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NALLAMUTHU GOUNDER MAHALINGAM COLLEGE

An Autonomous Institution, Affiliated to Bharathiar University, An ISO 9001:2015 Certified Institution,

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One day International Conference

EMERGING TRENDS IN SCIENCE AND TECHNOLOGY (ETIST-2021)

27th October 2021

Jointly Organized by

Department of Biological Science, Physical Science and Computational Science

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ABOUT THE INSTITUTION

A nations's growth is in proportion to education and intelligence spread among the masses. Having this idealistic vision, two great philanthropists late. S.P. Nallamuthu Gounder and Late. Arutchelver Padmabhushan Dr.N.Mahalingam formed an organization called Pollachi Kalvi Kazhagam, which started NGM College in 1957, to impart holistic education with an objective to cater to the higher educational needs of those who wish to aspire for excellence in knowledge and values. The College has achieved greater academic distinctions with the introduction of autonomous system from the academic year 1987-88. The college has been Re-Accredited by NAAC and it is ISO 9001 : 2015 Certified Institution. The total student strength is around 6000. Having celebrated its Diamond Jubilee in 2017, the college has blossomed into a premier Post-Graduate and Research Institution, offering 26 UG, 12 PG, 13 M.Phil and 10 Ph.D Programmes, apart from Diploma and Certificate Courses. The college has been ranked within Top 100 (72nd Rank) in India by NIRF 2021.

ABOUT CONFERENCE

The International conference on “Emerging Trends in Science and Technology (ETIST-2021)” is being jointly organized by Departments of Biological Science, Physical Science and Computational Science - Nallamuthu Gounder Mahalingam College, Pollachi along with ISTE, CSI, IETE, IEE & RIYASA LABS on 27th OCT 2021. The Conference will provide common platform for faculties, research scholars, industrialists to exchange and discus the innovative ideas and will promote to work in interdisciplinary mode.

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LIST OF ARTICLES

Identification of Weeds Using Soft Computing Techniques

C.S.Sumathi[1] - M.Kalpana[2]

ABSTRACT: Weeds play a key role in plant life and weed handling forms a major issue. Herbicides are used to control weeds in agricultural practices. Usually, weeds are controlled by spraying herbicides or practically removed by labors. Generally there is no sufficient spectrum of herbicide for special flowers, herbs and vegetable crops and this is removed through hand weeding. Further, labor shortages have resulted in higher costs for manual weeding. It is high time to develop labor-saving technologies for controlling weeds and achieve high production cost. In this paper, a feed forward neural network is used to automate the leaf recognition for weed classification. The classification accuracy of the proposed method Normalized Cubic Spline Feed Forward Neural Network (NCS-FFNN) is compared with RBF, CART and MLP. Thus with an automated weed identification system problems like herbicides affecting the agricultural fields can be avoided and reduce environment problems and give a better atmosphere for living beings and continue to improve crop growth and is more effective as well.

Keywords: Weed classification, feature selection, CART, NCS – FFNN, RBF

INTRODUCTION

A weed belongs to plant category and many times a plant in wrong place and not sown intentionally. They are strong competitor and mostly tend to dominate. Study reveals that weeds constitute about 250 species out of 2,50,500 plant species. Apart from that 30,000 species are grouped as weeds under world conditions. Every kind of weed has an identity as species. Weed identification on a farm is not that easy and not necessary always. But, as a first step towards effective control major weeds need to be identified at the right time. Sometimes weed species may look very similar during certain growth stages, but they differ very much in life cycle, reproduction, etc. Prominent characteristics that can help human identify the weed include: presence of spines, thorns, prickles etc., milky juice stain out when leaves are cut and stem square in cross section. Site-specific weed management and selective application of herbicides as eco-friendly techniques are still challenging tasks to perform, especially for densely cultivated crops [1]. Classification of weed species in their natural environment with robotic weed control is a great challenge [2]. According to plant shape taxonomy, plants are generally classified according to the shapes of their leaves and flowers. The shape of weed leaves are used here which is approximately two-dimensional rather than flowers which is three-dimensional. The complex 3D structures [3] of the shapes and structures of flowers make it difficult to be analyzed. Leaves are easily available in all seasons and can easily be obtained and collected everywhere but, flowers are only available

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during the blooming season. Hence, for computer-aided weed classification, leaves are used here. In this work, a feed forward neural network is used to automate the weed recognition and classification. The classification accuracy of the proposed Normalized Cubic Spline Feed Forward Neural Network (NCS – FFNN) is compared with RBF, CART and MLP. The paper is organized into introduction, reviews some of the related work, materials and methods used in this investigation and the last section discusses the results and conclusion.

MATERIALS AND METHODS

Feature Selection

The merit or the value of the subset of features is measured by Correlation based feature selection (CFS). The algorithm works on the basis “good feature subset contains highly correlated features but uncorrelated with each other”. Greedy stepwise is used by CFS and searches the features of attribute. It either performs a greedy backward or forward search through the attribute subsets. The feature subset is formed from starting with nothing or all attributes or from an arbitrary point in the space. The algorithm terminates when there is diminish in evaluation on addition or deletion of any remaining attributes. A ranked list of attributes can also produced by CFS on the basis of the order that attributes are selected.

Existing System

RBF

Neural networks has many variants and Radial Basis Function (RBF) is one among them, which performs better at interpolation, cluster modeling. RBF are embedded in two layer neural network and the radial activated function is implemented in the hidden layer. The network outputs are given to the inputs which are fitted to optimize the network parameters during training. Parameters are evaluated using cost function which returns the error between predicted outcomes compared with the actual outcomes. Pattern classification builds a function that maps the input feature space to an output space of two or more than two classes, the Gaussian activation function is used and is given by:

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

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:

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

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 sigmoidal function as follows:

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

CART

Classification and regression trees (CART) are a non-parametric technique [4] for producing either classification or regression trees. Trees are formed using a collection of rules and 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.

Proposed System

NCS Feed Forward Neural Network (NCS-FFNN)

Neural networks are comprised of multiple nodes of neuron layers or computational units. All the neurons are interconnected with each other. The input layer accepts the input, propagates through the network in forward direction through the hidden layers to produce 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 difference between the output obtained and desired output is the error reflected here. The algorithms used for calculating various parameters involved in training a neural network is given below.

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.

The input is taken by the activation function A_f 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 values generally limited to 0, 1 by the activation function using a sigmoid threshold function.

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

Generalized sigmoidal (GS) neuron is applied to build a spline-based NN, which contains adaptive parametric spline activation function [5]. The spline activation adapts easily for further implementation, retaining the squashing property of the sigmoid and smoothing characteristics. MLP built using spline activation function are universal approximators and have lesser structural complexity.

The spline activation function reproduces the shape of whole cubic spline along the directions specified by w_j, j=1,..,n [7].

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

$f(x)$ can be written as:

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

μ_j and w_j are found using backpropagation along with optimal set of parameters and coordinates. The tract in the spline is 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:

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

EXPERIMENTAL RESULTS

Nine species of weed leaves were selected [6] with 15 samples for each plant species. Sample image of the plant leaves used is shown in Fig. 1.

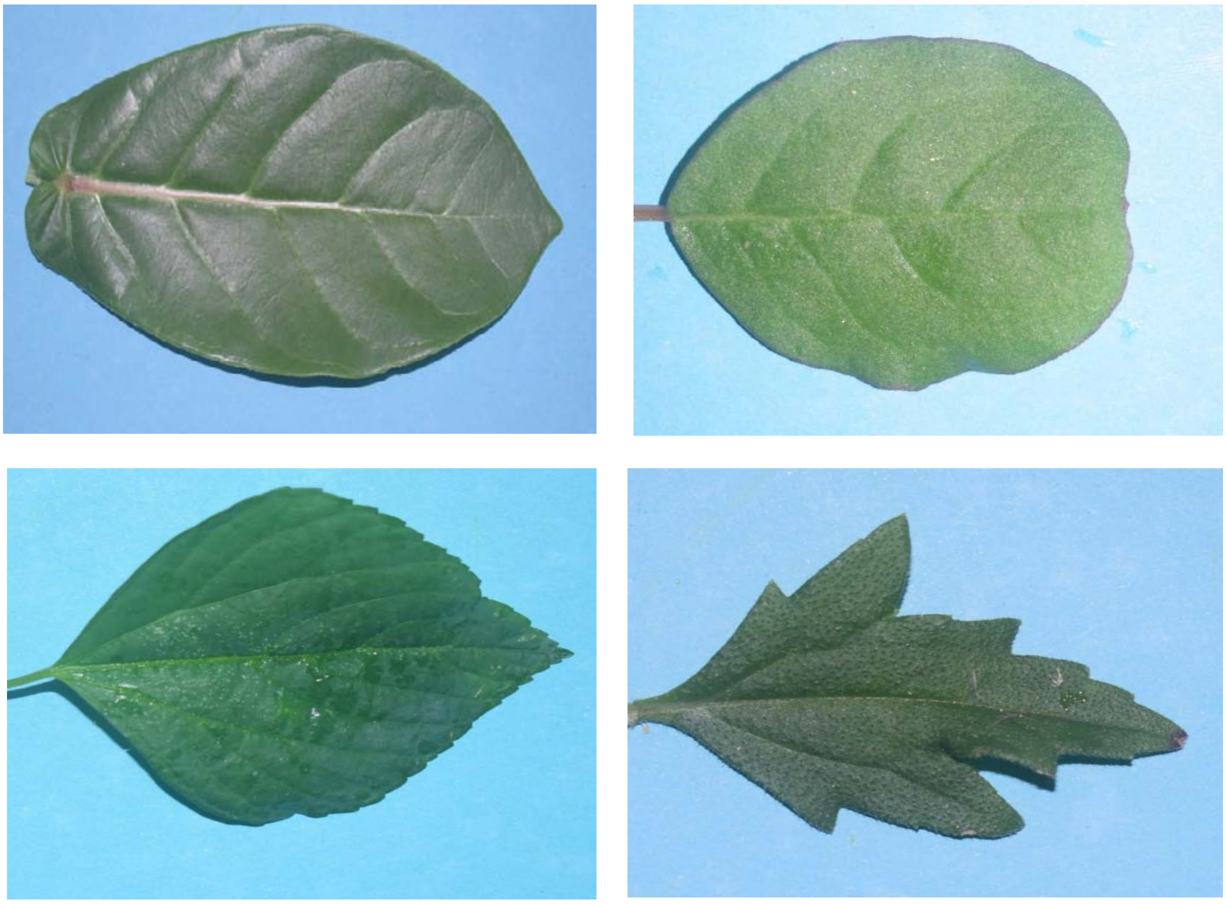

Figure 1: Weed samples used.

The features were extracted using Colab. The features extracted were given as inputs and used to train the classification algorithms. The features were classified using RBF, CART, MLP, and FFNN. The classification accuracy obtained is given in Table 1 and Fig. 2. Table 2 tabulates the precision, recall and f Measure for various algorithms and compared with the proposed method.

Table 1. Accuracy

Technique used	Classification accuracy (%)
RBF	91.1
CART	77.0
MLP	91.9
NCSFFNN	94.1

Table 2. Precision, recall and f measure

Technique	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
NCS FFNN	0.89	0.94	0.91

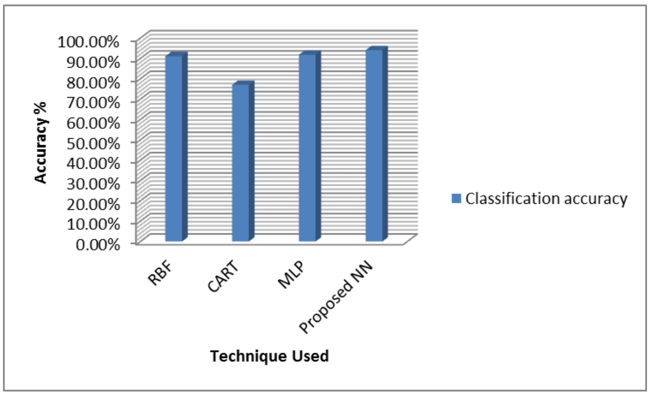

Figure 2: Classification accuracy

It is seen from Fig. 2 that an increased accuracy of 2.23% is achieved by the 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.

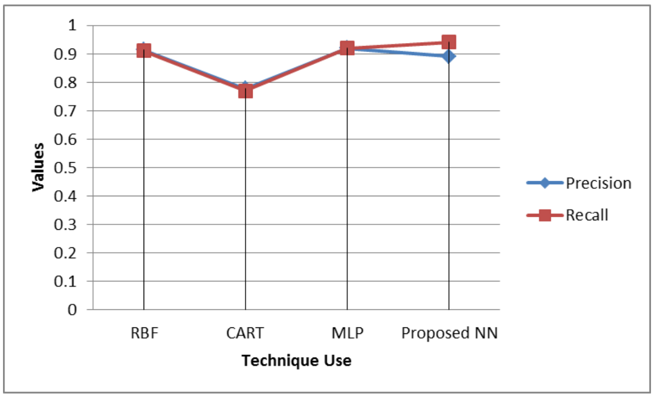

Figure 3: Precision and recall

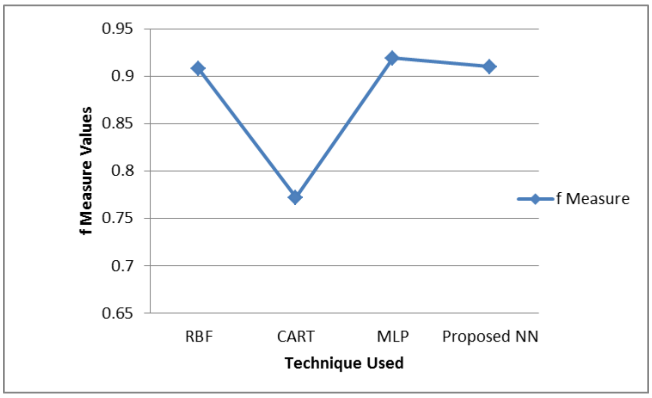

Figure 4: f measure

CONCLUSION

In this paper, a feed forward neural network is used to automate the weed recognition and classify the weed. The classification accuracy of this work is compared with RBF, CART and MLP. Correlation based feature selection is used for choosing the 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.

Further work in this area include: the accuracy and robustness of classifying the weed dataset can be further improved and these learning models can be used as the robotic weed detection system.

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