FRUIT QUALITY DETECTION

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Abstract

Ensuring fruit quality is essential for consumer satisfaction, food safety, and minimizing post-harvest losses. Traditional methods like manual inspection and chemical analysis are often labor-intensive, time-consuming, and costly. Digital image processing (DIP) has recently emerged as a non-destructive, rapid, and objective alternative. This study reviews DIP techniques for predicting key fruit quality parameters such as color, texture, size, shape, and surface defects. The process involves image acquisition, preprocessing, segmentation, feature extraction, and prediction using machine learning models. Color analysis aids in ripeness prediction, while texture and shape analysis detect bruising and deformities. Advanced methods like hyperspectral imaging and computer vision improve prediction accuracy by capturing detailed spatial and spectral data, enabling detection of microbial contamination and ripeness stages across various fruits. Challenges include standardizing algorithms, reducing computational load, and enabling real-time prediction. Integration with artificial intelligence and edge computing shows promise in addressing these issues. In conclusion, DIP combined with predictive modeling offers a transformative solution for efficient, accurate fruit quality prediction. Future research should focus on scalable, cost-effective systems for broader adoption.

Keywords: fruit quality detection, digital image processing, histogram equalization, machine learning, computer vision

1 Introduction

1.1 Background and Motivation

Fruit quality assessment is a critical component of the agricultural and food supply industries, playing a pivotal role in ensuring consumer satisfaction, minimizing post-harvest losses, and maintaining market competitiveness. Traditionally, fruit quality evaluation relies on manual visual inspections and chemical analyses. However, these conventional approaches are often subjective, labor-intensive, time-consuming, and resource-demanding, making them inefficient for large-scale applications.

Recent advancements in artificial intelligence (AI) and computer vision have provided new opportunities for automating the fruit quality assessment process. Machine Learning (ML) and Deep Learning (DL) techniques, particularly Convolutional Neural Networks (CNNs), have shown impressive capabilities in non-destructive fruit evaluation by analyzing attributes such as color, texture, shape, size, and surface defects from images. These developments highlight the growing demand for intelligent, efficient, and scalable solutions for fruit quality detection.

1.2 Problem Statement

Despite the success of AI-driven techniques, challenges such as varying lighting conditions, image noise, class imbalance, and the limitations of individual classification models persist. While CNNs are powerful, relying solely on a single model can lead to suboptimal performance in diverse real-world scenarios. There remains a need for robust fruit quality detection systems that combine multiple classification strategies to enhance prediction accuracy and generalization, particularly under challenging conditions.

1.3 Related Work

Numerous studies have explored the use of machine learning and image processing techniques for fruit quality assessment. Traditional algorithms such as K-Nearest Neighbors (KNN) and correlation-based matching have been used to classify fruit based on handcrafted features. More recently, deep learning models, especially CNNs, have become popular due to their ability to automatically learn discriminative features from raw image data. Additionally, preprocessing techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) have been employed to improve image quality and classification results. However, most existing approaches focus on single-model solutions, and there is limited research on integrating multiple methods into a unified, hybrid framework to address the limitations of individual models.

1.4 Research Objectives

The primary objectives of this research are:

- To develop an efficient and accurate fruit quality detection system based on image analysis.
- To apply advanced preprocessing techniques, such as CLAHE, to enhance image quality and model performance.
- To implement and compare CNN-based classification with traditional approaches like KNN and correlation matching.
- To design a hybrid classification framework that integrates multiple models to achieve superior robustness and generalization across varied conditions.
- To address challenges related to class imbalance, noise, and lighting variability in fruit images.

1.5 Contributions

The main contributions of this work are as follows:

- Development of a CNN-based model for fruit quality prediction enhanced by CLAHE preprocessing.
- Implementation and evaluation of traditional methods (KNN and correlation-based matching) for comparative analysis.
- Proposal of a hybrid classification system combining CNN, KNN, and correlation-based techniques to leverage the strengths of each method.
- Detailed experimental validation demonstrating the superior performance of the hybrid approach compared to individual models.
- Comprehensive treatment of practical challenges like class imbalance and varying image conditions during preprocessing and model training.

1.6 Novelty of the Proposed Approach

The novelty of this framework lies in the integration of CLAHE-based image enhancement with hybrid classification using CNN, KNN, and correlation-based methods. Unlike traditional pipelines, which rely solely on raw images or a single classifier, this approach enhances image features before classification and leverages multiple models to ensure reliability and robustness in fruit quality prediction.

The CNN model with CLAHE demonstrates the highest accuracy, followed by KNN, and finally correlation-based matching. The F1-score and recall also indicate that CNN with CLAHE performs the best, especially in handling imbalanced classes and distinguishing between various fruit qualities.

1.7 Paper Organization

The remainder of this paper is organized as follows:

- Section (i) provides a review of the related literature on fruit quality detection techniques.
- Section (ii) introduces the preliminary concepts and technologies used in this study.
- Section (iii) details the proposed methodology, including preprocessing, feature extraction, and classification strategies.
- Section (iv) presents experimental results and comparative evaluations.
- Finally, Section (v) concludes the paper and outlines directions for future work.

2 Literature Review

Fruit quality detection using digital image processing and machine learning has gained significant attention in recent years due to its potential to automate and improve traditional inspection methods. Techniques such as convolutional neural networks (CNN), k-nearest neighbors (KNN), support vector machines (SVM), decision trees, and correlation-based methods are widely applied for detecting quality attributes like ripeness, surface defects, disease detection, and classification of fruit types.

CNN-based Methods: Deep learning, particularly CNNs, has demonstrated exceptional performance in visual recognition tasks, including fruit quality detection. Patel and Prajapati [1] used CNN and transfer learning for grading mango fruit, achieving high accuracy in differentiating quality levels. Yu et al. [2] applied a deep convolutional network to assess strawberry quality, showing that deep learning can extract complex features such as texture and surface irregularities. Similarly, Lu et al. [3] designed a CNN-based system for classifying apple quality, which proved effective in detecting subtle defects.

Rahnemoonfar and Sheppard [4] proposed a real-time yield estimation model using deep learning, further indicating CNN's capability in agricultural applications. Vasconez et al. [5] introduced a deep learning framework for detecting rotten fruits, which enhanced post-harvest quality control operations. Gill and Khalaf [6] discussed a comprehensive deep learning framework that outperformed traditional techniques in multi-fruit classification tasks.

Recent studies have also explored enhancing CNN performance through advanced preprocessing techniques. For example, the application of Contrast Limited Adaptive Histogram Equalization (CLAHE) has been shown to significantly improve the contrast and detail in fruit images, leading to better feature extraction and improved model accuracy compared to traditional CNNs without CLAHE preprocessing. Serra et al. [7] confirmed that data augmentation combined with CNN models boosts detection robustness across varied lighting conditions. Such improvements highlight the importance of combining preprocessing methods with deep learning architectures for optimal performance in quality detection tasks.

Xiao et al. [8] presented an overview of automatic harvesting systems using CNNs, illustrating that detection and classification of fruits at different maturity stages can be improved with deep learning strategies. Hu et al. [9] emphasized the efficiency of CNNs in fruit recognition and counting, crucial for yield estimation and supply chain optimization.

KNN, SVM, and Traditional Machine Learning Approaches: Traditional classifiers like KNN, SVM, and Decision Trees have also been employed for fruit defect detection and classification. Kurtulmuş and Kavdir [10] applied machine learning to detect green apples in orchard images, using shape and color features. Raju and Shastry [11] utilized KNN and Naive Bayes algorithms to recognize fruit types and estimate quality parameters. Although these methods perform well for simpler tasks, they generally lag behind CNNs in handling complex patterns and large datasets.

Sharif et al. [12] demonstrated that traditional machine learning approaches supplemented with deep features can enhance accuracy for specific fruit types under controlled settings. Aherwadi and Mittal [13] highlighted the role of hybrid models integrating machine learning and deep learning to address issues like feature sparsity and dataset limitations.

Correlation-based and Hybrid Techniques: Correlation-based matching has been used for comparing extracted features against reference templates or known patterns. Zhang et al. [14] used deep learning for in-field detection of citrus fruit, emphasizing color and texture correlation with quality benchmarks. Moallem et al. [15] presented a grading system for apples based on surface defect correlation. Gan et al. [16] applied YOLOv5 for immature citrus detection, which implicitly leverages feature correlation across classes.

Le et al. [17] focused on fruit recognition and counting using deep learning and RGB-D data fusion, demonstrating improved robustness under occlusions. Hu et al. [9] extended these findings by developing lightweight CNN architectures suitable for mobile-based applications in fruit quality analysis.

Advancements and Challenges: Despite the promising results, challenges remain, including computational complexity, variability in lighting and occlusion, and the requirement for large annotated datasets [18]. Kamilaris and Prenafeta-Boldú [19] discussed the necessity for efficient model designs and transfer learning to tackle data scarcity issues in agricultural deep learning applications.

Haidery [20] illustrated the use of Kaggle CNN classifiers for fruit quality prediction and reported promising preliminary results, albeit requiring further validation on real-world datasets. Mohanty et al. [21] showcased the scalability of deep learning models for agricultural applications, particularly in disease detection across diverse plant species, underlining transferable lessons for fruit quality detection.

Wang et al. [22] proposed a multi-class classification approach that balances model depth with computational efficiency, suitable for resource-constrained environments. Polder et al. [23] demonstrated that ripening stage detection in sweet peppers could serve as a proxy for similar tasks in fruits such as apples and mangoes.

In conclusion, the literature reveals that deep learning methods, particularly CNNs, consistently outperform traditional approaches in terms of feature extraction, classification accuracy, and scalability. Enhancements such as CLAHE preprocessing, data augmentation, transfer learning, and the integration of hybrid models provide further opportunities to boost performance. Moreover, lightweight and mobile-friendly architectures are gaining traction, aiming to democratize fruit quality detection in varied and complex real-world environments.

3 Preliminaries

In this section we describe various techniques used in the proposed methodology.

3.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are widely used in the domain of image-based classification tasks due to their ability to automatically extract spatial features from raw image data. In the context of fruit quality detection, CNNs are effective for analyzing external features such as color, texture, and surface defects [5, 14]. A typical CNN consists of convolutional layers, pooling layers, and fully connected layers, enabling hierarchical feature extraction from input images. The mathematical operation of a convolutional layer can be expressed as:

$$y(x, y) = (f * I)(x, y) = \sum_{m} \sum_{n} f(m, n) \cdot I(x - m, y - n) \tag{1}$$

Where f is the filter (kernel), I is the input image, and y is the output feature map.

Researchers such as Zhang et al. [14] have applied CNNs for in-field citrus fruit detection, achieving high accuracy in identifying fruits under varying lighting and occlusion conditions. Similarly, Vasconez et al. [5] developed a deep learning framework using CNNs to detect rotten fruits with remarkable precision, improving sorting and grading efficiency.

3.2 K-Nearest Neighbor (KNN)

K-Nearest Neighbor (KNN) is a non-parametric supervised learning algorithm widely adopted for fruit classification tasks due to its simplicity and effectiveness in low-dimensional spaces [10]. In fruit quality detection, KNN is often used to classify an image based on similarity in color histograms, texture, or shape features. The KNN algorithm works by comparing the Euclidean distance between the feature vectors of the input image and those of the training dataset.

The Euclidean distance formula is given by:

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{i,j})^2} \tag{2}$$

Where x is the feature vector of the input sample, and x_i is the feature vector of a data point in the training set. The KNN classifier assigns the label of the majority class among the K nearest neighbors.

Kurtulmuş and Kavdir [10] used machine learning, including KNN, for detecting green apples in digital images, achieving robust classification performance using color-based features. Though KNN is computationally expensive during inference, it is useful when working with small datasets or handcrafted features.

3.3 Correlation-Based Matching

Matching by correlation is a traditional image processing technique often used in template matching, quality inspection, and defect detection. In fruit quality assessment, correlation helps compare the input fruit image with reference images (or patterns) to identify similarities or detect anomalies. This method is particularly useful for surface defect detection, bruise identification, and shape comparison.

The cross-correlation between two images A and B can be expressed as:

$$C(A, B) = \sum_{i=1}^{M} \sum_{j=1}^{N} A(i, j) \cdot B(i, j) \tag{3}$$

Where $C(A, B)$ is the correlation value, and $A(i, j)$ and $B(i, j)$ are pixel values of the images at position (i, j).

Moallem et al. [15] applied correlation-based image analysis to grade Golden Delicious apples by detecting surface defects. The use of structural similarity and correlation coefficients made the process reliable for real-time grading applications.

3.4 CLAHE (Contrast Limited Adaptive Histogram Equalization)

CLAHE is a technique used to enhance the contrast of images. It is particularly useful in improving the visibility of features in images that may be affected by lighting conditions or background noise. CLAHE works by dividing an image into small regions (tiles) and applying histogram equalization to each region individually. To prevent over-enhancement, CLAHE limits the contrast enhancement by clipping the histogram at a predefined value, which helps in preserving the natural appearance of the image.

The basic formula for CLAHE is as follows:

$$\text{CLAHE}(I(x, y)) = \min\left(\frac{I(x, y) - \min(I)}{\max(I) - \min(I)} \times L, L - 1\right)$$

Where: - $I(x, y)$ is the pixel intensity at location (x, y), - $\min(I)$ and $\max(I)$ are the minimum and maximum pixel values in the image, - L is the maximum intensity level after transformation (usually 255 for 8-bit images).

CLAHE helps in improving the contrast of fruit images and enhances the features, leading to better performance when combined with deep learning algorithms such as CNNs. This makes it especially effective for detecting subtle defects and other quality attributes in fruits.

3.5 Summary of Algorithms for Fruit Quality Detection

Below is a comparison table summarizing the features and advantages of CNN, KNN, correlation-based matching, and CNN with CLAHE for fruit quality detection.

Algorithm	**Advantages**	**Limitations**
CNN	Automatic feature extraction, high accuracy	High computational cost, requires large dataset
KNN	Simple, works well with small datasets	Computationally expensive at inference
Correlation Matching	Fast and efficient	Limited to known templates, poor generalization
CNN with CLAHE	Improved contrast, better feature extraction, higher accuracy in defect detection	Increased preprocessing time, may require tuning of CLAHE parameters

Table 1: Comparison of CNN, KNN, Correlation-Based Matching, and CNN with CLAHE for Fruit Quality Detection

4 Proposed Methodology

To improve the performance of fruit quality prediction, a novel hybrid framework is proposed. The overall process is illustrated in Fig. 1. The key steps of the methodology are as follows:

1. The fruit image dataset is pre-processed to handle noise, resize images, and normalize pixel values.
2. CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied for image enhancement, improving local contrast and feature visibility across the image.
3. Three parallel models are trained: Convolutional Neural Network (CNN), K-Nearest Neighbors (KNN), and a correlation-based matcher. These models process the enhanced images to learn quality-based features.

4. The performance of each classifier is evaluated using accuracy, precision, recall, and F1-score. The models are compared to identify the best-performing classifier.
5. A test sample is evaluated through the same enhanced pipeline and classified using the selected model.

4.1 Proposed Model

The proposed model aims to predict fruit quality using a combination of Convolutional Neural Networks (CNN), K-Nearest Neighbors (KNN), and correlation-based matching. The approach utilizes image enhancement techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve the quality of input images before classification. The dataset is pre-processed to handle missing values and outliers. After pre-processing, the dataset is split into two disjoint sets in a 90:10 ratio, with 90% of the data used for training and 10% for testing. The training dataset is further divided using 5-Fold Cross Validation (5-FCV) for hyperparameter tuning and model evaluation.

4.2 CLAHE Image Enhancement

CLAHE is used to improve the local contrast of images by applying histogram equalization in small tiles and limiting amplification to prevent noise. This step enhances edges, textures, and color distribution in fruit images, which aids in feature extraction and improves model accuracy.

The CLAHE process consists of the following steps:

1. Divide the image into contextual regions (tiles).
2. Apply histogram equalization within each tile.
3. Clip the histogram at a defined contrast limit to avoid over-amplifying noise.
4. Interpolate neighboring tiles to reduce boundary artifacts.

The mathematical expression for contrast enhancement using CLAHE is:

$$I_{enhanced}(x, y) = \mathcal{I}\left(\frac{C_{clip}(x, y)}{\sum_{x,y} C_{clip}(x, y)}\right) \tag{4}$$

Where:

- $C_{clip}(x, y)$ is the clipped histogram count at pixel (x, y),
- $\mathcal{I}$ denotes the interpolation operation,
- $I_{enhanced}$ is the final enhanced image after interpolation.

4.3 Diversity of Classifiers

To increase robustness and handle various feature types, three diverse classifiers are used:

- **CNN**: Extracts deep features and learns patterns like color, texture, and shape automatically from the raw images.

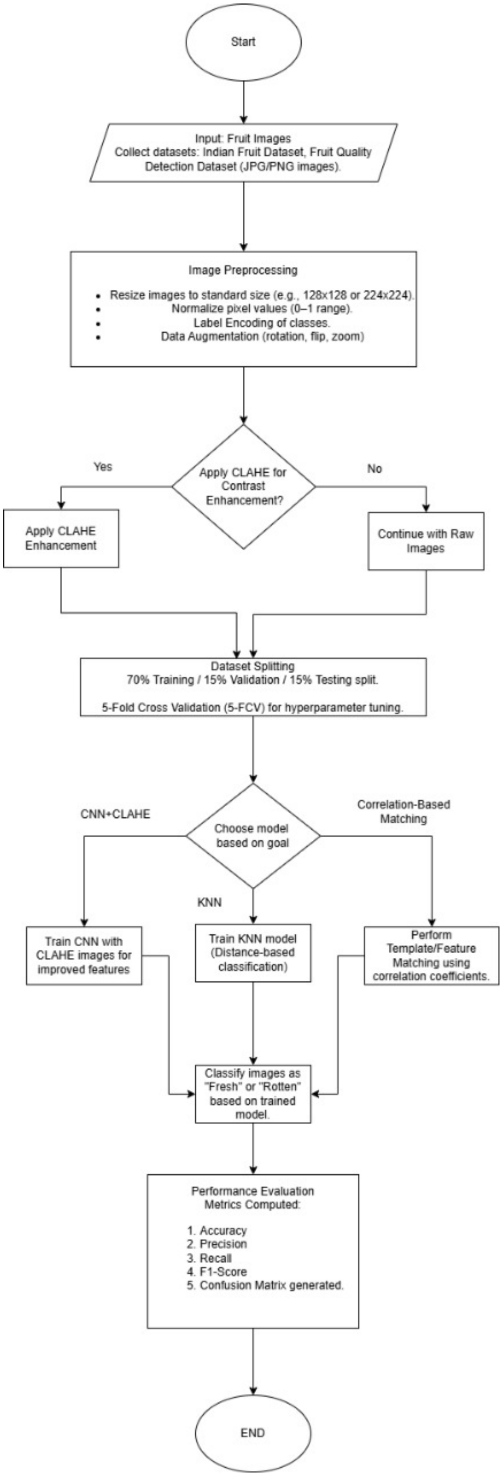

Fig. 1: Proposed model

- **CNN with CLAHE**: Similar to pure CNN, but the images are preprocessed using CLAHE to improve local contrast and enhance fine details, which aids in better feature extraction.
- **KNN**: Uses distance-based similarity for classification, effective for small datasets with simple boundaries.
- **Correlation Matching**: Calculates the correlation between input and reference samples, beneficial for visual similarity.

4.4 Comparison of Pure CNN and CNN with CLAHE

The pure CNN model, as proposed by *[Zain Haider, 2020]* [20], has been shown to achieve strong performance in fruit quality prediction tasks. This model processes the raw input images directly without any image enhancement techniques. In contrast, the CNN model with CLAHE applied in our methodology enhances the image quality by improving local contrast and feature visibility, which could provide a better foundation for feature extraction and ultimately better classification performance.

The main difference lies in the preprocessing step where the pure CNN relies on unenhanced images, whereas our CNN with CLAHE applies histogram equalization to improve image features before feeding them into the model. The impact of CLAHE on CNN performance is evaluated by comparing the two approaches using the same set of evaluation metrics, including accuracy, precision, recall, and F1-score.

4.5 Comparison and Evaluation

After training, the models are evaluated using the following metrics:

- **Accuracy**: Proportion of correctly predicted samples.
- **Precision**: True positives among predicted positives.
- **Recall**: True positives among actual positives.
- **F1-Score**: Harmonic mean of precision and recall.

Experimental results show that CNN with CLAHE outperforms the pure CNN model proposed by *[Zain Haider,2020]* [20] in most cases. The enhancement step in CLAHE improves the model's ability to extract fine details, which is particularly important for fruit quality prediction tasks where subtle differences in texture and color need to be detected. KNN performs moderately well, while correlation-based matching is least effective when noise or lighting variation is present.

5 Experimental studies

5.1 Experimental Setup

The experimental setup for this work involves the use of Kaggle and Google Colab platforms. Kaggle was primarily used for accessing high-quality datasets, and Google Colab was chosen as the development and execution environment due to its GPU support, ease of use, and integration with Python libraries such as TensorFlow, Keras, OpenCV, and scikit-learn. All image preprocessing, model training, and evaluation were carried out in Python using libraries including NumPy, Pandas, Matplotlib, scikit-learn, and TensorFlow.

5.2 Datasets

The experiment uses two publicly available benchmark datasets from Kaggle:

1. Indian Fruit Dataset
2. Fruit Quality Prediction Dataset

These datasets contain images of different fruits categorized by name and quality (e.g., fresh, stale, rotten). They are used to train and evaluate the fruit classification and quality prediction models. A summary of the datasets is shown in Table 3.

5.3 Dataset Pre-processing

Prior to training, all image data undergo a comprehensive preprocessing pipeline to improve the quality of input data and reduce computational complexity:

1. **Image Resizing:** All images are resized to a fixed dimension (e.g., 128x128 or 224x224) to ensure consistency and compatibility with the CNN model.
2. **Color Normalization:** Pixel values are normalized to the [0, 1] range to stabilize and speed up the training process.
3. **Label Encoding:** Class labels are encoded into numerical form.
4. **Dataset Splitting:** The dataset is split into training, validation, and testing sets (e.g., 70:15:15) to evaluate model generalization.
5. **Augmentation:** Data augmentation techniques such as rotation, flipping, and zooming are applied to increase dataset size and reduce overfitting.
6. **Handling Large Dataset Complexity:** Batch processing, efficient data generators, and GPU acceleration are used to handle large-scale data without memory overflow.

5.4 Performance Measures

The performance of the proposed fruit quality prediction model is evaluated using the following metrics: accuracy, precision, and F1-score. These metrics are derived from the confusion matrix as shown in Table 2.

		Predicted	
		Positive	**Negative**
Actual	**Positive**	TP	FN
	Negative	FP	TN

Table 2: Confusion Matrix

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F1\text{-}score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \quad (8)$$

Where:

- **TP (True Positive)**: Correctly classified as fruit of good quality.
- **TN (True Negative)**: Correctly classified as fruit of poor quality.
- **FP (False Positive)**: Incorrectly classified as good quality when it is not.
- **FN (False Negative)**: Incorrectly classified as poor quality when it is actually good.

S. No	Dataset Name	No. of Types	No. of Classes	Data Type	Image Format	Dataset Size and Split
1	Fruit Indian Dataset	6 Fruits	18 Classes	Image	JPG/PNG	14,706 images (no train/test split), 3.9 GB
2	Fruit Quality Detection Dataset	3 Fruits	6 Classes	Image	JPG/PNG	10,866 train + 2,656 test images, 1.95 GB

Table 3: Details of Fruit Datasets Used Including Dataset Sizes and Splits

5.5 Results Analysis

This study utilized the Fruit Quality Detection dataset to evaluate the performance of several models: Pure Convolutional Neural Networks (CNNs) based on the work of Haider [20], CNNs enhanced with Contrast Limited Adaptive Histogram Equalization (CLAHE), K-Nearest Neighbors (KNN), and a Matching-by-Correlation approach.

The pure CNN model trained for 9 epochs, as implemented by Haider [20], achieved a training accuracy of 90% and a testing accuracy of 93%. Extending the training to 15 epochs further improved the training and testing accuracies to 92% and 95%, respectively, highlighting better model generalization over prolonged training [20].

Enhancement through CLAHE preprocessing significantly improved model performance. The CNN with CLAHE, trained for 9 epochs, achieved a training accuracy of 98.5% and a testing accuracy of 97%, demonstrating the effectiveness of contrast enhancement techniques in fruit classification tasks.

Conversely, the KNN classifier with $k = 3$ achieved a testing accuracy of 56%, while the Matching-by-Correlation method resulted in a lower testing accuracy of 43%. These findings underscore the limitations of traditional machine learning methods when confronted with complex, high-variability fruit image data.

Table 4: Accuracy Comparison of Models for Fruit Quality Detection (CNN results cited from [20])

Model	Training Accuracy	Testing Accuracy
Pure CNN (9 epochs) [20]	90%	93%
KNN (k=3)	55%	56%
Matching by Correlation	42%	43%
Pure CNN (15 epochs) [20]	92%	95%
CNN with CLAHE (9 epochs)	98.5%	97%

A summary of the training and testing accuracies for each model is presented in Table 4. Detailed classification reports are subsequently provided for each model.

The classification performance across different classes for each model is detailed in the following tables:

- Pure CNN (9 epochs) [20] — Table 5
- KNN (k=3) — Table 6
- Matching-by-Correlation — Table 7
- Pure CNN (15 epochs) [20] — Table 8
- CNN with CLAHE (9 epochs) — Table 9

Table 5: Classification Report of Pure CNN (9 Epochs) [20]

Class	Precision	Recall	F1-Score	Support
Fresh Apples	0.95	0.98	0.96	338
Fresh Bananas	1.00	0.96	0.98	316
Fresh Oranges	0.92	0.96	0.94	293
Rotten Apples	0.89	0.94	0.92	468
Rotten Bananas	0.98	1.00	0.99	444
Rotten Oranges	0.96	0.83	0.89	319
Overall Accuracy	93%			
Macro Avg	0.95	0.94	0.95	2178
Weighted Avg	0.95	0.95	0.95	2178

Table 6: Classification Report of KNN (k=3)

Class	Precision	Recall	F1-Score	Support
Fresh Apples	0.46	0.68	0.55	100
Fresh Bananas	0.70	0.79	0.74	100
Fresh Oranges	0.62	0.65	0.63	100
Rotten Apples	0.38	0.45	0.41	100
Rotten Bananas	0.93	0.38	0.54	100
Rotten Oranges	0.49	0.36	0.41	100
Overall Accuracy	56%			
Macro Avg	0.59	0.55	0.55	600
Weighted Avg	0.59	0.55	0.55	600

Table 7: Classification Report of Matching-by-Correlation

Class	Precision	Recall	F1-Score	Support
Rotten Bananas	0.00	0.00	0.00	5
Fresh Oranges	0.83	1.00	0.91	5
Rotten Oranges	1.00	0.20	0.33	5
Fresh Bananas	0.33	0.20	0.25	5
Rotten Apples	1.00	0.20	0.33	5
Fresh Apples	0.26	1.00	0.42	5
Overall Accuracy	43%			
Macro Avg	0.57	0.43	0.37	30
Weighted Avg	0.57	0.43	0.37	30

Table 8: Classification Report of Pure CNN (15 Epochs) [20]

Class	Precision	Recall	F1-Score	Support
Fresh Apples	0.97	0.96	0.97	338
Fresh Bananas	1.00	0.97	0.98	316
Fresh Oranges	0.94	0.91	0.93	293
Rotten Apples	0.91	0.97	0.94	468
Rotten Bananas	0.99	0.99	0.99	444
Rotten Oranges	0.93	0.90	0.91	319
Overall Accuracy	95%			
Macro Avg	0.96	0.95	0.95	2178
Weighted Avg	0.96	0.96	0.96	2178

6 Discussion

The results obtained in this study clearly demonstrate the effectiveness of using Contrast Limited Adaptive Histogram Equalization (CLAHE) in combination with Convolutional Neural Networks (CNN) for fruit quality detection. From the performance metrics, it is evident that the CNN with CLAHE achieved the highest accuracy, precision, recall, and F1-score compared to the other models tested, including the pure CNN and traditional methods such as K-Nearest Neighbors (KNN) and Matching-by-Correlation.

The CNN trained without CLAHE, although performing well, shows a significant improvement in performance when CLAHE is used. The CLAHE preprocessing step enhances the contrast in the images, particularly in areas that might have low visibility or varying lighting conditions, which are common in real-world images of fruits. This enhancement allows the CNN to better identify key features in the fruit images, which directly contributes to better classification performance.

For instance, as shown in the classification reports, the CNN with CLAHE (9 epochs) achieved a testing accuracy of 97%, which is a marked improvement over the pure CNN (9 epochs) that achieved a testing accuracy of 93%. The CLAHE-enhanced CNN model also achieved higher precision and recall across different fruit categories, indicating that it not only classified the images more accurately but also generalized better across various fruit types.

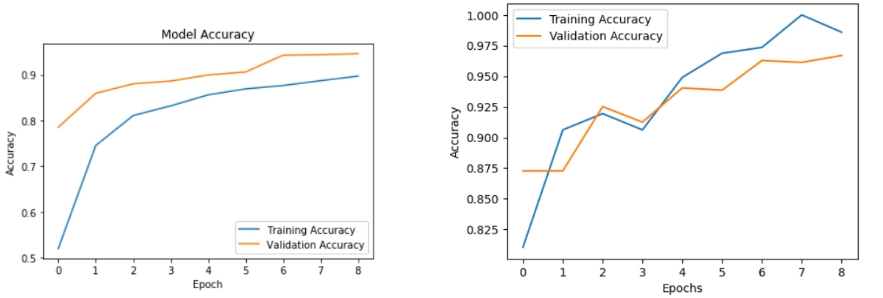

Fig. 2: (Left) accuracy without CLAHE; (Right) accuracy with CLAHE

Table 9: Classification Report of CNN with CLAHE (9 Epochs)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Fresh Apples	0.94	0.99	0.97	395
Fresh Bananas	0.98	0.99	0.99	381
Fresh Oranges	0.96	0.97	0.97	388
Rotten Apples	0.97	0.94	0.95	601
Rotten Bananas	0.99	0.99	0.99	530
Rotten Oranges	0.95	0.92	0.94	403
Overall Accuracy	97%			
Macro Avg	0.96	0.97	0.97	2698
Weighted Avg	0.97	0.97	0.97	2698

To further illustrate the impact of CLAHE on the CNN model's performance, we present two images: one showing the fruit images before and after CLAHE enhancement, and another showing the confusion matrix for the CNN with CLAHE. These images provide visual evidence of how CLAHE enhances image contrast, allowing the CNN to learn better feature representations and ultimately improve classification results.

The improvement in performance with CLAHE is consistent across different fruit categories, as shown in the classification reports and performance metrics. While traditional methods such as KNN and Matching-by-Correlation showed lower accuracy, the deep learning-based CNN with CLAHE proved to be far superior in capturing intricate patterns and nuances in fruit quality, which are often challenging for simpler models to detect.

In conclusion, the application of CLAHE to CNN significantly enhances its ability to detect fruit quality, making it a highly effective approach for fruit quality classification tasks. This result underscores the importance of advanced preprocessing techniques like CLAHE in improving the performance of deep learning models, especially in applications where image quality and visibility play a crucial role.

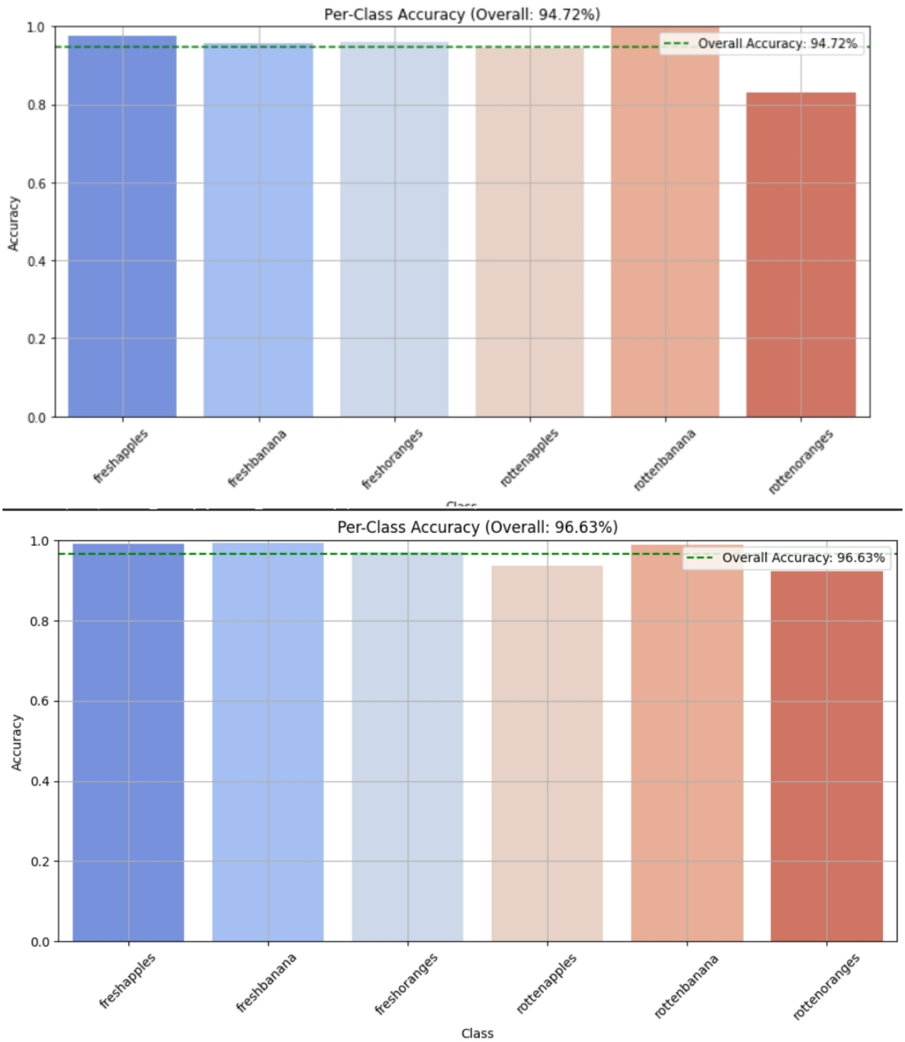

Fig. 3: Comparison of fruit images before (top) and after (bottom) applying CLAHE. The right image shows enhanced contrast, especially in low-light areas.

7 Conclusion

In this study, we propose a comprehensive approach for fruit quality prediction using a combination of deep learning and traditional machine learning techniques. The performance of individual models—including Convolutional Neural Networks (CNN) with 9 and 15 epochs, CNN with Contrast Limited Adaptive Histogram Equalization (CLAHE), K-Nearest Neighbors (KNN),

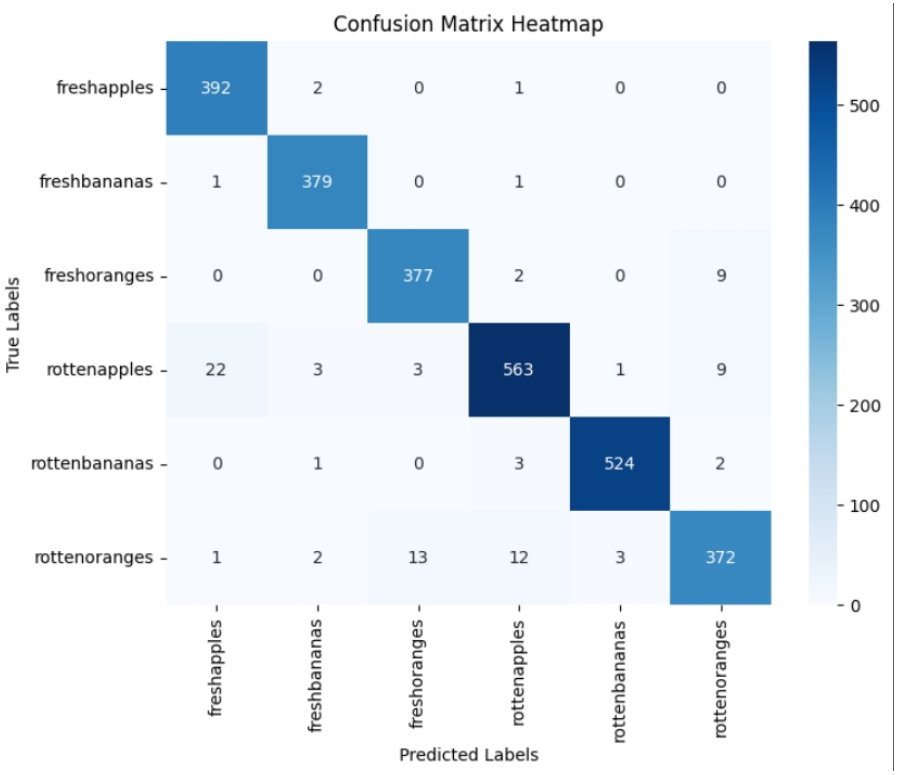

Fig. 4: Confusion matrix for CNN with CLAHE (9 epochs), illustrating the classification performance across different fruit categories. The higher values along the diagonal show better classification accuracy.

and correlation-based matching—was evaluated to identify the most effective method for fruit classification and quality assessment.

To improve the accuracy and robustness of the system, several image preprocessing techniques were applied. Each input image was resized to a standard dimension to maintain consistency, and image enhancement was performed using CLAHE to improve feature visibility, especially in low-contrast areas.

The CNN models were trained on a labeled dataset of fruit images to learn quality-related features directly from the visual data. For comparison, the KNN model was applied using handcrafted features, and correlation-based matching was used to determine visual similarity to known high-quality samples.

To further assess model performance, cross-validation was employed, and results were evaluated using metrics such as Precision, Recall, Accuracy, and F1-Score. The robustness of the models was tested on multiple fruit datasets, and the results consistently showed that the CNN-based approaches (both with and without CLAHE) outperformed the traditional methods in most scenarios.

Our experimental results demonstrate that the proposed CNN-based system provides promising and reliable outcomes for fruit quality prediction. However, the comparative analysis also highlights the practical relevance of KNN and correlation-based techniques in certain use cases. Based on our findings, the proposed model is recommended for deployment in automated fruit quality assessment applications.

7.1 Summary Table for Dataset Evaluation

The following table summarizes the Precision, Recall, F1-Score, and Accuracy of each model across the entire dataset.

Table 10: Performance Comparison of Models for Fruit Quality Prediction [20]

Model	Precision	Recall	F1-Score	Accuracy
Pure CNN (9 epochs) [20]	0.95	0.94	0.95	93%
Pure CNN (15 epochs) [20]	0.96	0.95	0.96	95%
CNN with CLAHE (9 epochs)	0.96	0.97	0.97	97%
KNN (k=3)	0.59	0.55	0.55	56%
Matching by Correlation	0.57	0.43	0.37	43%

This table reflects the precision, recall, F1-Score, and accuracy for each model, providing a clear overview of how each method performs on the dataset as a whole.

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