NEURAL NETWORK BASED MATHEMATICAL MODEL FOR IDENTIFICATION OF HERBAL PANTS ON THE BASES OF FEATURES OF LEAVES

Dr. Mukesh Patel

Assistant Professor, Department of Mathematics, Uka Tarsadia University, Bardoli, Gujarat, India

Abstract: This research presents a mathematical computation model includes the knowledge of digital image processing for identification of herbal plants having high mediational value can be used directly for curing disease. The herbal plants are identified from their diversified leaf pattern. The Independent Component Analysis (ICA) based features are extracted from pre-processed normalized leaf image of the herbal plants. Multi-layer Feed Forward with Back Propagation based Neural Network (NN) architecture is used as a classifier to classify the leaf image of respective herbal plant. A set of different herbal plants is experimented under the designed mathematical computational model and the training and testing accuracy along with the Mean Squared Error(MSE) is estimated.

Keyword: Herbal Plant, Leaf Image, ICA, Multi-layer Feed forward, Back Propagation, Neural Network

1. INTRODUCTION

The medical field is always come up with new disease in every certain time interval. Human species has been facing many different and unusual disease from his early growing period. It has also defeated the diseases many times by curing them using different approach of treatments. One of the most common approach to deal with disease is been medication. In modern era, there are different categories of medicine available such as Ayurvedic (Herbal), Allopathic, Antibiotics, Homeopathic etc. To prepare such medicines the ingredients are taken from soil, plant, animals, insects, bacteria etc. [7]. The mineral, vitamins, micro and macro nutrition are extracted from these ingredients and with the specification the medicines are prepared in laboratory. Although, the allopathic medicines are widely used in curing the disease but herbal medicine has also vital role in curing the disease. It is being one of the safest and secured type of medicine used by human being.

Ayurveda is the ancient therapy introduced to cure dieses not only for human but also for animal as well in which plants have always been the primary source of nutrition. The herbal medicine is generally prepared by using plant based different ingredients such as plant roots, branch, flower, fruits, leaves etc. Since each plant on the earth has its own medicinal value but some of the plants are high in its medicinal value. They are full of nutrition most suitable for hormonal level growth of a human being have a capacity to cure the disease. Some of the plants have direct usage as a medicine having significant impact on disease. Such plants can be identified or differentiate based on their different body components in which leaf is one of the unique representator with variety of features.

The proposed research work focuses on the identification of herbal plant based on the unique features of its leaf. The combination of knowledge of digital image processing, Mathematical modelling and computational approach makes the herbal plant identification successful. The calculation of accuracy level of identification and the error estimation can validate the significance of analysis.

2. Related Work

David D. Feng. (2007) proposed an ICA based algorithm to extract leaf vain to classify the plant and he showed that ICA perform good in the extraction of leaf vain [10]. Shanwen Zhang and Youqian Feng (2010) gave the feature extraction and reduction based plant classification using neighborhood rough set. They successfully classified total 30 classes of plant leaves during experiment [1]. C. S. Sumathi & A. V. Senthil Kumar (2013) did leaf classification using soft computing technique including feed forward neural network. They achieved better accuracy for nine-class classification problem [2]. Alex Olsen, Sunghyu Han, Brendan Calvert, Peter Ridd, Owen Kenny (2015) did situ leaf classification based on histogram of oriented gradient. They successfully classified the different species of plant by discrimination solely on the surface texture of leaves [11]. Cem Kalyoncu 1, Önsen Toygar (2016) worked on leaf classification using texture and color of leaf by GTCLC approach to improve the accuracy level of classification [3]. Phuchitsan Chaisuk, Krisada Phromsuthirak, and Vutipong Areekul (2017) performed leaf classification using quadratic curved axis by partitioned the morphological features and the tangent direction of the leaf contour by image CLFF and showed that hoe the shape of a leaf is transformed to reliable features [12]. Hassan Esmaeili & Thanathorn Phoka (2018) have given transfer learning based leaf classification using Convolutional Neural Network (CNN) was the best approach for the feature extraction of leaf and its classification [13]. Shubham Kumar Singh (2018) used machine learning based study for classification of leaf. He also performed comparative study with other approaches of supervised learning using canny method. The performance was excellent for the feature extraction and classification of leaf [4]. Fateme Mostajer Kheirkhah, Habibollah Asghari (2019) also worked on leaf classification using GIST texture as a feature. They used three different approaches for classification Pattern net neural, PCA and KNN algorithm. from which the KNN classifier gave best result of classification [7].

3. Proposed Method

The proposed method is basically performed into three different stages (i) Image normalization (ii) Feature extraction (iii) Image classification as shown in Figure 1.



Figure 1. Mathematical ICA-NN Architecture for Herbal Plant Classification

3.1. Image normalization [8]

The RGB digital color image of top view leaf of an herbal plant is taken as input for the classification of respective herbal plant in MATLAB mathematical Software. The input image of a leaf is pre-processed called image normalization before extracting unique feature from it. The normalization process improves the visibility of input image and makes it more suitable

for further feature extraction process. It includes different mathematical operations such as (i) Image Quantification (ii) Resolution Adjustment (iii) Dimension Reduction and (iv) Contrast level Enhancement which have different purposes of normalization.

3.1.1. Image Quantification:

An input RGB digital image of leaf is quantified into three different matrices of its Red Component (R), Green Component (G) and Blue Component using MATLAB command 'imread'. The matrix value of a cell indicates the value of each pixel of RGB components that vary in [0, 255] belongs to intensity of visible electromagnetic spectrum of light as shown in Figure 2.

Matrix	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			
RGB	R - Component	G - Component	B - Component			
Eigung 2 DCD Image Organification						

Figure 2. RGB Image Quantification

3.1.2. Resolution Adjustment:

The database of different leaf images of herbal plants has high resolution that can consume much memory and can take more processing time during classification while it is difficult to extract features from small size image. Also images in different sizes can cause trouble during computation so for betterment of process the images should not be so big not so small, thus they can be resized into not moderate size using MATLAB command 'imresize' as shown in Figure 3.



Figure 3. Image Resizing

3.1.3. Dimension Reduction:

To reduce the dimensionality of image the RGB colour resized leaf image is converted into grey scale image by the given relation as show in Figure 4. Also, in the ICA based feature extraction is independent with the colour image.

 $Grey = 0.2989 * \mathbf{R} + 0.5870 * \mathbf{G} + 0.1140 * \mathbf{B}$



Figure 4. RGB to Grey Image Conversion

3.1.4. Contrast level Enhancement:

To enhance the contrast level of an input grey image for better feature extraction the histogram equalization operation is performed on the image using MATLAB command 'histeq' as shown in Figure 5.



Figure 4. Histogram Equalization of Grey Image

Figure 4 shows the normalized image of leaf of an herbal plant which is further used for Independent Component Analysis (ICA) based feature extraction.

3.2. Feature Extraction – ICA [6],[8]

In the classification of objects, it is essential that every input objects and the objects stored in database have diversity in their appearance make the accurate judgment. When the we consider the whole leaf images as they are then they might have high similarity in major portion of surface area which dominate the minor diversify details and the classifier may be confused to make the correct judgment. Thus, to avoid such situation for classifier, in place of considering whole image as an input its appropriate feature is used for comparison and hence for classification. In this study of research Independent Component Analysis (ICA) is used as feature extractor to separate the feature from each input leaf images. The processes of ICA is discussed as follows;

3.2.1. Image Smoothening (blur): Gaussian Filter

The input histogram equalized image is smoothed by Gaussian filter which can reduce rather remove the noise involved in the image. The required Gaussian filter can be constructed by the Eq. (1).

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), \quad \sigma \text{ is standard deviation and } x, y \text{ are spatial}$$
(1) coordinate of pixel

Now, for smoothening the image a convolution (*) process is implemented on histogram equalized image using Gaussian filter G(x, y) as described in Eq. (2).

$$X_G = X \star G(x, y)$$
, X is input image, X_G is smoothed image by Gaussian filter (2)

3.2.2. Edge Detection: Gradient of the image

There are several methods or operator are used for edge detection such as Sobel, Robert, Prewitt etc. but Sobel is the most likely operator to derive edges of an object. Here the edges on a leaf are the prime feature to be consider for classification the ICA uses edge detection by Sobel operator. It gives the first derivate in the horizontal and vertical direction denoted by X_{Gx} and X_{Gy} respectively know as gradient of image I_G can be defined as in Eq. (3).

$$X_{grad} = \sqrt{X_{Gx}^2 + X_{Gy}^2}, \quad X_{grad} \text{ is the gradient image of } X_G$$
(3)

3.2.3. Edge Thinning: Non-maximum suppression

The edges are separated by finding the gradient of the leaf image which is still blur and quit inaccurate. To improve its characteristics edges are thinned by Non-maximum suppression method that finds the largest edge from the group of edges of a leaf. This method suppresses all the gradient values of edge to zero except the local maxima makes the edges sharp and accurate.

3.2.4. Double threshold

The double threshold is applied on the Non-maximum suppression edge to classify them into strong edge, weak edge or not an edge. Sometime the edge pixels are caused due to noise or the variation in color scale or texture artefacts. Thus the identification between true edge and pseudo edge becomes necessary for decision making and for that the double threshold strategy is adopted. In this method two different threshold value are chosen based on the observation of input image and the pixel values of edge which are less than lower threshold considered as not an edge are suppress to zero, those are greater than upper threshold value considered as strong edge preserved as it is and the pixel values between two thresholds are considered as weak edge are boosted up to high threshold.

3.2.5. ICA Algorithm

The process diagram along with learning rule of the ICA to extract the feature as Independent components (IC's) form the input image is expressed as in Figure 5.



Figure 5. Independent Component Analysis Algorithm

3.3. Image Classification [9]

The herbal plant is classified on the bases on the Independent Components (ICs) of their leaves images by Neural Network (NN). Here, a fully connected Multi-Layer Feed Forward Network with the Back Propagation strategy for weight update is adopted can be seen in Figure 6.



Figure 6. Multi – Layer Feed Forward NN Architecture

Figure 6. shows the NN-architecture for classification of leaf image includes an Input layer, one Hidden layer and an Output Layer. Here, X_i , i = 1, 2 ... n ICs are used as input of NN known as input neurons, O_k output neuron are set at output layer depends upon number of target vector to be set for classification while H_j hidden neurons are set at hidden layer based on trial and error at which the error is minimum. V_{ji} denotes the associated weight from i^{th} input neuron to j^{th} hidden layer similarly, W_{kj} denotes the associated weight from j^{th} hidden neuron to k^{th} output neuron. Furthermore the target vector t is the set of all elements corresponding to desire number of output means the herbal plants to be classified.

The whole NN process is expressed as follows with necessary components.

3.3.1. Forward Pass:

The forward pass is performed to derive the estimated error between output and target. *netH*:

A single set/sample of data is multiplied by the initial weight matrix (V). The input to the hidden neuron is the weighted sum of the outputs of the input neurons to get **netH**

$$etH_{j \times 1} = V_{j \times i+1} * [X B]'_{i+1 \times 1}$$
(4)

Where, $V_{j \times i+1}$ is the initial random weight matrix between Input-Hidden layer, X is number of inputs and B indicates bias at input layer.

outH:

An activation function is applied to the resultant weighted sum of the input neurons in to get **outH** which is given by the formula

$$\operatorname{putH}_{j \times 1} = \frac{1}{1 + e^{\left(-\operatorname{netH}_{j \times 1}\right)}}$$
(5)

Eq. (5) is known as the Sigmoidal activation function used at hidden layer.

<u>net0:</u>

outH is further multiplied by the weight matrix (W). The input to the output neurons is the weighted sum of the outputs of the hidden neurons to get **net0**

$$netO_{k \times 1} = W_{k \times j+1} * [outH; B]_{j+1 \times 1}$$
 (6)

Where, $W_{k \times i+1}$ is the initial random weight matrix between Hidden-Output layer, B indicates bias at output layer.

out0:

An activation function is applied to the resultant weighted sum to get **out0** which is given by the formula:

$$\text{putO}_{k \times 1} = \frac{1}{1 + e^{(-\text{netO}_{k \times 1})}}$$
(7)

Eq. (7) is the same Sigmoidal activation function used at output layer.

Error Estimation:

The difference between the target and output i.e., (*outO*) is squared in order to obtain the error which is denoted by Er and defined as in Eq. (8).

$$Er = \frac{1}{2} * (t - outO)^2$$
(8)

where t is the target value and **outO** is the output after one iteration is performed.

If the error is zero the result is optimum, otherwise the weights are needed to be updated which

is done using the Back propagation algorithm which is described in the next section. **3.3.2.** Back Propagation [9]

The Backpropagation algorithm looks for the minimum value of the error function in weight space using a technique called the delta rule or gradient descent. The weights that minimize the error function is then considered to be a solution to the learning problem. The update rules for weights and bias are defined as in Eq. (9) and (10) Respectively.

$$W_{jk}^{*} = W_{jk} - \eta * E_{total_grad(w)}$$

$$V_{ij}^{*} = V_{ij} - \eta * E_{total_grad(v)}$$
(9)

$$\{b\}_{0}^{*} = \eta(E_{total_{grad}(w)}) + \alpha(b)_{0}$$

$$\{b\}_{H}^{*} = \eta(E_{total_{grad}(w)}) + \alpha(b)_{H}$$

$$(10)$$

where, $E_{total_grad(w)} = \frac{\delta E_{total}}{\delta W_{jk}} = [\delta_0] * [outH]$ $E_{total_grad(v)} = \frac{\delta E_{total}}{\delta V_{ij}} = (\sum \delta_0 W_{jk}) * outH * (1 - outH) * X_i$ $\delta_{0k} = -(t_k - outO_k) * outO_k * (1 - outO_k)$

 η is learning rate and α is momentum rate generaly belongs to [0, 1]

3.3.3. Mean Square Error

Mean square error (MSE) is defined as mean or average of the square of the difference between actual and estimated values. Dividing the sum of E_{total} by the number of samples say (m) gives the mean square error (MSE) as shown in Eq. (11).

$$MSE = \frac{\sum E_{total}}{m} , \text{ where } E_{total} = \sum_{1}^{m} Er$$
(11)

3.3.4. Training and Testing Accuracy

The training and testing accuracy for given input sample is obtained as per Eq. (12)

Accuracy
$$= \frac{matched \ samples}{m} * 100$$
 (12)

Where, matched samples = $|target - output| \approx 0$

4. Experimental Results and Discussion

The proposed ICA-NN Mathematical model is simulated on a set of 10 different herbal plants. The different number of images of leaves of herbal plants are considered as training set to train the neural network. Appearance of the leaves of an herbal plant should be vary in nature so that the optimum weights can be achieved during training. Also, the optimum topology used to train neural network is expressed in Table 1.

Input Neurons	10
Output Neuron	1
Hidden layer	1
Hidden Neuron	16
Initial Weight	Input-Hidden layer: Random

	Hidden-Output layer: Random	
Activation Function	Both Hidden and Output Layer:	
	Sigmoidal	
Learning Rate (η)	0.6	
Momentum rate (α)	0.6	

The input images and the target vector for given NN is described in Table 2. Table 2: Input images and Target Vectors

Herbal Plant	Name of Plant	Image	Training Images	Target Vectors
HP1	Garlic Creeper		15	[0.9, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1
HP2	Red Spiderling		12	[0.1, 0.9, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1
HP3	Water hyssop		14	[0.1, 0.1, 0.9, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1]
HP4	Withania Somnifera		8	[0.1, 0.1, 0.1, 0.9, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1]
HP5	Malabar nut		10	[0.1, 0.1, 0.1, 0.1, 0.9, 0.1, 0.1, 0.1, 0.1, 0.1]
HP6	Holy basil		16	[0.1, 0.1, 0.1, 0.1, 0.1, 0.9, 0.1, 0.1, 0.1, 0.1]
HP7	Country almond		12	[0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.9, 0.1, 0.1, 0.1]
HP8	Amla		10	[0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.9, 0.1, 0.1]
HP9	Black Cardamom		8	[0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1,
HP10	Neem	A REAL PROPERTY OF	12	[0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1,

By adopting the topology for NN as shown in Table 1 and the Input images and target vectors as described in Table 2 the obtained results by Neural Network are as follows. Epoch = 64,08,550

MSE = 0.00001

Training Accuracy = 96.4207 %

Although, the result obtained for training accuracy is satisfactory but it has a scope of improvement. The 96.4207% accuracy indicates that if more number of images of respective

herbal plant's leaf that significantly vary from each other should be included in the training set so that the optimum accuracy can be achieved.

The weights obtained by the trained NN are used to obtained testing accuracy. Some of the images of leaves of the given set of herbal plants are considered for testing purpose. By adopting the similar topology of NN as described in Table 1 and the target vectors defined in Table 2 the obtained results for testing are expressed as in Table 3.

Herbal Plant	Name of Plant	Testing Images	Test Accuracy	MSE
HP1	Garlic Creeper	2		
HP2	Red Spiderling	3		
HP3	Water hyssop	2		
HP4	Withania Somnifera 1			
HP5	Malabar nut	2	04 2204	0.00001
HP6	Holy basil	2	94.32%	0.00001
HP7	Country almond	3		
HP8	Amla	2		
HP9	Black Cardamom	3		
HP10	Neem	2		

Table 3. NN results for Test Image Set

Table 3. shows that the accuracy level obtained during testing the NN is 94.32% which is significantly good for the identification of herbal plants on the basis of the features of their leaves along with the MSE 0.00001.

5. Conclusion

The ICA-NN based mathematical computation was an effective approach for identification of a high medicinal valued herbal plant on the basis of its leaf pattern. The whole approach was very well designed and the satisfactory outputs were successfully achieved with training accuracy of 96.4207% with MSE 0.00001. The trained NN with obtained weights has classified the test image set with 94.32% accuracy which shows the significance of the proposed mathematical computation approach.

REFERENCES

6.1. Journal Article

- [1] Zhang, S., & Feng, Y, "Plant leaf classification using plant leaves based on rough set",. International Conference on Computer Application and System Modeling (ICCASM), vol.15, (**2010**) pp.15-521.
- [2] Sumathi, C. S., & Kumar, A. S, "Plant Leaf Classification Using Soft Computing Techniques", International Journal of Future Computer and Communication, vol.2 no. 3, (2013), pp. 196-207.
- [3] Kalyoncu, C., & Toygar, Ö, "GTCLC: leaf classification method using multiple descriptors", IET Computer Vision, vol.10, no. 7, (**2016**), pp. 700-708.
- [4] Shubham Kumar Singh, "Review of Leaf Classification Techniques using Machine Learning", International Journal for Research in Applied Science and Engineering Technology, vol. 6, no. 5, (2018), pp. 2710-2715.

- [5] Kheirkhah, F. M., & Asghari, H, "Plant leaf classification using GIST texture features", IET Computer Vision, vol. 13, no. 4, (2018), pp. 369-375.
- [6] Dr. Mukesh Patel, "Neural Network based Identification of an Emotion using ICA of Hand Gestures of a Human Being", International Journal of Advance Engineering and Research Development (IJAERD), vol.5, no. 3, (**2018**), pp. 1488-1494.
- [7] Muhammad Majid Aziz et al., "Medicinal values of Herbs and Plants, Importance of Phytochemical evaluation and Ethnopharmacological Screening: An Illustrated review essay", Journal of Pharmaceutical and Cosmetic Sciences, vol.2, no.1, (**2014**), pp. 6-10.

6.2. Book

- [8] Rafael C. Gonzalez and Richard E. Woods, "Digital Image Processing 3rd Ed". Editor Pearson Education Inc. New Jersey, (2008).
- [9] Rajasekaran, S. and VijayalakshmiPai, G.A.: "Neural Networks, Fuzzy Logic and Genetic Algorithms: Synthesis and Applications", Prentice Hall of India, (2003).

6.3. Conference Proceedings

- [10] Yan Li at el., "Leaf Vein Extraction Using Independent Component Analysis", IEEE International Conference on Systems, Man and Cybernetics, (2006), pp. 3890-3894.
- [11] Olsen, A., Han, S., Calvert, B., Ridd, P., & Kenny, O, "Situ leaf classification using histograms of oriented gradients", International Conference on Digital Image Computing: Techniques and Applications (DICTA), (2015), pp. 1-8.
- [12] Chaisuk, P., Phromsuthirak, K., & Areekul, V, "Leaf lassification based on a quadratic curved axis", IEEE International Conference on Image Processing (ICIP), (2017), pp. 4472-4476.
- [13] Hassan Esmaeili; Thanathorn Phoka, "Transfer Learning for Leaf Classification with Convolutional Neural Networks", 15th International Joint Conference on Computer Science and Software Engineering (JCSSE), (2018), pp. 1-6.