Plant Leaf Classification Using Soft Computing Techniques

C. S. Sumathi and A. V. Senthil Kumar

Abstract—**For the existence of human living and development, plants play a crucial part. In order to effectively collect and preserve the genetic resources, the intra- and inter-specific variations must be estimated in proper manner. In plant classification, the leaf shape plays a significant role. In machine intelligence, the most significant part essential for both decision-making and data processing is shape recognition. In this paper, a feed forward neural network is used to automate the leaf recognition for plant classification. The classification accuracy of the proposed method Normalized Cubic Spline Feed Forward Neural Network (NCS – FFNN) is compared with RBF, CART and MLP.**

Index Terms—**CART, correlation based feature selection, normalized cubic spline feed forward neural network, plant leaf classification, RBF.**

I. Introduction

In the cycle of nature, plant plays the most essential partto sustain all the other life forms as the primary producer is plants. Among all the organisms, plants only have the capability to transform light energy from the sun into food. For the supply of food, animals that are unable to produce their own food depend directly or indirectly on plants. Plants are the source that produces all the available oxygen to the living organisms. As the natural environment is reduced, there is constant extinction of several plants species. About 400,000 species of plants exists, of which botanists have named and identified 270,000 species of plants. The further research on plants is complicated [1] as it is not possible for any botanist or non-professional researcher to identify than a little fraction from the overall number of named species. Cytotaxonomy, chemotaxonomy, serotaxonomy and cladistics, etc, are few novel popularly known plant taxonomy methods.But these methods are mostly carried out by botanists due to its complexity and time-consuming attributes.

In recent years, the deficiency of people's classification ability [2]-[6] is made up by introducing the information technologies comprising image processing and pattern recognition techniques into plant shape taxonomy.

The classification of plants is basically according to the shapes of their leaves and flowers, is according to the theory of plant shape taxonomy. Mostly the shape of leaves is approximately two-dimensional and it is three-dimensional for flowers. The complex 3D structures [7] of the shapes and structures of flowers make it difficult to be analyzed. And also, in all seasons leaves are easily obtained and collected everywhere whereas, only during the blooming season the flowers can be collected. Hence, for computer-aided plant classification, leaves are widely used.

In this paper, a feed forward neural network is used to automate the leaf recognition for plant classification. The classification accuracy of the proposed Normalized Cubic Spline Feed Forward Neural Network (NCS – FFNN) is compared with RBF, CART and MLP. The rest of this paper is organized as follows: in Section II, reviews some of the related work available in literature, Section III details the materials and methods used in this investigation, Section IV discusses the results and Section V concludes the paper.

II. Related Works

Wu et al., [8] utilized Probabilistic Neural Network (PNN) with image and data processing methods to employ universal purpose automated leaf recognition for the classification of plants. The method is carried out with the extraction and orthogonalization of 12 leaf features into 5 principal variables that includes the input vector of the PNN. The PNN achieves accuracy greater than 90% to classify 32 kinds of plants which are trained by 1800 leaves. The proposed algorithm is an exact artificial intelligence approach when compared with other approaches. The algorithm proposed is very easy for implementation and fast in execution. Other features having psychology proof that is useful for human to recognize things like the leaf, such as the surface qualities are also being worked on.

Gurpreet Kaur et al., [9] emphasized on implementing digital image processing for automating classification and recognition of plants based on the images of the leaves. Four major modules are present in the system: 1) image acquisition, 2) image preprocessing, 3) image recognition and 4) display result. By employing a digital camera, the image acquisition module leaf image is captured. To prepare a leaf image for the features extraction process, the image preprocessing module implements different image processing methods. The different features are extracted from the leaf image and recognize in the image recognition module. The recognition results are displayed in the display result module. The experiments were performed in 12 types of leaves. 97.9% of accuracy of the system was achieved.

Ji-Xiang Duet al., [10] proposed a computer-aided plant species identification (CAPSI) approach. Using a shape matching method, this approach is based on plant leaf images.

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Initially, to the original leaf shapes, a Douglas-Peucker approximation algorithm is adopted and to form the sequence of invariant attributes, the new shape representation is employed. Then for the plant leaf recognition, a modified dynamic programming (MDP) algorithm is proposed for the purpose of shape matching. Over 92% of the recognition accuracy was achieved for recognition of intact leaves. Because of the robustness of the proposed algorithm, the experimental result revealed that it is much appropriate for the recognition of not only intact but also for partial, distorted and overlapped plant leaves.

Neto, et al., [11] utilized Elliptic Fourier (EF) and discriminant analyses for leaf classification. Based on leaf boundary; the chain encoded Elliptic Fourier harmonic functions were produced. Using the variation among the consecutive EF functions, a complexity index of the leaf shape was computed. To choose the Fourier coefficients with the greatest discriminatory power, principle component analysis was used. To construct species identification models based on leaf shapes extracted from plant color images throughout the second and third weeks after germination, canonical discriminant analysis was employed. An average of correct classification rate of 89.4% was revealed by the plant species throughout the third week were successfully determined. On average: 77.9% of redroot pigweed, 93.8% of sunflower, 89.4% of velvetleaf and 96.5% of soybean was classified correctly by the discriminant model. The overall classification accuracy obtained was 89.2%, using all of the leaves extracted from the second and the third weeks. 76.4% of redroot pigweed, 93.6% of sunflower, 81.6% of velvetleaf, 91.5% of soybean leaf extracted from trifoliolate and 90.9% of soybean unifoliolate leaves were classified correctly by the discriminant model. Therefore for weed species identification and mapping, Elliptic Fourier shape feature analysis is an essential and precise tool.

For 3D shape retrieval, Marcin Novotni et al., [12] utilized the usage of 3D Zernike invariants as descriptors. The computation of invariants under rotation, translation and scaling are allowed by the basis polynomials of this representation. Practical analysis of these invariants along with the algorithms and computational details are provided. Additionally, the effect of the algorithm parameters such as the conversion into a volumetric function, number of utilized coefficients, etc was also provided with a complete discussion. 3D Zernike descriptors are natural extensions of at present initiated spherical harmonics based descriptors, is the illustrated from the study. Considering these computational aspects and shape retrieval performance implementing many quality measures and based on experiments on the Princeton Shape Benchmark, the 3D Zernike descriptors is compared to other descriptors in terms of robustness against topological, geometrical artifacts plaguing a most of freely available models and retrieval performance.

III. Materials and Methods

A. Feature Selection

Correlation based feature selection (CFS) measures the worth or the merit of the subset of features. The algorithm works on the basis "good feature subset contains highly correlated features but uncorrelated with each other". The CFS searches the features in greedy step wise. It either performs a greedy backward or forward search through the attribute subsets. Starting with nothing/all attributes or from an arbitrary point in the space the feature subset is formed. The algorithm stops when there is a decrease in evaluation on addition/deletion of any remaining attributes. CFS can also produce a ranked list of attributes on the basis of the order that attributes are selected.

B. Existing System

RBF Radial Basis Function (RBF) is a variant of neural networks, which performs better at interpolation, cluster modeling. RBF are embedded in two layer neural network with the radial activated function is implemented in the hidden layer. During training, the networks outputs to the given inputs are fitted to optimize the network parameters. Parameters are evaluated using Cost function and the cost function is usually assumed to be the square error. In pattern classification, the Gaussian activation function is used and is given by:

$$\phi_j(X) = \exp\left[-\left(X-\mu_j\right)^T \textstyle\sum_j^{-1}\left(X-\mu_j\right)\right]$$

For j=1,…, L, where X is the input feature vector, L is the number of hidden units, μ_j and $\sum_j$ are the mean and the covariance matrix of the jth Gaussian function.

The output layer implements a weighted sum of hidden-unit outputs:

$$\psi_k(X) = \sum_{j=1}^{L} \lambda_{jk}\varphi_j(X)$$

For k=1,…, M where λ_{jk} are the output weights, each corresponding to the connection between a hidden unit and an output unit and m represents the number of output units.

The output of the RBF is limited to the interval (0, 1) by a sigmoid function as follows:

$$Y_k(X) = \frac{1}{1+\exp\left[-\psi_k(X)\right]}$$

For k=1,…, M.

CART Classification and regression trees (CART) are a non-parametric technique [13] for producing either classification or regression trees. A collection of rules is used to form Trees. The rules are based on values of certain variables in the training data set. Rules are chosen based on the capability of splits formed on variables' values. 'Child' node formed by splitting a node into two, the same rule applies to it (recursive procedure).CART stops splitting when it detects that splitting has no further gain or pre-determined stopping rules are met. Terminal nodes form the end of each branch. Each observation falls into only one terminal node.Each terminal node is uniquely defined by a set of rules.

C. Proposed System

NCS Feed Forward Neural Network (NCS-FFNN)

Neural networks are made up of multiple layers of neurons or computational units. All the neurons are interconnected with each other. The inputs fed on the input layer, propagates through the network in forward direction through the hidden layers to give an output. Output signal is calculated using weights, bias and activation function. The neural network is trained using backpropagation rule by backpropagating the errors and changing weights of nodes. The error is the difference between the outputs obtained and desired output. The following are the algorithms used for calculating various parameters involved in training a neural network.

The total input for a given neuron is given by:

$$s_k = \sum_j w_{jk} y_j + \theta_k$$

where s_k is the total or effective input for unit k, w_{jk} the weight of the connection, y_k is current activation and θ_k is the bias.

Activation function A_f takes the input and current activation and gets the new activation value during learning by:

$$y_k(t) = A_f\left(y_k(t-1).s_k(t-1)\right)$$

The value of activation functions are generally limited to 0, 1 using a threshold function. Most commonly used is sigmoid function.

$$y_k = A(s_k) = \frac{1}{1 + e^{-s_k}}$$

The spline-based NN is built using generalized sigmoidal (GS) neuron, which contains adaptive parametric spline activation function [14]. The spline activation is easy to adapt and implement. It also retains squashing property of the sigmoid and smoothing characteristics. MLP built using spline activation function are universal approximators and have smaller structural complexity.

The spline activation function reproduces the shape of whole cubic spline along the directions specified by w_j, j=1,..,n [15].

$$\varphi(w_j x)\sum_{i=1}^{N} c_i \left| w_j x - \alpha_{ij} \right|^3$$

$f(x)$ can be written as:

$$f(x) = \sum_{j=1}^{n} \mu_j \varphi_j (w_j x)$$

μ_j and w_j Are found using backpropagation, thus optimal set of parameters and coordinates are found. The tracts in the spline are described by combination of coefficients. Local spline basis functions controlled by only 4 coefficients are used to represent the activation function. Catmull-Rom cubic spline is used and its ith tract is expressed as:

$$F_i(u) = \begin{bmatrix} F_{x,i}(u) \\ F_{y,i}(u) \end{bmatrix} = \frac{1}{2}\begin{bmatrix} u^3 & u^2 & u & 1 \end{bmatrix}$$

IV. Experimental Results

Nine species of plant leaves were selected [8] with 15 samples for each plant species. Sample image of the plant leaves used is shown in Fig. 1.

Fig. 1. Leaf samples used in this work.

Matlab was used to extract the features. The features extracted were used to train the classification algorithms. The features were classified using RBF, CART, MLP, and proposed FFNN. The classification accuracy obtained is given in Table I and Fig. 2. Table II tabulates the precision, recall and f Measure for various algorithms and compared with the proposed method.

TABLE I: Classification Accuracy

Technique Used	Classification accuracy
RBF	91.11%
CART	77.04%
MLP	91.85%
Proposed NCSFFNN	94.08%

TABLE II: Precision, Recall And F Measure

Technique Used	Precision	Recall	f Measure
RBF	0.913	0.911	0.908
CART	0.778	0.77	0.772
MLP	0.92	0.919	0.919
Proposed NCS FFNN	0.89	0.94	0.91

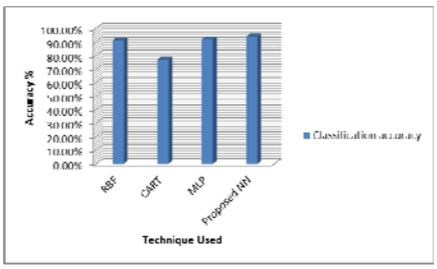

Fig. 2. Classification accuracy.

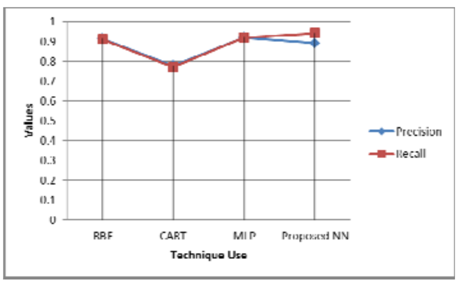

Fig. 3. Precision and recall.

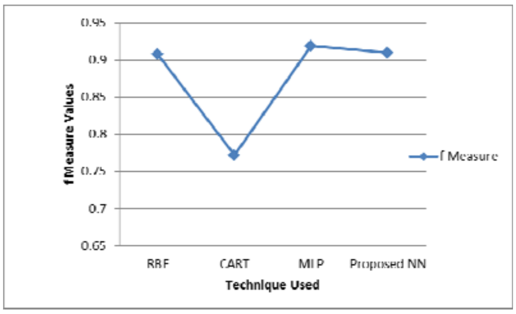

Fig. 4. F. Measure.

It is seen from Fig. 2 that an increased accuracy of 2.23% is achieved by the proposed NCSFFNN when compared to MLP. Table 3 tabulates the precision and recall for the various classification algorithms. Fig. 3 and 4 shows the precision & recall and f Measure of the classifiers respectively. The recall of the proposed method is higher when compared to other methods.

V. Conclusion

In this paper, a feed forward neural network is used to automate the leaf recognition for plant classification. The classification accuracy of the proposed neural network is compared with RBF, CART and MLP. Correlation feature selection is used for selecting features. The extracted features were trained using 10 fold cross validation and tested with CART, RBF, MLP classifiers and proposed neural network. The output obtained using proposed feed forward neural network for a nine class problem is satisfactory achieving better accuracy and recall.

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