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Research Article

An Identifying Plant Leaf Diseases Based on Color, Shape and Texture Features

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Abstract

An identification of disease on the plant is a very important key to prevent a heavy loss of yield and the quantity of agricultural product. The symptoms can be observed on the parts of the plants such as leaf, stems, lesions and fruits. The leaf shows the symptoms by changing color, changing shape and texture, by showing the spots, leaf rolling and holes on it. The aim of the project is to identify and classify the disease accurately from the leaf images. The analysis conducted by extracting color, shape and texture features from healthy and unhealthy tomato leaf and black gram leaf images. We propose a disease recognition and classification approach which consists of framework to pre-processing, segmenting, feature extraction, and diseases classification and recognition. In pre-processing diseased leaf image should be enhanced and then segmenting diseased leaf images by using K-means clustering, extracting shape and color features from lesion information, texture feature extracted by LGGP (combining LBP and Gabor filter) technique. Extracted features from segmented images fed to classification. Diseased leaf images classifying by using sparse representation approach. Combining of these proposed techniques efficiency can successfully detect and more accurately classify the examined diseases.

Keywords: K-means clustering; Gabor filter; Local Binary Pattern; Sparse representation.

Introduction

Image Processing forms core research area within engineering and computer science disciplines too. Pictures are the most common and convenient means of conveying or transmitting information. A picture is worth a thousand words. Pictures concisely convey information about positions, sizes and inter-relationships between objects. They portray spatial information that we can recognize as objects. Human beings are good at deriving information from such images, because of our innate visual and mental abilities. About 75% of the information received by human is in pictorial form. Image processing has been proved to be effective tool for analysis in various fields and applications [1].

Agricultural Image Processing is one of the core application of Image processing is one of the most growing research area that is having its participation in different application areas including the biometric system, biomedical system, etc. One of such application area is the agricultural industry. In this application area, image processing is been utilizing in different ways to identify the crop, plant, leaves, flower, fruits etc. as well as to identify the disease. Digital image processing is a technique used for enhancement of the image. Many of methods used for segmentation in image processing for agriculture field [2]. The image processing can be used in agricultural applications for purposes to detect diseased leaf, stem, fruit, quantify affected area by disease, find shape of affected area, determine color of affected area and determine size & shape of fruits [2,3].

Agriculture is not only to feed ever growing population but it also important source of energy. Plant diseases affect both quality and quantity of crops in agriculture production. Plant disease diagnosis is very essential in earlier stage in order to prevent and control them. Plant disease detection is emerging field in India as agriculture is important sector in Economy and Social life [4]. The naked eye observation of experts is the main approach adopted in for detection and identification of plant diseases. But the naked eye observation is time consuming, expensive and takes lots of efforts. Earlier unscientific methods were in existence. Gradually with technical and scientific

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advancement, more reliable methods through lowest turnaround time are developed and proposed for early detection of plant disease. Such techniques are widely used and proved beneficial to farmers as detection of plant disease is possible with minimal time span and corrective actions are carried out at appropriate time [4,5,6].

To remove drawbacks in existing system many systems have been proposed to overcome those drawbacks by using different techniques. The management of crops required close inspection especially for management of disease infected crop that can affect the quality and quantity of crop. The detection and classification of plant diseases are important task to increase plant productivity. To detect plant disease the image should go through some process like pre-processing, segmentation, feature extraction and classification processes. The pre-processing is an improvement process of image data to suppresses unwanted distortion or enhances some image features important for further processing. The segmentation process is to partition an image into meaningful regions and it is vital process through which image features are extracted. There are various features of an image such as grey level, colour, texture, shape etc. Classification process is used to classify the given input data into number of classes and groups. It classifies the data based upon selected features [4].

Proposed work

To detect plant disease the image which has some process like pre-processing, segmentation, feature extraction and classification processes. We propose a disease recognition and classification approach which consists of framework to pre-processing, segmenting, feature extraction, and diseases classification. In pre-processing, diseased leaf image should be enhanced and then segmenting diseased leaf image by K-means clustering, extracting shape and color features, texture feature extracted by LGGP (combining LBP and Gabor filter) technique. Extracted features from segmented images fed to classification. Diseased leaf images classifying by using sparse representation approach. Combining of these proposed techniques can successfully detect and classify the examined diseases.

System design

Figure 1 shows the overall design for leaf disease detection.

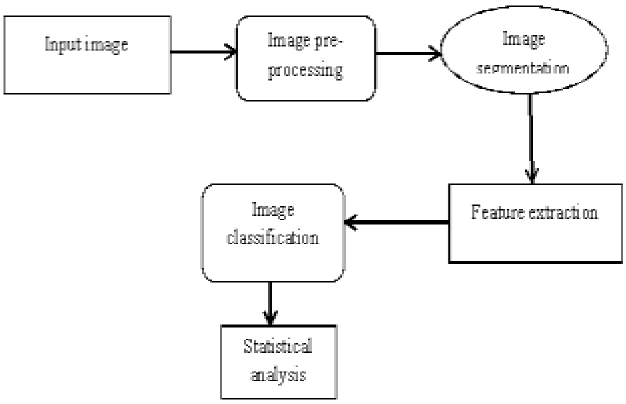

Figure 1. System design

Image pre-processing

Image pre-processing is a prophase relative to feature extraction and image recognizing. The images which have input are always not satisfactory regardless of what image acquisition devices are adopted. For e.g., there are noises in the image, the region of interest in the image is not clear or other objects interference exist in the image and so on. Image enhancement belongs to image pre-processing methods. Figure 2 shows the enhanced image.

Objective of image enhancement

Process the image (e.g. contrast improvement, image sharpening and so on) so that it is better suited for further processing or analysis. Every diseased leaf image is pre-processed by smoothing, enhancing, DE noising, alignment and is segmented by the K-means clustering algorithm [7].

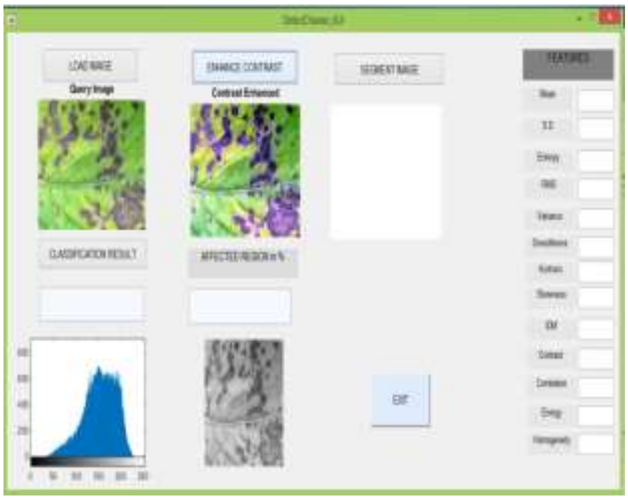

Figure 2. Enhanced image

Results and discussion

Image segmentation and feature extraction

Segmentation refers to the process of clustering the pixels with certain properties into salient regions and these regions correspond to different faces, things or natural parts of the things. The segmentation is an important step in recognition system of the damages and symptoms. The image will be segmented into different parts according to the region of interest. Purpose of image segmentation is to divide the image into some meaningful regions. Figure 3 shows the example of segmented image. K-Means is chosen as one of the method used for this research because it is easy to be implemented and fast in computation [1].

Figure 3. Segmentation and extraction of infected area from leaf area

K-means clustering

We proposed k-means segmentation technique to fragment goal areas. Target regions are those areas in the image that represented visual symptoms of a disease. It contains Thresholding, Binarization, and Segmentation. The segmentation consists of partitioning the input image in order to extract the infected area from the leaf area. K-means clustering method is used in this paper. Figure 4 shows the clustered image by using K-means algorithm. For that, the input image is segmented into three clusters (k=3). The algorithm of k-means clustering classifies the objects (pixels in our case) into k number of clusters based on a set of features. The classification of pixels is carried out by minimizing the sum of squares of distances between the data objects and the corresponding cluster. The squared Euclidean distance is used for the k-means clustering. We use the K-means clustering algorithm to segment lesion from diseased leaf images [8].

- ❖ Collect data. Read each image from the leaf image database. The leaf images are in any format.
- ❖ Convert each color image from RGB color space to L*a*b color model. The lesion information in the L*a*b color space is stored in only two channels (i.e., a* and b* components).
- ❖ Classify the colors in the ‘‘a*b*’’ space using the K-means clustering. Colors (carried by the ‘‘a*’’ and ‘‘b*’’ values) of the pixels in the lesion image are clustered by K-means using the Euclidean distance.
- ❖ Label every pixel in the image using the results from the K-means clustering. For each pixel in the input, K-means returns an index corresponding to a cluster. Label each pixel in the image with its cluster index.
- ❖ Segment the diseased leaf image by color. Using the pixel labels, the pixels in image can be separated by color, resulting in three images (i.e., K = 3).
- ❖ Select the lesion image from the cluster images. The selection process of the lesion cluster from among three clusters is based on the mean ‘‘a*’’ and ‘‘b*’’ value of each cluster. We experimentally determine the range ‘‘a*’’ and ‘‘b*’’. The cluster having the average ‘‘a*’’ and ‘‘b*’’ in this range is selected as the lesion cluster.

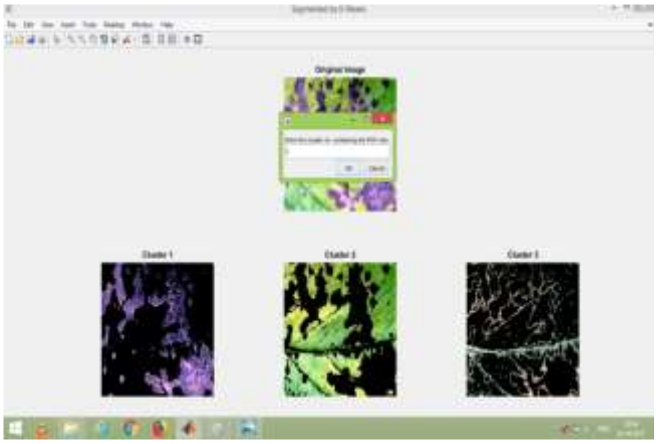

Figure 4. Clustered images

Texture feature

Texture is a repeated pattern of information or arrangement of the structure with regular intervals. In a general sense, texture refers to surface characteristics and appearance of an object given by the size, shape, density, arrangement, proportion of its elementary parts. A basic stage to collect such features through texture analysis process is called as texture feature extraction. Texture of a plant leaf is due to presence of veins in different directions or colors on it. Of the many texture feature extractor Gabor filter and Local Binary Pattern (LBP) are significant one. Generally for texture extraction Gabor filter followed by LBP is used. A Gabor filter is a linear filter used for edge detection in image processing which is named after Dennis Gabor. Gabor filter frequency and orientation representations are similar to those of human visual system, for texture representation and discrimination it has been found to be remarkably appropriate [9-11]. A sinusoidal plane wave has been modulating a 2D Gabor filter which is a Gaussian kernel function in the spatial domain. Basic 2D Gabor function can be stated as given in eq. (1).

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{\frac{1}{2}\left(\frac{x^2}{\sigma x^2}+\frac{y^2}{\sigma y^2}\right)} \times e^{2\pi i f x} \qquad (1)$$

The basic local binary pattern operator, introduced by Ojala was based on the assumption that texture has locally two complementary aspects, a pattern and its strength [12]. The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are threshold by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighbourhood consists of 8 pixels, a total of 28 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighbourhood [13-16].

$$LBP_{(P_c)} = \sum_{k=0}^{7} \delta\left(f_k - f_p\right) 2^k \qquad (2)$$

$$\delta(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x \leq 0 \end{cases} \qquad (3)$$

In basic LBP, the LBP operates on the original image. Many researchers used LBP for filtered images produced by Gabor filter. This technique is named as Local Gabor Binary Pattern (LGBP). LGGP is created by comparing the pixels of pattern formed by LBP and LGBP [11,16].

- Read Query color image Ic(x, y)
- Convert RGB color image to Gray image I(x, y)
- Compute LBP of gray image.

$$LBP = LBP\,[I(x, y)] \qquad (4)$$

- Apply Gabor filter to gray image.

$$G_I(x, y) = g_{ab}(x, y) \qquad (5)$$

- Compute LGBP i.e. LBP of real part of Gabor Filtered image.

$$LBP = LBP\left[Re\left(G_I(x,y)\right)\right] \qquad (6)$$

- Compare each pixel in LBP and LGBP using neighbourhood of (3 × 3) to generate LGGP.

$$LGGP(x,y) = \begin{cases} LBP(x,y) & \text{if } LBP(x,y) = LGBP(x,y) \\ 1 & \text{if } [A \cup B] \text{ have more 1's than 0's} \\ 0 & \text{otherwise} \end{cases} \qquad (7)$$

Where ‘A’ is adjacent neighbours of LBP(x, y) and ‘B’ is an adjacent neighbour of LGBP(x, y). After finding values of eight pixels, find its decimal equivalent which is the value of center pixel (x, y). Using this procedure all pixels of LGGP images were computed.

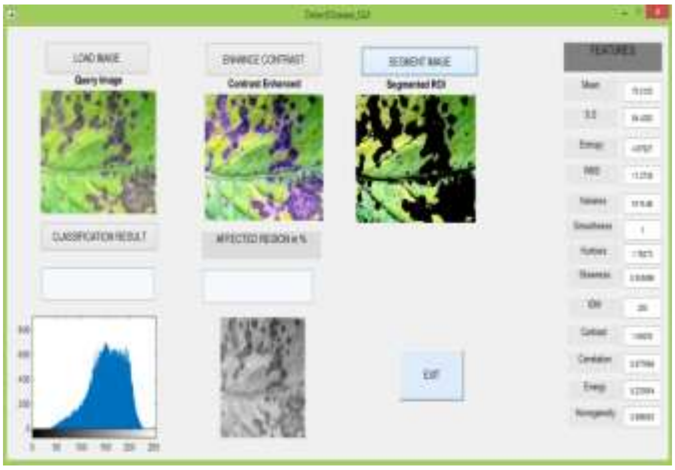

Figure 5. Selected Segmented image and evaluate features

Leaf disease recognition based SR

Sparse representation has attracted much attention in recent years and many examples in different fields can be found where sparse representation is definitely beneficial and favourable. The sparse representation based classification (SRC) method first assumes that the test sample can be sufficiently represented by samples from the same subject. Specifically, SRC exploits the linear combination of training samples to represent the test sample and computes sparse representation coefficients of the linear representation system, and then calculates the reconstruction residuals of each class employing the sparse representation coefficients and training samples. The test sample will be classified as a member of the class, which leads to the minimum reconstruction residual. Figure 6 shows disease identification of leaf image [8,17].

Step 1 Dataset preparation. Segment the lesion from each diseased leaf image by K-means clustering algorithm [8].

Step 2 Color feature extraction. Divide the lesion image into three L*a*b components, extract histograms of the L*a*b components, calculate their 128-point fast Fourier transform (FFT), and extract their log frequency histogram features, denoted as V^L, V^a, V^b, respectively.

Step 3 Shape feature extraction. Convert each lesion image into gray scale and re shape it as a vector $v \in R^m$, where m is the length of v.

Step 4 Feature combinations. For each lesion image, normalize and concatenate the shape feature v and three color features V^L, V^a, V^b, as a combined vector [v, V^L, V^a, V^b,] to describe this lesion image. Principal Component Analysis (PCA) is utilized to reduce the dimensionality of [v, V^L, V^a , V^b,] by retaining 95% energy. The reduced feature vector is also denoted as [v, V^L, V^a , V^b,] for simplicity.

Step 5 Randomly select n reduced feature vectors from each class as the training set, the remainder as the testing set. Construct an over-complete dictionary $A = [A_1, A_2, \dots, A_k] \in R^{n\times m}$ from the training set, where Ai is a sub-matrix formed by the reduced feature vectors belonging to the i^{th} class, $i = 1,2,\dots,k$

Step 6 Solve the optimization problem. For a given test image y, solve the optimization problem defined in following Eq. (8)

$$j(x,\lambda) = min\{\|Wx - y\|_2 + \lambda\|x\|_1\} \quad (8)$$

Step 7 Check whether the termination condition is satisfied, which is defined the ratio between the two smallest residual.

Step 8 Compute the residuals $r_i(y)$ between y and its estimate y' for each category by given Eq. (9)

$$x = (W^T W)^{-1} W^T y \qquad (9)$$

Let $\delta_i(x')$ keep only nonzero entries in x' that are associated with the ith class. Approximate the test vector y by $y' = W\delta_i(x')$ using only the coefficients of x' which correspond to the ith class. For each class, compute the residual $r_i(y) = \square - W\delta_i(x')_2$,

where $i = 1,2,\dots,k$

Step 9 Perform SR based classification using the decision rule: If $r_j(y) = min r_i(y)$, y is assigned to the class j.

Figure 5. Disease identification of leaf image

Conclusions

The use of automated monitoring and management systems are gaining increasing demand with the technological advancement. In agricultural field loss of yield mainly occurs due to widespread of disease. Mostly the detection and identification of the disease is noticed when the disease advances to severe stage and therefore causing the loss in terms of yield, time and money. The proposed system is capable of detecting the disease at the earlier stage as soon as it occurs on the leaf. Hence saving the loss and reducing the dependency on the expert to a certain extent is possible. It can provide the help for a person having less knowledge about the disease. Depending on these goals, we have to extract the features corresponding to the disease. In future, we will have extend my work to include this concept in Agricultural image processing to detect and classify examined leaf diseases with more accuracy for all agricultural/horticultural crops of more different species like commercial crops, cereals crops, vegetables crops, etc and to get perfect solution for that leaf diseases

Conflicts of interest

Authors declare no conflict of interest.

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