BRANN Model for Identification of Rice Leaf Diseases Using Texture Feature

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Abstract- On this paper, Bayesian Regularized Artificial Neural Network (BRANN) model is develope to detect rice disorders using the properties of the affected leaves. The work involves identifying healthy leaf and four types of disease, such as brown spot (BS), bacterial blight (BB), Leaf scald & Leaf blast (LB). The BRANN model was experimented with 100 number of samples with 20 number of each category. Here 75% data used as training purpose, 15% for validation and 15% for testing. Here k-means clustering used for extracting the diseased region, nine number of features extracted from affected region and then these features used for training and testing the model and achieve coefficient of regression, R-value 0.85.

Index Terms- rice leaf diseases identification; Bayesian regularized artificial neural network; image processing; texture feature.

1. INTRODUCTION

Agriculture is the backbone of India economy and rice is the most cultivated crop, rank second in world for production. The current population of India is 1,365,617,244 as of Tuesday, April 16, 2019, based on the latest United Nations estimates and is equivalent to 17.74% of the total world population [1]. So, to meet the growing population of the country, there is a need for rice production. More rice production jobs create a major challenge to meet the growing demand. Bug contagion on crop plants is one of the main reasons for crop production. A study conducted by IRRI [2] found that farmers reduced their rice rate of pest and disease by 37% and these losses could vary from 24% to 41% depending on the production rate. There are four common diseases in India: (1) Brown Spot, (2) Bacterial Blight (3) Leaf Blast (4) Leaf Scald [3].

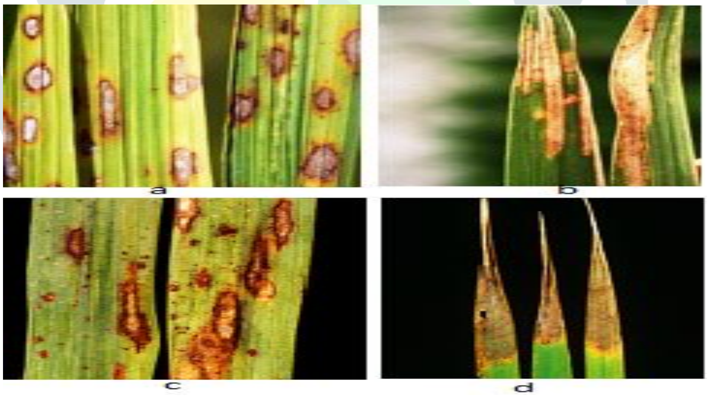


Fig.1 Sample of diseased rice leaf (a) Brown Spot (b) Bacterial blight (c) Leaf blast (d) Leaf scald.

The study conducted by Pugoy RADL, Mariano VY. (2011) [4] for automated rice leaf disease detection using color image analysis. Here they have prepared the base image with major color extraction of diseased region of leaf. First, the outlier of diseased region extracted by HIS color conversion with application of thresholding. Then four and five number of cluster center assigned for brown spot and leaf scald disease respectively according to color palette. Then, the test is matched with the base image by use of k-means clustering with consideration of Euclidean distance and achieve 25% & 40% of likeness for leaf scald & brown spot respectively. Gayathri Devi, T., & Neelamegam, P. (2018) [5] reported an automated rice leaf disease detection method. The five rice leaf diseases with 1000 number of samples considered for experimentation in the region of Thanjavur, Tamilnadu, India. Here three hybrid technique such as DWT (Discrete wavelet Transform), SIFT (Scale Invariant Fourier Transform) & GLCM were used for feature extraction. Then different classifier such as KNN, Naïve Bayes', and ANN & SVM used for identification of diseases. Finally, it concluded that SVM is perform better than other classifier with accuracy of 98.63%. Xiao, M. et al. (2018) [6] a rice blast recognition method based on principal component analysis & backpropagation neural network (PCA-BP). A total of 387 number of different lesion type rice leaf samples were collected from rice field in four different time (i.e. 8 Am, 10AM, 12PM, 2PM, 4PM & 6PM) of a day and captured by using ZEN Z3 with resolution of 4000×3000 with white back ground. Then all images transformed to a standard resolution of 700×200 pixel. Then 6 color features, 10 morphological features & 5 texture features were extracted for further processing. Again, out of 21 features some feature have approximately same value and do not have significant contribution for recognition. So PCA was used to reduce feature dimension by removing redundant feature i.e. 21 features become six principal component factors. Then, this principal component factor was fed to the three-layer BP-Neural network (6-11-4 structured) and recognized 4 type of blast lesion i.e. acute lesion, chronic lesion, brown spot lesion & white spot lesion with over all accuracy of 95.83%. Here it observed that, the histogram of R, G & B channels were varying with respect to shoot time even in same image. So instead of RGB value, HSI and YCbCr were used as color component as HSI & YCbCr were independent from color & brightness information. Sengupta, S., & Das, A. K. (2017) [7] proposed an association model of bug sorting using particle swarm optimization (PSO) based rice disorders with the acquisition of mining knowledge. The methodology successfully works in static as well as dynamic environment. It is very useful in real time system as the algorithm update itself with new incoming data time to time. The proposed incremental PSO (IPSO) achieved 84.02% of accuracy with different dataset of rice disease. It also has good accuracy of classification in some standard dataset available in UCI repository. Phadikar, S., Sil, J., Das, A.K., (2013) proposed an automated system for classifying rice diseases. The infected part of leaf separated by use of fermi energy-based segmentation. For classification shape & color feature are considered. Then Rough set theory (RST) was used for feature selection and finally rule based classifier identify the four diseases i.e. leaf blast, brown spot, bacterial blight & stem rot with accuracy of 94.21%. This paper develops an automated BRANN model based on texture feature of diseased region of leaf to identify the main four disease & healthy leaf, which helps to take necessary steps towards treatment of rice plant.

2. ANN

The artificial neural network can approximate intricate undeviating relationship models with any measurable functions. They can be used as a useful tool for shape sorting and grouping [9, 10]. They are particularly useful for the problem which establishes a hidden layer feed grid in which the sigmoidal nodes (estimated number) can be estimated as in the form of continuous mapping with estimated accuracy [11-14]. The feed-forward multilayer network is a network that takes place on a loop network path. A teaching rule is defined as the method of changing the weight and bias of a network in order to reduce the difference between the desired output and output from the network for an input. Learning rules / network training algorithm is used to adjust network weight and biases the network to yield network output near marks.

The classical backing propagation algorithm was the first training algorithm enhanced as ever [15]. The simplest implementation of the back propagation is the direction of network weight and network biasing, which reduces the effectiveness of the functions rapidly with gradient negative [15]. It uses a hidden network of nine inputs and five outputs. Activation tasks and output levels on an incognito level are tangent - hyperbolic (tanh) function. The network inputs are the nine-texture feature of diseased region of leaf and five output are the four diseases & healthy leaf, in total five category.

3. METHODOLOGY

The identification of rice disease model composed of three main section i.e. segmentation, feature extraction and classification.

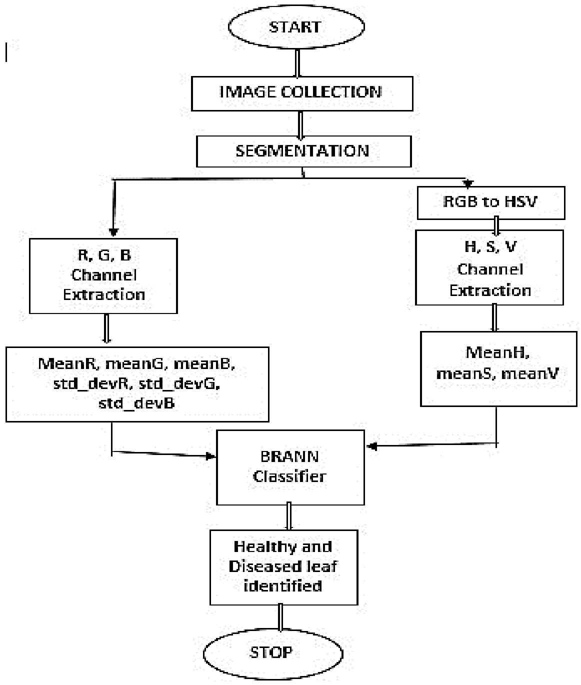


Fig.2 Flow chart of Rice Leaf Disease Identification.

3.1. *Image Collection*

The 100 samples with 20 of each five-category collected from IRRI website. The five category consists of healthy leaf and four type of diseased leaf such as brown spot, bacterial blight, leaf blast and leaf scald. Fig. 1 illustrate the healthy leaf and four diseased leaf.

3.2. *Segmentation*

The segmentation is the process to obtain the region of interest, which it needs to carry forward the analysis. Here k-means clustering used for segmentation purpose. The k- value is three as it clusters the background, foreground (except disease part of leaf) and diseased region of leaf. After diseased region obtained the feature extraction progresses.

3.3. *BRANN Classifier*

The Artificial Neural Network (ANN) imitates the running of the human brain and has the power to implement equivalent calculations for their planning, variable approximation, cataloguing, shape appreciation and processing. ANN inputs (estimate) and target (reply) variables can capture to a highly immune groups and helps to learn complex formulas. ANN permits favorable direction of the assumption of regular adjustments (contraction) parameters. Most common strategies for regular routine strategies in ANN are the Bayesian Regulation (BR) and initialization methods. Regular ANN (BRANN) of Bayesian regularization strategies, to strengthen specific distributions prior to model parameters and to punish heavyweight for achieving smooth plotting. The MLP feed forward architecture which might be a linear or non-linear model can accurately predict any degree that it seems from the hidden layer, yields the appropriacy of neurons explicitly which are in a good number. Yet, by adding extra neurons, the model offers the flexibility of predicting complex inequivalent agencies. It also grips true to the estimation of boundaries of an offline decision, with great accuracy, inference, planning, classification and shape appreciation. An MLP is similar to adding an additional plural form to a response model by adding an extra neuron to the hidden layer in the feed-finder, through ANN generalization practice. Generation is a method of indicating the exact complexity of the model, which is appropriate for the model [16], generally referred to as the experimental data set, to create accurate estimation information from training information used for fitting. The number of neurons in the hidden layer controls the number of parameters (weight and bias) in networks. Determining the best number of neurons concealed in the hidden layer is an important step in ANN's strategy. With ANN inputs and target variables with minority neurons, it may fail to capture complex patterns. On the contrary, with an additional number of neurons at the hidden level, it will be damaged by an ANN over-parameter, resulting in additional fittings and poor generalization [17]. The method of allowing parameter bias on disciplines being considered as a more probable value, which reduces the contradiction between estimating the cost of bias. In any other way, regularization parameters (weight and bias) can be seen as a way to compromise to reduce the relative function of the space. In the ideal practice of learning back propagation with an initial break, the data set is allocated in three sources: a training data set, a proof data set, and a test data set. In most ANN practices, the majority of the information is allocated to training data (70 % of the information here is given for training in MATLAB). During each ANN prediction process, each of these data sets has different functions. The training information set is used to estimate neural network weight, when the verification data set is used for network monitoring and the minimum error count is counted for the recurrence time until the network is closed. Last data set (test data set) invisible data and test data set by network reduces job bias and creates neutral estimates for predicting future results and generalization. The test data set for evaluating the performance of the models from an independently drawn sample is used at the end of the repetitive process [18]. Another regularization process in ANN is BR, which is a combination of aerial method aliens and ANN to automatically determine optimal regular parameters. Beijing's regular ANN (BRANN) model, the regularization strategy model parameters involve specific distances distributed and equation 1.

$$F = \beta E_D(D|\mathbf{w}, M) + \alpha E_W(\mathbf{w}|M). \quad (1)$$

where EW (w|M), is the sum of squares of architecture weightiness, M is the ANN architecture (model in statistical waffle), and α and β are unbiassed function parameters (also referred to as regularization parameters or hyper-parameters and take the positive values) that need to be estimated adaptively [17]. From right on the right side of equation 1 as αEW, the second word is known for weight loss and α, known with weight corrosion, the small value of w and reduces the trend of a model. [19]. Especially, in BRANNs, when input and target data are small, the data is not required to be shared in three subsets: training, proof and test set. Conversely, all available data sets are modeled on model fitting and modeling [20]. When the networks are trained with small data sets, this implementation is considered to be important that the BRT has more general power than initially closed. Network connection power, W, is considered a random variable and has no meaning before training. After receiving the information, the concentration density function can be updated according to the age rules by following from [12] as the methods of empirical Bayes. The next distribution of the given w is given by A, β, D, and M

$$P(\mathbf{w} \mid D, \alpha, \beta, M) = \frac{P(D|\mathbf{w}, \beta, M)P(\mathbf{w}|\alpha, M)}{P(D \mid \alpha, \beta, M)} \quad (2)$$

where D is the training data set and M is the specific functional form of the neural network architecture considered. The other terms in equation (2) are: Where D is training data sets and M is certain operating forms of intelligence network architecture.
Other Terms of Equation (2) are:

• P (w|D, α β, M) is the later likelihood of w,
• P (D|w, β, M) is the prospect function of w,
• P (w|α, M) is the erstwhile supply of weights under M, which is the likelihood of observing the data given w and
• P (D|α, β, M) is a normalization factor or evidence for hyperparameters α and β.

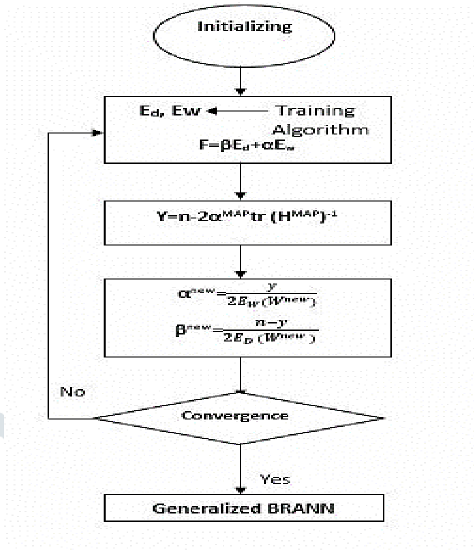
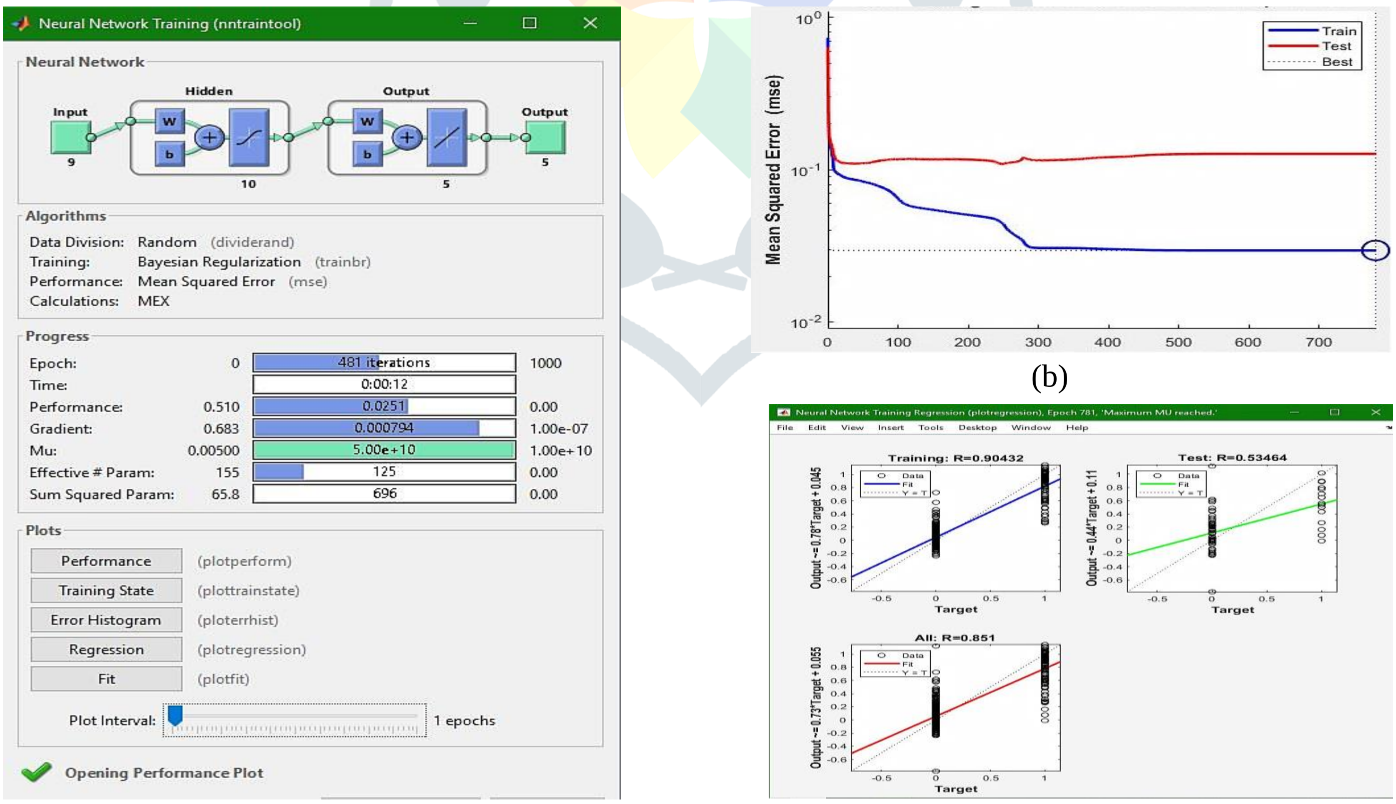


Fig.2 Flow Chart of BRANN Algorithm.

Step-1: initialize the algorithm to minimize objective function.
Step-2: compute effective number of parameters y via the Gaussian-Newton approximation to the Hessian.
Step-3: compute α and β.
Step-4: Iterate steps above until convergence.

4. RESULT AND DISCUSSION



(b)

(a) (c)

Fig.3 Output screens from MATLAB runs (a) BRANN model (b) performance (c) Regression.

Figure 3 shows MATLAB screen of BRANN model. The model consists of 9 number of input neuron (9-texture feature of rice leaf), 10 number of hidden neurons, (where we get best result) and 5 number of output neuron (as it classifies to 5 category). The result shows the performance and regression of the BRANN model for identification of healthy leaf and four type of disease such as brown spot, bacterial blight, leaf blast and leaf scald. The performance of model is measure in mean square error versus epoch and the best performance is 0.029486 at 786 epochs. The regression for training, testing and overall with coefficient of regression, R-value is 0.90432, 0.63464 and 0.851 respectively. The predicted correlation 0.85 is quite high, which is enough of the predictive power of the model to be used.

5. CONCLUSION AND FUTURE SCOPE

This proposed BRANN model with texture feature of region of interest of rice leaf successfully identify the healthy leaf and four diseased leaf such as brown spot, bacterial blight, leaf scald and leaf blast. The model has predictive correlation of 0.85, which is quite high. This work can carry further with a greater number of data sets with additional variety of diseases.

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