Defect Identification for Simple Fleshy Fruits by Statistical Image Feature Detection

Smita and Varsha Degaonkar

Abstract Maintaining the product quality of the fleshy fruits is the important criterion in the market. Quality assessment with computer vision techniques is possible with the proper selection of classifier which will give an optimal classification. Feature extraction is done in two steps: (1) Fruit image features were extracted using the 2-level discrete wavelet transform. (2) Statistical parameters like Mean and Variance of discrete wavelet transform features were calculated. A Feed-Forward back propagation neural classifier performed superior than the Support Vector Machine Linear classifier for identifying into three classes (Best, Average, and Poor) by achieving overall good accuracy.

Keywords Discrete wavelet transform · Mean · Variance · Feed-forward neural network · Support vector machine

1 Introduction

Pomegranate is the richest fruit in terms of its powerful medicinal properties and nutrients. As the saying goes prevention is better than cure, it is believed that the consumption of Pomegranate fruit is a preventive cure for many diseases including cancer and heart disease. It belongs to family Lythraceae and is a small tree or shrub. Pomegranate seeds may sometimes be sweet or some time sour. It is also widely consumed as juice.

Due to its rich, healthy benefits, it has become a popular fruit among the masses and is available in almost all markets. It is hence the fruit has a high export value which may still increase in the coming years. India also exports these fruits. Due to

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P.K. Sa et al. (eds.), *Progress in Intelligent Computing Techniques: Theory, Practice, and Applications*, Advances in Intelligent Systems and Computing 518,
DOI 10.1007/978-981-10-3373-5_16

its high produce, its essential to maintain the export quality grade and the common man should also be able to identify the quality of this fruit [1].

Following are the categories of identification:

1. Best—The pomegranate in this category is the superior class that is they must be free of defects in terms of shape and color, and these qualities are highly recommended for export.
2. Average—The pomegranate in this category should be of average quality. In this category, there may be a slight defect in the appearance of fruits which may include skin defect and defect in shape appearance. This category is not suitable for export.
3. Poor—This class does not qualify even the minimum requirements. This quality is absolutely poor in terms of shape coloring and skin disease. This quality is not advisable even for consumption.

The external appearance of the fruit gives the idea of the internal quality directly. Due to this, the purchasing of the fruits is affected a lot. Due to use of color grading in the system, the processing directly affects the fruit income as quality of fruit directly linked with color of fruit. In the existing systems, the quality of the fruit is given by color parameters [2].

Many rating systems are designed for fruit identification like a tomato is used as the product that to be tested for food superiority. The system was carried out to calculate the fruit ripeness based on their color. Evolutionary methodologies, by using several image processing techniques including image capture, image improvement, and feature extraction were implemented. To recover image superiority, the collected images were converted to color space format. A Back propagation neural network was used to perform classification of tomato ripeness based on color [3].

Through this research, we have used the following algorithm which will help to identify and distinguish between the various qualities of pomegranate fruit.

2 Feature Extraction

2.1 Database

We have created our own database. Color images of the pomegranate fruit samples are captured by using a regular digital camera. All images are resized to 256×256. The captured color image of fruit is converted into a gray color image. Preprocessing is done by the Gaussian filter for image database for removal of noise.

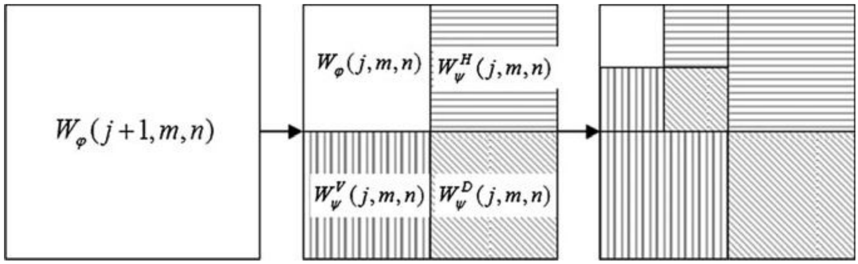

Fig. 1 A two-level decomposition

2.2 Discrete Wavelet Transform

Wavelets represent the scale of features in an image, as well as their position. DWT uses multi-resolution property. Wavelet extracts image information in terms of the frequency domain. In low frequency components subband, image energy is spread and preserved as features of the image. High frequency components subband contains image edge information which may degrade image quality, so high frequency components are rejected [4]. 2-level DWT x(t) is signified by translations and dilations of a fixed function called mother wavelet function. The representation of the DWT can be written as (1):

$$x(t) = \sum_{k=z} u_{j0,k}\phi_{jo,k}(t) + \sum_{j=-\infty}^{j_0} \sum_{k=z} w_{j,k}\psi_{j,k} \tag{1}$$

At the first level of decomposition, image is divided into four parts, as shown in Fig. 1 [5]. At the second level of decomposition, the low frequency component is again divided into four parts. These are considered as the features of the input image.

3 Classifiers

To classify pomegranate fruit into three classes (Best, Average and poor), two classifiers are developed, Linear SVM and ANN.

3.1 SVM

To classify pomegranate images, linear Support Vector Machine is used. SVM uses a main separating line and two other lines called hyperplane to classify the fruit images into three classes (Best, Average, and Poor). The best separating line is a line that located in the middle of classes. This best line obtained by maximizing margin between the hyperplane and main separating line [6]. Transposition of W and b compared to the margin width M. The margin function for an input is statistical DWT features of fruit image is given by Eq. (2) [7],

$$M(x) = W \cdot x - b \tag{2}$$

where,

$$x\epsilon \begin{cases} Class\ A\ (Best) & if\ M(x) > 0 \\ Class\ B\ (Average) & if\ M(x) < 0 \\ Class\ C\ (Poor) & if\ M(x) = 0 \end{cases} \tag{3}$$

The margin from x to the hyperplane is set by the Eq. (4)

$$\frac{M(x)}{||W||} \tag{4}$$

Input to Liner SVM classifier is features extracted from DWT. For each fruit image, 8 features are extracted. Let training data set for each fruit image of 8 points,

$$(\overrightarrow{x1}, y1), \ldots, (\overrightarrow{x8}, y8) \tag{5}$$

Let input features of the image represented by $x_1, \ldots, x_8$ and their individual group classification be represented by $y_1, \ldots, y_8$ Where [7]

$$f(x) = \begin{cases} +1, & x_i \epsilon \mathrm{A} \\ -1, & x_i \epsilon \mathrm{B} \\ 0, & x_i \epsilon \mathrm{C} \end{cases} \tag{6}$$

To maximize $\frac{M(x)}{||W||}$, it implies to minimize W and, in order to prevent data points falling into the margin M, add the limit to each equation [7]:

$$W \cdot x_i - b \geq +1,\ y_i = +1 \tag{7}$$

$$W \cdot x_i - b \leq -1,\ y_i = -1 \tag{8}$$

$$W \cdot x_i - b = 0,\ y_i = 0 \tag{9}$$

Thus, using the linear SVM classifier, the quality of pomegranate test is done by creating hyperplanes with margin for best fruit class and average or poor fruit class.

3.2 ANN

To classify pomegranate, according to good and defective quality, back propagation Feed-Forward multilayered network is used as a classifier. Statistical parameters are calculated from discrete wavelet transform features of fruit image, and these statistical parameters correspond to input layer neurons and the output layer neurons corresponds to three classes (Best, Average, and Poor) according to quality. The Feed-Forward neural network is developed and tested using statistical binary parameters (accuracy, sensitivity and specificity). The back propagation algorithm uses supervised learning; the algorithm includes the following steps [8]:

3.2.1 Training

1. Each input neuron from input layer receives image features x_i from feature extraction and apply it to the hidden layer neuron (i = 1 to n).
2. Input of the hidden layer neuron calculated by:

$$z_{inj} = v_{oj} + \sum_{i=1}^{n} x_i \cdot v_{ij} \tag{10}$$

   By applying activation functions, output of the hidden layer is calculated by:

$$z_j = f(z_{inj}) \tag{11}$$

3. Input of the output layer neuron is:

$$y_{ink} = w_{ok} + \sum_{j=1}^{p} z_j w_{jk} \tag{12}$$

   By applying activation functions, output of the outputlayer is calculated by:

$$z_k = f(y_{ink}) \tag{13}$$

4. To achieve the targeted class of fruits, the error function is calculated and according to that weights are updated in the training phase.

$$\begin{aligned} \delta_k &= (t_k - y_k)f'(y_i nk) \\ \Delta w_{jk} &= \alpha \delta_k z_j \\ w_{jk}(new) &= w_{jk}(old) + \Delta w_{jk} \\ w_{ok}(new) &= w_{ik}(old) + \Delta w_{ok} \\ v_{ij}(new) &= v_{ij}(old) + \Delta v_{ij} \end{aligned} \tag{14}$$

5. The training will stop when the target output is achieved according to fruit class (Best, Average and Poor).

3.2.2 Testing

1. Weights are taken from the training algorithm.
2. Input of the hidden layer neuron calculated by:

$$z_{inj} = v_{oj} + \sum_{i=1}^{n} x_i.v_{ij} \tag{15}$$

By applying activation functions, output of the hidden layer is calculated by:

$$z_j = f(z_{inj}) \tag{16}$$

3. Now, compute the output of the output layer unit. For $k = 1$ to me

$$y_{ink} = v_{ok} + \sum_{j=1}^{p} z_i.w_{jk} \tag{17}$$

$$y_k = f(y_{ink}) \tag{18}$$

Here, the sigmoid activation function is used to calculate the output.

4 Methodology

Methodology for the proposed work is as follows:

Step 1: Fruit images are captured and stored in database which includes Grade A (Best), Grade B (Better), Grade C (Poor), and Grade D (Worst) images.
Step 2: To get the precise features, preprocessing is done. Basically, the images which are obtained during image acquisition may not be directly suitable for identification and classification purposes because of some factors, such as noise, weather conditions, and poor resolution of an image and unwanted background.
Step 3: 2-level discrete wavelet transform is used to extract the features of these images.
Step 4: From these features, statistical parameters such as Mean and Variance is calculated.
Step 5: For defect identification of fleshy fruits, two classifiers (SVM and ANN) are trained with these statistical features.
Step 6: Performance of the classifiers is tested using statistical measures such as Accuracy, Sensitivity, and Specificity.

5 Result and Discussion

For defect identification, fruit database has been created, including 200 image samples of each class (Best, Average, Poor). For identifying the quality of pomegranate fruit images, ANN and SVM classifiers have been used. The 75% of pomegranate images have been used to train the system and remaining to test it. To measure the performance of classifiers (ANN and SVM), Binary classification and statistical parameters such as Sensitivity, Specificity, and Accuracy have been used. Sensitivity specifies the test prediction level of one category, and Specificity specifies the test prediction level of another category. Whereas Accuracy specifies the test prediction level of both categories [9].

5.1 Sensitivity [10]

Sensitivity specifies the test's ability to appropriately identify fruits category. Mathematically, this can be expressed as follows: Sensitivity = Correctly Selected/ Correctly Selected + Mistakenly Rejected.

5.2 Specificity [10]

Specificity relates to the test's ability to appropriately identify fruits without any condition. Mathematically, this can also be written as follows: Specificity = Correctly Rejected/Correctly Rejected + Mistakenly Selected.

5.3 Accuracy [10]

The accuracy is defined as the ratio of correctly recognized image samples to the total number of test image samples. Accuracy = (Correctly Selected + Correctly Rejected)/(Correctly Selected + Mistakenly Selected + Correctly Rejected + Mistakenly Rejected). Table 1 shows the Percentage Accuracy, Percentage Sensitivity, and Percentage Specificity.

Table 1 Percentage accuracy, percentage sensitivity, and percentage specificity

Fruit type	% Accuracy		% Sensitivity		% Specificity	
	ANN	SVM	ANN	SVM	ANN	SVM
Grad A Best	80.08	61.86	78.14	60.66	84.75	68.64
Grade B Good	86.54	75.64	75.38	64.18	84.62	56.41
Grade C Poor	88.75	76.25	85.86	75.86	81.75	62.5

6 Conclusion

For defect identification of fleshy fruits Pomegranate, linear SVM and ANN (Feed-Forward back propagation) classifiers have been implemented. As pomegranate fruit defect identification is done among three classes (Best, Average and Poor). In our fruit classification, multiple outputs are expected; here, SVM needs to be trained for each class, one by one where as ANN can be trained at a time for all fruit classes. ANN makes more sense than linear SVM, so it was difficult to use linear classifier.

The numerical values of sensitivity represent the probability of defective fruit taste. In the ANN, sensitivity of a classification is greater than SVM means test on a Pomegranate fruit with certain defect will be identified as average or poor class fruit. This test with high sensitivity is often used to identify defective fruit.

The numerical values of specificity represent the probability of defect-free fruit taste. In the ANN, specificity of a classification is greater than SVM means that the test on a Pomegranate fruit identifies as good class fruit. This is a test with high specificity is often used to identify for defect-free fruit.

Accuracy in ANN is more than SVM regardless of test results are accurate for both defective and defect-free fruit. Hence, for all these statistical parameters, ANN (Feed-Forward back propagation) classifier has given good results.

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