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Study of Feature Extraction Techniques for the Detection of Diseases of Agricultural Products

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Abstract: This article describes the feature extraction methods for crop and fruit diseases based on computer image processing in detail. Crop and fruit diseases are most important agricultural products. In order to obtain more value added products, a proper quality control is essentially required. There are various applications claimed to extract the accurate information from the coloured image database. The main purpose of this paper is to provide an interface for digitally illiterate users, especially farmers to efficiently and effectively retrieve information through internet. In addition, to enable the farmers to identify the disease in their crop, its causes and symptoms using image processing without classical approach and identify the disease.

Keywords: Image Processing, Feature Extraction, Crop and Fruit Diseases, Quality Control, Classical approach.

I. INTRODUCTION

Today India ranks second world wide in farm output. Agriculture is still the largest economic sector and plays a major role in socio-economic development of India. Agriculture in India is the means of livelihood of almost two thirds of the workforce in India. India has over 210 million acres of farm land. Wheat, maize, are the major cereals, Apple, banana, grapes, oranges are the most common fruits, Sugarcane, cotton, chilli, groundnuts are the major commercial crops. Crop cultivation depends on rainfall, quality of the soil and climatic conditions and short of any one of these leads to loss of crop. Diseases are major for loss of crop every year and really it is a challenge to control the diseases. Plant disease diagnosis is an art as well as science. The diagnostic process (i.e., recognition of symptoms and signs), is inherently visual and requires intuitive judgment as well as the use of scientific methods. Plant diseases reduce both quantity and quality of plant products. The prime objective of plant pathology is to prevent epidemic which are widespread outbreak of destructive diseases. Knowledge of different disease causing pathogen and their control is very essential in order to prevent the epidemics of the disease. Farmers are very much concerned about the huge costs involved in disease control activities and it causes severe loss. The cost intensity, automatic correct identification and classification of diseases based on their particular symptoms become essential and very useful to farmers and also agriculture scientists. Early detection of diseases is a major challenge in horticulture/agriculture science. Many disease produce symptoms which are the main tools for field diagnosis of diseases showing external symptoms out of a series of reactions that take place between host and pathogen. As such, several important decisions regarding safe practices, the production and processing of plant have been made in the recent past. One of the main concerns of scientists is the automatic disease diagnosis and control [1, 2]. Computer vision systems would help to tackle the problem. 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.

Crop and fruit diseases are caused by bacteria, fungi, virus, etc., of which fungi are responsible for a large number of diseases in plants. Some of the examples for apple fruit diseases are as shown in Fig.1.In the proposed work, we have focused on the various feature extraction techniques for the efficient detection of defected areas of agricultural products.

(a)White rot

(b) Powdery Mildew

(c) Scab

(d) Sooty Blotch

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II. PROPOSED METHODOLOGY

First, the images of various apple fruits are acquired using a digital camera. Then image-processing techniques are applied to the acquired images to extract useful features that are necessary for further analysis. After that, several analytical techniques are used to classify the images according to the specific problem at hand. Figure 2 depicts the basic procedure of the proposed vision-based detection algorithm in this paper.

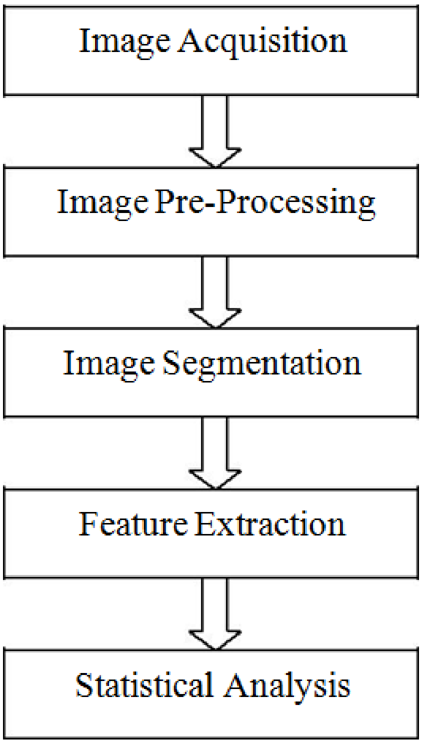


Fig.2. Proposed Methodology

The step-by-step procedure of the proposed system:

1) RGB image acquisition
2) Image pre processing:
   a) Convert the input image from RGB to HSV Format
   b) Histogram processing
   c) Masking the green-pixels
   d) Removal of masked green pixels
3) Image segmentation:
   a) Segment the components
   b) Obtain the useful segments
4) Computing the features using color-co-occurrence Methodology
5) Evaluation of texture statistics

1. RGB image acquisition

The first step in the proposed approach is to capture the sample from the digital camera and extract the features. Images are taken in controlled environment and are stored in the JPEG format. Infected fruit is placed on a white background; Light sources are placed at 45 degree on each side of the fruit so as to eliminate any reflection and to get even light everywhere, thus a better view and brightness. The fruit is zoomed on so as to ensure that the picture taken contains only the fruit and white background.

2. Image pre processing

Image pre processing is a sub-field of image processing and consists of techniques to improve the appearance of an image, to highlight the important features of an image and make the image more suitable for use in particular application. The abnormality of the defected fruit is revealed by the appearance of diseased spots. From the inspection of infected crops it was found that the spots have intensity values higher than the other normal areas. It consists of various sub-phases, some of which are described in detail which have significant role in the image pre processing phase.

(a) Color transformation structure (HSI transformation)

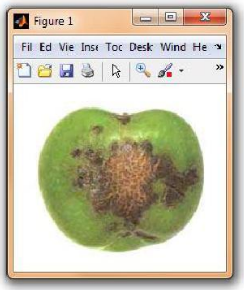
Color is perceived by humans as a combination of R, G, B bands which are called primary colors. Several color spaces, such as HSI and CIE are derived from primary colors using either linear or non-linear transformations, and utilized in color image segmentation. HSI (hue-saturation-intensity) system is a commonly used color space in an image processing, which is more intuitive for human vision [3-6]. HSI system separates the color information of an image from its intensity information. Color information is represented by hue and saturation values, while the intensity describes the brightness of an image [7]. The HSI system has a good capability of representing the colors for human perception, because human vision system can distinguish different hues easily. Whereas, the perception of different intensity or saturation does not imply the recognition of different colors [7]. The formula of HSI is:

$$H = ArcTan\left[\frac{(G-B)*\sqrt{3}}{(R-G)+(R-B)}\right] \quad (1)$$

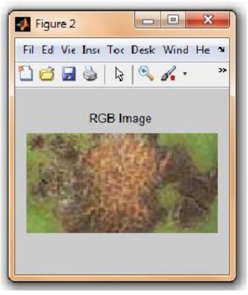
$$I = \frac{(R+G+B)}{3} \quad (2)$$

$$S = 1 - \frac{Min(R,G,B)}{I} \quad (3)$$

The result of HSI transformation is shown in the Fig. 3.



Original Image of Infected Apple Fruit



RGB of the Infected Region

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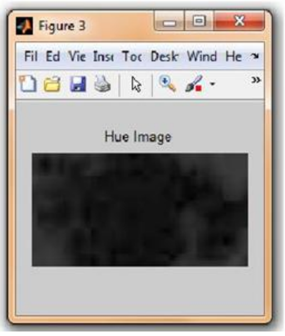
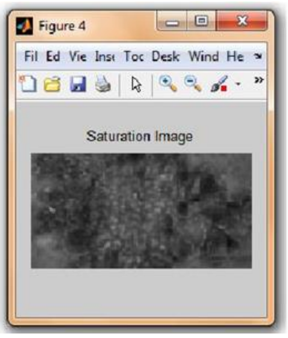


Hue Component



Saturation Component

Intensity Component
Fig.3. HSI transformation

(b) Histogram processing

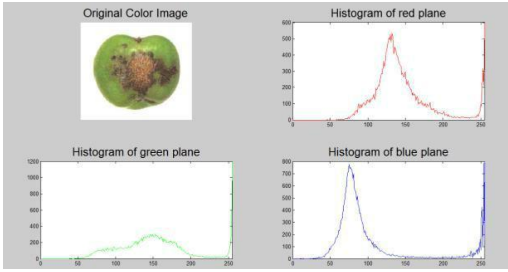
A color histogram is a vector where each entry stores the number of pixels of a given color in the image. All images are scaled to contain the same number of pixels before histogramming, and the colors of the image are mapped into a discrete color space containing n colors. Typically images are represented in the RGB color space, using a few of the most significant bits per color channel to discrete the space.

The histogram of a digital image with grey levels in the range (0 to L-1) is as discrete function p(r k)

$$p(r_k) = \frac{n_k}{n}$$, k=0, 1... L-1

Where L is the number of grey levels usually 256, n the total number of the image pixels, n k is the number of pixels having intensity level k. The image histogram carries important information about the image content.

Loosely speaking, $p(r_k)$ gives an estimate of the probability of occurrence of gray level r k.



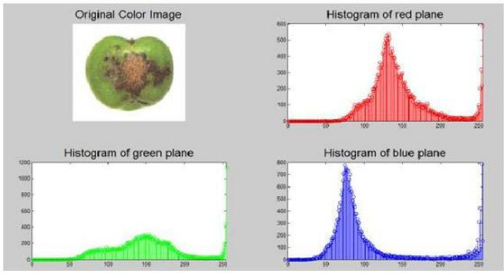


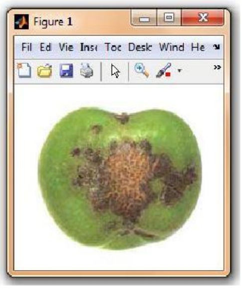
Fig.4. Histogram Processing

(c) *Masking and (d) removing green pixels*

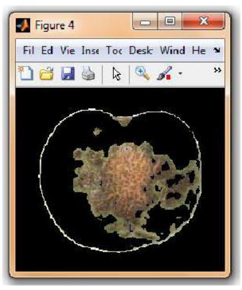
Masking means setting the pixel value in an image to zero or some other background value. In this step, we identify the mostly green coloured pixels. After that, based on specified threshold value that is computed for these pixels. The green components of the pixel intensities are set to zero if it is less than the pre-computed threshold value. Then red, green and blue components of the pixel are assigned to a value of zero by mapping of RGB components. [8] The green coloured pixels mostly represent the healthy areas of the fruit and they do not add any valuable weight to disease identification.

3. Image segmentation

Image segmentation is the first step in image analysis and pattern recognition. It is a critical and essential step and is one of the most difficult tasks in image processing, as it determines the quality of the final result of analysis. The segmentation of defected fruit images involves partitioning the image space into different cluster regions with similar intensity image values. The success of applying k-means to fit the segmentation problem depends mainly on adapting the input parameter values. These parameters include the feature of the data set and the optimal number of clusters. The result of applying the k-means clustering is depicted in the Fig.5 below.



Original Image



Segmented Image

Fig.5. Image Segmentation

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Now formulating the overall fruit disease diagnosis system is as shown in Fig. 6 (a) and (b) .

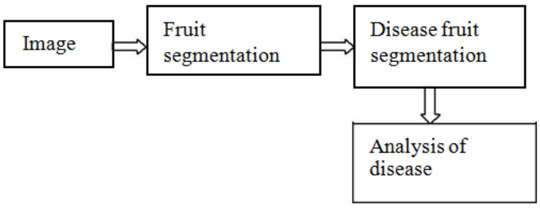

Fig.6 (a). Image Segmentation Technique

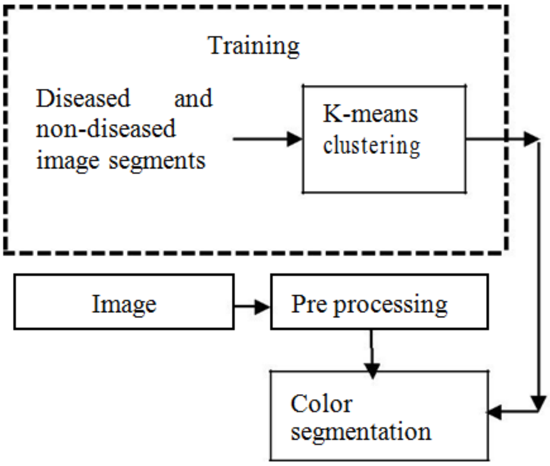

Fig.6 (b). Apple Fruit Disease Diagnosis System

4. Color co-occurrence Method

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image [9]. Spatial Gray-level Dependence Matrices (SGDM) method is a way of extracting statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element $P(i, j|\Delta x, \Delta y)$ is the relative frequency with which two pixels, separated by a pixel distance ($\Delta x, \Delta y)$ occur within a given neighbourhood, one with intensity i and the other with intensity j. The SGDM's are represented by the function P (i, j, d, ϴ) where I represent the gray level of the location, and j represents the gray level of the pixel at a distance d from location at an orientation angle of ϴ. SGDM's are generated for Hue image.

5. Texture features

Properties of Spatial Gray-level Dependence Matrices (SGDM) like Contrast, Energy, Local Homogeneity, and correlation are computed for the Hue content of the image as given in following equations [10]:

Contrast: Returns a measure of the intensity contrast between a pixel and its neighbour over the whole image. Range = [0 (size (SGDM, 1)-1) ^2] and Contrast is 0 for a constant image.

$$\text{Contrast} = \sum_{i,j=0}^{N-1} (i,j)^2 c(i,j) \quad (1)$$

Energy= Returns the sum of squared elements in the SGDM Range = [0 1], Energy is 1 for a constant image.

$$\text{Energy} = \sum_{i,j-0}^{N-1} c(i,j)^2 \quad (2)$$

Homogeneity= Returns a value that measures the closeness of the distribution of elements in the SGDM to the SGDM diagonal. Range = [0 1] and Homogeneity is 1 for a diagonal SGDM.

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{c(i,j)}{(1+(i-j)^2)} \quad (3)$$

Correlation= Returns a measure of how correlated a pixel is to its neighbour over the whole image. Range = [-1 1] and Correlation is 1 or -1 for a perfectly positively or negatively correlated image.

$$\text{Correlation} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{(i,j)*P(i,j)-(\mu_x-\mu_y)}{\sigma_x*\sigma_y} \quad (4)$$

III. FEATURE EXTRACTION TECHNIQUES IN THE PROPOSED APPROACH

In the proposed approach, we studied some state of the art color and texture features to validate the accuracy and efficiency. The features used for the apple fruit disease classification problem are Global Color Histogram, Color Coherence Vector, Local Binary Pattern, and Complete Local Binary Pattern.

1) Global Colour Histogram (GCH)

The Global Color Histogram (GCH) is the simplest approach to encode the information present in an image [11]. A GCH is a set of ordered values, for each distinct color, representing the probability of a pixel being of that color. Uniform normalization and quantization are used to avoid scaling bias and to reduce the number of distinct colors [11].

2) Color Coherence Vector (CCV)

An approach to compare images based on color coherence vectors are presented in [12]. They define color coherence as the degree to which image pixels of that color are members of a large region with homogeneous color. These regions are referred as coherent regions. Coherent pixels are belongs to some sizable contiguous region, whereas incoherent pixels are not.

In order to compute the CCVs, the method blurs and discretizes the image's color-space to eliminate small variations between neighbouring pixels. Then, it finds the connected components in the image in order to classify the pixels in a given color bucket is either coherent or incoherent. After classifying the image pixels, CCV computes two color histograms: one for coherent pixels and another for incoherent pixels. The two histograms are stored as a single histogram.

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3) Local Binary Pattern (LBP)

Given a pixel in the input image, LBP [8] is computed by comparing it with its neighbours: ,

$$LBP_{N,R} = \sum_{n=0}^{n-1} s(v_n - v_c)2^n$$

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

Where, is the value of the central pixel, is the value of its neighbours, R is the radius of the neighbourhood and N is the total number of neighbours. Suppose the coordinate of is (0, 0), then the coordinates of are (Rcos (2π n / N), Rsin (2π n / N)). The values of neighbours that are not present in the image grids may be estimated by interpolation. Let the size of image is I*J.

After the LBP code of each pixel is computed, a histogram is created to represent the texture image:

$$H(k) = \sum_{i=1}^{I} \sum_{j=1}^{J} f(LBP_{N,R}(i,j),k), k \in [0,K]$$

$$f(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases}$$

Where, K is the maximal LBP code value

4) Complete Local Binary Pattern (CLBP)

LBP feature considers only signs of local differences (i.e. difference of each pixel with its neighbours) whereas CLBP feature [13] considers both signs (S) and magnitude (M) of local differences as well as original centre gray level (C) value. CLBP feature is the combination of three features, namely CLBP_S, CLBP_M, and CLBP_C. CLBP_S is the same as the original LBP and used to code the sign information of local differences. CLBP_M is used to code the magnitude information of local differences:

$$CLBP_{N,R} = \sum_{n=0}^{n-1} t(m_n, c)2^n$$

$$t(x,c) = \begin{cases} 1, x \geq c \\ 0, x < c \end{cases}$$

Where, c is a threshold and set to the mean value of the input image in this experiment.

CLBP_C is used to code the information of original centre gray level value:

$$CLBP_{N,R} = t(g_c, c_1), \quad t(x,c) = \begin{cases} 1, x \geq c \\ 0, x < c \end{cases}$$

Where, threshold is set to the average gray level of the input image.

IV. CONCLUSION

An application of texture analysis in detecting the crop and fruit diseases has been explained in this paper. Thus the proposed algorithm was tested on the apple fruit images. Using the colour image segmentation method to exact intensity pattern to various diseases accordingly it is then possible to analyse the n no of diseases and it works very efficiently. Firstly by color transformation structure RGB is converted into HSV space because HSV is a good color descriptor. Masking and removing of green pixels with pre-computed threshold level. Then in the next step segmentation is performed using k- means clustering technique .These segments are used for texture analysis by color co-occurrence matrix. Finally texture parameters are compared to texture parameters of normal fruit image. The four different types of feature extraction techniques for efficient analysis are studied and expected to have an efficient detection and classification of fruit and vegetable diseases.

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