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A Novel Plant Leaf Ailment Recognition Method using Image Processing Algorithms

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In the 21st Century, agriculture still remains the major source of food for human beings and it has far shadowed other sources such as hunting, fishing and gathering. Since environmental conditions are beyond the scope of human control, plant illness identification is acting as a critical position in the agricultural field. This paper suggests a method to replace the traditional methods of identifying disease through the use of "image-processing" techniques. In this study, an image of the leaf of a diseased plant has been taken using a digital camera. Three segmentation algorithms namely Green Pixel Masking, "CIE L*a*b colour space" extraction and H element of HSV extraction have been used to split the image into diseased and healthy regions. The diseased region is then used to calculate 13 parameters which are utilized as inputs by a pre-trained neural network which utilizes "feed-forward back propagation algorithm" to determine the final output. The proposed methodology has achieved a maximum accuracy of 95.62% for Apple leaves, 91.62% for Grape leaves and 91.1% for Tomato leaves.

Keywords: Artificial Neural Network, Classification, Image Processing, Plant disease detection

Introduction

Plants form an integral part of the eco-system; they are needed for the survival of all life forms on planet Earth. One of the main sources of food for human beings are plants which is the main reason why Agriculture is acting a significant role in the economy and well-being of a country. Sixty percent of the world's population depends on agriculture for survival. Plants like all other life form are affected by various conditions which might result in their demise, such conditions are usually referred to as plant diseases. The field that deals with the study and research of plant diseases is called Plant Pathology. The traditional methods of identifying such diseases involve experiments or tests which are performed on the plants in specially controlled environments such as labs with the utilization of special lab equipment.

Every year, the actual yield of crops is always comparatively lower than the potential yield; this is due to the loss of crops to various diseases, pests and other environmental conditions. Crop diseases are of paramount problem in agriculture industry as they cause serious reduction in yield as well as quality of farm produce. Efficiency of farming is rather on top of which economy of many developing countries depend. Therefore, ailment recognition in plants is captivating an imperative responsibility in agriculture field. If appropriate care is not taken, it will result in heavy toll on the overall productivity. There arises the need for an automatic plant-disease detection system to benefit in monitoring of large fields. A computerised solution offers great opportunities for the automatic recognition of sick plants.

The task of monitoring and detecting the diseases, in crops of larger farms, using traditional and manual methods are very difficult, laborious and time consuming. Since timely intervention is crucial for the results, a computer based automated system for immediate disease detection would be a boon[1] as it could provide timely solution with minimum labourer. Image processing Techniques[2] can be designed for the identification of the diseased plants with more accuracy and efficiency than the manual techniques. A colour-based segmentation technique[3] to identify and detect disease from the infected plant leaves is being projected hereby. Employing "Computer vision-based segmentation methods" to extract precise information from images of plant leaves is the key technique for detection of plant diseases. The input

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leaf image of the diseased plant can be interpreted using Image segmentation techniques. The Image processing techniques will have more utility in the agriculture field apart from disease detection; they are to detect diseased part of the plant, to evaluate the intensity of the disease, to evaluate the dimension and outline of bug area and also to evaluate the yield level and productivity. This paper presents the techniques of using algorithms, CIE L*a*b colour space extraction, Green Pixel Masking and H component of HSV extraction[6] to detect diseases occurring on plant leaves and for segmenting the affected region. The disease affected area can be calculated using a set of parameters viz Homogeneity, Entropy and Shape, Contrast, Energy etc., The said parameters are pre-set into a pre-trained neural network to determine the name and nature of disease.

Proposed Methodology

The proposed technique utilises image detection, segmentation and identification. The process mentioned below provides a step-by-step approach to the proposed method for detection, segmentation and identification of the plant disease as mentioned in Fig. 1.

Image Possesion

The picture of various leaves of plants like grape, apple, strawberry, tomato and cherry are collected using a digital camera or smartphone camera.

Pre-Processing

The image is then subjected to resizing into 256*256 pixels followed by converting into the "CIE L*a*b colour space[7] and HSV colour space". The concerned converted images are split into their respective colour planes.

Detection and Segmentation

This stage involves determining the diseased region and separating the plant leaf image into healthy and disease regions as shown in Fig. 2. This is done using the following three algorithms—

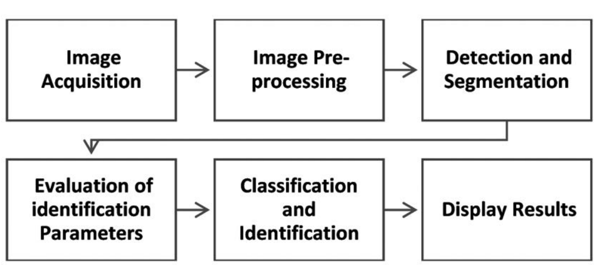

Fig. 1 — Block Diagram of planned process

Green Pixel Masking[8]

In green pixel masking process the pixel intensities are observed. Healthy portion of leaf is the one whose green intensity values are higher than red intensity and blue intensity values. This process is used to separate the healthy and diseased portions based on its colour of appearance. The diseased portion of the leaf is determined by masking the pixels with greater green plane intensity values and extracting only the pixels where the green plane intensity is less than the red and blue planes.

*"CIE L*a*b Colour Space" Extraction*

This colour space groups all colour variations as the eye perceives it. Hence a region consisting of different shades of brown will be grouped as one. This algorithm is used to group different ranges of a similar colour. The individual pixel is checked to determine the region with all plane values equal to 1 as diseased else as healthy region.

H component of HSV Extraction[8]

The HSV colour space is used to solve problems due to different illuminations or lighting conditions. Thus, in HSV (hue, saturation, value) image only the H component which is light independent component is used for segmentation and detection. The threshold value to separate diseased area and healthy area is estimated using trial and error method and it was found as 0.15 (threshold) and then if H value is below threshold value, then it is separated as diseased region or else it is separated as healthy region. Using the above algorithms, the pre-processed image is segmented into healthy and diseased region.

Evaluation of Decision Parameters[9]

This stage calculates the value of Contrast, Entropy, Energy, Homogeneity and Shape. These parameters play a vital role in determining the disease. They are fed to the neural network as inputs. The equations for the different parameters are mentioned below-

Contrast: $\sum_{j=0}^{N-1}(i,j)^2 C(i,j)$ ... (1)

Energy: $\sum_{j=0}^{N-1} C(i,j)^2$ ... (2)

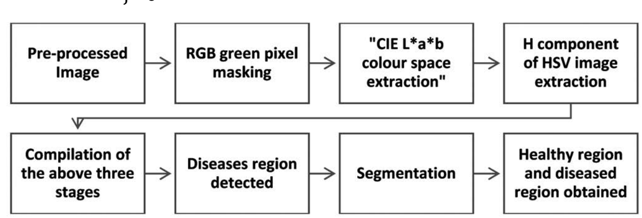

Fig. 2 — Block Diagram for detection and segmentation

Local Homogeneity: $\sum_{j=0}^{N-1} C(i,j)/(1+(i-j)^2)$ ... (3)

Entropy: sum (p.*log2(p)) ... (4)

Shape parameter: $\sum_{j=0}^{N-1} \frac{\text{major axis}}{\text{minor axis}}$ ... (5)

where, C (i, j) refers to the pixel intensity, i refers to the number of rows and j refers to the number of columns.

Factors a-d mentioned in Eqs 1–4 are calculated for three different forms of segmented images to enhance the accuracy of the result obtained. The evaluation parameters a-d are estimated for following form of image.

1 Convert segmented image into binary and estimation is done by taking the average value of each segment in diseased image.
2 Converting image to gray scale image.
3 An average of GLCM values of each segment of diseased image.
4 The shape parameter is calculated using Eq. 5

Classification and Identification

This stage the determined parameters are fed to a pre-trained neural network.[10,11] By evaluating the decision parameters for a total of 200 images per disease for different leaves such as Grape, Apple, Cherry, Strawberry and tomato, a database has been created. This database has then been worn to "train the neural network". In this paper, the "neural network utilizes feed forward back propagation algorithm". The accuracy has been determined for the three different networks, namely 3-layered, 4-layered and 5-layered neural networks.

Algorithm

The proposed algorithm involves three hybrid techniques to detect diseased portion of leaf from healthy leaf as shown in Fig. 3. They are separating RGB image in to R, G and B-plane and concentrating on G plane. If the G-plane pixel intensity is greater than B-plane pixel intensity and R-plane pixel intensity it is decided that the pixel is belonging to healthy portion otherwise diseased portion. In the second method H component is extracted and if the pixel intensity of H component is less than the predetermined threshold, that pixel is belonging to diseased group otherwise belonging to healthy portion. In the third method on the L component (Luminous), if the pixel intensity in R.G.B plane is found to be equal to 1 decided as diseased portion otherwise healthy portion. Diseased pixels decided in all three methods are combined together to segment diseased portion similarly all healthier pixels are grouped together to make healthier portion of leaf.

Results and Discussion

The simulation was conducted for Grape, Apple and Tomato. For each leaf species three separate diseases along with one healthy leaf set was

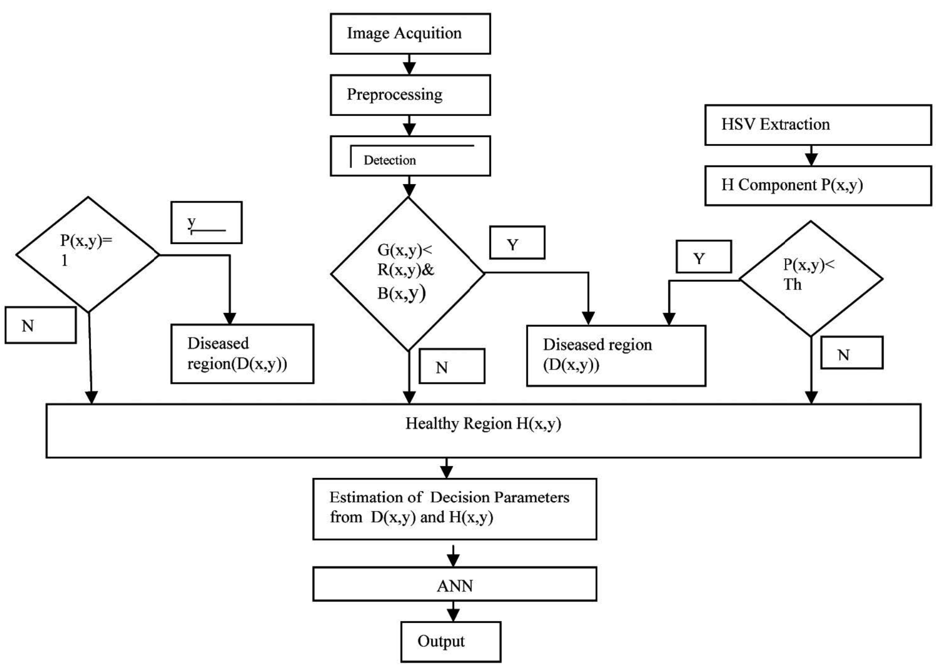

Fig. 3 — Flow diagram of algorithm

considered. The neural network was created with 200 training images for each of the different species. Three different neural networks were created with 3, 4 and 5 different layers. The images have been obtained from the Plant-Village Dataset. The accuracy with each leaf species has been displayed below.

The different plane in the RGB leaf image is depicted in Fig. 4 . The RGB image is separated into its red, blue and green planes respectively. The application green pixel masking is shown in Fig. 5. The result of Green Pixel Masking Algorithm is shown in Fig 5a. In Green pixel masking, a threshold value is considered by trial-and-error method, each and every pixel intensity is compared with this pre-defined threshold value. If the pixel intensity of the green component is lower than the pre assigned threshold value, then the corresponding red, blue and green components of that corresponding pixel is reassigned to zero instead of that original value. Healthy region classification using Green Pixel Masking Algorithm is given in Fig. 5b which is nothing but the cluster of the pixels other than the previously reassigned.

CIE L*a*b image and its planes namely luminosity and chromaticity components are shown in Fig. 6. RGB image was converted into CIE L*a*b image, then its components are separated. The functioning of threshold-based Extraction Algorithm on “CIE L*a*b Colour Space” is shown Fig. 6a. Here, individual pixels are classified as diseased pixel due to lower green pixel intensity than predefined threshold value or healthy pixel. The group of pixels categorised as healthy region classification using “CIE L*a*b Colour Space” Extraction Algorithm is shown in Fig. 6b.

The HSV image and its hue, saturation and value components are shown in Fig. 7. As a first step the “RGB image” was renewed into “HSV image” from which its components are separated. The working of threshold-based Extraction Algorithm on H component of HSV Algorithm is shown in Fig. 7a. In H component whichever pixel having intensity greater than the pre computed threshold value is targeted as healthy otherwise diseased pixel. The group of healthy pixels as healthy region classification using H component of HSV Algorithm is shown on Fig. 7b. The segmentation results are shown in Fig. 8 where the given input image or original image is separated into healthy region to which all pixels identified as healthy are added and diseased region to which all pixels identified as diseased are added then those regions are displayed as separate images.

Escalation Escalation in the number of hidden layers is a good deal for improving the accuracy

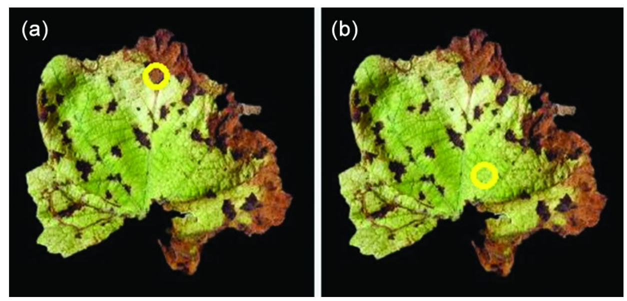

Fig. 5 — Green Pixel Masking

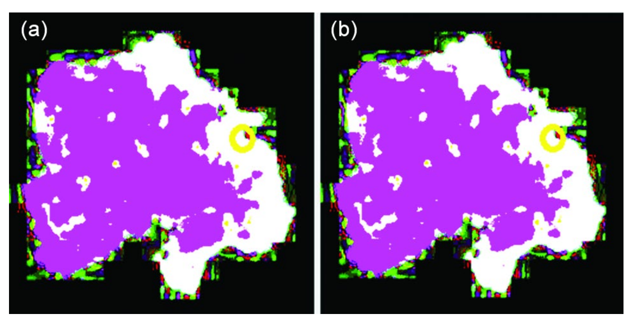

Fig. 6 — CIE L*a*b Colour Space Extraction

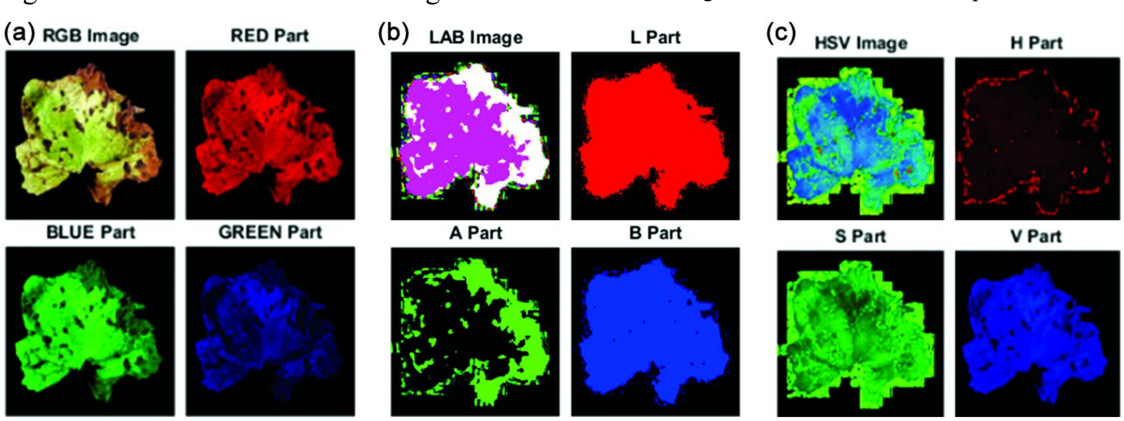

Fig. 4 — Pre-processed Images

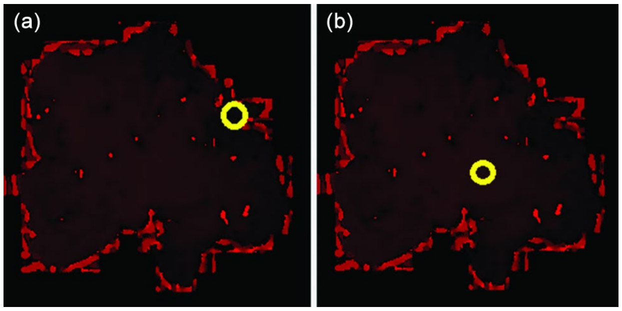

Fig. 7 — H component of HSV extraction

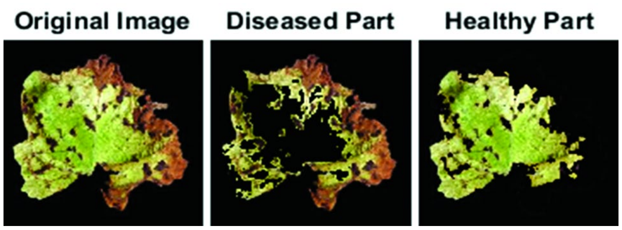

Fig. 8 — segmentation of the image into Diseased and Healthy regions

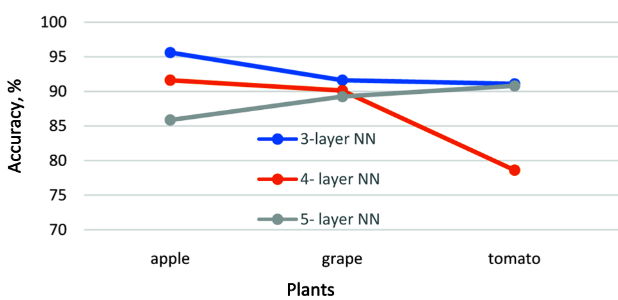

Fig. 9 — Accuracy Achieved for each plant leaf for different layers of ANN (%)

provided with adequate number of layers. Because a greater number of hidden layers will lead to over fit training data and will be incapable of take a broad view to new unnoticed data and also regularity in identification pattern will be reduced leads to declination in the accuracy.

The variations in accuracies of apple, grape and tomato when 3, 4 and 5 layered neural networks were used are shown as a graph in Fig. 9. It is evident that the designed model is overfitting for the lesser amount of data available. In the case of Apple plant leaf, the accuracy is better for 3 layers when compared to 5 layers. In the case of grape plant, the accuracy is almost same irrespective of the number of layers in ANN because the diseases Black rot, Black Measles, Leaf Blight and Healthy are dominantly noted by the reddish dark color which is readily measured by all three hybrid techniques. The best

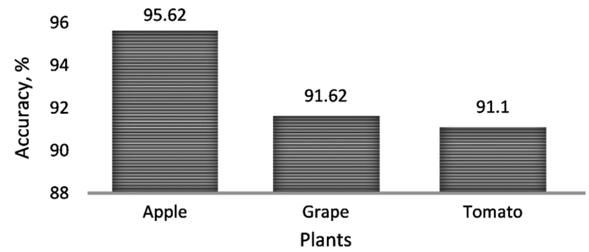

Fig. 10 — Best Accuracy Achieved for Apple, Grape and Tomoto plant leaf (%)

Table 1 — decision parameters evaluated

parameters	Binarised segments	GLCM matrix	Complete image
Energy	0.0856	0.5533	$5.0544e^{-04}$
Entropy	2.2270	0.6266	0.6019
Contrast	19.2337	0.4103	$4.0731e^{+03}$
Homogenity	0.4204	0.4204	0.0317
shape		1.8436	

Table 2 — Accuracy Achieved by the proposed method for Apple Leaves (%)

	3-Layered Neural Network	4-Layered Neural Network	5-Layered Neural Network
Apple Scab	94	91	91
Black Rot	96	90.5	66
Cedar	96.5	98	94.5
Healthy	95.62	87	92

accuracy achieved in the proposed methodology is evident from Fig. 10. It is evident that an average of 95.62% for Apple leaf, 91.62% for Grape leaf and 91.1% for Tomato leaf is observed.

The parameter values Energy, entropy, contrast, local homogeneity and shape values obtained using MATLAB are shown in Table 1. The first values shown is average value of each binarized segments, second values shown is average value of GLCM of each segment and third values shown is for entire diseased gray image. These decision parameters are fed to ANN for training and then the detection is done. The accuracy achieved for Apple plant leaf is listed in Table 2, the accuracy achieved for Grape plant leaf is shown in Table 3, and Table 4 shows the accuracy achieved for Tomato plant leaf.

It is observed from Table 5 and Fig. 9 that the maximum accuracy achieved by the proposed method is depending on no of layers as well as the species. The number of hidden layers in the ANN decides the accuracy if the data set has large no of data. For the same amount of data compared to three hidden

Table 3 — Accuracy achieved by the proposed method for Grape Leaves (%)

	3-Layered Neural Network	4-Layered Neural Network	5-Layered Neural Network
Black Rot	91	92	89
Black Measles	76	72	72
Leaf Blight	99.5	96.5	96
Healthy	100	100	100

Table 4 — Accuracy Achieved by the proposed method for Tomato Leaves (%)

	3-Layered Neural Network	4-Layered Neural Network	5-Layered Neural Network
Bacterial Spot	82.5	89	82.5
Early Blight	86	83.5	85
Curl Virus	100	76.5	99
Healthy	95.5	65.5	97

Table 5 — Overall-accuracy Achieved for each leaf (%)

	3-Layered Neural Network	4-Layered Neural Network	5-Layered Neural Network
Apple	95.62	91.62	85.87
Grape	91.62	90.125	89.25
Tomato	91.1	78.625	90.8

layered network the four and five hidden layered networks are showing poor performance because they are overfitting, means trained well but available less data to test. Accuracy also depends on the variety of disease. From the Table 4 it is clear that the diseases cedar and black rot have very high rate of detection accuracy for 3 and 4 layered networks. The achieved accuracy is 95.62%, 91.62%, 91.1% for Apple, Grape and Tomato respectively.

Conclusions

From the results obtained, it can be observed that the 3-layered “Neural Network using Feed-Forward Back Propagation” achieved the highest over-all accuracies for each of the different species involved. The utilization of “CIE L*a*b colour space and HSV colour space” based algorithms for segmentation process has reduced the noise and error involved due to different lighting conditions. It can be observed that increasing the number of layers results in lower accuracy. The proposed algorithm is applicable to diverse species of plants. As the proposed algorithm utilizes a supervised neural network, a well-defined database of images is required. The 13 parameters that have been mentioned in this paper can be utilized with other parameters to identify diseases from other parts of the plant, such as fruit, root and stem. Future work can involve expanding the number of species through the usage of extensive databases and/or through the utilization of IOT based methods. Such methods may involve various sensors that can be interfaced with the system along with the image-processing based techniques to identify diseases that are beyond the scope of visual identification.

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