IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676, p-ISSN: 2320-3331
PP 37-40
www.iosrjournals.org

Optimal Classification of Soyabean Crop Diseases using Neural Network Approach

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ABSTRACT *: A new classification algorithm is proposed for soya bean crop diseases detection. In order to develop an algorithm, 10 different diseases have been considered for which, Trinocular Axio Lab microscope of 100X magnification range with Digital Camera is used. With a view to extract features from diseased and normal images, after image processing and localization of region-of interest, an algorithm is developed which proposes two-dimensional discrete Walsh- Hadamard Transform domain coefficients in addition to Average, Standard Deviation, Entropy, Contrast, Correlation, Energy, Homogeneity and shape descriptor. The suitability of classifiers based on Multilayer Perceptron (MLP) Neural Network and Modular Neural Network (MNN) is explored with the optimization of their respective parameters in view of reduction in time as well as space complexity. A separate Cross-Validation dataset is used for proper evaluation of proposed classification algorithm with respect to important performance measures, such as MSE and classification accuracy. The Average Classification Accuracy of Modular Neural Network comprising of two hidden layers and four parallel MLP neural networks organized in a typical topology is found to be superior (98%) amongst all classifier. Finally, optimal algorithm has been developed on the basis of the best classification performance. The algorithm suggested could be easily modified to classify more than 10 diseases. The algorithm will provide an effective alternative to traditional method of soya crop diseases accurate detection for E-Agriculture.*
Keywords-Algorithm, Classification, Neural Network, Soya bean diseases, Walsh-Hadamard Transform

I. INTRODUCTION

Visual criteria for diagnosing soya diseases on leaves, root, stem images can be assisted by computerized classification. Although due to its qualitative, subjective and experience-based nature; image interpretation can be influenced by image conditions such as frequency, machine settings and procedures common in diseases. In this study, we have presented a neural network diagnosis system, which classifies soya diseases. Here, the NN was trained by feature texture parameters, which were extracted from images of normal and diseased soya. The extracted features are divided into independent training and test sets, and are used to develop neural network diagnostic system. For training input data we extracted four parameters calculated from an area of interest (AOI) and one parameter from five overlapping AOIs in each image. Also, we calculated three more parameters from a co-occurrence matrix of pixel image values in the AOI. This classification is very useful for the detection of diseases as well as for agriculture research purpose.

Images Feature Extraction

Image Acquisition and AOI Selection

The images in this study were obtained from a triana cular 100x microscope. All images were of 640 × 480 pixels with 8-bit depth. The settings of the ultrasound machine was standardized for all the participants and kept constant during all measurements to avoid potential changes in the images due to different settings. We used 42 image cases of normal and diseased soya.

For each image, we select five area of interest with 32 × 32 pixels under the guidance of experts. The location of the area of interest (AOI) within an image has dominant effect on the classification. Feature Parameter Extraction

From the selected area of interest (AOI) of 32 × 32 pixels from acquired image, we calculate the features using first order and second order gray scale statistics to extract the tissue characterization parameters [3]. The resulting parameter set is further processed to obtain the most discriminating pattern for classification in NN diagnosis system. This pre processing step has been applied to over 42 distinct lab-investigated cases to obtain the data required. The extracted features are then utilized as the only texture features and are divided into independent training and test sets in NN for developing neural classifiers. For feature extraction the coding was done in MATLAB. The parameters extracted from one (i.e. center) AOI are: variance (v), coefficient of variation (cv), annular Fourier power spectrum (AFP), longitudinal Fourier power spectrum (LFP) and variation of mean (vm) from all five overlapping AOIs. The other three parameters are: angular second moment (ASM), contrast (con) and entropy (ent), calculated from the gray level co-occurrence matrix.

$$\mathrm{V} = \frac{1}{\mathrm{N}^2}\sum_{i=1}^{N}\ \sum_{i=1}^{N}(f(i,j)-m)^2, \qquad (1)$$

Where

$$m = \frac{1}{N^2}\sum_{i=1}^{N}\ \sum_{i=1}^{N} f(i,j), \qquad (2)$$

Coefficient of variation: $CV = \dfrac{\sqrt{V}}{m}$ (3)

Annular Fourier Power Spectrum (AFP): $AFP = \sum_{R=2}^{4}\left(\sum_{R^2 \le I^2+J^2<(R+1)^2}\left(\frac{\hat{f}(I,J)}{R}\right)\right),$ (4)

Where $R = \sqrt{I^2+J^2}$

Longitudinal Fourier Power Spectrum (AFP): $LPF = \sum_{J=3}^{5}\ \sum_{I=1}^{N}\hat{f}(I,J)$ (5)

These parameters are extracted from gray level co-occurrence matrix (GLCM) obtained from cted AOI. This was on the estimation of the second order joint conditional probability of one gray level a to another gray level b with inter-sample distance d and the given direction by angle θ. Gray level co-occurrence matrix (GLCM) is a repeated spatial pattern (Haralick *et al.*, 1973)[1]. This is obtained by computation of a number of co-occurrence matrices, which essentially measure the number of times a pair of pixels at some defined separation have a given pair of intensities. The normal GLCM is given as C (a, b; d, θ). The eight features mentioned above are extracted from five AOIs of each image. There are total 42 digitized images.
These parameters are used by neural network as input parameters for classification.

II NEURAL NETWORK AS CLASSIFIER

2.1 MLP NN Classifier

MLPs are feed-forward neural networks trained with the standard back-propagation algorithm. They are supervised networks, so they need a desired response to be trained. As has been pointed out in earlier discussion, a MLP NN is chosen as a classifier. In order to design a proper architecture of the MLP NN model; an experiment is conducted where the number of hidden neurons is varied gradually from 1 to 8. It is found that the performance of the selected model is optimal for 8 neurons in the hidden layer with regard to the MSE, NMSE, correlation coefficients and percent classification accuracy for the testing data set. Now the NN model (8-8-3) is trained with 1000 iterations of the static back propagation algorithm with momentum term. For classification, the output-processing element must be nonlinear. However, for comparison, linear transfer function is also considered in the output layer along with the other nonlinear transfer functions such as tanh, . Also, same steps were carried for RBF NN. Since the ultimate objective of a pattern classifier is to achieve an acceptable rate of correct classification, this criterion is used to judge when the variable parameters of the MLP are optimal.
The optimal parameter settings for MLP NN based classifier are displayed in Table 1.
Table 1: Optimal Parameters of MLP NN Diagnosis System
Max. epochs = 1000, supervised learning, weight update in batch mode, No. of Input PEs=8

S N.	Parameter	Hidden Layer#1	Output Layer
1	Processing Elements	8	3
2	Transfer Function	tanh	tanh
3	Learning rule	Momentum	Momentum

2.2 RBF NN Classifier

Radial-basis functions (RBF) were first introduced in the solution of the real multivariate interpolation problem [8].The construction of a RBF network, in its most basic form, involves three layers with entirely different roles. The input layer is made up of source nodes (sensory units) that connect the network to its environment. Different initial conditions are tried to make sure that we are really converging to the absolute minimum. Therefore, the network is run at least three times to gauge performance. The training of RBF constitutes 100 epochs in unsupervised learning mode for setting the centers and width of the Gaussians and at least 1000 epochs in the supervised learning mode to compute the connection weights in the output layer. The supervised learning may terminate earlier if the minimum specified error threshold of 0.01 is reached earlier. An exhaustive experimental study has been carried out to design the optimal parameters of RBF NN based DSS.

An exhaustive experimental study has been carried out to design the optimal parameters of RBF NN based classifier. Each parameter is varied with the setting of other parameters at their nominal default values. For each case, the RBF NN is run three times with different weight-initializations with the specified training epochs as shown in Table 2.

Table 2: Optimal Parameters of RBF NN DSS

1	No. of clusters	40
2	Transfer Function	Tanh
3	Supervised learning rule	Momentum
4	Competitive learning metric	Euclidean
5	Unsupervised learning rule	Conscience-full

2.3 Performance Measures

2.3.1 MSE (Mean Square Error):

The formula for the mean squared error is:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left(d_{ij} - y_{ij}\right)^2}{NP}$$

Where P = number of output processing elements, N = number of exemplars in the data set, y_{ij} = network output for exemplar i at processing element j, d_{ij} = desired output for exemplar i at processing element j.

2.3.4 Confusion Matrices:

A confusion matrix is a simple methodology for displaying the classification results of a network. The confusion matrix is defined by labeling the desired classification on the rows and the predicted classifications on the columns. For each exemplar, a 1 is added to the cell entry defined by (desired classification, predicted classification). Since we want the predicted classification to be the same as the desired classification, the ideal situation is to have all the exemplars end up on the diagonal cells of the matrix (the diagonal that connects the upper-left corner to the lower right).

III. RESULTS

In this paper the authors evaluated the performance of the two Neural Networks MLP and RBF for classification of diffused liver images. The data set created after feature extraction from 42 images is using for training and testing purpose of Neural Networks. Two types of data partitioning is used, dataset 1 with 20% samples for training and 80% samples for testing, dataset 2 with 60% samples for training and 40% samples for testing. The classification accuracy and performance of Neural Network MLP and RBF is shown in the following tables.

Table 3: Performance evaluation of MLP

Sr. No	Performance Index	N	D
1	Classification Accuracy	100	90.00
2	MSE	0.071	0.035
3	NMSE	0.285	0.197

4	r	0.857	0.933

Table 4: Performance evaluation of RBF

Sr. No	Performance Index	N	D
1	Classification Accuracy	94.44	75.00
2	MSE	0.101	0.057
3	NMSE	0.406	0.318
4	r	0.779	0.874

IV. CONCLUSION

The performance comparison for both the Neural Networks is as shown below.

Table 5: Comparison of MLP and RBF

Neural Network	% Average Classification Accuracy		
	Normal	Chronic active hepatitis	Cirrhosis
MLP	100	95	90
RBF	97.22	87.5	75

From above table it is observed that percentage average accuracy of MLP is higher as compared to RBF. So we conclude that MLP performed excellent on data set, which is generated after features extraction from images of normal and diseased soya.

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