International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 8 (2015) pp. 19441-19456

http://www.ripublication.com

Maize Leaf Deficiency Identification Using Multivariate Partial Least Square Regression

[1]S. Sridevy and [2]Dr. Anna Saro Vijendran
[1]Assistant Professor, Dept. of PS&IT, AEC&RI, Tamil Nadu Agricultural University, Coimbatore
[2]Director & Head, Department of MCA in SNR Sons College, Coimbatore

Abstract

This paper is for identifying the deficiency part in the maize crop leaf. Nowadays leaf analysis is one of the innovative researches for many applications. Every plant and crop production need nutrient for their growth. Totally 16 nutrients are required for crop growth. The proposed system implements a novel approach to identify the lack of nutrients in the crop image. Images are collected from the Agricultural University, Coimbatore. The input images are processed in three steps: preprocessing, feature extraction and regression. In the preprocessing, HSV transformation and histogram enhancement are processed. After the preprocessing, ICA is carried out to extract a reference eigenmatrix. Three types of features are extracted from crop image, they are color, shape, texture features. From the extracted features, the nutrient deficiency is identified using Multivariate Partial Least Square (MPLS). After MPLS process Kappa coefficient is calculated in order to find the performance of the regression method. Experimental result proves the better regression output than existing one.

Introduction

Due to the increasing costs of crop production and to the progressing environmental pollution by agrochemicals, mineral fertilizers should be applied more efficiently. This concerns primarily N, because the over application of this element leads to low N recovery efficiency and to a risk of nitrate pollution of ground waters. The diagnostics of disease symptoms in plants, including those resulting from nutrient deficiencies, require quick, reliable and precise instrumental techniques enabling to recognize the symptoms of physiological disorders prior to the occurrence of responses to stress factors that can be observed visually. The majority of them affect the composition and proportions of pigments in leaf tissues [6].

For growth and development, plants need some food. Each plant wants 16 essential elements for its development. They are Carbon, hydrogen, and oxygen are derived from the atmosphere and soil water and the remaining 13 elements are nitrogen, phosphorus, potassium, calcium, magnesium, sulfur, iron, zinc, manganese, copper, boron, molybdenum, and chlorine. Based on soil minerals and soil organic matter these are supplied by organic and inorganic fertilizer [10].

If the nitrogen supply is decreases in plant then the Relative Growth Rate (RGR) for the respective plant is decreased. This type of decrease is mainly happened through decreases in leaf area ratio (LAR). It is also depend on the lower Leaf Mass Ratio (LMR), but it is not usual and also decreases in Specific Leaf Area (SLA) [7and 8].

Some of the nutrients in plants are changed. In [9] the author tells about the concentration of nitrate in sols and their changes. This type of concentration is affected by two processes they are denitrification and leaching. Denitrification is happen when the soil is undertaken with water temporarily and the oxygen part is removed from the soil pores. Leaching of nitrate occurs in soils when excessive water moves through the profile, especially sandy soils.

Literature Survey

Plant species identification is carried over in [11]. Here the author proposed an efficient algorithm to detect the leaf by using computer-aided plant species identification and this system is depend on the shape of the leaf images. Nevertheless, standard laboratory analysis of N concentration in the above-ground biomass is expensive and time consuming, especially if a rapid crop N status evaluation is required for in-season decision making procedures [12]. For this reason, quick and practical tests have been proposed, some of which are already spread among growers. Opto-electronic based techniques can strongly help to reach the previously mentioned goals, thanks to easiness of use and low costs. Two of the most common and simple of these are: the chlorophyll meter readings (e.g., SPAD-502, Minolta) and the measurements of N-NO3 concentration in petiole sap (SAP test).

In [13] studied the color of robusta (Cofea canephora Pierce ex Froehner) leaves, and noted the occurrence of a significant linear dependence between the N content of leaves and readings on a chlorophyll meter. In [14] analyzed leaf spectral reflectance, transmittance and absorbance under conditions of physiological stress in five plant species, and reported that the greatest differences occurred at wavelengths around 700 nm. The most significant changes in reflectance concerned the yellow-green color, which was ascribed to the effect of stress on a decrease in the chlorophyll content of leaves. However, in some cases these changes were not specific to particular stress factors, implying the need to continue research into changes in the color of leaves in plants exposed to stressors.

Nitrogen is one of the most important nutrients for plant growth and its fertilizer is used for the crop yield maximization [15, 16 and 17]. However, improper use of N fertilizer and other crop production management practices cancause nitrate (NO3) leaching below the crop root zone, which may eventually contaminate ground water [18 and 19].

The objective of this study was to determine changes in the color of the leaf to identify the deficiency of nutrients such as N, P, K and Mg. A number of supervised and unsupervised approaches are available in the literature to carry out defect identification in plants. But, most of the existing supervised techniques do not offer accurate results under non-linear problem conditions.

Methodology

In this paper proposed a novel approach to identify the deficiency of nutrients. The proposed system divides the system into preprocessing, feature extraction and regression. Classification system provides lack of transparency in result and also it is computationally expensive one. To overcome this, implement or introduce the regression method that regression model is fitted to each variable and give the predicted value. Better predictions are done using multivariate regression. The main thing to use regression than classification is predict the value of one variable given the value of another and learn how to control future values of a variable by controlling values of variables it's related it.

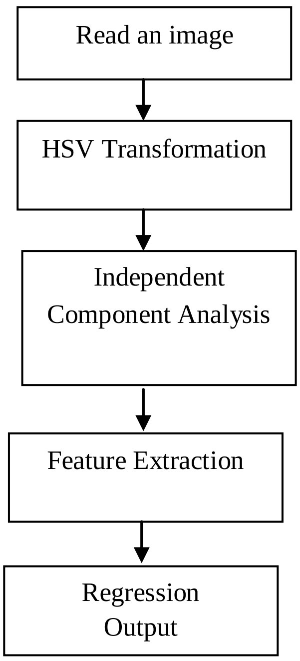


Figure 1: Overall Methodology

A. HSV Color Transformation

The HSV color space is essentially completely different from the wide noted RGB color space since it separates out the Intensity (luminance) from the color data (chromaticity). Again, of the two chromaticity axes, a distinction in Hue of a element is found to be visually a lot of distinguished compared to it of the Saturation. For every element, either its Hue or the Intensity is chosen because the dominant feature supported its Saturation. In situations where color description plays an integral role, the HSV color model is often preferred over the RGB model. The HSV model describes colors similarly to how the human eye tends to perceive color. RGB defines color in terms of a combination of primary colors, whereas, HSV describes color using more familiar comparisons such as color, vibrancy and brightness.

The significance of HSV over RGB is been clearly illustrated in. [1]. In [1] that the approximation done by the RGB feature blurs the distinction between two visually separable colors by changing the brightness. But, the HSV based approximation can determine the intensity and shade variations near the edges of an object, thereby sharpening the boundaries and retaining the color information of each pixel. This makes the HSV-based features very useful in image analysis. So, this approach uses HSV color transformation approach.

Initially, the RGB images of maize crop leaves are acquired. Then, RGB images are converted into Hue Saturation Value (HSV) color space representation. Hue is a color attribute that describes pure color as perceived by an observer. Saturation refers to the relative purity or the amount of white light added to hue and Value means amplitude of light. Considering that (I) exists in RGB color space, then

$$mx_{(i,j)} = max\left(I_{R(i,j)}, I_{G(i,j)}, I_{B(i,j)}\right) \tag{1}$$

$$min_{(i,j)} = min\left(I_{R(i,j)}, I_{G(i,j)}, I_{B(i,j)}\right) \tag{2}$$

$$H(i,j) = \begin{bmatrix} \frac{60*\left(I_{G(i,j)}-I_{B(i,j)}\right)}{mx-min} & I_{R(i,j)} > max\left(I_{G(i,j)}, I_{B(i,j)}\right) \\ \frac{180*\left(I_{B(i,j)}-I_{R(i,j)}\right)}{mx-min} & I_{G(i,j)} > max\left(I_{R(i,j)}, I_{B(i,j)}\right) \\ \frac{300*\left(I_{R(i,j)}-I_{G(i,j)}\right)}{mx-min} & I_{B(i,j)} > max\left(I_{R(i,j)}, I_{G(i,j)}\right) \end{bmatrix} \tag{3}$$

$$V(i,j) = [mx] \tag{4}$$

$$S(i,j) = \frac{[mx-min]}{mx} \tag{5}$$

After the transformation process, the Hue component is taken for further analysis. Saturation and Value are dropped since it does not give extra information. Figure 2 shows the H, S and V components.

B. Histogram Equalization for Image Enhancement

Histogram Equalization is a technique that generates a gray map which changes the histogram of an image and redistributing all pixels values to be as close as possible to a user –specified desired histogram. HE allows for areas of lower local contrast to gain a higher contrast. Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram. Histogram equalization is a method in image processing of contrast adjustment using the image histogram. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values [2].

Histogram equalization automatically determines a transformation that produces an image with uniform histogram of intensity values. Consider a discrete grayscale image {x} and let n_i be the number of occurrences of gray level i. The probability of an occurrence of a pixel of level i in the image is

$$P_x(i) = p(x = i) = \frac{n_i}{n}, 0 \leq i \leq L \tag{6}$$

Where L being the total number of gray levels in the image, n being the total number of pixels in the image, and $P_x(i)$ is the image's histogram for pixel value i, normalized to [0,1].Let us also define the cumulative distribution function corresponding to P_x as

$$cdf_x(i) = \sum \tag{7}$$

$$cdf_x(i) = \sum_{j=0} P_x(j) \tag{8}$$

This is also the image's accumulated normalized histogram. A transformation of the form y = T(x) is created to produce a new image {y}, such that its CDF will be linearized across the value range, i.e. for some constant K.

$$cdf_y(i) = iK \tag{9}$$

The properties of the CDF allow us to perform such a transform; it is defined as

$$y = T(x) = cdf_x(x) \tag{10}$$

The function T maps the levels into the range [0, 1]. The above describes histogram equalization on a gray scale image. However it can also be used on color images by applying the same method separately to the Red, Green and Blue components of the RGB color values of the image. The image is first converted to another color space, HSL/HSV color space in particular, then the algorithm can be applied to the luminance or value channel without resulting in changes to the hue and saturation of the image. The color intensities are spread uniformly leaving hues and saturation unchanged [3, 4].

C. Independent Component Analysis

Several ICA algorithms have been proposed so far, which are different in objective functions (or contrast functions) for statistical independence and how to derive ICA algorithms [1, 8, 9, 10]. In general, estimated independent components obtained by using these algorithms are different each other. However, it is difficult to discuss which algorithms are most appropriate for feature extraction of characters in the present circumstances. Hence, in the followings, we shall adopt Fast ICA algorithm proposed by Hyvarinen and Oja [5] from its convergence speed.

Suppose that we observe a m-dimensional zero mean input signal at time t, $v(t) = \{v_1, \ldots, v_m\}'$ where,$'$ means the transposition of matrices and vectors. Then the n-dimensional whitening signal, x (t), is given by the following equation:

$$x(t) = Mv(t) = D^{-1/2}E'v(t) \tag{17}$$

Where M means a n×m(n≤m) whitening matrix that is given by a matrix of eigen values, D, and a matrix of eigenvectors, E. Here, assume that v (t) is composed of n statistically independent signals, $s(t) = \{s_1(t), \dots, s_n(t)\}'$. Then, the following linear transformation from x(t) to s(t) exists:

$$s(t) = Wx(t) \tag{18}$$

$W = \{w_1, \dots, w_n\}'$ is often called a separating matrix, and it can be acquired through the training of a two-layer feed forward neural network. This neural network has n outputs denoted as $\hat{s}(t) = \{\hat{s}_1(t), \dots, \hat{s}_n(t)\}'$ and the ith row vector, $w_i'(i = 1, \dots, n)$ofW corresponds to a weight vector from inputs to the ith output$\hat{s}_i$. The term 'independent' is used here according to the following definition in statistics:

$$p[s_1(t), \dots, s_n(t)] = \prod_{i=1}^{n} pi[s_i(t)] \tag{19}$$

Where p[.] is a probability density function. Since the above probability density function is not preliminary unknown, suitable objective functions should be devised such that neural outputs $\hat{s}_i$ are satisfied with Eq. (19) as much as possible, that $\tilde{s}(t) \approx s(t)$. Karhunen and Oja have proposed the following objective function [10], J (.), to be maximized in terms of output signals$\hat{S}$:

$$J(\hat{s}) = \sum_{i=1}^{n} \left| E\{\tilde{s_i}^4\} - 3\left[E\{\grave{s_i}^2\}\right]^2 \right| \tag{20}$$

Where E{.} means expectation. As well known, Eq.(20) corresponds to the fourth-order cumulants of $\tilde{s}_i(t)$ called kurtosis. Learning algorithms for a separation matrix, W, are derived from the gradient of Eq. (20). In the followings, we adopt Fast ICA algorithm proposed by Hyvarinen & Oja in which fixed points of the gradient are obtained on-line.

Feature Extraction

Feature extractions are done by some parameters they are entropy, energy, eccentricity, perimeter, mean, standard deviation, and variance. Mean (E) - Mean value of pixel intensities in the block is defined as arithmetic average of distribution of pixels in the block. It is computed using the function mean () in mat lab.

$$\sum_{i}^{n-1} \sum x_i / N \tag{11}$$

Standard Deviation (σ) - Standard deviation of pixel intensities in the block is defined as calculated using the function std () in mat lab.

$$\sigma_i^{n-1} = \sum (x - \mu) \tag{12}$$

Variance (v) is the square of the standard deviation

$$v = (\sigma_i^{n-1})^2 \tag{13}$$

Perimeter (P) - Perimeter is defined as the distance around the block and computed using the formula

$$P = 2 * (H + W) \tag{14}$$

Energy (E) - It is defined as sum of squared elements in the image and is also known as uniformity or the angular second moment.

$$\sum_{i-1}^{n} = \sum x_i^2 \tag{15}$$

Entropy- It is defined as statistical measure of randomness that can be used to characterize the texture of the input image. It is calculated using the function entropy () in mat lab.

$$Entropy = \sum_{i,j} P(i,j) log P(i,j) \tag{16}$$

Multivariate Partial Least Square (MPLS)

Multivariate data analysis is the simultaneous observation of more than one characteristic. In contrast to the analysis of univariate data, in this approach not only a single variable or the relation between two variables can be investigated, but the relations between many attributes can be considered. In general consider an multivariate linear regression model with an n× m matrix X of predictors and an n × p matrix Y of dependent variables; both matrices are mean-centered. Similar to Principal component regression (PCR), approximate

$$X \approx TP^T$$

$$Y \approx UQ^T$$

In this equation T and U are the respective score matrices that consist of linear combination of the x and y variables. Then P and Q are the respective loading matrices of X and Y. Note that, unlike in PCR, in PLS in general not the loadings are orthogonal, but the scores a ≤ min(n; m) is the number of PLS components. Additionally, the x- and y-scores are related by the so-called inner relation a linear regression model maximizing the covariance between the x- and y-scores.

U=TD+H

The regression coefficients are stored in a diagonal matrix $D = diag(d_1, \dots, d_a)$ and the residuals in the matrix H. The OLS estimator for D gives us an estimate$\widehat{U} = T\widehat{D}$and thus$\widehat{Y} = T\widehat{D}Q^T$.Using $\widehat{Y} = X\widehat{B}$ then obtain

$$\widehat{B}_{PLS} = P\widehat{D}Q^T$$

The inner relation can destroy the uniqueness of the decomposition of the data matrices X and Y. Normalization constraints on the score vectors t and u avoid this problem. To fulfill these restrictions we need to introduce (orthogonal) weight vectors w and c such that

$$t = Xw \text{ } and \text{ } u = Yc$$

With

$$\|t\| = \|Xw\| = 1 \text{ } and \text{ } \|u\| = \|Yc\| = 1$$

Consequently, here the score vectors do not result from projection of X on loading vectors but on weights.

The objective function of PLS regression can then be written as

$$maxCov(Xw, Yc)$$

or

$$maxt^{T}u = (Xw)^{T}Yc = W^{T}X^{T}Yc$$

with the constraints (6). The maximization problems (7) and (8) are equivalent. From (8) we see that the first weight vectors w1 and c1 are the left and right eigenvectors of the SVD of $X^{T}Y$ corresponding to the largest singular value. In the univariate case $y = Xb + e$, approximate only $X \approx TP^{T}$ and the inner relation reduces to

$$y = Td + h$$

And the PLS estimator for b to

$$\hat{b}_{PLS} = P\hat{d}$$

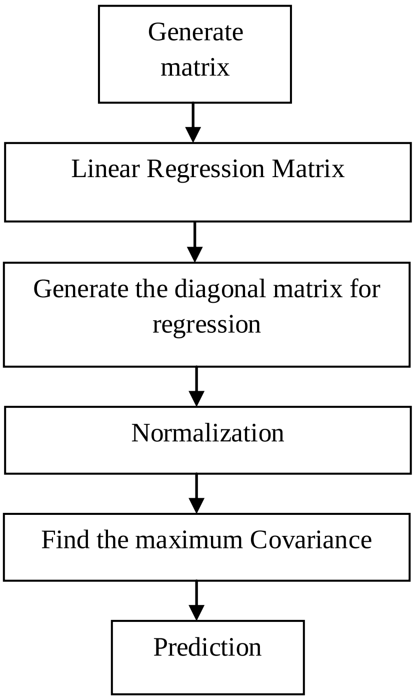


Figure 2: Flow Chart for MPLS algorithm

A. Kappa Co-Efficient

Using this kappa co-efficient the inter class variation can be measured, when two or more class evaluating the same thing. Kappa gives us a numerical rating of the degree to which this class agreement evaluation occurs. The calculation is based on the difference between how much the feature extracted is classified (observed agreement) to how much the feature extracted is expected to be classified by chance alone ("expected" agreement).). Kappa is a measure of this difference, standardized to lie on a -1 to 1 scale, where 1 is perfect agreement, 0 is exactly what would be expected by chance, and negative values indicate agreement less than chance, i.e., potential systematic disagreement between the observers. The overall accuracy of the proposed regression MPLS algorithm is calculated using Cohen's Kappa co-efficient. The kappa coefficient (K) is given by

$$K = \frac{P_A - P_E}{1 - P_E}$$

Where,
P_A is the overall percent classified
P_E is chance of classified.

The overall accuracy of the proposed regression MPLS algorithm is calculated using Cohen's Kappa co-efficient. The kappa coefficient (K) is given by

$$K = \frac{P_A - P_E}{1 - P_E}$$

Where
P_A is the overall percent classified
P_E is chance of classified.

Experimental Result

The experimental process is conducted in MATLAB. Total 60 images are collected from Agricultural University, Coimbatore [20], in those 30 images for training purpose and 30 images for testing purpose.

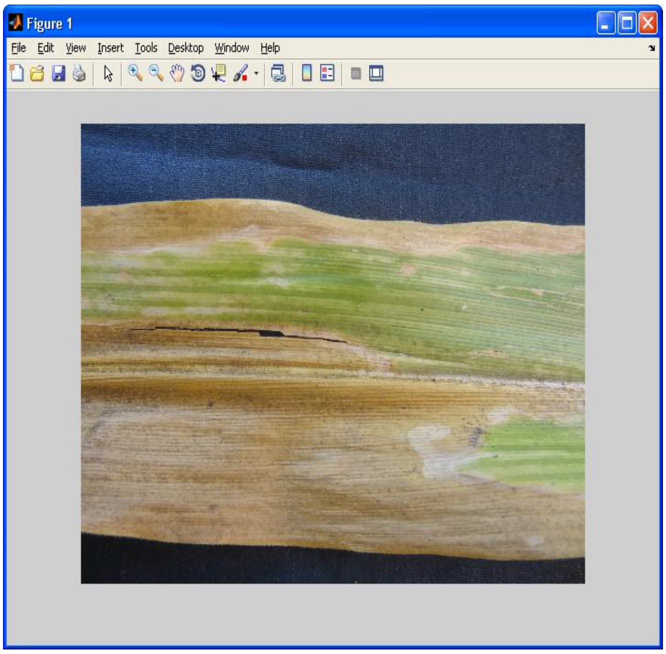


Figure 3: Original Image

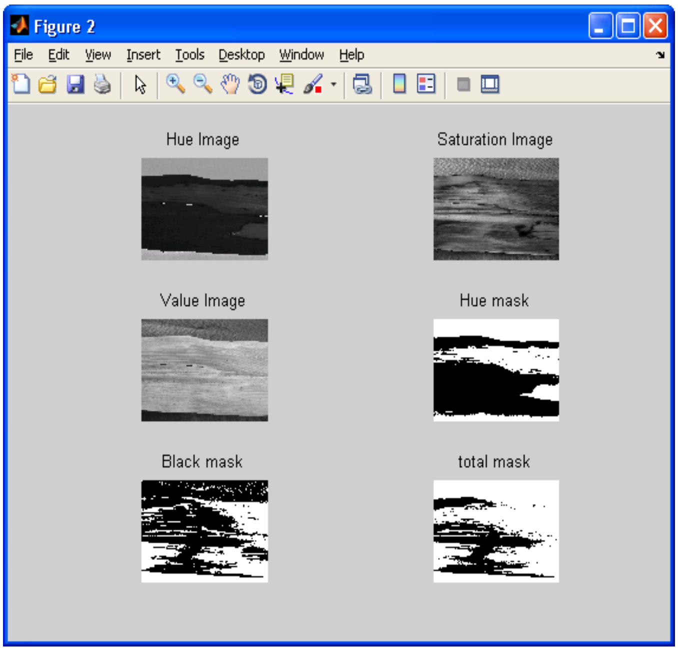


Figure 4: RGB to HSV

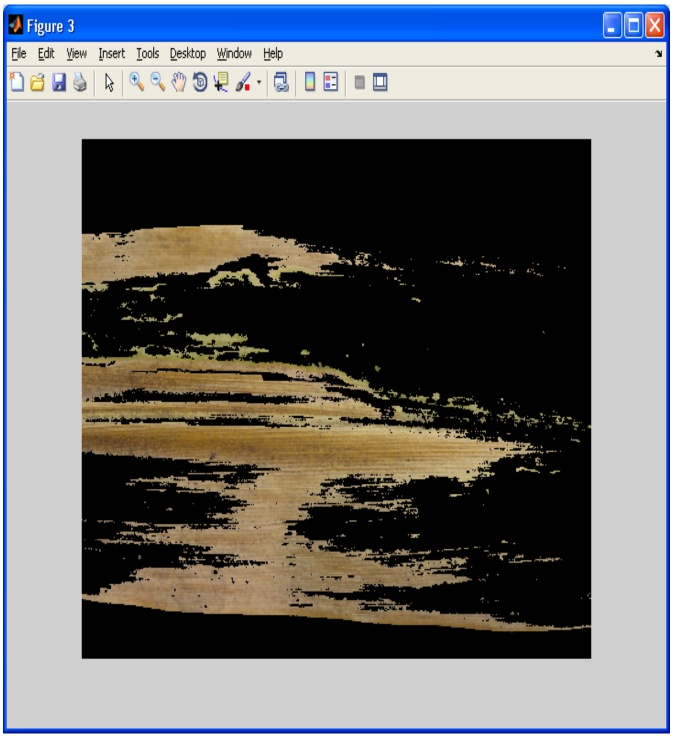


Figure 5: Deficiency Part

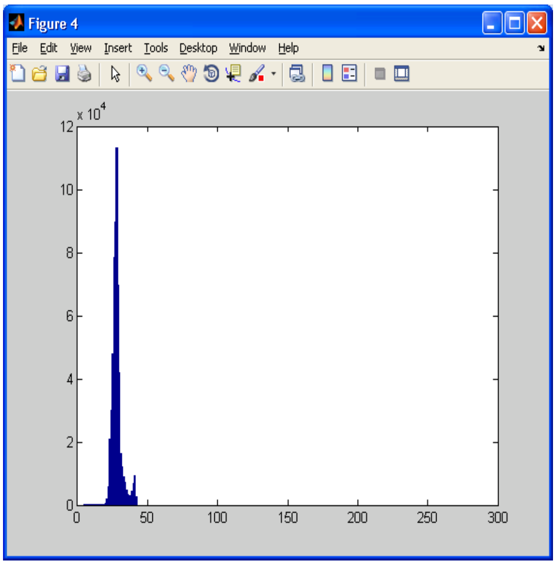
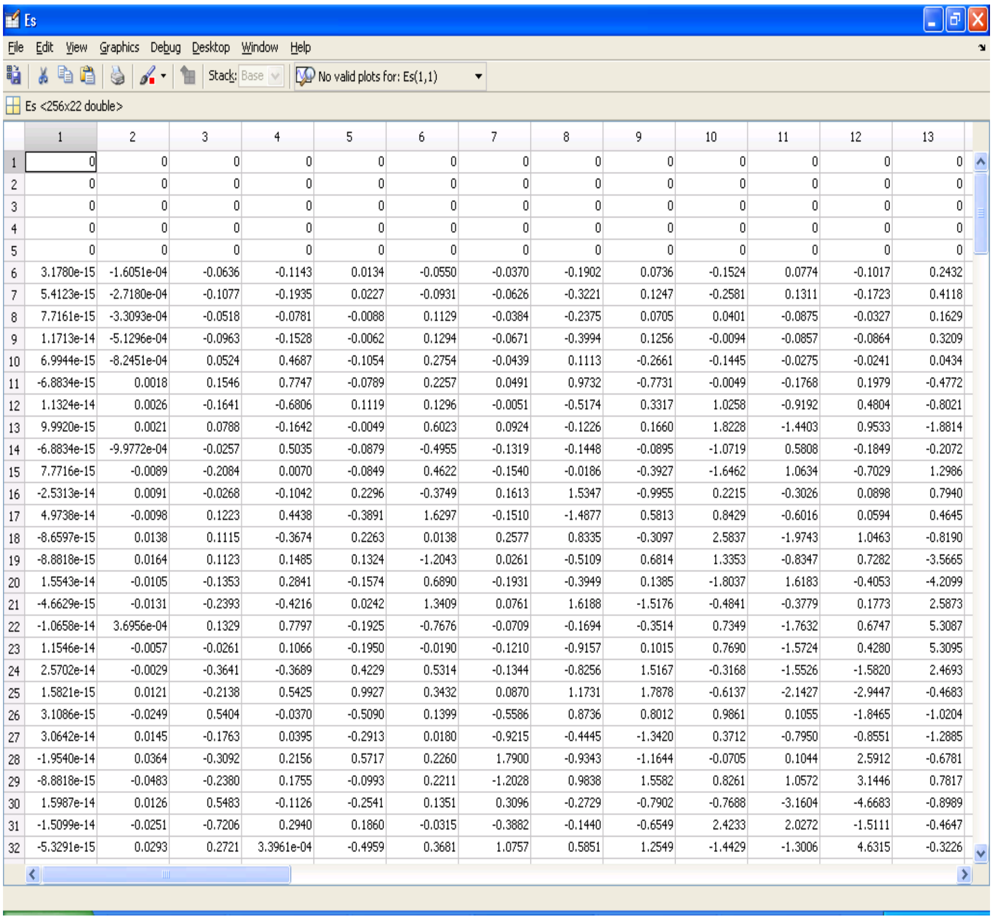


Figure 6: Histogram Plot



	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0
6	3.1780e-15	-1.6051e-04	-0.0636	-0.1143	0.0134	-0.0550	-0.0370	-0.1902	0.0736	-0.1524	0.0774	-0.1017	0.2432
7	5.4123e-15	-2.7180e-04	-0.1077	-0.1935	0.0227	-0.0931	-0.0626	-0.3221	0.1247	-0.2581	0.1311	-0.1723	0.4118
8	7.7161e-15	-3.3093e-04	-0.0518	-0.0781	-0.0088	0.1129	-0.0384	-0.2375	0.0705	0.0401	-0.0875	-0.0327	0.1629
9	1.1713e-14	-5.1296e-04	-0.0963	-0.1528	-0.0062	0.1294	-0.0671	-0.3994	0.1256	-0.0094	-0.0857	-0.0864	0.3209
10	6.9944e-15	-8.2451e-04	0.0524	0.4687	-0.1054	0.2754	-0.0439	0.1113	-0.2661	-0.1445	-0.0275	-0.0241	0.0434
11	-6.8834e-15	0.0018	0.1546	0.7747	-0.0789	0.2257	0.0491	0.9732	-0.7731	-0.0049	-0.1768	0.1979	-0.4772
12	1.1324e-14	0.0026	-0.1641	-0.6806	0.1119	0.1296	-0.0051	-0.5174	0.3317	1.0258	-0.9192	0.4804	-0.8021
13	9.9920e-15	0.0021	0.0788	-0.1642	-0.0049	0.6023	0.0924	-0.1226	0.1660	1.8228	-1.4403	0.9533	-1.8814
14	-6.8834e-15	-9.9772e-04	-0.0257	0.5035	-0.0879	-0.4955	-0.1319	-0.1448	-0.0895	-1.0719	0.5808	-0.1849	-0.2072
15	7.7716e-15	-0.0089	-0.2084	0.0070	-0.0849	0.4622	-0.1540	-0.0186	-0.3927	-1.6462	1.0634	-0.7029	1.2986
16	-2.5313e-14	0.0091	-0.0268	-0.1042	0.2296	-0.3749	0.1613	1.5347	-0.9955	0.2215	-0.3026	0.0898	0.7940
17	4.9738e-14	-0.0098	0.1223	0.4438	-0.3891	1.6297	-0.1510	-1.4877	0.5813	0.8429	-0.6016	0.0594	0.4645
18	-8.6597e-15	0.0138	0.1115	-0.3674	0.2263	0.0138	0.2577	0.8335	-0.3097	2.5837	-1.9743	1.0463	-0.8190
19	-8.8818e-15	0.0164	0.1123	0.1485	0.1324	-1.2043	0.0261	-0.5109	0.6814	1.3353	-0.8347	0.7282	-3.5665
20	1.5543e-14	-0.0105	-0.1353	0.2841	-0.1574	0.6890	-0.1931	-0.3949	0.1385	-1.8037	1.6183	-0.4053	-4.2099
21	-4.6629e-15	-0.0131	-0.2393	-0.4216	0.0242	1.3409	0.0761	1.6188	-1.5176	-0.4841	-0.3779	0.1773	2.5873
22	-1.0658e-14	3.6956e-04	0.1329	0.7797	-0.1925	-0.7676	-0.0709	-0.1694	-0.3514	0.7349	-1.7632	0.6747	5.3087
23	1.1546e-14	-0.0057	-0.0261	0.1066	-0.1950	-0.0190	-0.1210	-0.9157	0.1015	0.7690	-1.5724	0.4280	5.3095
24	2.5702e-14	-0.0029	-0.3641	-0.3689	0.4229	0.5314	-0.1344	-0.8256	1.5167	-0.3168	-1.5526	-1.5820	2.4693
25	1.5821e-15	0.0121	-0.2138	0.5425	0.9927	0.3432	0.0870	1.1731	1.7878	-0.6137	-2.1427	-2.9447	-0.4683
26	3.1086e-15	-0.0249	0.5404	-0.0370	-0.5090	0.1399	-0.5586	0.8736	0.8012	0.9861	0.1055	-1.8465	-1.0204
27	3.0642e-14	0.0145	-0.1763	0.0395	-0.2913	0.0180	-0.9215	-0.4445	-1.3420	0.3712	-0.7950	-0.8551	-1.2885
28	-1.9540e-14	0.0364	-0.3092	0.2156	0.5717	0.2260	1.7900	-0.9343	-1.1644	-0.0705	0.1044	2.5912	-0.6781
29	-8.8818e-15	-0.0483	-0.2380	0.1755	-0.0993	0.2211	-1.2028	0.9838	1.5582	0.8261	1.0572	3.1446	0.7817
30	1.5987e-14	0.0126	0.5483	-0.1126	-0.2541	0.1351	0.3096	-0.2729	-0.7902	-0.7688	-3.1604	-4.6683	-0.8989
31	-1.5099e-14	-0.0251	-0.7206	0.2940	0.1860	-0.0315	-0.3882	-0.1440	-0.6549	2.4233	2.0272	-1.5111	-0.4647
32	-5.3291e-15	0.0293	0.2721	3.3961e-04	-0.4959	0.3681	1.0757	0.5851	1.2549	-1.4429	-1.3006	4.6315	-0.3226

Figure 7: Result Values For Training Dataset –Phosphorous

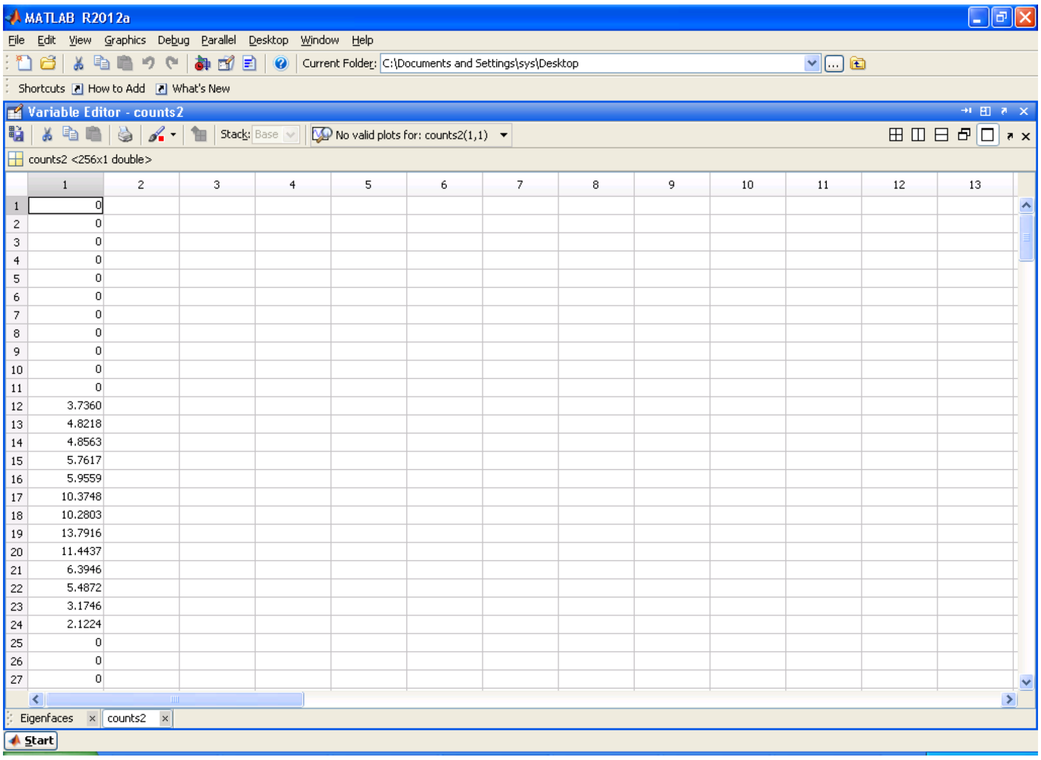


Figure 8: Testing Values of Phosphorus

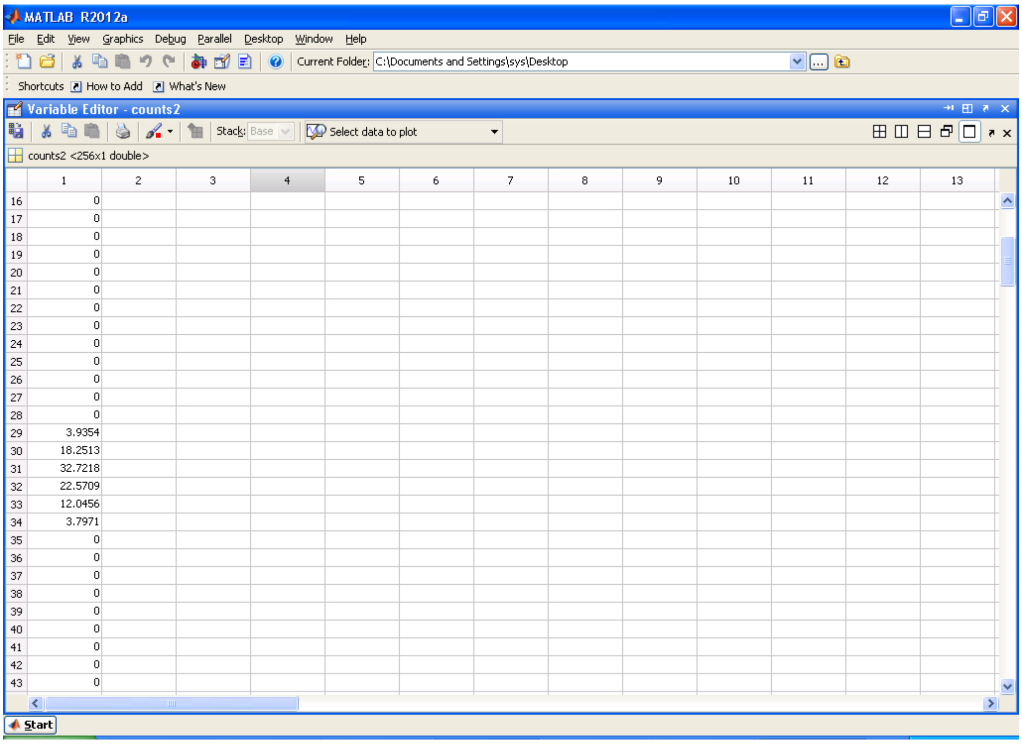


Figure 9: Testing Value of Nitrogen

Figure 10: Output

Table 1: Comparison of Accuracy

Techniques	Correctly detected Images	Accuracy
PCA	26/30	86
ICA	27/30	90
MPLS	28/30	93.3

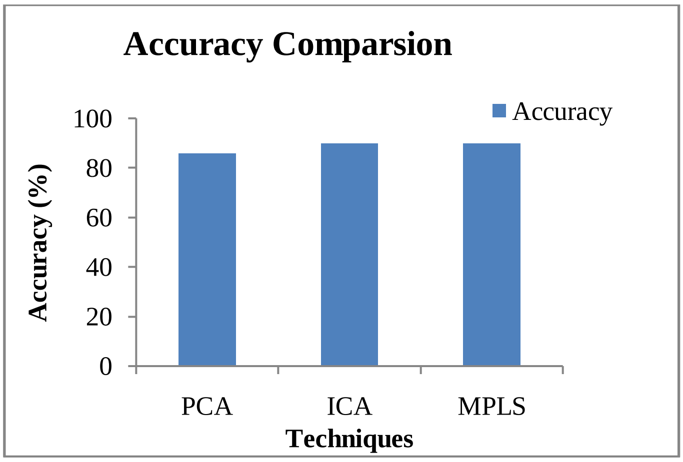


Figure 11: Comparison of Accuracy

Figure 3 provides the original image then the original image of RGB is converted into HSV and it is shown in Figure 4.Hue, Saturation and value images are produced through this Figure 4, and also get the deficiency part present in that image though mask process they are hue and black mask. This type of mask is used to get the deficiency part in the image by masking the green colored except brown to find out the deficiency. Histogram for the deficiency part was shown in Figure 6. This paper provides some of the result of training part and testing of phosphorous and nitrogen and the output of the nitrogen deficiency are shown in Figure 7, Figure 8, Figure 9 and Figure 10. Table 1 gives the comparison of accuracy between existing PCA and proposed ICA and MPLS. Proposed MPLS gives better accuracy than proposed ICA and existing PCA. That the accuracy is calculated from correctly detected images. PCA algorithm is detected 26 images out of 30 images, ICA algorithm detected 27 images out of 30 and gives the accuracy of 90% and proposed MPLS algorithm detected 28 images out of 30 and gives the accuracy of 93% of better classification than proposed ICA and existing PCA. Figure 11 illustrates the comparison of accuracy, from the figure it is clearly observed that the proposed MPLS algorithm classified better than the ICA and PCA.

Table 2: Comparison of Kappa's Coefficient

Technique	Kappa's Coefficient
PCA	83.72
ICA	88.88
MPLS	92.81

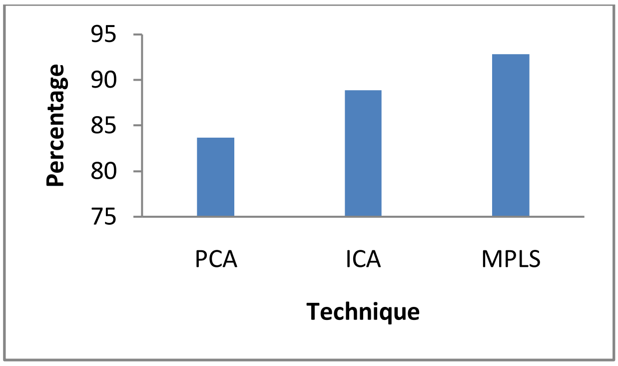


Figure 12: Comparison of Kappa's coefficient

Table 2 and Figure 12 show the comparison of kappa's coefficient for different techniques. From the figure itcan be easily stated that the proposed technique out-performs other techniques in terms of kappa's coefficient.

Conclusion

This paper use a MPLS approach for detects the nutrient deficiency in leaf image. Three steps are carried over in this paper they are preprocessing, feature extraction and regression. ICA technique is more natural than PCA method. Compared to PCA and ICA, proposed MPLS is evaluating more for dimensionality reduction. The performance of the regression method is evaluated using Kappa coefficient. From the experimental result it is clearly observed that the proposed method provides better result than existing method.

References

[1] Shamik Sural, Gang Qian and Sakti Pramanik, "Segmentation And Histogram Generation Using The HSV Color Space For Image Retrieval", International Conference on Image Processing, Volume: 2, 2007.

[2] H.D. Cheng and X.J. Shi, “A simple and effective histogram equalization approach to image enhancement”, Digital Signal Processing 14, 158–170, 2004.

[3] P.R. Rothe and R.V. Kshirsagar, “A Study on the Method of Image Preprocessing for Recognition of Crop Diseases”, International Conference on Benchmarks in Engineering Science and Technology ICBEST, 2012.

[4] Marian Wiwarta, Gabriel Fordon ski, Krystyna Zuk-Gołaszewska, “Early diagnostics of macronutrient deficiencies in three legume species by color image analysis”, computers and electronics in agriculture 65, 125–132, 2009.

[5] A. Hyvarinen and E. Oja, “A fast fixed-point algorithm for independent component analysis", Neural Computation, 9, 1483-1492, 1997.

[6] Arendonk J.J.C.M, Niemann G.J, Boon J.J, Lambers .H, “Effects of nitrogen supply on the anatomy and chemical composition of leaves of four grass species belonging to the genus Poa, as determined by image-processing analysis and pyrolisis-mass spectrometry”Plant Cell Environ. 20, 881–897, 1997.

[7] Hirose T, Freijsen A H J and Lambers H,“Modelling of response to nitrogen availability of two plantago species growth at a range of exponentional nutrient addition rates. Plant, Cell and Environment 11, 827-834.

[8] Lambers H and Poorter H, “Inherent variation in growth rate between higher plants: A search for physiological causes and ecological consequences”, Advances in Ecological Research 23, 187-261.

[9] Corn leaf analysis and interpretative Guidelines, Olsen’s Agricultural Laboratory, Inc, 2008.

[10] J. A. Silva and R. Uchida, “Essential Nutrients for Plant Growth: Nutrient Functions and Deficiency Symptoms”, College of Tropical Agriculture and Human Resources, University of Hawaii at Manoa, 2000.

[11] J. Du, D. Huang, X. Wang and X. Gu, “Computer-aided plant species identification (CAPSI) based on leaf shape matching technique,” Transactions of the Institute of Measurement and Control. 28, 3, pp. 275-284, 2000.

[12] Lemaire G, “Diagnostic Tool (s) for Plant and Crop N Status. Theory and Practice for Crop N Management” In Proceedings of the 15th N Workshop “Towards a Better Efficiency in N use”, Lleida, Spain, 28–30, pp. 15-29,May 2007.

[13] Netto A.T, Campostrin E, Gonc J, Oliveira A, Bressan-Smith R.E, “Photosynthetic pigments, nitrogen, chlorophyll afluorescence and SPAD-502 readings in coffee leaves” Sci. Hortic. 104, 199–209, 2005.

[14] Carter G.A, Knapp A.K, “Leaf optical properties in higher plants linking spectral characteristics to stress and chlorophyll concentration” Am. J. Bot. 88 (4), 677–684, 2001.

[15] Edmeades D. C,“The long-term effects of manures and fertilizers on soil productivity and quality: a review” Nutr.Cycl. Agroeco-system. 66: 165-180, 2003.
[16] Saleque M. A, Abedin M. J, Bhuiyan N. I, Zaman S. Kand Panaullah. G. M, “Long-term effects of inorganic and organic fertilizer sources on yield and nutrient accumulation of lowland rice” Field Crop Res. 86: 53-65, 2004.
[17] Wang Z. H, Li S. X and Malhi S,“Effects of fertilization and other agronomic measures on nutritional quality of crops” J. Sci. Food Agric. 88: 7-23, 2008.
[18] Strebel O, Duynisveld W. H. M and Bottcher J, “Nitrate pollution of groundwater in Western Europe” Agric. Ecosyst. Environ. 26: 189-214,1989.
[19] Aulakh M. S and Malhi S. S, “Interactions of nitrogen with other nutrients and water: effect on crop yield and quality, nutrient use efficiency, carbon sequestration, and environmental pollution”, Adv. Agron. 86: 341-409, 2005.
[20] URL: http://agritech.tnau.ac.in