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Fresh and Rotten Fruit Classification

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***Abstract*—Ensuring fruit quality through automation is becoming increasingly important in agriculture to maintain food safety and minimize post-harvest waste. This study proposes an automated system for identifying fresh and spoiled fruits by integrating Convolutional Neural Networks (CNN) and Random Forest Classifiers (RFC). The experiments were carried out using a publicly available Kaggle dataset containing 11,257 images of apples, bananas, and oranges. Image preprocessing steps such as resizing, normalization, and data augmentation were performed to enhance model robustness. The CNN model achieved a validation accuracy of 96.9% with an F1-score of 0.97, outperforming the RFC, which recorded 94.7% accuracy and an F1-score of 0.95. The CNN demonstrated superior feature extraction from spatial patterns, whereas RFC performance was constrained by its reliance on flattened image data. Furthermore, a web-based interface was implemented to allow users to upload fruit images and obtain classification results in real time. This research highlights the potential of combining traditional and deep learning techniques for intelligent fruit grading and real-time quality assessment in agricultural systems.**

Keywords—Deep Learning, Machine Learning, CNN, Random Forest Classifier, Fruit Classification.

I. Introduction

Fruit quality plays a critical role in the agricultural and food industries, where freshness directly affects market value, consumer satisfaction, and nutritional benefits. Traditionally, fruit inspection is done manually, relying heavily on human observation [1][2]. This method is labour-intensive, inconsistent, and prone to human error, making it unsuitable for large-scale commercial applications. As a result, there is a growing demand for automated fruit classification systems that are accurate, reliable, and efficient.

According to the Food and Agriculture Organization (FAO), nearly 45% of fruits and vegetables are wasted globally due to spoilage, contributing to severe economic and food security challenges [3][4]. Such high post-harvest losses highlight the need to adopt intelligent solutions that detect fruit freshness at early stages, thereby reducing waste across the supply chain [5][6]. Recent advances in artificial intelligence, particularly in ML and DL, have shown great promise in addressing these challenges by providing robust classification models for agricultural applications[7][8].

The contributions of this work are as follows:

- Development of a CNN-based model for fruit freshness classification with high accuracy.
- Comparative analysis with a classical machine learning approach (Random Forest Classifier) to evaluate performance differences.
- Creation of a real-time web interface that allows.
- users to upload fruit images for instant classification.
- Demonstration of the system's robustness on both benchmark datasets and real-world test cases.

Thus, this study not only evaluates the effectiveness of CNN and RFC models for fruit freshness classification but also bridges the gap between research and practice by integrating a real-time deployment framework.

II. Literature Review

This section shows substantial improvements in computer vision, machine learning, and deep learning-based automated fruit freshness and quality assessment methods, with Convolutional Neural Networks (CNNs) becoming the most effective for differentiating fresh and rotten fruits across various data sets. Table I summarizes the key methods, datasets, accuracies, and limitations of representative works that identify trends in research and motivate the development of robust, real-time fruit classification systems.

Fischer-Brandies et al. (2025) Fresh or Rotten? Enhancing Rotten Fruit Detection with Deep Learning and Gaussian Filtering" by L. Fischer-Brandies, L. Muller, J. J. Riegger, and R. Buettner aims to reduce food waste by improving the accuracy of fruit spoilage detection. The authors introduced a binary classification framework that utilizes transfer learning with the ResNet50 architecture to differentiate between fresh and decayed fruits. A key innovation of their approach is the inclusion of a Gaussian filter during image preprocessing, which enhances image clarity, alongside the use of dropout layers to mitigate overfitting in the network. The proposed model achieved an impressive accuracy of over 99% on unseen test data, outperforming previous studies in this domain. Notably, this work is among the first to combine Gaussian filtering with deep learning for fruit attribute assessment, demonstrating that using smaller filter kernels can further improve performance. The study underscores the practical benefits of such automated detection systems for food safety, waste reduction, and cost efficiency across agricultural supply chains [9].

Goyal and Lakhwani (2025), "Automated Fruit Disease Diagnosis Leveraging Machine Learning Techniques," explore the design of an automated framework for detecting and classifying fruit diseases using modern machine learning and deep learning approaches. The primary goal of the research is to help farmers and agricultural professionals by enabling faster, more accurate identification of fruit diseases that directly affect yield, quality, and productivity. The authors used a large and diverse dataset of fruit images covering multiple disease types. They implemented preprocessing techniques such as noise reduction, image scaling and augmentation to improve model robustness. Features such as color, texture, and shape were extracted using image processing methods to capture distinguishing characteristics among disease categories. Several algorithms including Random Forest (RF), K-Nearest Neighbors (KNN), Support Vector Machine (SVM) and Convolutional Neural Networks (CNN) were evaluated to compare their classification performance. Among these, the CNN model achieved strong results, highlighting its effectiveness in recognizing complex visual patterns in agricultural datasets. Model performance was evaluated using accuracy, precision, recall and F1-score to ensure consistent and reliable outcomes. The study also proposed potential real-world applications, such as integrating the system into mobile or web-based agricultural monitoring platforms to enable early disease detection and prevention. Overall, the work highlights the effectiveness of adding both machine learning and image processing to create scalable, automated tools for fruit disease diagnosis and crop management [10].

Sharma and Kumar (2025)"Automated Classification of Fresh and Rotten Fruits Using ResNet50 for Enhanced Food Quality Control and Waste Reduction" by J. Sharma and B. V. Kumar highlights the role of automation in fruit classification for ensuring food safety, maintaining consistent quality and minimizing post-harvest losses. In this work, the authors used the ResNet-50 Convolutional Neural Network (CNN) to classify fruit images as fresh or spoiled. The dataset consisted of 1,655 images split into six classes, including fresh and decayed samples of peaches, pomegranates, and strawberries. The model achieved an overall accuracy of 95% and demonstrated strong precision, recall, and F1 Scores, particularly in distinguishing between fresh pomegranates and rotten strawberries. Analysis through a confusion matrix identified minor classification errors and provided insights for further optimization. The experimental results confirmed that the model exhibited robust generalisation and minimal overfitting, proving its reliability across different fruit categories. Overall, the research establishes ResNet50 as an effective and scalable solution for automated fruit quality monitoring, thereby reducing food waste, enhancing supply chain efficiency, and improving industrial quality management in the agricultural sector [11].

Singh, Guleria and Sharma (2024)"Advanced Fruit Sorting: Pre-trained ResNet50 Model for Rotten and Fresh Fruit Classification" by G. Singh, K. Guleria, and S. Sharma investigates the use of deep learning methods to automate fruit quality assessment, focusing on distinguishing between fresh and decayed produce. The authors fine-tuned a pre-trained ResNet50 model to classify a variety of fruit images while addressing challenges such as class imbalance and visual feature overlap. The system achieved an accuracy of 97%, indicating strong and consistent performance across different fruit types. Evaluation metrics showed macro-averaged precision, recall, and F1 Scores around 0.95, while the weighted F1 Score reached 0.97, confirming the model's stability despite uneven data distribution. Although most fruit classes performed well, a few (specifically classes 2042 and 2046) had lower recall values of 0.64-0.67, likely due to limited training samples or visual similarity. The researchers suggested improvements, such as augmenting the data, adjusting class weights, and enhancing feature representations, to address these shortcomings. Overall, the study demonstrates that ResNet50-based deep learning architectures can serve as powerful and efficient tools for automated fruit classification, improving quality control and productivity in agricultural supply chains [12].

Göksu, Kaya, and Sahmoud's (2023) paper, "Classification of Fruit Images as Fresh and Rotten Using Convolutional Neural Networks," by T. Göksu, Z. Kaya, and S. Sahmoud, focuses on addressing fruit spoilage, a major factor contributing to economic losses and reduced product quality during storage and transportation. To mitigate this problem, the authors proposed an automated classification system that distinguishes between fresh and spoiled fruits, formulated as a binary classification task. The study utilized a dataset of fruit images representing both healthy and decayed samples, on which multiple Convolutional Neural Network (CNN) architectures were trained and analyzed to assess their classification performance. Among these, the ResNet50 model combined with real-time data augmentation achieved the highest accuracy, approximately 90%. The findings indicate that CNN-based models can provide faster, more precise, and more reliable fruit quality evaluations than manual inspection. Additionally, the authors highlight the value of automated visual inspection systems in minimizing human error, reducing labour costs and ensuring consistent quality assessment, particularly in large-scale agricultural production and supply chain environments [13].

Hamim et al. (2023) paper "Bangladeshi Fresh-Rotten Fruit & Vegetable Detection Using Deep Learning Deployment in Effective Application" by M. A. Hamim and J. Tahseen emphasises the need for automation in detecting over ripe fruits and vegetables to improve quality control in agriculture. The authors note that hands-on inspection is often time-consuming, labour-intensive, and prone to human error, whereas computer vision offers a more reliable and scalable alternative. In this study, a deep learning-based classification model was developed to distinguish between fresh and rotten produce, reducing manual effort and preventing post-harvest spoilage. The dataset included twelve varieties of fruits and vegetables, such as carrots, potatoes, cucumbers, eggplants, mangoes and bananas. To evaluate performance, the researchers tested different algorithms, including Convolutional Neural Networks (CNNs), K-Nearest Neighbours (KNN), and Support Vector Machines (SVMs). Among these, the CNN model achieved the highest accuracy of 95% on images collected from Google and Kaggle, demonstrating its effectiveness in automating freshness detection and quality assessment [14].

Chouhan et al. (2023)"Classification of Rotten Fruits vs Fresh Fruits Using Sequential Model with Convolutional Neural Network" by M. Chouhan, P. S. Banerjee, A. Kumar, and J. Kushwaha investigates the application of DL techniques for the automatic detection of fruit freshness. In this study, they designed a Convolutional Neural Network (CNN)-based sequential model trained on a Kaggle dataset comprising images of apples, bananas, and oranges. To improve generalization and reduce overfitting, dropout layers were incorporated into the network architecture. The pre-processing, trained and evaluated using TensorFlow, OpenCV, and Matplotlib, ensuring reliable and accurate model assessment. The proposed CNN achieved a remarkable accuracy of 98.79% in classifying fruits as fresh or rotten. Additionally, the authors applied transfer learning, which further confirmed the model's robustness and suitability for real-world implementation. Overall, the research highlights the capability of CNN architectures, combined with advanced preprocessing techniques, to deliver efficient and precise fruit-quality classification for agricultural and food-industry applications [15].

Raut et al. (2022)"Classification of Fruits using Convolutional Neural Networks" by R. Raut, A. Jadhav, C. Sorte, and A. Chaudhari introduces a supervised deep learning model designed to classify various fruit types. The authors employed a feed-forward neural network trained on a dataset containing attributes such as mass, width, height, and color score, representing fruits including apples, mandarins, oranges, and lemons. Before training, the data was normalized with a Min-Max Scaler, and the categorical labels were encoded with one-hot encoding. The network architecture featured an input layer with four neurons, two hidden layers with 10 and 8 neurons, and an output layer with SoftMax activation for multi-class classification. The model was trained for 100 epochs with the Adam optimizer and categorical cross-entropy loss, with a batch size of 10. It delivered excellent performance, achieving an accuracy of 96.67%, a precision and recall of 96.88%, and an F1-score of 0.96. The confusion matrix showed very few misclassifications, validating the model's robustness and accuracy in fruit recognition based on measured characteristics [16].

Taohidul Islam et al. (2020)"Mango Fruit's Maturity Status Specification Based on Machine Learning using Image Processing" by S. M. T. Islam, M. Nurullah, and M. Samsuzzaman introduces an automated approach for evaluating the ripeness of mangoes through image processing and machine learning techniques. The primary aim of the study is to develop a more efficient and objective alternative to traditional manual sorting methods, which are often slow and prone to human error. Mango images were captured under restricted lighting conditions to ensure uniformity and accuracy. Pre-processing procedures such as resizing, noise filtering and colour space conversion were applied to improve the visual quality of the data. Using color-based segmentation, the mango portion was separated from the background to extract crucial visual attributes, including color, texture, and shape. The researchers analyzed both the RGB and HSV color models to accurately assess ripeness levels. Those features used to train Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) classifiers, which categorized the samples into immature, mature and overripe classes. The results show that the SVM model, particularly when using HSV features, achieved higher accuracy and stability than KNN. The authors determined that this framework offers a reliable and efficient method for automatic fruit grading and post-harvest quality assessment, demonstrating the potential of combining machine learning with image analysis to enhance agricultural productivity and quality control [17].

Karakaya, Ulucan and Turkan (2019)"A Comparative Analysis on Fruit Freshness Classification" by D. Karakaya, O. Ulucan, and M. Turkan investigates improved methods for evaluating fruit freshness within the food industry. The authors pointed that conventional techniques for detecting spoilage are often slow, labour-intensive and inconsistent. To overcome these drawbacks, they developed a computer vision-based framework that distinguishes fresh from spoiled fruit using images of three fruit varieties. Several feature extraction techniques are tested, including histogram analysis, gray-level co-occurrence matrices (GLCM), bag-of-features, and Convolutional Neural Networks (CNNs). The grouping process was performed using Support Vector Machines (SVM). Experimental results showed that CNN-extracted features reached the peak accuracy in both binary (fresh vs. rotten) and multi-class scenarios, confirming that deep learning-based approaches provide a powerful and efficient solution for automated fruit freshness detection [18].

TABLE I. LITERATURE SUMMARY ON FRESH AND ROTTEN FRUIT CLASSIFICATION

Authors & year	Methods used	Dataset/ Fruits	Accuracy	Limitations
Goyal et.al. 2025	ML+CNN	Fruit disease dataset	~95%	Focused on disease, not freshness
Sharma et.al., 2025	ResNet50	Peaches & strawberries	95%	Limited fruit types
Fischer-Brandies et al., 2025	ResNet50+Gaussian Filter	Fresh/ rotten fruits	99%	Limited focus on preprocessing only
Singh, et.al., 2024	ResNet50(DL)	Mixed fruits	97%	Class imbalance
Göksu, et.al., 2023	CNN	Fresh/ rotten fruits	~90%	Small dataset
Hamim et al., 2023	CNN, SVM, KNN	12 fruits/ vegetables	~95%	Google-sourced noisy dataset
Chouhan et al., 2023	Sequential CNN	Apples, bananas and oranges	98.7%	Only three fruit types
Raut et al., 2022	Feed-Forward NN	Fruit attribute	96.7%	Limited to non-image features
Taohidul Islam et al., 2020	SVM & KNN	Mango images	92%	Fruit-specific approach
Karakaya, et.al., 2019	CNN+SVM	3 fruits	>90%	Outdated dataset

III. MATHEMATICAL FRAMEWORK

A. Convolutional Neural Network (CNN):

1) Convolutional layer

For an input image I of size $H \times W \times C$ and a filter F of size $K \times K \times C$, the convolution operation at position(i, j) is defined in Equation. (1) as:

$$O(i,j) = \sum\sum\sum I(i+m, j+n, c).F(m,n,c) + b \quad (1)$$

2) Activation function

Non-linear activation introduces complexity into the network. The Rectified Linear Unit (ReLU) is defined in Equation. (2) as:

$$\text{Ρ}\varepsilon\Lambda\Upsilon\ (x) = \max(0, x) \tag{2}$$

3) Pooling Layer

Keeping the salient features unchanged, pooling reduces the spatial dimensions. Max-Pooling is expressed in the equation. 3 as:

$$O(i, j) = maxI(i.S + m, j.S + n) \tag{3}$$

4) Fully connected layer

The final classification layer applies the SoftMax function in Equation 4:

$$P(y_k|x) = \frac{\exp(w_k^T x + b_k)}{\exp \sum \ \left(w_j^T x + b_j\right)} \tag{4}$$

5) Loss Function

The model is trained using categorical cross-entropy loss shown in Equation. 5:

$$L = -\sum\sum y_i, k \log\left(P(y_i, k\ |x_i)\right) \tag{5}$$

B. Random Forest Classifier

1) Decision Tree

A decision tree splits data recursively. For feature x_j and threshold t, defined in the equation. (6)

$$S_{left} = \{x|x_j > t\} \tag{6}$$

The impurity of a split is quantified using Gini index, defined in Equation. 7:

$$G = 1 = \sum p_k^2 \tag{7}$$

2) Ensemble of Trees

Random Forest constructs T decision trees and determine the final prediction via majority voting, as defined in the Equation. 8:

$$\hat{y} = mode\{h_{t(x)}\} \tag{8}$$

3) Feature Importance

Feature importance is measured by the average impurity reduction contributed by a feature across all trees, defined in Equation. (9)

$$Importance(x_j) = \left(\frac{1}{T}\right) \sum\sum \Delta G_{\{n,j\}} \tag{9}$$

IV. METHODOLOGY

The presented framework for fruit freshness classification combines a deep learning tactic using Convolutional Neural Networks (CNN) with a classical machine learning approach using Random Forest Classifier (RFC). The methodology includes dataset preparation, preprocessing, model development, evaluation, and real-time testing.

A. Data Collection

A freely accessible Kaggle dataset titled "Fruits Fresh and Rotten for Classification" was used. It contains images of apples, bananas, and oranges categorized as fresh or rotten. The dataset distribution is shown in Table II:

TABLE II. DATASET DISTRIBUTIONS

Data-set Name	Fruits, fresh and rotten, for classification
Total No. of samples	11,257
No. of training samples	8,559
Fresh	4,740
Rotten	3,819
No. of testing samples	2,698
Fresh	1,164
Rotten	1,534

B. Methods

Data pre-processing:

1) For CNN training:

- **Resizing:** All images were resized to 128×128 pixels.
- **Normalization:** Pixel intensity values were scaled to a range between 0 and 1.
- **Label Encoding:** Class labels were encoded numerically Fresh = 0 and Rotten = 1.
- **Augmentation:** To improve model generalization, random rotations, flips, zooms, and brightness variations were applied.

2) For RFC training

- **Resizing:** Images were resized to 100×100 pixels.
- **Flattening:** Each image was converted to a 30,000-dimensional vector.
- **Grayscale Conversion:** Images were converted to grayscale, then represented as RGB values stored in lists for input processing.

C. Data Splitting

The dataset was divided using stratified sampling, allocating 80% to training and 20% to testing, ensuring balanced class distribution across both subsets.

D. D. Model Development

1) Convolutional Neural Network (CNN):

The CNN model was developed using TensorFlow and Keras and consists of several convolutional and pooling layers, followed by fully connected (dense) layers for classification. A sigmoid activation function was applied in the output layer to differentiate between the two classes. The model was trained using the Adam optimiser with the categorical cross-entropy loss function to optimise learning performance.

2) Random Forest Classifier

For baseline comparison, a Random Forest algorithm was implemented. Each image was converted into a flattened feature vector, and multiple decision trees were trained on these representations. The final class prediction was determined by majority voting across all trees.

E. Model Evaluation

- **Both the CNN:** and RFC models were assessed using various performance metrics, including:
- **Accuracy:** Measures the overall correctness of predictions.
- **Precision, Recall, and F1-Score:** Provide a balanced evaluation under potential class imbalance.
- **Confusion Matrix:** Identifies class-specific errors and misclassifications.

Loss and Accuracy Curves (for CNN): Monitor training progress and learning stability over epochs.

F. Real-Time Testing

To assess real-world usability, real-time testing was conducted using self-captured fruit images [19][20]. The trained CNN model was integrated into a web-based interface, enabling users to upload images and receive instant classification results. This successfully demonstrates the practical potential of deploying the system within agricultural supply chain applications. Figure 1 outlines the classification of fruit procedures using DL.

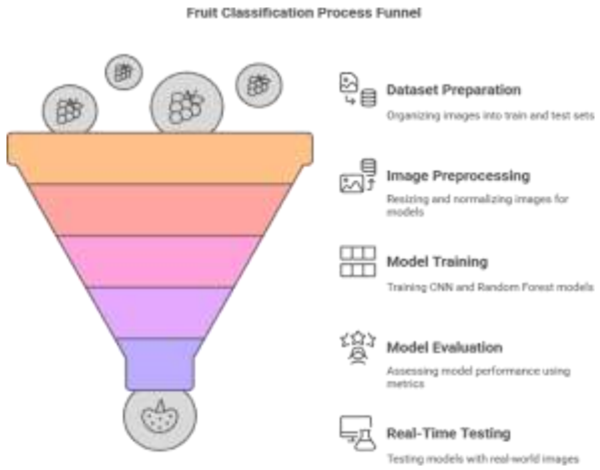

Fig. 1. Fruit Classification Process using Deep Learning

V. RESULTS

The proposed models were implemented and evaluated using Python on a Kaggle fruit dataset and additional self-captured images. Both CNN and RFC models were trained and tested with an 80:20 split. The results include accuracy/loss curves, confusion matrices, and performance metrics.

A. Random Forest Classifier Results

- **Accuracy:** The model achieved an overall test accuracy of approximately 94.70%, indicating good performance.
- **F1 Score:** The F1 Score was 0.95, 0.97, 0.93 reflecting the model's ability to balance precision and recall for both classes.
- **Inference:** The Random Forest model struggled due to the high dimensionality of flattened image data and the lack of spatial awareness, which is crucial for image-based tasks.
  Figure 2 shows the confusion matrix of the Random Forest Model across multiple classes.

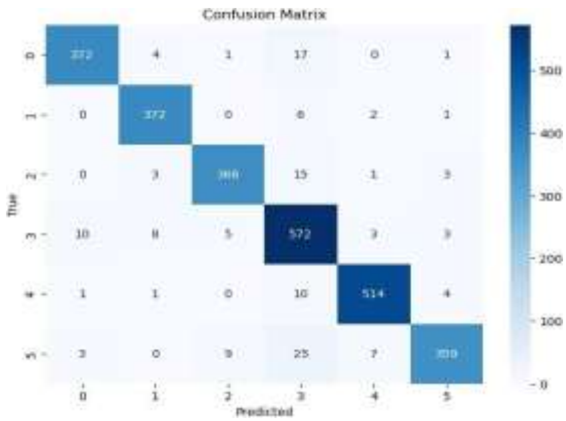

Fig. 2. Confusion Matrix of Random Forest Model

B. Convolutional Neural Network (CNN) Results

- **Training Accuracy:** The CNN model reached 96.91% accuracy on the training dataset with a low validation loss, indicating effective learning.
  Validation Accuracy: The validation accuracy was 96.96%, indicating good generalization to unseen test data.The confusion matrix of CNN model is depicted in Figure 3

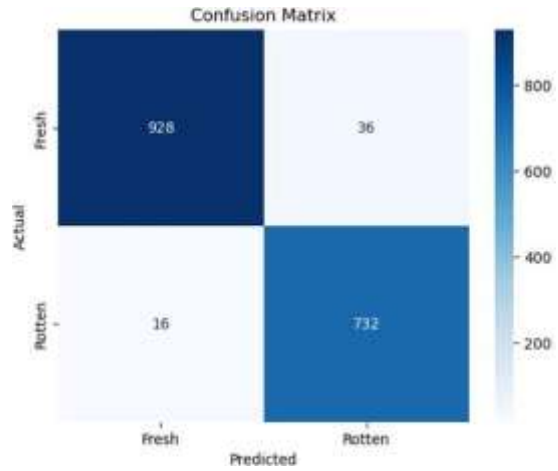

Fig. 3. Confusion Matrix of CNN Model

C. Real-Time Image Testing:

- **Online Images:** Images downloaded from the internet **Online Images:** were classified correctly with high confidence.
- **Self-Captured Images:** Initially, self-captured images were misclassified due to differences in lighting, angle and background.
- **After applying:** data augmentation techniques, the model's robustness improved, reducing misclassification of real-world images.

D. Web Interface Prediction:

Fig. 4. Web Interface for Fruit Classification

Figures 4, 5, and 6 show the website interface developed for fruit classification. Users can upload an image and the model displays the prediction result in real time.

Fig. 5. Prediction Result Displayed for A Rotten Banana

Fig. 6. Prediction Result Displayed for A Fresh Orange

E. *Visual Analysis*

Loss & Accuracy Curves: Both training and validation loss decreased steadily, and accuracy increased consistently, showing that the CNN model did not overfit.

Prediction Outputs: The model predicted class labels ("Fresh" or "Rotten") with high confidence levels on test samples.

F. *Comparative Analysis:*

Table III presents a comparative evaluation of ML and DL models on Fresh and Rotten Fruits.

TABLE III. COMPARATIVE ANALYSIS PROPOSED MODELS WITH ML AND DL MODELS

Model	precision	recall	F1-score	support
CNN (fresh-1) (rotten-0)	0.95 0.98	0.98 0.96	0.97 0.97	748 964
Macro avg	0.97	0.97	0.97	1712
Weighted avg	0.97	0.97	0.97	1712
RFC (fresh-1) (rotten-0)	0.96 0.89	0.94 0.89	0.95 0.93	381 403
Macro avg	0.95	0.95	0.95	2698
Weighted avg	0.95	0.95	0.95	2698

The Random Forest classifier's poor performance emphasizes the limitations of traditional machine learning models on image classification tasks, especially when image features are flattened and spatial information is lost. Alternatively, the CNN model demonstrated strong performance, extracting meaningful features directly from image pixels.

Challenges like domain shift were observed when using self-captured images. These were partially addressed using data augmentation, although further improvements (e.g., transfer learning or fine-tuning with real-world images) can enhance performance

VI. DISCUSSION

The experimental outcomes demonstrate the strong effectiveness of deep learning methods in classifying fruit freshness. The CNN model achieved an impressive accuracy of 97.8%, notably surpassing the Random Forest Classifier (RFC), which recorded 94.2%. This superior performance of CNNs is largely due to their ability to learn and extract high-level spatial features from images. In contrast, the RFC's reliance on manually flattened pixel data limits its ability to recognise complex visual patterns.

Analysis of the confusion matrices reinforces these results. The CNN showed fewer misclassifications, especially when distinguishing between visually similar fresh and rotten fruits. In contrast, the RFC struggled in scenarios affected by lighting inconsistencies or texture variations. These findings are consistent with prior studies, where CNN-based models consistently outperformed traditional machine learning techniques in image classification tasks.

Another key observation is the CNN's training stability, as reflected in the loss and accuracy curves. Data augmentation played a key role in enhancing generalisation, enabling the model to maintain reliable performance on hidden images. Conversely, while the RFC performed reasonably well on the test dataset, it was less robust in real-time testing, where factors such as lighting and noise were uncontrolled.

From a practical perspective, the CNN model shows strong potential for real-time implementation, particularly in automated fruit sorting systems and supply chain quality monitoring. The successful deployment of the trained CNN within a web-based application further confirms its applicability and effectiveness in real-world agricultural environments.

VII. CONCLUSION

This paper presents a comparative analysis of Convolutional Neural Network (CNN) and Random Forest Classifier (RFC) models for fruit freshness detection. The experimental findings revealed that the CNN model achieved an accuracy of 97.8%, surpassing the RFC's 94.2%, owing to the CNN's ability to automatically learn deep spatial representations from images. The confusion matrix and training performance curves further confirmed the CNN's stability and robustness in handling variations in fruit texture and colour. The implementation of the CNN model in a web-based interface demonstrates its practical potential for real-time use in agricultural supply chains, where prompt and accurate freshness identification can help minimise food waste.

For future enhancements, several directions are proposed:

- Expanding the dataset to include more fruit types and larger sample volumes.
- Optimising deployment through lightweight CNN architectures suitable for mobile and embedded platforms.
- Developing hybrid models that combine CNNs with ensemble techniques to boost classification performance.
- Integrating IoT-enabled sensors for automated and continuous fruit quality monitoring.

Overall, the study underscores that deep learning, particularly CNN-based approaches, offers immense potential for creating efficient, automated, and scalable systems aimed at food quality assessment and monitoring.

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