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A Review of techniques for Automatic detection and diagnose of mango pathologies

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Abstract

The agriculture is the sole area that serves the entire life on earth. With aid of advanced technology research with new challenges in the field of agriculture is increase the production and profit. The different diseases and symptoms on any part of plant cause significant loss in production and economy to farmers as well as country. Thus the techniques for automatic disease detection and diagnose of agriculture crop or plant plays a major in disease management. This paper presents a review on methods that use digital image processing techniques to detect, recognize and classify plant diseases from digital image and concludes with discussion of more useful problems in the domain and future direction.

1. Introduction

Agriculture is the backbone of India, Plants or crops have become an important source of energy and economy, Where in Cash crops play a significant role for the development of Economy and society. As diseases of the plants are inevitable, there are several diseases that affect plants which cause devastating economical, social and ecological losses(*Jayme Garcia Arnal Barbebo* 2013). In this context, detecting and identifying of disease plays a major role in the field of Agriculture. Diagnosing such a disease in early and accurate way is a most important. There are various ways to detect plant pathologies, the open eye observation of experts is the main approach used in practice for detection and identification of plant diseases. But, this needs continuous monitoring of experts. When there is a large farm, this approach might be more expensive. Further, farmers may have to go long distances to contact experts, this makes consulting experts too expensive and time consuming and moreover farmers are unaware of most diseases. So Automatic detection of plant diseases in agriculture is an important research topic as it may prove benefits in monitoring large field of crops. Among various agriculture and horticulture crops mango is one of the finest fruits of the world with a great market value. India has been traditionally the major producer of mango in the world; we have got two excellent mango varieties with high export quality. These varieties are Dashehari, grown in north and Alphonso in south India. Still, we lag far behind in the world export market because our mango production is beset with several problems; such as insect pests, diseases and physiological disorders being major ones. These constraint reduce our total production also badly hamper the fruit quality. One such an application is ability to detect and recognize the diseases on mango crop automatically from symptoms that appear on plant leaves, flowers, fruits and stem, etc. Thus automatic detection of plant disease with the help of image processing technique provides more accurate direction for disease management. Depending on the application, many of problems may be solved, or at least reduced, by the use of digital images, pattern recognition and automatic classification tools. Many systems have been proposed previously, and this paper tries to organize and present those in a meaningful and useful way.

2. Techniques for Detection and Recognition

This section has three parts presents Detection, recognition and segmentation methods, The summarization table contains information about plant or crop,fruit,leaf diseases considered and technical solution adopted

2.1 Detection

The K-means and unsupervised learning approach proposed by Shitala Prasad et al(2014) uses mobile phones for real-time on-field imaging of diseased plants followed by disease diagnosis via analysis of visual phenotypes. A threshold based offloading scheme is employed for judicious sharing of the computational load between the mobile device and a central server at the plant pathology laboratory, thereby offering a trade-off between the power consumption in the mobile device and the transmission cost.

The part of the processing carried out in the mobile device includes leaf image segmentation and spotting of disease patch using improved k-means clustering. The algorithm is simple and hence suitable for Android based mobile devices. The segmented image is subsequently communicated to the central server. This ensures reduced transmission cost compared to that in transmitting full leaf image.

Automatic plant identification using shape, color and texture feature is proposed by **B. Yanikoglu et al (2014)** In addition to common difficulties faced in object recognition, such as light, pose and orientation variations, there are further difficulties particular to this problem, such as changing leaf shapes according to plant age and changes in the overall shape due to leaf composition. This system uses a rich variety of shape, texture and color features, some being specific to the plant domain. The results show 61 and 81 % accuracies in classifying the 126 different plant species in the top-1 and top-5 choices.

In automatic segmentation the image is first simplified by means of marginal color quasi-flat zones, a morphology-based image-partitioning method based on constrained connectivity, that creates flat zones based on both local and global spectral variation criteria. Next, they compute its morphological color gradient in the LSH color space, taking into accounts both chromatic and achromatic variation, followed by the application of the watershed transform. Hence, obtain a first partition with spectrally homogeneous regions and spatially consistent borders, albeit with a serious over-segmentation ratio which is compensated for by merging basins below a certain area threshold. At this point, initial assumption about central location of the object of interest is used, as we employ the central 2/3 area of the image to determine its dominant color, obtained by means of histogram clustering in the LSH colour space. Assuming that the mean color of the most significant cluster (i.e. reference color) belongs to the leaf/plant, then switch to spectral techniques, so as to determine its watershed basins. Since camera reflections can be problematic due to their low saturation, so compute both the achromatic, i.e. grayscale distance image from the reference gray and the angular hue distance image from the reference hue *h*ref :

$$\forall\ h, h\text{ref} \in [0, 2\pi],$$

$$d_\theta(h, h_{\text{ref}}) = \begin{cases} |h - h_{\text{ref}}| & \text{if } |h - h_{\text{ref}}| < \pi \\ 2\pi - |h - h_{\text{ref}}| & \text{otherwise} \end{cases}$$

Then apply Otsu's method on both distance images, providing us with two masks, representing spectrally interesting areas with respect to the reference color.

Delia Lorente et al (2013) proposed Optimal Wavelength Features for Decay Detection in Citrus Fruit Using the ROC Curve and Neural Networks. to select features in multiclass classification problems using the receiver operating characteristic curve, in order to detect rottenness in citrus fruits by means of hyper spectral images. The classifier used is a multilayer perceptron, trained with a new learning algorithm called extreme learning machine. The results are obtained using images of mandarins with the pixels labelled in five different classes: two kinds of sound skin, two kinds of decay and scars. This method yields a reduced set of features and a classification success rate of around 89%.

The feature selection methodology proposed to expand the use of the ROC curve to multi-class classification problems consists of two parts: (1) obtaining a ranking of features ordered according to the discriminant relevance of the features and (2) the choice of an optimal number of features from the feature ranking. Discriminant relevance of feature xi (DRi), which is defined as the difference between the area under the ROC curve of the classifier using all the features (AUC0) and the area without taking into account the effect of feature xi (AUCi). This parameter indicates the importance of a feature for the discrimination process carried out by the classifier, considering that the higher the discriminated relevance of a feature is, the more discriminatory that feature will be. A z statistic of feature xi (zi) is calculated from the discriminated relevance of feature xi (DRi), as shown in Eq below

$$z_i = \frac{\text{AUC}_0 - \text{AUC}_i}{\sqrt{\text{SE}_0^2 + \text{SE}_i^2 + 2 \cdot \rho \cdot \text{SE}_0 \cdot \text{SE}_i}}$$

Where SE0 and SEi are the standard errors of AUC0 and AUCi, respectively, and ρ is the correlation between AUC0 and AUCi. In this work, a feature is considered to be relevant for the problem when its corresponding z value exceeds 95%, this level being chosen empirically Then consists of obtaining a global feature ranking. After obtaining the partial rankings corresponding to each class, the next step is to perform a single global ranking that includes all the classes.

Information system for the assessment of plant disorders Anyela Camargo et al (2012) provides suggestions which disorders may affect the crop, and which measures would be effective against these disorders. Experts provide system with descriptions of actual incidents where they have identified the disorder. system uses a computational classifier to provide suggestions to users autonomously. The classifier is constructed based on expert's inputs. Suggestions of disorders and countermeasures are presented as ranked lists, leaving the final identification of the disorder and decisions of countermeasures to the user, as they may have additional information beyond the attributes used by system. The performance of the classifier was evaluated by generating data

that reflects the envisaged usage of the Isacrodi system. Data on crop disorders provided by experts was used to train the classifier and data that simulated the growers wishing to find out which disorder affects their crop was used to test the classifier.
The results show that with limited expert input and errors in data provided by users, the classifier is capable of identifying disorders with reasonable accuracy, particularly when the user considers the three top scoring disorders rather than just the top one. Isacrodi can provide valuable support to farmers in absence of human experts.

Zulkifli Bin Husin et all(2012) discussed the effective way used in performing early detection of chili disease through leaf features inspection. Leaf image is captured and processed to determine the health status of each plant. Currently the chemicals are applied to the plants periodically without considering the requirement of each plant. This technique will ensure that the chemicals only applied when the plants are detected to be effected with the diseases. The image processing techniques are used to perform hundreds of chili disease images. The plant chili disease detection through leaf image and data processing techniques is very useful and inexpensive system especially for assisting farmers in monitoring the big plantation area.

Strawberry Disease Identification Based on Image Processing and Pattern Recognition presented by Changqi Ouyang et all(2013) synthesis a segmentation algorithm is designed for the real-time online diseased strawberry images in greenhouse. First, preprocess images to eliminate the impact of uneven illumination through the “top-hat” transform, and remove noise interference by median filtering. After comprehensively applying the methods of gray morphology, logical operation, OTSU and mean shift segmentation, we can obtain the complete strawberry fruit area of the image. Normalize the extracted eigen values, and use eigenvectors of part of the samples for training the BP neural network and support vector machine, the remaining samples were tested in two kinds of disease strawberry recognition model. Results show that support vector machines have a higher recognition rate than the BP neural network.

Wavelets and PCA for Identification of Leaf Diseases in Tomato Plant is proposed by D.N.D.Harini et al(2011). The development of digital camera and growth of data storage has led to a huge amount of image databases. There are a lot of content-based retrieval systems which are mostly applied to general image databases (CBIR) and there are very few for plant databases. The use of plants is plenty such as foodstuff, medicine and industry. This has led to the thought of identifying the different diseases of a leaves of a plant available around us which might be useful to the common man. Inspired in the active field of CBIR, it is proposed a new methodology for automatic identification of diseased leaves based on Wavelets and PCA.

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. They can be combined, using a "shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal. As a mathematical tool, wavelets can be used to extract information from audio signals and images Wavelets have their basis from Fourier theory which tells that a signal can be expressed as the sum of a possibly infinite series of sines and cosines which is also referred to as a Fourier expansion. The various kinds of wavelet transforms can be performed on an image are Continuous wavelet transform (CWT), Discrete wavelet transform (DWT), Fast wavelet transform (FWT), Lifting scheme & Generalized Lifting Scheme, Wavelet packet decomposition (WPD), Stationary wavelet transform (SWT), Fractional. In the proposed methodology, discrete wavelet transform (DWT) thar is Haar wavelet transform is used.

The Haar transform can be expressed in the matrix form:

T = HFHT

Where T = N x N transformed image,

H = N x N Haar transformation matrix,

F = N x N image.

The Haar basis functions are**:**

$$h_0(z) = h_{00}(z) = \frac{1}{\sqrt{\mathrm{N}}}, \qquad z \in [0,1]$$

$$h_k(z) = h_{pq}(Z)$$

$$= \frac{1}{\sqrt{N}} \begin{cases} 2^{p/2} & (q-1)/2^p \le z < (q-0.5/2^p) \\ -2^{p/2} & (q-0.5)/2^p \le z < q/2^p \\ 0 & otherwise, z \epsilon [0,1] \end{cases}$$

The steps involved in PCA can be summarized as – Obtaining the input matrix, calculating and subtraction of mean, calculation of covariance matrix, the eigen vectors, eigen values and then forming a new feature vector .Once the new feature vector is formed, the new data set with low dimensions is derived. The eigenvectors with the highest eigen value is the principal component of the data set and the eigenvalues are ordered from highest to lowest. To reduce the dimensions, the first sets of eigenvectors are selected. The covariance matrix of the input data is calculated starting from the algorithmic mean – of all M Eigen vectors can be given as

$$\varphi = \frac{1}{M}\sum_{i=0}^{M} I_i$$

Subtracting the mean δ, $\delta = I_i - \varphi$, Calculating the covariance matrix, C

$$C = \frac{1}{M}\sum_{i=0}^{M} \delta\, \delta^T$$

Calculating the Eigen vectors Ev and Eigen values Es from the covariance matrix by the given relationship

$$E_s = \frac{1}{M}\sum_{i=0}^{M}(E_v^T\, \delta^T)^2$$

2.2 Recognition

Liwen Wanget al(2014) proposed an Improved Rotational Kernel Transformation Directional Feature for Recognition of Wheat Stripe Rust and Powdery Mildew. A novel directional feature based on improved rotational kernel transformation (IRKT) can calculate the statistics of direction distribution of infected leaf images in spatial domain. These calculated IRKT are insensitive to noise and can lead to good description of direction distribution of object which is suitable for recognition of powdery mildew and wheat stripe rust and provide methods to represent other plant diseases. The accuracy claimed here is 97.5%. the specific process of this method is for an image I, the direction number need to count is Ndir, K is size of kernel here K=(Ndir+2)/2. Generate multi directional kernels according to Ndir, each kernel is defined as Ki then execute convolutions to I with Ki. Calculate standard deviation σ

$$I_{edge}(x,y) = \begin{cases} 1 & \sigma(x,y) > T_\sigma \\ 0 & \sigma(x,y) \le T_\sigma \end{cases}$$

$$T_\sigma = \frac{\max(\sigma_p) + \min(\sigma_p)}{2}$$

Where T is threshold

First calculating the mean value of IKRT directional feature vector according to equation

$$m = \frac{1}{Ndir}\sum_{i=1}^{Ndir} Val(k_i) \qquad i = 1,2,\ldots,Ndir$$

Where m is mean value of directional IRKT feature vector, the statistics on direction Ki is Val(Ki), then standard deviation of direction histogram is..

$$\sigma = \sqrt{\frac{\sum_{i=1}^{Ndir}(m - Val(k_i))^2}{Ndir}}$$

This article uses otsu's method to calculate disease spots classification threshold T, so

$\sigma \geq$ T judged as stripe rust

$\sigma <$ T judged as powdery mildew

Xin Liu et al. (2013) presented Perceptual Hash Algorithm in Agriculture Images .According to the characteristics of agriculture image, new image recognition scheme and image authentication scheme were designed, which based on perceptual hash algorithm. Some tomato leaf diseases pictures were used to achieve image perceptual hash feature extraction. And the experimental results show that the same diseases images have closer perceptual hash characteristics.

Feature ranking using thresholding subset selection for Automatic recognition of quarantine citrus diseases Georgina Stegmayer. (2013) presents presents a model of automatic recognizer, It is based on the combination of a feature selection method and a classifier that has been trained on quarantine illness symptoms. Citrus samples with citrus canker, black spot, scab and other diseases were evaluated. Experimental work was performed on 212 samples. The proposed approach achieved a classification rate of quarantine/not-quarantine samples of over 83% for all classes, even when using a small subset (14) of all the available features (90). The results obtained show that the proposed method can be suitable for helping the task of citrus visual diagnosis, in particular, quarantine diseases recognition in fruits.Techniques for feature selection can be divided in two approaches: feature ranking, where features are ranked by some criteria and then features above a defined threshold are selected; and subset selection, where one searches a space of feature subsets for the optimal subset. Such approach works by using a function that takes a subset and generates an evaluation value for that subset. In this work best-fit search method has been used for feature selection.

Neural Networks and texture features in Recognition of Plant Diseases is described by Haiguang Wang et al. (2012) , In order to find out a method to realize image recognition of plant diseases, four kinds of neural networks including back propagation (BP) networks, radial basis function (RBF) neural networks, generalized regression networks (GRNNs) and probabilistic neural networks (PNNs) were used to distinguish wheat stripe rust from wheat leaf rust and to distinguish grape downy mildew from grape powdery mildew based on color features, shape features and texture features extracted from the disease images. The results showed that identification and diagnosis of the plant diseases could be effectively achieved using BP networks, RBF neural networks, GRNNs and PNNs based on image processing. For the two kinds of wheat diseases, the best prediction accuracy was 100% with the fitting accuracy equal to 100% while BP networks, GRNNs or PNNs were used, and the best prediction accuracy was 97.50%with the fitting accuracy equal to 100% while RBF neural networks were used. For the two kinds of grape diseases, the best prediction accuracy was 100% with the fitting accuracy equal to 100% while BP networks, GRNNs or PNNs were used, and the best prediction accuracy was 94.29％ with the fitting accuracy equal to 100% while RBF neural networks were used.

Guanlin Li et al. (2012) proposed Back propagation Networks for Recognition of Plant Diseases In this two kinds of grape diseases (grape downy mildew and grape powdery mildew) and two kinds of wheat diseases (wheat stripe rust and wheat leaf rust) were selected as research objects, and the image recognition of the diseases was conducted based on image processing and pattern recognition. After image preprocessing including image compression, image cropping and image denoising, *K*_means clustering algorithm was used to segment the disease images, and then 21 color features, 4 shape features and 25 texture features were extracted from the images. Backpropagation (BP) networks were used as the classifiers to identify grape diseases and wheat diseases, respectively. The results showed that identification of the diseases could be effectively achieved using BP networks. While the dimensions of the feature data were not reduced by using principal component analysis (PCA), the optimal recognition results for grape diseases were obtained as the fitting accuracy and the prediction accuracy were both 100%, and that for wheat diseases were obtained as the fitting accuracy and the prediction accuracy were both 100%. While the dimensions of the feature data were reduced by using PCA, the optimal recognition result for grape diseases was obtained as the fitting accuracy was 100% and the prediction accuracy was 97.14%, and that for wheat diseases was obtained as the fitting accuracy and the prediction accuracy were both 100%..

*K*_means clustering algorithm was used to segment the plant disease images firstly the images were converted from RGB color space to XYZ color space, and then were converted from XYZ color space to L*a*b* color space using the color differences in a*b* two-dimensional data space, the clustering of color was conducted with squared Euclidean distance (D) as the similarity distance and with mean square error (e) as the clustering criterion function, and mathematical morphology algorithm was used to amend the clustering results. Finally, binary segmentation and color segmentation of the disease images were achieved. D was calculated by using the equation $D=D2(A,C)$, and $D(A,C)$ was calculated using the following equation,

$$D(A,C)=\sqrt{(x-x_0)^2+(y-y_0)^2}$$

in which, $A(x,y)$ is the coordinate of any data object, and $C(x0,y0)$ is the coordinate of the cluster center. Mean square error was calculated by using the equation $e = E / n$, in which
E was calculated using the following equation,

$$E=\sum_{i=1}^{k}\sum_{w\in W_j}\left|w-C_j\right|^2$$

in which, E is the sum-of-squared-error criterion function value, w is the given data object in the cluster Wj, and Cj is the mean of the cluster Wj.

IBLE Algorithm in agricultural disease diagnosis is proposed by Jin HaiYue and Song Kai. (2010) is one kind of advanced version decision-making tree it mainly is used in the information theory. The channel capacity concept to take chooses the important characteristic to the entity in the measure. Combines the rule with many characteristics the point to distinguish the example can effectively the correct distinction. this algorithm in the oral cavity disease diagnosis, the experimental result indicated this algorithm has the very strong recognition capability to agriculture case diagnosis to very good assistance diagnosis function.

Ma Xiao-dan et al. (2010) presented Improved Genetic algorithm for Investigation of Soybean Brown Spot. Aiming at extracting the diseased spots and calculating the feature parameters of diseased spots, Firstly, obtain the image, and then recognize the diseased spots through genetic algorithm .At last, compute the feature parameter of diseased spots using the technology of digital image processing. The result indicates that this method can extract the diseased spot efficaciously and calculate the feature parameter accurately which can provide the foundation for recognition of disease category in advance.

The first step of setting up improved genetic network is to determine the coding criterion when using improved genetic algorithm to extract diseased spot, the second step was to determine the fitness degree ,according to which, the problem-solving ability of a certain chromosome could be evaluated.

Discernibility Function is expressed as follows

$$s(x_j, x_k) = \begin{cases} 0, x_j, x_k \in c_i \\ 1, x_j \notin c_i, x_k \in c_i \end{cases}$$

The degree of individual distinction can be described as

$$\varepsilon(x_j, x_k) = \frac{1}{\lambda} \sum_{1}^{|\lambda|} s(x_j, x_k)$$

The Discernibility degree in one class is defined as

$$\theta = \frac{1}{n_1^{\ 2}} \sum_{1}^{n_1^2} \varepsilon(x_j, x_k)$$

where η_1 represent number of individuals in one class and Discernibility degree among classes is

$$\varepsilon(x_j, x_k) = \frac{1}{\lambda} \sum_{1}^{|\lambda|} s(x_j, x_k)$$

Multiple Classifier Combination For Recognition of Wheat Leaf Diseases by **Yuan Tian et al. (2009).** Proposes a new strategy of Multi-Classifier System based on SVM for pattern recognition of wheat leaf diseases for higher recognition accuracy. Diseased leaf samples with Powdery Mildew, Rust Puccinia Triticina, Leaf Blight, Puccinia Striiformis were collected in the field and images were captured before a uniform black background. Three feature sets including color feature set, shape feature set and texture feature set were created for classification analysis. The proposed combination strategy was based on stacked generalization and included two-level structure: base-level was a module of three kinds of SVM-based classifiers trained by three feature sets and meta-level was one module of SVM-based decision classifier trained by meta-feature set which are generated through a new data fusion mechanism. Compared with other single classifiers and other strategy of classifier ensembles for wheat leaf diseases, this approach is more flexible and has higher success rate of recognition.

2.3 Classification

Support vector machine and Otsu's method for image segmentation is presented by Akira Mizushima and Renfu Lu (2013). On the development of an automatic adjustable algorithm for segmentation of color images, using linear support vector machine (SVM) and Otsu's threshold method, The method automatically adjusts the classification hyperplane calculated by using linear SVM and requires minimum training and time. It also avoids the problems caused by variations in the lighting condition and/or the color of the fruit. To evaluate the robustness and accuracy of the proposed segmentation method, tests were conducted for 300 'Delicious' apples using three training samples with different color characteristics (i.e., orange, stripe, and dark red) and their combination. The segmentation error varied from 3% to 25% for the fixed SVM, while the adjustable SVM achieved consistent and accurate results for each training set, with the segmentation error of less than 2%.

Otsu's method automatically finds the threshold using the histogram of a gray scale image ,based on the idea of finding the threshold that maximizes the between class variance $\sigma_B^2(t)$,which isexpressed as follows:

$$\sigma_B^2(t) = \frac{[m_G P(t) - m(t)]^2}{P(t)[1 - P(t)]}$$

where m_G is the average intensity ofthe entire image, m(t) isthe cumula tive mean up to level t, P(t) is the cumulative sum of probability assigned to object (background).The optimum threshold is the value t, that maximizes as follows:.

$$\sigma_B^2(t)\ t^* = \arg\max_{0 \leqslant t \leqslant L-1} \sigma_B^2(t)$$

The soft margin hyperplane algorithm is applied for non-separable data. Given a training set of instance label pairs (xi, ti), i = 1. . . l where $\mathbf{x}_i \in R^n$ is the training sample and $t_i \in \{-1, +1\}$ is the class label,the linear SVM requires to find the solution of the dual representation of the maximum margin problem.

$$L_D(\alpha) = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j t_i t_j \mathbf{x}_i \cdot \mathbf{x}_j$$

Subject to:

$$0 \leqslant \alpha_i \leqslant C,$$

$$\sum_i \alpha_i t_i = 0$$

where ai is the positive Lagrange multipliers and paramete r C (>0) controls the trade-of between the training error and the margin; a larger C means assigning a higher penalty toerrors. ai can be obtained by solving the quadratic programming problem. The separation hyper lane is given by...

$$f(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + b$$

$$\mathbf{w} = \sum_{i=1}^{N_S} \alpha_i t_i \mathbf{x}_i$$

$$b = t_i - \mathbf{w}^{\mathrm{T}}\mathbf{x}_i$$

Where w is the surface normal to the hyperplane,|b|/||w|| is the per- pendic ular distance from the hyper lane to the origin,||w|| isthe Euclidean norm of w, and NS is the number of support vectors. The new data point x is classified by evaluating the sign of f(x). When linear SVM is applied to the color RGB image segmentation, it calculates a classification hyper plane in the 3-D RGB space equation f(x) is rewritten as a linear combination of red, green and blue as follows

$$Z(x,y) = w_R R(x,y) + w_G G(x,y) + w_B B(x,y) + b$$

$$w_R = \sum_{i=1}^{N_S} \alpha_i t_i R_i, \;\; w_G = \sum_{i=1}^{N_S} \alpha_i t_i G_i, \;\; w_B = \sum_{i=1}^{N_S} \alpha_i t_i B_i$$

In their work Santanu Phadikar et al. (2013) presented **Fermi energy based segmentation** using feature selection and rule generation techniques [8] aims at classifying different types of rice diseases by extracting features from the infected regions of the rice plant images. Fermi energy based segmentation method has been proposed in the paper to isolate the infected region of the image from its background. Based on the field experts' opinions, symptoms of the diseases are characterized using features like colour, shape and position of the infected portion and extracted by developing novel algorithms. To reduce complexity of the classifier, important features are selected using rough set theory (RST) to minimize the loss of information. Finally using selected features, a rule base classifier has been built that cover all the diseased rice plant images and provides superior result compare to traditional classifiers.

A concept based on Pauli Exclusion Principle states that Fermi energy is attained when temperature of a material is lowered to absolute zero. The Fermi energy or Fermi level is expressed using Equation.

$$E_F = \frac{\hbar^2 \pi^2}{2ML^2}\left(\frac{3N}{\pi}\right)^{\frac{2}{3}}$$

where N is the number of particles, M is the mass of the particles, L is the length of the cube and h is the Planck constant. When an image is acquired using a physical source, the information content in the image is proportional to the energy radiated by the source. Fermi

energy (EF) of an image is computed using Eq. (1), where N is mapped as the number of pixels having distinct colour values in the image, number of grey levels (256) is equivalent to

length L and mass of the image (M) is calculated by aggregating the mass (m^{ij}_{rgb}) of each pixel (i, j) using Eq. (2).

$$m^{ij}_{rgb} = \frac{H_{r,g,b}}{p \times q}(r + g + b) \qquad (2)$$

Where Hr,g,b is the number of pixels having a particular intensity with r, g and b grey level values corresponding to Red, Green and Blue colour planes respectively and p q is the size of the image. Energy E(i, j) at (i, j)th pixel position is calculated using Eq. (3) and compared with the threshold value EF for segmenting the infected region of the image.

$$Ei,j = E_{r,g,b} = \frac{\hbar^2 \Pi^2}{2m_{\mathrm{rgb}}^{\mathrm{ij}} \times L^2}\left(r^2 + g^2 + b^2\right) \quad (3)$$

If E(i, j) ≥ E_F then the pixel (i, j) is treated as part of the infected region, otherwise in background region. To reduce computational complexity constants ⁄, P and L are eliminated from Eqs. (1) and (3) as the values are compared.

J. L. González-Pérez et al. (2013) proposed perceptual spaces through applets for determining and preventing diseases in chilli peppers. Proposes a method for knowing and preventing the disease in chili peppers plant through a color image processing, using online system developed in Java applets. The system gets results in real time and remotely (Internet). The images are converted to perceptual spaces [hue, saturation and lightness (HSL), hue, saturation, and intensity (HSI) and hue saturation and value (HSV)]. Sequence was applied to the proposed method. HSI color space was the best detected disease. The percentage of disease in the leaf is of 12.42%. HSL and HSV do not expose the exact area of the disease compared to the HSI color space. Finally, images were analyzed and the disease is known by the expert in plant pathology to take preventive or corrective actions.

Gaussian Markov random fields for Segmentation of Rumex obtusifolius is described by Santosh Hiremath et al (2013) Rumex obtusifolius is a common weed that is difficult to control. The most common way to control weeds—using herbicides—is being reconsidered because of its adverse environmental impact. Robotic systems are regarded as a viable non-chemical alternative for treating *R.* obtusifolius and also other weeds. In this work develop a new algorithm for segmentation of *R.* Obtusifolius using texture features based on Markov random fields that works in real-time under natural lighting conditions. Shown its performance by comparing it with an existing realtime algorithm that uses spectral power as texture feature. It is show that the new algorithm is not only accurate with detection rate of 97.8 % and average error of 56 mm in estimating the location of the tap-root of the plant, but is also fast taking just 0.18 s to process an image of size 576 × 432 pixels making it feasible for real-time applications. To specify Markov Random field specifying the conditional probability $P(x_i \mid x_j, j \in \eta_i)$. This is done by specifying the Gibbs distribution given by

$$P(x) = \frac{1}{Z} e^{\{-U(\boldsymbol{x})\}}$$

where $U(\boldsymbol{x})$ is called the potential function and Z is the normalizing constant known as the partition function. To define $U(\boldsymbol{x})$, there is a need to define cliques associated to a neighbourhood system and the corresponding clique potentials. A clique $c \in S$, is a set of pixels such that every distinct pair of pixels in the set are neighbours. A clique potential, $V_c(\boldsymbol{x})$, is a potential function associated with a clique type c, whose value is dependent on the structure of c. The potential function $U(\boldsymbol{x})$, is defined as

$$U(x) = \sum_{c \in C} V_c(x)$$

MRFs can be used in Bayesian context for a MAP-MRF formulation of the segmentation problem where the solution is given by finding the *Maximum a Posteriori* estimate, also known as the MAP estimate. where the posterior potential $U(\boldsymbol{x} \mid \boldsymbol{y})$ is given by

$$U(x \mid y) = U(y \mid x) + \lambda U(x) =$$

$$\sum_{i=1}^{m} V_1(y_i|x_i) + \lambda \sum_{i=1}^{m} \sum_{i,j \in c_2} V_2(x_i, x_j)$$

Juan-hua Zhu et al (2012) proposed Corn Leaf Diseases Diagnostic Techniques Based on Histogram and Threshold. The method here is separated into three steps. First, the gray-scale images are gotten from color images which were caught by numeral camera, which is enhanced by histogram equalization method, and the unwanted noise is removed from the image. Secondly, the disease spots were segmented from leaves based on the iterative threshold method and morphological methods. Finally, the shape characteristic parameters of disease spots, such as area, perimeter, rectangularity, circularity and shape complexity, are extracted, which are used to identify and diagnose diseases. The results show that the corn leaf diseases be well diagnosed with a diagnostic rate of 80%.The iterative threshold segmentation method and morphological methods for optimization of segmented binary image are adopted.

$$u_1 = \frac{\sum_{i=0}^{T_i} in_i}{\sum_{i=0}^{T_i} n_i} \qquad , u_2 = \frac{\sum_{i=T_i}^{L-1} in_i}{\sum_{i=T_i}^{L-1} n_i}$$

T1 is initial threshold value usually the middle value, new threshold value T2 = (μ1 + μ2) / 2.

Back propagation neural network for dates grading by Yousef Al Ohali (2010) is used to design and implement a prototypical computer vision based date grading and sorting system. here defined a set of external quality features. The system uses RGB images of the date fruits. From these images, it automatically extracts the aforementioned external date quality features. Based on the extracted features it classifies dates into three quality categories (grades 1, 2 and 3) defined by experts. studied the performance of a back propagation neural network classifier and tested the accuracy of the system on preselected date samples. The test results show that the system can sort 80% dates accurately.

A. Camargoa, J.S. Smith (2009) reports a machine vision system for the identification of the visual symptoms of plant diseases,from color images. Diseased regions crops were enhanced, segmented, and a set of features were extracted from each of them. Features were then used as inputs to a Support Vector Machine (SVM) classifier and tests were performed to identify the best classification model. And hypothesised that given the characteristics of the images, there should be a subset of features more informative of the image domain. To test this hypothesis, several classification models were assessed via cross-validation. The results of this study suggested that: texture-related features might be used as discriminators when the target images do not follow a well defined color or shape domain pattern; and that machine vision systems might lead to the successful discrimination of targets when fed with appropriate information.

The co-occurrence matrix, among other existent techniques, was used to calculate image texture. This method measures occurrence of grey levels between a specific position $P(i, j)$ in the image and a neighboring pixel, according to a given distance d and direction Measurements that is possible to estimate via the co-occurrence matrix are: energy, inertia entropy, homogeneity, and correlation. Each of these measurements were extracted from the image's RGB and HSV channels, when relative locations between pixels were at 0◦, 45◦, 90◦,135◦, and within 1, 3 and 5 pixel-to-pixel distances. Finally, relative location measurements according to pixel distance were averaged, which resulted in one value for each distance.

Table 1. Summarization of studies

Fruit/Leaf	Pathogen	Method type	Main tool	Reference

Wheat	Powdery mildew Stripe rust	Recognition	IRKT directional feature	Liwen Wangetet al(2014)
Leaf	Visual spots	Identification	K-means,thresholding	Shitala Prasad et al(2014)
Tomato	Powdery mildew Blight	Recognition	Perceptual hash algorithm	Xin Liu et al(2013)
Citrus	Quarantine	Recognition	Thresholding	Georgina et al(2013)
Rice	Blast,Brown,Blight	Classification	Fermi-region	Santanu Phadikar et al(2013)
Citrus	Decay	Detection	ROC Curve,NN	Nuria Aleixos (2013)
Chilli pepper	Bactirial	Segmentation	Perceptual spaces	González-Pérez et al(2013)
Rumex	-	Segmentation	Gaussian MRF	Santosh Hiremath et al(2013)
Cotton, Maize	worms,bugs looper	Classification	SVM	Anyela Camargo et al(2012)
Grape,wheat	Powdery mildew Downy mildew	Recognition	BP, Radial base Regression,PNN	Haiguang Wang et al(2012)
Chilli Stunted growth	Abnormal and	Detection Histogram	color cluster,	Zulkifli Bin Husin et al(2012)
Grape,Wheat	Powdery mildew	Recognition	BPNN,PCA	Guanlin Li et all (2012)
Corn leaf	Blight,Spots	Recognition	Morpology Histogram Threshold	Juan-hua Zhu et all(2012)
Strawberry	Powdery mildew Shrink,uneven ripe	Identification	OTSU,Mean shift BPNN,SVM	Changqi Ouyang et all(2013)
Tomato Stemphyllium	White spot powder Peppery spot	Identification	Wavelets,PCA	D.N.D.Harini et al(2011)
Date	-	Classification	SVM	Yousef Al Ohali (2011)
Cucumber Grape,Corn	Downy mildew Anthracnose Leaf spot	Classification	IBLE algorithm	Jin HaiYue et al (2010)
Soyabean	Brown spot	Recognition	Genetic algorithm NN	Ma Xiao-dan et al(2010)
Hazulnut	Peeling	detection	KNN, RMSE	Federico Pallottino (2010)
Cotton	Green sink bug Bacterial angular Ascochyta blight	Identification	SVM, Co-occurrence metric	A. Camargo et al (2009)
Wheat Leaf blight	Pwdery mildew Rust Puccina	Recognition	SVM	Yuan Tian et al (2009)

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Conclusion

The advancement in the digital camera and smart phones has created the alternate challenges in image processing to handle images acquired from such devices. The process of detection and diagnose of disease from such a image has been a active research area useful in development of several applications to help formers to know about diseases affecting their yield and prevent with expert suggestions. Hence this paper tries to present comprehensive survey on several image processing methods. The papers were selected as to consider the largest number of different problems as possible Despite of several techniques available for disease diagnose of plant/crop, more scope exists to develop computationally inexpensive, robust and high detection and recognition rate techniques.

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