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A REVIEW FOR AGRICULTURAL PLANT DISEASES DETECTION USING DIFFERENT TECHNIQUES

Mr.N.P.Kumbhar[1], Dr.Mrs S.B.Patil[2]

[1]*Assisitant Professor . Department of Electronics Engg. PVPIT Budhgaon,Maharashtra,India*

[2]*Associate Professor, Department of Electronics Engg. JJMCOE,Jaysingpur, Maharashtra,India*

ABSTRACT

This paper presents the different advanced techniques to detect and classify plant leaf.The crop disease causes losses in Production and economics in agricultural field. Generally through the naked eyes the observations taken by the Experts ancient time for the detection and identification of crop diseases. But for this the continuous monitoring is required by the Experts and It is too expensive in large fields. So many under developed countries in agricultural area, farmer needs to take lots of efforts. Simultaneously it will be so expensive and time consuming also for both experts and farmers. Early information of plant health and disease detection can control of diseases through proper management such as vector control such as pesticide applications.

The present review describes the technologies used in monitoring health and diseases in plants under field conditions.These technologies include spectroscopic and imaging based, and volatile profiling-based plant disease detection methods. The paper compares the benefits and limitations of these methods.

Keywords: imaging, profiling. spectroscopic, volatile.

I.INTRODUCTION

The crop disease causes losses in Production and economics in agricultural field It is estimated that the crop losses due to plant pathogens in United Stated result in about 33 billion dollars every year. Of this, about 65% (21 billion dollars) could be attributed to non-native plant pathogens (Pimentel et al., 2005). Some of the diseases caused by introduced pathogenic species are chestnut blight fungus, Dutch elm disease, and huanglong bing citrus disease (Pimentel et al., 2005[1]; Li et al., 2006[2]). The bacterial, fungal, and viral infections, along with infestations by insects result in plant diseases and damage. There are about 50,000 parasitic and non-parasitic plant diseases of plants in United States (Pimentel et al., 2005). Upon infection, a plant develops symptoms that appear on different parts of the plants causing a significant agronomic impact (Lopez et al.,2003[3]).many

such microbial diseases with time spread over a larger area in groves and plantations through accidental introduction of vectors or through infected plant materials.This paper describes an approach taken to detect plant diseses.The approach involves the application of diseases. The approach involves the application of spectroscopic and imaging techniques for disease detection, This approach was selected for a fast, reliable, and real-time plant disease monitoring for disease control and management. The early detection of plant diseases

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could be a valuable source of information for executing proper pest management strategies and disease control measures to prevent the development and the spread of diseases.

II. SPECTROSCOPIC AND IMAGING TECHNIQUES FOR DISEASE DETECTION

Recent developments in agricultural technology demands for an automated non-destructive methods of plant disease detection. The plant disease detection tool should be rapid, specific to a particular disease, and sensitive for detection at the early onset of the symptoms (López et al., 2003). The spectroscopic and imaging techniques are used to detect diseases and stress due to various factors, in plants and trees. Some the methods of spectroscopic and imaging techniques are:fluorescence imaging (Bravo et al., 2004[4]; Moshou et al.,2005[5]; chaerle et al.,2007[6]), multispectral or hyper spectral imaging (Moshou et al., 2004[7]; Shafri and Hamdan,2009[8];Qin et al.,2009[9]), infrared spectroscopy (Spinelli et al. 2006[10]Purecel et al. 2009[11]), fluorescence

Spectroscopy (Marcassa et al.,2006[12]; Belasque et al.,2008 [13]; Lins et al.,2009[14]) Visible/multiband spectroscop (Yang et al., 2007[15]; Delalieux et al., 2007[16]; Chen et al., 2008.[17]) Spectroscopic technology has been successfully applied for plant stress detection such as water-stress detection and nutrient-stress detection. Tables 1 and 2 summarize the different plant disease detection techniques using spectroscopic and imaging.

2.1.Fluorescence spectroscopy

Fluorescence spectroscopy is a spectroscopic method, after excitation of a beam of light the fluorescence from the object is measured. Belasque et al.(2008)[18] described fluorescence spect- roscopy to detect stress caused by citrus canker (bacterial disease caused by Xanthomonas citri–X. axonopodis pv. citri) and mechanical injury. Here a portable fluorescence spectroscopy system was taken to the greenhouse and the measurement probe was placed 2mmabove the leaf (attached to greenhouse plants) for collecting data from different samples during the period of study (60 days). The spectral data were further processed and analyzed in the laboratory. A 532nm 10mW excitation laser was used for excitation and ratios between fluorescence at different wavelengths were employed to monitor the stress caused by bacterial infection. The samples of leaves collected from the field (detached leaves) as well as leaves from greenhouse plants (attached leaves) were analyzed using the system. The three ratios used were: (i) ratio between fluorescence intensity at 452 and 685 nm, (ii) ratio between fluorescence intensity at 452nm and 735 nm, and (iii) ratio between fluorescence intensity at 685nm and 735 nm. Fluorescence of citrus leaves was monitored for 60 days under four different conditions: leaves with no stress, leaves with mechanical stress, leaves with disease.The studies reported the potential of fluorescence spectroscopy for disease detection and discrimination between the mechanical and diseased stress. A similar approach was taken to detect water stress and differentiate citrus canker leaves from variegated chlorosis leaves (Marcassa et al., 2006[12]). The above studies could classify healthy from citrus canker-affected leaves, but were unable to identify water stress and distinguish between variegated chlorosis and citrus canker-infected leaves. The authors did not yet present any statistical analysis to evaluate the ability of the technique to discriminate or classify different plant conditions.

Methods such as principal component analysis (PCA), discriminant analysis, and neural network-based classification algorithms can be applied to analyze the results obtained from fluorescence spectroscopy. Also parallel factor analysis, cluster analysis, partial least square (PLS) regression, and Fischer's linear discriminant analysis (LDA) can be applied for classifying fluorescent spectrometric data having two or more classes (Guimet, 2005[19]).

2.2. Visible and infrared spectroscopy

The detection of plant diseases for cost-effective, a rapid and non-destructive method is nothing but visible and infrared spectroscopy.This technology used for varied applications(Ramon et al.,2002[20]:Delwiche and Graybosch 2002 [21]; Pontius et al., 2005[22]; Gomez et al., 2006[23]; Zhang et al., 2008[24]; Guo et al., 2009[25]; Sundaram et al., 2009[26]). The visible and infrared regions of the electromagnetic spectra provide the maximum information on the physiological stress levels in the plants (Muhammed, 2002, [27]; Xu et al.,2007[28]) so some of these wavebands specific to a disease can be used to detect plant diseases (West et al., 2003[29]), even before the symptoms are visible. Most of the times, combination of visible spectroscopy and infrared spectroscopy is used for disease detection in plants (Malthus and Madeira, 1993[30]; Bravo et al.,2003[29];Huang et al.,2004[31];Larsolle and Muhammed, 2007[32]).

Naidu et al. (2009) [33] identified viral infection by using leaf spectral reflectance under field conditions in grapevines (Vitis vinifera L.) that cause grapevine leaf roll disease. A portable spectrometer was used to collect reflectance data from each leaf of the plant using a plant-probe attachment device having a leaf clip. In addition to the green, near infrared, and mid infrared region of the spectra, vegetative indices were used to assess the applicability of spectral reflectance in identifying the disease. Discriminate analysis was performed to classify the infected leaves with and without symptoms with that of non-infected leaves. The different categories of leaves could be clearly differentiated with improved accuracies when both the vegetative indices and individual reflectance bands were used. A maximum of 75% accuracy was achieved in the study. Huang and Apan (2006)[34] detected Sclerotinia rot disease in celery, hyperspectral data collected using portable spectrometer under field conditions. PLS regression analysis was performed to analyze the spectral reflectance data. The first and second derivatives were estimated to test their effectiveness in reducing the root mean square error during the validation of the developed model. The raw data-based model produced lower root mean square errors than the first and second derivatives. The authors also stated that the reflectance in the visible and infrared range from 400 to 1300nm were sufficient in acquiring similar results as that of entire spectra (400–2500 nm).

Simone Graeff et al. (2006) [35] identified powdery mildew in wheat. Leaf reflectance was measured with a digital imager (Leica S1 Pro, Leica, Germany) under controlled light conditions in various wavelength ranges covering the visible and the near-infrared spectra (380 -1300 nm). Leaf scans were evaluated by means of L*a*b*-color system. The reflectance image at 490_{780} nm (r2 = 0.69), 510_{780}nm (r2 = 0.74), 516_{1300}nm (r2 = 0.62) and 540_{1300} nm (r2 = 0.60) were acquired leaf spectra for evaluation. Among the evaluated spectra the range of 490_{780}nm showed most sensitive response to damage caused by powdery mildew and take-all infestation.

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2.3. Fluorescence imaging

Fluorescence imaging is an advancement of fluorescence spectroscopy, where fluorescence images (rather than single spectra) are obtained using a camera. A xenon or halogen lamp is used as a UV light source for fluorescence excitation, and the fluorescence at specific wavelengths are recorded using the charge coupled device (CCD)-based camera system (Bravo et al., 2004[36]; Lenk and Buschmann, 2006[37]; Chaerle and Lenk et al., 2007[38]).

Bravo et al. (2004)[36] detected yellow rust in winter wheat,for this fluorescence used. They acquired two fluorescence images: a background image without the xenon lamp source and a fluorescence image with the xenon lamp source during the experiments. The fluorescence measured at certain frequency such as 450, 550, 690, and 740 nm. The authors stated that the difference between the fluorescence at 550 and 690nmwere higher in the diseased portion of the leaves, while it was very low for healthy regions of the leaves. Quadratic discriminant analysis (QDA) used for analysis. QDA classified healthy and diseased plants with an accuracy of 71% and 96%, respectively.

Moshou et al.(2005)[39] stated combination of hyperspectral reflectance and multispectral fluorescence imaging through sensor fusion for the detection of yellow rust disease of winter wheat. The hyperspectral images were taken under ambient condition in winter wheat plots and fluorescence imaging under UV excitation. The classification accuracy due to QDA ,improved from 71–90% to 97%.when the self-organizing map (SOM)-based neural network used for classification of the diseased plants and healthy plants, The classification accuracy increased to 98.7% and 99.4% respectively.

2.4. Hyperspectral imaging

The imaging techniques are an improvement over Spectroscopic techniques as these methods acquire spectral information over a larger area and provide three-dimensional spectral information in the form of images.

In recent years, hyperspectral imaging is gaining considerable interest for its application in precision agriculture (Okamoto et al.,2009)[40]. In the hyperspectral imaging, the spectral reflectance of each pixel is acquired for a range of wavelengths in the electromagnetic spectra. The wavelengths may include the visible and infrared regions of the electromagnetic spectra. The hyperspectral imaging is similar to multispectral imaging, the difference being a broader range of wavelengths (more number of spectral bands) being scanned for each pixel in the hyperspectral imaging. The resulting information is a set of pixel values (intensity of the reflectance) at each wavelength of the spectra in the form of an image. (Sindhuja Sankaran et al.,2010)[41].

Dimitrios Moshou et al. (2004) [42]used to detect yellow rust in wheat using spectral reflectance between healthy and diseased wheat plants In-field spectral images were taken with a spectrograph mounted at spray boom level. For detection purpose Self-Organizing Maps and for classification neural networks, so classification performance increased from 95% to more than 99% using a total of 5137. The reflectance image at 463 and 895 nm were acquired leaf spectra for evaluation Experiments were performed at Rothamsted Research, UK. Winter wheat was sown on October 6th, 2000 with row spacing 12.5 cm and at a rate of 350 seeds/m2. Cultivar ‘Madrigal’was chosen, as itwas highly susceptible to the race of yellow rust to be inoculated, but moderatelyresistant to most other diseases.Six plots,each 9m×10m (surrounded by 3m guard rows), inoculated with yellow rust but not treated with any fungicide, were used to study disease development and detection, while similar uninoculated plots provided healthy crop canopies for comparison

A-K. Mahlein et al. (2006)[43] detected the three leaf diseases Cercospora leaf spot, sugar beet rust and powdery mildew of Sugar beet plants. Hyperspectral reflectance of healthy and diseased sugar beet leaves were assessed with a non-imaging spectroradiometer . The normalized differences from 450 to 950 nm, describing the impact of a disease on sugar beet leaves were extracted from the data-set using the RELIEF-F algorithm. To develop hyperspectral indices for the detection of sugar beet diseases the best weighted combination of a single wavelength and a normalized wavelength difference was exhaustively searched testing all possible combinations. The optimized disease indices were tested for their ability to detect and to classify healthy and diseased sugar beet leaves. The classification accuracy of healthy sugar beet leaves and leaves, infected with Cercospora leaf spot, sugar beet rust and powdery mildew was89%, 92%, 87%, 85%, respectively

Hamed Hamid Muhammed.(2005)[44] applied nearest neighbor classifier to classify the new data against the reference data. This paper recognized Fungal Disease Severity in Wheat. The objective of this work was to use remotely sensed hyperspectral reflectance data to discriminate between healthy and diseased plants in a spring wheat crop suffering from fungal infestation, and to determine plant-cover damage levels in the diseased plants. The proposed method was applied to hyperspectral crop reflectance data, of 164 spectral bands in the spectral region 360–900 nm.

T.Rumpfa et al.,(2010) identified sugar beet diseases. This was estimated by Support Vector Machines and spectral vegetation indices. Hyperspectral data were recorded from healthy leaves and leaves inoculated with the pathogens Cercospora beticola, Uromyces betae or Erysiphe betae causing Cercospora leaf spot, sugar beet rust and powdery mildew, respectively for a period of 21 days after inoculation. Nine spectral vegetation indices, related to physiological parameters were used as features for an automatic classification. Early differentiation between healthy and inoculated plants as well as among specific diseases can be achieved by a Support Vector Machine with a radial basis function as kernel.The classification accuracy was up to 97%. Remote Distinction of A Noxious Weed (Musk Thistle: *Carduus Nutans)* Using Airborne Hyperspectral Imagery and the Support Vector Machine Classifier (Mustafa Mirik et al.(2013)[46]) designed to explore the ability of hyperspectral imagery for mapping infestation of musk thistle (*Carduus nutans*) on a native grassland during the preflowering stage in mid-April and during the peak flowering stage in mid-June using the support vector machine classifier. Spectral reflectance for plant species in the visible and NIR regions were tested for statistical significance using paired *t*-tests assuming unequal variance at $\alpha = 0.05$ The classification accuracy were 79% and 91%.respectively.

New Optimized Spectral Indices for Identifying and Monitoring Winter Wheat Diseases(Wenjiang Huang et al.2014)[47] developed new spectral indices (NSIs) for identifying different diseases on crops. Three different pests (powdery mildew, yellow rust, and aphids) in winter wheat were used in this study. The new optimized spectral indices were derived from a weighted combination of a single band and a normalized wavelength difference of two bands. The most and least relevant wavelengths for different diseases were first extracted from leaf spectral data using the RELIEF-F algorithm. Reflectance of a single band extracted from the most relevant wavelengths and the normalized wavelength difference from all possible combinations of the most and least relevant wavelengths were used to form the optimized spectral indices. The classification accuracies of these new indices for healthy leaves and leaves infected with powdery mildew, yellow rust, and aphids were 86.5%, 85.2%, 91.6%, and 93.5%, respectively. Wenjiang Huang et al.(2007)[48] evaluated accuracy of the spectro-optical, photochemical reflectance index (PRI) for quantifying the disease index (DI) of yellow rust (Biotroph Puccinia striiformis) in wheat (Triticum aestivum L.), and its applicability in the detection of the disease using hyperspectral imagery. The experiment was conducted at Beijing Xiaotangshan Precision Agriculture Experimental Base, in Changping district,Beiing(40_10.60 N,116_26:30 E) for the 2001-2002 and 2002-2003 growing seasons.Experimental data from 2001 to 2002 were used to establish the statistical models, and the data for 2002–2003 were used to validate the models developed. The field site had a warm temperate climate, with a mean annual rainfall of 507.7 mm and a mean annual temperate of 13_C. In this region a significant proportion of growing days are cloudless during April to June. The soil at the sites is a silt-clay loam. The average topsoil nutrient status (0–0.30 m depth) was as follows: organic matter 1.42–1.48%, total nitrogen 0.08–0.10%, alkali-hydrolysis nitrogen 58.6–68.0 mg kg–1, available phosphorus 20.1–55.4 mg kg–1, and rapidly available potassium 117.6–129.1 mg kg–1.

R. Devadas et al.(2009)[49] evaluated ten spectral vegetation indices for identifying rust infection in individual wheat leaves. Wheat (Triticum aestivum L.) plants were grown in controlled conditions in the Cereal Rust Laboratory at the University of Sydney, Cobbitty, New South Wales, Australia. All seedlings were inoculated at the 2–3 leaf stage (Zadok growth stage Z12–14) (Zadoks et al. 1974)[50] by suspending urediospores of the three rust species separately in Shellsol TK oil and spraying onto selected seedlings using an ultra low volume spray unit. A single, second-emerged leaf was targeted for laboratory leaf spectral analysis from individual plants at the early tillering stage of development (Zadok growth stage Z21–23). Infected leaves had 50–90% of the leaf area covered in rust pustules whilst the healthy leaves (not sprayed) had no observable pustules. Individual leaf spectral reflectance data were collected using the spectrometer. Thirty leaf samples each were collected, one from each plant, from healthy plants and those infected with each of the rust species. Vegetation indices (VIs) were calculated for each recorded spectrum. ANOVA was used to test healthy and diseased samples. Levene's test was used to confirm homogeneity of error variances, the LSD was used to compare means.

Table 1 Examples of studies on plant disease detection using spectroscopic techniques.

Plant	**Disease/ Damage**	**Statistical Methods**	**Optimum spectral range**	**Reference**
Citrus	Citrus canker	--	452, 685 and 735nm	Belasque et al. (2008)
Rice	Infested with brown planthopper	-	737–925nm	Yang and Cheng (2001)
Wheat	Powdery mildew and	Analysis of variance,	490nm to780nm, 510nm	Graeff et al. (2006)

	take-all disease	correlation and regression analysis	to780nm , 516nm to1300nm and 540nm to1300 nm	
Rice	Brown planthopper and leaffolder infestation	Linear regression models	426nm	Yang et al. (2007)
Kiwifruit	Gray mold, Sclerotinia rot	Principal component analysis	-	Costa et al. (2007)
Wheat	Yellow rust	Regression	-	Huang et al. (2007)
Tomato	Leaf miner damage		800 to 1100 nm, 1450 and 1900nm	Xu et al. (2007)
Grapevine	Grapevine leafroll disease	Discriminant analysis	752, 684 and 970nm	Naidu et al. (2009)

Table 2 Examples of studies on plant disease detection using imaging techniques.

Plant	**Disease/ Damage**	**Statistical Methods**	**Optimum spectral range**	**Reference**
Wheat	Scab (Fusarium head blight)	Step discrimination and discriminant analysis	568, 715nm (550, 605, 623, 660, 697 and 733 nm)	Delwiche and Kim (2000)
Tomato	Late blight disease	Minimum noise fraction transformation and spectral angle mapping-based classification	700–750 nm, 750–930 nm, 950–1,030 nm, and 1,040–1,130nm	Zhang et al. (2003, 2005)
Wheat	Yellow rust, nutrient deficiency	Self-organizing map neural network, quadratic discriminant analysis	680, 725 and 750nm	Moshou et al. (2005, 2006)

Wheat	Yellow rust	Regression analysis	-	Huang et al. (2007)
Grapefruit (fruit)	Citrus canker	Principal component analysis	553, 677, 718 and 858nm	Qin et al. (2008)

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