IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-6, June 2019 E-ISSN: 2347-2693

Tomato Nutrient Deficiency Detection On The Basis Of Visible Symptoms Using Digital Image Processing

R.V.Ahire[1*], S.L. Nalbalwar[2], N.S. Jadhav[3], Sachin Singh[4]

[1,2,3]Dept. of Electronics and Telecommunication, Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra, India, 402103
[4]Dept. of Electrical Engineering, Institute of Engineering and Technology, Lucknow, Uttar Pradesh, India, 226021

Corresponding Author: ahire.rahul666@gmail.com, Mob. : 8237619237

DOI: https://doi.org/10.26438/ijcse/v7i6.683689 | Available online at: www.ijcseonline.org

Accepted: 10/Jun/2019, Published: 30/Jun/2019

Abstract— Nutrient deficiency may cause degradation in productivity of crop, the commercial plants like tomato usually gets affected by Nutrient deficiency. There is requirement of device which will predict Nutrient deficiency on the basis of visual symptoms. We have analysed tomato leaf using parameters like Uniformness detection (Deviation matrix method and Histogram analysis method), Lightness in colour detection, Chlorosis and Necrosis detection and by using some structural parameters like Status of Major vein, Length to Width ratio etc. On the basis of above parameters and PH of soil, we can accurately predict the Nutrient deficiency through which plant is suffering from. It is more relevant and non-destructive method of Nutrient deficiency detection. This method can detect deficiency at any stage of growth. Also similar techniques can be used for Nutrient deficiency detection of other plants like pomegranate, chilly, grape etc.

Keywords—Nutrient deficiency, Tomato leaf processing, Image processing in Agriculture, Machine Vision in Agriculture, Deficiency Symptoms.

I. INTRODUCTION

The commercial plants like tomato, chilly, pomegranate, grapes need regular health inspection. If plant is suffering from certain disease or deficiency, may degrade performance of plant growth and will result into degradation in the productivity and quality of fruits. The tomato plant more sensitive to deficiency. If required action is not taken in time, it may damage whole crop and that will affect productivity. But difficulty is that, new farmers are unaware of symptoms of deficiencies. They usually have to approach expertise to sort-out problems. But in rural and inaccessible areas there might be issue of unavailability of experts. In such cases farmers used to choose medicine and fertilizers randomly, which may not be so efficient and effective.

Any plant when suffers from deficiency, some symptoms appears on surface of leaf e.g. if leaf is getting light green uniform coloration then it must be either Nitrogen or Sulphur deficiency [12]. Also nutrients are of two categories Mobile and Immobile, mobile nutrients may get transferred to newer leaves whenever there is stress. While immobile nutrients cannot be transferred from older to newer leaf. Hence mobile nutrient deficiency generally visible on older leaves [12]. Nutrient deficiencies also depend upon PH of soil. When PH of soil is acidic, plant may have Macronutrient deficiency, and when basic there may be Micronutrient [12]. Above mentioned visual deficiency symptoms are used as analysis parameter for this research.

The objective of this study is to predict deficiencies on the basis of visual symptoms appearing on leaf of tomato plant. The images are then captured in closed environment, processed using Image processing library, Results are gathered on the basis of analysis of sample tomato leaves using different parameters like uniformness in intensity using deviation matrix method and histogram analysis method, chlorosis and necrosis detection using hue component also structural parameters like status of major vein, length to width ratio of leaf. On the basis of all this parameters deficiencies were predicted. This analysis is more useful for the design of electronic device used for prediction of deficiencies and suggesting remedial medicines to farmers.

Rest of the paper as follows, section I contains Introduction to the study, section II contains detailed survey of previous work and contribution made by others regarding the subject of study. Section III contains experimentation and methodology of research. Section IV gives analysis of results obtained from experimentation. The meaning and

implications of study is given in section V. Future scope and importance of study is described in section VI.

II. RELATED WORK

Previously, different researches have been carried out for the detection of nutrient deficiency in various plants. Relative difference function using percent histogram, Fourier transform and Wavelet packet decomposition, can be used as input analysis vectors given to fuzzy K- nearest neighbour method to identify Nitrogen and Potassium deficient tomato leaves [1]. Analysis of rice plant from plantation to its maturity using colour and shape of leaf are used to diagnose nitrogen status and also compared with predetermined Nitrogen level [3]. HSI model, L^*, a^*, b^* model and Euclidian distance calculation between leaves at successive nodes were used to determine Nitrogen, Phosphorus, Potassium and Magnesium deficiencies on three legume species [4]. Nitrogen status determination on tomato seedlings was done on the basis of colour of leaf and compared with SPAD 502 chlorophyll meter readings [5]. For the determination of calcium deficiency of lettuce plant in controlled environment, machine vision guided plant monitoring systems were also designed for green house purposes [2]. For paddy leaf, on the basis of colour features like ratio of green/red or red/ blue and texture features like holes in image are used to determine pair of Nitrogen-Potassium or Nitrogen-Phosphorus deficiencies. Appropriate selection of leaf for the processing purpose is more important as older or newer leaf may not show deficiency symptoms correctly due to inactiveness of photosynthesis and mobile and immobile nature of nutrients respectively. Leaf in middle part of leaf more suitable for analysis purpose [7]. K-means clustering method was used to determine deficiencies in Mango plant [9]. Edges and veins plays important role in identification of deficiencies. Canny edge detection algorithm with locally determined thresholds can be used to detect veins [11].

III. METHODOLOGY

1.1 Database creation

Three month old tomato plant (variety number-Syngenta 1057) were chosen for collection of images, required as an input sample image for analysis of tomato nutrient deficiency. Sample leaves were classified manually on the basis of visual symptoms [12]. Images were captured under controlled environment with uniform light arrangement using pi-camera module (fig 1), overall image acquisition chamber is shown in fig1. For each deficiency symptom at least 10 leaf images were captured from different plants with more or less concentration of deficiency. Acquired images were preprocessed with different preprocessing algorithm such as geometric mean filtering and background was removed. Most suitable images were selected for analysis of nutrient deficiency.

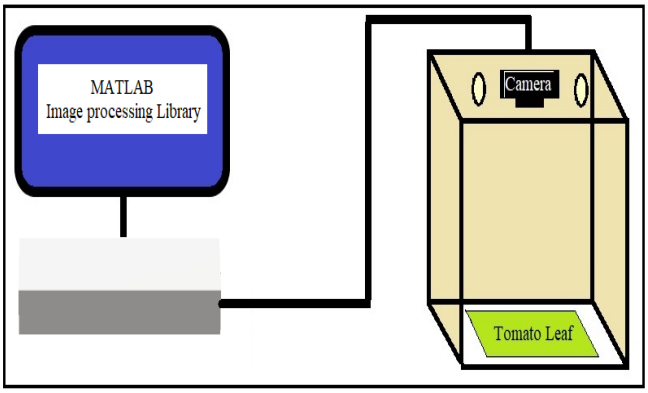

Fig 1 (Image Acquisition System)

1.2 Methods

A) Major vein detection

It is very difficult to detect major vein using edge detection algorithm or 1st and 2nd order derivatives. General observation is that major vein is vertically at middle of leaf canopy.

S_1 is starting point of leaf in image, S_2 is last point of leaf in image, $[E_1]_{x,y}$ array of left side boundary or boundary 1 points , $[E_2]_{x,y}$ array of right side boundary or boundary 2 points, $[mid]_{x,y}$ array of mid points.

Midpoint array is calculated form S_2 towards S_1

$$[mid]_{x,y} = \frac{[E_1]_{x,y} + [E_2]_{x,y}}{2} \quad (1(a))$$

But structure of tomato leaf is not bisectionally symmetric, mid points of right and left boundary co-ordinates are not sufficient to calculate major vein points. If both edges are turning in same direction then midpoint calculation should be with respective angle of turning of leaf margins. Angle at point of sample can be calculated by slope approximation. Here slope is angle made by tangent with respect to current boundary pixel.

$$\theta = \tan^{-1}(\frac{Y}{X}) \quad (1(b), 1(c))$$

$$Y = E_{x,y+2} - E_{x,y+1} - E_{x,y} - E_{x,y-1} - E_{x,y-2}$$

θ Is angle of turning and Y is variation of boundary points in upward direction, if boundary point is moving in right direction, difference of column should be positive for upper two boundary points and if lower two boundary points are lesser than current midpoint then slope becomes positive. That means the boundary points if moves in right side should show positive slope and if movement is in left side then slope should be negative. Y Is showing column wise difference. X Shows vertical or row wise difference and it is equal to sampling factor. Midpoint should be calculated at normal to

the angle θ. When boundary moves with positive slope, normal angle β is given by

$$\alpha = 90 - \theta \text{.....if } \theta \text{ is positive}$$
$$\beta = 360 - \alpha \quad (1(d), 1(e))$$

When boundary moves with negative slope, normal angle β is given by

$$\alpha = 180 - \theta \text{.....if } \theta \text{ is negative}$$
$$\beta = 90 + \alpha \quad (1(f), 1(g))$$

For left boundary points $E_1(x, y)$ with slope β, normal intersects certain boundary point $E_2(x, y)$ then it should satisfy the equation that line.

$$-(row) - \tan\theta \times (column) + c = 0$$

row: row number of boundary point

$column$: column number of boundary point

c : constant (1(h))

$$[mid]_x = \frac{E_2(x) + E_1(x)}{2}$$
$$[mid]_y = \frac{E_2(y) + E_1(y)}{2} \quad (1(i), 1(j))$$

$[mid]_x$ is row value of midpoint, $[mid]_y$ is column value of midpoint, $E_2(x), E_1(x)$ row value of boundary 1 and boundary 2 respectively and $E_2(y), E_1(y)$ are column points of boundary 1 and boundary 2 respectively. Further horizontal midpoints and angled midpoints are need to be approximated with respect to adjacent midpoints because of bisectional asymmetry and irregular shape of leaf. It is necessary to check that if adjacent midpoint is having distance more than predefined threshold value then it is to be again normalized to midpoint of upper and lower midpoints. Finally approximated vein points are given by eq. 1(k) and eq. 1(l), upper and lower boundary points are considered.

$$[mid]_x = \frac{mid_{x+1} + mid_{x-1}}{2}$$
$$[mid]_y = \frac{mid_{y+1} + mid_{y-1}}{2} \quad (1(k), 1(l))$$

B) *Uniformness of intensity on leaf*

Most relevant symptom was uniform effect of lightness in leaf colour and then yellowing [12]. Uniformness is function of deviation of intensity values from mean intensity.

$$[\mu] = \frac{\max[A] + \min[A]}{2} \quad (2(a))$$

$$[D] = |[A] - [\mu]| \quad (2(b))$$

max. is maximum intensity value associated with leaf, min. is minimum intensity value other than zero [A] is grayscale image of leaf, [D] is deviation matrix and μ is mean intensity value. As the deviation matrix has higher values (except background pixels) consequently more the deviation of intensity from mean or average intensity of leaf (fig 2b).

Another way to calculate the uniformness is histogram analysis, except the background pixels majority of leaf pixels should gathered around mean value. There should not be more than one hill (fig 2b). If there are more than one considerable hills there is possibility of certain pattern in leaf image (fig 2b). To calculate existence of more than one hill, histogram array of image [A] is calculated say [h]. Array [h] is sorted in descending order. First elements of sorted array will show peaks (fig 2b) in histogram, similarly while sorting elements if there indices are traced will give the position of peak in histogram. If the distance between successive maximum values is considerably large say more than certain Threshold value then they are belonging to different hills otherwise belonging to same hill. Also width of hills is very important factor. It can be calculated by distance between the positions of 1st peak to the position of last element who is having magnitude of pixel less than magnitude of 1st peak /4. Existence of 2nd peak, width of 1st and 2nd peak and distance between 1st and 2nd peak are very important parameters.

C) *Dark green to light green coloration*

To calculate colour change form dark green to light green, intensity of leaf calculated by

$$I = \frac{R + G + B}{3} \quad (3)$$

R is red component of image [A], similarly B and G are blue and green components of image [A], I is average intensity value plane. Position of 1st peak in histogram shows average intensity, more lightness in leaf colour should shift the peak towards higher intensities.

D) Color feature extraction

a) Chlorosis detection

In HSI colour map hue value indicates amount of original colour (fig 2c) green colour has hue value around 120(fig 2c 1st & 2nd leaf) and yellow colour have hue colour around 60(fig 2c 3rd, 4th & 5th leaf). If the histogram of hue plane contains 1st peak nearer to 60 shows yellow coloration.

b) Inter venial chlorosis detection

Chlorotic spots between veins detected with chlorosis detection and highlighted by white pixels in equivalent binary image. If each row is traversed on both sides of major vein in search of alternate black and white patterns. Then higher value of alternate chlorotic region shows interveinal chlorosis.

c) Necrotic spot detection

Necrotic spots are the spoiled areas shows more relevance with red color that mean hue value should be nearer to 0 or 360(fig 2d). Similarly the intensity value at chlorotic areas should be less as compared to other parts of leaf.

E) Structural features of leaf

a) Length of leaf is distance between first pixel S_1 of leaf and last pixel S_2 of leaf (fig 3)

$$length = S_1(y) - S_2(y) \quad (4)$$

b) Width of leaf is horizontal distance between boundary 1 $[E_1]_{x,y}$ and boundary 2 $[E_2]_{x,y}$ corresponding points (fig 3).

$$[width] = E_1(x) - E_2(x) \quad (5)$$

Maximum value of width array is width of leaf.

c) Tip of leaf is upper 6th portion of canopy out of 6 portions divided on the basis of *length* of Leaf in image (fig 3).

d) Base of leaf is 1st portion of leaf in image out of 6 portions (fig 3).

e) Margins of leaf can be calculated by dilation of edge pixels of image and applying dilated image as mask to r-g-b image to extract margins.

IV. RESULTS

3.1 *Major vein detection*

Analysis of major vein is very important as it is useful in detection of interveinal chlorosis. But for normal tomato leaf, major vein or sub veins does not show any significant colour difference or intensity difference. It is very tedious task to find major vein by colour or intensity difference. Usually major vein is vertically at the centre of leaf. In few plants like mango or chili leaf shows bisectionally symmetric structure, but in tomato it is not symmetric in all regions of leaf. So just by finding midpoints using equation 1 gives vein shown in fig 2a as vein detected without slope approximation. These are the vein points estimated as a midpoint of respective boundary points lying on same horizontal line. We can see clearly that at the tip region of leaf there is incorrect approximation of vein points. This error is due to one side movement of boundary points. Whenever leaf structure is turned at tip of leaf in some direction equation 1(a) gives incorrect estimation of vein points in those region. If we observe from last point of leaf to upwards, left boundary points and right boundary points generally moves in opposite direction but at the apex region both boundaries moving in same direction hence horizontal boundary points does not gives correct vein points. For correct estimation of vein points, we can use line with respect to direction of movement of boundary points and slope of curve. Equation 1(b) gives angle of tangent to the curve with respect to horizontal. Normal to point of curve can be given by line passing through this point at an angle given by equation 1(d) or 1(f) with respect to horizontal. By using equation 1(i) and 1(j) the points satisfying equation of normal can give correct vein points as shown in fig 2a titled as vein detected with slope approximation. Dilation of vein points will give exact position of major vein

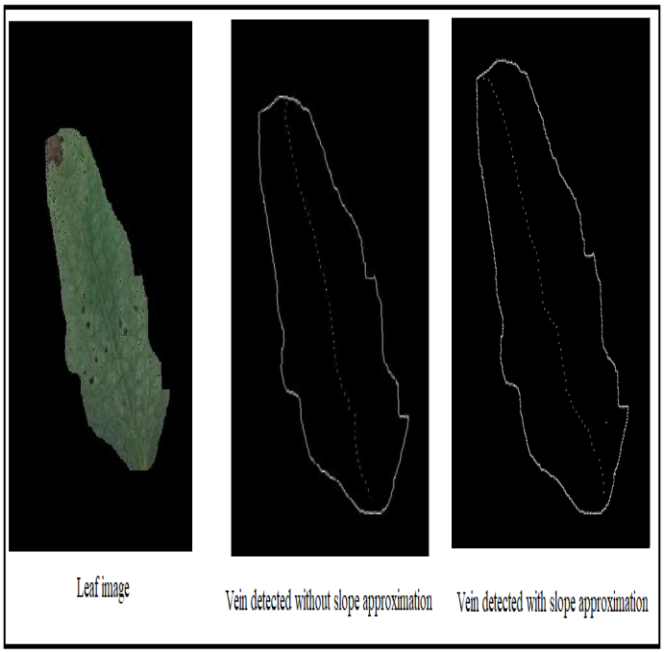

Fig 2a (Major vein detection)

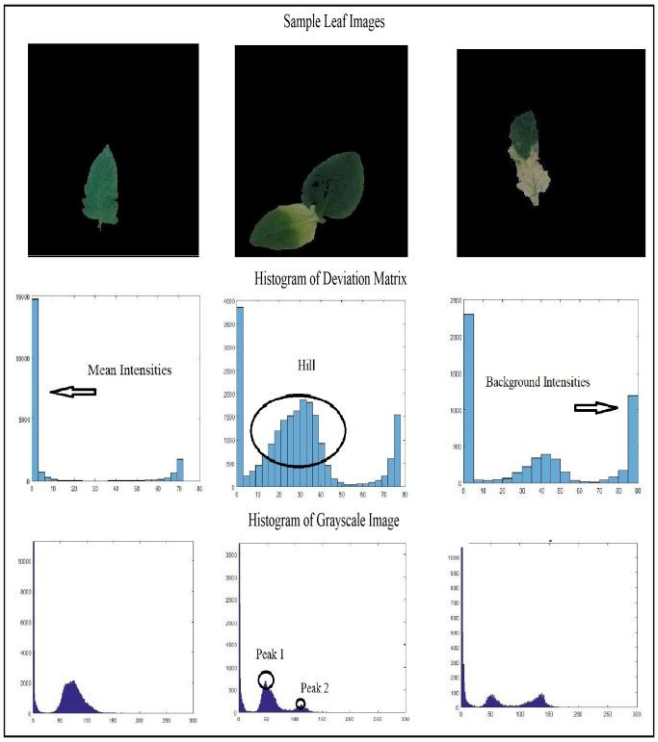

Fig 2b (Uniformness detection)

3.2 *Uniformness of intensity on leaf*

If leaf is not having any deficiency then it should have equal intensity pattern throughout the leaf. In case if it has some deficiency there should be some pattern on leaf associated with that deficiency. But in Nitrogen deficiency and Sulphur deficiency there is uniform yellowing effect throughout the leaf [12], it does not show any pattern on leaf. Uniformness of intensity is function of deviation matrix, it is given by equation 2(b). If we observe the histogram plot of deviation matrix, maximum intensity values are located at origin, one hill nearer to origin and few bars at another end. Maximum pixel intensity values on origin are showing number of intensity values belonging to mean value given by equation 2(a). The hill nearer to origin along with origin intensity values showing intensity values associated with leaf. And the bar at other end is showing background pixels. If hill is sprayed more instead of concentrated nearer to origin shows less uniformness. If hill is much nearer to origin with maximum intensity values concentrated towards origin shows high uniformness. Figure 2b shows how position and concentration of intensities on hill changes as uniformness decreased. Also grayscale leaf image analysis gives significant information about uniformness. 3rd row in fig 2b shows histogram plot of grayscale leaf images. If leaf is having certain deficiency pattern on it, there is difference in intensity between normal pixels and deficiency pattern pixels. In histogram it is observed as multiple significant hills. Fig 2b shows few important parameters like number of hills, distance between hills, and width of hills etc. Multiple hills clearly states un-uniformness, if distance between hills is less there is gradual change in intensities. To discriminate peaks of same hill, width of hill is considered up to bars having magnitude of peak/4 intensity associated with hill.

3.3 *Dark green to light green coloration*

As it is clear from fig 2b gray scale leaf image histogram plot, for dark green leaf hill is very nearer to origin but as color of leaf changes to light green hill gets shifted towards high intensities i.e. away from origin. In some leaves 2nd hill is more away from origin than 1st hill which ultimately implies light coloration regions.

3.4 *Color feature extraction*

3.4.1 Chlorosis detection

Chlorosis of leaves is identified by yellow coloration of leaves, hue component of image shows presence of particular color. Histogram plot of hue component are shown in fig 2c. 0 to 360 values of hue components are approximated to 0 to 255. Leaf having green colored pixels have hue value around 100 to 130, hue value bar at 65 shows background pixels. Also leaf with yellow color shows hue values around 40 to 60. In leaves where patch of yellow and green color are present showing hills at yellow and green color hue regions.

3.4.2 Interveinal Chlorosis

When chlorotic spots appears between the veins of leaf, it is termed as interveinal chlorosis. In interveinal chlorosis vein remains green but remaining parts of leaf starts yellowing. If vein is found green on the basis of hue values then interveinal chlorosis will produce alternate yellow and green patches.

3.4.3 Necrosis detection

Necrosis is term used to show dead or spoiled area, generally necrotic spot shows hue values nearer to 0 or 255 i.e. red color component. Necrosis becomes significant when it is at tip of leaf. Fig 2d shows the necrotic and healthy tip of leaf. Hue components of necrotic spots maximally crowded near 0 value or 255 value.

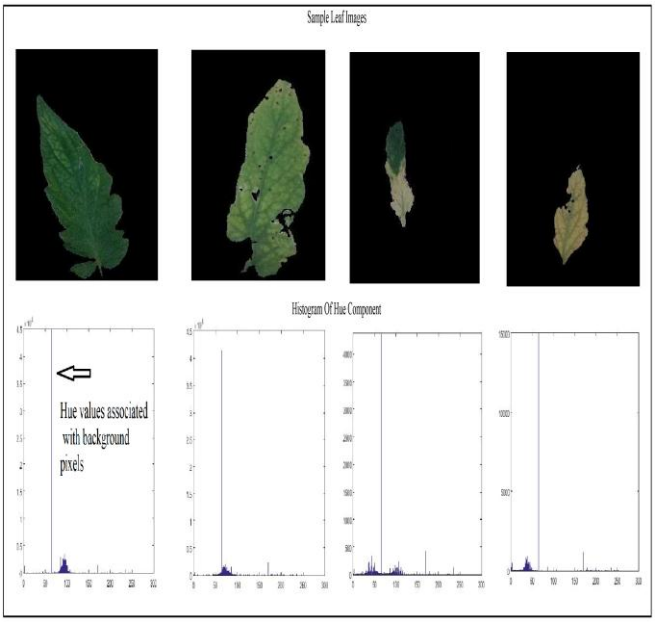

Fig 2c (Chlorosis detection)

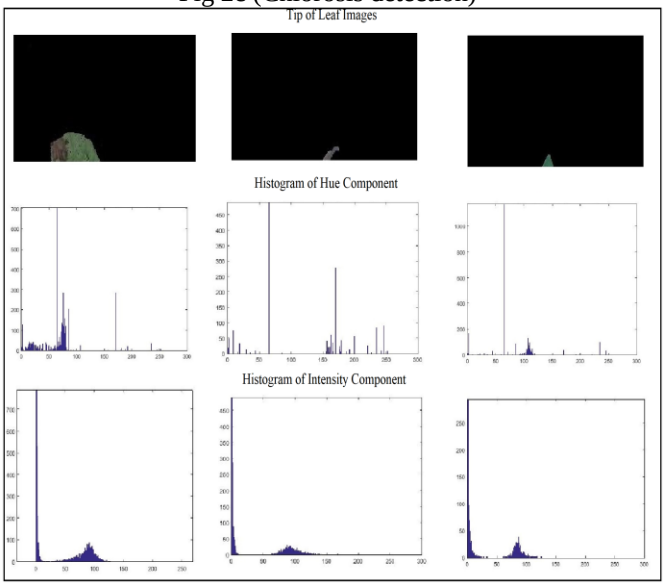

Fig 2d (Necrosis detection at tip of leaf)

V. DISCUSSION

Structural features of leaf

The length of major vein is nothing but length of leaf, width of leaf is distance between minimum of y co-ordinate and maximum of y co-ordinate of boundary pixels (fig 3) if the leaf is divided in six portions as shown in fig 3 upper 6^{th} portion shows tip of leaf or it is the upper endpoint region of major vein. Lower 6^{th} portion shows base of leaf or lower end of major vein. Length to width ratio is very important parameter to identify rolling of leaf. If this ratio is greater than 3 can be either showing cupped or rolled leaves. In case of rolling of leaf, back side of leaf appears in front side image of leaf that means two kind of green shades appear in front side image. Also boundary pixels of leaf can be found out by boundary descriptors. These parameters are very useful to correlate visual symptoms of deficiencies.

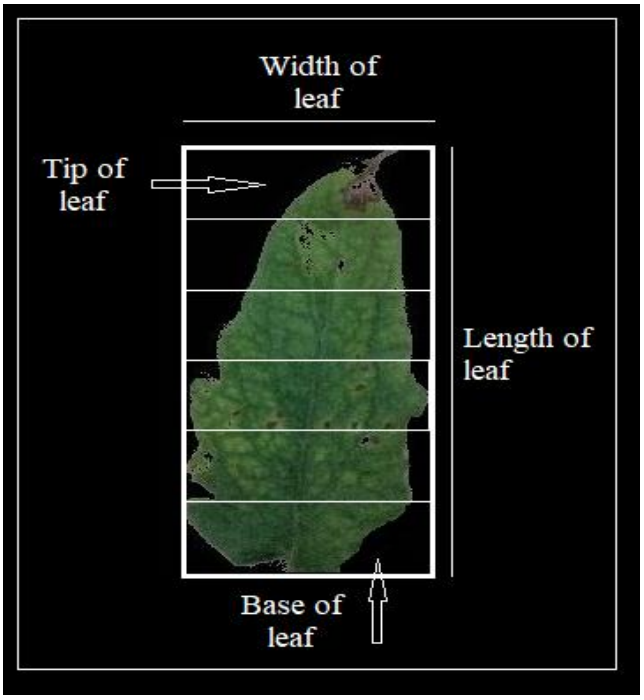

Fig 3 (Leaf structural parameters)

Nitrogen (N) and Sulphur (S) deficiencies are the function of uniformness in intensity and Lightness in colour also when there is Sever deficiency situation leaf shows yellow or white coloration [12]. By using deviation matrix method or histogram analysis it is possible to detect presence of uniform intensity variation. With uniformness, if there is lightness in colour as compared to healthy leaf or presence of yellow colour can predict N and S deficiency. With this if PH of soil is acidic in nature above symptoms shows N deficiency and if PH is basic in nature it shows S deficiency [12], as N is Macronutrient and S is Micronutrient. If image does not have uniform intensity variation and there is existence of yellow colour patches (except veins) shows Magnesium (M) deficiency it may also have some necrotic spots. If necrosis is along leaf margins then it should be Potassium (K) deficiency. If tip of leaf is died i.e. necrotic with this there is no other symptom then it is showing Calcium (Ca) deficiency. With necrosis of tip if there is interveinal chlorosis i.e. yellow patches other than veins shows Copper (C) deficiency. If leaf is rolled and boundary pixels showing necrosis and tip is weathered, it is showing Boron (B) deficiency. If without tip necrosis and rolling of leaf there is only existence of necrosis along boundary pixels then it is ultimately showing Chlorine (Cl) deficiency. Sometimes there is no necrosis of leaves along boundary but whole leaf gets uniformly light green or pale yellow coloration but leaf gets rolled this symptom is showing Molybdenum (Mo) deficiency. In case of phosphorus deficiency back side of leaf gets whitish appearance or front side gets purple coloration. On the basis of hue component analysis it is possible to detect phosphorus deficiency as well. In case of Iron (Fe) deficiency chlorotic patches appears near the base of leaf i.e. in lower 6^{th} part of leaf.

Uniformness of intensity by using deviation matrix method or histogram analysis method, dark to light green coloration analysis, chlorosis, interveinal chlorosis and necrosis detection also structural parameters such as length and width of leaf and major vein detection are the parameters on the basis of which we can predict any deficiency. Image processing is the tool by which we can analyse visual symptoms of leaf and predict it at any stage.

VI. CONCLUSION AND FUTURE SCOPE

The research was conducted on 3 month old tomato plant leaves, on the basis of visual symptoms and information of PH of soil we can predict deficiency through which plant is suffering from. As the result of analysis showing great correlation between visible symptoms of leaf and leaf image parameters like uniformity of intensity, lightness in leaf colour, interveinal chlorosis, necrosis, and with few important structural features such as status of major vein, length of leaf and width of leaf. 90% of plant leaves were correctly identified with nutrient deficiencies. Also PH of soil is very useful parameter to differentiate deficiencies which are having similar visual symptoms. If deficiencies not encountered within time may results into stress to plant. Hence this analysis helps to detect deficiencies on tomato plant at any stage of growth.

When deficiency symptoms appears on leaf simultaneously if plant is suffering from certain disease, its effect will also appear on leaf. So sometimes it is needed to analyse deficiency patterns along with disease patterns which may include error in analysis. Future work can be done to detect both deficiency and disease detection simultaneously. There is huge demand from farmers to have such deficiency

detection android application. And can be fulfilled with development of android application based on above research.

REFERENCES

[1] G. Xu, F. Zhang, S. G. Shah, Y. Ye, H. Mao, "Use of leaf color images to identify nitrogen and potassium deficient tomatoes", Pattern Recognition Letters 32, 1584–1590, ELSEVIER, 2011.

[2] D. Story, M. Kacira, C. Kubota, A. Akoglu, L. An, "Lettuce calcium deficiency detection with machine vision computed plant features in controlled environment" Computer and Electronics in Agriculture 74, 238-243, ELSEVIER, 2010.

[3] Y. Sun, S. Zhu, X. Yang, M. V. Weston, Ke Wang, Z. Shen, H. Xu, L. Chen, "Nitrogen diagnosis based on dynamic characteristics of rice leaf image" PLoS ONE 13(4):e0196298, 2018.

[4] M. Wiwart, G. Fordonski, K. Zuk-Golaszewska, E. Suchowisska, "Early diagnostics of macronutrient deficiencies in tree legume species by color image analysis". Computer and Electronics in Agriculture 65, 125-132. ELSEVIER, 2009.

[5] A. Mercado-Luna1, E. Rico-Garcia, A. Lara-Herrera, G. Soto-Zarazua, R. Ocampo-Velazquez, R. Guevara-Gonzalez1, G. Herrera-Ruiz and I. Torres-Pacheco1 "Nitrogen determination on tomato (Lycopersicon esculentum Mill.) seedlings by color image analysis (RGB)", African Journal of Biotechnology Vol. 9(33), pp. 5326-5332, 2010.

[6] M. V. Latte, S. Shidnal, "Multiple Nutrient Deficiency Detection in Paddy Leaf Images using Color and Pattern Analysis", International Conference on Communication and Signal Processing, IEEE, 2016.

[7] M. A Hairuddin , L. M. Romualdo, "Overview of Image Processing Approach for Nutrient Deficiencies Detection in Elaeis Guineensis" , IEEE International Conference on System Engineering and Technology (ICSET), 2011.

[8] R. H. M. Condori, L. M. Romualdo, "Comparison between traditional texture methods and deep learning descriptors for detection of nitrogen deficiency in maize crops", Workshop of Computer Vision, IEEE, 2017.

[9] M. Merchant, V. Paradkar, M Khanna, S. Gokhale, "Mango Leaf Deficiency Detection Using Digital Image Processing and Machine Learning", Third International Conference On Convergence In Technology (I2CT), IEEE, 2018.

[10] S.Kawashima, M,Nakatani , "An algorithm for estimating chlorophyll content in leaves using a video camera", Ann. Bot. 81: 4954, 1998.

[11] R. Radha, S. Jeyalakshmi, "An Effective Algorithm for Edges and Veins Detection in Leaf Images", World Congress on Computing and Communication Technologies, IEEE, 2014.

[12] A. McCauley, C. Jones, J. Jacobsen, "Plant Nutrient Functions and Deficiency and Toxicity Symptoms", Montana state university extension 4449-9, june 2011.

Authors Profile

Mr. Rahul Vasant Ahire completed Bachelor of Engineering from Savitribai Phule Pune University,India in 2016. He is currently pursuing Master of Technology in Dr.BabasahebAmbedkar Technological University lonere, India

Dr S. L. Nalbalwar completed Bachelors of Engineering in 1990 and Master of Engineering from SGGS Nanded,India, in year 1996. He completed Ph.D. form IIT Delhi in 2008 and currently working as Professor in Department of Electronics and Telecommunication, Dbatu lonere since 1996.. He has published more than 100 research papers in reputed international journals and more than 70 conferences including IEEE and it's also available online. His main research work focuses on signal matched filterbanks, and signal processing. He has 28 years of teaching experience and 4 years of Research Experience.

Dr N.S. Jadhav completed Bachelor of Technology from Dbatu lonere Maharashtra, Master of Technology from Dbatu lonere Maharashtra,. He completed Ph.D. from Dr. Babasaheb Ambedkar Technological University lonere, Maharashtra and currently working as assistant Professor in Department of Electronics and Telecommunication, Dbatu lonere.He has published research papers in reputed international journals and conferences including IEEE and it's also available online. His main research work focuses on VLSI and Biomedical Signal Processing.

Dr Sachin Singh completed Bachelor of Technology from UNSIET, VBS Purvanchal University, India, Master of Engineering from Birla Institute of Technology, India. He completed Ph.D. from Birla Institute of Technology, India and currently working as assistant Professor in Department of Electical Engineering, Institute of Engineering and Technology, Lucknow. He has published research papers in reputed international journals and conferences and it's also available online. His main research work focuses on Planning and analysis of Electrical Distribution System & Micro-Grid. Power System analysis and optimization.

