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A REVIEW ON DIAGNOSIS OF NUTRIENT DEFICIENCY SYMPTOMS IN PLANT LEAF IMAGE USING DIGITAL IMAGE PROCESSING

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Abstract

Plants, for their growth and survival, need 13 mineral nutrients. Toxicity or deficiency in any one or more of these nutrients affects the growth of plant and may even cause the destruction of the plant. Hence, a constant monitoring system for tracking the nutrient status in plants becomes essential for increase in production as well as quality of yield. A diagnostic system using digital image processing would diagnose the deficiency symptoms much earlier than human eyes could recognize. This will enable the farmers to adopt appropriate remedial action in time. This paper focuses on the review of work using image processing techniques for diagnosing nutrient deficiency in plants.

Keywords:

Color Segmentation, Color Space, Mathematical Morphology, Color Feature Extraction, Classifier

1. INTRODUCTION

Plants and crops require 13 essential mineral nutrients to grow and survive. They acquire these nutrients from the soil. Deficiency of these nutrients affects the growth and quality of the plant/crop. Thus, diagnosing nutrient status of minerals plays a crucial role in agriculture and farming.

Nutrient deficiency symptoms in plants/crops would normally be visible in leaves. These symptoms include interveinal chlorosis, marginal chlorosis, uniform chlorosis, necrosis, distorted edges, reduction in size of the leaf etc. Even though similar symptom present in old and young leaves, the deficient nutrient may vary. The Fig.1 depicts some of the visual deficiency symptoms shown by plants on leaves.

The mineral nutrients classified into macro and micro nutrients. Plants need large quantity of macronutrients and small quantity of micro nutrients for survival. Macronutrients include Nitrogen, Potassium, Sulfur, Calcium, Magnesium and Phosphorous. Micronutrients include Boron, Copper, Iron, Chloride, Manganese, Molybdenum and Zinc.

1.1 COMPONENTS OF NUTRIENT DEFICIENCY DIAGNOSTIC SYSTEM

The diagnostic system would include the following components using image processing techniques:

- Leaf area measurement
- Segmentation of edge and veins of the leaf
- Determining the Shape of the leaf
- Classification of the deficient mineral
- Determining the age of leaf
- Extraction of color features of the leaf

(a) Iron Deficiency | (b) Boron Deficiency | (c) Magnesium Deficiency

(d) Phosphorous Deficiency | (e) Nitrogen Deficiency | (f) Molybdenum Deficiency

Fig.1. Visual symptoms shown on Plant/Crop Leaves for various mineral deficiencies

2. RELATED WORKS

Many methods of diagnosing nutrient deficiencies in plants or crops have been proposed in the field of image processing. In this paper, the various research works and algorithms developed in detecting the healthy regions, unhealthy regions and classifying them into the appropriate type of nutrient disease or deficiency symptoms are discussed. The performance measures of the algorithms are presented in Table.1 through 7.

2.1 LEAF AREA MEASUREMENT

Patil and Bodhe [1] have discussed an algorithm to measure area of Betel leaf. Initially, the leaf outline was drawn on a graph paper with 1mm grid size and the leaf area was calculated by counting number of grids. This value was taken as true value. Then, the original RGB leaf image with reference object was binarized to count number of pixels using image processing method. A reference object, a one rupee coin, with known area was used to convert pixel count of binarized leaf image into leaf area. This measured area was compared with measured true value and relative error was calculated. The algorithm gave an accurate result with least relative error.

Li et al. [11] have devised an algorithm to calculate leaf area of different species. RGB image of leaf on the rectangular shaped paper was captured and the count of number of pixels of leaf and rectangular paper were calculated. Leaf area was calculated using number of pixel counts with the help of pre-measured area of rectangular paper. The resultant calculated value of area was compared with the value of area calculated using counting grid method. Total of 60 leaf samples of 6 different species had been used and had obtained an accurate value of leaf area with a relatively small error rate.

Chen et al. [12] have developed a method for measuring leaf area of Japan Euonymus Plant leaves. The leaf image was captured with square shaped paper as background. This square shaped paper was used as reference object. In this algorithm number of pixels were calculated, firstly, in the image with background and then after removing background using RGB thresholding. The ratio of leaf area to the background was calculated as the ratio of number of leaf pixels to the number of background pixels. 30 samples were tested and the algorithm gave a good result with relatively small Root Mean Square Error (RMSE). The RMSE remained same even for higher resolution RMSE but required long processing time.

Table.1. Performance analysis of leaf area measurement

Author	Specie	Method	Accuracy/ Benefit
Ayane et al. [16]	Cotton	Image Histogram	Positive results
Patil and Bodhe [1]	Betel	Binarization; One rupee coin used as reference object	Error rate =0.029
Chen et al. [12]	Japan Euonymus	RGB thresholding; Square shaped paper was used as background and reference object	Mean Relative Error=0.2%
Patil and Bodhe [13]	Sugarcane	Binarization, Edge Detection; One rupee coin was used as reference object	Error rate =0.0106
Marcon et al. [14]	Perennial Plant	Area projection	R^2 = 0.54 with outlier = 0.91 without it
Li et al. [11]	Eucommia Bark, Paulownia, Maidenhair tree, Bamboo, Cycad, Weed	Binarization; Rectangular shaped paper was used as background as well as reference object	Error rate =5.051

Patil and Bodhe [13] have developed an image processing algorithm to measure sugarcane leaf area. In this method, they have used a white paper as the background of the image and a one rupee coin as the reference object. The image was first binarized, edges detected and holes filled to obtain the leaf and coin regions. Then, the number of pixels in leaf and coin were calculated and leaf area measured with the known area of reference object.

Marcon et al. [14] have developed two models for estimating the total leaf area in perennial plants using image analysis. The first one measures total leaf area based on height and width of canopies and the other on digital image of a tree. The results obtained from both the models were compared against the real area of the leaves using destructive approach with area measured using digital scanner. Regression curves fitted with R^2 value of 0.82 with the model using the height and the width values and about 0.91 in the second model which used the area projection.

Ayane et al. [16] have written an algorithm to measure cotton leaf area. In this algorithm leaf area was calculated by measuring number of pixels. A one rupee coin with known area was used as reference object to translate pixel count into area.

2.2 EDGE AND VEIN SEGMENTATION

Sannakki et al. [9] have compared different leaf edge detection algorithms like binary morphology, Sobel edge detector and have proved that fuzzy mathematical morphology to be the efficient one. In this algorithm, fuzzy dilation followed by fuzzy erosion was applied on the leaf image and finally, the image was reconstructed using moment-preserving.

Auerunyawat et al. [17] have developed a method to automatic detection of nitrogen status in sugarcane leaf image. In this method adaptive threshold of mean was applied to both gray scale image and YCrCb color space image to extract leaf edge from background. The quality of extracted edge in the former method included shadow on background. The quality of result obtained with latter was good but couldn't extract midrib. Hence, both results were ANDed and the result was multiplied with color image. Sobel algorithm was applied on this output which resulted in leaf edges with spiky noise. Series of morphological open and close were applied to remove noise. Finally, active contour model was applied to determine boundary of the leaf.

Table.2. Performance analysis of methods used in extracting leaf edge and veins

Author	Specie	Method(s) Used	Accuracy / Benefits
Wang et al. [44]	Jujube	Adaptive Thresholding Algorithm, Otsu method, Canny Operator, Mapping function, Shape Identification algorithm, Morphological Methods, Logical operations	83.75%, 72.5% for images acquired using CMOS network camera and CCD Camera respectively.
Du et al. [45]	Plant Leaves	Multiple Threshold Edge Detection method, Ring Projection wavelet fractal dimension feature (FDF)	FDF produced effective result
Sannakki, et al. [9]	Plant Leaves	Comparison of binary morphology, Sobel with Fuzzy Mathematical	High effective result from FMM,

		Morphology(FMM), Moment Preserving	No threshold required, high immunity to noise
Auerunyawat et al. [17]	Sugarcane	Sobel Algorithm, Active Contour Model	R^2 =0.94, and 0.61 for RGB with IR images in 2 months and 4 months old models respectively
Price et al [20]	Plant Leaves	Image Thresholding and Segmentation	Leaf network and areole information extracted accurately and rapidly
Zheng et al. [27]	Various Plant Leaves	Gray-scale Morphology Otsu method	Effective result
Park et al. [46]	Plant Leaves	Curvature Scale Space Corner Detection algorithm, Canny Edge Detection method, Density distribution analysis of venation branching points	Average time to extract feature point = 0.55 s to categorize leaf venation = 0.08 s
Li et al. [26]	21 kind of tree leaf	Independent Component Analysis	Good result
Clarke et al. [29]	Ivy, Monstera, Nettle, Ochna, Ribes	Comparison of Adobe photoshop, scale space and smooth edge methods	Scale-space analysis gave good result.
Katyal et al. [28]	Plant Leaves	Odd Gabor filters and Morphological operations	Processing Time: 12 s and 10 s for large and small images respectively.

Price et al. [20] developed a Graphical User Interface (GUI) for segmenting and analyzing the structure of leaf veins and Areoles. The foreground, leaf portion of the image, was segmented using image thresholding. Veins with very less number of pixels were considered as noise and hence were removed. The image was skeletonized by thinning the image repeatedly. Pixels with more than 3 neighbors were treated as nodes and the veins connecting them were treated as edges. The nodes and edges of veins were segemented and labeled. A connectivity matrix of size $N \times N$ was generated where N is the number of nodes. The row and column indices represent list of nodes and the matrix entries were the labels of edges that connect nodes.

A novel approach in extracting venation using Independent Component Analysis (ICA) was presented by Li et al. [26]. A set of features or linear basis functions of the leaf were extracted from patches of leaf images using ICA. The resultant linear basis functions were used as pattern maps in extracting leaf veins.

Gray-scale morphological methods were used in extracting leaf vein from leaf images by Zheng et al. [27]. The RGB leaf image was converted into gray-scale and any color overlapping found on the leaf image was removed using morphological operations. Contrast of the image was enhanced to distinguish veins from background. Finally, venation pattern segmented from background using Otsu method.

An effective vein extraction method using Odd Gabor filters was formulated by Katyal et al. [28]. Morphological close operation was used in preserving the background regions that have a similar shape to the structuring element. The contrast of the resultant image was enhanced to improve the final venation pattern. The algorithm gave an extremely accurate output. The algorithm took around 12 seconds for large images and less than 10 seconds for small images.

Pattern recognition technique was used to detect venation patterns on leaves by Clarke et al. [29]. The leaf venation pattern was detected and analyzed using adobe Photoshop, scale space approach and simple smooth edge and the results were compared. The smooth edge method gave a clear venation pattern and with less time.

Wang et al. [44] designed a new adaptive thresholding algorithm for segmenting single leaf acquired from real time video system. To extract leaf edge shape identification algorithm, morphological and logical operators were used. The extracted edges were clear and accurate.

Du et al. [45] have devised a new method of describing the characteristics of plant leaves based on the outline fractal dimension and venation fractal dimension. Multiple direction edge detection method was used to separate leaf edge and vein. The two-dimensional fractal dimension of the leaf edge image and multiple vein images were calculated and a new ring projection wavelet fractal feature for leaf shape was also adopted. The above features were used in classifying and recognizing plant leaves.

Park et al. [46] proposed a Content Based Image retrieval algorithm for retrieving leaf image. In this algorithm leaf was categorized by analyzing venation pattern. The feature points of leaf images were extracted using Curvature Scale Space Corner Detection algorithm. The contrast of image enhanced in order to extract thick and non-broken edges. Then, using canny edge detection method, edges were extracted. The venation feature points detected, i.e., points where venation gets branched out and ended, where the curvature gets maximum value. Then, branching and ending points of veins distinguished. Density distribution, whether the feature points are distributed along a line or around one point, of branching and ending points calculated to categorize venation pattern. If a vertically related Branching Point is dominant, a real primary vein is found and the Branching Points were on it. In this case, the leaf image can be classified as a pinnate venation or parallel venation. If a maximum density value is found at the top of the venation, this leaf will be classified as a parallel venation. Otherwise, it is a pinnate venation. Dominant branching points of palmate venation have relations in both the direction.

2.3 COLOR SEGMENTATION

A Corn disease diagnostic system using image processing and pattern recognition technique was developed by Zhu et al. [4]. First, the algorithm converts color leaf image into gray scale to improve recognition speed. In this paper contrast of the image was enhanced using histogram equalization and further denoised using neighborhood average method. Using iterative segmentation method the image was binarized and the resultant image was optimized using morphological operations. Finally, the boundary of the leaf detected using 8-connected chain code.

Tian et al. [5] have proposed a grading method for detecting crop disease. The RGB leaf image was enhanced by applying an improved vector median filtering method on the R, G, and B value of each pixel as a feature vector. They have developed a classifier to segment diseased spot (lesion) from normal portion of the leaf using statistical pattern recognition classifier. The experiments gave positive results. The crop disease classification level was calculated as the ratio of the number of lesion pixels to that of normal pixels in the leaf.

Sanjay et al. [6] have designed an algorithm for segmenting disease region in an RGB leaf image. In this algorithm RGB image was converted into HSI color space to eliminate light factors and to extract only color components. Image was converted into gray scale and binarized using Triangle threshold method. The disease severity is measured by counting number of white pixels (disease areas).

Daygude and Kumbhar [7] have proposed a method for segmenting infected portion in leaf image. In this method the RGB image was first converted into HSV image and only Hue component was taken discarding Saturation and Value Components for further processing. The method uses Color co-occurrence method for texture feature extraction. Spatial Gray-level Dependence Matrices (SGDM), for the Hue content of the image, was used to extract statistical texture feature like Contrast, Energy, Local Homogeneity and correlation. Healthy regions were removed from the leaf by assigning zero to R, G and B components of green pixels thus extracting the infected region. The infected regions further segmented into patches of equal size. Patches having more than 50% infected areas were considered for further analysis.

Chaudhary et al. [8] compares various ways to detect disease spot on monocot and dicot family plant leaf. In this paper, RGB leaf image was transformed into CIELAB, HSI or YCbCr color space. Then image smoothening was done using Median filter to eliminate noise due to camera flash, noisy background and veins in plant leaf. The color components *A* component from CIELAB color space, *H* component from HSI color space or ‘Cr’ component from YCbCr color space were extracted and disease spots were detected by applying Otsu threshold on color component.

Medina et al. [18] have proposed an innovative algorithm for detecting unhealthiness in leaf images. They have devised methods for detecting chlorosis, leaf deformation, white spots, necrosis and mosaics and tested the algorithms on bean, pepper, pumpkin plants. An algorithm for calculating chlorotic area algorithm works in two stages. The first stage calculates the area of the leaf and determines how the chlorotic symptoms appear in the whole leaf. The second stage, divides the leaf area into 4 regions using the centroid coordinates, determine whether the chlorophyll symptoms were localized or generalized. Another algorithm, quantifies the necrotic area of bean leaf. In this algorithm, green component was used in isolating necrotic area of the leaf because it provides a better contrast between necrotic and non-necrotic regions. Leaf- deformation algorithm was developed using blue component which is less sensitive to chlorotic symptoms. Sphericity indices of healthy and unhealthy regions of leaf were compared to quantitatively determine how the unhealthy region was deformed taking as reference the healthy leaf. White spot detection algorithm estimates the area occupied by white spots. Binarized blue component of image isolated from background by pre-defined thresholding value.

Table.3. Performance analysis of color segmentation methods

Author	Specie	Method Used	Accuracy / Benefit
Daygude and Kumbhar [7]	Plant Leaves	Masking green pixels, Color co-occurrence method	Good result
Zhu et al. [4]	Corn	Iterative Segmentation, Morphological operations, 8-connected chain code	Recognition rate– 80%
Tian et al. [5]	Corn,Grape, Cucumber	Statistical pattern recognition classification	Accuracy 98.60%
Chaudhary et al. [8]	Monocot and Dicot family plant leaf	Otsu threshold applied on color components	Accurate detection of disease spot
Medina et al. [18]	Bean, Pepper, Pumpkin	Centroid Co-ordinate, Binarization with pre-defined thresholding, Sphericity index, Canny edge detection	**Symptom** – **Processing Time (ms)** Chlorosis 123.398 Necrosis 12.289 Deformation 48.49 White Spots 264.192 Mosaic 354.080
Sanjay et al. [6]	Sugarcane	Histogram, Triangle threshold method	Accuracy 98.60%
Prasad et al. [24]	Groundnut, Tomato, Corn,	Block based unsupervised learning	Good result

	Apple, Grape		
Ambatkar et al. [52]	Rose	Thresholding Hue Value	Good result

The leaf area without white spot were obtained using connectivity algorithm by complementing the image. An increased number of venations in leaf indicate the symptom of mosaic. The following steps were performed with blue component in detecting mosaic symptoms: Histogram equalization, contrast enhancement by applying top-hat and bottom-hat algorithm and canny edge detection algorithm to detect edge and veins in the leaf image. Finally, the leaf venation was quantified to detect mosaic symptoms.

Prasad et al. [24] have proposed an algorithm to detect fungal diseases in plants using block- based unsupervised color image segmentation. In this work, the original color image was converted into HSI color space and was divided into 25 blocks of equal size. Each of these blocks was passed on to unsupervised segmentation which minimizes the energy. A mask was created and diseased areas were detected. The experiment was carried out for different species and gave excellent result.

M. Mukherjee et al. [38] have developed a method for detecting damaged paddy leaf. Blast, Bacterial leaf Blight and Rice Tungro were detected at very early stage itself using these proposed methods. The algorithm works in following stages: Image Enhancement, Preprocessing, Segmentation, Histogram transformation and disease detection. The algorithm resulted in 87%, 92% and 90% accuracy in detecting Blast, Bacterial Leaf Blight, Tungro diseases respectively.

Amruta Ambatkar et al. [52] have proposed an algorithm to detect three common rose diseases viz. Black Spot, Anthracnose and Rust. The RGB image was converted into HIS color space and boundary of leaf image detected using 8-connected boundary detection algorithm. Hue Component of image, which contributes to color of image, was considered for further processing. Green colored pixels, healthy portions of leaf image, were masked by thresholding Hue value. The resultant leaf image had only infected regions of leaf.

2.4 FEATURE EXTRACTION

Patil and Kumar [3] have designed a method for extracting color feature for detecting disease in crop. They have extracted first, second and third order color moments in this algorithm.

Patil and Kumar [25] have proposed a method of extracting features of diseased leaf image. They have extracted features of diseased leaf by computing first, second and third order moments of HSV histogram of leaf image. The texture features like inertia, correlation, homogeneity and energy were obtained by computing the gray level co-occurrence matrix of the leaf image.

Tewari et al. [31] have developed an algorithm for estimating nitrogen content by extracting color features of plant leaf image. Image features such as Red, Green, Blue components, normalized R and normalized G components were extracted and analyzed using histogram. Leaf chlorophyll content was measured using SPAD meter. A regression model was developed to correlate between features of plant extracted using image processing method. The features R, G, normalized R and normalized G were selected to develop regression model as they gave highest value for the correlation coefficients. They acquired minimum prediction accuracy of 75% maximum prediction accuracy of 88%, average prediction accuracy of 75%. The actual and predicted nitrogen content of plant were linearly related with R^2 value of 0.95.

Table.4. Performance analysis of feature extraction method

Author	Specie	Method Used	Accuracy/ Benefits
Sanjana et al. [40]	Rice	Mathematical Morphology, A Classification method of membership function.	Good result
Shergill et al. [49]	Rice	Stem, Stairs Plots, Canny Edges; Surf, entropy, warp and standard deviation Features	Promising results
Miyatra and Solanki [36]	Cotton	Template Matching, Color Histogram	More accurate results
Sunagar et al. [37]	Maize	Gray Level Co-occurrence Matrix	Less time and more accurate
Surendrababu et al.[41]	Rice	Chaos and Fractal Dimension	Early detection of disease
Tewari et al [31]	Paddy	Regression Model	Average prediction accuracy: 75%
Patil and Raj Kumar [25]	Maize	Gray Level Co-occurrence Matrix	Good results
Vakilian and Massah [35]	Cucumber	Textual feature extraction using Machine Vision and Color Feature Extraction using Image Processing	$R^2 \approx 0.97$
Patil and Kumar [3]	Tomato	Color Moments Extraction	Good results
Nisale et al. [32]	Groundnut	Geometric Moments	93%
Xu et al.[43]	Tomato	Percent Histogram(Intensity, Differential), Fourier Transform and Wavelet Packet, Genetic Algorithm	82.5% ; 6 to 8 days early detection of disease
Dang et al. [34]	Plant Leaves	Hue-Saturation 2D Histogram	Classification accuracy of 81.5% for sick plants and 75% for healthy plants

Nisale et al. [32] designed an algorithm to detect various stages and deficiencies in plant by extracting geometric moment features of leaf image. The algorithm gave 93% of accuracy.

Dang et al. [34] proposed an image processing method to classify nutrient deficiency symptoms in plant images. They have developed this method as a preliminary technique for deciding on whether the image need to be transmitted over wireless multimedia sensor network, hence minimizing network traffic. The first step, image segmentation was based on HSV color space. The method segments noisy portion, water drops and leaf reflection by setting up appropriate threshold values for saturation component. Green portions of leaf image were removed to preserve only the unhealthy region for future processing. Morphological operations were applied on resultant image to retrieve location and shape information of affected area. Hue-Saturation 2D histogram was used to extract features of affected area and classification accuracy of 81.5% for sick plants and 75% for healthy plants were obtained in this method.

Vakilian and Massah [35] have applied machine vision and image processing techniques to detect nitrogen deficiency in cucumber plant. A remote controlled robotic moving camera system was setup to acquire image. Two rows of cultivated plants control (healthy) row and treatment (nitrogen deficient) row were taken for research. From acquired image, textural features such as entropy, energy and homogeneity were extracted using machine vision and color features were extracted using image processing. These parameters were examined to detect point of change between the control row and treatment row. The changes (deficiency symptoms) had been detected before two days prior to the appearance of symptoms visible for the human eye.

Miyatra and Solanki [36] have proposed a method for detecting Alternatia leaf spot disease using template matching and nutrient deficiencies in Cotton leaf, Nitrogen, Phosphorous and Sulfur detected using color histogram.

Sunagar et al. [37] have proposed an innovative approach to detect Nitrogen deficiency in Maize leaf. Grain noises in image removed by using median filter. Nitrogen content in the leaf was estimated, using color features and texture features. Color features Red, Green, Blue, Hue, Saturation and Value components were extracted and anlalyzed. Texture features entropy, energy, contrast and homogeneity were extracted by calculating Gray level co-occurrence matrix and Nitrogen content of the plant estimated. This estimated value was compared against the values obtained from laboratory tests.

Y. Sanjana et al. [40] have proposed a crop disease recognition and classification system. Leaf image was segmented using mathematical morphology. The Geometric features area, perimeter, circularity and eccentricity and the statistical features mean, variance, entropy and correlation were extracted. The membership function was used in classifying among three types of diseases Rice Blast, Rice Sheath Blight and Brown spot.

Surendrababu et al. [41] have proposed a novel method for detecting rice leaf diseases using image processing. Diseased leaf image was analyzed using image pattern and fractal dimension quantities were calculated using box-counting ratio method. The disease pattern's self-similarity was used to identify the infected disease. The self-similarity and recreation of fractal was implemented using Chaos game plot.

Xu et al. [43] have proposed a new method for diagnosing nitrogen and potassium deficiency in tomato plant, using computer vision. Color and texture features of leaf image extracted using percent intensity histogram and percent differential histogram, Fourier transform and wavelet packet. Genetic algorithm was used in feature selection for disease diagnosis. The proposed algorithm could obtain an accuracy of 82.5% and could diagnose the disease 6-10 days before experts could determine.

Shergill et al. [49] have developed a new method for detecting disease in rice crop. In this method, the leaf image was resized and leaf features were extracted. The RGB image was converted into grayscale and stem, stairs and canny edges were created. The features like surf, entropy, warp and standard deviation were extracted for healthy and diseased leaves and these features were compared to detect diseased area of leaf.

2.5 CLASSIFIERS

2.5.1 Artificial Neural Network:

Moghaddam et al. [2] have designed an algorithm for estimating chlorophyll content of sugar beet leaf which is an important criterion in estimating nitrogen status. In this paper, the chlorophyll concentration of leaf is measured using chlorophyll meter (SPAD-502). A multilayer perceptron neural network with back propagation was developed for finding chlorophyll content. Three neurons in input layer and one neuron in output layer were used to match 3 components(R, G, and B) in input layer and 1 data (measure of chlorophyll content) in output layer. An optimum model with 1 hidden layer consisting of 10 neurons and the sigmoid function in the hidden layer and linear function in the output layer was formulated. Number of hidden layers was found using training error method. A Linear regression model, that fits a line, estimates the chlorophyll content (Y axis) for the R, G and B components (X axis), was developed. The result of this model was compared against ANN model.

Table.5. Performance analysis of neural network classifiers

Author	Specie	Method Used	Accuracy/ Benefit
Tigadi and Sharma [50]	Banana	Histogram Of Template Feature, Color Feature , Feed-forward back propagation Artificial Neural Network	Can replace manual system
Vinushree et al. [30]	Plant Leaves	Supervised Neural Network with three Layes, Kernal based Fuzzy C-Means Clustering Algorithm	Increased throughput
Moghaddam et al. [2]	Sugar beet	Multilayer Perceptron Neural Network with back propagation	R^2=0.94, Mean Square Error =0.006
Zang and Zang [19]	Tobacco	Machine Vision, Nueral Network, Fuzzy-Comprehensive Evaluation	*Classification Accuracy* Trained leaves - 94% Non trained - 72%
Gulhane and Gurjar [33]	Cotton	Back Propagation Neural Network	85 to 91%

Zang and Zang [19] have proposed a classification and quality evaluation of Tobacco leaves. Color, shape and texture features of the leaves were extracted using machine vision. The membership functions of the features were evaluated using neural networks. Using the two level Fuzzy-Comprehensive Evaluation (FCE), the leaves were classified and obtained an accuracy rate of 94% for the trained tobacco leaves and an accuracy rate of 72% for non-trained tobacco leaves.

Vinushree et al. [30] have proposed an algorithm to calculate the density of pest in plants. A supervised neural network with three layers was created to extract leaf features. The kernel-based fuzzy c- means clustering algorithm was developed in identifying density of insects.

Gulhane and Gurjar [33] have proposed an overall cotton leaf diagnostic system. In this algorithm, the input leaf image was enhanced using antisotropic-diffusion technique. Then leaf color was extracted from background using HIS color space and B component was extracted from LAB color space. An unsupervised SOFM network was developed to cluster the resultant color pixels. To detect disease part of color leaf image, back propogation neural network was applied. Depending on the image quality this algorithm gave 85 to 91% of accuracy.

Tigadi and Sharma [50] have proposed a new method of classifying Banana Pant diseases Banana Bunchy Top Virus, Black Sigatoka, Yellow Sigatoka, Panama Wilt and Banana Streak Virus using ANN. Resized RGB image converted to HSV color space and gray scale. Two types of features Histogram of Template (HOT) and color features Mean and Standard Deviation of Hue, Saturation and Value components were extracted from leaf image. Texture and gradient magnitude information were calculated using HOT features. The feed-forward back propagation neural network was used in classifying diseases. The percentage of affected leaf area was used in grading the disease.

2.5.2 SVM Classifier:

Sun et al. [15] proposes an algorithm to judge paddy rice's nitrogen deficiency. In this algorithm leaf was placed on a white paper and image was captured to simplify the image background removal. The color characteristics of the image R, G, B, H, S and I were determined along with color parameters such as R/(G+B), G/(R+B),B/(R+G), R/B, G/B as these parameters are related to nitrogen content. The Recognition was made using SVM sorting model and an accuracy rate of 95% was obtained.

Table 6. Performance analysis of classification using SVM classifier

Author	Specie	Method Used	Accuracy / Benefits
Larese et al. [42]	Soybean, Red and White beans	Unconstrained hit-or-miss transform and Adaptive Thresholding, SVM Classifier (Linear and Gaussian Kernel),PDA classifier	PDA classifier accuracy: 89.9±2.7
Arivazhagan et al.[22]	Banana, Beans, Guaua, Jackfruit, Lemon, Mango, Potato, Sapota, Tomato	Minimum Co-occurrence matrix, SVM Classifier,	Accuracy 94%
Asraf et al. [47]	Palm	SVM classifier (kernels, linear, polynomial with soft margin and polynomial with hard margin	Classification accuracy: 95%
Muhammed et al.[21]	Elaeis Guineensis	ANOVA,MCP test, Multilayer Perceptron Classifier with 3 Layers	Accuracy with ANOVA and MCP :86.11%
Madhogaria et al. [23]	Plant Leaves	Convex Energy Functional SVM Classifier	Promising result

Muhammed et al. [21] designed an algorithm to detect nutrients, Nitrogen, Potassium and Magnesium, deficiencies in Elaeis crop. They have extracted Leaf Color Features, Histogram-based Texture Features and Gray level Co-occurrence Matrices and features selected by applying ANOVA and Multiple Comparison Procedure test. An accuracy level of 86% was attained in categorizing nutritional lacking in Elaeis crop using ANN Mutilayer Perceptron classifier with 3 layers.

Arivazhagan et al. [22] proposes an algorithm to detect unhealthy region of plant leaves and classification of plant leaf diseases. To detect unhealthy region, RGB leaf image was converted into HSI color space, green pixels (healthy regions) were masked by thresholding hue component. The resultant leaf image, with only infected regions, was segmented into patches of equal size. Texture features like Contrast, Energy, Local Homogeneity and Cluster Prominence were computed for the Hue component. These features were used to classify various types of plant diseases. Minimum distance criterions were applied to co-occurrence features for classification and the success of classification was measured using classification gain. Using SVM classifier with 5% of images used as training set, the remaining images were tested and obtained a detection accuracy of 94.74%.

Madhogaria et al. [23] devised an algorithm to detect unhealthy regions infected by Salmonella bacteria in leaf images. Convex Energy Function was used to segment foreground and background of leaf image in I1I2I3 color space. Healthy and Unhealthy leaves were classified using Support Vector Machines (SVM) classifier. Neighborhood check was used to remove isolated infected pixels and keep only densed infected regions.

Larese et al. [42] have proposed a method to automate classification of legumes based on analysis of veins. Three species soybean, red and white beans were studied. Unconstrained hit-or-miss transform and adaptive thresholding techniques were used to segment veins. Legumes classified using linear SVM classifier, Gaussian kernels SVM classifier penalized discriminant analysis and random forests. The results were compared and obtained an average classification accuracy of 87% with the PDA classifier.

Asraf et al. [47] have extracted color histogram based features contrast, correlation homogeneity, energy, and entropy features using gray level co-occurrence matrix. The nutrient diseases N, P and Mg deficiencies in plant were detected using SVM classifier. Three different kernels, linear, polynomial with soft margin and polynomial with hard margins of SVM classifier were evaluated and compared. The polynomial kernel with soft margin gave an accuracy of 95% in classifying nutrient disease in oil palm leaves.

2.5.3 Other Classifiers:

Shikora et al. [39] have devised a probabilistic method of classifying disease symptoms caused by salmonella on Arabidopsis thaliana plant. Leaf image was segmented using globally optimal color segmentation. Two-dimensional data points, the second and third channels of I1I2I3 color space, were clustered into M (e.g., with value 3) clusters using k-means algorithm. A probabilistic model *M*, of color distribution, for a healthy leaf was modeled. In this model, each pixel of the leaf was checked for the likelihood for being healthy and accordingly the leaf was classified as healthy or unhealthy.

2.6 OTHER METHODS

Table.7. Performance analysis methods other than digital image processing

Author	Specie	Method Used	Accuracy/ Benefits
Sridevy and Vijendran [51]	Maize	Independent Component Analysis, Multivariate Image Analysis, Multivariate Partial Least Square Method	Acts as advisor to farmers
Thangadurai and Padmavathi [48]	Various Plant	Histogram Equalization	Good results
Mukherjee et al. [38]	Paddy	Histogram	Promising results
Patil et al. [10]	Crop	Web Based Expert System	Good results

Patil et al. [10] have developed a web based Expert System for identification of nutrient deficiency in plants. The system uses Mineral Information System, which contains information about minerals, deficiency symptoms, prevention and remedy, as production rules. A classification model of nutrient deficiency symptoms was implemented.

Thangadurai and Padmavathi [48] have proposed an algorithm to detect disease in plant leaves. The RGB image was converted into grayscale for easy processing. The image clarity was improved by using Histogram Equalization. New leaf image was built using the values calculated from histogram equalization and the cumulative histogram of new leaf image compared with the original leaf image in order to detect disease.

Sridevy and Vijendran [51] have designed an Expert System for detecting nutrient deficiency in Maize plant using image processing technique. RGB image was converted into HSV color space and the infected regions of leaf extracted by masking green colored pixels using Otsu method. The contrast of the image was adjusted using Histogram Equalization and Eigen matrix was extracted using Independent Component Analysis. Energy and Entropy features of the leaf image were extracted. Multivariate Image Analysis and Multivariate Partial Least Square methods were used in classifying the type of nutrient deficiency in Maize leaf.

3. CONCLUSION AND FUTURE WORK

Plant unhealthiness may be caused by living organism like insects, fungi, bacteria etc. or nonliving factors like nutrient imbalances, drought or excess soil moistures, limited light, reduced oxygen availability etc. The various methods used in diagnosing nutrient deficiency symptoms in plants/crops in the literature were studied in this paper. The existing methods focus on diagnosing macro nutrient deficiencies Nitrogen, Phosphorous and Potassium etc. Only very few works have been taken place for diagnosing micronutrient deficiency symptoms which also cause serious damage to the growth of the plant/ crop. Hence, the future work would concentrate on diagnosing micronutrient deficiencies Iron, Boron, Manganese, Zinc etc. Also, other symptoms of unhealthiness in plants that may be considered for future work would include blight (death of plant part), bleaching (white coloration on leaves) or rust (formation of orange to reddish-brown spots) etc. Color image processing places a vital role in diagnosing unhealthiness in plants since many of these symptoms are expressed in colors by plants.

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