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Recommendations for the Diagnosis of Nutrient Deficiency Syndromes in Plant Leaf Imagery through DIGITAL IMAGING PROCESSING are presented.

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Abstract v vcccccccccccccc

Thirteen different mineral nutrients are required for plant development and survival. A plant's development might be stunted or even stunted to death if it lacks one or more of these essential nutrients. As a result, a system for continuously checking the nutritional status of plants is crucial for increasing productivity and improving crop quality. The signs of a deficit might be detected by a diagnostic system that uses digital image processing rather than the human eye. The farmers will be able to take corrective measures sooner rather than later. Image processing methods are reviewed in this research to help identify nutrient deficiencies in plants.

Keywords: Mathematical Morphology; Color Segmentation; Color Feature Extraction; Classifier; Color

INTRODUCTION

Plants and crops need a total of 13 mineral nutrients in order to thrive and flourish. The earth provides them with the nutrition they need. Growth and quality are negatively impacted by a lack of essential nutrients. Thus, the importance of mineral nutrient status in agriculture and farming cannot be overstated. Leaf signs of nutrient insufficiency are typical in plants and crops. These signs include interveinal chlorosis, marginal chlorosis, uniform chlorosis, necrosis, deformed margins, and a decrease in the leaf's diameter. The deficiency nutrient may differ even when comparable symptoms are evident in both old and young leaves. Figure 1 displays some of the leaf signs of plant visual impairment. The mineral nutrients are broken down into macro and micro nutrients.. macronutrients and micronutrients are essential for the survival of plants. Carbon, hydrogen, oxygen, sulphur and phosphorus are all macronutrients. Boron, Copper, Iron, Chloride, Manganese, Molybdenum, and Zinc are examples of micronutrients.

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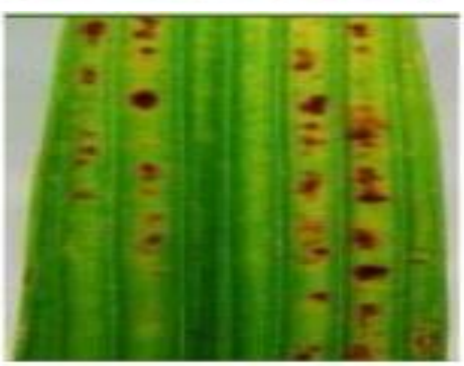
COMPONENTS OF NUTRIENT DEFICIENCY DIAGNOSTIC SYSTEM

The following elements would be included into the diagnostic system via the use of image processing techniques: Determining the shape of the leaf

- Segmentation of the edge and veins of the leaf
- Classifying insufficient mineral
- Identifying the leaf's age

Extracting the lea's chromatic information



Iron deficiency, Boron deficiency, magnesium deficiency, phosphorous deficiency, nitrogen deficiency, and molybdenum deficiency are just a few of the many deficiencies that may occur.Fig.1 illustrates the visual signs of different mineral deficits on plant/crop leaves.

RELATED WORKS

The field of image processing has been offered several ways to identify crop or plant deficits in terms of nutrient levels. Many studies and methods have been established over the years in order to accurately assess nutrient shortage or illness symptoms, and this article discusses them. Tables 1 through 7 show the results of the algorithms' performance tests.

LEAF AREA MEASUREMENT

An approach for calculating the surface area of a Betel leaf has been proposed by Patil and Bodhe [1]. To begin, a leaf shape was created on graph paper with a 1mm grid size, and the area of the leaf was estimated by counting the number of grids there were on the sheet of paper. It was assumed that this was the real value. Once the original RGB leaf picture with the reference object was binarized, an image processing approach was used to count the number of pixels. It was necessary to compare the binarized leaf image's pixel count with the known area of another reference item, in this case a one rupee coin. In order to determine the relative inaccuracy, the measured area was compared to the actual real value of the object. A precise answer with the least amount of relative error was generated by the method An method for calculating the leaf area of several species was developed by Li et al. [11]. Rgb picture was taken and pixel count for both leaf and paper were determined from this. With the use of a pre-measured rectangle of paper, pixel counts were used to compute the leaf area. Comparing the results of utilising the counting grid technique and calculating area using the subsequent computed value of area, With 60 leaf samples from six distinct species, the researchers were able to calculate the correct area of each leaf. The leaf area of Japan Euonymus Plants was recently measured by Chen et al. [12]. As a backdrop, I used a square piece of paper to photograph the leaf. As a point of reference, this square of paper was utilised. Using RGB thresholding, we first computed the number of pixels in the picture with the background, and then when the background was removed, we used the method. The number of leaf pixels divided by the total number of pixels in the backdrop was used to compute the leaf area to background ratio. Using 30 samples, the method performed well, with an RSE of less than one standard deviation (RMSE). Although the RMSE stayed the same even with higher resolution RMSEs, the processing time needed was much longer.

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

Sugarcane leaf area was recently measured using an image processing method developed by Patil and Bodhe [13]. A white sheet of paper serves as the picture backdrop, and a one rupee coin serves as the reference object, in this technique of image creation. To acquire the leaf and coin areas, the picture was binarized and then edge detection and hole filling were performed on it. Afterwards, the number of pixels in the leaf and the coin were computed and the leaf area was measured using the known area of the reference item. Perennial plants' total leaf area may be estimated using two new models established by Marcon et al. [14]. The first one uses the height and breadth of the canopies to calculate the total leaf area, while the second uses a digital picture of a tree. With the use of a digital scanner, we compared the output from both models against the actual leaf surface area. R2 values were 0.82 in the first model, and roughly 0.91 in the second model, which employed the area projection to match the regression curves. Cotton leaf area may be measured using an algorithm developed by Ayane et al. [16]. The number of pixels was used to compute the leaf area in this approach. To convert pixel count to area, we utilised a known-area reference object: a one rupee coin.

EDGE AND VEIN SEGMENTATION

As far as leaf edge identification goes, Sannakki and colleagues [9] found that the most effective method is the fuzzy mathematical method of morphology. The leaf picture was first distorted, then eroded, and ultimately recreated using moment-preserving fuzzy dilation and elongation. Sugarcane leaf images may now be automatically analysed for nitrogen levels, thanks to a technique developed by Auerunyawat et al [17]. For the leaf edge to be discerned from the background, an adaptive threshold of mean was applied to both grayscale picture and colour space image. When using the first approach, the edge quality was enhanced by the presence of shadows on the backdrop. Even though the quality of the final product was excellent, we were unable to remove the midrib using this method. This result was then multiplied by a colour picture by ANDing the two outcomes. Leaf edges with spiky noise were produced using the Sobel algorithm on this output. Noise was reduced by using a series of morphological open and close operations. Lastly, the leaf's border was determined by using an active contour model.

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 Morphology(FMM), Moment Preserving	High effective result from FMM, No threshold required, high immunity to noise
Aucrunyawat 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.

The number of nodes was N, and the number of nodes was multiplied by N. An edge's label may be found in the row and column indices of a matrix, which are lists of nodes. Li et al. [26] reported on a new method for obtaining venation using Independent Component Analysis (ICA). ICA was used to extract a collection of leaf characteristics or linear basis functions from pictures of leaf patches. Extracting leaf veins was made easier with the help of the pattern maps generated by linear basis functions. Zheng et al. [27] employed gray-scale morphological approaches to extract leaf veins from leaf pictures. Any overlapping colours discovered on the leaf picture were eliminated using morphological techniques on the RGB leaf image. To make veins stand out against the backdrop, the image's contrast was boosted. Otsu technique separated venation pattern from background. Odd Gabor filters may be used to extract veins effectively, according to Katyal and colleagues [28]. The background areas that are comparable in form to the structuring element were preserved using morphological close technique. The final venation pattern was improved by increasing the image's contrast. The result of the algorithm was exceedingly precise. Large photographs took roughly 12 seconds to process, whereas smaller ones took less than 10 seconds. Clarke et al. [29] employed pattern recognition to determine venation patterns on leaves. Photoshop, scale space method, and basic smooth edge were used to identify and assess the leaf venation pattern. The findings were then compared. The smooth edge approach produced a distinct venation pattern in a shorter amount of time. It was developed by Wang et al [44] to segment a single leaf in real time video using an adaptive thresholding technique. An algorithm for identifying the form of leaf edges was developed using morphological and logical operators. There was no ambiguity in the edges that were extracted. Using the outline and venation fractal dimensions, Du et al. [45] have come up with a novel way to describe the properties of plant leaves. To distinguish between the vein and the leaf edge, a technique known as multiple direction edge detection was used. A novel ring projection wavelet fractal feature for leaf shape was also introduced, which estimated the two-dimensional fractal dimension of the leaf edge picture and numerous vein images. Classifying and identifying plant leaves relied on the following characteristics: For recovering leaf images, Park et al. [46] suggested a Content-Based Image Retrieval method. The venation pattern of a leaf was used to classify it in this approach. Using the Curvature Scale Space Corner Detection technique, we were able to identify the feature points in leaf pictures. The image's contrast was boosted in order to extract sharp edges with thick black bars. The edges were then retrieved using a clever edge detecting approach. For example, the point at which the curvature achieves its greatest value, or the sites where venation branches out and ends, are the venation feature points. After that, veins' branching and terminating places were identified and documented. It is determined by the density distribution of branching and terminating points, whether they are scattered along a line or around one single point, to characterise venation pattern. The Branching Points were on a major vein if it had a prominent vertically connected Branching Point. Pinnate venation or parallel venation might be used to classify this picture of a leaf. If the maximum density is reached,

COLOR SEGMENTATION

Zhu et al. [4] created an image processing and pattern recognition system for the diagnosis of corn disease. In the beginning, the algorithm reduces the colour leaf picture to grayscale in order to speed up the recognition process. It was decided to use histogram equalisation to boost picture contrast and neighbourhood average approach to further denoise it. Morphological procedures were used to improve the picture after a series of repetitive segmentation steps. Finally, an 8-connected chain code was used to determine the leaf's border. Crop disease detection has been simplified thanks to a new grading system suggested by Tian et al. An improved vector median filtering approach was used to the R, G, and B values of each pixel as a feature vector to enhance the RGB leaf picture. In order to distinguish the sick spot (lesion) from the rest of the leaf, a statistical pattern recognition classifier has been created. The findings of the trials were favourable. The ratio of lesion pixels to leaf normal pixels was used to determine the crop disease categorization level. There is a new method developed by Sanjay and his colleagues to identify diseased areas in an RGB leaf picture. The RGB picture was transformed into HSI colour space to remove light factors and extract just colour components in this approach. For binarization, a triangle threshold approach was used to transform the image to grey scale. By measuring the amount of white pixels, a disease's severity may be determined (disease areas). An infected area of a leaf picture may be segmented by Daygude and Kumbhar [7]. To begin, the RGB picture was turned into an HSV image, which was then reduced to a single Hue component, excluding the Saturation and Value components. Extraction of texture features is accomplished via the use of the Color Co-occurrence Method. Statistical texture features including contrast, energy, local homogeneity, and correlation were extracted using Spatial Gray Level Dependence Matrices (SGDM) for the image's hue content. Assigning 0 to the R, G, and B components of green pixels destroyed the healthy areas of the leaf. Patches of comparable size were created in the affected zones. Patches with more than 50% contaminated regions were recommended for further investigation. Different methods for detecting disease spots on monocot and dicot family plants are compared by Chaudhary et al. [8]. A leaf picture was converted to CIELAB, HSI or RGB colour space in this study. An image smoothing technique was used to remove camera flash, noisy backdrop, and plant veins. Components of colour Color components from CIELAB, HSI, or YCbCrcolour spaces were extracted and illness spots were recognised by applying the Otsu threshold to the colour component. Medina et al. [18] have developed a novel method for identifying disease in leaf pictures that has been published in Nature Communications. On bean, pepper, and pumpkin plants, they have evaluated the algorithms for identifying chlorosis, leaf deformation, white spot necrosis, and mosaics. A two-stage technique is used to calculate chlorotic area. Chlorotic signs may be seen across the leaf in the first stage, which measures the leaf's area. To evaluate whether the chlorophyll symptoms were localised or widespread, the second step splits the leaf area into four areas using the centroid coordinates of the centroid points. The necrotic region of a bean leaf may be quantified using another technique. The green component of the leaf was employed in this method in order to better distinguish necrotic and non-necrotic areas of the leaf. Using a blue component that is less susceptible to chlorotic symptoms, a leaf-deformation algorithm was constructed. It was determined how the leaf's healthy and unhealthy areas were distorted quantitatively by comparing the leaf's sphericity indices to the healthy leaf. A white spot detection algorithm calculates the area occupied by white spots based on the data provided. Using a predetermined thresholding setting, a blue component of the picture is separated from the backdrop.

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

By combining a picture with a connectivity method, the leaf region without the white spot was retrieved. When the leaf has more venations, it indicates the presence of mosaic. In order to diagnose mosaic symptoms, the blue component was used in the following manner: Leaf veins and edges are detected using canny edge detection algorithm and histogram equalisation as well as contrast enhancement using top-hat and bottom-hat algorithms. Finally, the venation of leaves was measured to look for signs of mosaicism. Using block-based unsupervised colour picture segmentation, Prasad et al. [24] have developed an algorithm for detecting fungal infections in plants. HSI colour space was used to transform the original colour picture into 25 equal-sized pieces. Using unsupervised segmentation, each of these blocks was reduced in energy. A mask was constructed, and the presence of diseased tissue was discovered. For a variety of different species, the experiment produced good results. For identifying damaged rice leaves, a technique developed by Mukherjee et al. [38] has been devised. With these new technologies, Blast, Bacterial leaf Blight, and Rice Tungro were all discovered at an early stage in the disease cycle. Following the algorithm's steps are image enhancement, preprocessing and segmentation. Histogram transformation and illness diagnosis are also included. The system was able to identify Blast, Bacterial Leaf Blight, and Tungro illnesses with 87%, 92%, and 90% accuracy, respectively. Three common rose diseases, Black Spot, Anthracnose, and Rust, may be detected using an algorithm presented by Amruta Ambatkar et al. [52]. The RGB picture was transformed into HIS colour space, and the leaf image's border was determined using an 8-connected technique. Further processing took into account the image's hue component, which is responsible for the image's colour. Hue value thresholding concealed healthy green pixels in the leaf picture. Only some parts of the leaf were infected in the resulting photograph.

FEATURE EXTRACTION

Patil and Kumar [3] have created a technique for extracting colour characteristic for identifying illness in crop. They have retrieved first, second and third order colour moments in this approach. Patil and Kumar [25] have presented a technique of extracting aspects of sick leaf picture. They have retrieved characteristics of sick leaf by calculating first, second and third order moments of HSV histogram of leaf picture. The texture properties including inertia, correlation, homogeneity and energy were derived by calculating the grey level co-occurrence matrix of the leaf picture. Tewari et al. [31] have developed an algorithm for calculating nitrogen concentration by extracting colour aspects of plant leaf picture. Image attributes such as Red, Green, Blue components, normalised R and normalised G components were extracted and evaluated using histogram. Leaf chlorophyll content was measured using SPAD metre. A regression model was created to correlate between properties of plant collected using image processing technology. The characteristics R, G, normalised R and normalised G were used to create regression model as they delivered greatest value for the correlation coefficients. They got minimum prediction accuracy of 75 percent maximum prediction accuracy of 88 percent , average prediction accuracy of 75 percent . The real and anticipated nitrogen content of plant were linearly connected with R2 value of 0.95.

Table.4. Performance study of feature extraction technique.

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

Classification of nutrient shortage symptoms in plant pictures was suggested by Dang and colleagues [34]. In order to reduce network traffic, they created this approach to determine if images should be sent via a wireless multimedia sensor network. Image segmentation was performed using the HSV colour space as a starting point. Saturation thresholds are used to segment the noisy section, water droplets, and leaf reflections. Removed healthy parts of the leaf picture for further processing while keeping the bad parts. Using the resulting picture and morphological processes, we were able to locate and determine the geometry of the impacted region. Classification accuracy of 81.5 percent for ill plants and 75 percent for healthy plants was achieved using the Hue Saturation 2D histogram. Machine vision and image processing methods have been used to identify nitrogen deficit in cucumber plants by Vakilian and Massah [35]. To capture images, a robotic moving camera system was put up and operated through a handheld remote control. Two rows of planted plants were collected for research: the control (healthy) row and the treatment (nitrogen deficiency). Machine vision was used to extract textural information including entropy, energy, and homogeneity from the obtained picture, while image processing was used to retrieve colour features. These variables were compared between the control and treatment groups to see whether there was any evidence of change. Prior to the manifestation of apparent signs, the alterations (deficiency symptoms) had already been discovered. Template matching and nutrient deficits in Cotton leaf, Nitrogen, Phosphorous, and Sulfur discovered using a colour histogram were suggested by Miyatra and Solanki [36] as a technique for identifying Alternatia leaf spot disease. To identify nitrogen deficit in Maize leaf, Sunagar et al. [37] have presented a novel technique. Using the median filter, grain noises may be eliminated from a picture. Color and textural traits were used to determine the leaf's nitrogen concentration. Features of various hues Thecolours red, green, and blue, as well as their hue, saturation, and value, were separated and analysed. Using Gray level co-occurrence matrix, the entropy, energy, contrast, and homogeneity of the texture were determined. The results of laboratory testing were compared to this estimated value. A crop disease detection and categorization method has been suggested by Y. Sanjana et al [40]. Leaf images were segmented using morphological analysis. The statistical characteristics mean, variance, entropy, and correlation were retrieved from the geometry and statistics. Rice Blast, Rice Sheath Blight, and Brown Spot were the three illnesses classified using the membership function. New techniques for identifying rice leaf diseases have been suggested by Surendrababu and colleagues [41]. The image pattern approach was used to evaluate the diseased leaf picture, and the box-counting ratio method was used to determine the fractal dimension values. The self-similarity of the illness pattern helped to pinpoint the source of the infection. In order to achieve fractal self-similarity and reproduction, the Chaos game plot was used. Computer vision has been used by Xu et al. [43] to develop a novel approach for detecting nitrogen and potassium deficiencies in tomato plants. Fourier transform, wavelet packet, and percent differential histogram were used to extract the leaf image's colour and texture information. Feature selection for illness diagnosis was carried out using a genetic algorithm. The suggested algorithm has an accuracy rate of 82.5 percent and can detect the ailment six to ten days earlier than specialists can.. A novel approach for identifying illness in rice crops was developed by Shergill et al. [49]. These characteristics were retrieved by reducing the size of the leaf picture. Stems, staircases, and canny edges were added to the grayscale picture. Healthy and sick leaves were analysed for parameters including surf, entropy, warp, and standard deviation, and then these variables were compared to discover unhealthy leaf areas.

CLASSIFIERS

Artificial Neural Network

Algorithms based on chlorophyll concentration of sugar beet leaves have been developed by Moghaddam and colleagues [2] to estimate nitrogen status. A chlorophyll metre is used to determine the leaf's chlorophyll content in this study (SPAD-502). For the purpose of determining chlorophyll content, a multilayer perceptron neural network with back propagation was created. For the matching of three components (R, G, and B) in the input layer and one data point (a measure of chlorophyll content) in the output layer, three input layer neurons and one output layer neuron were used A sigmoid function in the hidden layer and a linear function in the output layer were found to be the most optimal. By measuring the amount of training error, we were able to ascertain the exact number of hidden layers. In order to estimate chlorophyll concentration (Y axis) for the R, G, and B components, a Linear regression model was created. This model's output was compared to that of an 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%

In Zang and Zang [19], Tobacco leaves have been categorised and rated on quality. Machine vision was used to extract leaf colour, shape, and texture information. Neural networks were used to assess the characteristics' membership functions. Fuzzy-Comprehensive Evaluation (FCE) was used to classify the leaves, with a classification accuracy of 94% for tobacco leaves that had been trained and a classification accuracy of 72% for tobacco leaves that had not been trained. Plant pest density may be calculated using an algorithm provided by Vinushree et al. [30]. A three-layer supervised neural network was used to retrieve leaf characteristics. An method for grouping insects based on fuzzy c-means was developed. A cotton leaf diagnostic technique has been presented by Gulhane and Gurjar [33]. The antisotropic-diffusion approach was used to improve the input leaf picture in this algorithm. Colors were retrieved from the backdrop using HIS colour space and B components from LAB colour space, respectively. Color pixels were clustered using an unsupervised SOFM network. A back propagation neural network was used to identify diseased areas in a colour leaf picture. This algorithm's accuracy ranged from 85 to 91 percent, depending on the quality of the picture. An ANN-based classification approach for Banana Pant illnesses has been developed by Tigadi and Sharma [50]. Image resized from RGB to HSV and grayscaled. There are two kinds of features. Template (HOT) and colour characteristics are shown in a histogram. The leaf picture was used to extract the mean and standard deviation of the hue, saturation, and value components. In order to get information about texture and gradient magnitude, we used HOT features. Using a neural network with feed-forward back propagation, scientists were able to sort disorders. The illness was graded based on the proportion of afflicted leaf area.

SVM Classifier

To make removing the picture backdrop as simple as possible, a leaf was put on a sheet of white paper and an image was shot. Color parameters such as R/(G+B), G/(R+B),B/(R+G), R/B, G/B as these factors are connected to nitrogen content were determined for the picture R, G, B, H, S, and I. SVM sorting model was used for the recognition, which yielded a 95% accuracy rate.

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

In Zang and Zang [19], Tobacco leaves have been categorised and rated on quality. Machine vision was used to extract leaf colour, shape, and texture information. Neural networks were used to assess the characteristics' membership functions. Fuzzy-Comprehensive Evaluation (FCE) was used to classify the leaves, with a classification accuracy of 94% for tobacco leaves that had been trained and a classification accuracy of 72% for tobacco leaves that had not been trained. Plant pest density may be calculated using an algorithm provided by Vinushree et al. [30]. A three-layer supervised neural network was used to retrieve leaf characteristics. An method for grouping insects based on fuzzy c-means was developed. A cotton leaf diagnostic technique has been presented by Gulhane and Gurjar [33]. The antisotropic-diffusion approach was used to improve the input leaf picture in this algorithm. Colors were retrieved from the backdrop using HIS colour space and B components from LAB colour space, respectively. Color pixels were clustered using an unsupervised SOFM network. A back propagation neural network was used to identify diseased areas in a colour leaf picture. This algorithm's accuracy ranged from 85 to 91 percent, depending on the quality of the picture. An ANN-based classification approach for Banana Pant illnesses has been developed by Tigadi and Sharma [50]. Image resized from RGB to HSV and grayscaled. There are two kinds of features. Template (HOT) and colour characteristics are shown in a histogram. The leaf picture was used to extract the mean and standard deviation of the hue, saturation, and value components. In order to get information about texture and gradient magnitude, we used HOT features. Using a neural network with feed-forward back propagation, scientists were able to sort disorders. The illness was graded based on the proportion of afflicted leaf area.

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