Identification of Wheat Leaf Rust using Hyperspectral Data at Canopy Level: A Review

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Abstract— **Plant disease detection and identification has become a challenging task in agriculture field. Identification of the disease is inappropriate there is enormous loss in the production of the crop. The symptoms can be observed on the various parts of the plant. The leaf shows variation in the color if the disease is being detected. Detection of the plant disease can be done manually which is time consuming. Automatic identification and detection is essential for reducing the time constraint for detection of the plant disease. Several challenges exist in the identifying plant disease like multiple simultaneous disorders, image background, etc. This paper reviews the various techniques currently used and their challenges.**

Keywords— **Vegetation Indices, Plant Disease Detection, Plant Disease Identification, Hyperspectral Technique, Image Processing**

I. Introduction

The reliable plant disease stress detection and identification are recent challenges in agriculture [1]. The current crop monitoring techniques are time consuming. At the initial stage the diseases affect the small region, due to the time constraint disease can spread in larger area and crop get damaged or infected, thus changing the crop management strategies is the crucial step [2]. The disease like yellow rust in wheat is visible to the human eye but the diseases like the apple scab are invisible. Owing to such problems in the field of agriculture it is essential for atomization, sensitive approach and replacing the manual process. There are various multispectral techniques, hyperspectral techniques, image processing, 3D sensors techniques available. Image processing and hyperspectral techniques are mostly preferred by the researchers [3].

In image processing several computational techniques are available which are able to extract the information with the digital cameras. The images can be captured with smartphones, digital cameras etc.

The hyperspectral camera is the advance technology which is able to capture more information than the traditional cameras. The cameras has a wide spectrum range that is beyond the human vision, thus hyperspectral camera can identify the diseases more effectively than the traditional cameras.

In this review focus is on the image processing and hyperspectral imagining, starting from the image processing with the background theory and overview of the techniques used in image processing for disease detection. Further we provide a survey of the hyperspectral techniques.

II. Techniques Used for plant disease detection

A. Color Digital Imaging

Digital images are significant tools in plant pathology to estimate plant health. For retrieving information of disease detection and identification, digital cameras a source of RGB (red, green, and blue) digital images. The technical constraints unsophisticated, handheld devices such as the light sensitivity, optical and digital focus and spatial resolution have improved significantly every year.

The color in electromagnetic spectrum is visible to human eye at a very small wavelength range from 400nm to 700nm. For detection of vegetation, the wavelength useful for the analysis purpose is visible range combined with the near infrared range. Leaf pigments changes can be captured in this range (400-700nm) whereas; to capture the changes in water content 1300-2500 nm wavelengths can be used [4].

Usama Mokhtar et.al. used image processing technique for diseases detection in tomato leaves. In image acquisition, early blight and powdery mildew tomato diseases infected leaves were collected .In pre-processing phase image enhancement, remove noise, smoothness, image resizing, image isolation, and background removing techniques were applied. Tomato diseases were identified and classified using Gabor wavelet transformation and Support vector machine (SVM) algorithms. In feature extraction phase, using Gabor wavelet transform feature vectors were acquired for classification. Support vector machine (SVM) used in the classification phase for training and identifying the type of tomato diseases. The inputs of SVM are feature vectors, whereas the output is to detect tomato's leaf disease. SVM is implemented using Invmult Kernel, Cauchy Kernel and Laplacian Kernel functions. Performance evaluation is done by Grid search and N-fold cross-validation techniques [5].

Sabah Bashir et.al image processing technique was used for detecting the Malus Domestica leaves disease. Using histogram equalization Intensity values for grayscale images were acquired. In image segmentation, for texture analysis Co-occurrence matrix method algorithm is used and for color analysis K-means clustering algorithm is used. Texture analysis is characterization of regions in an image by texture content. In threshold technique individual pixels value is compared with threshold value, if value of the threshold is greater, it is marked as object pixel. Plant diseases detection is done using texture and color analysis images which is compared with the previous images for disease detection [6].

III. HYPERSPECTRAL REMOTE SENSING TECHNOLOGY

The sensors started with multispectral sensors, and then were unfolded in hyperspectral sensors. The development of hyperspectral sensors enhanced the complexity of measuring the data by a spectral range of up to 350 to 2,500 nm with possible narrow spectral resolution below 1 nm [7]. Hyperspectral imaging systems in disease analysis still has a great scope for research [8]. The optical properties of leaves can be categorized by (i) transmission of light through leaf, (ii) absorption of light by chemicals in leaf (e.g., pigments, water, and amino acids), and (iii) spectral reflectance of light from internal structures of leaf.

Reflectance sensors are categorized depending on their spatial scale, spectral resolution, and the type of detector, i.e. imaging like Pika-L or non-imaging like ASDFieldSpec 4 sensor systems.

There are two types of approaches in hyperspectral technology for plant disease detection 1) Laboratory-Based Imaging Approach 2) Field Based Approach. Laboratory –Based approach is a setup in the closed lab using the artificial light. Conversely the Field-Based approach [9] is done under the natural sun light, the atmospheric effects and the scattering of light has to be taken under consideration. The environmental factor can change the spectral signature. Spectral signature is the discrepancy of emittance of a material concerning to wavelengths. Light intensity is the challenging task as the spectral signature may change even distance of the source light changes [10].

IV. EXISTING VEGETATION AND DISEASE INDICES

Vegetation Indices (VIs) are used for extracting features from the spectral reflectance. Two or more wavelengths are combined that are related to characteristics of plants. However, most VIs implemented for remote sensing, which are not different for different diseases [11].

Vegetation indices are mainly obtained by the electromagnetic wave reflectance from canopies. The spectral reflectance from plants changes with crop type, water content, chlorophyll content etc [12]. Remote sensing of vegetation are based on the spectra: (i) the ultraviolet region (10-380 nm); (ii) the visible spectra, which has blue (450–495 nm), green (495−570 nm), and red (620–750 nm) wavelength; (iii) the near and mid infrared band (850–1700 nm) [11, 12]. Using the hyperspectral sensor, the number of bands obtained increases, and the bandwidth becomes narrower [13].

Most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI) which is normalized ratio between the red and near infrared bands [14]. Yellow rust was detected by NDVI [15]. NDVI is used for many purposes, for example, to identify stress due to the Sun pest/cereal pest, Eurygaster integriceps Put. (Hemiptera: Scutelleridae), in wheat [16]. T.Rumpfaet al.,(2010) recognized sugar beet diseases. Support Vector Machines and spectral vegetation indices were used for disease detection [17].

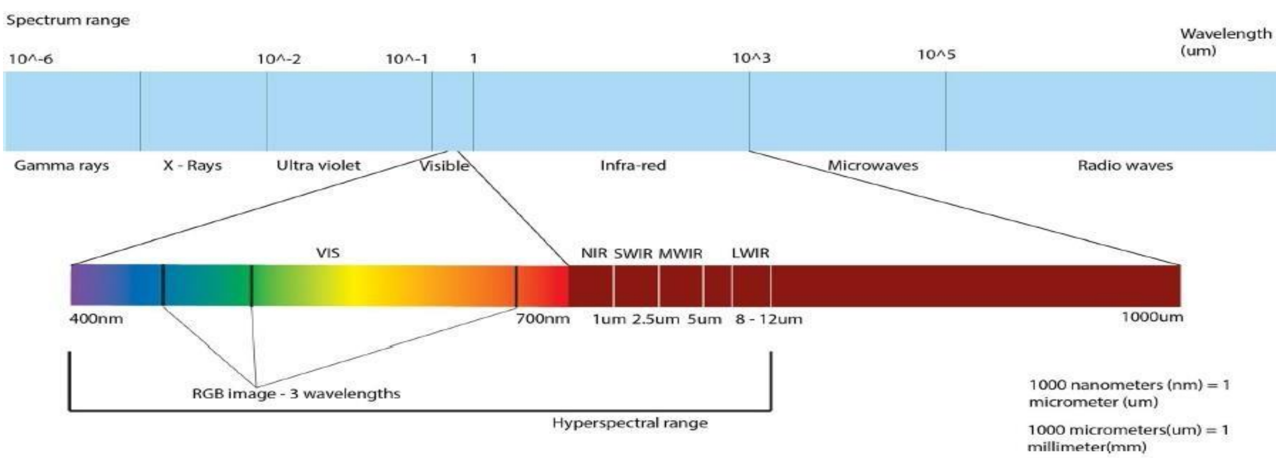

Fig 1: Electromagnetic spectrum with the lower bar displaying visible and infra-red light [18]

TABLE I
VEGETATION INDICES

VI	Formula	Information
Normalized difference vegetation index (NDVI) [19]	$(R_{NIR} - R_{RED})/(R_{NIR} + R_{RED})$ $R_{RED}\sim 680,\ R_{NIR}\sim 800$	Range: − 1 to 1 Common range: 0.2–0.8 Broadband

Red edge NDVI [19]	$(R_{750}\text{-}R_{705})/\ (R_{750}\text{-}R_{705})$	Range: − 1 to 1 healthy range: 0.2 to 0.9 Narrowband (hyperspectral data)
Simple ratio index (SRI) [20]	(R_{NIR}/R_{RED}) R_{RED}~680, R_{INR}~800	Range: 0 to > 30 Typical healthy range: ~ 2–8 Broadband
Photochemical reflectance index (PRI) [21]	$(R_{531}\text{-}R_{570})/\ (R_{531}+ R_{570})$	Range: − 1 to 1 healthy range: − 0.2 to 0.2 Vegetation health prior to senescence
Plant senescence reflectance index (PSRI) [22]	(Red–Green)/NIR	Range: − 1 to 1 healthy range: − 0.1 to 0.2 >PSRI ~ canopy stress, onset of senescence, fruit ripening
Normalized phaeophytinization index (NPQI) [23]	$(R_{415}\text{-}R_{435})/\ (R_{415}+ R_{435})$	Chlorophyll degradation 0.56–1.41
Structure Independent Pigment Index (SIPI)[24]	$(R_{800}\text{-}R_{445})/\ (R_{800}+ R_{680})$	Range: 0–2 healthy range: 0.8–1.8 Good with canopy variety
Leaf rust disease severity index (LRDSI)	$6.9 \times (R_{605}\text{-}R_{455}) - 1.2$	Achieved accuracy of 89%

V. CHALLANGES IN PLANT DISEASE DETECTION AND IDENTIFICATION

A. *Multiple Simultaneous Disorders*

Many algorithms deduce that only one disease is existing in each image. However, other diseases, as well as other kinds of disorders such as nutritional deficiencies and pests, may be observed simultaneously.

Fig 2: Coffee leaf with rust and Cercospora leaf spot

Fig 3**:** Wheat leaf with yellow rust and mildew

B. *Image Background*

First step in image processing for leaf analysis is leaf segmentation. If some blue or white color panel is placed in the background, the task can be performed without in any problem. In case different plant leafs, soil are present in the background that can create a challenge in the leaf segmentation. Zhang and Meng (2011) used a two-step hierarchical matching for separating the lesions from leaf and its background [25]. Alenya et al. used depth information for concentrating on the leaves and extracting it from the remaining image [26].

Fig 4**:** Example of busy background

Other researchers addressed the problem under controlled situations, in which images of plants in pots were captured in the laboratory. In this case, usually we remove the pot and compost from the image. The elucidations used in this instance range from traditional vegetation indices to probabilistic contexts [27].

C. Image Capture Conditions

Several aspects may affect the physical appearance of the images, making it more inconvenient for an automatic algorithm to accomplish an analysis. Preferably, images should be captured under the same conditions. In practice, this can only be done in a controlled environment, such as a laboratory. Illumination are very important in the field, where aspects such as time of day, sun position according to the leaf, overcast conditions, may affect image features. Illumination matters with specular lighting; it is a reflection with high intensity that arises at certain angles of view. This can be minimized by varying the angle of capture and varying the leaf position. Another issue that impacts the image is the angle in which image is to be captured. Ideally, the leaf must be perpendicular to the sensor during the image capture, because some parts of the leaf are not captured properly if the angle is slanted.

Fig 5: Leaf image with specular reflections and several light/shadow transitions.

VI. CLASSIFICATION TECHNIQUES

Al Bashish, D et al. developed Neural Network classifier based on statistical classification gives better results in all types of leaf diseases and can detect and classify the diseases with accuracy around 93% [28]. Neha Sharma et al. development an automatic detection system for plant diseases consider the features like texture, shapes etc. and classification was done using ANN with accuracy 90% [29]. Sladojevic detected 13 diseases using CNN on different crop plants, including Apple (powdery mildew, rust), pear (leaf spot), grapevine (powdery mildew, downey mildew) used dataset of 30,000 images with and achieved accuracy of 96.3% using CaffeNet [30].

Savita N. Ghaiwat, Parul Arora used techniques such as K-NN Classifier, Probabilistic NN, GA, SVM and PCA, ANN, Fuzzy logic for the classification of plant leaf disease. K-NN method resulted highest accuracy [31]. Jagadeesh D. Pujari, Rajesh Yakkundimath et al. studied that SVM technique has resulted the better accuracy (92.17%), accuracy was better than ANN classifier accuracy (87.48%) [32].

TABLE I
CLASSIFICATION TECHNIQUES

Technique	Plant disease	Accuracy
Partial least square regression (PLSR) [33]	Wheat (yellow rust)	92%
Fishers linear determinant analysis [34]	Wheat (aphid) Wheat (powdery mildew) Wheat (powdery mildew)	60% 90%
Fishers linear determinant analysis (FLDA) [35]	Wheat (yellow rust) Wheat (powdery mildew)	93%
Artificial neural network (ANN) [36]	Sugarbeet (cerospora leaf spot) Sugarbeet (powdery mildew) Sugarbeet (leaf rust)	96% 91% 95%
Support vector machine (SVM)	Sugarbeet (cerospora leaf spot) Sugarbeet (powdery mildew) Sugarbeet (leaf rust)	97% 93% 93%

VI. CONCLUSIONS

This review paper deals with several techniques for plant disease identification and detection. The color digital imaging, hyperspectral imagining techniques and the calculation of the vegetation indices used for the identification and detection of the plant diseases. Spectral signature is used for the discrimination of the plant diseases; it can be used for the further study of the severity of the diseases. Still there are several challenges regarding the accuracy of the disease identification.

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