Rice Grain Identification Model based on Bayesian Regularization of Artificial Neural Network using Geometrical Feature

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Abstract- Rice grain identification is a challenging research in current time, as many young farmer unable to identifymany species of rice by observing its external appearance. This paper develop a novel model based on Bayesian regularization of artificial neural network (BRANN) using texture feature of rice grain. The model is develop using 13 input neuron, 15 hidden neuron & 6-output neuron and achieve predictive correlation, R of 0.93, which is quit high, leads a reliable model for identification of rice grain.

Index term- Rice grain identification, geometrical feature, image processing, Bayesian regularization.

1. INTRODUCTION

Rice grain identificationmade to obtain information about grain type, variety, quality. Determination of the type, variety and quality of seeds, is necessary for certification procedures. In addition, it is the first step of the seed processing operation in the seed separation machines. Use of certified seeds, increases the quality and quantity of yield. Typically, for the certification, experts using visual characteristics of the seeds make the analysis and classification process. These conventional methods are very time consuming, very tedious, costly, and depend on the person. In the seed separation machines, the determination of the seed properties process, identification of the seed type, varieties and identification of diseased and structural deformed seeds operations performed [1]. The western Odisha especially Bargarh district is famous for rice cultivation and known as Rice Bowl. In Bargarh, district and its neighbour district like Sambalpur &Sonepur large variety of rice are cultivated. The qualitative variety of rice in this region are Asanchudi, Badakadalia, Babulal, Chit Pagalia, Radhajugal and Sahabhagi. In our previous work [2], we have successfully identified these six variety of rice grain based on support vector machine (SVM) using texture feature & geometrical feature with accuracy of 92%. In this work, we have taken the same samples and feature dataset of our previous work. Here we are only consider the nine number of geometrical feature and four shape factor. Many researcher reported image-processing methods for classification, qualityassessment and grading of agricultural grains.DuboscaldP. et al.[3] developed an automated evaluation system of grain. The methodology have two parts, first one separate individual grain image from the bulk image, which are place in a tray. The second approach is energy minimization through mark point processes.The first approach adopted for the segmentation step is based on simple criteria such as regions, edges and normals to the boundary. By combination of both approach, quality of grain is measure based on shape and color descriptor.Mebatsion, H [4] developed an automation model for classification of six type of cereal grains i.e. barely, oat, rye and two variety of wheat. Least square classifier using color feature such as three-color indices with L & G color value and shape feature such as aspect ratio, major diameter, roundness and achieve 99% accuracy of classification.Chaugule, A. A. [5] proposed new feature extraction technique based on horizontal-vertical, front –rear angle with angle fusion for classification of four variety of rice grain. Twelve number of features are extract in this model and train ANN for classification. This method perform well as it have accuracy of 97% with just twelve number of feature as compared to color-shape-texture have eight four number of feature with accuracy of 95.2% only with same ANN classifier.Pearson. T. [6] designed a high-speed, low-cost, image-based sorting device was develop to detect and separate grainshaving slight color differences or small defects. The device directly combines a complementarymetal–oxide–semiconductor (CMOS) color image sensor with a field-programmable gate array (FPGA) which was programme to execute image processing in real-time, without the need of an external computer.Zapotoczny et al. [7] compare three classifier such as principal component analysis (PCA), linear discriminant analysis (LDA) and nonlinear discriminant analysis (NDA) for classification of barely grain. Here fifty-four number of morphological feature used for classification and implied LDA is the best.

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 [8, 9]. 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 [10-13]. 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. Learningrules / 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 [14]. 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 [14]. 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.. In this paper, a thirteen input and five output network is used. The network uses only one hidden layer. The activation functions at the hidden layer and the output layers are the tangent – hyperbolic (*tanh*) function. The network inputs are thirteen neuron as we consider thirteen feature (nine geometrical and four-shape factor) of rice grain and six-output neuron as 6 variety of rice grain and 15 hidden neuron.

3. METHODOLOGY

The methodology is examined by using the samples of our previous work [2]. The rice seed varieties are AsanChudi, BadaKadalia, Babulal, Chit Pagalia, RadhaJugala and Sahabhagi. In our previous work we consider 21 texture feature, 11 geometrical feature and 4 shape factor, in total 36 number of feature. By considering 36 number of feature, SVM is trained for classification and achieve 92% of accuracy. But in our current work, we only consider only consider 13 number of feature i.e. nine number of geometrical feature and four shape factor.In this work we develop a BRANN model for classification which identify the rice grain variety and the literature & working process of BRANN is depicted in following section.

3.1 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 [15], 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 [16]. 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 [17]. 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.

$$F = \beta E_D(D/w, M) + \alpha E_w(w/M) \qquad (1)$$

where E_W (w|M), is the sum of squares of architecture weightiness, M is the ANN architecture (model in statistical waffle), and α and β are unbiased function parameters (also referred to as regularization parameters or hyper-parameters and take the positive values) that need to be estimated adaptively [18]. 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 [18]. 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 [19]. 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 [11] as the methods of empirical Bayes. The next distribution of the given w is given by A, β, D, and M

$$P(w/D, \alpha, \beta, M) = \frac{P(D/w, \beta, M)P(w/\alpha, M)}{P(D/\alpha, \beta, M)} \qquad (2)$$

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 hyper parameters α and β.

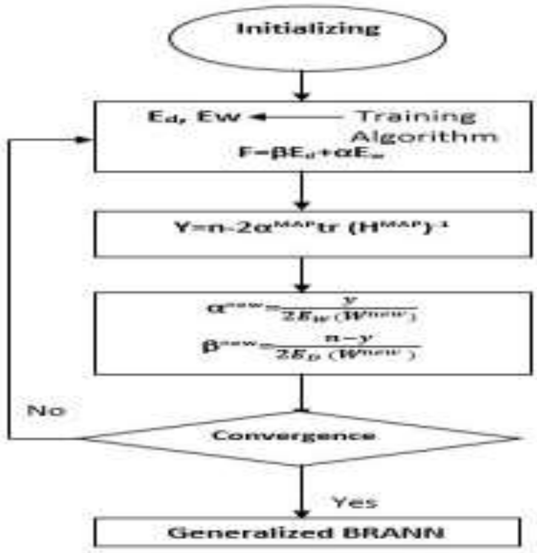
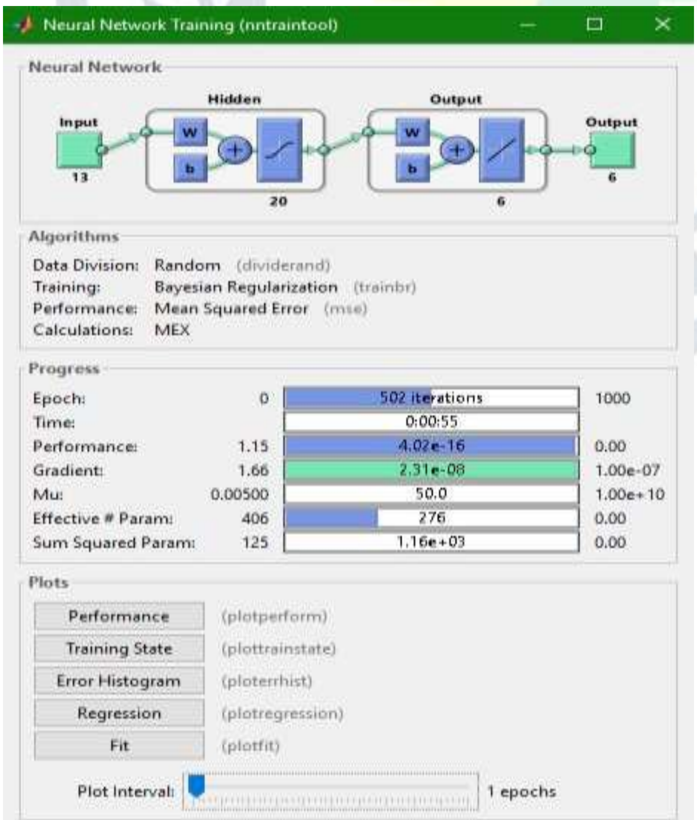


Fig.2 Flow Chart of BRANN Algorithm.

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



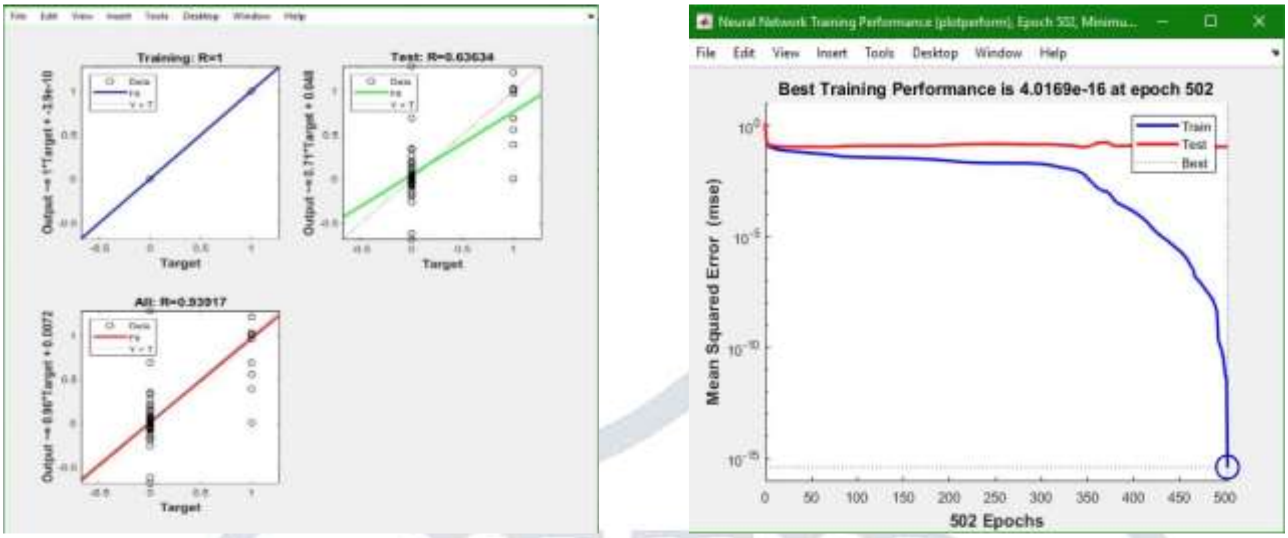


Fig.3 Output screens from MATLAB runs (a) BRANN model (b) performance (c) Regression.

Figure 3 shows Matlab screen of BRANN model. The model consists of 13 number of input neuron (9-texture feature & 4-shape factor), 20 number of hidden neuron, (where we get best result) and 6 number of output neuron (as it classify to 6 category). The result show the performance and regression of the BRANN model for identification of six variety of rice grain. The performance of model is measure in mean square error versus epoch and the best performance is $4.02e^{-16}$ at 502 epoch. The regression for training, testing and overall with coefficient of regression, R-value is 1, 0.63 and 0.93 respectively. The predictive correlation 0.93 is quite very high, implying that the predictive ability of the model used is sufficient.

5. CONCLUSION AND FUTURE SCOPE

This proposed BRANN model with geometrical feature of rice grain successfully identify six variety pf rice graini.eAsanchudi, Badakadalia, Babulal, Chit Pagalia, Radhajugal and Sahabhagi. The model have predictive correlation of 0.93, which is quit very high. This work can carry further with more number of data sets with additional variety of grains.

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