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Recognition of Fruits and Vegetables Diseases using distance based classifier

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Abstract: *Recently, a lot of activity in the area of Image Categorization has been done. In respect of produce fruit and vegetable classification problem, Veggie-vision [2] was the first attempt of a fruit and vegetable recognition system. The system uses texture, color and density (thus requiring some extra information from the system). This system does not take some advantage of recent developments, because it was created some time ago. The reported accuracy was around 95% in some scenarios but it uses the top four responses to achieve such result. Our data set is more demanding in some respects; while the data set of Veggie-vision had some extra classes, the hardware that captures the images gave a suppressed specular lights and more uniform color. The data set gathered in the super market has more illumination differences and much color variation among different images, and there is no measure for the suppression of specularities. Diseases in fruit cause devastating problem in production and economy in agricultural industry worldwide. Till now experts identify the presence of the disease in the fruits manually, but it is expensive for a former to consult an expert due to their distant availability, so it is required to detect the symptoms of the fruit diseases automatically as early as they appear on the growing fruits. Apple fruit diseases can cause major losses in yield and quality appeared in harvesting. To know what control factors to take next year to avoid losses, it is crucial to recognize what is being observed. Some disease also infects other areas of the tree causing diseases of twigs, leaves, and branches. Some common diseases of apple fruits are apple scab, apple rot, and apple blotch [52]. Apple scabs are gray or brown corky spots. Apple rot infections produce slightly sunken, circular brown or black spots that may be covered by a red halo. Apple blotch is a fungal disease and appears on the surface of the fruit as dark, irregular or lobed edges.*

1. INTRODUCTION

In agricultural science, images are the important source of data and information. To reproduce and report such data photography was the only method used in recent years. It is difficult to process or quantify the photographic data mathematically. Digital image analysis and image processing technology circumvent these problems based on the advances in computers and microelectronics associated with traditional photography. This tool helps to improve images from microscopic to telescopic visual range and offers a scope for their analysis. Several applications of image processing technology have been developed for the agricultural operations. These applications involve implementation of the camera based hardware systems or color scanners for inputting the images. We have attempted to extend image processing and analysis technology to a broad spectrum of problems in the field of agriculture. The computer based image processing is undergoing rapid evolution with ever changing computing systems. The dedicated imaging systems available in the market, where user can press a few keys and get the results, are not very versatile and more importantly, they

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have a high price tag on them. Additionally, it is hard to understand as to how the results are being produced. We have tried to develop a solution which presents classification problem in a most realistic way possible. Recognition system is a 'grand challenge' for the computer vision to achieve near human levels of recognition. The fruits and vegetables classification is useful in the super markets where prices for fruits purchased by a customer can be determined automatically. Fruits and vegetables classification can also be used in computer vision for the automatic sorting of fruits from a set, consisting of different kinds of fruit.

we propose and experimentally evaluate a framework for the detection and classification of fruit diseases. The proposed framework is composed of the following steps; in first step the fruit images are segmented using Distance based classifier technique.

2. Literature Review

A unified approach [9] is presented in Rocha et al. that can combine many features and classifiers. The author approaches the multi-class classification problem as a set of binary classification problem in such a way that one can assemble together diverse features and classifier approaches custom-tailored to parts of the problem. They define a class binarization as a mapping of a multi-class problem onto two-class problems (divide-and-conquer) and referred binary classifier as a base learner. They calculate the minimum distance of the generated vector (binary outcomes) to the binary pattern (ID) representing each class, in order to find the final outcome. They have categorized the test case into that class for which the distance between ID of that class and binary outcomes was be minimum.

Photographs differ from paintings in their edge, color, and texture properties. In [10] the problem of automatically differentiating photographs of paintings from photographs of real scenes is addressed. The authors used color, edge, and texture properties to demonstrate the problem. Using single features they have achieved 70– 80% correct discrimination performance, whereas they have achieved more than 90% correct discrimination results by a classifier using multiple features. But they did not observe any differences in the edge structure of paintings and photographs in our images.

Low- and middle-level features are used to distinguish broad classes of images in [11]. The author has shown that a low complexity, low dimensional feature set can, in fact, be used to achieve a high indoor/outdoor classification rate when applied in a two stage SVM classification scheme. The combination of low-level and semantic features increases the classification accuracy.

In addition, an approach to establish image categories automatically using histograms, shape and colors descriptors with an unsupervised learning method is presented in [12]. Recently, Agarwal et al. [13] and Jurie and Triggs [14] adopted approaches that take categorization problem as the recognition of specific parts that are characteristic of each object class.

Marszalek and Schmid [15] have extended the category classification with bag-of-features, which represents an image as an order less distribution of features. They have given a method to exploit spatial relations between the features by utilizing object boundaries when supervised training is in progress. They increase the weights of features that agree on the shape and position of the objects and suppress the weights of features that used in the background.

The object categories presented in a set of unlabelled images are discovered in [17]. It is achieved in the statistical text literature: probabilistic Latent Semantic

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Analysis by using a model developed. This is used to discover topics using the bag- of-words document representation in a corpus in the text analysis. Here object categories are equivalent to the topics, so that an image having instances of several categories is constructed as a mixture of topics. By using a visual analogue of a word, the model is applied to images, formed by vector quantizing SIFT-like region descriptors. Such techniques, called as bag-of-features showed better results even though they do not try to model spatial constraints among features.

Another interesting technique was proposed in [18]. The author has calculated feature points from the gradient image. By a joining path, the points are connected and a match is finalized if contour found is similar enough to the one presents in the database. A very serious drawback of such method for produce fruit and vegetable classification is that such method requires a nonlinear optimization step for the finding of best contour; still it relies too heavily on the silhouette cues, which are not very informative cues for fruits like lemons, melons and oranges.

3. Proposed Framework

The steps of the proposed approach are shown in the Figure 4.1. Defect segmentation, feature extraction, training and classification are the major task in this approach. For the fruit disease classification problem, precise image segmentation is required; otherwise the features of the non-infected region will dominate over the features of the infected region. In this approach K-means based image segmentation is used to detect the region of interest which is the infected part only. The proposed approach operates in two phases training and classification. Training is required to learn the system with the characteristics of each type of disease. First we extract the feature from segmented portion of all the images that are used for the training and store it in a feature database. Then we train the support vector machine with the features stored in the feature database. Finally any input image can be classified into one of the classes using feature derived from segmented part of the input image and trained support vector machine.

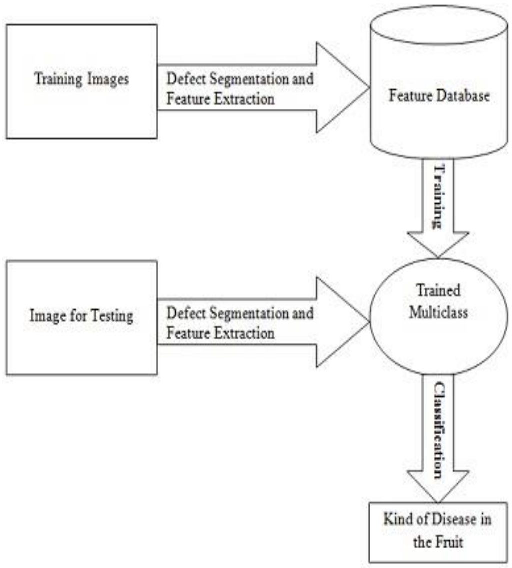

Fig 3.1.Proposed Approach for the Fruit Disease Recognition

4. Defect Segmentation

Distance based means clustering technique is used for the defect segmentation. In the chapter 3 we have used image segmentation based on the K-means clustering technique but there are some differences between the algorithm used in this and previous chapter. In previous chapter we have used only S-channel of the HSV image for segmentation because we were interested only in foreground and background of the image so only a single channel was sufficient with two clusters one for foreground and one for background. But in disease detection we have to identify only the infected region in the image so using only a single channel and two clusters are not sufficient, so here we use more than two clusters and consider

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more than one channel of the color images for the precise disease segmentation. In this experiment images are partitioned into four clusters in which one cluster contains the majority of the diseased parts of the image

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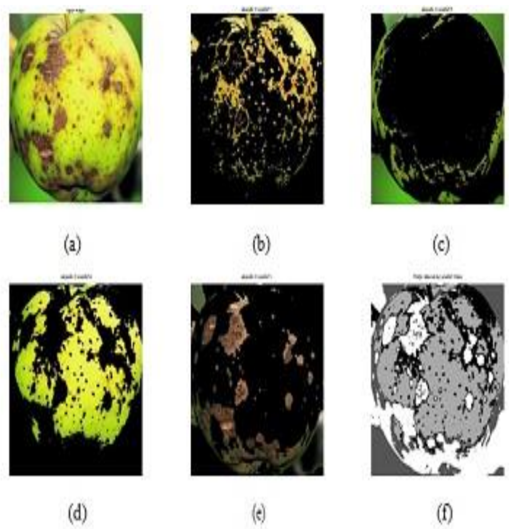

Fig 4.1.K-Means clustering for an apple fruit that is infected with apple scab disease (a) The infected fruit image, (b) first cluster, (c) second cluster, (d) third cluster, and (e) fourth cluster, respectively, (f) single gray-scale image colored based on their cluster index.

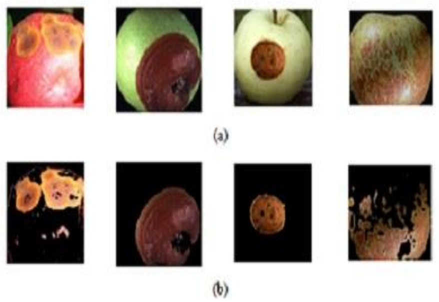

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Fig 4.2. Image segmentation results (a) Images before segmentation, (b) Images after segmentation

4.1 Difference based classifier

We have to use following difference based classification technique

Euclidean distance

If the two points A, B is having Cartesian coordinates A (A_1 , A_2 , A_3,…………A_n) & B (B_1 , B_2 , B_3……….B_n), then the Euclidean distance between them

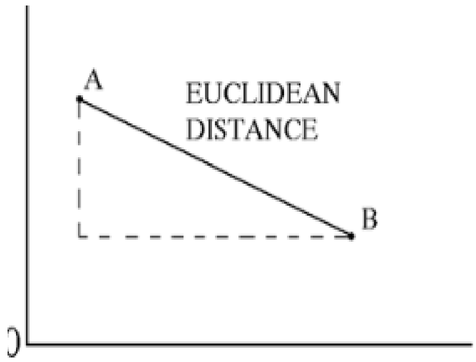

Fig 4.1.1 In the diagram A and B are that points, we have to find out the distance between them by using Euclidean distance method

$$D(A,B)=D(B,A)$$

$$=\sqrt{(A_1-B_1)^2+(A_2-B_2)^2+\cdots(A_n-B_n)^2}$$

$$=\sqrt{\sum_{i=1}^{n}(A_i-B_i)^2}$$

If Euclidean vector is a position of points a Euclidean n-space. So A & B are eigen vector.

$$||A||=\sqrt{A1^2+A2^2\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots An^2}$$

$$=\sqrt{A.A}$$

A vector also described a line segment from origin of Euclidean space to the point at that space.

Manhattan distance

Manhattan distance, the distance between two points, which is measured along with axes at right angles.

$D(A, B) = \| A - B \|_1 = \sum_{i=0}^{n} | Ai - Bi|$

Where (A, B) are vectors, A = (A_1, A_2, A_3… A_n) &

B = (B_1, B_2, B_3… B_n), for example distance between points (A_1, A_2) & (B_1, B_2) is the,

$$= | A_1 - A_2 | + | B_1 - B_2 |$$

Negative distance

Negative distances are the weighted function, which applies to input to get the weighted inputs. For example, if we have to random weight matrix A and B then the negative distance X defined as

X = -sqrt(sum(A - B)ˆ2)

4.2 Feature Extraction

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In the proposed approach, we have used 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 Completed Local Binary Pattern. We have already discussed Global Color Histogram (GCH) and Color Coherence Vector (CCV) in the previous chapter in the section 3.3.2. In this section we discuss Local Binary Pattern and Completed Local Binary Pattern in brief

Local Binary Pattern (LBP)

Given a pixel in the input image, LBP [27] is computed by comparing it with its neighbors:

$$LBP_{N,R} = \sum_{n=0}^{n-1} s(v_n - v_c)2^n, s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

Where, v_C is the value of the central pixel, v_n is the value of its neighbors, R is the radius of the neighborhood and N is the total number of neighbors. Suppose the coordinate of v_C is (0, 0), then the coordinates of v_n are $(R\cos(2\pi n / N), R\sin(2\pi n / N))$. The values of neighbors 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.

In this experiment the value of 'N' and 'R' are set to '8' and '1' respectively to compute the LBP feature.

Completed Local Binary Pattern (CLBP)

LBP feature considers only signs of local differences (i.e. difference of each pixel with its neighbors) whereas CLBP feature [31] considers both signs (S) and magnitude (M) of local differences as well as original center gray level (C) value. CLBP feature is the combination of three features, namely CLBP_S, CLBP_M, and CLBP_C.

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

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

4.3 Data Set Preparation

To demonstrate the performance of the proposed approach, we have used a data set of normal and diseased apple fruits, which comprises four different categories: Apple Blotch (104), Apple rot (107), Apple scab (100), and Normal Apple (80). The total number of apple fruit images (N) is 391. Figure 4.4 depicts the classes of the data set. Presence of a lot of variations in the type and color of apple makes the data set more realistic.

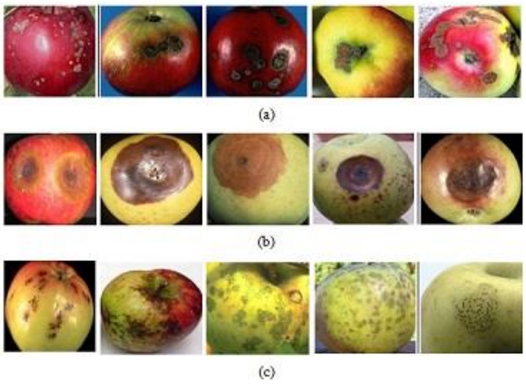

Fig 4.3.Sample images from the data set of type (a) apple scab, (b) apple rot, (c) apple blotch

5. Results and Discussion

In this section we show data set of apple fruit diseases and present a detailed result of the produce fruit disease classification problem and discuss various

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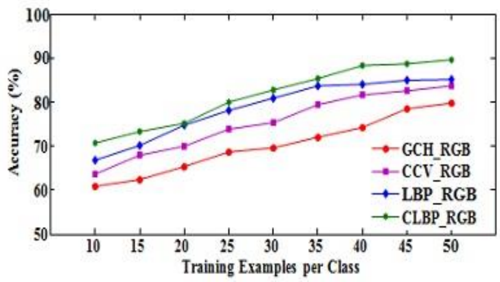
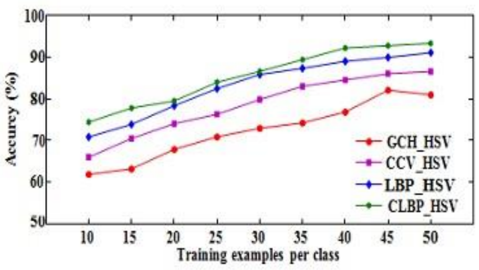
issues regarding the performance and efficiency of the system. In the section 4.3.1, we discuss about the data set used in this work and difficulties that may appear in the processing. In the section 4.3.2, the performance of proposed framework is presented by using four different descriptors and a comparison is made for these features. We also consider and compare the performance of the system in two color-spaces (i.e. RGB and HSV color-space). This section also compares the result for different types of diseases present in the apple with the aim to find out those diseases which are very difficult to detect and classify from the images.

$$\text{Accuracy}(\%) = \frac{\text{Total number of images correctly classified}}{\text{Total number of images used for testing}} * 100$$



(a) Using RGB color image



(b) Using HSV color image

Accuracy (%) for the GCH, CCV, LBP, and CLBP features derived from RGB and HSV color images considering MSVM classifier

We also observe across the plots that each feature performs better in the HSV color space than the RGB color space as shown in the Figure 4.6 (a-b). For 45 training examples and CLBP feature, for instance, reported classification error is 88.74% in

RGB and 92.65% in HSV. One important aspect when dealing with apple fruit disease classification is the accuracy per class. This information points out the classes that need more attention when solving the confusions. Figure 4.7 and 4.8 depicts the accuracy for each one of 4 classes using LBP and CLBP features in RGB and HSV color spaces. Clearly, Apple Blotch is one class that needs attention in both color spaces. It yields the lowest accuracy when compared to other classes in both color spaces.

5.1. **Summary**

An image processing based approach is proposed and evaluated in this chapter for fruit disease detection and classification problem. The proposed approach is composed of mainly three steps. In the first step defect segmentation is performed using K-means clustering technique. In the second step features are extracted. In the third step training and classification are performed on a Multiclass SVM. We have used three types of apple diseases namely: Apple Blotch, Apple Rot, and Apple Scab as a case study and evaluated our program.

Our experimental results indicate that the proposed solution can significantly support automatic detection and classification of apple fruit diseases. Based on our experiments, we have found that normal apples are easily distinguishable with the diseased apples and CLBP feature shows more accurate result for the classification of apple fruit diseases and achieved more than 93% classification accuracy. Further work includes consideration of fusion of more than one feature to improve the output of the proposed method.

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