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Rule Based Approach to Determine Nutrient Deficiency in Paddy Leaf Images

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Rice is one of the most consumed grains among the human society especially in Asia, but is easily affected by the deficiency caused due to lack of nutrient elements. Identifying nutrient deficiencies of paddy crop is very essential in overcoming these and thereby enhancing yield. Color of paddy leaves plays important role in identifying major deficiencies such as NPK (Nitrogen, phosphorus and Potassium) when crop is in its middle of its growth. In order to do so a database of healthy, nitrogen defected, phosphorus defected and potassium defected leaves is created. Color features of both healthy and defected paddy leaves are extracted using HSV color model. Similarly color features of test image is extracted and compared against database properties. Comparison results are validated against the rules set to determine the specific deficiency. The rules are framed based on rigorous experiment. The efficiency can be further increased by including leaf pattern analysis.

Keywords: HSV, Paddy leaves, healthy, Nitrogen, Phosphorus and Potassium Deficiency.

Introduction

Image processing applications in agriculture sector is advancing with new techniques. Some applications include fruit grading, weed detection, crop detection, crop management etc. Paddy being the prominent crop, proper diagnosis and timely solving of deficiencies is an important factor of crop management. This assures an optimum use of nutrient elements for enhanced productivity which leads to increased profit. Paddy crop in farmer's fields are affected by many plant diseases in every season. Disease can affect paddy at all growth stages. Plant disease can be broadly categorized into two groups namely plant diseases and plant disorder. A plant disease is an impairment caused to normal functioning of plant. These are caused by agents like fungi, bacteria or viruses. The plant disease are infected and transformed from unhealthy to healthy plant. Plant disorder on the other hand is a state of disruption of healthy

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plant. This is caused by external factors like soil problems, environmental stresses and physiological effects or due to deficiencies of nitrogen, phosphorus and potassium. These symptoms are not transformed from unhealthy to healthy plant. To give justification for the present work literature survey was carried out. The gist of the surveyed papers is discussed in the next section.

Literature Survey

Aakanksha Rastogi *et al*, (2015) have proposed leaf disease identification in two phases. In first phase leaf is recognized based on preprocessing on stages of image processing and artificial neural network is used as a classifier. During second phase k-means based segmentation is used to identify defected area. Douglas Baquero *et al*. (2014) proposed a novel strategy for image retrieval of tomato leaves which helps to diagnose diseases. Strategy is based on color structure descriptors and nearest neighbor. Ratih Kartika Dewi *et al*, (2014) proposes an image pattern classification using combination of color and texture features to identify rust disease in sugarcane leaf with classification accuracy of 97.5%. E Sandeep kumar and Vishwanath Talasila (2014) focusses on automatic identification of medicinal plants using gaussian distribution method. Jayamala K Patil and Raj Kumar (2011) propose an advanced method used to study plant disease using image processing. The method ensures increased throughput. Song Kai *et al* proposes an image recognition method of corn leaf diseases. It uses YCbCr color space and co-occurrence matrix to extract disease spot texture feature. BP neural network is used as a classifier with an accuracy of 98%. Lili Ma *et al*, (2010) proposed a method to analyze nitrogen content in soybean plant. Author uses leaf images of six stages of soybean growth with different percentage of fertilizer applied. The leaf images are analyzed using RGB and HSI model. Mohammad Zare *et al*, (2011) propose pseudo coloring technique to analyze and identify color surfaces of sample images. The method uses different values of R, G B layers of a color image and histogram characterization. Nithin S *et al*, (2014) has surveyed several research papers on detection of diseases in cotton plant. The survey is based on detection of disease by extracting color feature, shape feature and by texture features. Noor A Ibrahim *et al*, (2012) proposes a review on most popular color models. Author discusses application areas, usage and classification of color models, advantages and disadvantages of different color models. P R Rothe *et al*, (2015) proposed an active contour model which uses neuro fuzzy inference system to classify three cotton leaf diseases. i.e. bacterial blight, myrothecium and alternaria with classification accuracy of 85%. Parag Bhandarkar *et al*, (2014) proposed a method of structural decomposition of edges and the features extracted are independent of leaf size and orientation. The proposed method gives an accuracy rate of 67.5%. Jagadeesh D Pujari *et al*, (2014) presents a study on the image processing techniques for early detection and classify fungal disease symptoms on different agricultural crops. Shitala Prasad *et al*, (2014) proposed an android based application for detecting spotting of disease patch in plant leaves using k means clustering. The method ensures reduced transmission cost. Wang Li Shu *et al*, (2013) uses computer visual and image information collected through preprocessing based on pattern recognition of soybean for nitrogen element detection. The work focuses on using HSV color model and rules defined to compare trained database against tested database to find NPK deficiency in paddy leaves. The remaining part of the paper is organized into four sections. Section two discusses literature Survey. Section three deals with methodology which further explain input image, feature extraction and classification in two stages. Section four gives with results and discussion and finally section five deals with conclusion.

Methodology

The proposed methodology uses HSV color features for two way classification of paddy leaf images. First classification is based on healthy and unhealthy features. Unhealthy leaves are further classified as nitrogen, phosphorus and potassium deficient paddy leaf images. Leaf image classification of paddy is divided into three steps, namely, Input image, Feature extraction and Classification as shown in figure1.

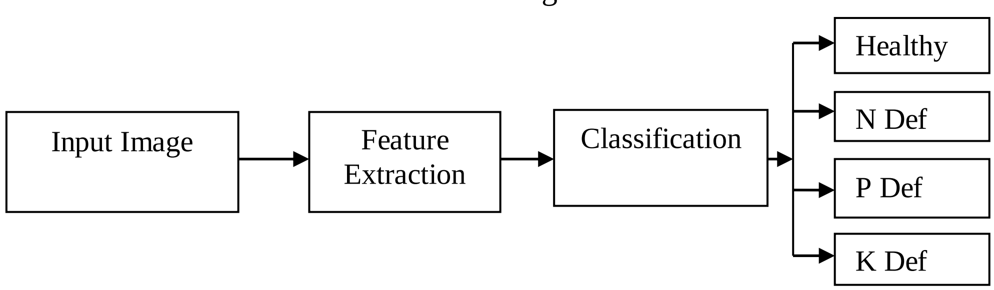

Fig. 1. Block Diagram of the Proposed Work

Input Image

All the paddy crop images are taken in Nanjangudu from Karnataka during summer season. For the proposed methodology paddy leaf images are captured under normal illumination condition around 10 in the morning on a white background using Sony 20.1 mega pixel camera. Both healthy and defective images are considered for the experiment. Around 400 images are captured considering 60 images in each category such as healthy, nitrogen deficient, potassium deficient and phosphorus deficient and remaining images are used for testing. Leaves with nitrogen deficiency become light green or pale yellow. In phosphorous deficiency older leaves become dark brown. Rusty brown or irregular necrotic spots appear on the leaf under severe potassium deficiency. Sample leaf images of healthy and unhealthy leaf image is as shown in figure 2. Leaves infected by pathogen are not considered for the study.

Fig. 2. Healthy, nitrogen, phosphorus and potassium defected paddy leaf images.

Paddy leaf images captured are 2592X1944 pixels in size. Manual Cropping of the images is done by focusing defective region. The leaves are then resized to 250X250 pixel size images using MATLAB tool and the noise in the image is reduced using median filter. Sample phosphorus defected image before and after filtering is as shown in figure 3.

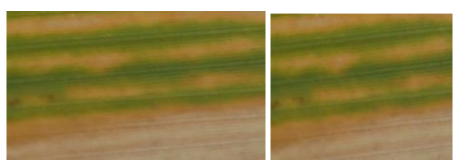

Fig. 3. Sample image before and after filtering.

Feature Extraction

Various color models are used to extract color features from images like RGB, HSV, CMY etc. HSV color model is chosen as a best approach compared to RGB color model as it is not distracted from natural light. Color properties such as hue, saturation and value are extracted for each leaves of healthy, nitrogen, phosphorus and potassium defected image dataset.

HSV

Color has the major importance in content based image retrieval system. Our initial study was basically done using HSV color space and then additional features were considered in order to increase the identification rate of deficiency in paddy leaf images. Computer graphics frequently use HSV color space. It is a bit from human perception. The three colors are Hue, Saturation and Intensity also called as brightness. Hue is the Wavelength within the visible light spectrum at which the energy output from a source is greatest. Expression for the relative bandwidth of the visible output from a light source is called saturation. And relative expression of the intensity of the energy output of a visible light source is called brightness. It can also be expressed as the amplitude at the wavelength where the intensity is greatest. For the proposed work 60 leaf images were considered in each category such as healthy, nitrogen defective, phosphorus defective and potassium defective and more than 150 images were used as test images. HSV color features are extracted from these four categories along with test images. Based on Hue, Saturation and Intensity (HSV) color model, mean, minimum, maximum, deviation values are computed for every image in each dataset. Then minimum of minimum value, maximum of maximum value are also computed. Since hue value resulted in accurate results compared to saturation and value, average hue, minimum hue and maximum hue and deviation value of all four categories are extracted. A sample potassium defected paddy leaf with hue, saturation and intensity image is as shown in figure 4.

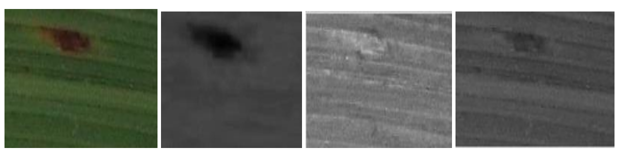

Fig 4. Hue, saturation and value of a sample potassium defected paddy leaf

Healthy leaf images database values to be compared against unhealthy leaf images are as shown in table 1 and the database values for nitrogen defective paddy leaf images to be compared against test images are as shown in table 2.

Table 1. Healthy leaf data base properties

Healthy	Min	Max	Mean	Deviation
Average Hue value	0.2157	0.2869	0.2418	0.0138
Minimum Hue value	0.1810	0.2389	0.2050	0.0122
Max Hue value	0.2398	0.3333	0.2775	0.020

Table 2. Defective portion of Nitrogen data base Hue values

Nitrogen Defected	Min	Max	Mean	Deviation
Average Hue value	0.1303	0.1760	0.1525	0.0147
Minimum Hue value	0.0667	0.1608	0.0936	0.0325
Max Hue value	0.1647	0.1804	0.1779	0.0055

The database values for phosphorus defective paddy leaf images to be compared against test images are as shown in table 3.

Table 3. Defective portion of Phosphorous Defect data base Hue values

Phosphorous Defected	Min	Max	Mean	Deviation
Average Hue value	0.0533	0.13	0.0953	0.0164
Minimum Hue value	0.0196	0.0745	0.0565	0.0213
Max Hue value	0.0745	0.1804	0.1431	0.0383

The database values for potassium defective paddy leaf images to be compared against test images are as shown in table 4.

Table 4. Defective portion of Potassium Defect data base Hue values

Potassium Defected	Min	Max	Mean	Deviation
Average Hue value	0.0861	0.1280	0.1310	0.02
Minimum Hue value	0.0078	0.0275	0.0126	0.02
Max Hue value	0.1804	0.1804	0.1804	0.0

The mean and the deviation values for the healthy, nitrogen defected, potassium defected and phosphorus defected leaf image is as shown in the table 5.

Table 5. Mean and Deviation values

Hue value	Mean Value(μ)	Deviation(σ)
Healthy pixels	0.2418	0.0138
Nitrogen defective pixels	0.1525	0.0147
Phosphorous defective pixels	0.0953	0.0164
Potassium defective pixels	0.1310	0.02

The mean values of healthy green paddy leaves is highest compared with unhealthy paddy leaves as shown in the figure 5.

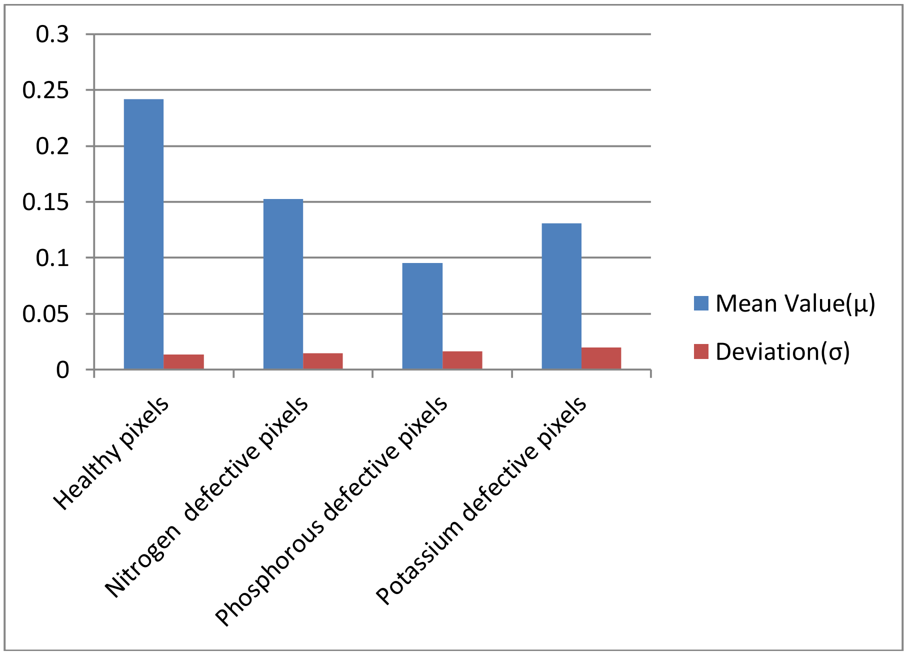

Fig 5. Mean and Deviation plot.

Classification

Classification is attempted in two stages. First level is to classify healthy and non-healthy paddy leaves and second level is to classify unhealthy paddy leaves as nitrogen, phosphorus and potassium defective paddy leaf images as shown in figure 6.

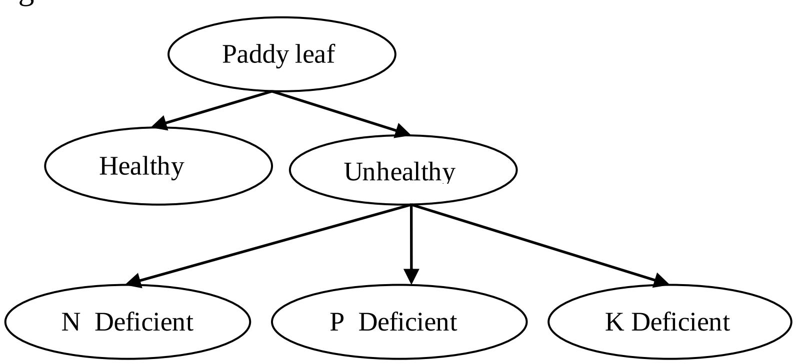

Fig 6. Classification diagram

First Level

The first level of classification is to identify the given image as healthy or unhealthy.

1. Identify number of pixels which are non-healthy in the test image to compute percentage of deviation from being healthy.
2. If the percentage of failure samples in test image is less than the percentage of failure samples in nitrogen, phosphorus or potassium defected paddy leaf then image shall be considered as healthy otherwise the image is unhealthy paddy leaf image.

Second Level

The second level further classifies an unhealthy image as nitrogen defective, phosphorus defective or potassium defective image.

1. Identify number of pixels which are non-healthy in the test image to compute percent of deviation from being healthy.
2. If the percentage of failure samples in test leaf is more than or equal to the percentage of failure samples in trained nitrogen, phosphorus or potassium defected leaf then image shall be considered as defective leaf.
3. Extract the computed hue properties for failure portion in the test image.
4. Calculate the mean hue, minimum hue and maximum hue and deviation value of failure portion.
5. Compare with database properties and identify the defective type of leaf.

The rule set to identify a leaf as healthy or nitrogen defected, phosphorus defected or potassium defected is as shown in table 6. Rule 1 is used for first level classification to recognize healthy and unhealthy paddy leaves. And Rule two is used for second level classification to further classify unhealthy paddy leaf as a particular nutrient deficient paddy leaf.

Table 6. Rules used for classification

Rule No		Rules	Healthy	Unhealthy
1		If percentage of failure samples in test leaf is less than minimum percentage of failure samples in nitrogen, phosphorus and potassium defected paddy leafs.	Yes	No
2	2.1	If test image hue mean lies in the range of hue mean - deviation and hue mean + deviation of a particular deficient image database. (N, P or K) AND	No	Nitrogen deficient or Phosphorus deficient or Potassium deficient
	2.2	Percentage of failure samples in test image is greater than equal to minimum of percentage of failure samples of all images in particular deficient image database AND		
	2.3	If test image hue minimum value is greater than or equal to minimum of all image hue minimum and test image hue maximum is less than or equal to maximum of all image hue maximum		

Around 46 images are tested against trained healthy paddy leaf image database. Hue value of each paddy leaf and percentage of failure samples are as shown in table 7. Percentage of failure samples is calculated using the formula 1 after comparing test leaf hue value with minimum hue and maximum hue of the healthy leaf trained data base.

Percentage of failure samples = (Deviated pixels*100)/Total number of pixels. (1)

Table 7. Hue value of healthy tested images and percentage of failure samples.

Sl No	Hue value of healthy tested images	Percentage of failure samples	Sl No	Hue value of healthy tested images	Percentage of failure samples
1	0.248069	0	24	0.233658	0
2	0.248069	0	25	0.241522	0
3	0.285777	0	26	0.241358	0
4	0.243574	0	27	0.235212	0
5	0.247562	0	28	0.232799	0
6	0.235304	0	29	0.232799	0
7	0.244014	0	30	0.247877	0
8	0.252194	0	31	0.243025	0
9	0.252194	0	32	0.237785	0
10	0.286885	0	33	0.228118	0
11	0.238702	0	34	0.233671	0
12	0.238091	0	35	0.228417	0
13	0.245782	0	36	0.238262	0
14	0.249931	0	37	0.230850	0.0032
15	0.266499	0	38	0.233357	0
16	0.269291	0	39	0.232209	0
17	0.266499	0	40	0.235235	0
18	0.258397	0	41	0.232717	0
19	0.250556	0	42	0.240587	0
20	0.250184	0	43	0.240659	0
21	0.215742	0	44	0.237395	0
22	0.236714	0	45	0.239659	0
23	0.232207	0	46	0.236583	0

Around 31 images are tested against trained nitrogen defected paddy leaf image database. Hue value of each paddy leaf and percentage of failure samples are as shown in table 8. Around 36 images are tested against trained phosphorus defected paddy leaf image database. Hue value of each paddy leaf and percentage of failure samples are as shown in table 9.

Table 8. Hue value of nitrogen defect tested images and percentage of failure samples.

Sl No	Hue value of nitrogen defect tested images	Percentage of failure samples	Sl No	Hue value of nitrogen defect tested images	Percentage of failure samples
1	0.134596	100	17	0.160486	77.03
2	0.167915	30.86	18	0.154354	72.48
3	0.153462	98.78	19	0.148074	97.16
4	0.161595	91.16	20	0.141928	99.65
5	0.149005	92.75	21	0.152544	99.92
6	0.149805	99.95	22	0.142279	100
7	0.149805	99.95	23	0.162888	74.68
8	0.145841	77.37	24	0.158903	94.89
9	0.165736	7.12	25	0.138938	100
10	0.149371	100	26	0.164605	86.48
11	0.204975	1.70	27	0.204975	1.32
12	0.204975	1.99	28	0.159595	99.83
13	0.161336	99.69	29	0.144792	99.90
14	0.130296	100	30	0.141023	86.78
15	0.141644	99.95	31	0.147919	94.73
16	0.155109	76.32			

Table 9. Hue value of phosphorus defect tested images and percentage of failure samples.

Sl No	Hue value of phosphorus defect tested images	Percentage of failure samples	Sl No	Hue value of phosphorus defect tested images	Percentage of failure samples
1	0.123539	87.80	19	0.143273	43.39
2	0.106017	97.64	20	0.097192	100
3	0.129967	99.16	21	0.091197	100
4	0.126915	97.69	22	0.137474	94.95
5	0.092637	100	23	0.103898	99.99
6	0.056903	100	24	0.094969	100
7	0.060051	100	25	0.097027	100
8	0.099510	100	26	0.096177	100
9	0.105383	100	27	0.107080	100
10	0.127358	71.35	28	0.138879	99.11
11	0.134762	85.46	29	0.121373	100.00
12	0.128882	100	30	0.129747	100
13	0.053272	100	31	0.133399	100
14	0.129626	100	32	0.100634	98.28
15	0.075904	100	33	0.105161	93.71
16	0.137390	100	34	0.132975	100
17	0.083487	100	35	0.106905	97.74
18	0.086761	100	36	0.122344	81.31

Around 50 images are tested against trained potassium defected paddy leaf image database. Hue value of each paddy leaf and percentage of failure samples are as shown in table 10.

Table 10. Hue value of potassium defect tested images and percentage of failure samples.

Sl No	Hue value of potassium defect tested images	Percentage of failure samples	Sl No	Hue value of potassium defect tested images	Percentage of failure samples
1	0.151121	47.89	26	0.130508	5.74
2	0.129001	8.41	27	0.143294	52.98
3	0.150868	26.36	28	0.149321	21.61
4	0.109651	14.60	29	0.146439	12.29
5	0.157679	67.27	30	0.133315	4.33
6	0.153380	24.77	31	0.126529	8.11
7	0.131198	7.54	32	0.128024	5.50
8	0.116937	62.96	33	0.150251	12.83
9	0.147841	10.99	34	0.116061	12.89
10	0.131002	50.33	35	0.089781	4.13
11	0.095254	53.42	36	0.115379	4.77
12	0.155893	12.23	37	0.204975	3.63
13	0.129222	6.84	38	0.100956	14.38
14	0.154092	10.59	39	0.098774	6.34
15	0.134959	16.39	40	0.104904	4.62
16	0.126018	24.84	41	0.086129	13.76
17	0.146253	7.72	42	0.090158	13.09
18	0.152118	59.89	43	0.130077	4.94
19	0.153114	35.25	44	0.138466	5.27
20	0.126793	16.20	45	0.094432	49.39
21	0.122179	43.14	46	0.108758	9.01
22	0.113225	19.35	47	0.112316	13.46
23	0.204975	3.31	48	0.129771	3.75
24	0.099053	3.85	49	0.154425	13.74
25	0.146365	37.58	50	0.127182	68.00

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Results and Discussion

A total of 165 images were considered for testing. Results show whether an input test image is healthy or non-healthy. If it is not healthy it further classifies as nitrogen, phosphorus or potassium defective leaf. To classify test image as healthy its hue value is computed and compared with pre computed database properties as shown in table 1. If the percentage of defective pixels of test image is greater than percentage of defective pixels of nitrogen, phosphorus and potassium defective images then given test image is unhealthy paddy leaf image otherwise the test image is healthy. Healthy tested hue values and percentage of failure samples are as shown in figure 7 and 8.

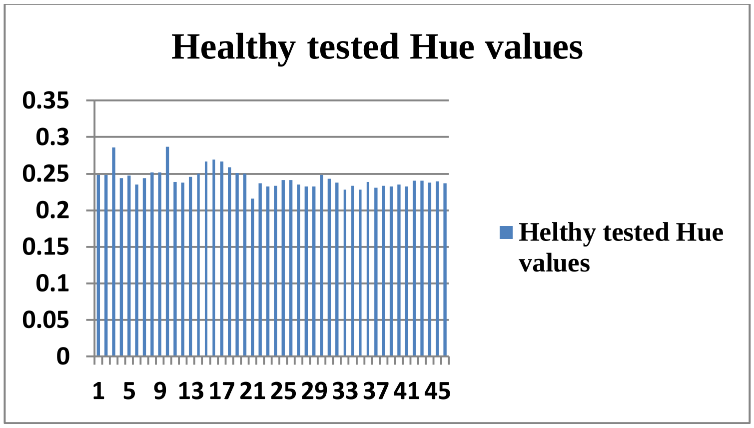

Fig 7. Healthy tested hue values.

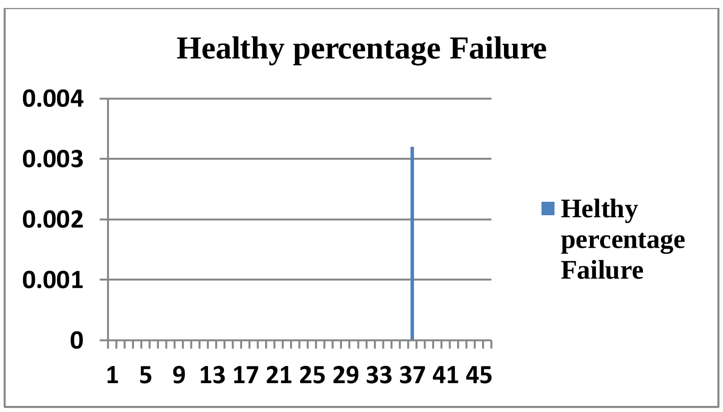

Fig 8. Healthy percentage of failure samples.

To further classify test image as nitrogen defective the hue value is compared with the minimum green value of healthy database to obtain the binary image, later binary image is logically AND operated with hue matrix of original image to obtain resultant image. Along with the binary image percentage of deviation from being healthy is calculated using the formula 1. The above procedure is repeated for phosphorus and potassium defective images. The test image hue minimum, hue maximum, hue mean and deviation are extracted and are compared with the rules 2.1 to 2.3 from the rule set table 6 to detect a test image as nitrogen defected paddy leaf or not. Sample nitrogen defective image and its binary image are as shown in figure 9. Nitrogen tested hue values and percentage of failure samples are as shown in fig 10 and 11.

Fig 9. Sample nitrogen defective image, binary image.

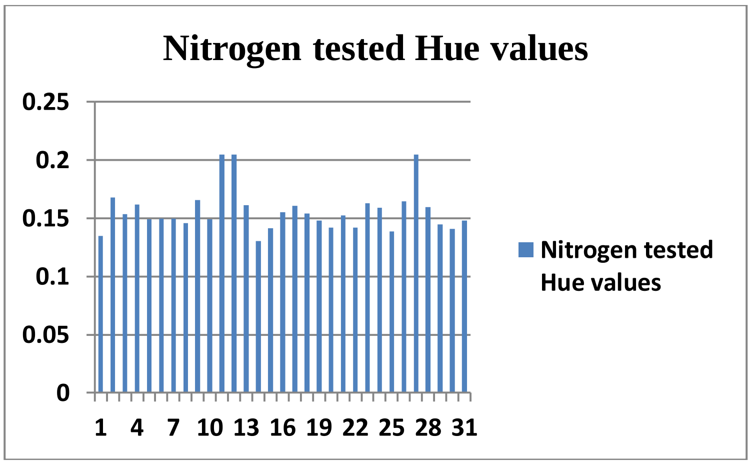

Fig 10. Nitrogen tested hue values.

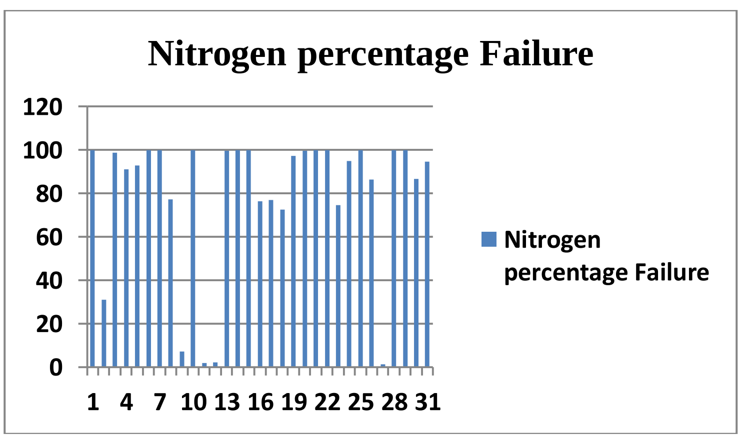

Fig 11. Nitrogen percentage of failure samples.

The test image hue minimum, hue maximum, hue mean and deviation are extracted and are compared with the rules 2.1 to 2.3 from the rule set table 6 to detect a test image as phosphorus defected paddy leaf or not.

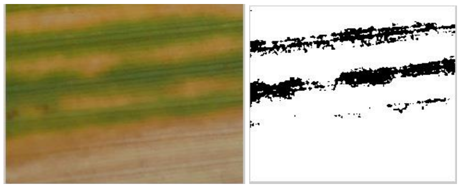

Fig 12. Sample phosphorus defected leaf image with its binary image.

Sample phosphorus defective image and its binary image are as shown in figure 12. Phosphorus tested hue values and percentage of failure samples are as shown in figure 13 and figure 14.

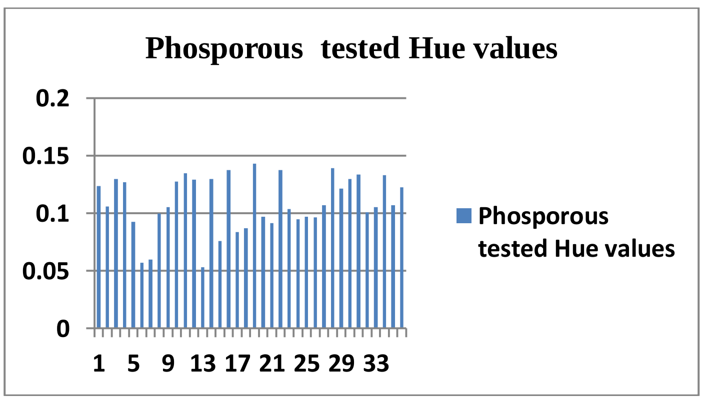

Fig 13. Nitrogen tested hue values.

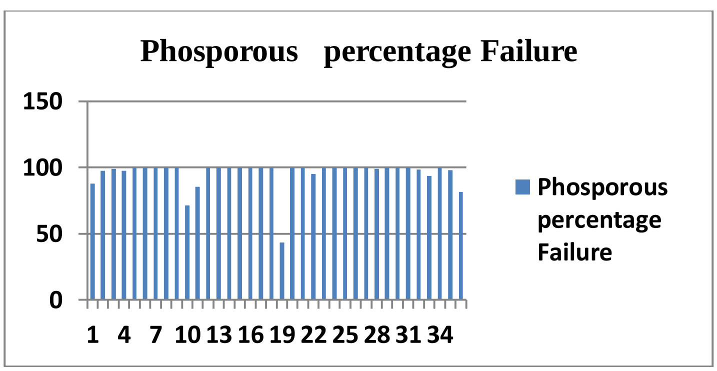

Fig 14. Phosphorus percentage of failure samples.

The test image hue minimum, hue maximum, hue mean and deviation are extracted and are compared with the rules 2.1 to 2.3 from the rule set table 6 to detect a test image as potassium defected paddy leaf or not.

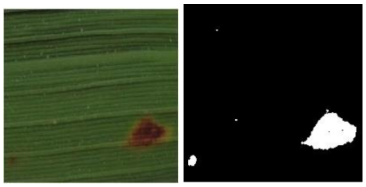

Fig 15. Sample potassium defective image and its binary image.

Sample potassium defective image and its binary image are as shown in figure 15. Potassium tested hue values and percentage of failure samples are as shown in fig 16 and figure 17.

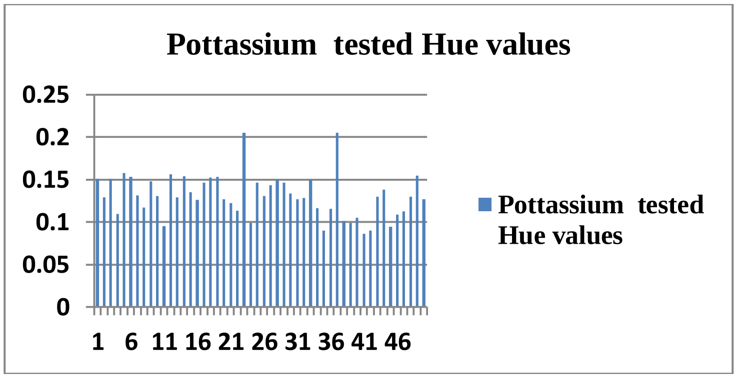

Fig 16. Potassium tested hue values.

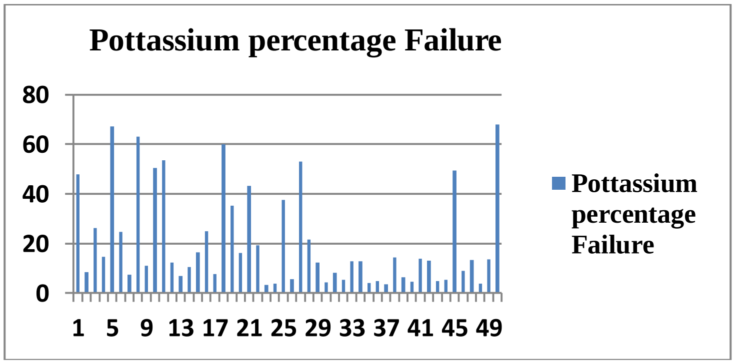

Fig 17. Potassium percentage failure samples.

The average hue value of all the healthy and nutrient defective paddy leaf is as shown in figure 18. The average hue values match with that of trained database. The average percentage of failure samples of all the tested images are as shown in figure 19. The percentage of failure samples of healthy images is zero as all the pixels are green in color and satisfy all the rules defined in the rule set. The precentage of failure samples in potassium defected paddy leaf is also less because most part of the leaf is green except for the brown spots in the leaf. Phosphorus and nitrogen defected leaf has more defective samples as the leaf is non green in color.

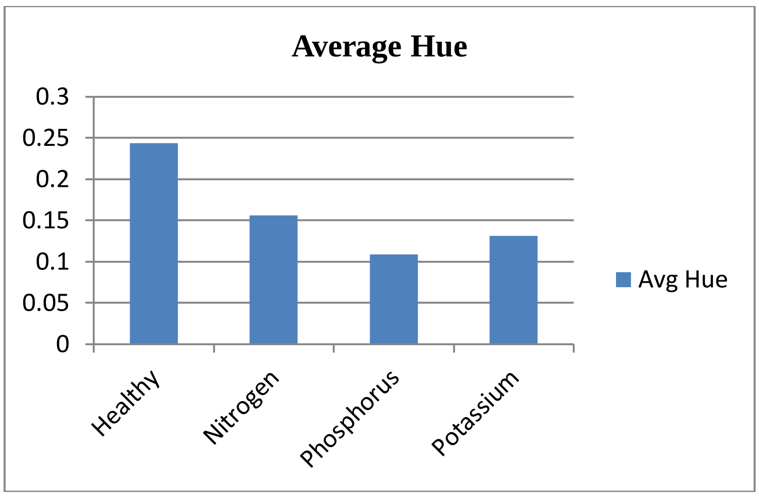

Fig 18. Average Hue value of all tested images

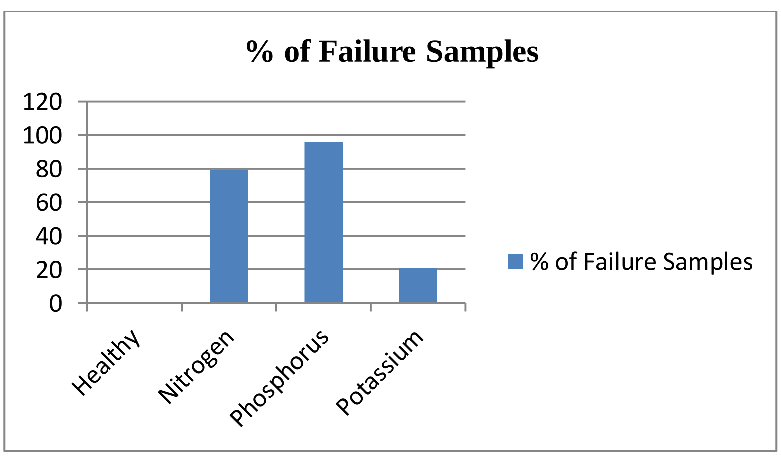

Fig 19. Average percentage of failure samples of all tested images

The accuracy chart which expains the number of images trained in each category, the number of images tested and its rate of identification is as shown in the table 11.

Table 11. Result of defective leaf detection algorithm**.**

Leaf Image	No of Images used for Training	No of Images used for testing	No of Images detected as a particular nutrient	Detection Accuracy
Healthy	60	46	46	100.00%
Nitrogen	60	31	28	90.32%
Phosphorous	60	36	35	97.22%
Potassium	60	50	47	94.00%
Overall Accuracy				95.39%

Conclusion

A total of 165 test images were used for identifying healthy and specific nutrient element deficiency in paddy leaves. Results show healthy leaf classification accuracy up to 100%, rate of nitrogen, phosphorus and potassium deficiency identification was 90.32%, 97.22% and 94% respectively with an overall identification accuracy of 95.39%. The proposed work finds its application in timely recognition of nutrient deficiency in paddy crop. The work concentrates on paddy leaves and NPK deficiency only which can be further extended for other nutrient deficiencies like boron, manganese etc. and also be applied on entire paddy field images.

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