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Statistical Methods for Quantitatively Detecting Fungal Disease from Fruits' Images

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Abstract: In this paper, we have proposed statistical methods for detecting and classifying fungal disease. The classification is done based on disease severity levels. In this work, we have considered fungal disease symptoms affected on fruits like mango, pomegranate and grape. In this study, images of fruits affected by different fungal symptoms are collected and categorized based on disease severity as partially affected, moderately affected, severely affected and normal. Statistical features using block wise, Gray Level Co-occurrence Matrix (GLCM), Gray Level Run-length Matrix (GLRM) are extracted from these images. The Nearest Neighbor classifier using Euclidean distance is used to classify images as partially affected, moderately affected, severely affected and normal. The average classification accuracies are 91.37% and 86.715% using GLCM and GLRM features. The average classification accuracy has increased to 94.085% using block wise features.

Keywords: *Fungal disease, Disease severity, Fruits, Statistical features, Euclidean distance, Nearest Neighbor*.

1. Introduction

Fruit industry is a major industry which contributes 20% of the nation's growth. Increase in the production and productivity is largely due to the adoption of improved technologies, which include quality planting material, balanced nutrients and timely protection against major insect-pests and diseases. 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.

In spite of the fact that India is blessed with a wide range of soil and climatic conditions for growing large number of horticultural crops, there are still several constraints which adversely affect development of a sound horticulture industry. 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 by diseases which results in huge loss of revenue to the farmers and the nation. Non adoption of adequate and timely control measures against pests and diseases also cause major fruit losses. In the absence of comprehensive knowledge, disputes over costs, benefits, and the potential for harm of chemical pesticides easily become polarized [31]. Farmers are also concerned about the huge costs involved in these activities and severe loss. The cost intensity, automatic correct identification of diseases based on their particular symptoms is very useful to farmers and also agriculture scientists. Detection of diseases is a major challenge in horticulture / agriculture science. Development of proper methodology, certainly of use in these areas. One of the main concerns of scientists is the automatic disease diagnosis and control [15].

Computer vision systems developed for agricultural applications, namely detection of weeds, sorting of fruits in fruit processing, classification of grains, recognition of food products in food processing, medicinal plant recognition etc. In all these techniques, digital images are acquired in a given domain using digital camera and image processing techniques are applied on these images to extract useful features that are necessary for further analysis. To know the state-of-the-art in automation of the task/activities in horticulture field and automatic detection of fruit disease using computer vision techniques, a survey is made. The gist of a survey which carried out is given as follows.

(Jagadeesh D.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. GLRM was used to extract texture features and further classified fungal affected mango images from normal using Artificial Neural Network (ANN) classifier. (Sudheer reddy 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 Matrix (CCM) and classified using various classifiers. (Shiv Ram Dubey et al; 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 (SVM). (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 and homogeneity were obtained by computing GLCM. (Jayamala K. Patil and Raj Kumar, 2011) have provided advances in various methods used to study plant diseases/traits using image processing. The methods studied were for increasing throughput and reducing subjectiveness arising from human experts in detecting the plant diseases. (D. Moshou et al; 2011) developed a prototype system

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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, Geostationary Positioning System (GPS) and a data processing unit was constructed and calibrated. (D.S.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. (H. 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 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 soybean rust severity from multi-spectral images. To achieve automatic rust detection, an alternative method of analyzing 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 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. (Geng Ying et al., 2008) have provided various methods of image preprocessing techniques for recognition of crop diseases. (Di Cui et al; 2008) proposed a method to detect the infection and severity of of soybean rust. The test performed using multispectral image sensor could quantitatively detect soybean rust compared to laboratory-scale research. (Kuo-Yi Huang, 2007) have presented an application of neural network and image processing techniques for detecting and classifying phalaenopsis seedling diseases. The texture features using GLCM and color features were used in the classification procedure. A Back Propagation Neural Network (BPNN) classifier was employed to classify phalaenopsis seedlings diseases. (Alexander A. doudkin et al., 2007) have proposed a neural network clusterization algorithm for segmentation of the color images of crop field infected by diseases that change usual color of agricultural plants. (Pydipati et al., 2006) have used a computer vision and image processing techniques in the early detection and classification of diseased citrus leaves from normal citrus leaves. The color texture features using CCM was used as input to various classifiers. (Hamid Muhammed and Hammed, 2005) work was concerned with characterizing and estimating fungal disease severity in a spring wheat crop. This goal can be accomplished by using a reference data set consisting of hyperspectral crop reflectance data vectors and the corresponding disease severity field assessments. (Marc Lefebvre et al., 1993) have presented the problem in automatzing pulp sampling of potatoes such as their shape, color or texture in order to detect viral diseases. The sprouts, where the viral activity is maximum, were then detected by an active vision process operating on multiple views.

Most of the published work has mainly focused on generic diseases affected on single crop/fruit type. Most fruits diseases are caused by bacteria, fungi, virus, etc of which fungi are responsible for a large number of diseases in fruits. Fruits get affected are common and not much work is cited on fruits like mango, pomegranate and grape affected by fungal disease. Although several image processing approaches have been presented, no attempts are made for quantitatively detecting fungal affected fruits and classifying based on disease severity levels. In this paper, we have developed a methodology for recognition of fungal disease severity and determine whether fruit is partially affected, moderately affected, severely affected or normal. The samples of fungal affected images are shown in (Figure.1 & 2).

Figure 1. Images showing the visual symptoms cause by fungal disease

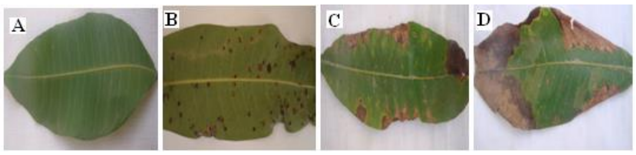

Figure 2. Images corresponding to different fungal disease severity levels: normal (A); partially affected (B); moderately affected(C); severely affected (D).

The paper is organized into four sections. Section.2 gives 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, preprocessing, feature extraction, classification are carried out. The classification tree is given in (Figure.3). The detailed block diagram of adopted methodology is shown in (Figure.4).

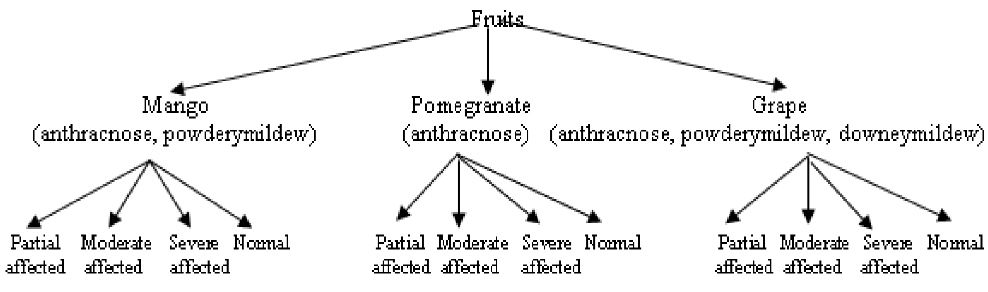

Figure 3. Classification tree

Table 1. Scientific classification of fungal symptoms affected on each fruit type

Fungal Symptom	*Causal organism*	*Family*	*Order*	*Class*	*Subdivision*	*Affected part*
Mango Anthracnose	Glomerella cingulata	Glomerellaceae	Incertaesedis	Sordariomycetes	Sordariomycetidae	stem, leaf, fruit
Mango Powdery mildew	Oidium mangiferae	Erysiphaceae	Erysiphales	Leotiomycetes	Leotiomycetidae	stem, leaf, fruit
Pomegranate Anthracnose	Glomerella cingulata	Glomerellaceae	Melanconiales	Sordariomycetes	Pezizomycotina	stem, leaf, fruit
Grape Anthracnose	Elsinoë ampelina	Elsinoaceae	Incertaesedis	Dothideomycetes	Dothideomycetidae	stem, leaf, fruit
Grape Downey mildew	Plasmopara viticola	Peronosporaceae	Pleosporales	Oomycota	Mastigomycotina	stem, leaf, fruit
Grape powdery mildew	Uncinula necator	Erysiphaceae	Erysiphales	Leotiomycetes	Ascomycota	stem, leaf, fruit

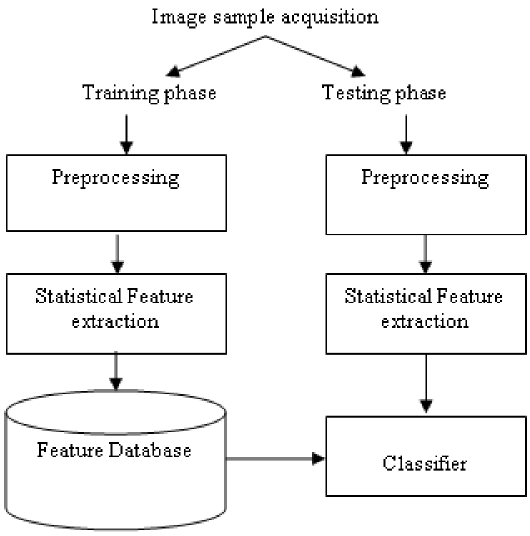

Figure 4. Block diagram of proposed methodology

2.1. Image Set

The set of 929 image samples of fruits affected by fungal disease symptoms are considered for the work. Fruits like mango (Mauls domestic), pomegranate (Punic granite) and grape (Vitas viniferous) are considered for the study. The chosen fungal disease symptoms affected on each fruit type are i)anthracnose, powdery mildew affected on mango, ii) anthracnose affected on pomegranate, iii) anthracnose, powdery mildew, downey mildew affected on grape. In this work, we have considered image samples of fungal disease affected on different parts of the plant like stem, leaf and fruit. These fungal affected image samples are further categorized into 246 partially affected, 168 moderately affected, 215 severely affected and 300 normal, which are considered for classification purpose. The scientific classification of fungal symptom affected on each fruit type along with affected part is shown in (Table.1).

2.2. Preprocessing

The single fungal affected fruit image is captured by analog camera. Then preprocessing steps applied over image. The preprocessing of image includes shade correction, removing artifacts, formatting, binarization and edge detection. Formatting deals with storage representation and setting the attributes of the image. This formatted image is used as input to the binarization and edge detection process. The preprocessing is done at two phases. In the first phase, input image is preprocessed for binarization and noise removal is done using median filtering. The filtered image is resized to a constant resolution of size 30x30. Further, the image is thinned and bounding box is generated. In the second phase, input image is preprocessed for edge detection using canny edge detector. An edge-detection filter imfilter is used to improve the appearance of blurred or anti-aliased images. The output of this phase is edge detected image. The preprocessed image of an input image sample for phase one and two is shown in (Figure.5). The preprocessing procedure is given in (Algorithm.1 & 2).

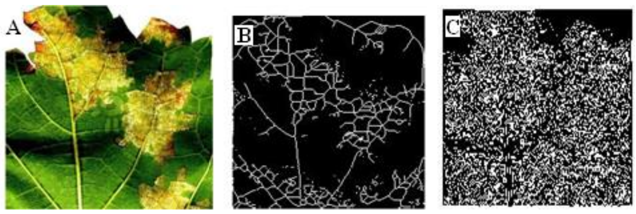

Figure 5. Preprocessed image: Input image (A); binary image (B); edge detected image(C)

Algorithm 1: Image acquisition and preprocessing
Input: Original 24-bit Color Image
Output: Binary image
Start
Step 1: Capture the image of fungal affected fruit using analog camera and save it in personal computer.
Step 2: Read input image from specified location.
Step 3: Apply shade correction on input image.
Step 4: Improve the quality of image by removing artifacts.
Step 5: Convert the input image into black and white image
Step 6: Filter the binary image using median filtering
Step 7: Resize the image to 30*30
Step 6: Generate thinned image
Step 7: Crop thinned image
Stop.

Algorithm 2: Image acquisition and preprocessing
Input: Original 24-bit Color Image
Output: Edge detected image
Start
Step 1: Capture the image of fungal affected fruit using analog camera and save it in personal computer.
Step 2: Read input image from specified location.
Step 3: Apply shade correction on input image.
Step 4: Improve the quality of image by removing artifacts.
Step 5: Apply canny edge detector over input image.
Step 6: Filter the edge detected image using imfilter function.
Stop.

2.3. Feature Extraction

Features are the descriptors which specifies the different properties of an image for example color, size, shape, intensity, texture etc. Feature extraction is the processing of getting the statistical values from the image by some sort of calculations. In this work, we have used statistical based feature extraction methods for detection of fungal affected fruit.

Texture is an important characteristic of many natural surfaces and naturally occurring patterns. There are two widely used approaches to describe the texture of a region, namely statistical and structural. The statistical approaches considers that the intensities are generated by a two dimensional random field. The methods used are based on spatial frequencies and yield characterization of textures as smooth, coarse and grainy. Second order statistical texture features like GLCM and GLRM are used to carry out texture analysis. These methods are compared with first order block wise feature extraction method. First order statistics can be used as the most basic texture feature extraction methods, which are based on the probability of pixel intensity values occurring in digital images. The preprocessed image is given as input to block wise, GLCM, GLRM feature extraction methods.

2.3.1. Block wise feature extraction

The preprocessed image generated using Algorithm.1 is divided into various blocks each of size 5*5 as shown in (Figure.6). Then features are extracted from each row and column. The features are stored into a feature vector *F*. Totally 36 features are stored in feature vector *F*. The feature vector *F* is described in (Equation.1).

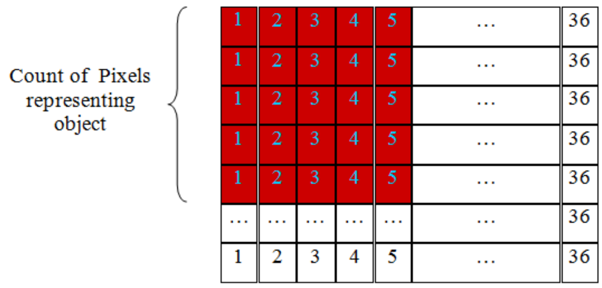

Figure 6. Image blocks

$$F = [f_i]; \quad 1 \le i \le 36 \tag{1}$$

Where, f_i is feature vector of i^{th} block.

The block wise feature values of all blocks extracted from each row and column is shown in (Figure.7) for preprocessed image shown in (Figure.5 (B)).The block wise feature extraction procedure is given in (Algorithm.3).

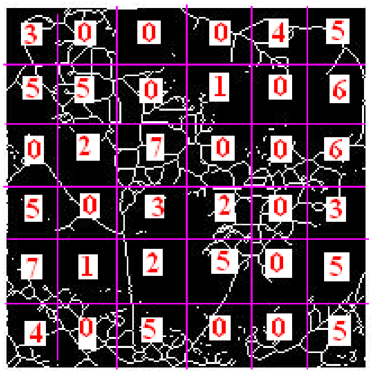

Figure 7. Row-column wise features for all blocks

F= [3 0 0 0 4 5 5 5 0 1 0 6 0 2 7 0 0 6 5 0 3 2 0 3 7 1 2 5 0 5 4 0 5 0 0 5]

Algorithm.3 : Block wise Feature Extraction

Input**:** Preprocessed Image (Output of Algorithm.1)

Output**:** Feature vector.

Start

Step 1: Divide the image into 5*5 blocks and find the number of pixels representing image in each block

Step 2: Find the size of image and store in variables, row and column

Step 3: Divide the value of row by 6

Step 4: Divide the value of column by 6

Step 5: Trace the row and column, start and end respectively for each block

Step 6: Extract the pixels in each block

Step 7: Count the number of each pixel and store into feature vector

Stop.

2.3.2. Gray Level Co-occurrence Matrix

The GLCM method of texture description is based on the repeated occurrence of some gray-level configuration in the texture. It was proposed by Haralick [33]. Haralick features calculation is done in two phases, i)Calculation of the Co-occurrence Matrices, ii)Calculation of the features based on the Co-occurrence Matrix. The textural features are evaluated using (Equations.2 to 10). The Co-occurrence Matrix is computed using (Algorithm.4). The textural feature extraction procedure is given in (Algorithm.5).

$$\text{Mean } (\mu) = \sum_x x \sum_y P(x,y) \tag{2}$$

$$\text{Variance} = \sum_{x,y} (x-\mu)^2 P(x,y) \tag{3}$$

$$\text{Range } = Max(p(x,y)) - min(p(x,y)) \tag{4}$$

$$\text{Energy} = \sum_{i=1}^{Ng} \sum_{j=1} p^2 d(i,j) \tag{5}$$

$$\text{Entropy} = -\sum_{I,J} P(i,j) \log P(i,j) \tag{6}$$

$$\text{Homogeneity} = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} \frac{p_d(i,j)}{1+|i-j|} \tag{7}$$

$$\text{Maximum Probability} = \max(P(x,y)) \tag{8}$$

$$\text{Contrast} = \sum_{n=0}^{Ng-1} n^2 \sum_{|i-j|} Pd(i,j) \tag{9}$$

$$\text{Inverse Difference Moment} = \sum_{x,y;x \ne y} \frac{P^{\lambda}(x,y)}{|x-y|^k} \tag{10}$$

Where $\mu_x, \mu_y, \sigma_x, \sigma_y$ are means and standard deviations defined by (Equations.11 to 14).

$$\mu_x = \sum_x x \sum_y P(x,y) \tag{11}$$

$$\mu_y = \sum_y y \sum_x P(x,y) \quad (12)$$

$$\sigma_x = \sum_x (x-\mu_x)^2 \sum_y P(x,y) \quad (13)$$

$$\sigma_y = \sum_y (y-\mu_y)^2 \sum_x P(x,y) \quad (14)$$

Algorithm. 4: Calculation of Co-occurrence Matrix $P_{f,d}$(x, y) from the image f(x, y).

Input: Input gray level image f(x, y) (matrix of size M*N)

Output: Co-occurrence Matrix $P_{f,d}$(x, y) for d=1 in the direction f.

Start

Step 1: Assign $P_{f,d}$(x, y) =0 for all x, y Є [0, L], where L is the maximum gray level.

Step 2: For all pixels(x1, y1) in the image, determine (x2, y2), which is at distance d in direction f and perform $P_{f,d}$ [f(x1, y1), f(x2, y2)] = $P_{f,d}$ [f(x1, y1), f(x2, y2)] + 1

Stop.

Algorithm. 5: GLCM Textural Feature Extraction

Input: Preprocessed image (Output of Algorithm.2)

Output: Textural features

Start

Step 1: Derive the Gray Level Co-occurrence Matrices (GLCM) *Pφ, d (x, y)* for four different values of direction *φ* (0^0, 45^0, 90^0 *and* 135^0) and d=*1* which are dependent on direction *φ.*

Step 2: Compute the Co-occurrence Matrix, which is independent of direction using *Algorithm.4.*

Step 3: GLCM features are calculated using Equations.(2) thru (10).

Stop.

We have found that only three features contribute as discriminating features as this is essential for better recognition and classification. Hence we have considered only variance, sum mean, and contrast as significant features. The reduced three GLCM texture features are shown in (Figure.8).

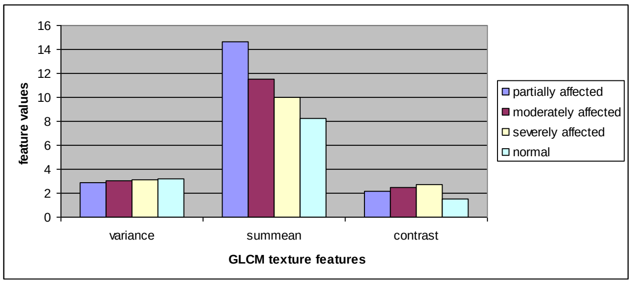

Figure 8. Texture features

2.3.3. Gray Level Run-length Matrix (GLRM)

Gray Level Run-length Matrix uses the basic idea of Run-length statistics for extracting such information from gray level runs of an image. Consecutive pixels of the same gray value or level, in a given direction, constitute a run. The number of runs of different lengths and gray values form a two dimensional matrix called Run-length matrix. An element of a RM, Q(x, y) represents the number of x gray values y is the considered Run-length [1].The feature extraction is done in two phases, i)Development of Run-length Matrix, ii)Calculation of features based on the Run-length Matrix. We have obtained from the Run-length matrix seven different texture features like Short Run Emphasis (SRE), Long Run Emphasis (LRE), Run Length Non-uniformity (RLN), Gray Level Non-uniformity (GLN), High Gray level Run-length Emphasis (HGRE), Low Gray level Run-length Emphasis (LGRE) and Run Percentage (RP). These features are obtained using (Equations.15 to 21). The Run-length Matrix is computed using (Algorithm.6). The textural feature extraction procedure is given in (Algorithm.7).

$$SRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j)}{j^2} \quad (15)$$

$$LRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j).j^2 \quad (16)$$

$$GLN = \frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N}P(i,j)\right)^2 \quad (17)$$

$$RLN = \frac{1}{n_r}\sum_{i=1}^{N}\left(\sum_{j=1}^{M}P(i,j)\right)^2 \quad (18)$$

$$RP = \frac{n_r}{n_p} \quad (19)$$

$$LGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j)}{i^2} \quad (20)$$

$$HGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j).i^2 \quad (21)$$

Algorithm 6: Development of Run-length Matrix Qφ (x, y) from the Image f(x, y).

Input: Gray level image f(x, y) of size M*N

Output: Run-length matrix Qφ(x, y) in the direction φ.

Start

Step 1: Assign Qφ(x, y) =0 for all x, y ε [0, L], L is the maximum gray level.

Step 2: Find the matrix Qφ(x, y), for a given angle φ. The entry Q(x, y) is the (x, y)th entry in the Run-length matrix, where ‘x’ is the gray level and ‘y’ is the Run-length.

Stop.

Algorithm 7: GLRM Texture Feature Extraction

Input: Preprocessed image (Output of Algorithm.2)

Output: Textural features

Start

Step 1: Derive the Run-length Matrices Qφ(x, y) for four different directions φ (00, 450, 900 and 1350).

Step 2: Compute the Run-length matrix, independent of direction using the equations (15) thru (21)

Step 3: Run-length matrix features are calculated using Equations.(15) thru (21).

Stop.

We have found that only two features contribute as discriminating features as this is essential for better recognition and classification. Hence we have considered only Run Length Non-uniformity (RLN), Gray Level Non-uniformity (GLN) as significant features. The reduced two GLRM texture features are shown in (Figure.9).

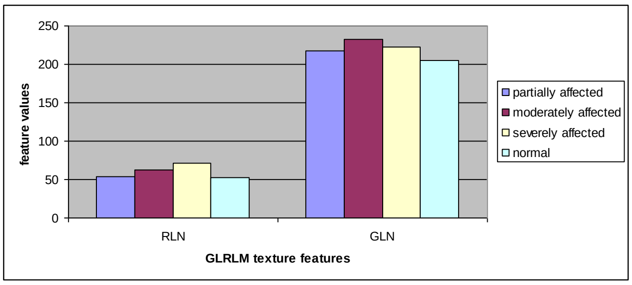

Figure 9. Texture features

2.4. Classifier

We have used a Nearest Neighbor classifier for classification purpose. This is amongst the simplest of all classification algorithms in supervised learning. This is a method of classifying patterns based on the class label of the closest training patterns in the feature space. There is no training time required for this classifier. Every time a test pattern is to be classified, it has to be compared with all the training patterns, to find the closest pattern. The classification is done according to some similarity of the test pattern to the training patterns. To determine this similarity/dissimilarity, proximity measures are used. The distance between two patterns is used as a proximity measure. The Euclidean distance is the most popular distance measure. This is because Euclidean distance is easy for human comprehension, rotation and translation invariant.

The training phase constitutes calculation of statistical features extracted from fungal affected fruit image samples. The extracted features are stored into database. The classifier is tested on the test images for each class. The classifier is based on the Euclidean distance from the feature vector representing the test image and every record in feature database using (Equation.22). The classifier used the Nearest Neighbor principle.

$$\text{Distance}(Test, Train) = \sqrt{\sum (DTest - TrainD)^2} \qquad (22)$$

The test image is classified as belonging to a particular class to which its Euclidean distance is minimum among the calculated distances.

3. Results and Discussion

All the algorithms used in this work are implemented using MATLAB 7.0. The image samples are divided into two halves and one half is used for training and other is for testing. 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.23).

Percentage accuracy (%) =

$$\frac{\text{Correctly Recognized Image Samples}}{\text{Total Number of Test Image Samples}} * 100. \qquad (23)$$

The individual average classification accuracy based on disease severity levels is shown in (Figure.10). The highest recognition and classification accuracy of 98.76% is observed with severely affected and the lowest of 88.32% is observed with normal using block wise feature extraction. The highest recognition and classification accuracy of 95% is observed with severely affected and the lowest of 85% is observed with normal using GLCM feature extraction. The highest recognition and classification accuracy of 92% is observed with severely affected and the lowest of 81.33% is observed with normal using GLRLM feature extraction.

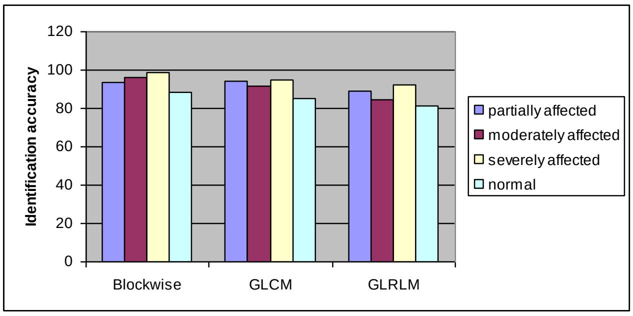

Figure 10. Classification accuracy based on disease severity levels

The average classification accuracies using feature extraction methods block wise, GLCM, GLRM are 94.085%, 91.37% and 86.715% for fungal affected fruits' image samples is shown in (Figure.11).

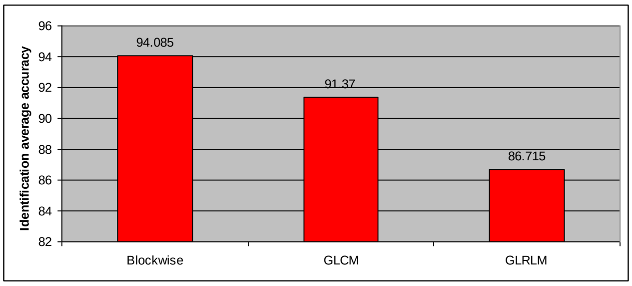

Figure 11. Average classification accuracy for each feature type

The image samples are selected randomly for training and testing. For each training and testing, experimentation is performed 10 times (trials) and classification is calculated for each time. The minimum classification, maximum classification and average classification accuracy obtained across 10 trials is shown in (Figure.12).

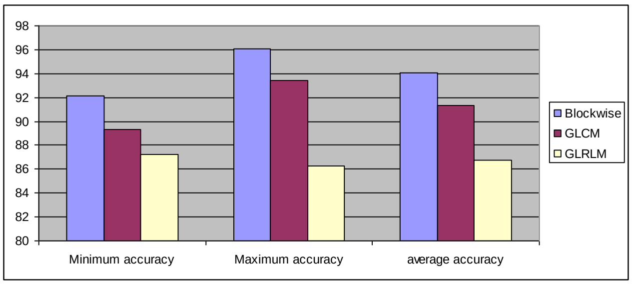

Figure 12. Classification results using statistical features

The GLCM and GLRM computes properties of the image related to second-order statistics which considers the relationship among pixels or groups of pixels, whereas, fungal affected areas have no spatial relationship among pixels and hence block wise features related to first order statistics will give better results than GLCM and GLRM.

4. Conclusion

We have developed statistical methodologies for detection of fruits' image samples affected by fungal disease based on disease severity levels. The evaluation of statistical features like block wise, GLCM and GLRM is done. The classification is performed using nearest neighbor with Euclidean distance. The work finds application in automatic recognition and classification of disease affected on fruits by the service robots in the real world.

For future study, further different neural network architectures, SVM, fuzzy based classifiers can be used for classification. We can extend this work to classify fungal disease symptoms affected on commercial crops, cereals, vegetables .The work can also be extended to identify various diseases like viral, bacterial affected on agriculture/horticulture produce.

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