Reduced Color and Texture features based Identification and Classification of Affected and Normal fruits’ images

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Abstract
In this paper, we have presented a reduced feature set based approach for recognition and classification on images of fruits into normal and affected. The RGB (Red Green Blue) color features are reduced from 18 to 2 and GLCM (Gray-level Co-occurrence Matrix) texture features are reduced from 30 to 2. The reduced feature set comprises of 4 features namely, green mean, saturation mean, red GLCM summean and green GLCM summean. A feedback from classifier, performance is used in reducing the features. The average accuracy of 89.15% for normal type and 88.58% for affected type is obtained using 2 color features. The average accuracy of 93.15% for normal type and 89.50% for affected type is obtained using 2 texture features. The average accuracies have increased to 96.85% for normal type and 93.89% for affected type when the reduced color and texture features are combined. The work finds application in developing a machine vision system in agriculture and horticulture fields.

Keywords: feature extraction, feature reduction, fruits, computer vision, ANN (Artificial Neural Network) classifier.

1. Introduction
India is the second largest producer of fruits with a production of 44.04 million tonnes from an area of 3.72 million hectares. This accounts 10% of the world fruit production. A large variety of fruits are grown in India of which apple, citrus, banana, grape, mango, guava, are the major ones. Also, India is a large low cost producer of fruit, and horticulture has huge export potential.

Fruit industry is a major industry which contributes 20% of the nation’s growth. But due to improper cultivation of fruits, lack of maintenance and manual inspection there has been a decrease in production of good quality of fruits. Farmers are finding difficulty, especially in finding the fruits affected which results in huge loss of revenue to the farmers and the nation.

In the past few years, automation and intelligent sensing technologies have revolutionized our fruit production and processing routines. These initiatives have been accredited to the rising concerns about fruit quality and safety. Also, rising labour costs, shortage of skilled workers, and the need to improve production processes have all put pressure on producers and processors. In such a scenario, automation can reduce the costs by promoting production efficiency. Automated solutions, such as quality grading and monitoring, post-harvest product sorting, and robotics for field operations often integrate machine vision technology for sensing due to its non-destructive and accurate measurement capability.

To know the state-of-the-art in automation of the task/activities in horticulture field and automatic detection of fruit using computer vision techniques, a survey is made. The gist of a survey which carried out is given as follows.

(Pujari et al; 2013) proposed grading and classification of anthracnose fungal disease in mangoes. Different types of segmentation techniques were used to separate and grade percentage of affected areas. Statistical textures using gray-level runlength matrix (GLRLM) were used to extract features and classified as fungal affected and healthy fruit using artificial neural network (ANN) classifier. (Bandi et al; 2013) proposed Machine vision and Image processing techniques in sleuthing the disease mark in citrus leaves. Citrus leaves were investigated using texture analysis based on the color co-occurrence method (CCM) and classified using various classifiers. (Dubey and Jalal 2012) proposed image processing based approach to evaluate diseases of apple. Local binary features were extracted from the
segmented image, and finally images were classified using a Multi-class Support Vector Machine. (Patil et al; 2012) describes the method for extraction of color & texture features of diseased leaves of maize. The textures features like correlation, energy, inertia & homogeneity were obtained by computing gray level co-occurrence matrix of an image. (Patil and Raj Kumar 2011) have provided advances in various methods used to study plant diseases/trait using image processing. The methods studied were for increasing throughput & reducing subjectiveness arising from human experts in detecting the plant diseases. (Moshou et al; 2011) developed a prototype system for detection of plant diseases in arable crops automatically at an early stage of fungal disease development and during field operations. Hyperspectral reflectance and multi-spectral imaging techniques were developed for simultaneous acquisition of images. An intelligent multi-sensor fusion decision system based on neural networks was developed to predict the presence of diseases. A robust multi-sensor platform integrating optical sensing, GPS (Geostationary Positioning System) and a data processing unit was constructed and calibrated. (Anami et al., 2011) have presented classification of normal and affected agriculture/ horticulture produce. Combined color and texture features were extracted and fed as input to ANN Classifier. (Guru et al., 2011) have presented a novel algorithm for extracting lesion area and application of neural network to classify tobacco seedling diseases. First order statistical texture features were extracted from lesion area and Probabilistic Neural Network (PNN) is employed to classify anthracnose and frog-eye spots present on tobacco seedling leaves. (Al-Hiary et al., 2011) have evaluated a software solution for automatic detection and classification of plant leaf diseases. The affected area was segmented and texture analysis was done using color CCM. Neural network classifier was used to classify various plant diseases. (Di Cui et al; 2010) reports research outcomes from developing image processing methods for quantitatively detecting soyabean rust severity from multispectral images. To achieve automatic rust detection, an alternative method of analysing the centroid of leaf color distribution in the polar coordinate system was investigated. Leaf images with various levels of rust severity were collected and analyzed. (Qing Yao et al., 2009) presented an application of image processing techniques and Support Vector Machine (SVM) for detecting rice diseases using shape and texture features. (Dae Gwan Kim et al; 2009) investigated the potential of using color texture features for detecting citrus peel diseases. Classification models were constructed using the reduced texture feature sets through a discriminant function based on a measure of the generalized squared distance. (Anami et al., 2009) have presented the use of computer vision technique on spectral images. To achieve automatic rust detection, an alternative method of analysing the centroid of leaf color distribution in the polar coordinate system was investigated. (Marc Lefebvre, et al., 1993) have presented the problem in automating pulp sampling of potatoes such as their shape, color or texture in order to detect viral diseases. This paper presents two computer vision approaches that have been implemented and tested, as well as the robotic apparatus required for the complete installation. Most of the published research has mainly focused on affected single crop type. The conventional quality evaluation procedures in the fruit industry are facing unprecedented challenges due to the fast changing market requirements. These quality assessment procedures are carried out by experienced personnel. However, due to factors like different working conditions, personal judgment, and level of fatigue, grading results often turn out to be inconsistent among individual inspectors. In future scenario, industry needs to secure its hard-won reputation in fruit quality and meanwhile increase fruit handling capacity of current facilities. To achieve this objective, the current visual inspection methods need to be automated. The fruit industry desires real-time quality evaluation tools capable of working consistently and objectively. Recent research has shown that machine vision has the potential to become a viable tool to identify fruit type. Fruits’ get affected are common and not much work is cited on affected on bulk fruits samples and feature reduction technique. Hence, it is the motivation for the present work on images of normal and affected fruit.
produce based on reduced color and texture features. In this paper, we have developed a methodology for determining whether, it is affected or normal using image processing techniques. The samples of images of normal and affected fruit produce are shown in (Fig.1 & 2).

**Figure 1.** Images of normal fruit produce: (a) apple, (b) banana1, (c) chikoo, (d) pomegranate.

**Figure 2.** Images of affected fruit produce: (a) apple, (b) banana1, (c) chikoo, (d) pomegranate.

The chosen normal types are apple (*Malus domestica*), banana1 (*Musa* sp.), banana2 (*Musa* sp.), chikoo (*Manilkara zapota*), dry fruit (*Phoenix Dactylifera*), grape1 (*Vitis vinifera*), grape2 (*Vitis vinifera*), mosambi (*Citrus sinensis*), orange (*Citrus sinensis*), pomegranate (*Punica granatum*) and affected types are apple, banana1, banana2, chikoo, dry fruit, grape1, grape2, mosambi, orange, pomegranate.

The paper is organized into four sections. Section 2 gives the proposed methodology. Section 3 describes results and discussion. Section 4 gives conclusion of the work.

### 2 Proposed Methodology

In the present work, tasks like image acquisition, feature extraction, feature reduction and classification are carried out. The classification tree is given in (Fig.3). The detailed block diagram of adopted methodology is shown in (Fig.4).

**Figure 3.** Classification tree

**Figure 4.** Block diagram of proposed methodology.

#### 2.1 Image acquisition

First the normal fruits’ images are acquired with a color Digital Camera having a resolution of 12 mega pixels connected to a personal computer, Pentium IV, 2.5 GHz. The images are taken keeping a distance of 0.5m from the samples. The same fruits’ samples are kept for 7 days to get affected, later the images of affected samples are acquired with same camera. The camera was mounted over the illumination chamber on a copy stand, which provided easy vertical movement to finely tune the position of the camera from the fruits’ samples. The images are illuminated with light source of 100W, 230 V fit to the test table at an angle of 45° from the camera. The set up used to obtain the image samples is shown in (Fig 5).

**Figure 5.** Image acquisition setup.

#### 2.2 Feature Extraction and Reduction

Fruits appear in different shapes, sizes, colors, taste, and chemical composition. Fruits have dominant colors and hence are differentiated from one another by color features. Hence we have considered color features for the classification of fruits’ into normal and affected.

##### 2.2.1 Color Features

RGB color model is adopted to extract color features. The Red, Green, Blue (RGB) components are separated from the original image. The Hue (H), Saturation(S) and luminance(Y) are extracted from RGB components. The Luminance(Y) components finds to be more significant in image samples than intensity(I) components that’s why we have chosen luminance(Y) rather than intensity(I). For Luminance(Y), YCbCr model is adopted. The equations (1), (2) and (3) are used to calculate Hue (H), Saturation(S) and Luminance(Y).

\[
H = \cos^{-1} \left( \frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}} \right)
\]

\[
S = 1 - \frac{3}{(R+G+B)} \min(R, G, B)
\]

\[
\begin{bmatrix}
Y \\
Cb \\
Cr
\end{bmatrix} = \begin{bmatrix}
0.299 & 0.587 & 0.114 \\
-0.169 & -0.331 & 0.590 \\
0.500 & -0.149 & -0.981
\end{bmatrix} \begin{bmatrix}
R \\
G \\
B
\end{bmatrix}
\]

The images of fruits’ samples are recognized by quantifying the distribution of color, change in the color with reference to average or mean and difference between the highest and lowest color values. This quantification is obtained by computing mean, variance and range for a
given color image. Since these features represent global characteristics for a given image. Hence we adopted the color features namely mean, variance, and range in this work. The equations (4), (5) and (6) are used to evaluate mean, variance and range of the image samples.

Mean \( \mu = \sum_x \sum_y P(x, y) \)  

Variance \( = \sum_{x,y}(x-\mu)^2P(x,y) \)  

Range \( = \max(P(x,y)) - \min(P(x,y)) \)  

The list of extracted color features is shown in (Table 1). The color feature values for each normal and affected fruit produce are shown in (Fig.6 & 7).

2.2.2 Feature Reduction

From (Fig.6 & 7), we have found through experimentation that only 10 features, which are common in both normal and affected fruit produce, finds to be significant. Hence these 10 features contribute more to the classification of fruits into affected and normal. Therefore we have considered 10 features as first-level feature reduction shown in (Fig.8 & 9). The reduction is done based on threshold. Any feature values below threshold are discarded. The threshold is chosen based on average of minimum feature value and maximum feature value. The threshold obtained is 0.5.

Delta is the minimum difference between two feature values and is set to \(10^{-3}\).

The reduced 2 color feature values for each normal and affected fruit produce is shown in (Fig.10 & 11). The procedure involved in color feature extraction and reduction is explained in (Algorithm 1). The color features reduced to 10 and 2 are listed in (Table 2 & 3).

Algorithm 1: Color Feature Extraction and Reduction

Input: Original 24-bit color image.

Output: Reduced feature vector

Description: Delta is the minimum difference between two features and is set to \(10^{-3}\). Threshold is the average of minimum and maximum feature value and is set to 0.5.

Start

Step 1: Accept 24-bit color image of a fruit

Step 2: Separate the RGB components

Step 3: Obtain the HSY components using the equations (1), (2) and (3).

Step 4: Compute mean, variance, and range for each RGB and HSY components using the equations (4) thru (6).

Step 5: Threshold = (minimum feature value + maximum feature value)/2

Step 6: Initialize feature vector to zeros

Step 7: For (i =1 to size of the feature vector)

If (value of feature (i) >threshold),
Table 1. Color Features

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Feature</th>
<th>Sl. No</th>
<th>Feature</th>
<th>Sl. No</th>
<th>Feature</th>
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<td>Green mean</td>
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<td>Hue mean</td>
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<td>Luminance mean</td>
</tr>
<tr>
<td>5</td>
<td>Green variance</td>
<td>11</td>
<td>Hue range</td>
<td>17</td>
<td>Luminance variance</td>
</tr>
<tr>
<td>6</td>
<td>Green range</td>
<td>12</td>
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<td>18</td>
<td>Luminance range</td>
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Table 2. Reduced ten Color Features

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Feature</th>
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<th>Feature</th>
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</thead>
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<tr>
<td>1</td>
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<td>Hue range</td>
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<tr>
<td>2</td>
<td>Red range</td>
<td>7</td>
<td>Saturation mean</td>
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<td>3</td>
<td>Green mean</td>
<td>8</td>
<td>Saturation range</td>
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<tr>
<td>4</td>
<td>Green range</td>
<td>9</td>
<td>Luminance mean</td>
</tr>
<tr>
<td>5</td>
<td>Hue mean</td>
<td>10</td>
<td>Luminance range</td>
</tr>
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</table>

Table 3. Reduced two Color Features

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Green mean</td>
</tr>
<tr>
<td>2</td>
<td>Saturation mean</td>
</tr>
</tbody>
</table>

Select as reduced feature

Step 8: For (i=1 to size of the reduced feature vector)

- Compare each feature with the other
- If (features values are equal OR feature values differ by delta)
- Discard the feature
- Else
- Select as reduced feature

Stop

The classification accuracies of image samples using reduced 2 color features for normal and affected fruit produce are shown in (Fig.12 & 13).

When we consider bulk image samples of such fruit type, the surface patterns vary from produce to produce. In such cases texture becomes ideal for recognition. In this work gray-level Co-Occurrence matrix, is used to carry out texture analysis. The Co-Occurrence matrix is basically a reduced mixture of gray values in the range 0 to 255. The co-occurrence matrix method of texture description is based on the repeated occurrence of gray level configuration in the texture. This configuration varies rapidly with distance in fine textures and slowly in coarse textures. An occurrence of a gray level configuration is described by a matrix of relative frequencies $P_\phi (x, y)$, giving how frequently two pixels with gray levels $x, y$ appear in the window separated by a distance $d$ in direction $\phi$.

The Differentiation between image samples is carried out in the simplest way, quantifying average gray levels within the matrix change in the gray level with respect to average level of minimum and maximum gray levels present in the matrix. Hence we have used basic Co-Occurrence features namely, mean, variance and range using equations (4), (5) and (6). The list of extracted texture features is shown in (Table 4). The texture feature values for each normal and affected fruit produce are shown in (Fig.14 & 15).

2.2.3 Texture Features

In certain fruit image samples color features overlap, however texture change from one fruit type to another.

Figure 12. Based on two color features for each normal type.

Figure 13. Based on two color features for each affected type.

Figure 14. Texture features (threshold=100).

Figure 15. Texture features (threshold=100).
2.2.4 Feature Reduction
From (Fig.14 & 15), we have found through experimentation that only 5 features, which are common in both normal and affected fruit produce found to be significant. Hence these 5 features contribute more to the classification of fruits into affected and normal. Therefore we considered 5 features as first-level feature reduction shown in (Fig.16 & 17). The reduction is done based threshold. Any feature values below threshold are discarded. The threshold is chosen based on average of minimum feature value and maximum feature value. The threshold obtained is 100.

Table 4. Texture Features Based on Co-Occurrence Matrix

<table>
<thead>
<tr>
<th>Sl. No</th>
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<th>Sl. No</th>
<th>Features</th>
<th>Sl. No</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>11</td>
<td>Green GLCM mean</td>
<td>21</td>
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</tr>
<tr>
<td>2</td>
<td>Red GLCM variance</td>
<td>12</td>
<td>Green GLCM variance</td>
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</tr>
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<td>3</td>
<td>Red GLCM range</td>
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<td>Blue GLCM range</td>
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<tr>
<td>4</td>
<td>Red GLCM energy</td>
<td>14</td>
<td>Green GLCM energy</td>
<td>24</td>
<td>Blue GLCM energy</td>
</tr>
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<td>Red GLCM Entropy</td>
<td>15</td>
<td>Green GLCM Entropy</td>
<td>25</td>
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</tr>
<tr>
<td>6</td>
<td>Red GLCM Homogeneity</td>
<td>16</td>
<td>Green GLCM Homogeneity</td>
<td>26</td>
<td>Blue GLCM Homogeneity</td>
</tr>
<tr>
<td>7</td>
<td>Red GLCM sum mean</td>
<td>17</td>
<td>Green GLCM sum</td>
<td>27</td>
<td>Red GLCM sum mean</td>
</tr>
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<td>8</td>
<td>Red GLCM MP</td>
<td>18</td>
<td>Green GLCM MP</td>
<td>28</td>
<td>Blue GLCM MP</td>
</tr>
<tr>
<td>9</td>
<td>Red GLCM contrast</td>
<td>19</td>
<td>Green GLCM contrast</td>
<td>29</td>
<td>Blue GLCM contrast</td>
</tr>
<tr>
<td>10</td>
<td>Red GLCM IDM</td>
<td>20</td>
<td>Green GLCM IDM</td>
<td>30</td>
<td>Blue GLCM IDM</td>
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Table 5. Reduced five Texture Features Based on Co-Occurrence Matrix

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<th>Sl. No</th>
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<tr>
<td>2</td>
<td>Red GLCM sum mean</td>
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<tr>
<td>3</td>
<td>Green GLCM Variance</td>
</tr>
<tr>
<td>4</td>
<td>Green GLCM sum mean</td>
</tr>
<tr>
<td>5</td>
<td>Blue GLCM sum mean</td>
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</table>

Table 6. Reduced two Texture Features Based on Co-Occurrence Matrix

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Features</th>
</tr>
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<td>1</td>
<td>Red GLCM sum mean</td>
</tr>
<tr>
<td>2</td>
<td>Green GLCM sum mean</td>
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</tbody>
</table>

Table 7. Combined Reduced features

<table>
<thead>
<tr>
<th>Sl. No</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Green mean</td>
</tr>
<tr>
<td>2</td>
<td>Saturation mean</td>
</tr>
<tr>
<td>3</td>
<td>Red GLCM sum mean</td>
</tr>
<tr>
<td>4</td>
<td>Green GLCM sum mean</td>
</tr>
</tbody>
</table>

Algorithm 2: Textural Feature Extraction

Input: RGB components of original image
Output: Reduced texture features

Description: \( P_{\phi, d}(x,y) \) means GLCM matrices in the direction \((\phi=0^\circ, 45^\circ, 90^\circ, 135^\circ)\) and \(d\) is the distance. Delta is the minimum difference between two features and is set to \(10^{-3}\). Threshold is the average of minimum and maximum feature value and is set to 100.

Start
Step 1: Accept 24-bit color image of a fruit
Step 2: For all the separated RGB components, derive the Co-Occurrence
Matrices \( P_{\phi, d}(x,y) \) in four directions \(0^\circ, 45^\circ, 90^\circ, 135^\circ\) and \(d=1\).
Step 3: Compute mean, variance, and range for each RGB components using the equations (4) thru (6).
Step 4: Threshold = (minimum feature value + maximum feature value)/2
Step 5: Initialize feature vector to zeros
Step 6: For \(i=1\) to size of the feature vector
   If (value of feature \(i\) > threshold),
      Select as reduced feature
Step 7: For \(i=1\) to size of the reduced feature vector
      Compare each feature with the other

Figure 16. Features values based on five texture features for normal type.

Figure 17. Features values based on five texture features for affected type.

From (Fig.16 & 17), we have found that only 2 features contribute as discriminating features as this is essential for better classification. Hence we have considered only 2 features as second-level feature reduction based on delta. Delta is the minimum difference between two feature values and is set to \(10^{-3}\).

The reduced 2 texture feature values for each normal and affected fruit produce (Fig.18 & 19). The procedure involved in texture feature extraction and reduction is explained in (Algorithm 2). The texture features reduced to 5 and 2 are listed in (Table 5 & 6).

Figure 18. Texture Features for normal type.

Figure 19. Texture Features for affected type.
If (features values are equal OR feature values differ by delta)
Discard the feature
Else
Select as reduced feature
Stop

The classification accuracies of image samples using reduced 2 texture features for normal and affected fruit produce are shown in (Fig 20 & 21).

The classification accuracies of image samples for reduced combined features for normal and affected fruit produce are given in (Fig. 22 & 23).

The classification accuracies of image samples for reduced combined features for normal and affected fruit produce are given in (Fig. 22 & 23).

Figure 22. Reduced Combined Color and CM Texture Features for normal type.

Figure 23. Reduced Combined Color and CM Texture Features for affected type.

Figure 24. Average accuracy using reduced color, texture and combined features.

2.3 Classifier
We have used a multilayered back propagation neural network (BPNN) as a classifier. The number of neurons in the input layer corresponds to the number of input features and the number of neurons in the output layer corresponds to the number of classes. The classifier is trained, validated and tested using images of different normal and affected fruit produce. We have kept the hidden layers to two arbitrarily. The developed neural network model performance is verified in terms of accuracy rate. The iterative reduction neural network model is analyzed. This indicates that as we reduce the number of redundant features from input layer accuracy reaches the maximum rate.

3 Results and Discussion
The MATLAB 7.0 with artificial neural network tool box is used to implement the developed algorithms. We have considered 100 images of 10 normal and 10 affected types amounting to a total of 2000 image samples. The network is trained with 80 images of each type. The remaining 20 images are used for testing. Around 15% of the image samples from the training set are used for
validation of the designed classifier model. Since we are recognizing and classifying 20 different fruit type, the output vector \( P \) has 20 different output patterns. The percentage accuracy is defined as the ratio of correctly recognized image samples to the total number of test image samples. The Percentage accuracy is given by equation (7).

\[
\text{Percentage Accuracy} = \frac{\text{Correctly Recognized Image Samples}}{\text{Total Number of Test Image}} \times 100
\]  

(7)

### 3.1 Identification Efficiency based on reduced two Color features

The reduced 2 color features are extracted using (Algorithm 1). The number of input nodes is 2 and the number of output nodes is 20, for classifier. From (Fig.12 & 13), the highest recognition and classification accuracy of 94% is observed with mosambi and the lowest of 83% is observed with grape2 in case normal type and 96.18% is observed with abanana2 and the lowest of 80% with aorange in case of affected type.

### 3.2 Identification Efficiency based on reduced two texture features

The reduced 2 texture features are extracted using (Algorithm 2). The number of input nodes is 2 and the number of output nodes is 20, for classifier. From (Fig. 20 & 21), the highest recognition and classification accuracy of 98% is observed with banana2 and the lowest of 90% is observed with dryfruit and mosambi in case of normal type and highest recognition and classification accuracy of 95% is observed with agrape2 and lowest of 82% with aorange.

### 3.3 Identification Efficiency based on reduced combined features

The reduced combined features are extracted using (Algorithm 1 & 2). The number of input nodes is 4 and number of output nodes is 20, for classifier. From (Fig. 22 & 23), the highest recognition and classification accuracy of 100% is observed with mosambi and the lowest of 92% is observed with dryfruit in case of normal type and highest recognition and classification accuracy of 96% is observed with agrape2, aopomegranate and lowest of 92% with adryfruit.

The average accuracy of 89.15%, for normal type and 88.58% for affected type is achieved in case of 2 color features. The average accuracy of 93.019% for normal type and 89.50% for affected type is achieved in case of 2 texture features. The combination of color and texture features is tested to take advantage of both the features. It is also observed that this idea of combining both features has outperformed the individual features. The average accuracies have been increased to 96.85% for normal type and 93.89% for affected type is achieved. A BPNN classifier is found suitable in this work. Thus we have conclusion that as the number of redundant features are reduced then accuracy of network reaches maximum.

The results from this study can be used for identification of normal and affected fruits’ types by designing an elevator that can move a fruits’ across camera which acquires side view of fruit and decides quality and type of fruit . Since this classification technique does not require time consuming image processing routines such as Fourier descriptors, it can readily be implemented using commercial imaging libraries with Digital Signal Processing (DSP) boards for real time operations. The work carried out has relevance to the real world classification of fruits’ and it involves both image processing and pattern recognition techniques. The work supports non destructive quality measurement of fruits’ system.

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### References


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