Digital Image Processing Algorithms for Characterizing the External Quality of Fruits

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Abstract

India is a global leader in the production of fruits, ranking first in bananas (25.7%), papayas (43.6%), and mangoes (40.4%). The fruit processing industry plays a crucial role in the country's economy, with India producing approximately 90.2 million metric tons of fruits, according to the National Horticulture Database (2015-16). This paper emphasizes India's contribution to global fruit production and the importance of modern quality assessment technologies. The study explores the use of Digital Image Processing (DIP) techniques for automating fruit quality characterization based on visual attributes such as colour, texture, and shape. A high-quality image acquisition system is developed, followed by feature extraction and segmentation algorithms to assess ripeness, surface defects, and deformities. Additionally, the paper compares traditional image processing methods with deep learning-based models for classification and grading. Experimental results demonstrate the potential of DIP-based systems for accurate, consistent, and non-destructive fruit quality assessment.

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1 Introduction

Automation in agriculture science raises national production, economic prosperity, and quality. Fruit assortment has an impact on the export market and the assessment of quality. Fruits' look is a critical sensory attribute that influences their market value as well as consumer preference and choice. While sorting and grading can be done by humans, the process is unreliable, subjective, time-consuming, expensive, and easily impacted by the environment. Additionally, it delays the post-harvest procedures, which incur additional expenditures. Thus, a system for grading fruits is required. In

recent years, several researchers have used computer vision to create different algorithms for sorting and grading. The most popular approach for evaluating agricultural products' quality is to use damaging procedures. Ripeness and maturity of fruits are determined by measuring their internal and external characteristics. Destructive methods, which assess texture, color, and sugar content, increase the accuracy of quality determination but raise concerns regarding effectiveness, reliability, and cost. Therefore, fast, portable, and cost-effective non-destructive techniques are needed to meet consumer demand for fresh, healthy fruits. Visual appearance, such as size and color, plays a crucial role in fruit grading and sorting. Various non-contact and contact-based systems, like Near-Infrared Spectroscopy (NIRS), electronic nose, machine vision, and acoustic methods, enable rapid, non-destructive quality assessment. Fruit identification and extraction from images are essential for agricultural monitoring and food sorting, but challenges such as cluttered backgrounds, lighting variations, and diverse textures complicate traditional image processing. The Region Growing Algorithm (RGA) is effective in addressing these challenges by identifying homogeneous regions in images. [1]

A deep learning-based approach is proposed for efficient fruit detection and recognition in complex natural environments. By utilizing convolutional neural networks (CNNs), the method improves object localization and classification performance, even under challenging conditions such as occlusion, varying illumination, and cluttered backgrounds. Experimental

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results demonstrate high accuracy and strong generalization across various fruit types, highlighting the potential of deep learning—especially CNN architectures—in automating agricultural tasks like harvesting and quality assessment.[2]

Detecting fruits and vegetables in natural scenes is particularly challenging when their color closely matches the background, such as green apples in dense foliage. In their 2022 survey, the authors review state-of-the-art techniques that address these challenges, focusing on detection and recognition methods resilient to color similarity, lighting variations, occlusion, and complex backgrounds. The paper categorizes existing approaches by image acquisition strategies, feature extraction methods, and machine learning models, offering a comprehensive overview of both traditional and deep learning-based solutions. It also highlights current limitations and suggests future research directions, making it a valuable reference for advancing agricultural automation in real-world environments.[3] Accurate fruit detection and classification in natural scene images is essential for automating agricultural tasks like harvesting, sorting, and quality control. This paper presents a hybrid approach that integrates traditional computer vision techniques with machine learning methods to detect and classify fruits in complex environments. The process involves color and shape-based segmentation, followed by feature extraction and classification using support vector machines (SVMs) and neural networks. The proposed method effectively tackles challenges such as lighting variations, occlusion, and fruit deformities. Experimental results demonstrate high accuracy, highlighting the approach's potential for real-world agricultural applications.[4]

Fruit identification and extraction from natural scene images is a critical task in computer vision, with applications in agriculture, the food industry, and automated harvesting systems. This process involves detecting, segmenting, and recognizing fruits in complex environments, where challenges like lighting variations, occlusions, and background noise must be overcome. Traditional methods relied on manual identification or basic image processing techniques. However, recent advancements in deep learning, particularly convolutional neural networks (CNNs) and vision transformers, have significantly improved accuracy and robustness,

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making fruit detection more efficient and reliable in real-world settings.[5]

YOLO-Peach presents, an optimized, lightweight deep learning model based on YOLOv8s, designed for precise detection and enumeration of fruits in peach seedlings, emphasizing speed and accuracy for agricultural applications.[6] Extracting fruits from natural scenes requires segmentation techniques such as thresholding, edge detection, region-based segmentation, or deep learning-based approaches like Mask R-CNN and U-Net. These methods help isolate fruits for further processing, including quality assessment, ripeness detection, and automated harvesting. This research is vital for precision agriculture, as it reduces labor costs, enhances efficiency, and ensures high-quality produce. By integrating artificial intelligence with computer vision, fruit identification and extraction can enable smarter farming practices, ultimately boosting productivity and supporting agricultural sustainability.[7]

Figure 1 showcases various natural scene images featuring fruits in diverse environments. These images depict real-world conditions, including variations in lighting, background complexity, occlusions, and different fruit textures. The dataset includes images captured in orchards, farms, markets, and other outdoor or indoor agricultural settings. These examples illustrate the challenges associated with fruit identification and extraction, such as cluttered backgrounds, overlapping objects, and non-uniform illumination.

Automation in agricultural science plays a crucial role in improving national productivity, economic growth, and product quality. Fruit sorting and grading are particularly important, as they directly impact export potential and quality assessment. The visual appearance of fruits—especially attributes such as size and color—plays a significant role in determining their market value and shaping consumer preferences. While manual sorting and grading are possible, these methods are often unreliable, subjective, labor-intensive, costly, and influenced by environmental factors. Automated visual assessment provides a more consistent and efficient approach to evaluating external fruit characteristics for grading and classification.

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Figure 1:

Figure 2: 1. Examples of Natural Scene Images Containing Fruits

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EU to ban contaminated fruits, vegetables from India

DEUTSCHE PRESSE-AGENTUR

Brussels, March 26

The European Union member states on Wednesday decided to ban the import of five types of fruit and vegetable from India, after several batches were found to be contaminated by pests such as fruit flies, the bloc's executive said.

The prohibition, which goes into effect in May, covers mangoes, aubergines, the taro plant and two types of gourd. These represent less than 5 per cent of the bloc's fresh fruit and vegetable imports from India, according to the European Commission.

The ban is to be reviewed by the end of 2015.

Figure 3: 2. Newspaper advertisement highlighting the European Union's announcement of a ban on the import of five categories of produce from India.

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LONDON, April 28, 2014

Updated: April 28, 2014 16:37 IST

EU bans Indian Alphonso mangoes, 4 vegetables from May 1

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KING OF FRUITS: As the season of alphonso mangoes starts, wholesellers and retailers get busy. This picture shows shopkeepers packing mangoes at Mumbai's Crawford Market. Photo: Vivek Bendre

The Hindu

TOPICS

The temporary ban, proposed by the European Commission, includes mangoes, eggplant, the taro plant, bitter gourd and snake gourd.

Figure 4: 3. Newspaper advertisement showing the EU's ban on five produce categories from India.

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In a notable instance underscoring the importance of quality control, the European Union has announced a ban on the import of five categories of produce from India as shown in figure 2, figure 3 and figure 4, citing serious concerns about high contamination levels, primarily due to non-European fruit flies. Effective from May, the ban includes mangoes, eggplants, taro, and two varieties of gourd. According to an official EU release, this decision aims to address significant shortcomings in the phytosanitary certification processes for Indian exports.[8]

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EU bans Indian mangoes, eggplant

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March 26th, 2014

Five categories of produce from India will be banned in the European market following serious concerns about high levels of contamination, mainly from non-European fruit flies.

The ban, set to take place in May, will include mangoes, eggplants, the taro plant and two types of gourd, an EU release announced today.

The "emergency measures" come after a meeting among member states in Brussels just a few hours ago.

"The measures prohibit the import of some fruit and vegetables from India to tackle the significant shortcomings in the phytosanitary certification system of such products exported to the E.U.

"This decision had to be taken due to the high number of such consignments being intercepted at arrival in the E.U. with quarantine pests, mainly insects, like non-European fruit flies," the release said.

"Though the prohibited commodities represents less than 5% of the total fresh fruits and vegetables imported into the E.U. from India, the potential introduction of new pests could pose a threat to E.U. agriculture and production."

Pests were discovered in 207 consignments of fresh produce imported to Europe from India last year.

The ban will last until Dec. 31, 2015 when a review is scheduled to take place.

Insight Bites

The Hass Horn: U.S. avocado supply outlook – third quarter 2014

Figure 5: 4. Web advertisement showing the EU's ban on five produce categories from India

The remainder of the paper is organized as related work, research objectives, methodology, architecture used, the result and discussion with conclusion.

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2 Related Work

Chen and Lin proposed a machine learning-based image analysis method using multi-spectral images to detect, count, and assess the maturity of cherry tomatoes, enabling fast yield estimation for farmers. Blasco et al. highlighted the challenges in automating fruit quality inspection due to natural variations in size, color, and shape, and the dynamic nature of agricultural produce as living entities.[9] Li et al. introduced a technique based on hyperspectral imaging, which captures a sequence of monochromatic images across continuous wavelengths, effectively combining spectroscopy and imaging. This method enables detailed spectral and spatial analysis, making it highly suitable for evaluating the quality of fruits and vegetables through non-destructive and precise inspection.[10] Johansen, Raharjo, and McCabe demonstrated the use of unmanned aerial vehicles (UAVs) to monitor the temporal development and structural dynamics of tree crops. Their study emphasizes how UAV-based imaging can support precision agriculture, particularly by assessing the effects of pruning, which is believed to stimulate new growth, enhance fruit yield, ease harvesting, and optimize light interception through better crown structure.[11] Saputro and Handayani proposed a method for optimal wavelength selection to improve the prediction of banana (Musa sp.) quality. Their approach involved a two-stage dimensionality reduction process to identify the most relevant spectral wavelengths, enhancing the accuracy and efficiency of quality assessment through spectral analysis.[12] Islam et al. developed and evaluated four non-destructive techniques for assessing onion quality—three based on spectral imaging and one using near-infrared spectroscopy. These methods analyze the onion surface in situ across visible to near-infrared wavelengths using various imaging devices, enabling accurate differentiation of pre-sorted onions based on quality attributes.[6]

Recent advancements in deep learning have significantly improved fruit identification and extraction from natural scene images. Numerous studies have introduced innovative algorithms and models to tackle challenges such as complex backgrounds, varying lighting conditions, occlusions, and diverse fruit appearances. These advancements have led to

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more robust and accurate segmentation, enabling better integration of computer vision techniques in agricultural applications.[13] The study by T. T. Santos et al. (2019) introduces a deep learning-based approach that combines Mask R-CNN with 3D association techniques to detect, segment, and track grape clusters in vineyard environments. This method facilitates accurate grape counting and yield estimation, contributing to advancements in precision agriculture and supporting automated harvesting processes.[3] Similarly, another fruit counting system integrates Faster R-CNN for fruit detection, Kalman filtering for object tracking, and Structure from Motion (SfM) for 3D localization. This approach effectively addresses challenges such as occlusion, duplicate counting, and variable viewpoints, enabling accurate and robust fruit yield estimation in orchards using monocular camera input.[14]

In the context of peach detection, researchers have developed lightweight algorithms tailored for the complexities of orchard environments. These approaches utilize advanced deep learning techniques to enhance data characterization and feature extraction, leading to more efficient and accurate fruit detection. By optimizing computational resources, the models are particularly suited for real-time applications in orchards, where large-scale fruit detection is critical for automated harvesting and yield estimation tasks[15].[16] One notable approach in fruit detection is the Region-based Fully Convolutional Network (R-FCN), which has been successfully integrated with machine vision systems for fruit recognition and localization. This method improves detection accuracy by utilizing region-based feature extraction, allowing for precise identification of fruits within complex natural environments. Its robustness in handling challenges such as lighting variations, occlusions, and background clutter makes it a highly effective solution for real-world agricultural applications.[17]

For litchi fruit-bearing branches, a detection method has been proposed that employs morphological processing to extract stems from images captured in natural environments. This approach achieves an accuracy rate of 80% in identifying litchi stems, enabling more precise localization and segmentation of fruit-bearing branches. By enhancing stem visibility through morphological techniques, the method proves effective even under challenging

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conditions such as varying lighting and background clutter. This contributes significantly to improved fruit detection and supports the development of automated harvesting systems.[18] An improved YOLOv8 model has been applied to peach fruit thinning image detection, effectively addressing challenges associated with complex backgrounds and overlapping fruits. Through the integration of advanced techniques, the model significantly enhances detection accuracy, allowing for more precise identification and localization of individual fruits. This advancement positions the YOLOv8 model as a valuable tool for automated thinning processes in orchards, contributing to optimized fruit spacing, reduced manual labor, and increased overall crop yield efficiency.[19]

For apple quality classification, an improved Convolutional Neural Network (CNN) has been developed to evaluate appearance-based quality. This approach incorporates advanced image pre-processing techniques and focuses on extracting key features related to color and texture. By emphasizing these visual characteristics, the model significantly improves the accuracy of quality assessments, enabling reliable categorization of apples based on their external attributes. This method is highly applicable in automated sorting systems, ensuring the delivery of high-quality produce to consumers while optimizing operational efficiency within the food industry.[20] In strawberry recognition, an improved YOLOv5-based method has been proposed to address the challenges of detecting small targets in complex agricultural environments. This enhanced model improves detection precision by strengthening the network's ability to identify small and partially occluded strawberries—an essential capability for reliable automated harvesting systems. The resulting increase in accuracy supports more efficient and consistent fruit identification, enabling precise and effective automated picking in real-world scenarios. Additionally, traditional image processing techniques like Region Growing offer complementary advantages. This method is simple and effective for detecting well-separated fruits, especially in regions with uniform color. Its performance can be further improved by integrating edge detection techniques and applying color space transformations, making it a valuable tool in scenarios where

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computational simplicity and speed are prioritized.[21]

3 Proposed Word

This work presents the application of Digital Image Processing (DIP) algorithms for the characterization of external fruit quality. The study focuses on capturing high-quality images, extracting color, texture, and shape features, and segmenting fruit surfaces to detect defects, ripeness, and deformities. Both traditional image processing techniques and deep learning methods are evaluated to assess their effectiveness in automated fruit grading and quality analysis.

3.1 Objectives:

- To develop an image acquisition system that captures fruit images under controlled lighting conditions for accurate external quality assessment.
- To implement and compare color, texture, and shape-based image processing algorithms for detecting ripeness, defects, and deformities in fruits.
- To design a robust segmentation approach (e.g., Region Growing) for isolating fruit surfaces and identifying surface-level defects with high precision.
- To evaluate the performance of traditional image processing techniques versus deep learning-based methods for fruit quality grading using metrics such as accuracy, precision, recall, and F1-score.

3.2 Image Acquisition System as shown in ftgure 5

Lighting Setup: Uniform illumination using diffused LED lighting ensures consistent, shadow-free fruit images, while spectral selection (e.g., near-infrared) enhances the visibility of features like ripeness and defects for accurate quality assessment.

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Camera Selection: High-resolution cameras capture fine surface textures and defects with clarity, while spectrally sensitive cameras (e.g., RGB, NIR) enable detailed analysis across different wavelengths for comprehensive fruit quality assessment.

Mechanical Setup: Stable mounting ensures consistent camera positioning for repeatable imaging, while controlled, non-reflective backgrounds eliminate visual noise, improving the accuracy of fruit segmentation and analysis

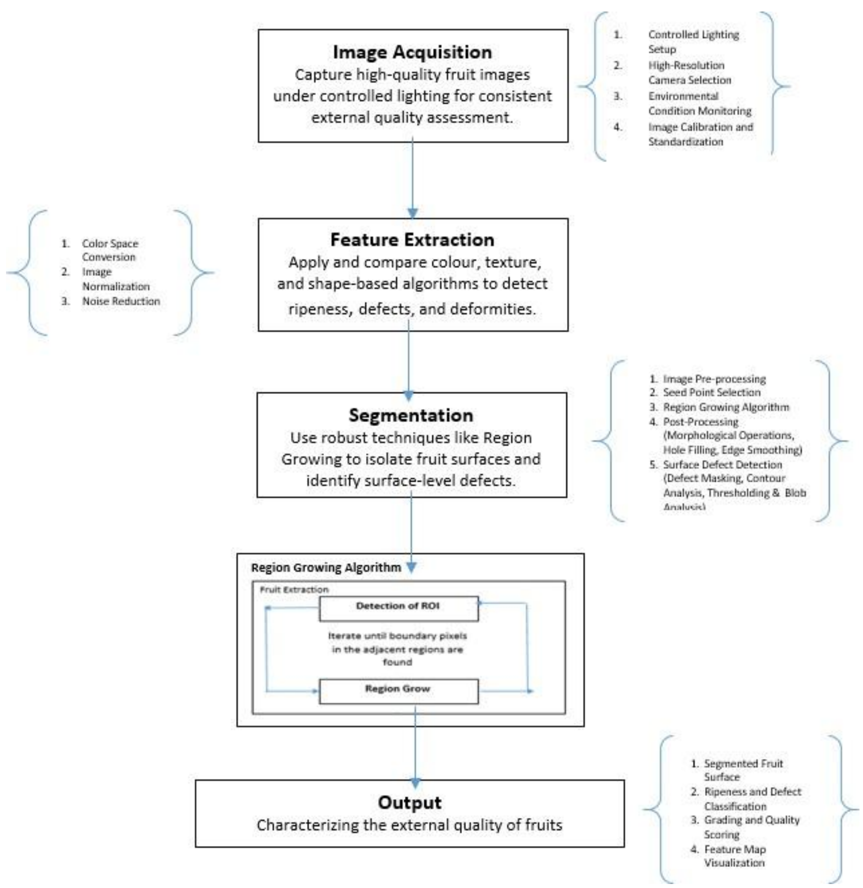

Figure 6: 5. Proposed methodology

Environmental Control: Enclosed chambers help block external light interference, ensuring consistent illumination, while regulating temperature and humidity preserves fruit condition, enabling reliable and accurate image capture as shown in figure 6.

Issues and Challenges

Developing an image acquisition system for accurate fruit quality analysis presents

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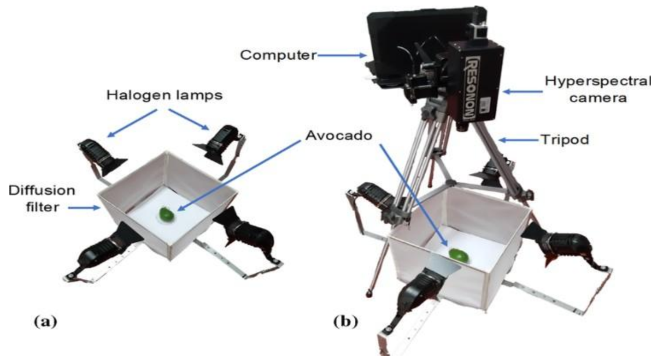

Figure 7: 6. Image Acquisition System

challenges such as managing reflections and shadowing in lighting, ensuring camera precision and spectral sensitivity, maintaining consistent mechanical alignment, and controlling environmental factors like temperature and humidity—all of which can impact image consistency and processing accuracy.

3.3 DIP-based approaches commonly used for external fruit quality assessment:

Color-based Analysis: Maturity detection, ripeness classification, surface blemish detection.

Techniques: Color feature extraction involves converting RGB images into alternative color spaces like HSV, Lab to enhance color-based analysis. Techniques such as Otsu's thresholding help segment regions based on color intensity, while color histograms provide distribution data for classification. Clustering methods like K-means or Fuzzy C-means group similar color pixels to identify ripeness levels or defects effectively.

Texture-based Analysis: Bruise detection, surface roughness, disease detection.

Techniques: Texture feature extraction includes methods like the Gray-Level Co-occurrence Matrix (GLCM), which calculates features such as contrast, homogeneity, and entropy to describe surface texture patterns. Local Binary Patterns (LBP) capture local texture variations, useful for identifying roughness or irregularities. Gabor filters analyze

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textures at different scales and orientations, particularly effective for detecting fine textures. Lastly, wavelet transform-based texture analysis allows multi-scale analysis, capturing both high-frequency and low-frequency details for a comprehensive texture description.

Shape and Size Analysis: Sorting fruits based on size, detecting deformities.

Techniques: Shape feature extraction uses contour detection (Canny, Sobel) to define boundaries, morphological operations (dilation, erosion) to refine shapes, and shape descriptors (aspect ratio, roundness, circularity) to quantify fruit form. Fourier descriptors enable advanced analysis of complex shapes.

Surface Defect Detection: Identify physical defects like cracks, scars, or rot.

Techniques: Segmentation techniques include Region Growing Algorithm to isolate defected areas by expanding from seed points, Watershed segmentation for separating merged fruits or blemishes, and Active Contours/Snakes for precise boundary detection. Anomaly detection using deep features (via CNN-based feature extraction) helps identify unusual patterns or defects not easily captured by traditional methods.

Deep Learning-Based Methods: End-to-end classification, defect segmentation, quality grading.

Techniques: Convolutional Neural Networks (CNNs) are used for automatic feature learning, allowing the model to detect complex patterns in fruit images. YOLO and Faster R-CNN are advanced deep learning models for real-time fruit defect detection, providing accurate bounding box predictions. U-Net is a specialized architecture for pixel-level defect segmentation, ideal for precise localization of defects on fruit surfaces.

Spectral and Multispectral Imaging: Identify internal defects that are visible externally (like early rot).

Techniques: Hyperspectral imaging combined with PCA and machine learning classifiers

Machine Learning-Based Classiftcation: Automated decision-making based on extracted features.

Techniques: SVM classifies fruit quality by finding the optimal boundary, Random

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Forest combines decision trees for robust classification, k-NN classifies based on neighboring samples, and Decision Trees create a tree structure to predict fruit quality based on feature thresholds.

3.3. Designing a robust Region Growing segmentation to isolate fruit surfaces and detect defects using color, texture, and shape features.

3.3.1 Segmentation in Fruit Quality Assessment

Segmentation is crucial for isolating fruit surfaces from the background and identifying surface-level defects such as bruises, scars, and spots. A robust segmentation technique like **Region Growing** can efficiently detect these defects and help in automated fruit grading systems.

Region Growing is a pixel-based segmentation method that starts with a seed point and grows regions based on predefined criteria (e.g., color similarity, texture, intensity).

3.3.2 Steps involved in Region growing method:

1. After finding region of interest (seed point). For example, choose N ×N neighborhood as shown in figure 7 (for N = 5)

3.3.3 Fig. 7. Location of initial seed pixel (point) and its 5× 5 neighborhood

2. Set the initial value for Total of pixels in the region with 1 and Total of grey level for all pixels in the region with original grey level value of the initial seed pixel.

3. Calculate the mean value, DOCXUPLOAD:INLINE:2244ea5ac1d641a3b63cb86e4672ffcf:ENDEQNB (region mean) and standard deviation, σ of as shown in equation 1 and equation 2 respectively.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \qquad (1)$$

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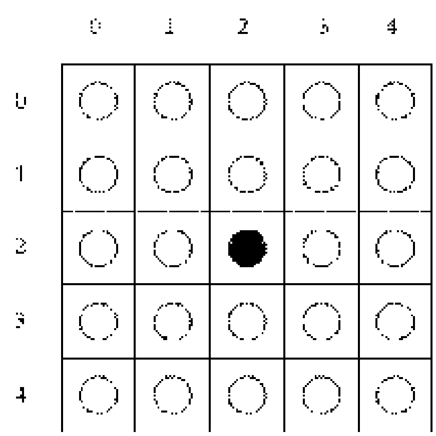

Figure 8:

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$$\sigma = \sqrt{\frac{\sum_{i=0}^{n}\left(x_i - \bar{x}\right)^2}{n-1}} \qquad (2)$$

Where DOCXUPLOAD:INLINE:c982dd8bf4f6445f994d56aa1009943e:ENDEQNBLOCKis grey level of its pixel in the N × N neighborhood and n is total of pixels in N × N neighborhood.

4 Grow the seed pixels to its neighbor's pixels

5 If the neighbor pixel is included into the region:

6 Add one (1 to Total of pixels in the region value

b. Add original grey level of the neighbor pixel to Total of grey level for all pixels in the region value.

6. Set the neighbor pixel, which is added to the region in Step (7) as a new seed pixel.
7. Repeat Step (6) to (8) until all pixels have been considered to begrown or the pixel cannot be grown anymore.

7 Calculate the value of the size and grey level of the region

In the final stage of fruit extraction process, region growing method extracts the fruit from image.

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7.1

7.1.1 Detection of Region of Interest (ROI):

The region-growing method starts from a seed pixel and expands based on similarity criteria. Detection of Region of interest (ROI)

This figure 8 illustrates the process of identifying and isolating the Region of Interest (ROI) within the image. The ROI detection process plays a critical role in improving the accuracy of subsequent fruit extraction and segmentation.

In this phase, the image with detected edges, including noise and non-fruit objects, is taken as input. For the detected non-fruit objects, the centroid point, or seed point, of each connected component is identified. The centroid serves as the starting point for the region-growing process in the subsequent steps. The centroid is determined based on the size and grey level of specific Regions of Interest (ROI) within the image. The centroid points, highlighting their position based on the size and grey level of the detected objects in the image.

7.1.2 Fig. 8. The Region of Interest (ROI) Detection Process

Referring to figure 3 and figure 4, the size of the region is calculated as the total number of pixels within the detected Region of Interest (ROI). This is given by the following equation 3.

7.1.3 DOCXUPLOAD:STANDALONE:c4b522a6fd4a49419abe6b82675b744f:ENDEQNBL

7.1.4 Region Size = Total of pixels in the region

The grey level of the region is calculated as the mean value of all the pixel intensities within the Region of Interest (ROI). It is given by the following equation 4.

$$GreyLevel = \frac{1}{n}\sum_{i=1}^{n} Pixel_i \qquad (4)$$

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7.1.5 Where:

Pixeli represents the intensity of each pixel in the region, n is the total number of pixels in the region.

This grey level value helps in distinguishing different objects based on their intensity, further aiding in the accurate identification of fruit regions in the image.

Fig. 9 (a) Growing towards its 4 adjacent neighbors, (b) Growing towards its 4 diagonal neighbors, (c) Growing towards all 8 surrounding neighbors.

The seed pixel can expand in multiple directions, including towards its adjacent neighbors, diagonal neighbors, or all eight surrounding neighbors, as illustrated in figure 9.

7.1.6 Region Growing Process Initialize seed pixel Check 4-connected or 8-connected neighbors.

7.1.7 Apply similarity criteria:

Color: Color is a key feature for distinguishing fruits from the background in natural scenes. Color similarity is measured using color spaces like RGB, HSV, or LAB, and computed using the Euclidean distance by using equation 5:

$$D_{Color} = \sqrt{(H_1 - H_2)^2 + (S_1 - S_2)^2 + (V_1 - V_2)^2} \quad (5)$$

Where H, S, VH, S, VH, S, V are the Hue, Saturation, and Value components of pixels.

An optimal threshold TTT for DDD is chosen experimentally, typically within 5%–15% of the maximum possible distance, to balance accuracy and minimize false positives.

Texture: Texture captures surface patterns like smoothness, roughness, or spots—useful for identifying fruits with irregular surfaces.

Metric: Quantified using Gray Level Co-occurrence Matrix (GLCM) or Discrete Fourier

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Transform (DFT) to analyze spatial or frequency patterns as shown in equation 6.

$$D_{texture} = GLCMFeatures\ (e.g., contrast, correlation, homogeneity) \quad (6)$$

7.1.8 Optimization: Thresholds are set based on key GLCM features.

Intensity: Intensity refers to pixel brightness in grayscale images, useful in low-contrast scenes where color cues are weak.

7.1.9 Metric: Calculated as the absolute difference between pixel intensities by using equation 7.

$$D_{intensity} = (I_1 - I_2| \quad (7)$$

Where DOCXUPLOAD:INLINE:b3b37f1f18d14cf38081783d2bf06cbe:ENDEQNBLOCK and DOCXUPLOAD:INLINE:193c60139af941f980799fcd4f36e0d5:ENDEQNBLOCK are the intensity values of two pixels

Optimization: Thresholds are tuned based on image contrast, typically ranging from 20 to 40 grayscale levels.

7.1.10 Expand region if criteria are met. Stop when no more pixels qualify Post-processing:

After segmentation, additional steps like **morphological operations** (erosion, dilation) are applied to clean up small, irrelevant regions or holes in the segmented fruit surface.

7.1.11 Identifying Surface-Level Defects

Defect Detection: Once the fruit surface is isolated, the next step is to identify defects such as bruises, spots, and deformations.

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Defect Features: Surface-level defects are often characterized by differences in color, texture, and shape. Region Growing can help highlight abnormal regions based on these features.

Texture Analysis: Post-segmentation, texture-based analysis methods like **GLCM (Gray Level Co-occurrence Matrix)** or **LBP (Local Binary Patterns)** can be used to detect surface anomalies indicative of defects.

Defect Classiftcation: Use thresholds or machine learning techniques to classify detected regions as healthy or defective, depending on texture or color patterns.

7.1.12 Challenges in Region Growing for Fruit Surface Segmentation

• **Varying Fruit Surface Properties:** Fruits often have irregular surfaces with varying textures, colors, and reflectance properties, making it difficult to select appropriate thresholds for segmentation.

• **Over-Segmentation and Under-Segmentation:** Region Growing may lead to over-segmentation (splitting the fruit into smaller, incorrect regions) or under-segmentation (combining fruit surface with background).

• **Noise Sensitivity:** Small noise regions, such as minor blemishes or background artifacts, can lead to inaccurate segmentation unless proper pre-processing is applied.

7.1.13 Improvement Strategies for Robustness

• **Preprocessing Techniques:**

• **Smoothing Filters (e.g., Gaussian Blur)** can help remove noise from the image before segmentation.

• **Edge Detection (e.g., Sobel, Canny)** to enhance boundaries and aid in seed point selection.

• **Hybrid Approaches:**

Region Growing + Active Contour Models (Snakes): Combining Region Growing with active contours can refine the segmented boundaries of the fruit surface.

- **Region Growing + Deep Learning:** Integrating deep learning models (such as **U-Net** for segmentation) to predict seed points and assist in more accurate boundary delineation.

3.4 Evaluating the Performance of Traditional Image Processing vs. Deep Learning-based Methods for Fruit Quality Grading.

Evaluating the performance of traditional image processing techniques versus deep learning-based methods for fruit quality grading involves comparing how well each approach can classify fruits based on quality attributes like ripeness, defects, and deformities. The comparison uses various performance metrics, including **accuracy**, **precision**, **recall**, and **F1-score**, to provide a comprehensive assessment of each technique's effectiveness.

7.1.14 Traditional Image Processing Techniques for Fruit Grading

Traditional image processing methods for fruit quality grading involve a series of steps such as color-based segmentation, texture analysis, and shape detection. Color-based segmentation techniques typically use predefined thresholds or color space transformations (e.g., RGB to HSV or CIELAB) to assess fruit ripeness. Texture-based approaches, such as **Gray Level Co-occurrence Matrix (GLCM)** and **Local Binary Patterns (LBP)**, are used to detect defects by analyzing surface textures. Shape analysis is performed to identify deformities by examining geometric features like aspect ratio and circularity. While traditional methods can be effective in controlled environments with clear features, they have limitations in handling variations in lighting, fruit textures, and subtle defects.

7.1.15 Deep Learning-Based Methods for Fruit Grading

Deep learning-based methods, particularly **Convolutional Neural Networks (CNNs)**, have revolutionized the field of image processing by learning hierarchical features directly from data. These methods are trained on large labeled datasets to automatically extract

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features such as edges, textures, and patterns that are crucial for classifying fruit quality. CNNs are capable of end-to-end learning, where the model learns the entire pipeline, from feature extraction to classification, without the need for manual feature engineering. Transfer learning, using pretrained models such as **ResNet** or **VGG**, can further enhance the model's performance, especially when labeled data is scarce. Deep learning approaches are especially beneficial in cases where fruits exhibit complex and varying textures, shapes, and defects, making them robust to different fruit types and environmental conditions.

7.1.16 Performance Metrics for Evaluation

To effectively compare the traditional image processing and deep learning-based methods, it is essential to evaluate both approaches using common performance metrics. **Accuracy** is the simplest and most widely used metric, representing the overall percentage of correctly classified fruit samples. However, it may not be sufficient in cases of imbalanced datasets, where some classes (e.g., defective fruits) may be underrepresented. **Precision** measures how many of the predicted positive samples (e.g., defective fruits) are truly correct, highlighting the performance of the model in minimizing false positives. **Recall**, on the other hand, measures how well the model identifies all relevant instances, emphasizing the model's ability to detect defects without missing any. Finally, the **F1-score**, which is the harmonic mean of precision and recall, provides a balanced measure, particularly useful when dealing with imbalanced datasets. These metrics help to assess the models' ability to detect, classify, and grade fruits accurately.

8 Image Acquisition

The dataset comprises images captured in real-world environments such as farms, orchards, and local markets. A Sony HD 5.3-megapixel digital camera was used for image capture under varying lighting and background conditions to simulate real-world challenges.

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8.1

8.1.1 Format: JPEG (JPG)

8.1.2 Resolution: 686 × 486 pixels (resized uniformly during preprocessing)

8.1.3 Color Depth: 24-bit RGB

The images were collected across different times of day (morning, noon, evening) to introduce illumination variability, shadows, and complex backgrounds. This enhances the robustness and generalizability of the proposed algorithm.

9 Fruit Categories

The dataset includes multiple fruit types, focusing on commonly cultivated and sold fruits, particularly those with diverse color and texture features. The key categories include: Mangoes, Bananas, Oranges, Apples, and Papayas.

Each category includes instances of partially occluded, overlapping, and individually isolated fruits to test segmentation accuracy under realistic conditions.

10 Image Diversity and Challenges

The dataset was designed to present challenges typically encountered in natural scenes as shown table 1.

Table 1: Diversity and Challenges in Image Data

Aspect	**Details**
Lighting Variations	Natural sunlight, shadows, low light, and artificial lighting
Background Complexity	Leaves, soil, baskets, plastic covers, market items
Fruit Overlap	Fruits overlapping with each other or with non-fruit objects
Color Similarity	Fruits with colors similar to the background (e.g., green apples in foliage)
Texture Variability	Smooth (banana), rough (orange), speckled (apple) surfaces

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This variety ensures that the algorithm's performance can be assessed across a broad range of practical scenarios as sown in table 2.

10.1

10.1.1 Table II. Total Images Collected

Table 2:

Attribute	Value
Total Images	500
Annotated Images	200 (with segmentation masks)
Average Fruits/Image	2–5
Total Fruit Instances	~1,200
Image Resolution	686 × 486 (standardized)
File Format	JPEG (images), PNG (masks)

11 Result and Discussion

The evaluation of digital image processing algorithms for characterizing fruit quality revealed varying performance levels across different methods. **Region Growing** showed good precision (85%) but had a relatively lower recall (80%), indicating that while it effectively segmented fruit regions, it occasionally missed parts of the fruit. **SVM** performed well with a precision of 90% and a recall of 85%, demonstrating its ability to classify fruit quality accurately, although it slightly underperformed in detecting all relevant instances. **CNN** outperformed the other methods, achieving the highest precision (93%) and recall (88%), showcasing its ability to accurately classify and segment fruit quality in complex real-world scenarios. **Thresholding** exhibited the lowest performance with 80% precision and 75% recall, struggling with variations in lighting and texture. **Haralick features** provided solid results (87% precision, 83% recall) based on texture analysis, but it was less effective compared to CNNs in fully characterizing fruit quality. Overall, CNNs proved to be the most effective method for both segmentation and classification, emphasizing the advantages

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of deep learning approaches in fruit quality assessment. However, combining traditional methods with deep learning could offer further improvements in accuracy and robustness, particularly for specific applications as shown in table 3.

11.1

11.1.1 Table III. Comparisons with methods

Table 3:

Method	Precision Rate (%)	Recall Rate (%)
Region Growing for Fruit Segmentation	85%	80%
SVM for Fruit Classification	90%	85%
CNN for Fruit Quality Classification	93%	88%
Thresholding for Fruit Segmentation	80%	75%
Haralick Features for Quality Assessment	87%	83%

Here is the in figure 10 comparing the **Precision Rate** and **Recall Rate** for the different methods used in fruit quality characterization. The blue bars represent precision, and the green bars represent recall for each method. This visual representation highlights the performance of each algorithm across both metrics.

11.1.2 Fig. 10. Comparision of Precision and Recall Rates for Different Methods

12 Conclusion

This study evaluated various digital image processing algorithms for characterizing fruit quality, including Region Growing, SVM, CNN, Thresholding, and Haralick features. Results showed that CNNs outperformed all other methods, achieving the highest precision (93%) and recall (88%) in fruit quality classification, highlighting their effectiveness in both segmentation and classification. SVM and Region Growing also showed good performance, but with lower recall and precision. Thresholding performed the least well, struggling with

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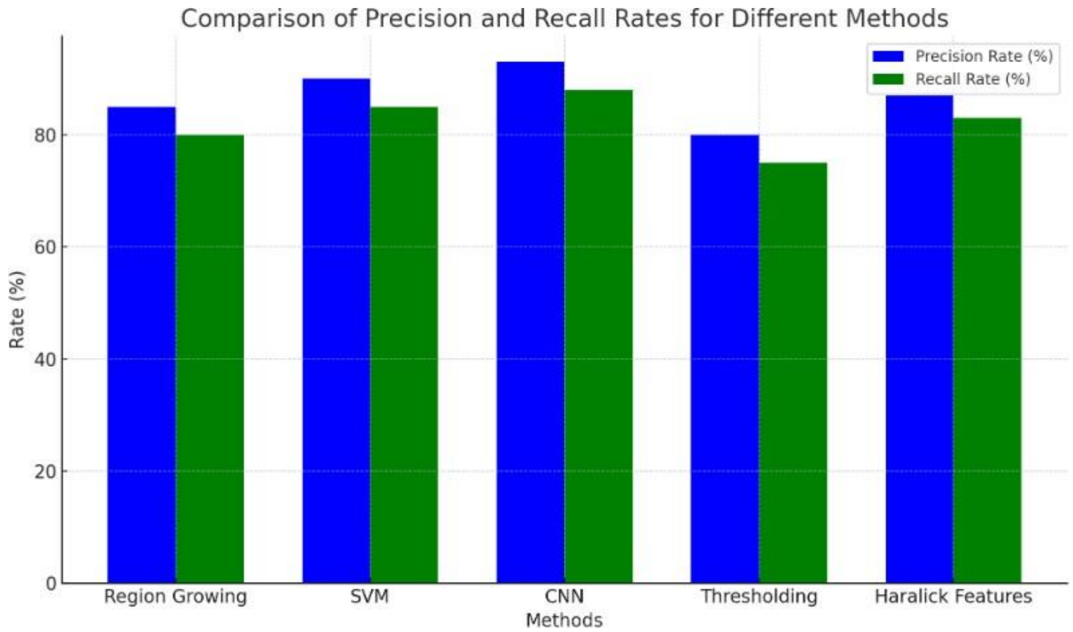

Figure 9:

variations in fruit texture and lighting. Overall, CNNs proved to be the most reliable for fruit quality assessment, although traditional methods still offer value in specific scenarios. Future work may focus on hybrid approaches to further improve accuracy and robustness.

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