Nitrogen level and disease detection in Wheat Leaves using Image Processing

Mrs. Kavita Joshi[1], Mr. Saurabh Deshkar[2], Ms. Kirti Turkane[3], Ms. Sushmita Chatterjee[4]

[1] *Assistant Professor at D.Y. Patil Institute of Engineering, Management and Research, Akurdi. E-*

[2,3,4] *BE Students (Electronics and Telecommunication),D.Y. Patil Institute of Engineering, Management and Research, Akurdi.*

Abstract

Spectral vegetation indices (SVIs) have been widely used to detect different plant diseases. Wheat leaf rust and other diseases manifests itself as an early symptom with the leaves turning yellow and orange. The sign of advancing disease is the leaf colour changing to brown while the final symptom is when the leaf becomes dry. The goal of this work is to develop spectral disease indices for the detection of leaf rust. The reflectance spectra of the wheat's infected and non-infected leaves at different disease stages were collected using a spectroradiometer. As ground truth, the ratio of the disease-affected area to the total leaf area and the fractions of the different symptoms were extracted using an RGB digital camera. Fractions of the various disease symptoms extracted by the digital camera and the measured reflectance spectra of the infected leaves were used as input to the spectral mixture analysis (SMA). Then, the spectral reflectance of the different disease symptoms were estimated using SMA and the least squares method. The reflectance of different disease symptoms in the 450~1000 nm were studied carefully using the Fisher function. Two spectral disease indices were developed based on the reflectance at the 605, 695 and 455 nm wavelengths. In both indices, the R 2 between the estimated and the observed was as high as 0.94 We propose the development of deep sparse extreme learning machines (DSELM) fusion and genetic algorithm (GA) to normalize plant images as well as to reduce color variability due to a variation of sunlight intensities. We also apply the DSELM in image segmentation to differentiate wheat leaves from a complex background. In this paper, four moments of color distribution of the leaf images (mean, variance, skewness, and kurtosis) are extracted and utilized as predictors in the nutrient estimation. We combine a number of DSELMs with committee machine and optimize them using the GA to estimate nitrogen content in leaves.

Keywords: *wheat leaf rust; hyperspectral measurement; spectral disease indices; disease symptoms, nutrient estimate.*

I. INTRODUCTION

Various spectroscopic and imaging techniques have been developed to detect disease and stress in plants and trees .Spectral data at different scales including leaf, canopy and landscape-level have been widely used to improve precision. In recent years, researchers have studied various spectral vegetation indices (SVIs) to detect different vegetation diseases. Efficient use of spectral data in detection of plant disease depends on the application. The spectral regions from 400 to 700 and 700 to 1100 are mainly influenced by leaf composition of pigments, structure, and water content. The effect of a disease on the pigments and structure of a plant and the change in their spectral responses enable spectroradiometry and remote sensing techniques to detect plant disease effectively.

There are indices derived from reflectance values at several wavelengths that are able to detect and quantify the leaf content substances such as chlorophyll, anthocyanin, and water. Nalta et al. used leaf spectral reflectance to detect viral infection. In this study SVIs were used to identify infected and non infected leaves with maximum accuracy of 70%. Chen et al. used hyperspectral measurement to identify cotton infected by verticillium wilt. The first derivatives between 731 and 1317 nm were the most effective in predicting disease. Mohammad et al. showed that the visible and infrared regions of the electromagnetic spectra provide the maximum information on physiological stress levels in an affected plant. Some of the wavelengths specific to a disease can be used to detect plant disease .Optimum spectral ranges have been suggested to detect different disease; 425, 685 and 735 nm to detect citrus canker, 737–925 nm to detect brown plant hopper disease of rice, 426 nm for brown plant hopper and leaf folder infestation of rice, and 800 to 1100 nm to identify leaf miner damage of tomato . However, each disease may affect the leaf reflectance spectrum in a specific way.

Therefore, special spectral disease indices (SDIs) must be developed to detect plant disease .In the SDIs and SVIs developed thus far, less attention has been paid to the effect of disease symptoms on the reflectance spectra. It is therefore beneficial to design specific indices for each disease based on the progression of disease symptoms. Wheat has three types of rust disease called yellow rust, leaf rust, and stem rust. Leaf rust disease has the highest frequency of occurrence compared to the other two types, giving it higher priority for further investigations. Each year, this disease damages crops all around the world, decreasing yield dramatically. Symptoms begin by manifesting themselves in yellow, orange, and then dark brown colours. The final symptom is dry leaf. It is worth noting that the different symptoms of leaf rust can be simultaneously observed in various parts of a leaf .A few investigations have shown the potential of SVIs for disease detection. Mahlein et al. and Rump et al. demonstrated the effect of disease symptoms on recorded reflectance spectra . This is a low-cost and accurate non-destructive image-based technique to estimate nitrogen amount in wheat crops on the field with various sunlight intensities using a conventional digital camera.

The intensity of the light source will dominantly affect the appearance of the wheat plants images even they are acquired from the same field with the same fertilizing level treatment. These images need to be normalized prior to subsequent image processing steps. The colour variation of the wheat leaves after image normalization process is merely influenced by the difference of fertilizing concentrations. Generally, the lesser the nitrogen fertilizer applied to plants, the green color of the leaves will be much lighter. In this step, we introduce a method for color normalization by using fusion of deep sparse extreme learning machines (DSELMs) with genetic algorithm (GA) and 24-patch Macbeth color checker as the color reference. Extreme learning machine is well-known as one of the recent successful approaches in machine learning with much faster training speed than the ordinary multilayer perceptron (MLP). The GA is one of the evolutionary algorithms which involves selection, crossover, and mutation operators to make its population more diverse and thus prevent the algorithm to be trapped in a local optimum. Theoretically, the diversity will increase the algorithm‘s speed to achieve global optimum since it will countenance the algorithm to explore the solution space faster. Macbeth color checker is usually used as a reference target for photographic and video production work as well as calibration process. As it has various standard color patches, it is beneficial to use this chart as a color reference to normalize and correct plant images under various sunlight intensities. The next step is image segmentation and features extraction. In this step, we utilize DSELM to distinguish wheat leaves as the object of interest from undesired images, such as soil, weeds, dried leaves, stems and stones. We propose the utilization of various statistical features as predictors since they indicate the color distributions of wheat leaves more significantly rather than a single color channel from a certain color model or combinations of some color channels. In the nutrient estimation step, we combine several DSELMs with different hidden layer numbers using committee machine and optimizing the results with GA. The estimation results of the proposed approach are then compared with other common and existing nutrient estimation methods.

Our project is studied for three purposes: (a) to estimate the reflectance spectra of various disease symptoms; and (b) to introduce an index for precise determination of disease severity using the spectral reflectance comparison of five different leaf colour symptoms.(C)To detect the nitrogen level of wheat plant.

II. OBJECTIVE

The proposed system tries to fulfill the following objectives:

1. Estimate nutrient content in leaves by analyzing color features of the leaf images captured on field with various lighting conditions.
2. Normalize plant images as well as to reduce color variability due to a variation of sunlight intensities.
3. Estimate nitrogen content in given leaves.
4. To predict the early diseases of wheat plant

III. DESIGN SYSTEM

We propose a low-cost, simple, and accurate technique to estimate nitrogen content in wheat leaves and early disease detection by analyzing RGB color of the leaf images. We also found that the developed DSELMs fusion has enabled better performance in normalizing images and is faster than other neural network types, i.e., back propagation-based multilayer perceptron and original extreme learning machine.

In image segmentation step, the established DSELM shows good performance to recognize and distinguish wheat leaves from other undesired background images. Furthermore, the developed weighted DSELMs have demonstrated enhanced ability in estimating nutrient content.

It is a very challenging task to analyse nitrogen content in crops non-destructively according to the colour features of plant leaves images which are captured in farm under sunlight. We will be programming the Image Recognition software using the Python Language and collecting the dataset from various websites (such as leafsnap.com). The result of color recognition will be displayed on the computer and will also give us an approximation of the health of the photographed plant. In order to measure spectral reflectance of the rust infected leaves, a spectroradiometer (Analytical Spectral Device, Boulder, CO, USA) with a 25° field of view was used. The spectra were collected in the 350–2500 nm range with a bandwidth of 1 to 4 nm. The Spectralon plate (Labsphere, Halma Co., USA) with a dimension of 40 × 40 cm was used as a reference. A contact probe (with leaf holder) was employed to reduce the effect of environmental light scattering and to improve the measurement accuracy. The distance from the probe inside contact probe to the target was 5.2 cm. Each of the leaves contained various disease symptom areas ranging from yellow to dark brown. After measuring the spectrum of each infected area, an RGB digital photo was taken. Each infected leaf was used only once for measurement. Various symptoms of the leaf disease, including yellow, orange, dark brown and dry leaf, were extracted from the digital photos. After spectrometry, photography was performed outdoors. Therefore, in order to remove the effect of the light intensity, the HIS system was used instead of the RGB system. This algorithm is based on the transformation from the RGB to HIS space aiming to remove the effect of outdoor light intensity variations. Meanwhile, in this research, texture recognition algorithms were used to determine the boundaries of infected areas. The steps of classifying the disease symptoms by the images of the RGB digital camera are shown in Figure 1C. The amounts of different symptoms of the disease were determined by calculating the ratio of the areas of the infected spots to the total leaf area for each infected leaf. It must be taken into account that these measurements were conducted in the same area upon which the spectrometry had been performed. The exact location of the spectral reflectance region on the leaf was marked with the contact probe so that the ratio and symptom of the disease could be extracted by the RGB digital camera. This area is displayed by a white circle in Figure 1D. Inside the marked area, a green mask was applied using a threshold value. The aim was to classify infected areas of the leaf with more precision. In addition, training samples were collected from the disease symptoms. Then, the maximum likelihood classification was applied on the H and S components in order to extract disease symptoms as shown in Figure 1C. The disease symptom fractions were used along with the spectra of the infected leaf as ground truth to evaluate the SVIs.

Figure 2. (A) Disease progress of wheat leaf ; (B) Different symptoms of wheat leaf ; (C) Classification steps of disease symptoms of wheat leaf by RGB digital camera; (D) Classification of different symptoms and masking green area of wheat leaf , the leaf area (leaves were placed next to each other) marked by the contact probe is shown by the white circle.

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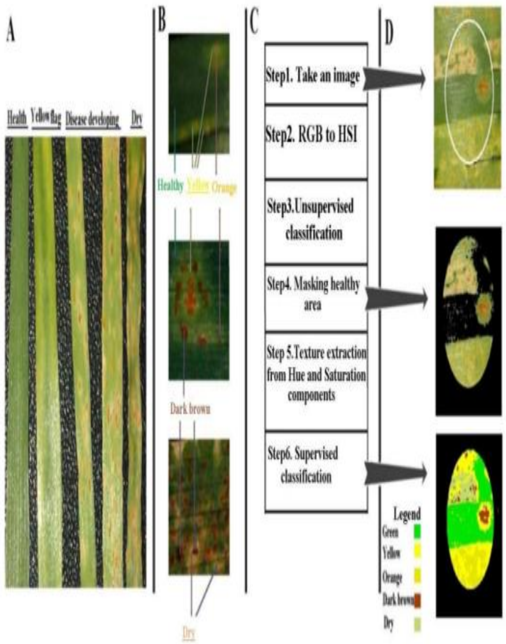
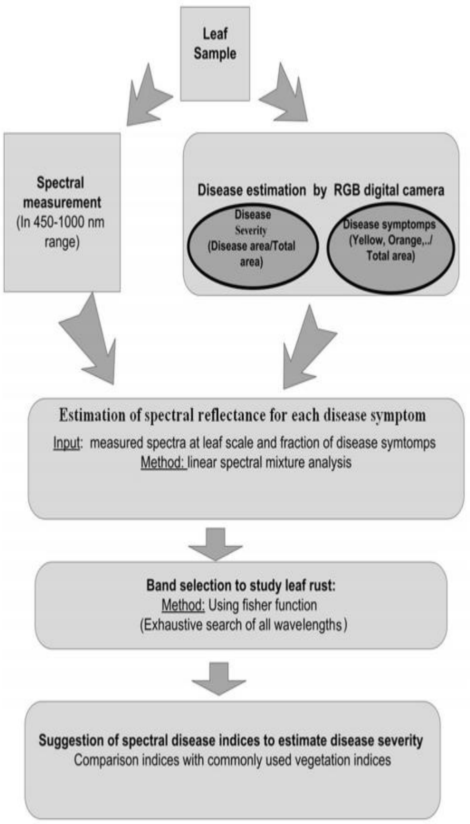
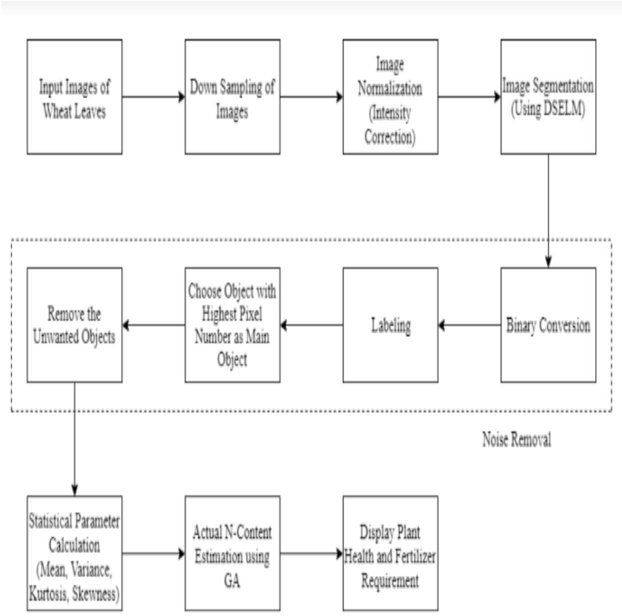




- FOR NITROGEN LEVEL DETECTION



1. Images are given to the system by either capturing them live in the field, or by transmitting the required image using Bluetooth, USB or E- Mail.
2. This input image is then given to a segmentation algorithm for Labelling and Classifying the background data from the foreground subject.
3. DSELM is the preferred Learning Machine application as one of the recent successful approaches in machine learning with much faster training speed than the ordinary multilayer perceptron (MLP).
4. This also enables us to isolate the segments of the image that are the object of interest from undesired images, such as soil, weeds, dried leaves, stems and stones in our case.
5. Post-segmentation, we display the segmented parts of the image and compare their colours with the pre-established colour palate for estimating the N-content at the current lux level.
6. The images were captured at 1632×1224 pixels, but then sampled down to 448×336 pixels to assist with the effectiveness of the image processing.
7. After image segmentation, 12 statistical features from four types of parameters of each RGB color channel, i.e., mean, variance, skewness, and kurtosis will be extracted from the segmented images as nutrient estimation predictors.
8. These statistical features will be used as predictors since they indicate the color distributions of leaves more accurately.

IV. OTHER SPECIFICATIONS

ADVANTAGES

1. Image Processing is a non-destructive technique that allows us to simply scan and recognize our objects of interest without needing to chemically or mechanically break them into parts.
2. It is cheaper, faster and has high repeatability.
3. Created databases can be repurposed by adding tags and extracting newer data if required.
4. High accuracy which only increases with repeated uses due to Machine Learning integration.
5. Adding newer features requires device drivers and relevant data variables.
6. Help to predict the diseases

DISADVANTAGES

1. Time required to gather enough data for a database/dataset is relatively high.
2. The set of parameters used for consideration is very large, making the programme relatively heavier on the RAM.
3. Adding newer features is relatively difficult as the device drivers may or may not interact well with the program.

4. Dedicated image processing chips are required for the program to run as efficiently as possible.
5. Without a relatively large dataset, the accuracy of the program is relatively low.

FUTURE SCOPE
1. Adding more Disease Recognition in plants by comparing images of diseased leaves.
2. Image segmentation algorithms which will allow the program to scan and recognize multiple leaves from an image.
3. Automatic saving an image clicked or scanned in the program on a cloud-based server to increase the usable dataset.

CONCLUSION

The accurately detection and classification of the wheat plant disease and nitrogen level is very important for the successful cultivation of wheat plant and this can be done using image processing. This paper discussed various techniques to segment the disease part and nitrogen level of the wheat plant.

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