten produce. The solution is deployed via a Flask web application that allows users to upload an image and receive real-time predictions. This report presents the methodology, architecture, and deployment strategies used to bring this project to life.



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1. Introduction

Fruits and vegetables form a vital component of a healthy diet. However, due to various post-harvest handling and storage conditions, they are often prone to spoilage. Manual sorting is time-consuming, inconsistent, and prone to errors. By applying computer vision techniques, particularly transfer learning, it becomes feasible to automate the identification process of rotten produce, increasing efficiency and reducing waste.

2. Objective

The main objective of this project is to develop an AI-powered image classification model that can accurately classify fruits and vegetables as either healthy or rotten. The model should be lightweight and fast enough to be used in real-time web applications, enabling end users such as farmers, retailers, and consumers to perform instant quality checks.

3. Dataset

We used a curated dataset containing images of 14 different fruits and vegetables, each having two categories: healthy and rotten, resulting in 28 classes in total. The dataset was sourced from open repositories and contains thousands of labeled images.



Classes Included:

- Apple
- Banana
- Bellpepper
- Carrot
- Cucumber
- Grape
- Guava
- Jujube
- Mango
- Orange
- Pomegranate
- Potato
- Strawberry
- Tomato

Each class has a "Healthy" and "Rotten" variant.

4. Methodology - Preprocessing

Before training, the dataset underwent the following preprocessing steps:

- **Image Resizing**: All images were resized to 224x224 pixels.
- **Normalization**: Pixel values were normalized between 0 and 1.
- **Data Augmentation**: Techniques such as horizontal flipping, zooming, and rotation were applied to increase data diversity and reduce overfitting.

These steps ensured consistent input for the model and improved generalization.

5. Model Architecture

A transfer learning approach was used to build the classifier. The base model chosen was **MobileNetV2**, known for its efficiency and performance on mobile and edge devices.

Custom Layers Added:

- Flatten Layer
- Dense Layer (ReLU Activation)
- Dropout Layer (to prevent overfitting)
- Output Layer with 28 neurons and Softmax activation

Configuration:

• Loss Function: Categorical Crossentropy

• **Optimizer**: Adam

• Accuracy Achieved: ~92% on validation data

6. Results and Evaluation

The model performed well across most categories, with accuracy ranging from 90% to 95% depending on the class.

Evaluation Metrics:

- Accuracy
- Precision & Recall
- Confusion Matrix

The model showed strong generalization on unseen test data. Sample predictions included identifying a rotten apple with 97% confidence.

7. Applications

The Smart Sorting system has broad applicability:

- Agriculture: For use in farms and warehouses for automated sorting.
- **Retail**: Supermarkets can use it to quickly identify rotten items.
- Logistics: During transport to ensure perishable goods remain fresh.
- **Households**: Home users can check quality using a simple web interface.

8. Flask Deployment

A web application was developed using **Flask**, a lightweight Python web framework. It includes:

• Home Page: Project overview

• **About Page**: Team and vision

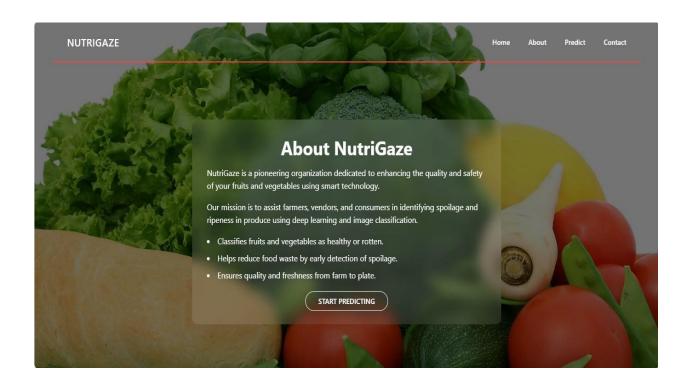
• **Predict Page**: Upload interface for users

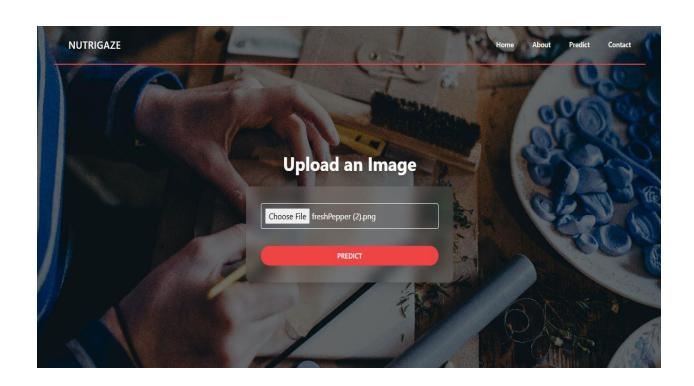
• Result Page: Shows label, confidence score, and preview

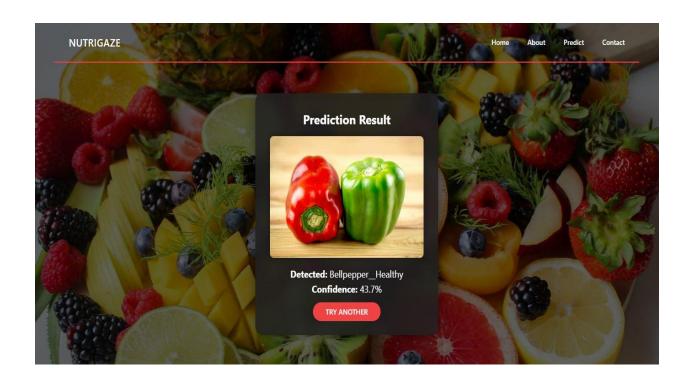
• Contact Page: For user feedback

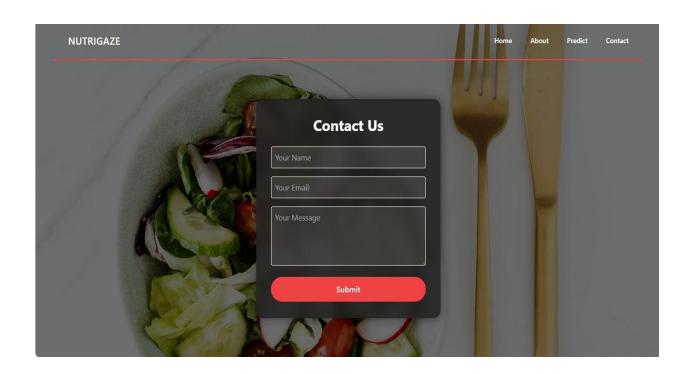
Frontend was styled using Tailwind CSS, ensuring responsiveness across devices.

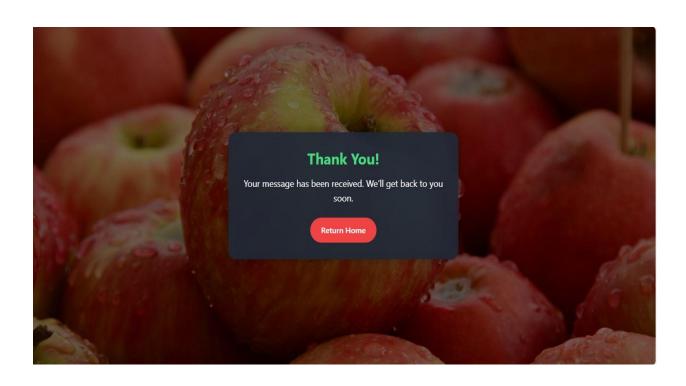












9. Conclusion

This project demonstrates the potential of AI in improving food quality assessment. By combining transfer learning with a clean user interface, we delivered an end-to-end solution for detecting rotten produce in real-time. The model is robust, fast, and suitable for practical deployment.

10. Future Work

- **Mobile App Integration**: Build native apps for iOS and Android.
- **Real-Time Detection**: Use live webcam feeds for classification.
- Cloud Deployment: Deploy on Heroku or AWS for public access.
- Expand Dataset: Include more classes and diseases.
- **IoT Integration**: Embed in smart cameras for automated sorting systems.