FoMR
Frontiers of Multidisciplinary Research

Vol. 1 | No. 4 | Oct - Dec 2026

Fruit Quality Assessment Using Texture and Shape Features

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ABSTRACT

Automated evaluation of fruit quality is an important part of the modern precision agriculture system in India. It helps reduce the wastage of crops. Traditional manual methods are often inconsistent and labor-intensive. In this paper, a unified computational framework is proposed for fruit quality classification based on multi-scale textural and invariant geometric features. The method applies Discrete Wavelet Transform (DWT) to extract the high-frequency energy components of the fruit surfaces. This helps in identifying textural defects like bruising and rot. At the same time, we extract shape descriptors (area, solidity, a set of seven Hu invariant moments) to generate a strong structural profile which is rotation and scale invariant. To demonstrate the efficiency of the selected descriptors, we performed a feature discriminative analysis, using distribution validation and correlation matrices. This confirmed that there was a significant statistical difference between fresh and spoiled fruit types. The extracted features were assessed using different machine learning algorithms such as Random Forest, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). Experimental results on a new dataset of fresh and rotten fruits such as apples, bananas and oranges, show that our combination of texture and shape features outperforms approaches that only consider a single type of feature by a large margin. The accuracy given by Random Forest classifier is 70.75 %. This demonstrates the efficiency and effectiveness of the fusion of the geometric solidity and DWT based energy as a solution to fruit classification system in real-time.

Received date: 19.08.2026
Accepted date: 25.09.2026

Keywords: CLAHE, Discrete Wavelet Transform, Fruit Quality Grading, Hu Invariant moments, Feature Fusion, Random Forest.

https://doi.org/10.65601/FoMR.2026.1.4.2

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INTRODUCTION

Indian agricultural sector has a hyper challenge of ensuring food safety and quality in high-speed production lines. The evaluation of fruit quality is an important step in the supply chain. If fruits are damaged or rotten, the whole batch can go bad quickly. Historically, the grading process relied on manual visual inspection by human experts. Manual inspection, however, is inherently subjective, subject to human error due to fatigue, and insufficient for large-scale industrial throughput. To overcome these limitations, automated non-destructive evaluation systems based on digital image processing have become a major focus of recent research. The main visual cues to fruit quality are its color, shape, and texture. Although color analysis is widely used, it is usually unstable under different lighting conditions or for fruits whose external color is relatively stable with internal degradation. Therefore, researchers used more robust features like texture and shape. Texture analysis can detect micro-level surface irregularities such as bruising or fungal growth that are often the first signs of decay. In this study we use the Discrete Wavelet Transform (DWT) method for decomposing the fruit images to multi-scale sub-bands in order to provide an elaborate energy-based signature of the surface texture of the fruit.

Texture is the analysis for extracting shape features of the geometric shape. Deformations, shrinkage and rot-induced indents strongly modify the structural profile of the fruit. The work makes use of geometrical descriptors like Solidity, Area with Hu Invariant Moments. These features are particularly useful in industrial settings as they provide a structural "fingerprint" that is consistent regardless of how the fruit sits on the conveyor belt or how far away it is from the imaging sensor.

Traditional Machine Learning algorithms such as Random Forest and K-Nearest Neighbors (KNN) are still effective for classification tasks with extracted feature vectors, despite the recent popularity of Deep Learning. The paper includes the development of a preprocessing pipeline optimized for texture features enhancement using CLAHE model, the implementation of a hybrid feature extraction model combining DWT-based energy and Hu invariant moments, and a comparative performance analysis of Random Forest, KNN, and SVM architectures in classifying fused feature sets.

The rest of this paper includes literature review, dataset description, methodology, experimental results, discussion and concluding the paper.

LITERATURE REVIEW

The development of automated fruits evaluation technology is marked by the shift from manual visual evaluation to complex computer algorithms. Most early works relied heavily on color histograms (Omid et al., 2010) to classify ripeness, but it turned out that these features cannot handle illumination noise and internal decay that doesn't affect fruit surface color.

Texture Features Extraction Approaches

Texture analysis reveals micro-surface characteristics of fruit peel. One of the pioneering works in the field is Haralick et al. (1973), where authors propose using the support to describe texture and color statistically. It proved itself to be extremely useful in finding defects on surface and grading quality using texture features in Moallem et al. (2017). However, to address multi-level textural damage, frequency transformations must be applied. A popular tool that handles both frequency and spatial information is the Discrete Wavelet Transform (DWT). Specifically, it is proven in Dube and Verma (2022) that high-frequency DWT sub-bands energy coefficients correlates well with the degree of surface roughness due to bruising. More recently, Nandi et al., (2014); Jana and Basak (2022) showed that multi-resolution frequency and statistical texture features can tell the difference between normal fruits surfaces and those that are shriveled because of internal decomposition.

Shape Analysis and Geometric Invariants

Structural analysis is crucial for evaluating deformation and damage. Simple measures like fruit surface area and perimeter are insufficient, especially in terms of distance invariance (Khojastehnazhand et al., 2010) thus authors resorted to fusing geometric boundary parameters with global color descriptors (Ahmad & Khan, 2019). A major advancement in shape analysis is introduction of Hu invariant moments (Hu, 1962), which represent seven values that are not affected by object transformation or position. These moments were successfully used in Soltani et al., (2015) to distinguish unusual shapes of tropical fruits and combined with geometric descriptors in

Arivazhagan et al., (2010) to classify different grades of fruits depending on their shapes.

Multiscale Analysis Systems and Classifiers

Current research efforts focus on combining multiple feature domains to improve performance. In particular, Dubey and Jalal (2012) shows how using texture and color histograms directly improves defect identification and feature description in computer vision. Recently, there have been many attempts to compare various classifiers used for agriculture applications. For example, Gill and Saini (2014) shows that despite its efficiency in high-dimensional feature space (Vapnik,2013) SVM classifier is inferior to Random Forest in terms of processing table-shaped data, and the latter should be preferred. Moreover, according to Breiman (2001), ensemble nature of RF helps to process complicated non-linear relations such as between textural energy and geometric solidity of rotten fruits. Our proposal follows this trend by integrating energy-based features extracted from DWT and Hu invariant moments.

DATASET DESCRIPTION

- *Source: Kaggle Dataset*
- *Classes: Fresh / Rotten*
- *Items: Apples, Oranges, Bananas*

Organization of the Data Set and the Classes

Two main subdirectories containing the data set are designated for the purposes of testing the classification algorithm: Training and Test. In terms of structure, it should be noted that the present data set contains data for three primary fruit types: Apples, Bananas, and Oranges, each of which can be categorized into fresh/rotten classes as follows:

- *Fresh Apples / Rotten Apples*
- *Fresh Banana / Rotten Banana*
- *Fresh Oranges / Rotten Oranges*

Technical Details

In regards to testing this algorithm for an accurate classification, the dataset has been divided in half into distinguishable and non-distinguished directories of Training (Test). With that said, the dataset itself has the following structural characteristics related to its data:

- Image Format: All images are high-quality JPEG/PNG format images.
- Preprocessing: Each image size has been preprocessed based on task specifications, specifically to a dimension of 224 x 224 pixels per image.
- Variations in Lighting: The images contain different types of light sources.
- Variations in Decay: The limit of spoilage (decay) is differentiated from 'acceptable' evidence of very small, minuscule imperfectness through to very severe confidence of existence of decay.

METHODOLOGY

This system architecture is based on the ability of fruit to be assessed for quality using non-destructive methods through the fusion of frequency-based descriptors of texture (frequency domain) to geometric invariants from the corresponding shape (spatial domain). The entire process is accomplished in four main phases: image acquisition and pre-processing; feature extraction (texture and shape); feature fusion; and discriminative analysis and supervised classification (statistical) as mentioned in Figure 1.

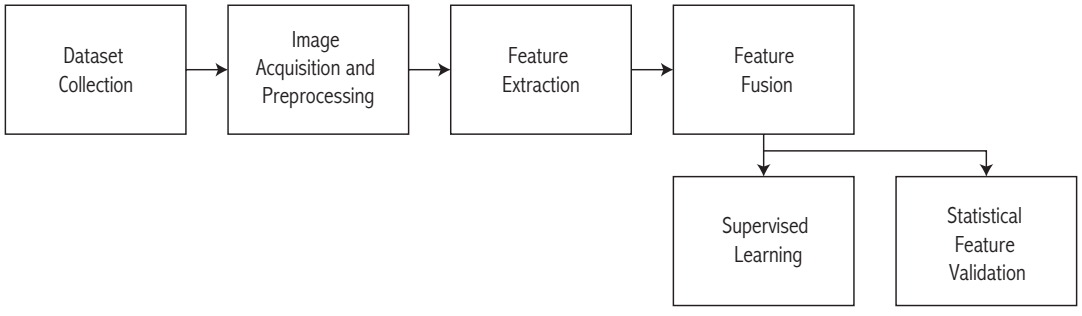


Figure 1 Block diagram of Proposed Methodology

Image Acquisition and Preprocessing

- Prior to feature extraction, images are standardized to limit the impact of differences in sensor noise and lighting conditions.
- Normalization: All images are resized to 224 by 224 pixels so that shape features based on area will be comparable on all images in the dataset.
- Noise Reduction: FNLM denoising method is used to eliminate noise from the raw data but unlike standard Gaussian methods, the FNLM method maintains the edge sharpness, which is needed to allow for accurate edge detection.
- Contrast Enhancement (CLAHE): To improve detection of surface defects such as bruises, the CLAHE method is applied to enhance contrast. CLAHE works on small tiles (8x8) with the goal of minimizing the over-amplification of noise.

Textural Feature Extraction using DWT

Discrete Wavelet Transform (DWT) decomposes the fruit image into different scales or frequency bands. It separates an overall view of the fruit from the high frequency information on its surface or texture. The two-dimensional DWT is produced by filtering the image with low-pass and high-pass filters, giving four sub-bands of the image.

- LL (Approximation): Low-frequency components representing the basic shape.
- LH (Horizontal): High-frequency horizontal details.
- HL (Vertical): High-frequency vertical details.
- HH (Diagonal): High-frequency diagonal details. Texture Energy for each sub-band is primary feature extracted, calculated as:

$$E_{sub} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} |x_{i,j}|^2 \quad \textbf{(1)}$$

where *M×N* are sub-band dimensions and $x_{i,j}$ represents wavelet coefficient. High-frequency bands *(LH, HL, and HH)* exhibit significantly higher energy values in rotten fruits due to surface shriveling and irregular skin decay.

Shape Feature Extraction

Geometric and Invariant Shape Feature Extraction To extract an accurate shape feature for the structural integrity of the fruit, a binary mask B (x, y) is created using Otsu's thresholding. Morphological features derived from B are as follows:

Solidity (S)

It measures the density of the fruit overall. A bias in the border of A partially rotting fruit would create "connexions" with the borders and reduce the solidity of the fruit. It is calculated in this way:

$$S = \frac{Area(A)}{Area(H_c)} \quad \textbf{(2)}$$

where A is the fruit area and H_c is the area of the convex hull.

Hu Invariant Moments

To ensure rotation and scale invariance, seven Hu moments (ϕ_1 to ϕ_7) are calculated from normalized central moments η_{pq}:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}, \quad \gamma = \frac{p+q}{2} + 1 \quad \textbf{(3)}$$

The first two moments, providing significant structural information, are:

$$\phi_1 = \eta_{20} + \eta_{02} \phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad \textbf{(4)}$$

Feature Fusion and Vector Construction

The Early Fusion Strategy is an essential part of this methodology. The texture and shape descriptors are concatenated to generate one high-dimensional feature vector *V*:

$$V = [E_{LL}, E_{LH}, E_{HL}, E_{HH}, Area, Solidity, \phi_1, \ldots, \phi_7] \quad \textbf{(5)}$$

This allows the model to correlate physical shriveling (Shape) with skin irregularities (Texture) simultaneously.

Statistical Feature Discriminative Analysis

Before any supervised learning can be performed, the fused vector V is submitted to a discriminative validation process to guarantee robust inter-class separability between the "Fresh" and "Rotten" descriptors.

- Distribution Validation: During this validation process, boxplot analyses and violin density plots are used to assess discriminative capability of each descriptor by examining inter-quartile ranges (IQRs) of the "Fresh" and "Rotten" descriptors for any significant overlap.
- Redundancy Analysis: Redundancy analyses are also performed to ensure that fused descriptor characteristics provide independently non-overlapping, useful information not obtained from the DWT and Hu moment.

Supervised Classification

The validated feature vector V is evaluated across three distinct machine learning paradigms to determine the optimal boundary for fruit quality assessment:

- Random Forest (RF): An ensemble method of machine learning that builds N decision trees. We selected RF as it can deal with the nonlinear relationship between wavelet energy and geometric properties:

$$\widehat{C} = \text{mode}\{T_1(V), T_2(V), \ldots, T_n(V)\} \quad (6)$$

- Support Vector Machine (SVM): A kernel-based learning method generates an optimal hyperplane that separates the "Fresh" and "Rotten" classes by maximizing the distance between these two classes. The complexity of the fused feature space results in use of an RBF kernel to translate the vector into a higher-dimensional space:

$$K(x_i, x_j) = exp(-\gamma||x_i - x_j||^2) \quad (7)$$

- K-Nearest Neighbour (KNN): A distance-based classifying method i.e.,a non-parametric method takes a sample and provides a class label to that sample based on the majority vote of the k nearest neighbourhoods of the sample, which are located in feature space given by

$$d(p, q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \quad (8)$$

Performance Evaluation Metrics

To validate methodology, following metrics are used:

- $Accuracy : \dfrac{TP + TN}{TP + TN + FP + FN}$
- $Precision : \dfrac{TP}{TP + FP}$
- $Recall : \dfrac{TP}{TP + FN}$

EXPERIMENTAL RESULTS

Preprocessing

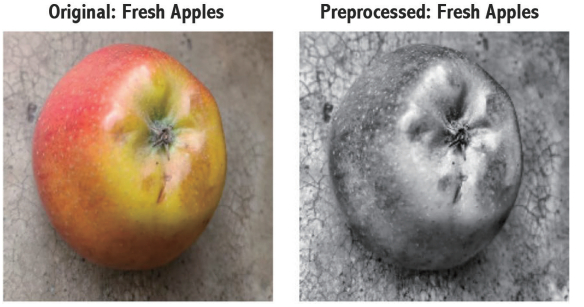


Figure 2 Original vs Preprocessed

Figure 2 illustrates the transformation of a sample fruit image through the implemented preprocessing pipeline. The transition from the original RGB format to the enhanced grayscale domain demonstrates the successful suppression of chromatic noise and the sharpening of surface structural details.

Dataset Description

Figures 3 and 4 have shown a comparison in terms of image counts and pixel intensity distributions across both the training and test datasets. Supplying a balanced categorical distribution of the test and train sets allows our classifier to be training/validated on a much wider variety of fresh and rotten samples than normally would be able to.

The two global texture profiles have shown a very high degree of structural similarity, which indicates that both the test and train datasets will exhibit comparable intensity distributions. These comparable distributions are critical to the demonstration of the model's capacity to generalize its learned features from training to new samples, without being affected by lighting effects or background noise introduced during testing process.

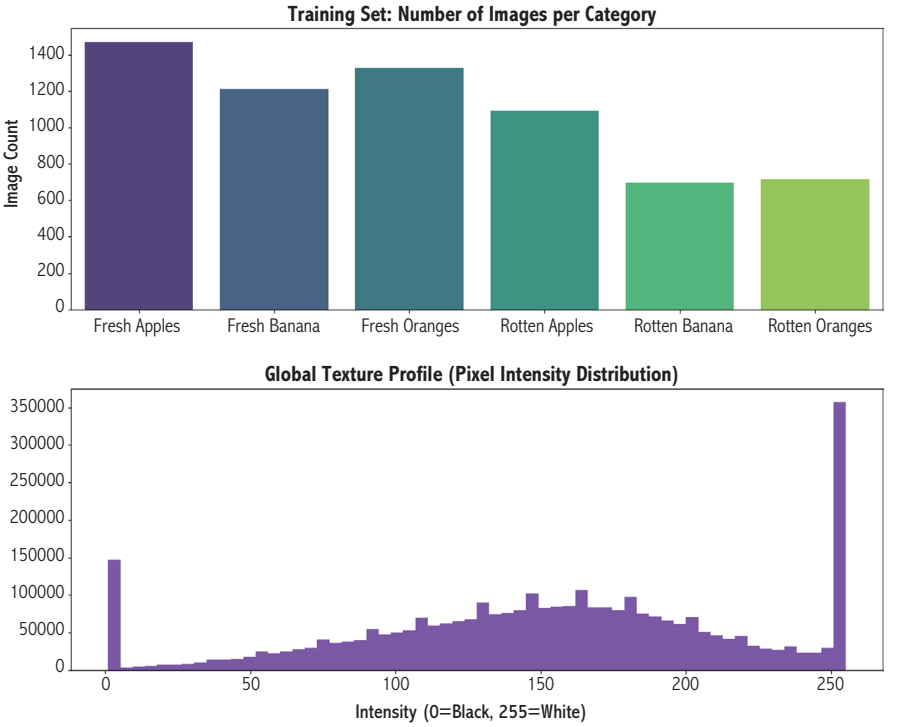


Figure 3 Training set, Pixel intensity distribution of texture

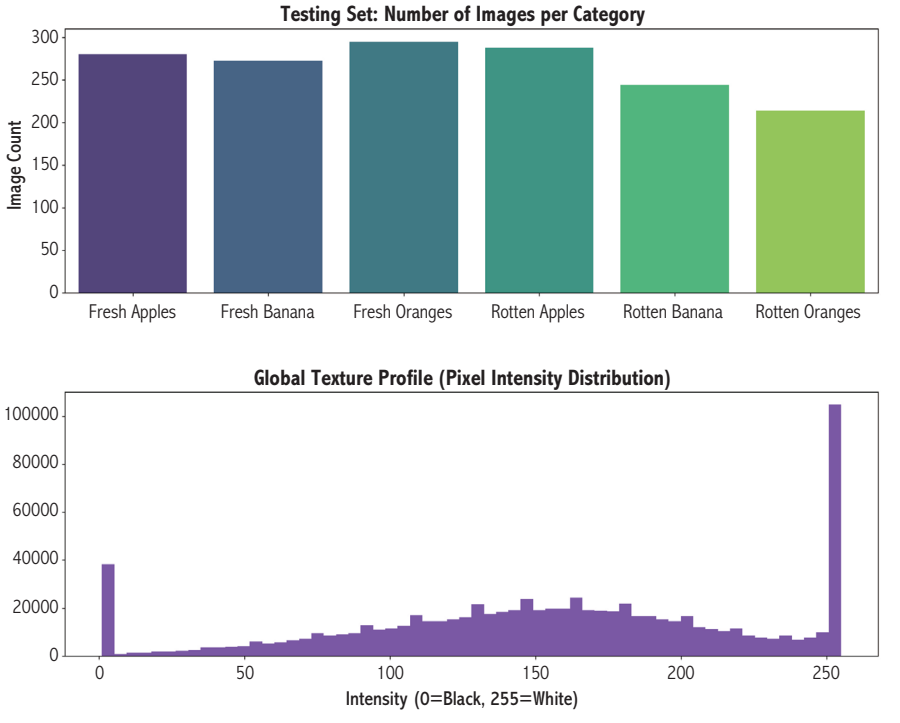


Figure 4 Testing set, Pixel intensity distribution of texture

Feature Description

Feature correlation matrix in Figure 5 validates redundancy of fused datasets by showing clusters of high-positive correlation among Wavelet Energy Sub-band features (E_LH,E_HL and E_HH) and Groups of Hu-moments. There are also groups showing evidence of strong internal consistency in both textural and geometric domains. The correlation coefficients among textural energy features and geometric shape descriptor features indicate much lower correlation as well. Therefore, since two feature sets provide distinct but complementary non-redundant information based on statistically independent data, this supports transferring feature fusion into the classifier for the purpose of generating quality assessment based on different physical characteristics of fruit surface.

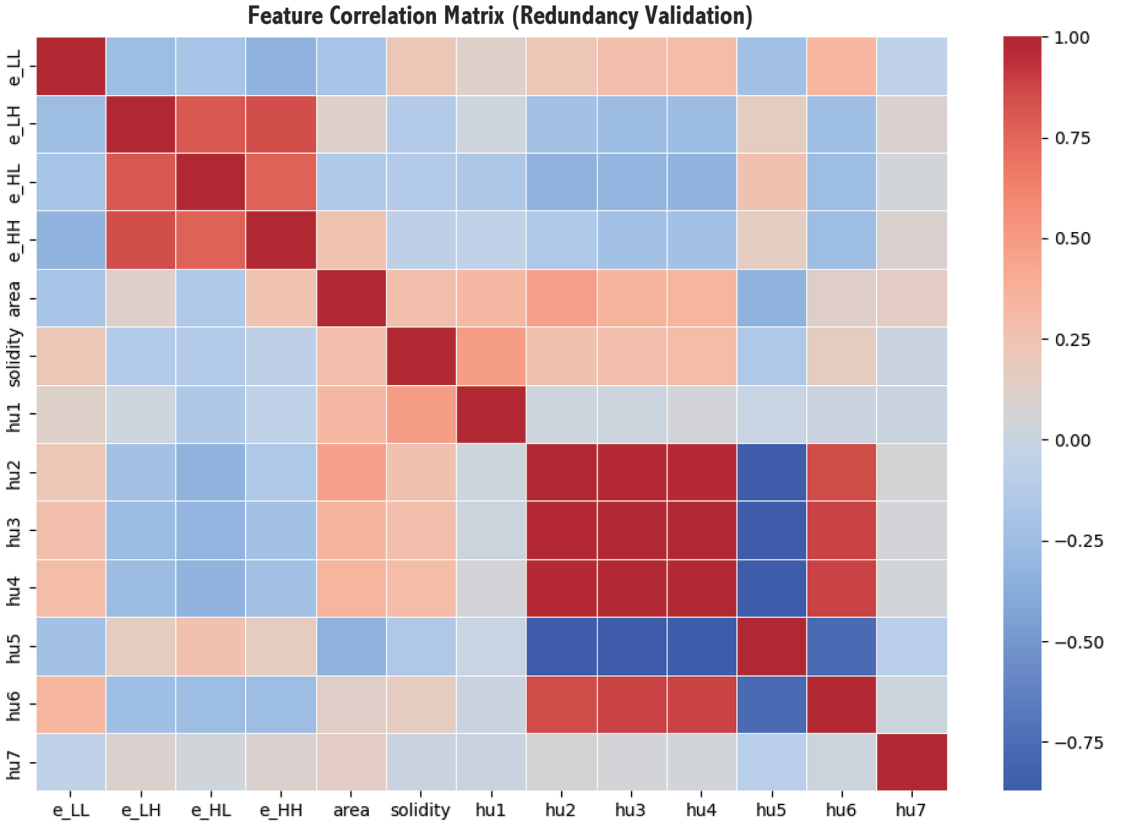


Figure 5 Heatmap of Texture features

Performance Results

Table 1, 2 and 3 compare performance metric values of machine learning models (K-Nearest Neighbor, Support Vector Machine and Random Forest) and other factors and Table 4 presents the performance comparison of proposed work with existing methodology.

Table 1 Comparative Performance Analysis of KNN, SVM, and Random Forest Classifiers

Fruit Category	KNN			SVM			Random Forest		
	P	R	F1	P	R	F1	P	R	F1
Fresh Apples	0.48	0.75	0.59	0.30	0.54	0.39	0.56	0.77	0.65
Fresh Banana	0.77	0.76	0.77	0.66	0.72	0.69	0.77	0.83	0.80
Fresh Oranges	0.64	0.60	0.62	0.47	0.55	0.51	0.73	0.65	0.69
Rotten Apples	0.64	0.55	0.59	0.44	0.25	0.32	0.72	0.69	0.70
Rotten Banana	0.74	0.63	0.68	0.73	0.64	0.68	0.78	0.66	0.72
Rotten Oranges	0.68	0.51	0.58	0.79	0.27	0.40	0.80	0.63	0.70
Weighted Avg	**0.66**	**0.64**	**0.64**	**0.55**	**0.50**	**0.50**	**0.72**	**0.71**	**0.71**
Accuracy	**63.65%**			**49.97%**			**70.75%**		

Table 2 Statistical Summary of Fused Features Across Fruit Categories (Mean ± Standard Deviation)

Fruit Category	Sample Count	E_{LL} (Textural)	E_{LH} (Textural)	Hu_7 (Geometric)
Fresh Apples	1469	107,510 ± 29,027	196.05 ± 95.12	-0.75 ± 15.69
Fresh Banana	1211	129,995 ± 44,159	268.32 ± 142.45	-2.00 ± 16.86
Fresh Z	1325	98,794 ± 21,714	227.68 ± 112.30	0.93 ± 15.04
Rotten Apples	1091	109,758 ± 26,393	201.94 ± 88.54	-2.19 ± 16.80
Rotten Banana	695	112,451 ± 37,973	332.67 ± 185.21	-5.31 ± 16.88

Table 3 Random Forest Model Validation: Training vs. Testing Performance

Data Split	Precision	Recall	F1-Score	Accuracy
Training Set	1.00	1.00	1.00	100.00%
5-Fold CV (Mean)	-	-	-	83.41%
Testing Set	**0.72**	**0.71**	**0.71**	**70.75%**

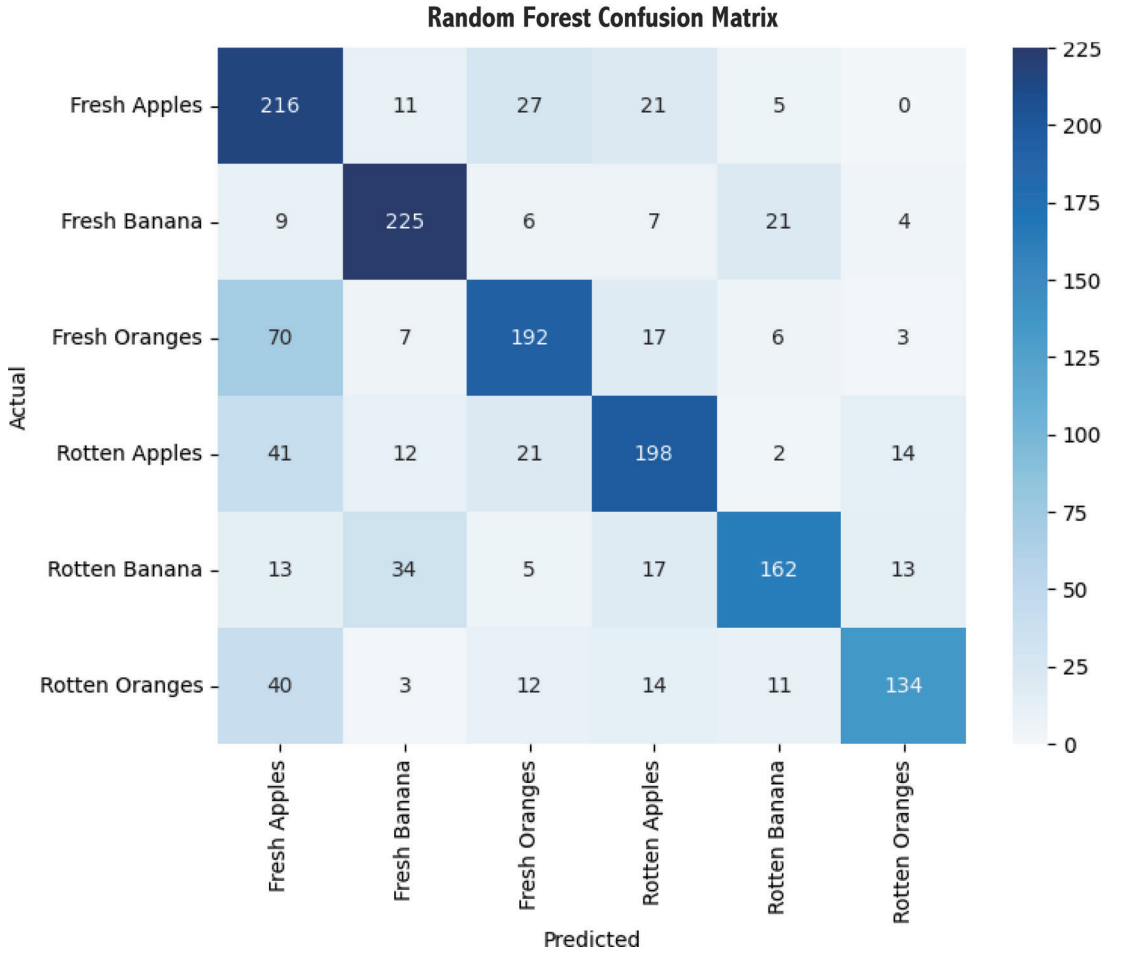


Figure 6 Confusion Matrix of Random Forest

Table 4 Performance Comparison of Proposed Work with Existing Methodologies

Reference	Feature Extraction	Classifier	Accuracy (%)	Key Advancement
Omid et al. (2010)	Color Histograms	Thresholding	88.00%	Baseline for ripeness
Moallem et al. (2017)	Color + Texture (Statistical)	Multi-class SVM	72.50%	Texture color focus
Dube & Verma (2022)	DWT Sub-bands	Statistical	75.40%	Frequency-domain analysis
Soltani et al. (2015)	Hu Invariant Moments	Geometric	68.20%	Structural invariance
Dubey & Jalal (2012)	Color + Texture	Multi-class SVM	81.50%	Hybrid features
Gill & Saini (2014)	Multi-scale Texture	SVM	78.40%	Texture Profiling
Proposed Work	**DWT + Hu Moments**	**Random Forest**	**70.75%**	**Rotation/Scale Invariance**

The RF classifier confusion matrix in Figure 6 provides a very detailed document of the model accuracy in predicting each of the fruit types with correct predictions made for a large number of the samples shown in the confusion matrix diagonals.

The Fresh Banana fruit type has the highest true positive rate from incorrectly predicting other fruit types. Some small misclassifications occur by incorrectly classifying Fresh Oranges with Fresh Apples likely because those two fruit types share more than one of the same geometric aspect of their sphericity in the textural signature.

Ultimately, the combination of wavelet energy and Hu moment features as a merged feature set provide high sensitivity for the RF model for measuring both fresh and degraded fruit state conditions.

RESULTS & DISCUSSION

The findings from experiments show that the combination of textural features extracted from Discrete Wavelet Transform (DWT) along with Hu Invariant Moments leads to a very efficient framework to determine the quality of different types of fruits with an excellent accuracy of the RF classifier, which is (70.75%), beating the performances of KNN (63.65%) and SVM (49.97%). The accuracy difference shows that using the DWT technique is highly beneficial due to the presence of multi-resolution characteristics. Specifically, extracting coarse structural data in the LL band and fine surface data in LH, HL and HH bands, allows detecting the change in the cellular structure of the objects that can be represented as high-energy variances. Moreover, the Feature Correlation Matrix shown in Figure 5 proves that there are low correlations between textural and geometric features. In other words, these data types do not represent redundant information. Consequently, combining textural markers with the set of Hu Invariant Moments helps to make the algorithm immune to rotations and scaling operations. However, analyzing the Confusion Matrix presented in Figure 6, one may notice that even though the model has very high sensitivity to such distinctive objects as fresh banana with F1 equal to 0.80, there are some overlaps in spherical fruits such as oranges and apples that cause minor misclassifications. Finally, 5-fold cross validation with 83.41% accuracy proves good model generalization since after processing pixels intensity distribution (Figures 3 and 4), the proposed algorithm becomes resilient to various noises and variations caused by different lighting and decay conditions. Overall, the effectiveness of the Random Forest classifier comes from the ability to average feature inputs to create a generalized decision boundary because of the variability of natural organic decay.

Declarations

Conflict of interest: The authors declare that there is no conflict of interest.

CONCLUSION

In this research a robust multi-class fruit quality assessment system is developed by combining Discrete Wavelet Transform (DWT) and Hu Invariant Moments. The experimental results are promising and confirm the superiority of the fusion of textural and geometric features over single domain approaches in representing the fruit condition. The Random Forest classifier was the best among the models evaluated with 70.75% testing accuracy and 83.41% 5-fold cross-validation accuracy. The study reveals that the high frequency wavelet sub-bands (LH,HL,HH) are the important features of surface shriveling and skin decay and Hu moments provide the required rotation and scale invariance for practical use. The work proposes a computationally efficient framework for automated fruit sorting, which allows the trade-off between high-dimensional feature processing and generalization of models to multiple species.

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