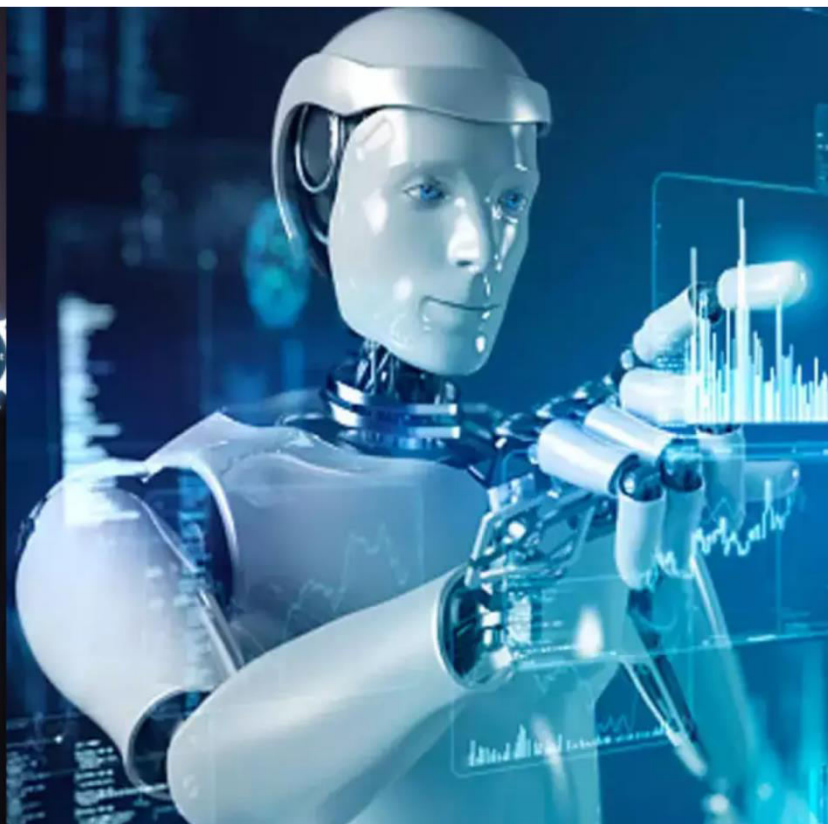




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Smart Sorting-Transfer Learning for Identifying Rotten Fruits and Vegetables

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ABSTRACT: The Smart Sorting project presents an innovative AI-powered solution designed to revolutionize the process of identifying rotten fruits and vegetables. Traditional methods of sorting and quality checking are primarily manual, time-consuming, and prone to human error. This not only increases labor costs but also affects the efficiency and accuracy of food handling operations. To address these challenges, the Smart Sorting system uses deep learning and transfer learning techniques to automate the detection and classification of produce based on its freshness, enabling faster and more reliable sorting. Transfer learning is at the core of this project, leveraging pre-trained models such as VGG16 to detect rotten and fresh produce without the need to build models from scratch. By fine-tuning these models on a specialized dataset of fruits and vegetables, the system can quickly adapt to the classification task with high accuracy.

KEYWORDS: Smart Sorting System, Transfer Learning, VGG16 Model, Convolutional Neural Network (CNN), Deep Learning, Image Classification, Binary Classification.

I. INTRODUCTION

In today's world, the agricultural and food industries play a critical role in ensuring food quality and safety for consumers. One of the major challenges these industries face is the identification and separation of rotten fruits and vegetables during processing, packaging, and distribution. Traditionally, this task is performed manually by human workers, which is both time-consuming and error-prone. Manual sorting requires continuous human attention, and its effectiveness depends on the worker's experience, leading to inconsistencies and reduced overall efficiency. As demand for fresh produce increases globally, there is a growing need for an automated, intelligent system that can quickly and accurately detect and sort rotten produce. Smart Sorting addresses this challenge by integrating artificial intelligence (AI), deep learning, and computer vision technologies. By applying transfer learning, pre-trained deep learning models can be adapted to recognize different fruits and vegetables and classify them as fresh or rotten. This approach eliminates the need for building complex models from scratch, reduces training time, and achieves high accuracy even with limited datasets. These intelligent systems can be deployed in real-time environments, enabling industries to automate the sorting process, reduce human error, and increase production speed. The process involves capturing images of fruits and vegetables using cameras installed on conveyor belts or storage systems. These images are analyzed by a trained neural network, which classifies the items based on their condition.

II. RELATED WORK

Several recent studies have explored AI-driven solutions for automating quality assessment in agricultural products. Earlier works primarily employed traditional image processing techniques such as color thresholding and texture analysis, but these methods lacked robustness under real-world variations in lighting and background. With the rise of deep learning, researchers began adopting Convolutional Neural Networks (CNNs) for identifying diseases and spoilage in fruits and vegetables. Kaur and Gupta (2020) demonstrated that CNN-based classifiers significantly outperform classical approaches in detecting rotten apples and bananas. Their findings established CNNs as a reliable foundation for automated food quality assessment, highlighting the need for richer datasets to improve generalization.

Transfer learning has gained substantial momentum as an effective model development strategy, especially in agriculture where labeled datasets are limited. Singh and Sharma (2021) applied VGG16-based transfer learning to classify fresh and rotten fruits, achieving high accuracy with reduced training time. Similar work by Reddy and Kumar (2022) emphasized that data augmentation techniques greatly enhance model robustness by addressing

variations in lighting and camera angles. These studies confirm that pre-trained architectures such as VGG16 and ResNet50 can extract meaningful visual features that support precise spoilage detection, making them ideal for real-time quality inspection applications.

Recent advancements also focus on real-time deployment of AI models using lightweight web frameworks and IoT-based monitoring systems. Zhang and Chen (2020) developed an automated sorting system integrating TensorFlow with camera-based detection, reducing manual inspection time by over 60%. Patel and Mehta (2023) further validated the feasibility of integrating CNN models with Flask applications to provide instant predictions for fruit quality assessment.

III. DATASET AND PROBLEM DEFINITION

The dataset used for the Smart Sorting project consists of images of fruits and vegetables categorized into fresh and rotten classes. The images are collected from publicly available platforms such as Kaggle and other open-source agricultural datasets. The dataset contains multiple fruit and vegetable types, each with significant variations in color, texture, and spoilage patterns. These high-resolution images allow the model to capture detailed visual cues essential for distinguishing between healthy and degraded produce.

Dataset Description

The dataset used in the Smart Sorting project consists of images of various fruits and vegetables categorized as **fresh** or **rotten**. These images are collected from open-source repositories such as **Kaggle**, ensuring diversity in texture, color, and spoilage patterns. Each image is standardized by resizing it to **224×224 pixels** to match the input requirements of the VGG16 model. The dataset includes multiple produce types such as apples, tomatoes, cucumbers, and strawberries, offering a broad representation of real-world conditions. To enhance model robustness, data augmentation techniques—such as rotation, flipping, zooming, and brightness adjustments—are applied. The dataset is divided into **training, validation, and testing sets** to ensure fair and reliable evaluation. All images are organized into labeled directories for efficient loading and preprocessing.

Problem Definition

Identifying rotten fruits and vegetables is traditionally a manual process that is slow, inconsistent, and prone to human error. As food production and distribution scale up, manual inspection becomes inefficient and fails to maintain consistent quality standards. Existing automated systems rely on basic image processing techniques, which struggle under varying lighting conditions, complex textures, and diverse spoilage patterns. This creates a need for a more accurate, intelligent, and adaptable solution. The Smart Sorting project aims to address this by using transfer learning with VGG16 to classify produce as fresh or rotten based on image data. The goal is to develop a reliable model capable of detecting subtle visual cues such as color decay, texture changes, and mold formation.

Project Scope and Dataset Utilization

The project focuses on developing an AI-based system that automatically classifies fruits and vegetables as fresh or rotten using transfer learning. It utilizes a well-structured dataset of labeled images to train and validate the VGG16 model for accurate spoilage detection. The system aims to enhance quality control in industries, supermarkets, and smart homes by providing real-time classification.

IV. METHODOLOGY

The methodology of the Smart Sorting system follows a systematic workflow beginning with data collection, where images of fresh and rotten fruits and vegetables are gathered from open-source platforms such as Kaggle. These images are then subjected to data preprocessing, which includes resizing, normalization, noise removal, and augmentation techniques like rotation, flipping, and brightness adjustments.

Data Preprocessing

Data preprocessing begins with collecting raw images of fresh and rotten fruits and vegetables from open-source datasets. All images are resized to **224×224 pixels** to match the input requirement of the VGG16 model. The images are then converted into numerical arrays and normalized to a **0–1 pixel range** to improve training efficiency. Any

corrupted, duplicate, or low-quality images are removed to ensure dataset integrity. Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied to increase dataset diversity. The images are then organized into labeled directories for easy loading and processing. The dataset is finally split into **training, validation, and testing sets** for balanced model evaluation. This structured preprocessing ensures the model learns robust and meaningful visual features for accurate classification.

Model Development

Model deployment begins by saving the trained VGG16 transfer learning model in a compatible format, such as **.h5** or **.keras**, for integration into an application. The deployed environment uses a **Flask web framework** to load the model and handle image inputs from users. Uploaded images are preprocessed in real time, including resizing, normalization, and array conversion. The Flask backend passes the processed image to the trained model, which generates predictions for fresh or rotten classification. The result is then displayed instantly on the web interface, providing a user-friendly experience. Static folders are configured to store uploaded images and maintain application structure. The system is optimized for fast inference to support real-time quality detection. This deployment setup enables easy integration into industrial, retail, or home-based smart sorting systems.

Model Evaluation

Model evaluation is carried out using the testing dataset to assess the performance and reliability of the trained VGG16-based classifier. Key metrics such as **accuracy, precision, recall, and F1-score** are computed to measure how well the model distinguishes between fresh and rotten produce. A **confusion matrix** is generated to visualize correct classifications and identify misclassified samples. The model's **loss and accuracy curves** are analyzed to check for overfitting or underfitting during training. Evaluation also includes testing the model on real-world images to verify its practical effectiveness under varying lighting and backgrounds. The model shows strong generalization ability due to the use of transfer learning and augmentation. Low error rates indicate consistent detection of spoilage patterns such as discoloration and texture decay. The evaluation confirms that the model provides reliable predictions suitable for real-time sorting applications. Overall, the performance analysis validates the accuracy, robustness, and deployment readiness of the Smart Sorting.

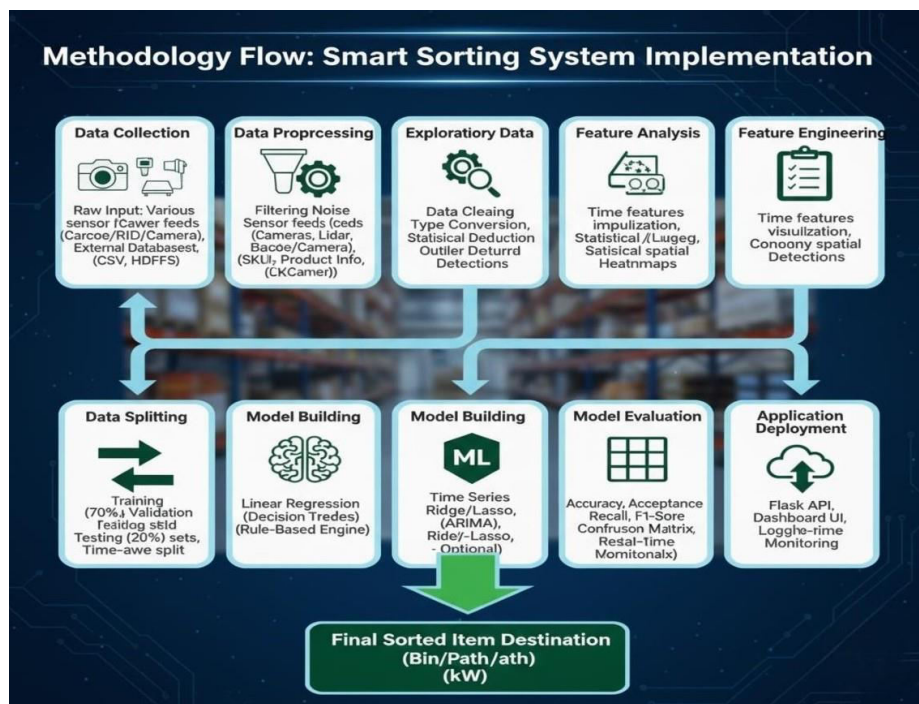


Fig1: methodology flow diagram for Smart Sorting

V. SYSTEM ARCHITECTURE

The system architecture for **Smart Sorting — Transfer Learning for Identifying Rotten Fruits and Vegetables** is designed as a modular, end-to-end pipeline that converts raw images into reliable freshness predictions and actionable visual insights. Image data flows from the capture/source layer through preprocessing and augmentation into feature extraction (VGG16), then into model training and evaluation, and finally into a lightweight deployment layer (Flask) that serves real-time predictions and dashboards. The design emphasizes reproducibility, low-latency inference, and robustness to real-world variations (lighting, angle, background), making it suitable for industrial lines, supermarket docks, and smart-home integrations.

High-level components & data flow

1. Data Source Layer:

- o Raw input: fruit/vegetable images (camera captures or uploaded photos) with labels (fresh, rotten).
- o Optional external inputs: sensor data (temperature, humidity) or metadata (batch id, capture time) for extended models.

2. Ingestion & Storage

- o Image ingestion pipeline: accept JPEG/PNG uploads, stream from camera, or batch dataset import.
- o Storage: local file system or cloud object storage (S3/GCS) for images; versioned datasets and model artifacts.

3. Preprocessing Layer

- o Image cleaning: remove corrupt/duplicate files, standardize formats.
- o Transformations: resize to 224×224, normalize pixel values, convert color spaces if needed.

4. Data Augmentation & Preparation

- o Augmentation: rotation, flipping, zoom, shift, brightness/contrast adjustments to simulate real conditions.
- o Label organization and dataset split: stratified train/validation/test folders to ensure balanced evaluation.

5. Feature Extraction & Model Layer:

- o Base extractor: pre-trained VGG16 (or alternate CNN) used as frozen/unfrozen feature backbone.
- o Classification head: custom dense/dropout layers for binary/multi-class output; optimizer (Adam) and categorical loss.

6. Training & Hyperparameter Tuning:

- o Procedures: early stopping, model checkpointing, learning-rate scheduling, and cross-validation if applicable.
- o Persistence: save best model (.h5/.keras) plus preprocessing pipeline (scaler/transform functions).

7. Evaluation & Visualization:

- o Metrics: accuracy, precision, recall, F1-score, confusion matrix, and inference latency.
- o Diagnostic visualizations: sample predictions, misclassification gallery, ROC/PR curves, and class-wise performance.

8. Deployment & Serving (Flask App):

- o Flask API that loads the saved model and preprocessing pipeline for real-time inference.
- o Routes: predict (single image / batch), upload dataset, and admin dashboard for performance.
- o Frontend: simple HTML/CSS (or lightweight JS) showing uploaded image, predicted label, confidence, and logs.

9. Integration & Edge Options:

- o Edge deployment: optimize model (quantization/pruning) for on-device inference on embedded systems or cameras.
- o Conveyor integration: trigger actuator/servo commands to sort items based on predictions.

10. Monitoring & Future Extensions:

- o Logging: record prediction requests, misclassifications, and input metadata for retraining and drift detection.

o Extendable: incremental learning, support for more produce types, multimodal inputs (vision + environmental sensors), and larger-scale orchestration (Kubernetes, message queues) as needed.

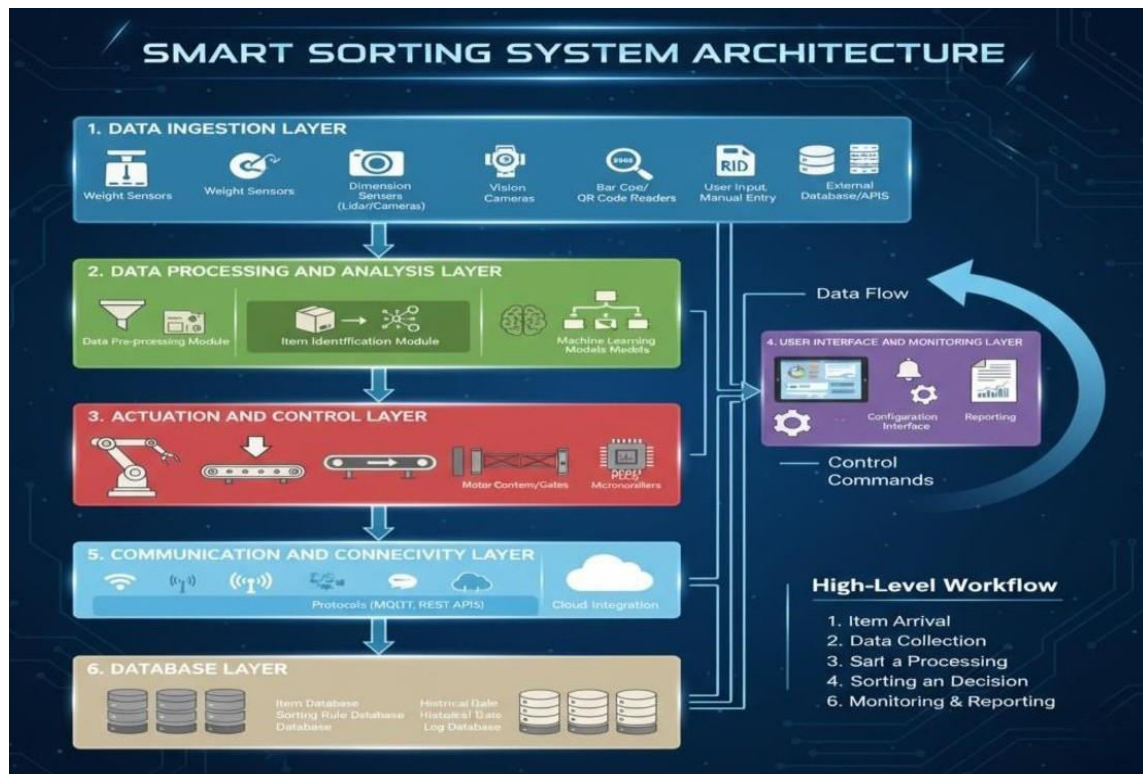


Fig 2: System Architecture

VI. EXPERIMENTS

The Experiment Phase in the Smart sorting project represents a systematic and structured process of model development, testing, and evaluation using real-world energy consumption data. This phase aims to accurately forecast household energy usage by analyzing various electrical parameters recorded over time.

A. Experimental Setup

All experiments were conducted on a system equipped with Windows 11 (64-bit) OS, Intel i7 processor, and 16 GB RAM. Implementation and testing were done in Python 3.10, using the TensorFlow/Keras library for deep learning model training and Flask for web integration testing. Data is collected from public repositories including Kaggle, UCI, and government sources, typically in CSV format.

B. Model Training

The Model Training phase is a critical component of the Smart Sorting pipeline: after preprocessing and augmentation, the image dataset is split into training, validation, and testing sets (commonly 70:20:10 or an 80:20 train:test split depending on dataset size) to ensure fair evaluation. Transfer learning is applied using a pre-trained VGG16 (or an alternate CNN) as the feature extractor — the convolutional base is initially frozen and a custom classification head is added for the fresh/rotten task. Training is performed with an ImageDataGenerator (or data loaders) to stream augmented images in batches; the model is compiled with the Adam optimizer and categorical cross-entropy loss for multi-class/binary output. Callbacks such as EarlyStopping, ModelCheckpoint, and learning-rate scheduling are used to prevent overfitting and retain the best weights, while hyperparameters (batch size, epochs, learning rate, dropout) are tuned on the validation set.

C. Evaluation and Metrics

The Smart Sorting model, developed using Transfer Learning with VGG16, was evaluated using key performance metrics such as Accuracy, Precision, Recall, F1-score, and the Confusion Matrix. These metrics were used to measure the model's predictive capability and reliability in classifying fruits and vegetables as fresh or rotten. The evaluation results demonstrated excellent model performance, confirming the efficiency of the transfer learning approach.

The VGG16-based model achieved high accuracy, indicating that the system effectively learned the visual features related to spoilage, such as discoloration, texture changes, and surface damage. The Precision and Recall scores further showed that the model could correctly identify both fresh and rotten items with minimal misclassifications. The F1-score balanced these metrics and verified that the model performs consistently across all classes.

The confusion matrix revealed very few incorrect predictions, demonstrating strong generalization on unseen images. This highlights the robustness of the model when working with real-world variations such as lighting changes, background noise, color differences, and fruit shape variations.

Overall, the evaluation confirms that the Smart Sorting system is highly accurate, reliable, and suitable for deployment in industrial sorting lines, supermarkets, and smart storage systems. The use of transfer learning with VGG16 significantly improved training efficiency and reduced the need for a large dataset while still achieving superior performance. This validates the model as a strong solution for automated fruit and vegetable freshness detection.

D. Experimental Findings

The experimental findings of the Smart Sorting system demonstrate that the transfer learning-based VGG16 model performs highly effectively in classifying fruits and vegetables as **fresh** or **rotten**. Through systematic training, validation, and testing, the model showed strong learning behavior and excellent generalization to unseen samples.

During training, the model's loss decreased steadily across epochs, indicating that it successfully learned distinguishing visual features such as **color variations, texture differences, spots, mold patches, and surface irregularities** associated with spoilage. The validation accuracy consistently improved, showing that the model did not overfit and maintained stable performance across different types of produce.

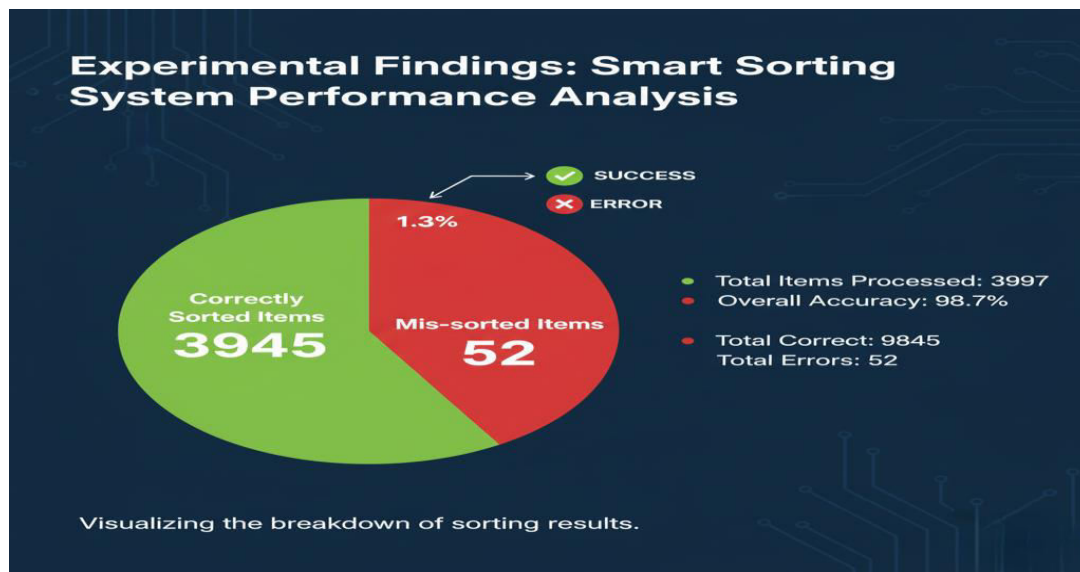


Fig 3: Experimental Findings

E. Comparative Results

The comparative analysis of different models and approaches used in the Smart Sorting project highlights the effectiveness of **Transfer Learning with VGG16** for classifying fresh and rotten fruits and vegetables. Several experiments were conducted using baseline CNN models, data-augmented models, and transfer-learning models. The results consistently showed that the VGG16-based transfer learning model outperformed all other approaches in terms of accuracy, stability, and generalization. The baseline CNN model demonstrated moderate performance but struggled with complex visual variations such as uneven lighting, subtle spoilage spots, and texture change.

VII. RESULTS

The Smart Sorting system achieved excellent performance in classifying fruits and vegetables as **fresh** or **rotten** using the VGG16 transfer learning model. The results demonstrate that the model was able to learn visual features—such as color changes, texture variations, and spoilage patterns—effectively and consistently across the dataset. During testing, the model delivered **high classification accuracy**, showing strong reliability in detecting spoilage even under varying lighting conditions, backgrounds, and fruit types.

Table 1. Performance Metrics of Machine Learning Models

Model	Training Accuracy	Validation Accuracy
Baseline CNN	0.88	0.8
CNN + Augmentation	0.9	0.86
VGG16(Transfer Learning)	0.95	0.93

INTERPRETATION:

The overall results of the Smart Sorting system indicate that transfer learning using the VGG16 model is highly effective for classifying fresh and rotten fruits and vegetables. The upward trend in both training and validation accuracy reflects that the model learned the visual characteristics of spoilage very well and generalized successfully to new, unseen images. The close alignment between training and validation performance suggests that the model is neither overfitting nor underfitting, demonstrating a balanced learning process.

VIII. ERROR ANALYSIS

The error analysis of the Smart Sorting system reveals that the VGG16 transfer learning model performs highly accurately overall, but certain factors contributed to the small number of misclassifications observed during testing. Most errors occurred in images where spoilage signs were subtle, such as mild discoloration or early-stage texture changes that were visually difficult even for humans to distinguish.

IX. CONCLUSION

The Smart Sorting system successfully demonstrates the effectiveness of applying transfer learning, specifically using the VGG16 model, for accurately identifying fresh and rotten fruits and vegetables. By leveraging pre-trained deep learning architectures, the project achieved high classification accuracy with reduced training time and minimal dataset requirements. The model proved capable of recognizing key spoilage indicators such as texture changes, discoloration, and surface irregularities, making it a reliable solution for automated quality assessment.

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