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Fuzzy and Neural Network based Tomato Plant Disease Classification using Natural Outdoor Images

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Abstract

Objectives: The aim of the study is to automate the plant disease recognition and classification process by using image processing and soft computing techniques. **Methods/Analysis:** The proposed method examined the five types of tomato plant diseases using natural outdoor images in the study. The tomato plant images categorized into six categories including five disease infected that are bacterial leaf spot, fungal septoria leaf spot, bacterial canker, fungal lateblight, tomato leaf curl and one non-infected (healthy). The total 180 images of the dataset used for training and testing purpose. The total thirteen features computed by using CIE XYZ color space conversions that included color moments, histogram, and color coherence vector features. For classification, computed features are fed into three classifiers, i.e., "Fuzzy Inference System based on subtractive clustering", "Adaptive neuro-fuzzy inference system using hybrid learning algorithm and multi-layer feed forward back propagation neural network" for classification of six injured and healthy tomato plant disease. **Finding:** The classification accuracy is best yielded with multi-layer feed forward back propagation classifier of 87.2%. **Novelty/Improvement:** Usually, in the studies the only one type of plant disease considered for the recognition and classification purpose. The current study considered five different types of tomato plant diseases including fungal, bacterial and viral. It indicates that the proposed algorithm could reliably classify the different types of plant diseases in digital images.

Keywords: Color Space Conversion, Disease Recognition, Fuzzy, Tomato Plant Disease Classification, Natural Outdoor Images, Neural Network

1. Introduction

The production of several vegetable plants are struggling worldwide due to the different type of pathogens including fungal, bacterial, virus, etc., which can cause yield loss, affects plant growth and crop production every year. The presence of the pathogen depends on the favorable environment conditions and varieties of crops grown, which is the reason for occurrence and prevalence of plant diseases. These pathologies later give visual symptoms on the plant leaves, stems and fruits in changes in color. There are various plant disease management programs that will help to reduce losses in yields and grain qualit[1]. As plant disease identification and recognition is the wide area of research concern, there are methods proposed for the plant disease prediction[2]. From the last more than 30 years, research in the field of automation of plant disease identification and classification undoubtedly contributed greatly to limit the losses due to the effect of various kind of disease. The correct identification of diseases on early will may help in taking action to prevent losses produce and high-quality yield of great good grain. Initially, it seems very difficult to identify the stress by the human eye but later it can distinguish by its shape, color, and size. The visual inspection is an expensive and time-consuming process to some extent[3]. The manual procedure for feature extraction from plant leaf is an efficient and accurate method. The image processing techniques are also used, studied and proposed to automate the accurate plant identification processes. With the growth of technology, the computer vision providing many

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solutions to healthy plant growth.Digital image processing based system can give a solution to visual inspection of disease symptoms. These systems can contribute to design applications for crop management, crop quality improvement, and crop monitoring. Using image processing techniques for automatic recognition and assessment of plant diseases have studied[4-10]. The computer-based automatic diagnosis system using plant disease symptoms could accurately provide timely information about the disease for agricultural technicians and farmers, and it reduces the dependency on experts in the area concerned. The characteristic feature of plant diseaseextracted from the diseased region of the disease affected images using image processing techniques. The recognition of the disease-infected plant done by pattern recognition methods such as "neural networks"[11-15], "support vector machine"[16,17], "fuzzy inference system"[18,19],"adaptive neuro-fuzzy inference system"[20], etc. The features extracted from plant disease images include "color features"[21-23], "shape features"[15,24], "texture"[25] and so on.To achieve automatic plant disease identification and diagnosis using image processing, recognition of severaldiseases in digital images found on most of the horticulture plants. In thepresentstudy,wetest and compare the classification of tomato plant is healthy or injured from five diseases i.e. fungal late blight,Septorialeaf spot, bacterial leaf spot,bacterial canker, leaf curlRGB images of thetomato plant, caused by the fungus, bacteria and virus. The aim of the experiment was to compare that which classifier provided the classification performance by using computed feature vectors.

2. Material and Methods

2.1 The Image Datasets

The sample images acquired from commercial tomato farms in Raipur, District Durg Chhattisgarh, India. Chhattisgarh is one of the major provinces of exporting tomatoes (NHB Database 2013-14). The size of images while capturing was 5152 X 3864 in jpg format and images acquisition performed with the digital camera Sony Cyber-Shot DSC-H300 under day sunlight. In the study, images of leaf and stems of tomato plant included only.

2.2 Building Images Dataset

The original images then croppedto thesize of 1001 X 801 with jpg format. The images categorizedby disease affected and non-affected. The six categories of tomato plant image shown in shown in Figure 1. The total images are 180 of all categories as in Figure 1(a) Healthy (Non-affected): 58(b) Bacterial Leaf Spot: 32 (c) Septoria Leaf Spot:14 (d) Fungal Late Blight: 22 (e) Bacterial Canker:22(f)Leaf Curl:32.

2.3 Plant Disease Classification Method

In the study, the CIE XYZ colour space conversion and total 13 extracted features included Mean, Variance, Skewness, Histogram of each R,G,B component and Colour Coherence vector used.The algorithm has six steps as shown in Figure 2. In the first step images of six categories

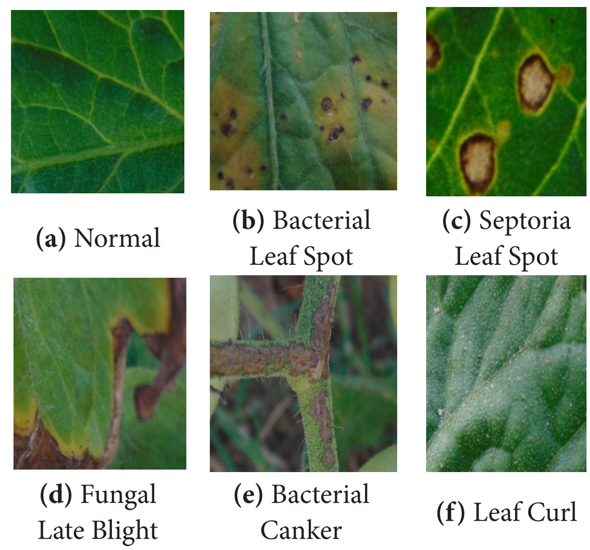

Figure 1. **(a)** Non-affected (Normal) **(b)** Bacterial Leaf Spot **(c)** Septoria Leaf Spot **(d)** Fungal Late Blight **(e)** Bacterial Canker and **(f)** Leaf Curl.

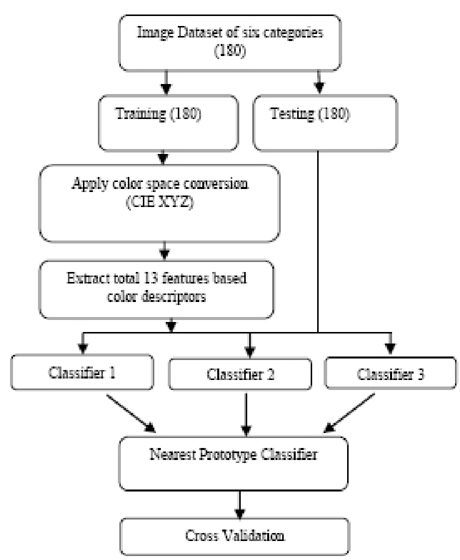

Figure 2. Steps for classification of tomato plant diseases.

stored in six different folders, denoted as Cat 1(Bacterial Leaf Spot), Cat 2 (Fungal Septoria Leaf Spot), Cat 3 (Fungal Late Blight), Cat 4 (Normal), Cat 5 (Bacterial Canker) and Cat 6 (Leaf Curl) as shown in Figure 2. Secondly, apply CIE XYZ colour space conversion to each of these tomato plant images categories. Third, computed and extracted thirteen features to submit to three different classifiers Section 2.4: Classifier 1: Fuzzy Inference Model, Classifier 2: Adaptive Neuro-Fuzzy Classifier and Classifier 3: Multi-Layer Feed Forward Backpropagation Classifier to classify that the particular tomato image belongs to which category. Next, for testing the performance of the classifier, we passed the same training dataset i.e. 180 images for testing purpose,i.e., also 180. We used nearest prototype classifier for testing the classification. The nearest prototype classifier used a Euclidean distance to measure the distance between the training set and the images used for testing purpose (also same) that whether classifier is accurately classifying the same dataset or not. If the distance is minimum, then the images are classifying correctly. In the last step, cross validation performed to decide which classifier based on computer colour descriptors yielded the best classification accuracy. The classifiers also applied to all those 180 images for validation. In the study all the methods realized in Matlab (Ver, R2010a, Mathworks, Natrick, MA, USA. The overall classification reported 87.2% multi-layer feed forward back propagation classifier. The second best classification accuracy yielded 86.0% with fuzzy inference classifier.

2.3.1 Applied Color-based Feature Vectors

In this section, we introduced colour based feature vectors or colour descriptors: total 13 feature vectors included the colour moments: 9, colour histogram: 3 and colour coherence vector: 1.

2.3.1.1 Color Moments

The "use three central moments of an image's color distribution. The first order (mean), the second (variance) and the third order (skewness) colour moment's have an assumption of distribution of colour in an image"[26].

The color moments as follows:

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \tag{1}$$

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\llbracket f_{ij} - \mu_i\right)\rrbracket^2} \tag{2}$$

$$s_i = \sqrt[3]{\frac{1}{N}\sum_{j=1}^{N} f_{ij} - \mu_i{}^3} \tag{3}$$

where f_{ij} is the value of the i-th colour component of the image pixel j, and N is the number of pixels in the image. The moments calculated for each colour component in an image. Therefore, it is featured by nine moments (3 moments for each three colour).

2.3.1.2 Color Histogram

The "colour histogram" is the easy way to compute the number of times a particular colour has occurred in the image. The detail description and capacity of a color histogram given in[27] and provide an effective methodfor weighted-distance indexing of color histograms[28]. For a given image, the color histogram is the summary of color. The color histograms are compared using sum squared Differences (D_2-distance) or the sum of absolute value of Differences (D_1-disatnce), as i is the given image and i' is the retrieved similar image".

$$\|CH_i - CH_i'\| = \sum_{j=1}^{n}\left(\mathbf{CH_i[j]} - \mathbf{CH_{i'}[j]}\right) \tag{4}$$

For distance D_1

$$\|CH_i - CH_i'\| = \sum_{j=1}^{n}\left(\mathbf{CH_i[j]} - \mathbf{CH_{i'}[j]}\right)^{2} \tag{5}$$

For distance D_2

2.3.1.3 Color Coherence Vector

In[29], "the colour coherence vector is more complex than a color histogram". It is used to classify the each pixel as either coherent or incoherent. If it belongs to large connected component then i.e. coherent and incoherent, if it belongs to the small connected component.

2.4 Classification Algorithm

2.4.1 Tomato Plant Disease Classification using "Sugeno-Type Fuzzy based on Subtractive Clustering"

"The Takagi-Sugeno-Kang method of fuzzy inference first introduced" in 1985[18,19]. The Sugeno system was proposed to design an organized method to producing fuzzy rules from given input and output data. A conventional fuzzy rule in a zero-order in the model has the rules form:

If an in A and b in B ……….and j in J then z = K

Where A, B to J are fuzzy sets in the predecessor while K is a crispy defined constant in the consequent.

First order Sugeno fuzzy model has rules form

If a in A and b in B……… and j in J then $z = p^{*}a+q^{*}b….+s^{*}j+r$

where A, B to J is fuzzy sets in the predecessor. The rule base for Sugeno FIS presented in the paper is given by

$$R_r = if F_1\ is C_r^1 and if F_2\ is C_r^1 and..and F_m is C_r^m then y_r fr(F)$$

where $fr(F) = \alpha_r^0 + \alpha_r^1 + \cdots + \alpha_r^m$. In which r=(1,…,m) and $F_i(1 \le j \le m)$ are the input variables and y_r is the consequent of r^{th} rule, C_r^m and α_r^m are membership functions and regression parameter in r^{th} rule and $fr(F)$ is a linear function, respectively.

M is the total number of features extracted i.e. 13. C is the total number of clusters generated by subtractive clustering and $fr(F)$ is the total number of images category i.e. 6 (included category of disease affected and non-affected images).

The sugeno based model includes two steps: first, structure identification and second is parameters estimation[18]. Structure identification is to generate initial rules that are generated by fuzzy clustering. The parameter estimation is done by the least square method to estimate consequent parameters[30]. In the study, subtractive clustering used to extract rules from data. "The subtractive clustering" proposed by[30]. In subtractive clustering, the number of clusters and initial cluster centers estimated and extract the sugeno based fuzzy rules from training data. "The method used to find the point with the highest number of neighbors as a center of a cluster"[31]. The method described as follows:

The collection of n data points $\{x_1, x_2, ..., x_n\}$ is an N-dimensional space and all the data points considered as a possible cluster center. The data points assumed as normalized without the loss of generality. Then the possible cluster center is calculated by:

$$p_i = \sum_{j=1}^{n} e^{-\alpha\|x_i - x_j\|^2} \quad (6)$$

$$\alpha = \frac{4}{r_a^2}$$

Where $\|.\|$ denotes the Euclidian distance and r_a are a positive constant known as cluster radius. After the possible cluster centre for each data, location calculated, the possible elevated cluster selected as a first cluster centre. Let x_i is the center of the all the clusters and p_i is possible values. The possible value p_k for each data point x_k is calculated as:

$$p_i = p_i - p_k e^{-\beta\|x_i - x_k\|^2} \quad (7)$$

$$\beta = \frac{4}{r_b^2}, r_b = \eta r_a$$

Where $\eta \ge 1$ a positive constant i.e. quash factor. While obtaining a new cluster, if a possible cluster doesn't fulfil the following condition eq.8, then it is not accepted as a cluster centre and its possible cluster sets to 0.

$$\frac{d_{mn}}{r_a} + \frac{p_k}{p_1} \ge 1 \quad (8)$$

where p_k is considered the next cluster found c_k and d_{mn} are the minimum distance between the first cluster c_1 and the previously found clusters. The ratio of accepted clusters is called accept ratio and ratio of rejected clusters is called reject ratio.

2.4.2 *Plant Disease Classification using "Adaptive Neuro-Fuzzy Classification Model based on Hybrid Learning Algorithm"*

"Adaptive Neuro-Fuzzy Inference System" proposed by[20]. As fuzzy inference system, ANFIS can easily implement on given input-output task. The ANFIS architecture is designed and implemented in the study using hybrid learning algorithm. The adaptive neuro-fuzzy architecture of linear Takagi-Sugeno type has adopted for plant disease classification in this study. The main aim of using ANFIS is that it enhances the fuzzy system with self-learning capability for achieving the objective of plant disease classification. ANFIS is a "multi-layer feed forward network". In the study, we extract 13 color feature vectors. There are 13 input variables and one output variable,i.e., Classification Category. The ANFIS architecture for plant disease classification using color moment model consists of 5 layers as shown in Figure 3.

Layer 1: Each node i in the layer is an adaptive node with node function

$$L_{1,i} = \mu_{Ai}(x_k) \quad (9)$$

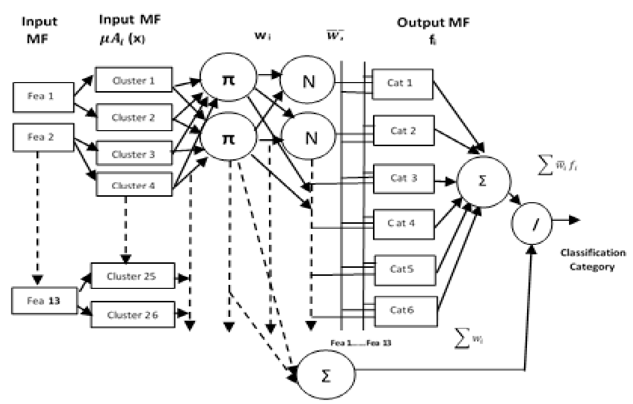

Figure 3. ANFIS architecture based tomato plant disease classification.

Where L_1 is the layer, x_k; k=1, 2….13 is input to node i and A_i are label assigned to the node. For member function, we use Gaussian Member Function (MFs)

$$\mu_{Ai}(x_k) = e^{-\frac{1}{2\left(\frac{x_k - c}{\sigma}\right)^2}} \tag{10}$$

where {c, σ } is the parameter set, 'c' representing center. 'σ' representing width of the membership function. These parameters are refers as "premise parameters".

Layer 2: Each node in this layer labeled as Π is the fixed node which is equal to the product of all inputs.

$$L_{2,i} = w_i = \mu_{Aj}(x_1)\mu_{Bk}(x_2)\dots\dots\mu_{Mn}(x_{13}) \tag{11}$$

Where i= 1,2,3…..26; j,k=1,2; n=n-1

Layer 3: Each node in the third layer is a fixed node labeled N. The i^{th} nodes compute the ratio of the i^{th} rule calculating the strength to the sum of the rules given by

$$L_{3,i} = \bar{w}_i = \frac{w_i}{\sum_i w_i} : i = 1,2,\dots\dots 26 \tag{12}$$

The output of this layer is normalized.

Layer 4: Each node in the fourth layer is an adaptive node

$$L_{4,i} = \bar{w}_i f_i = w_i(p_i x_1 + q_i x_2 + \cdots \dots + s_i x_{13}) \tag{13}$$

Where $\bar{w}_i$ is the normalized output of layer 3, i = 1,2,3….26 and $\{p_i, q_i, s_i\}$ is the "parameter set" of present the node. The parameter of the layer refers as "consequent parameters".

Layer 5: The Layer computes the overall output as the sum of all inputs given as

$$L_{5,i} = \sum \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{14}$$

Here, in this study, the ANFIS used hybrid learning rule for training. According to hybrid learning, two different procedures are follows. First is the forward pass input, and related functional signals go forward to layer 4 and "least square estimation method" is used to identified "consequent parameters". Second is the backward pass; the "premise parameters" updated by "gradient descent method" corresponding to the sum of all nodes error rate from output to the input. The hybrid approaches reduce the search space dimension and are much faster than the original back propagation[20].

2.4.2.1 *Hybrid Learning Algorithm*

The "hybrid learning algorithm" composed of two different approaches i.e. "least squares method and gradient descent method" are used to train ANFIS.

2.4.2.1.1 *Least Squares Method*

Using the matrix notation, the set of equation obtained regression function substituting training data pairs can write as

$$A\theta + e = y \tag{15}$$

where, A is m*n matrix of input data, θ is n*1 unknown parameter vector, y being the m*1 parameter vector and e is an error vector.

The sum of squared error can define as

$$E(\theta) = \sum_{i=1}^{m} (y_i - a_i^T \theta) = e^T e = (y - A\theta)^T (y - A\theta) \tag{16}$$

The mean square error obtained from Eq. 16 and square error minimized for certain θ as an estimator.

2.4.2.1.2 *Gradient Descent Method*

The gradient descent method is efficient to determine the search directions to an objective function. Here, objection function is E defined as n-dimensional input space $\theta = (\theta_1, \theta_2, \dots\dots, \theta_n)^T$. The objective is to find the minimum error E (θ) .

$$E(\theta_{k+1}) = E(\theta_{k+1} + \eta d) < E(\theta_k) \tag{17}$$

Where η the learning is rate and determined by line search method. The d direction is determined on the basis of the gradient of an objective E.

2.4.3 Plant Disease Classification using "Multi-Layer Feed Forward Back Propagation Network"

The objective of the method is that to "develop a learning algorithm based on multilayer feed forward back propagationneural network"[32] for plant disease classification. The method used to train to perform an implicit mapping of the given pixel values of plant images in the form of pattern pairs based on input-output sets. The input contains an extracted 13 features based on color descriptors from diseases affected or non-affected plant images. The outputs to classification categories that are Normal (Healthy), Bacterial Spot, Septoria Leaf Spot, Late Blight, Bacterial Canker and Leaf Curl. The approach followed the "gradient descent along the error surface" to reach the optimal set of weights. The square difference between the actual output and desired output is known as the error.The final output generated byusing all the weights in all the layers. The expected characteristic of the proposed learning algorithm is to define growing update of the weights of the networks for each pair of input-output data in such way that plant disease classification error can minimize. The proposed algorithm for plant disease classification as follows:

1. Let a pair of input-output patterns (a_i, b_i), $k=1,2,\ldots,13$ where the k^{th} input vector $a_i=(a_{l1}, a_{l2}, \ldots, a_{l13})^T$ and the k^{th} output vector $b_l=(b_{l1}, b_{l2}, \ldots, b_{l5})^T$. [$a_i$ is 13 extracted features and b_i is 5 classification category]
2. Suppose in the hidden layer there is the number of neurons lie between $k<H<20$
3. Let [a] and [b] represents the weights of synapses connecting input neuron and hidden neuron and connecting the output of hidden neuron and output neuron.

   $[a]^0$=[random weights]

   $[b]^0$=[random weights]

   $[\Delta a]^0=[\Delta b]^0=[0]$

   The threshold value assumed as 0.5 and learning rate $\lambda = 1$.
4. The input to input layer $\{A\}_I$. The output of the input layer by using linear activation function as $\left\{\begin{matrix} C \\ l*1 \end{matrix}\right\}_I = \left\{\begin{matrix} A \\ l*1 \end{matrix}\right\}_I$
5. Multiply input to the hidden layer by corresponding weights equation 18 and multiply the output of the hidden layer by corresponding weights equation 19.

$$\underset{m*1}{[A]_H} = \underset{m*l}{[a]}^T \cdot \underset{l*1}{[C]_I} \tag{18}$$

$$\underset{n*1}{[A]_O} = \underset{n*m}{[b]}^T \cdot \underset{m*1}{[C]_H} \tag{19}$$

6. Hidden and output layer evaluates the output using sigmoidal function as following

   Hidden layer unit

$$\{C\}_H = \underset{m*1}{\left\{ \frac{1}{\left(1+e^{-A_{Hi}}\right)} \right\}} \tag{20}$$

Output layer unit

$$\{C\}_O = \left\{ \frac{1}{\left(1+e^{-A_{On}}\right)} \right\} \tag{21}$$

7. Compute the error by using the difference between the network output and the desired output for the n^{th} training set as

$$E = \frac{\sqrt{\Sigma (T_n - C_{On})^2}}{N} \tag{22}$$

8. This process from Step 5 to 7 executes until the error minimized.

3. Results and Discussion

The results of proposed the methodology are shown in Figure 1. We tested the three classifiers for plant disease classification accuracy as shown in Table 1. The table shows that the Multi-layer feed forward back propagation classifier yielded the best classification accuracy of 87.2% for CIE XYZ colour space and using 13 colour descriptors. The second classification accuracy reported to Fuzzy Inference System yielded classification accuracy with 86.0% for CIE XYZ colour space and using 13 colour descriptors. The performance result of Sugeno-Type Fuzzy Inference Classifier based on five colour space shown in Table1. Under this, the classification of each tomato plant image is categorized and correct classification for Cat 1 with 81.2, Cat 2 with 85.7%, Cat 4 100%, Cat 5 with 96.9%, Cat 6 with 89.3% except the Cat 3 with 54.5%. The Adaptive Neuro-Fuzzy Inference Classifier reported the poor performance and overall classification yielded

Table 1. Tomato Plant disease classification accuracy

Classifier	Bacterial Leaf Spot	Fungal Septoria Leaf Spot	Fungal Late Blight	Healthy (Normal)	Bacterial Canker	Leaf Curl Virus	Total Accuracy
FIS	81.2%	85.2%	54.5%	100%	90.9%	84.3%	**86.0%**
ANFIS	37.5%	28.5%	18.1%	34.4%	27.2%	50.5%	34.4%
MLBPNN	93.3%	64.7%	54.5%	96.5%	100%	87.5%	**87.2%**

only 34.4%. Finally, the "Multi-Layer Feed Forward Back Propagation Neural Network" Classifier shows the best classification with overall 87.2% accuracy. The classification accuracy by using 13 feature vectors, MLBPN classification accuracy for Cat 1 with 93.3%, Cat 2 with 64.7%, Cat 3 with 54.3%, Cat 4 with 96.5%, Cat 5 with 100% and Cat 6 with 87.5% in Table 1.

4. Conclusion

The two color spaces with computed its feature vectors and three classification techniques were compared to verify an accurate technique for plant disease classification of healthy and five type of injured tomato RGB images acquired using a standard digital camera. Three different classifiers and thirteen features vectors based on CIE XYZ color space evaluated. The MLBPN based approach yielded an overall classification accuracy of 87.2% and was robust with a relatively little difference with CIE XYZ with FIS classifier i.e. reported 86.0% of classification performance. It proved that the color features vectors information required for the classification of different types of diseases of the plant. Other then we have to work to improve the performance of ANFIS classifier as it reported with worst classification performance. It can apply to the real applications for plant disease classification and recognition. In conclusion, we have seen that the MLBPN classifier combined with a CIE XYZ color feature vector can supply prompt and accurate plant disease classification using natural outdoor images of injured tomato leaf and stems.

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