Spectral Discrimination of Healthy and Diseased Plants Using Non Imaging Hyper spectral Data-A Review

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Spectral Discrimination of Healthy and Diseased Plants Using Non Imaging Hyper spectral Data – A Review

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Abstract— **Discrimination of healthy and diseased plants and disease detection proves to be essential in the food agriculture. In this study Hyperspectral remote sensing was sued to detect disease on crops and also discriminate amongst disease and healthy leaves. ASD FieldSpectroradiometer was used which has range of 350-2500nm using VNIR, SWIR1, SWIR2, region of wavelengths. These regions were studied using wavelength values. Spectral Vegetation Indices were applied and using various techniques for classification such as PLSR and SMLR, SVM, Regression. The result indicated the health of crop either as healthy or diseased .**

Keywords— Crop Diseasess , Hyperpsectral Remote Sensing, ASD Fieldspectroradiometer.

I. INTRODUCTION

The responsibility of protecting food crops from the diseases and pests is rising due to changing weather and environmental challenges. Remote sensing is the technology that is widely used and preferred by researchers and scientists for the identification of biotic and abiotic stresses through biophysical and biochemical changes such as reduced biomass and chlorosis. These factors can be easily detected through VNIR region [1]. Hyperspectral sesnsors capture light within range of 350 nm-2500nm.This range consists of visible NIR, SWIR bands. Sensors collect the data in the form of tens to hundereds of narrow spectral bands. After infection, some plants develop symptoms that are visible on different parts of plant. Large area in plantations through accidental introductionof vectors affect with the microbial diseases. [2]. A quantitative relationship between weather and diseases infection from fields studies were not always successful. Disease severity and weather could not be related. Any specific sequence of weather and the infestation of plants [3].Pigments such as chlorophyll and carotenoids causes absorption in the visible parts of the spectrum. In the variation of reflectance, NIR and the middle-IR absorption by water is important. [4]

II. LITERATURE REVIEW

Sindhuja Sankaran, Reza Ehsani and their other researchers evaluated the capability of using features extracted from 350nm- 2500nm spectrortadiometer reflectance data for detecting citrus greening in leaves. Applicability of using features extracted form 350nm-2500nm spectrortadiometer reflectance data for greening in leaves. Disease detection processes were enhanced using spectral features by enhancing the portability of the sensors. Using spectral features with some discriminatory power while differentiating healthy and diseased leaf. [5].

Pooja Vinod Janse, Ratnadeep R. Deshmukh, Studied that SDA technique is useful for identification of optimum band. The suitable four bands for pulse discrimination were identified in NIR and early MIR region. The bands were useful 750,800,940, 960 nm. The useful bands that played critical role were 420, 470, 480, 570, 730, 740, 940, 950, 970, 1030 nm.[6]

Minghua Zhang, Zhihao Qin, Xue Liu, Susan L. Ustin concluded that the diseased plants and healthy plants revealed the average reflectance which was very low and was in the range of 0.4 – 0.4 mu. In the range of 0.7 – 1.35 mu, the average reflectance spectra was apperantly lower than that of the field spectra. The separation capability was generally lower in the range lab spectra than in the field spectra and the comparisons were made among 0.4- 0.5 mu, 0.6- 0.69, 0.75- 0.93, 1.04- 11.30, 1.45 – 1.85. The general difference of spectral reflectance between healthy and diseased plants was attenuated by atmosphere and environmental factor. NIR region consists of narrow peak region such as 0.75- 0.9 and 0.95- 1 mu[7].

M.K. Maid, R.R. Deshmukh studied that improving precision was achieved within the help of spectral data at different scales including leaf, canopy, and landscape level. Different vegetation diseases were detected using various spectral vegetation indices. Spectral data for the detection of plant disease could be utilized within an application.Leaf composition of pigments, structure, water content were influenced were indicated in 400 – 700 nm content.[8]

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Abel Chemura, Onisimo Mutanga & Mbulisi Sibanda & Pardon Chidoko studied that stable model for developing a predictor using vegetation indices was difficult to design. Each individual variable may be unique in their contribution to the outcome, hence a band based model producing high level accuracy could be designed. To obtain high accuracy and to cinfirm the spectral setting were used and suited for vegetation assessment ramoleo used only spectral bands.[9]

Sujan Sarkar, Sanket Biswas, Avinaba Tapadar, Pritam Saha studied that the study and analysis of spectra can be performed processing and analysis such as histogram generation, grey-level correction, feature extraction etc. For early and accurate detection of disease, application of image processing and SVM were used mostly. Crop samples were classified to analyse their texture to extract, to extract the feature. Classification performed on the basis of selected shape and texture of diseased spot. Disease such as leaf blight, seth blight and rice blast were identified using SVM. The accuracy achieved using SVM was 97.2 %.[10]

III. METHODOLOGY

A. Methodology

Data acquisition : Various samples were collected in a set. ASD Fieldspec4 spectroradimeter was used to observe and process these samples. Range of the device specified was 350nm- 2500nm . For the controlling of operations of ASD Spectroradiometer, RS^3 was sued to receive and store the spectral data.

B. Preprocessing

Normal distribution of wavelength variables must be processed with VNIR SWIR spectra and vegetation attributes from statistical analysis of relationship. The distribution of wavelength variables could affect samples preparation process and spectral preprocessing [11]. The software used is ViewSpec pro. The data obtained is non-imaging data. ASCII file was obtained from spectral signature with the help of PLSR [12]. First derivative and second derivative is calculated as per the requirement. Unscramble is used for smoothing operation with Savitzky Golay method. Result Analysis was simplified with the help of statistical tests. To perform variance analysis, these methods use standardized which were with respect to hyperspectral data.

C. Supervised Classification :

1. An input and output mapped and classified with the machine learning approach based on the input output pairs is known as Supervised learning.
2. Training data consisting of set of examples were used in it.
3. The use of supervise classification is to analyse the training data, to produce the inferred function, and further this function used to map new examples.
4. Non imaging hyperpsectral data having parameters like
   - Heterogeneity of data
   - Redundancy of the data
   - Presence of interactions and non linerities
5. Accuracy as per the varience based data could be achieved using several algorithms such as :
   - Support Vector Machine
   - Linear Regression
   - Logistic Regression
   - Naïve Bayes
   - Linear Discrimination Analysis
   - Decision Tree
   - K- Nearest
   - Neural Neywork
   - Multilayer Perceptron [13]

Especially for classification tasks, discriminative modelsusually perform better than generative models[14].

IV. VEGETATION INDICES

Characteristic feature of vegetation spectra was used to standardized Traditional VI like NDVI, GNDVI, SAVI, OSAVI etc. Features included lower magnitude of reflectance in Red region (VIS) of spectrum. Internal scattering causes high reflectance in NIR range of spectrum. All these indices, contents in VIS and NIR ranges and attained significant level of nutrient prediction. Linear correlation analysis of nutrient concentrations was consisting of significant correlation coefficients [15]. By calculating different spectra, ration or derivations modifications in spectral reflections and differences between spectral signature can be distinguished. Comparison of spectra of healthy and diseased plants could be done using this methodology. Using specific wavelength of spectral signatures. Spectral algorithms have been developed in remote sensing of vegetation [16]. Reflectance at 531nm and 570nm considered since it occurred in narrow waveband reflectance. The result of operation of Xanthophyll cycle causes subtle changes in leaf reflectance at 531nm. Photosynthetic radiation use & canopies of both leaves could be correlated to PRI. Across a number of species, functional types & nutrient treatement a consistent relationship between PRI & RUE could be shown.

PRI accounted for 42%, 59%, 62% of the variability of RUE at leaf, canopy, and ecosystem levels respectively, according to the recent review of PRI & RUI [17].An increasing trend with cumulative time for the 3 VI's could be shown by RVI-GPPCum2. Some vegetation indices did not respond to the short-term environmental changes.[18]

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V. Result Analysis

Reflectance at wavebands and disease level were used as parameters for co-relation analysis. NIR & Blue wavebands were found less sensitive as compared to 500-700nm wavelength. The identification of symptomatic disease level proved to be difficult. Poor performance was noticed for now spectra with PLSR model. To obtain better results, preprocessing was performance 2 approaches mainly 1. Log(1/R) 2. First- Derative. First derivative observed to give better results than log(1/R)[19] . Simple correlation was used and preferred with linear Discriminant Analysis, logistic Discriminant Analytsis and it selected top 10 wavebands. Linear discriminant analysis and logistic analysis used blue, red, red edge, of logistic discriminant analysis. NDVI, GNDVI, MSAVI, PRI, MSR, EIP, WDRVI, SIPI,TVI, NDRE, RVI, MCARI indices were found to be essential in discriminating helahty and diseased plants [20]. Logistic model in a forward- selection, backward elimination process consisted of most significant independent variable. Midpoint between 0 and 1 was used for the accuracy of the models [21]. Adjusted coefficients of determination (R2a) were used to select best models. Regression models were developed with the help of different number and combination of input variables with modeling approach [22].

VI. DISCUSSION

The maximum values of reflectance and transmittance was observed and absorbed was low since the leaf pigments and cellulose are different, for range 700-1300nm [23]. Red region consisted of 694 & 688nm which were top bands identified for the disease discrimination. Top bands identified in correlation method were 560nm. Disease identification was done with the help of bands and band values near to them. These bands found to be critical and values were 570nm, 700nm Vs. 701 nm, 690 Vs. 694 nm, 730nm Vs. 733nm. Correlation, linear and logistic discriminant analysis were the preferable methods [24, 25]. Sprouted & intact crop kernels were distinguished using a VNIR spectroradiometer (400-1000nm) in a reflectance mode. Changed and intact kernel were identified using reflectance at 728nm – 878nm. [26]

Efficiency and reliability of optimal wavenumber selection, indicating a great potential for practical application could be suggested by result of optimal wavenumber selection and caliberation model using selected optimal wavenumber of 2 sample sets [27]. The foundation of the large- scale predicted all disease crops could be laid down with the help of relationship between use of spectral curve and disease severity establishment of disease level monitoring model based on spectral data [28]. Severely changed kernels possessed correct recognition rates of intact, changed, severely changed kernels. Preservations of variance without labels and therefore patterns can be removed for specific task as the major drawback of PCA [29]. The visible region consisted of highest correlation coefficient (r = 0.85). The spectroradiometer in range of (400-1050 nm) used on field to obtain spectral reflectance [30].

The spectral characteristics of a leaf changed after experiencing the disease and stress also caused marked effects on plant structure and water content [31].Loss in many crops caused due to the manifestation of pathogens in plantation. Automatic classification and actual classification used the energy of wavelet transform and SVM and classifies diseases based on feature extraction [32]. Multitudes of biotic and abiotic factors could cause Agriculture system in particular and biological system to be complex system. Several interrelated factors that cannot be dealt with normal mathematical or statistical method. Hence we cannot be dependent study of inter related factors [33].

VII. CONCLUSION

Leaves did not possess any visual symptoms for some group of samples. Some part of the leaves may possess concentric spots, dark leaves, dark brown spots [34]. The diseased leaves which have spot and scars could be detected in visible region. Absorption in the diseased leaves in the reflectance found to be less in color in green (495-570nm) and red region (640 nm) and red region [35] .Red edge differed in the spectrum slope which was an indicator of the plant chlorophyll content. Water content of a leaf was studied laboratory and found out in the near infrared region of leaf (780nm- 2500nm). Strong spectral change was observed in symptomatic leaves. No significant change was observed in the spectral range of 1000 nm & above. Specific pathogens affect enzymes and proteins which represents the result in the range of 1000nm -2500nm[36].

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