Analysis of Plant Leaves Disease Classification Using Feed Forward and Cascade Forward Neural Network

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***Abstract*-- This paper describes the analysis of plant leaves disease classification using feed forward neural network (FFNN) and cascade forward neural network (CFNN). Features play a vital role for any classification which is one of the deciding factors for the performance of classification accuracy. Initially, the features for classification is extracted from the segmented image after the processing of segmentation using Particle swarm optimization (PSO).This paper mainly focus on extraction of features such as color, shape and texture. Then, the extracted features are trained by the neural networks such as FFNN and CFNN and also the performance is analyzed for different disease affected plant leaves using confusion matrix. Experimental results demonstrate the performance of the proposed approach producing comparable classification accuracy of plant leaves with disease.**

Keywords- Features extraction, color image segmentation, particle swarm optimization, feed forward neural network, cascade forward neural network, confusion matrix.

I. INTRODUCTION

An image may be defined as a two dimensional function f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of co-ordinates (x, y) is called the intensity or gray level of the image at that point [10], [15]. The region of interest in the image can be degraded by the impact of imperfect instrument, the problem with data acquisition process and interfering natural phenomena. Therefore, the original image may not be suitable for analysis. Thus image segmentation technique is often necessary and should be taken as significant step during image is processed and analyzed. Repeatable experiments with published benchmarks are required for this research field to progress. Choosing an appropriate model for segmentation is a difficult task to achieve better segmentation with reduced computational time. The problem is reformed with minimized computational time and high quality of the results.

The classification of unnatural plant leaves is a crucial process in botany and other industries. Moreover, the morphological features of leaves are used for plant classification or in the early diagnosis of certain plant diseases [3]. This paper presents the design and implementation of an artificial vision system capable of extracting HFE features from unnatural plant leaves. Initially, leaves taken from plants leaves are collected from nearby surroundings and used as samples for testing the proposed system. Later, additional samples originating from diverse environments are used for classification [8]. The proposed system consists of: a) an artificial vision system (camera) b) a combination of image processing algorithms such as filtering, segmentation using PSO and extraction of features are implemented in Matlab and c) a feed-forward neural network (FFNN) and cascade forward neural network (CFNN) based classifier implemented in Matlab [4],[5]. The image processing part is responsible for image capture and image pre-processing in order to obtain normalized features [6], [7] and for determining some critical geometrical characteristics. The HFE feature has been extensively used in this proposed work.

Artificial neural networks are biologically stimulated classification algorithms that consist of an input layer of nodes, one or more hidden layers and an output layer [20]. Each node in a layer has one corresponding node in the next layer, thus creating the stacking effect [1]. Artificial neural networks are the very adaptable tools and have been widely used to tackle many issues. Feed-forward neural networks (FNN) are one of the admired structures among artificial neural networks [14]. These well-organized networks are widely used to solve complex problems by modeling complex input-output relationships. Neural networks are well known as powerful tools in the area of pattern classification [2]. In principle, multi-layer feed-forward networks with just a single hidden layer is universal approximators for arbitrary finite-input environment measures. However, It does not imply that a neural network can easily be trained the underlying functional mapping between the input data and the desired output. In fact, the most important drawbacks of neural networks are problems associated with local minima and the slow convergence of the learning process. To tackle these problems, neural networks are used to reduce learning complexity [12].

The paper is organized as follows, In Section II shows the problem statement and data description .Materials and methods are described in Section III. In Section IV, a brief description of the different classifiers and its performance measures are discussed and the Section V contains the summary of conclusion.

II. PROBLEM STATEMENT AND DATA DESCRIPTION

This aim of the research work is to evaluate the performance of unnatural plants data set classification using FFNN and CFNN, which is described as follows:

Proposed unnatural plants data set: The new data base is named as unnatural plant leaves data set. It has bitter guard, beans, chilly, cotton, pigeon pea and tomato leaves images and it is considered for this research. It consists of 470 image databases which are taken from the field by a digital camera under natural light condition with certain specification. This data set contains 6 classes, where each class refers to a type of unnatural plant leaves of six different plants. The data base contains the following features [18].

1. Texture features: It contains four attributes such as contrast, correlation, energy and homogeneity .

2. Shape features: It contains five attributes such as area, perimeter, major axis length, minor axis length and eccentricity.

3. Color features: It contains twelve attributes such as mean_ R, mean_ G, Mean_ B, Variance_ R, Variance_ G, Variance_ B, Standard deviation_ R, Standard deviation_ G, Standard deviation_ B, median_ R, median_ G, median_ B.

4. Classes: Unnatural plant leaves of bitter guard, beans, chilly, cotton, pigeon pea and tomato.

The goal of this research is to demonstrate the process of building a neural network based classifier that solves the classification problem and compare performance of the classifiers such as feed forward neural network (FFNN) and cascade forward neural network (CFNN) using confusion matrix and other performance metrics such as sensitivity, specificity, precision ,recall and F_measure.

The images used in this work were taken with the following image acquisition system. Sony Cyber-Shot Dsc-W830 Point & Shoot digital camera with 20.1 Mega Pixels of resolution, placed vertically at a distance of 20 cm from the samples. The angle between the axis of the lens and the sources of illumination is approximately 45degree. The images were taken at maximum resolution (4608 x 3456 pixels). Fig.1 shows the functional block diagram of the proposed unnatural plant leaves data set (features) extraction process. Here more numbers of disease infected plant leaves data bases are collected by means of image acquisition [6]. It is then applied for image segmentation using particle swarm optimization (PSO) after the process of image preprocessing. The features such as texture features from the gray level co-occurance matrix, shape features from the binary image of the original image and color features from the R, G and B individual plane of the original image is extracted [1]. After extracting the features, the best features is to be find for better classification and the performance measures are analyzes with the help of confusion matrix as well as some metrics.

A. Method for Feature Extraction

Gray level co-occurance matrix (GLCM) is a method for texture feature calculation [9]. When the GLCM is generated, there are a total of 14 textures features that could be computed from the GLCM, such as contrast, variance, sum average etc [19].The four common textures features discussed here are contrast, correlation, energy, and homogeneity. Contrast is used to measure the local variations.

III. MATERIALS AND METHODS

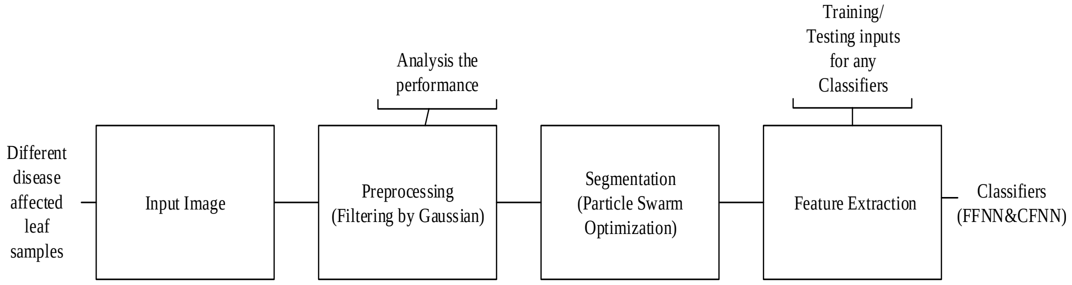

Fig. 1 Proposed Description Model- Plant Leaves Disease Classification

Correlation is used to measure the probability of occurrence for a pair of specific pixels. Energy is also known as uniformity of ASM (angular second moment) which is the sum of squared elements from GLCM, and homogeneity is to measure the distribution of elements in the GLCM with respect to the diagonal. A gray-level co-occurrence matrix (GLCM) is essentially a two-dimensional histogram in which the (i, j) th element is the frequency of event 'i' co-occurs with event 'j'. A co-occurrence matrix is specified by the relative frequencies P (i, j, d, ø) in which two pixels, separated by distance d occur in a direction specified by the angle ø, one with gray level i and the other with gray level j. A co-occurrence matrix is therefore called as a function of distance r, angle ø and grayscales i and j [13].

B. Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in (1995), inspired by social behavior of bird flocking or fish schooling.PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.

C. Multilayer Feed Forward Back Propagation Neural Network

Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors [1]. The linear output layers of the network produce values outside the range -1 to +1. Network architecture is determined by the number of hidden layers and by the number of neurons in each hidden layer. The network is trained by the back propagation learning rule.

To build a neural network, it is sufficient to combine the neural layers. Each layer has its own matrix weight W^k, where k designates the index of the layer. Thus, the vectors b^k, n^k and a^k are associated to the layer k. To specify the neural network structure, the number of layers and the number of neurons in each layer must be chosen. The learning step is a dynamic and iterative process which consists in modifying the parameters of the network after receiving the inputs from its environment. The learning type is determined by the way the change of parameters occurs [14]. Most of the neural architectures encountered, the learning results in the synaptic modification of the weights connecting one neuron to the other. If $w_{ij}(t)$ designates the weight connecting the neuron i to its entry j and at time t, a change $\Delta w_{ij}(t)$ of the weights can simply be expressed by the Equation (1):

$$\Delta w_{ij}(t) = w_{ij}(t+1) - w_{ij}(t) \qquad (1)$$

Where $w_{ij}(t+1)$represents the new entry value of the weight w_{ij}.

A set of well-defined rules that allow realizing a weight adaptation process is designated by a learning algorithm of the neural network.

D. The Feed Forward Back Propagation Method Used by a Multilayer Neural Network

Let us consider the multilayer neural network (composed of M layers)[21]. The equation describing the outputs of the layer k is:

$$a^k = f^k(w^k a^{k-1} - b^k), k = 1,2, \dots .M \qquad (2)$$

In the presence of sample-data combinations *entries/outputs* $\{(p_q, d_q)\}, q = 1 \dots Q,$ where p_q designates an entry-vector and d_q desired output-vectors, we can forward propagate at each instant t, an entry-vector $P(t)$ through the neural network in order to get an output-vector $a(t)$.

Given here are $e(t)$, the error produced by the network calculation for an entry, and the corresponding desired output $d(t)$:

$$e(t) = d(t) - a(t) \qquad (3)$$

The performance function F that permits minimizing the root mean square error is defined by the following expression:

$$F(x) = E[e^T(t).e(t)] \qquad (4)$$

Where E [ ] and x are respectively the mean and the vector grouping the set of the weights and the bias of the neural network. F is approximated on a layer with the instantaneous error:

$$\hat{F}(x) = e^T(t).e(t) \qquad (5)$$

The method of the steepest falling gradient is used to optimize X with the help of the following equations:

$$\Delta w_{ij}^k(t) = -\eta.\frac{\partial \hat{F}}{\partial w_{ij}^k}$$
$$\Delta b_i^k(t) = -\eta.\frac{\partial \hat{F}}{\partial b_i^k} \qquad (6)$$

where η designates the learning rate of the neural network. To calculate the partial derivatives of $\hat{F}$ the rule of composition functions is used

$$\frac{\partial \hat{F}}{\partial w_{ij}^k} = \frac{\partial \hat{F}}{\partial n_i^k}.\frac{\partial n_i^k}{\partial w_{ij}^k} \quad \text{and}$$
$$\frac{\partial \hat{F}}{\partial b_i^k} = \frac{\partial \hat{F}}{\partial n_i^k}.\frac{\partial n_i^k}{\partial b_i^k} \qquad (7)$$

The activation levels n_i^k of the layer k depend directly on the weights and biases on this layer, and can be expressed by the following relation:

$$n_i^k = \sum_{j=1}^{s^{k-1}} w_{ij}^k a_j^{k-1} - b_i^k,$$
$$k = 1,2, \dots .M \qquad (8)$$

Now, for the first terms of the Equation (9), we define the sensitivities δ_i^k of $\hat{F}$ in relation with the changes of the activation level n_i^k of the neuron i belonging to the layer k by the equation:

$$\delta_i^k = \frac{\partial \hat{F}}{\partial n_i^k} \qquad (9)$$

The expressions of $\Delta w_{ij}^k(t)$ and $\Delta b_i^k(t)$ become:

$$\Delta w^k(t) = -\eta.\delta^k(t).(a^{k-1})^T(t)$$
and
$$\Delta b^k(t) = \eta.\delta^k(t) \qquad (10)$$

Equation (10) is responsible for the modification of the

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weight connections and biases and the different iteration learning steps of the neural network presented in Section 3.3.1.

E. The Cascade Forward Back Propagation Method Used by a Multilayer Neural Network

By considering different analyzes, we will give an abstract of the methodology used in the learning process that we have implemented [17].

1. Initialize the weights with small random values;

2. For each combination (p_q, d_q) in the learning sample:

Propagate the entries p_q forward through the neural network layers:

$$a^0 = p_q;$$
$$a^k = f^k(w^k a^{k-1} - b^k),$$
$$k = 1,2, \dots . M \qquad (11)$$

Back propagate the sensitivities through the neural network layers:

$$\delta^M = -2f^M(n^M)(d_q - a^M);$$
$$\delta^k = f^k(n^k)(w^{k+1})^T \delta^{k+1},$$
$$k = M - 1, \dots 1 \qquad (12)$$

Modify the weights and biases:

$$\Delta w^k = -\boldsymbol{\eta} \delta^k (a^{k-1})^T, k = 1, \dots M \qquad (13)$$
$$\Delta b^k = \boldsymbol{\eta} \delta^k, k = 1, \dots M \qquad (14)$$

3. If the stopping criteria are reached then stop; if not reached, they permute the presentation order of the combination built from the learning database, and begin again at Step 2.

F. Cross-Validation

Cross-validation procedure is applied to provide better generalization of neural network classifiers. To perform the cross-validation procedure, the input data is partitioned into 3 sets: 1) Training set 2) Validation set 3) Test set

The training set is used to train the network. The validation set is used to validate the network and to adjust network design parameters. The test set is used to test the generalization performance of the selected design of neural network. The partitioning of input data is performed randomly with a certain ratio of input entities to be stored as training set, validation set and test set (0.8, 0.1 and 0.1 respectively).

IV.RESULTS AND DISCUSSIONS

The disease affected leaves dataset are collected from south zone of Tamil Nadu at Pavoorchatram in the district of Tirunelveli in the month of July to September 2014.The infected plant leaves are collected and kept in a plastic cover for image acquisition. Here, the data base size is 470 images which are collected from the field.

In this research, the dataset is captured and collected by camera (Sony) in the above said areas. Six types of disease affected plant leaves such as Bittergaurd, Beans, Chilly, Cotton, Pigeon and Tomato were used for analysis [16],[21].

The implementation starts with initialize the training database then resize the images of size 256*256. Next Gaussian special filter was used to remove the noise and to improve the image quality. Features extracted from the test image (new features) are compared with the features available in the training set (features). Texture, Shape and color features are extracted and stored as inputs [7] [11]. We have evaluated the mean squared error (mse) by using equation (15).

$$MSE = \frac{\sum_{i=1}^{N} E_i^2}{N-1} \qquad (15)$$

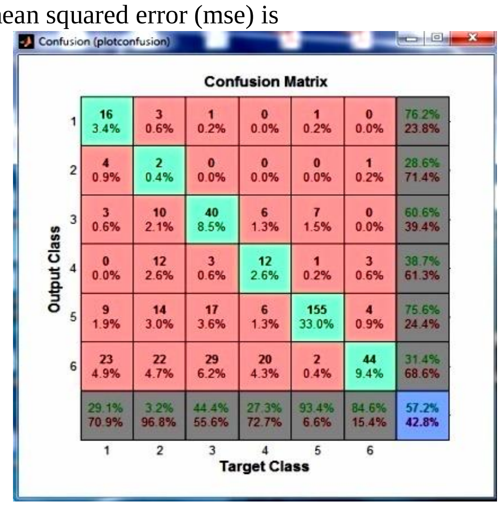
Where Ei: Error (observed value−Neural Network estimate); and N: Number of observed values.

A. Experimental Results and Analysis for Feed Forward Back Propagation Neural Network

The analysis of feed forward back propagation neural network (FFNN) results from confusion matrix is based on the features of texture, shape and color features of different classes of unnatural plant leaves and results are shown in Fig,2.

B. Results and Analysis of FFNN Using Confusion Matrix for Different Features of Class=6

The classification result for the confusion matrix obtained under positive versus negative classification model is shown in Fig. 2. The overall classification accuracy of FFNN is 57.2%, 50.9% and 59.1% for texture, shape and color and its corresponding error rate is 42.8% ,49.1%, 40.9% for Class=6. For example in Fig.2 (a), the true positive value for unnatural bitterguard, beans, chilly, cotton, pigeon pea and tomato leaves are 29.1%, 3.3%, 44.4%, 27.3%, 93.4% and 84.6% respectively and its corresponding false rate of the unnatural leaves are 70.9%, 96.8%, 55.6%, 72.7%, 6.6% and 15.4%.Then, the error rate is calculated by using mean squared error (mse) and the best validation performance of the mean squared error (mse) is



1.5765 at one epoch and is shown in Fig. 2(b).

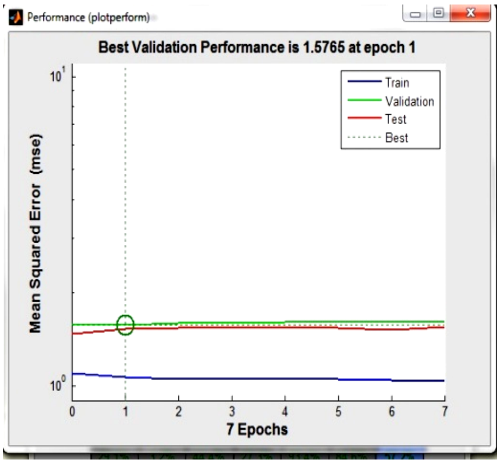


Fig. 2(a) Results of the confusion matrix of performance analysis of FFNN a) texture, class=6,(b) Results of the MSE (training, validation and testing)

Similarly the overall classification accuracy, error rate of classification, true positive and false rate for individual infected plant leaves are calculated from the confusion matrices. From these confusion matrix analyzes, the performance of the FFNN is very low for texture features and clearly says the better features for better classification.

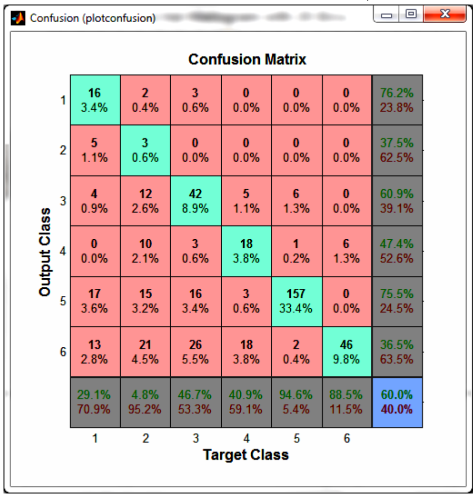
C. Experimental Results and Analysis for Cascade Forward Back Propagation Neural Network

The analysis of cascade forward back propagation neural network (CFNN) results from confusion matrix is based on the features of texture, shape and color features for different classes of unnatural plant leaves that results are shown in section 4.2.1 [17].

D. Results and Analysis of CFNN Using Confusion Matrix for Different Features of Class=6

The classification result for the confusion matrix obtained under positive versus negative classification model is shown in Fig.3.

The overall classification accuracy of CFNN is 60%, 50.2% and 62.8% for texture, shape and color and its corresponding error rate is 40% ,49.8%, 37.2% for Class=6. For example in Fig.3 (a), the true positive value for unnatural bitterguard, beans, chilly, cotton, pigeon pea and tomato leaves are 29.1%, 4.8%, 46.7%, 40.9%, 94.6% and 88.5% respectively and its corresponding false rate of the unnatural leaves are 70.9%, 95.2%, 53.3%, 59.1%, 5.4% and 11.5%.Then, the error rate is calculated by using mean squared error (mse) and the best validation performance of the mean squared error (mse) is 1.5765 at one epoch which is shown in Fig.3(b). Similarly, the overall classification accuracy, error rate of classification, true positive and false rate for individual infected plant leaves are calculated from confusion matrices. From these confusion matrix analyzes, CFNN gives the optimal results compared to FFNN based classification. Table 2, demonstrates the results of evaluation of the performance measures for classifier FFNN and CFNN of disease affected leaves for different features, Class=6.



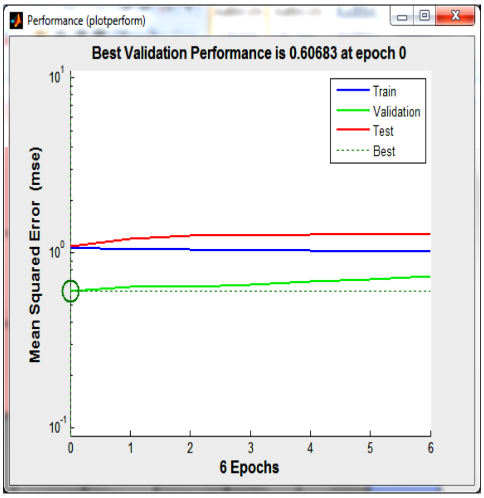


Fig. 3(a) Results of the confusion matrix of performance analysis of CFNN a) texture, class=6, (b) Results of the MSE (training, validation and testing)

E. Comparison of the Result Performance between FFNN and CFNN

The performance comparison of feed forward back propagation neural network (FFNN) and cascade forward back propagation neural Network (CFNN) is based on the features of texture, shape and color features for class=6 of unnatural plant leaves that results are shown table.1

Table 1 Analysis of features (texture, shape and color), class=6

Performance metrics	Techniques	Bitterguard (Class1)	Beans (Class2)	Chilly (Class3)	Cotton (Class4)	Pigeon pea (Class5)	Tomato (Class6)
Accuracy	FFNN	0.127	0.175	0.678	0.659	0.97	0.923
	CFNN	0.309	0.397	0.867	0.864	0.976	0.942
Sensitivity	FFNN	0.127273	0.174603	0.677778	0.659091	0.96988	0.923077
	CFNN	0.309091	0.396825	0.866667	0.863636	0.975904	0.942308
Specificity	FFNN	0.875	0.578947	0.717647	0.707317	0.755869	0.461538
	CFNN	1	0.675676	0.722222	0.77551	0.84375	0.731343
Precision	FFNN	0.875	0.578947	0.717647	0.707317	0.755869	0.461538
	CFNN	1	0.675676	0.722222	0.77551	0.84375	0.731343
Recall	FFNN	0.127273	0.174603	0.677778	0.659091	0.96988	0.923077
	CFNN	0.309091	0.396825	0.866667	0.863636	0.975904	0.942308
F_measure	FFNN	0.222222	0.268293	0.697143	0.682353	0.849604	0.615385
	CFNN	0.472222	0.5	0.787879	0.817204	0.905028	0.823529

Table 2 Analysis of classification accuracy for features, class=6

No of Class	Features	Accuracy of Classifiers (%)	
		FFNN	CFNN
6	Texture	57.2	60
	Shape	50.9	50.2
	Color	59.1	62.8

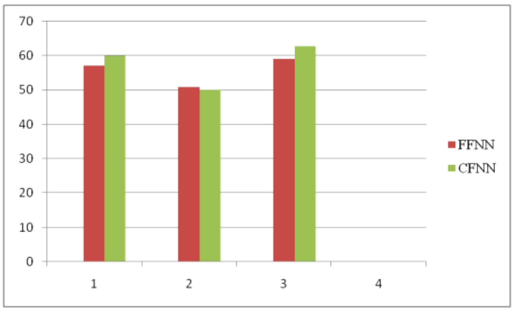


Fig.4 Results of the Comparison of Performance analysis of FFNN and CFNN using (Texture, shape and color) features for class=6, 3and 2

The Fig.4 shows the comparison of the results of FFNN and CFNN. This result clearly mentioned that the classification accuracy of classifiers using color features gives optimal results comparably to other features.

V. CONCLUSIONS

In this paper, the disease infected plant leaves classification is presented and classified by using back propagation algorithm based FFNN and CFNN. Here, the image segmentation was done by PSO. After segmenting the disease affected portion of the leaves, the texture features were extracted by using gray level cooccurance matrix. Similarly, shape features extracted from the binary image of the database and color features were extracted from the individual R, G, and B color plane of the original image. Then the performances of the neural networks were analyzed by using texture, shape and color features separately. According to the performance measurement indicators, the CFNN is indeed slightly superior to the FFNN under certain conditions. Here the classification accuracy of CFNN using color feature is better than other features.

As the extension of this work, the hybrid features based plant leaves disease classification will be considered for our research work and also it will produce better results for classification compared to the current features.

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