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Research Article

Quantitative detection of soybean rust using image processing techniques

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Abstract: Rust caused by *Phakopsora pachyrhizi* Syd. is a major constraint to soybean product in Asia. Early detection and possibilities of controlling plant diseases by the integration of several image processing methods has been the subject of extensive research. The main contribution of this paper is to present different methodologies for quantitatively detecting soybean rust at each stage of disease development, identify disease even before specific symptoms become visible and grade based on percentage of disease severity. Severity of rust infection levels at each stage of disease development was observed for 25 days on soybean leaf. Then color distribution and pixel relationship in rust infected leaf image was calculated based on global and local features for quantifying rust severity. Further, rust disease was categorized into grades based on infection severity levels and percentage disease index (PDI) was calculated. The maximum PDI of 95.5 was observed at 25th day and minimum PDI of 0.2 was observed at 6th day.

Keywords: disease severity,color features, global region, local region, soybean rust

Introduction

Soybean, *Glycine max* (L.) Merrill, is a protein rich oilseed crop. It is considered as a golden bean, miracle bean and wonder crop of the 20th century because of its characteristics and usage. Soybean evolved from *Glycine ursuricusi,* a wild legume native to china. Since eleventh century B.C., though soybean is considered as a legume crop, it is used as oilseed crop due to an account of inherent presence of trypsin inhibitor that limits its usage as pulse crop. It is economically the most important legume in the world, which contributed to agriculture economy. The information of soybean used as a basis for wide range of food and industrial products is discussed by Sinclair and Shurtell (1975). In a country like India, people are largely dependent on vegetable oil in diet and soybean plays an important role in supplementing fats and oils of vegetarian origin. Cultivation of soybean in India was negligible till 1970, but production rapidly increased crossing over six million tons in 2004.

At present, area under soybean cultivation in India is 10.275 mha with a production of 11.0mt. In India, losses due to various diseases are estimated to an extent of 12% of total production. The diseases include rust, wilts, leaf spot, rots, powdery mildew, bacterial, viral and nematode diseases. Sinclair and Shurtell (1975) listed in their paper about 100 pathogens of soybean crop. Major obstacle to grow soybean is rust caused by *Phakopsora pachyrhizi* Syd. causing losses upto 80%. Yang (1977) and

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Bromfield and Yang (1976) focused on rust of soybean caused by *Ph. Pachyrhizi* as the most widespread and important disease in Asia and Australia and its potential threat to soybean production in the different regions of the world. The soybean growers of the sub-continent have been facing serious infestation of rust disease in last one decade with yield losses ranging from 30-100%. There are no resistant cultivars at present for soybean rust and continuous application of fungicides has further aggravated the concern over pesticide resistance and economic burden on the farmers. Hence, keeping in view, to develop machine vision system which forms the basis for early diagnosis of rust disease infection of soybean and sustainable management of rust disease in the sub-continent and also to help farming community, challenging automation is deployed. In order to know the state-of-the-art in this area, literature survey has been carried out.

Lefebvre *et al.* (1993) have presented the problem in automatizing pulp sampling of potatoes to detect viral diseases using shape, color and texture features. Sena *et al.* (2003) have developed and evaluated an algorithm at simplified lighting conditions for identifying damaged and non-damaged maize plants by the fall armyworm using digital color images. Muhammed and Hammed (2005) have been concerned with characterizing and estimating fungal disease severity field assessments in a spring wheat crop based on hyperspectral crop reflectance data vectors. Pydipati *et al.* (2006) have used a computer vision and image processing techniques in the early detection and classification of diseased citrus leaves from normal citrus leaves. Doudkin *et al.* (2007) have proposed a neural network clusterization algorithm for segmentation of the color images of crop field infected by diseases that change usual color of agricultural plants. Huang (2007) has presented an application of neural network and image processing techniques for detecting and classifying phalaenopsis seedling diseases using Gray-Level Co-occurrence Matrix (GLCM) and Artificial Neural Network (ANN) classifier. Ying *et al.* (2008) have provided various methods of image preprocessing techniques for recognition of crop diseases. Tuker and Chakraborty (2008) have presented software which detects, characterizes and calculates percentage of leaf area diseased using digital image processing. Camargo and Smith (2009) have reported a machine vision system for the identification of the visual symptoms of plant diseases, from colored images using Support Vector Machine (SVM). Cui *et al.* (2009) have explored feasible methods for detecting soybean rust and quantifying rust severity. Kim *et al.* (2009) have investigated the potential of using color texture features for detecting citrus peel diseases. Features are further reduced through a discriminant function and classified based on a measure of the generalized squared distance. Yao *et al.* (2009) have presented an application of image processing techniques for detecting and classifying rice diseases. Cui *et al.* (2010) have reported research outcomes from developing image processing methods for quantitatively detecting soybean rust severity from multi-spectral images. Rumpf *et al.* (2010) have proposed automatic methods for an early detection and differentiation of sugar beet diseases based on SVM and Spectral Vegetation Indices (SVIs). Sankaran *et al.* (2010) have reviewed advanced techniques, namely, spectroscopic and imaging techniques and volatile organic compounds profiling-based technique for recognizing plant diseases. Al-Hiary *et al.* (2011) have evaluated a software solution for automatic detection and classification of plant leaf diseases using Color Co-occurrence Matrix (CCM) and neural network classifier. Bauer *et al.* (2011) have described the methods of automatic classification of leaf diseases based on high-resolution multi-spectral stereo images. Guru *et al.* (2011) have presented a novel algorithm for extracting anthracnose and frog-eye spots present on tobacco seedling diseases using first order statistical texture features and Probabilistic Neural Network (PNN). Moshou *et al.* (2011) have developed an intelligent multi-sensor fusion decision system based on neural networks for detection of plant diseases in arable crops automatically using hyper-spectral reflectance and multi-spectral imaging. Patil and Kumar (2012) have provided advances in various methods used to study plant diseases/traits using

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image processing. The methods studied are for increasing throughput and reducing subjectiveness arising from human experts in detecting the plant diseases. Dubey and Jalal (2012) have proposed image processing based approach to evaluate diseases of apple. Local binary features are extracted from the segmented image, and finally images are classified using a Multi-class Support Vector Machine (MSVM). Patil and Kumar (2012) have described the methods for extraction of color and texture features of diseased leaves of maize. The textures features like correlation, energy, inertia and homogeneity were obtained by computing gray level co-occurrence matrix of an image. Bandi *et al.* (2013) have proposed machine vision and image processing techniques in sleuthing the disease mark in citrus leaves. Citrus leaves are investigated using texture analysis based on the CCM and classified using various classifiers. Barbedo (2013) has presented a survey on methods that use digital image processing techniques to detect, quantify and classify plant diseases from digital images in the visible spectrum according to their objective: detection, severity quantification, and classification.

Recent research has shown that machine vision has the potential to become a viable tool to identify disease type. From the literature survey, it is observed that the work on detecting soybean rust and quantifying disease severity at each stage of disease development is not attempted to the best of our knowledge. Although several image processing approaches have been presented for detecting plant diseases using color, texture, and shape features, no attempts are made for detecting plant disease based on infection levels using color features by exploiting global and local regions. The goal of this study is to investigate the possibility of quantitatively detecting soybean rust infection at each stage of disease development and identify rust disease even before specific symptoms become visible. The present work has the following objectives: (i) to record grades and calculate percentage of disease severity, (ii) to detect the soybean rust disease severity using global features based on color distribution in the image, (iii) to observe how the spatial relationship varies among pixels in the rust infected image based on local features.

Materials and Methods

Present investigation was carried out during the period 1st-25th September 2013. Ten soybean plants were grown in clay pots. The healthy leaves in plants were stapled with rust infected leaf. The healthy leaves were also inculcated by spraying with inoculum prepared out of rust infected leaves and covered with polythene. Observations on appearance and development/severity of disease on soybean leaves were made daily to record the first appearance of the disease. The observations on disease severity at different levels were recorded for 25 days after inoculation (dai). The severity of rust disease was recorded by following 0-9 scale discussed by Mayee *et al.* (1986) given in Table 1. Further these scales were converted to Percent Disease Index (PDI) according to Wheeler *et al.* (1969) using the Equation (1).

$$\text{PDI} = \frac{\text{Sum of disease ratings}}{\text{Total number of plants observed} \times \text{Maximum disease rating}} \times 100 \qquad (1)$$

Table 1 Scoring for soybean rust.

Rating	Description
0	No lesions/spots
1	1% leaf area covered with lesions/spots
3	1.1-10% leaf area covered with lesions/spots, no spots on stem
5	10.1-25% of the leaf area covered, no defoliation, little damage
7	25.1-50% leaf area covered, some leaves drop, death of a few plants, damage conspicuous
9	More than 50% area covered, lesions/spot very common on all plants, defoliation common, death of plants common, damage more than 50%

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During cropping period, maximum temperature ranged from 24.9 to 30 ^{0}C, minimum temperature 18.6 to 20.7 ^{0}C, maximum relative humidity 87.9 to 97%, and minimum relative humidity from 53.3 to 88.8%. The rainfall received ranged from 4.8 to 57.2 mm.

The study of *Ph. pachyrhizi* variation on soybean has exclusively focused on quantitative differences in virulence. This quantitative nature of virulence is based on three infection types on soybean (i) reddish brown lesions with either no uredinia or sparsely sporulating uredinia, (ii) tan lesions with many uredinia and abundant sporulation, (iii) no color lesions with no visible infection. This quantitative difference in virulence could detect both major and partial resistance of soybean to rust. The colors of different infection levels varied from yellowish brown, orange brown, dark brown, light brown or pale yellow at different stages of inoculation shown in Fig. 1.

Human vision system is more sensitive to color information. Color is the most significant and straight-forward feature that humans perceive while viewing images in the real world. All the existing colors are seen as variable combinations of three primary colors, namely, Red (R), Green (G) and Blue (B). Hence, suitability of RGB color features has been tested for detection of rust disease severity. Color is usually used as a global feature based on visual similarity in many image processing applications. Color features are considered as global descriptor in which attributes are computed on the whole image and further local descriptor attributes are computed on regions of the image. The detailed block diagram of adopted methodology is shown in Fig. 2.

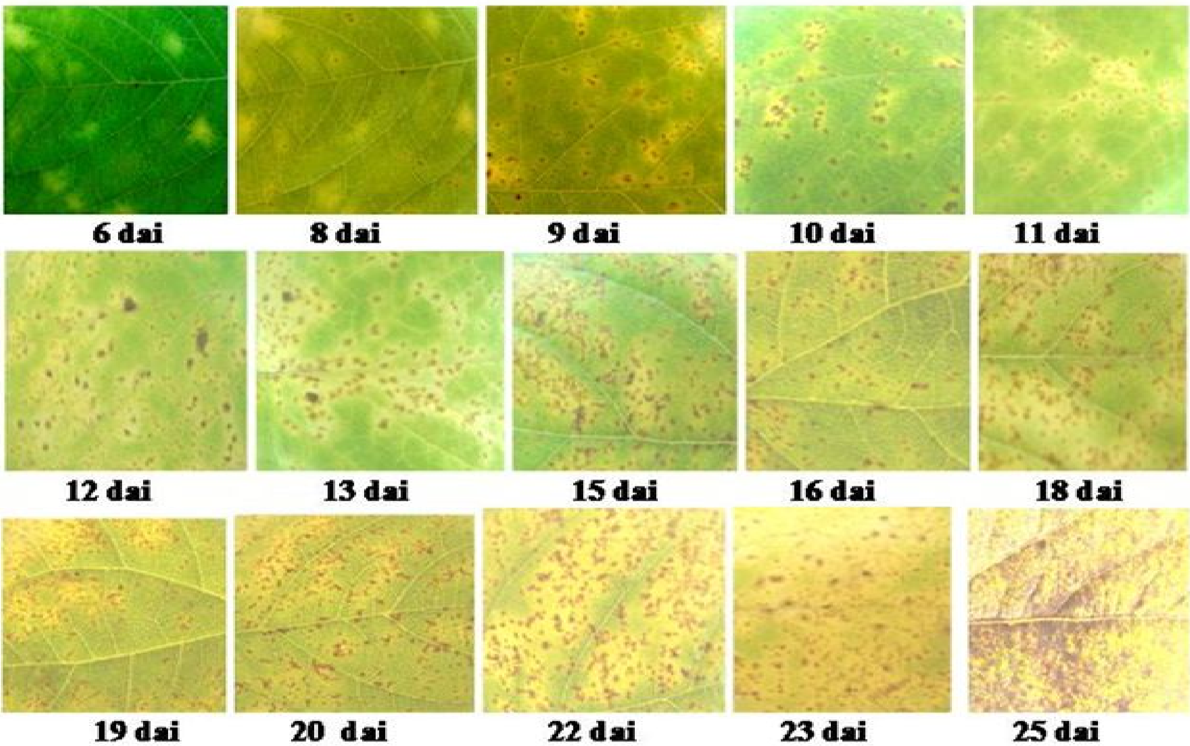

Figure 1 Development of rust disease symptom on soybean leaf at each stage of inoculation.

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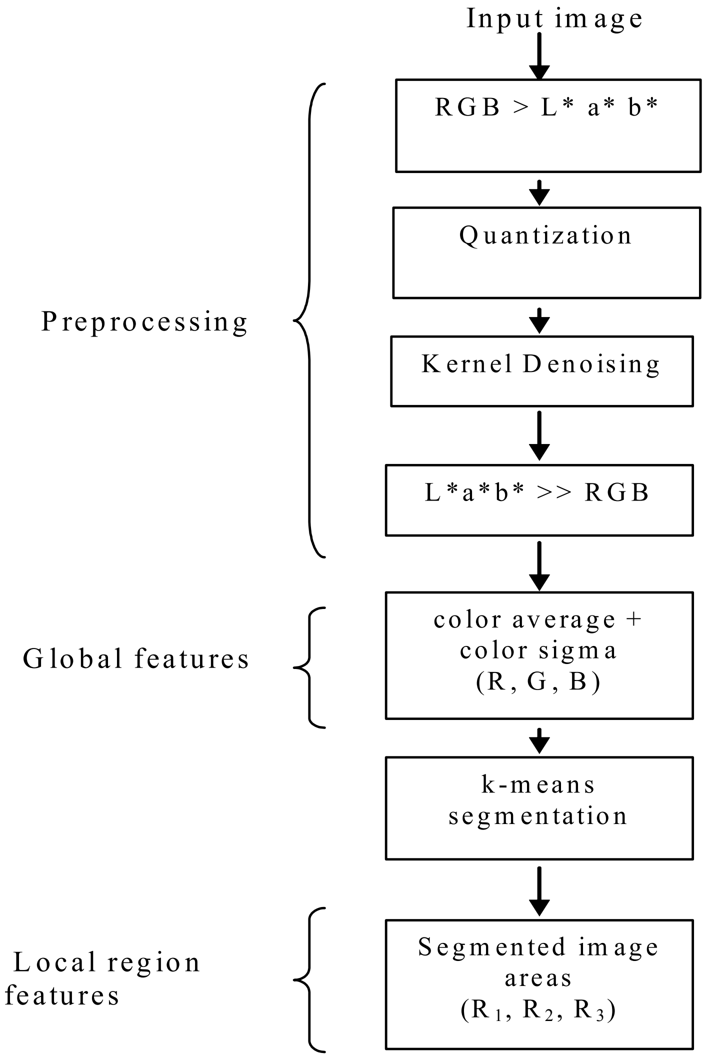

Figure 2 Block diagram for the proposed methodology.

Image acquisition and pre-processing
The single color image of soybean rust infected leaf was captured with a digital camera at each stage of disease development. For image acquisition, a color camera (DXC-3000A, Sony, Tokyo, Japan) was used. The camera has a zoom lens of 10-120 mm focal length and a 72 mm close-up lens set. The camera was vertically oriented and approximately a distance of 0.5 meter was maintained while capturing the images. In order to perform some basic tasks to render the resulting image more suitable for the job to follow, image pre-processing techniques were applied. Image pre-processing techniques are used to bring out details that are obscured or simply to highlight certain features of interest in the image. Pre-processing of the image includes shade correction, removing artifacts, and formatting. Some images, originally from camera, manifest uneven lighting called shade. Due to variation in lightning conditions some regions are brighter and some others are darker than the mean value for the whole image. This phenomenon is a consequence of inaccuracy in the system. Precise tuning of camera was done to minimize this effect. Some artifacts like, scratches, coat or mark,

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lumps of dust or abrasive particles are induced on the surface of images. Median filter has been used to remove such artifacts. Formatting deals with storage representation and setting the attributes of the image. The images acquired from the camera were of 1920 × 1080 pixels and were reduced to 400 × 400 size for the reasons of reducing computational time required for feature extraction and their storage on the medium.

Color transformation structure

The color transformation structure was created for the image. Color transformation structure is the transformation of representation of a color from one color space to another. Then the device-independent color space transformation was applied where the resultant color depends on the equipment and the set-up used to produce it as referred in the paper Al-Hiary *et al.* (2011). A device independent color space is one where the coordinates used to specify the color will produce the same color when applied. In the proposed work, CIE *L*a*b** color space was used which is based on human perception of color in the eye, the color receptors, namely, red, green, and blue. The phase starts by separating the RGB components from the original color image. The RGB components were converted into *L*a*b** color space representation. An image was digitized in amplitude for further computer processing and feature extraction. The idea was to reduce the color space while gaining the ability to localize color information spatially. The image was quantized at *L*a*b** color space so that features could be easily extracted with less color space. Noise in quantized images was removed by convolution using median filter. Every pixel was replaced by the median of the color levels in a neighborhood of that pixel for each color component. Lastly, color space for *L*a*b* was* converted back into RGB.

Global feature extraction

The global features are computed based on color distribution in the whole image. The images of rust infected leaf are recognized by quantifying the distribution of color throughout the image, change in the color with reference to average or mean, variance, and standard deviation. Since these features represent global characteristics for an image, color features namely, mean and standard deviation have been adopted in this work. The amount of red, green, and blue color contribution in the image is computed. One could identify area covered in terms of rust infected areas using color differentiation based on assumption that the leaf color would be changed following severity of rust infection at each stage of disease development. Red (R), Green (G), and Blue (B) values are used to characterize the colors.

Color Average

Color images are generally quantified by Red (R), Green (G), and Blue (B) values representing integrated responses over RGB spectral bands measured through color filters. The RGB response is affected by the specific configuration of a color vision system, including factors related to the intensity and the spectral distributions of illumination. The extraction of RGB features was as follows: First step in extraction of RGB features was separation of RGB components from the color images of infected soybean leaves. The average values in the RGB image were computed by adding every pixel for each color component and dividing by total number of pixels using Equation (2).

Mean μ

$$\frac{1}{N}\sum_{i=1}^{N} X_i = \frac{X_1 + X_2 + \ldots + X_N}{N} \tag{2}$$

Where, N is the total number of pixels, x_i is the i^{th} pixel value

Color Sigma

Color sigma or standard deviation represents pixel intensities in the image. Since RGB color space is used, there are three values of standard deviation for each color component. The color sigma is calculated using Equation (3).

Standard deviation

$$\sigma = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(X_i - \mu)^2} \tag{3}$$

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Local region based features

Local region features is concerned with small sub-images in isolation in which attributes are computed. The local features are computed based on color distribution in sub-images. The image is clustered into regions based on intensity level and these regions are identified and computed based on spatial information. Then local features for each of the regions are calculated. The process of clustering the pixels into local regions is done using k-means clustering based segmentation method as discussed by Pujari *et al*. (2013). For each separated region, values for color pixels and gray pixels are calculated. Each of the pixels in a region is similar with respect to characteristic or computed property.

Segmentation

Image Segmentation is the process of assigning a label to every pixel in an image so that pixels with the same label share certain visual characteristics and are grouped into regions. There are certain existing techniques which have been proposed by Kompatsiaris *et al*. (2001) for the segmentation of color image. K-means clustering is widely used segmentation method which aims to partition *n* observations into *k* clusters. Each observation belongs to the cluster with the nearest mean based on intensity value. This makes k-means clustering method particularly useful for the color clustering. The image is clustered into regions based on intensity level and these regions are identified based on spatial information. Furthermore, region/local features are calculated for each of the regions. The number of regions generated by clustering algorithm is three (R_1, R_2, R_3). Since in these regions, color intensity values in color space are appropriately discriminated, clustering of three regions is considered. The color feature values finds to be more significant in these three regions, as this is essential for better recognition of rust disease severity in the image. For each separated region, k-means clustering will give K intensity values. Each region will have a color value corresponding with the K intensity value. The pixel intensities are computed for color and gray levels in each separated region.

Results and Discussion

Detection of rust disease severity based on PDI

The scoring rate at different stages of soybean rust disease development after inoculation is shown in Fig. 3. It is observed that the disease severity is more at 16 dai to 25 dai ranging in grade score from 7-9, disease severity is less at 6 dai to 13 dai ranging from 1-3 grade and moderate disease severity at 15 dai to 18 dai with 5 grade. The grades are computed based on Table 1.

The graph shown in Fig. 4 gives Percentage Disease Index with different scoring rates for rust infected soybean leaf based on disease severity. From Fig. 4, the maximum disease severity of 95.5 PDI is observed with more than 50% area covered with lesions/spot (9 grade) and minimum disease severity of 0.2 PDI is observed with 1% leaf area covered with lesions/spots (1 grade).

Detection of rust disease severity based on global features

Color distribution of red, green and blue components at each stage after inoculation is given in Table 2. It is observed from Table 2 that as the rust disease severity increases, the contribution of green color decreases. This indicates that the values of green pixels have negligible contribution as the severity level of rust infection increases and most probably green pixels represent healthy areas on the soybean leaf. It is also observed that values of red pixels contribution is more as soybean rust disease symptom shows reddish brown lesions indicating increase in disease severity.

The histogram plot of RGB values in rust infected soybean leaf image at each stage of disease development are shown in Fig. 5. It is observed that the average values for green in the image at 6 dai are 66.3842 and at 25 dai are 34.7661. The average values for red in the image at 6 dai are 41.51 and at 25 dai are 70.76.

Figure 6 gives values for RGB pixels in soybean rust infected leaf image at each stage of disease development. From the graph, it is observed that the values of green pixels at 6 dai are 77.58 and at 25dai are 44.51. The values of red pixels at 6 dai are 49.38 and at 25 dai are 83.36.

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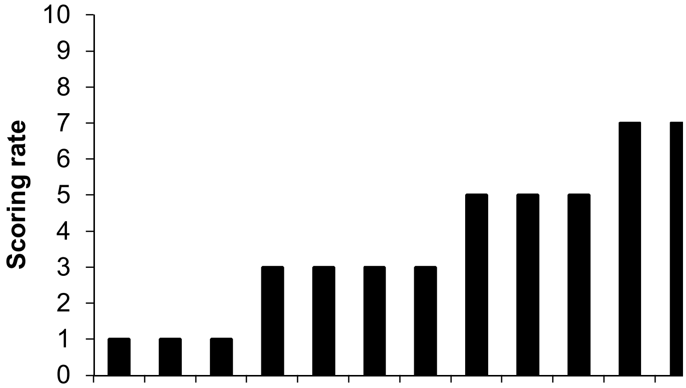

Figure 3 Grading of soybean rust disease severity after inoculation.

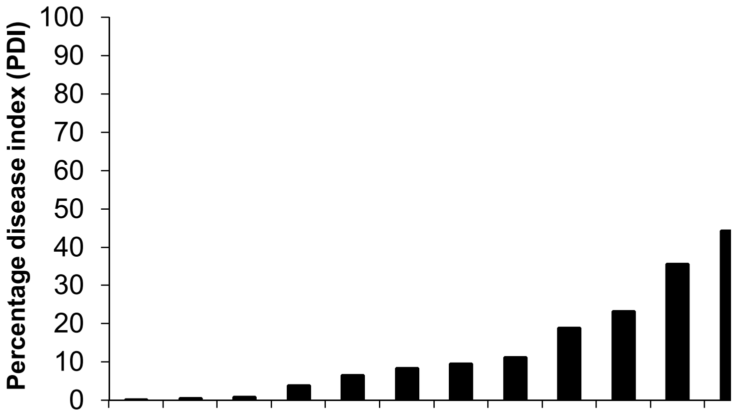

Figure 4 Percentage disease index with scoring rate based on soybean rust disease severity.

Table 2 Color distribution on rust infected soybean leaf after inoculation.

Day after inoculation	Global features					
	Color average			Standard deviation		
	Red	Green	Blue	Red	Green	Blue
6	41.5	66.3	30.5	49.3	77.5	37.3
8	41.8	65.8	20.6	51.4	77.2	24.9
9	42.1	60.9	23.7	52.4	73.2	29.2
10	48.3	60.6	28.1	57.3	71.3	34.1
11	50.9	59.4	22.0	61.7	69.9	28.6
12	52.6	58.5	17.0	62.3	68.5	20.3
13	54.3	58.1	23.8	64.3	67.8	28.5
15	57.6	56.4	29.8	68.2	67.1	37.3
16	57.7	56.3	25.7	68.6	67.4	31.6
18	57.7	55.2	25.4	68.9	64.6	34.0
19	60.0	53.4	21.3	71.1	63.4	26.2
20	60.8	53.2	20.1	71.8	63.2	24.4
22	61.0	52.7	20.9	72.5	63.2	25.8
23	61.5	48.8	27.5	73.1	57.6	35.7
25	70.7	34.7	20.2	83.3	44.5	25.6

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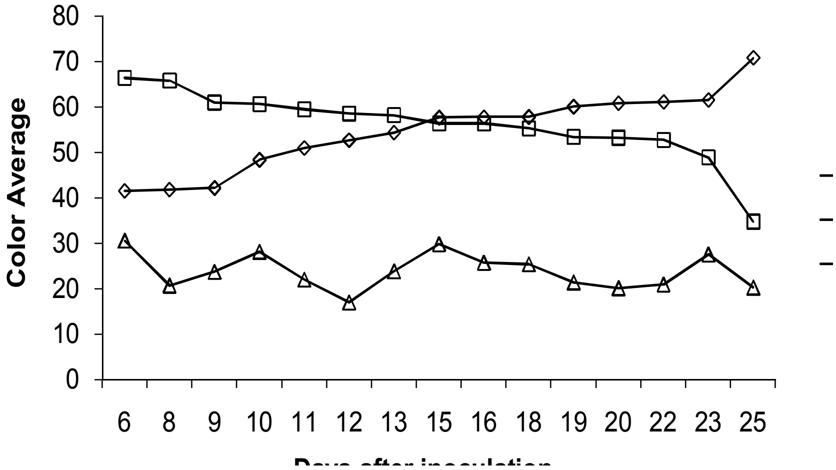

Figure 5 Amount of color distribution at each stage of disease development.

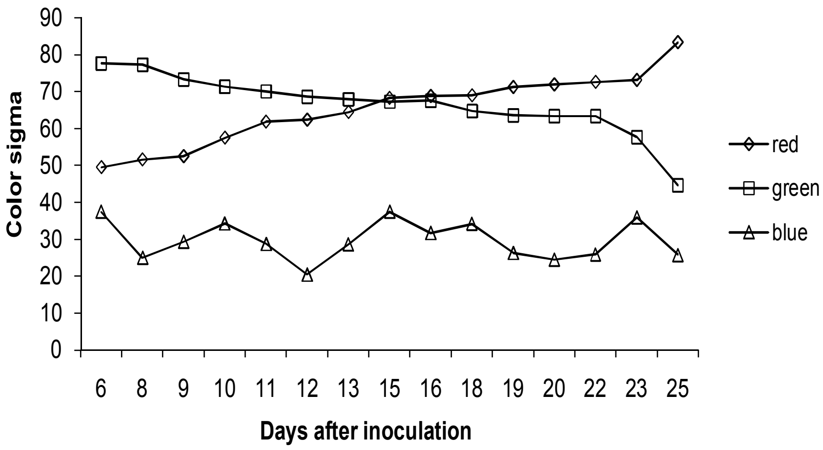

Figure 6 Color pixel intensity values at each stage of disease development.

Detection of rust disease severity based on local features

Table 3 gives values for RGB and its corresponding gray pixels in soybean infected leaf image from 6 dai to 25 dai for local regions R_1, R_2, and R_3. It is observed that the difference in values of color and gray pixels between R_1, R_2, R_3 increases at stage of inoculation (Table 3).

The relationship among values of color and gray pixels in each local regions (R_1, R_2, R_3) based on Table 3 is shown in Fig. 7 and 8. It is observed that the spatial relationship for values of color and gray pixels is more at 6 dai and relationship deviates for subsequent days of inoculation. The difference in values of RGB and gray pixels corresponding to R_1, R_2, R_3 shows that pixel relationship decreases as rust disease severity increases. The study reveals that, the local region feature values for color and gray pixels estimates image properties related to second-order statistics which considers the relationship between groups of two (usually neighboring) pixels, whereas pixels on rust disease infected areas on soybean leaf image do not consider spatial relationship (Fig. 7 and 8).

The rust disease infection on soybean leaf is observed at each stage of disease development and severity of infection level is calculated based on PDI. The maximum PDI of 95.5 is observed at 25 dai and minimum PDI of 0.2 is observed at 6 dai. The study of color distribution based on local

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and global features is observed on soybean rust infected leaf image. The results obtained show that the contribution of green color decreases with increase in disease severity. It is also observed that spatial relationship among color and gray pixels decreases with increase in disease severity.

For future study, the work can be extended to detect disease symptoms quantitatively, using texture and shape features. The proposed technique can be implemented to recognize and classify various plant disease symptoms affecting agriculture/horticulture crops. The proposed method can be further applied to remotely monitor the crop for possible diseases and detect as early as possible to avoid further loss of crop using GSM, remote sensing or other modern means of telecommunication technologies resulting in intelligent farming.

Table 3 Local features corresponding to different regions after inoculation.

Day after inoculation	Local region based features					
	Color pixels			Gray level pixels		
	R_1	R_2	R_3	R_1	R_2	R_3
6	41878	37814	78708	105.0	108.0	99.8
8	55038	25222	54140	103.0	104.8	109.7
9	90983	46400	22217	115.2	130.3	131.8
10	28387	50282	63331	107.7	125.4	112.4
11	23994	59693	73913	101.2	103.4	85.4
12	65792	31677	53331	121.0	125.1	105.7
13	66769	21877	58154	122.7	135.7	115.4
15	65500	38653	33277	99.8	116.9	96.2
16	61316	38104	11380	116.4	103.7	95.8
18	15650	77706	66244	81.1	85.6	104.3
19	81091	44568	19941	100.8	132.8	97.3
20	74036	19820	65344	98.6	82.3	119.2
22	56950	27843	50807	123.0	85.2	101.8
23	35751	11202	39252	138.6	98.7	120.0
25	37162	51569	57547	98.8	57.4	77.3

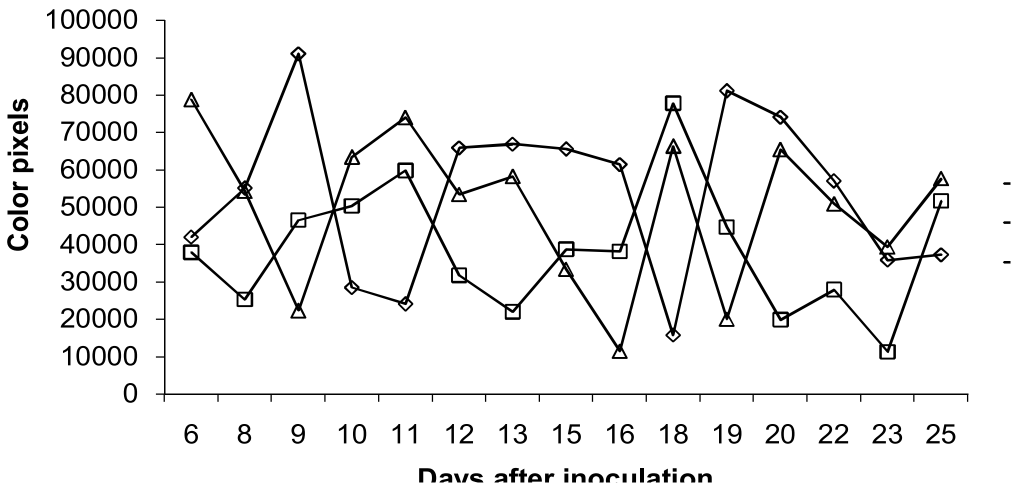

Figure 7 Relationship among color values corresponding to each local region.

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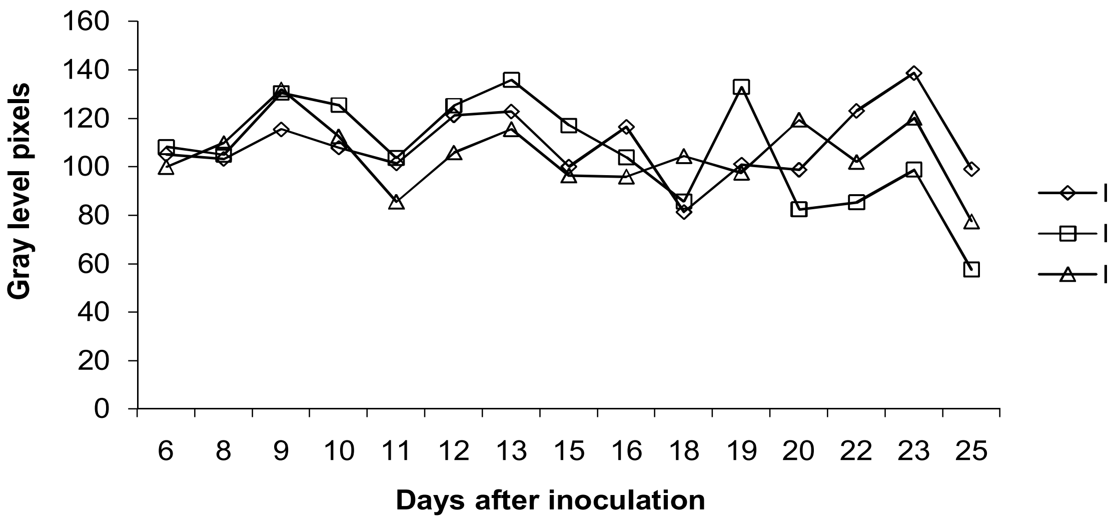

Figure 8 Relationship among gray values corresponding to each local region.

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ردیابی کمّی زنگ سویا با استفاده از تکنیک‌های پردازش تصویری

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چکیده: قارچ .Phakopsora pachyrhizi* Syd* عامل بیماری زنگ سویا یک از عوامل عمده تولید سویا در آسیا به شمار می رود. درخصوص ردیابی زودهنگام بیماری با استفاده از تلفیق چندین روش پردازش تصویر تحقیقات وسیعی انجام شده است. یافته‌های این تحقیق روی روش‌های مختلف برای ردیابی کمّی زنگ سویا در هر مرحله از توسعه بیماری و حتی تشخیص پیش‌ازظهور علایم خاص و تعیین درجه شدت بیماری متمرکز شده است. شدت سطوح مختلف آلودگی به زنگ در هر مرحله از توسعه بیماری ۲۵ روز پس از مایه‌زنی روی برگ‌های سویا مشاهده شد. سپس توزیع رنگ و رابطه آن با پیکسل‌ها در تصویر برگ آلوده به زنگ براساس جنبه‌های کلی و محلی برای کمّی کردن شدت زنگ محاسبه شد. در مرحله بعد بیماری زنگ براساس سطوح شدت آلودگی دسته‌بندی شده و درصد شاخص بیماری محاسبه شد. بیشینه شاخص بیماری برابر ۹۵/۵ درصد ۲۵ روز بعد از مایه‌زنی و کمینه آن معادل ۰/۲درصد ۶ روز پس از مایه‌زنی مشاهده شد.

واژگان کلیدی: شدت بیماری، ویژگی‌های رنگ، ناحیه عمومی، ناحیه موضعی، بیماری زنگ سویا