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Comparison of Abilities of Different Activation Functions of Artificial Neural Network to Predict Crop Area and Crop Production

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ABSTRACT

India is a agricultural based country. The accurate information on crop area and crop production is very important for the development of Agriculture sector. It helps the planners to take certain decisions for solving the agricultural problem. Different Artificial Neural Network (ANN) models have been found to be suitable to predict crop area and crop production more accurately than the traditional equations. The present work has been carried out to find the best activation function of the multilayer perceptron (MLP) neural network to predict crop area and crop production of North Bank Plain Zone of (NBPZ) of Assam. The MLP models have been tested with three different types of activation function viz. Log-sigmoid, Hyperbolic tangent and linear transfer function. The performance of the developed models have been evaluated using Root Mean Square Error and Correlation Coefficient. It is found that ANN model with log-sigmoid transfer function in the hidden as well as output layer provides more accurate results compared to other configuration with the dataset considered.

Key words: *Artificial neural network; Multilayer perceptron; Activation function; Crop area, Crop Production RMSE, CC.*

INTRODUCTION

The agricultural production information is very important for planning and allocation of resources to different sectors of agriculture. The advance estimates of crop production are needed much before the actual harvest of crops for making various decisions such as pricing, distribution, export and import etc. Nowadays, various soft-computing techniques have been employed for prediction of crop production using weather parameters. Amongst the soft-computing techniques, Artificial Neural Network (ANN) is found to be most suitable technique for prediction of crop production[1]. Apart from agricultural field ANNs are also being used in other fields like Civil Engineering for different prediction purposes[2]. In recent years, Researchers have found Soft-computing techniques *viz.* Artificial Neural Networks (ANNs) to be one of most appropriate techniques to handle these problems.

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ANNs are useful tools for prediction, function approximation and classification. It is well suited for extracting information from imprecise and non-linear data. Neural networks can map a random input pattern to a random output pattern[3]. The main advantage of the ANN approach is that it does not require any assumption of any functional relationship between its input variables and the corresponding output. Instead, it is able to learn and build its own non-linear model from a relationship between input variables and output during the training process. It is widely accepted that the application of ANN is quite appropriate when the functional relationship between input variables and output is complex. Several researchers have reported the attempt to apply the ANN approach in the forecast of agricultural crop production[4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25]. The majority of the ANN model used in the previous researches for forecasting is a multi-layered feedforward network or MLP using backpropagation learning algorithm which is of a supervised learning type.

ANN is comprising of different types of networks and Multilayer Perceptron (MLP). ANN is composed of densely interconnected processing nodes (neurons) which has the ability to extract and store the information from few training patterns through learning. Multilayer perceptron is a special class of ANN. A neuron with n input is shown in Fig.1[26]. The individual inputs $x_1, x_2, \ldots, x_n$ are multiplied by the corresponding elements $w_{11}, w_{12}, \ldots, w_{1n}$ of the weight matrix W. An activation function is a mathematical representation, in terms of spatial or temporal frequency, of the relation between the input and output. Generally, non-linear activation functions are used, since this makes the network capable of storing non linear relationships between the inputs and outputs[27]. Some of the available activation functions are sigmoid function, linear function, piecewise linear functions and step functions.

Amongst activation functions stated above, the most commonly used activation functions is the Log-sigmoid activation function[28] which is shown in Figure 2a. This function takes the input in the range of plus infinity to minus infinity and squashes the output into the range 0 to 1. Due to the differentiable property of log-sigmoid transfer function, it is commonly used in multilayer networks that are trained using the backpropagation algorithm.

Hyperbolic tangent sigmoid (Tan-sigmoid) activation function also takes the input in the range of plus infinity to minus infinity but squashes the output into the range -1 to +1. Figure 2b represents hyperbolic activation transfer function.

Linear activation function is used in the model when the input-output characteristic is linear. There are different types of linear transfer function and the pictorial representation of the most commonly used linear function is shown in Figure. 2c.

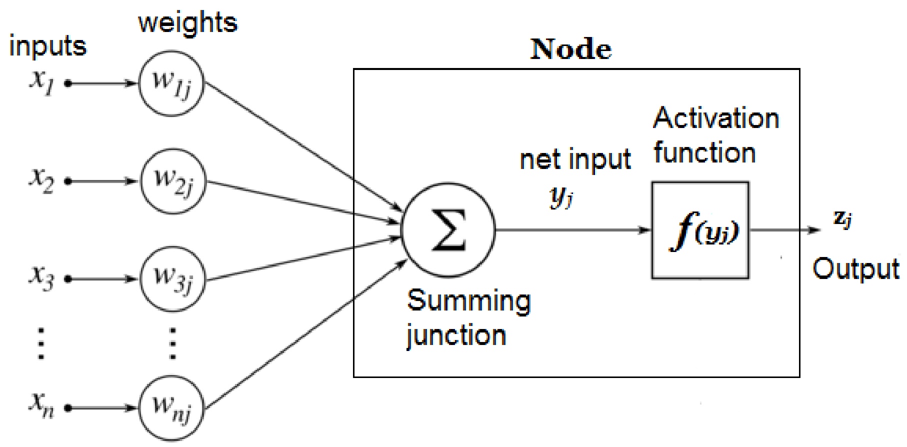
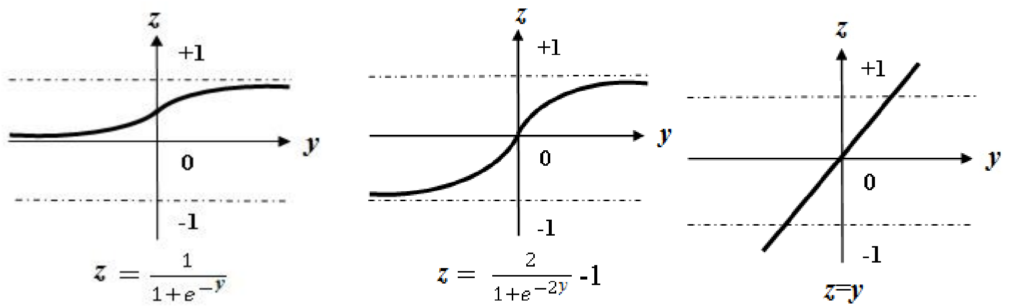


Figure 1: A neuron with *n* input



(a) Log-sigmoid (b) Tan-sigmoid (c) Linear

Figure 2: Activation Functions

The suitability of different ANN transfer functions is studied to predict crop area and crop production. Many studies as stated above are available in the literature to predict crop production with ANN models and was providing good performance. Although, it is reported that MLP provides best performance among the ANN models in crop production, there is no studies about the optimum activation function to predict crop production. The main objective of the present work is to find the best transfer function of the MLP model to predict crop area and crop production.

The rest of the paper is organized as follows. Section 2 discusses materials and methods employed in this study. Section 3 introduces ANN models viz. MLP while ANN modeling has been discussed in section 4. Section 5 describes results and discussion and section 6 concludes the paper.

MATERIALS AND METHODS.

Study region

In the present study, out of six agro-climatic zones of North Bank Plain Zone (NBP Zone). consisting of four districts has been considered.

Data collection and Processing

The study is based on secondary data for the last 30 years for the period 1981-1982 to 2010-2011 Two types of data considered are – Crop data and Meteorological data. The crop Rice is considered which comes under kharif crop and cultivated during May to September every year

Crop-wise Area in hectare, Production in tonnes and Technology Index (Fertilizer consumption, High yielding varieties) have been considered in Crop data while Monthly Total Rainfall in mm for each year, Monthly Mean Maximum Temperature, Monthly Mean Minimum Temperature in degree Celsius (^{o}C) and Monthly Total Sunshine in Hours (from May to September) have been considered in Meteorological data.

District-wise data for the zone of crop Area and Production of the crops Rice and Maize for the period 1981-1982 to 2010-2011 were obtained from the Directorate of Economics and Statistics, Directorate of Agriculture, Govt. of Assam, Guwahati and the Data on Technology index (Fertilizer consumption and High yielding varieties) have been collected from the Directorate of Agro-Economic Research Centre, Assam Agricultural University, Jorhat and from the Directorate of Agriculture, Govt. of Assam, Guwahati. District-wise Meteorological data have been obtained from National Data Centre, India Meteorological Department (IMD), Pune; Regional Meteorological Centre, IMD, Borjhar, Guwahati and from the Department of Agrometeorology, Assam Agricultural University, Jorhat, Assam.

ARTIFICIAL NEURAL NETWORK MODELS

This section provides a brief introduction of MLP.

Multilayer Perceptron Network (MLP)

An MLP is very popular and is used very often than other types of neural network. Relatively little memory is required for the MLP network as compared to other ANN models and is generally fast[29]. Data move through the layers in one direction from the input through the hidden to the output layers. Generally an MLP architecture can have a number of hidden layers and different number of hidden units per layer. During training of the network, it produces its own output and tries to minimize the error between its own output and the target output. The minimization of the error is done by the weight adjustment during the learning process. Backpropagation is the most commonly used method for training MLP or multilayered feedforward networks. Backpropagation is a form of supervised learning where the error rate is sent back through the network to change the weights to improve prediction and decrease error. This network is a universal approximator[26]. In the present study, backpropagation learning algorithm has been used to train the network.

The structure of the MLP network depends on the number of dependent and independent variables present. In the present study, there are two predictor variables available, one is Area and another is Production. Area has two inputs - Technology Index (TI), Rainfall Index (RI) and Production has six inputs – Predicted Area (PA), TI, RI, Temperature Maximum (TMX), Temperature Minimum (TMN) and Sunshine Hour (SH). Therefore, the MLP structure for Prediction of Area and Production is presented in Figure. 1 and Figure 2 respectively Both the models consist of three layers – an input layer, a hidden layer and an output layer. The input and out layers contain nodes that represent input and output variables respectively. The output (v_j) of the j^{th} hidden node is given by:

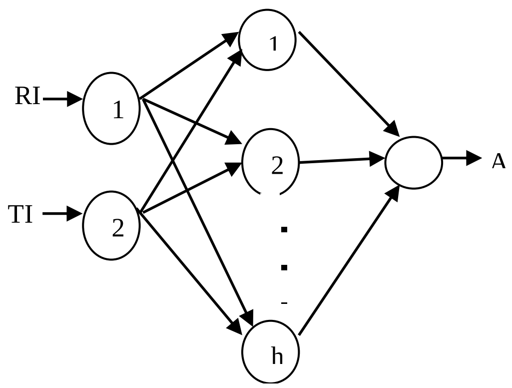
$$v_j = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \qquad (2)$$

where, x_i is the number of input, n is the number of input nodes, w_{ji} is the weight of connection between j^{th} hidden node and i^{th} input node and f is the transfer function is associated with j^{th} hidden node.

The outputs of the networks for Area (A) and Production (P) are derived from the equation (3)

$$d = f\left(\sum_{i=1}^{h} w_{ji} v_j\right) \qquad (3)$$

where, d is the desired output for Area and Production and h is the number of hidden nodes.



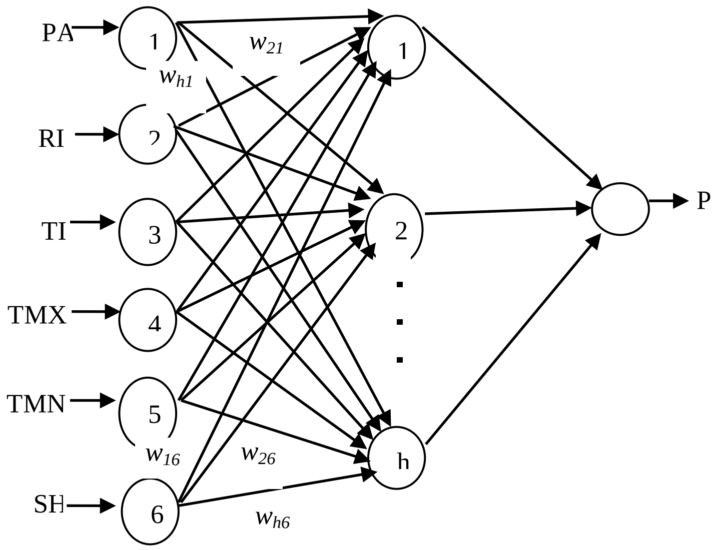


Figure 1: MLP for Prediction of Area under Rice **Figure 2: MLP for Prediction of Rice**

ANN MODELLING

The dataset for training the MLP models were collected from the sources as stated in section 2.2. The 30 years data have been divided randomly into a training set and a testing set. The training and testing set consists of 24 data points and 6 data points respectively.

The data of input and output variable were first normalized within the range 0.1–0.9 as follows:

$$x_N = \frac{0.9 - 0.1}{x_{max} - x_{min}}(x - x_{\min}) + 0.1 \qquad (4)$$

where, x_N is the normalized value of x, x_{max} and x_{min} are the maximum and minimum value of each parameter in the original data. The normalization is done for effective training of the network.

The network for prediction of crop area consists of two input nodes (*RI and TI*) and the network for prediction of crop production consists of four input nodes as shown in Figure.1 and Figure.2 respectively; single hidden layer of neurons and one output node. The transfer functions of the hidden layers are log-sigmoid and tan-sigmoid whereas in the output layer log-sigmoid and tan-sigmoid and linear transfer functions are used. The networks have been trained with the normalized data, and the weights (w) were determined in such a way as to minimize the following cost function:

$$E = \frac{1}{2}\sum_{p=1}^{N}(t^p - y^p)^2 \qquad (5)$$

where, t^p, y^p are target and network output for p^{th} training pattern and N is the total number of training patterns.

The optimum transfer functions are determined by trial and error method with an objective to minimize the difference among the network predicted values and the target values. The performance of each configuration was evaluated based on the root mean square error (RMSE) and correlation coefficient (CC) as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{p=1}^{N}(t^p - y^p)^2} \qquad (6)$$

$$CC = \frac{\sum_{p=1}^{n}(y^p - \overline{y})(t^p - \overline{t})}{\sqrt{\sum_{p=1}^{N}(y^p - \overline{y})^2 \sum_{p=1}^{N}(t^p - \overline{t})^2}} \qquad (7)$$

where, $\overline{y}$ and $\overline{t}$ are average over network and target outputs.

The optimal configuration, based upon minimizing the difference between the neural networks predicted outputs and the target outputs, corresponds to the minimum value of RMSE and the maximum value of CC.

RESULTS AND DISCUSSION

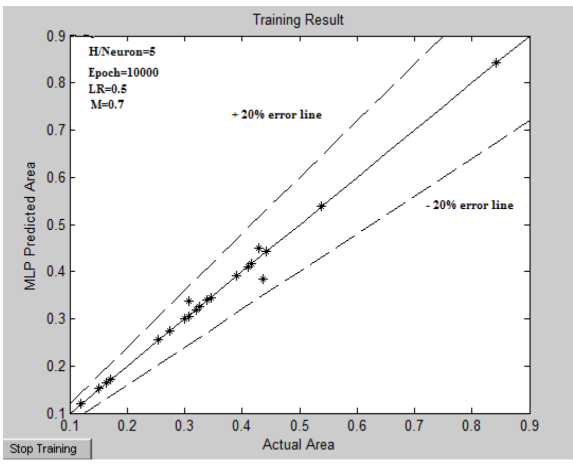
The MLP neural network model is implemented in Matlab 7.9 environment. The training and testing results obtained are used to form an MLP model that can estimate crop area and crop production for the crop rice. The reliability of the predicted values not only depends on the ANN structure but also on the input data. The input data used for training the MLP model in the present study has been collected from respective sources as stated in sub section 2.2 and thus are assumed to be reliable.

The training dataset is used to train the network and testing dataset is used to test the performance of the network. The next step is to select the optimum activation function. To find the optimum activation function, the individual test cases were ranked according to the magnitude of RMSE and CC. The model having the minimum RMSE and maximum CC is selected as the optimum. Amongst 126 tested cases of MLP for crop area and crop production, a shortlist of the best cases has been tabulated in Table 1. It is observed from the table that the model with Log-sigmoid activation function in the hidden as well as the output layers provides the minimum RMSE and maximum CC for crop area and crop production and considered as the optimal model.

Table 1: Training and Testing Results

Prediction of	Transfer Function		Training		Testing	
	Hidden Layer	Output Layer	RMSE	CC	RMSE	CC
Area	Log-sigmoid	Log-sigmoid	0.0852	0.9371	**0.0042**	**0.9796**
		Tan-sigmoid	0.0955	0.9287	0.0077	0.9483
		Linear	0.0865	0.9397	0.0076	0.9593
	Tan-sigmoid	Log-sigmoid	0.0863	0.9341	0.0533	0.9613
		Tan-sigmoid	0.0971	0.9106	0.0812	0.9636
		Linear	0.0805	0.9514	0.0128	0.9287
Production	Log-sigmoid	Log-sigmoid	0.0072	0.9999	0.0563	0.3542
		Tan-sigmoid	0.0061	0.9925	**0.0167**	**0.8290**
		Linear	0.0054	0.9928	0.0658	0.7488
	Tan-sigmoid	Log-sigmoid	0.0016	0.9987	0.0597	0.6424
		Tan-sigmoid	0.0078	0.9908	0.0737	0.7807
		Linear	0.0072	0.9976	0.0744	0.6971

The training and testing results of the optimum MLP model for prediction of crop area has been plotted in Fig. 3, Fig. 4 on the other hand, for crop production it has been plotted Fig. 5, Fig. 6 respectively. From the figures, it has been observed that the target and predicted values are within ±20% error.



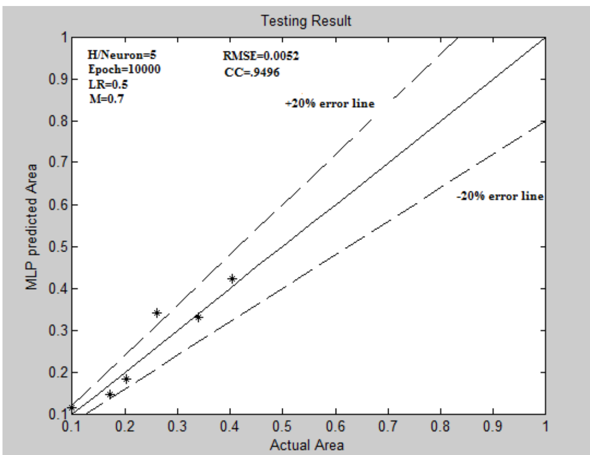


Figure 3: Comparison of Actual and MLP Predicted Area under Rice (Training)

Figure 4: Comparison of actual and MLP Predicted Area under Rice (Testing)

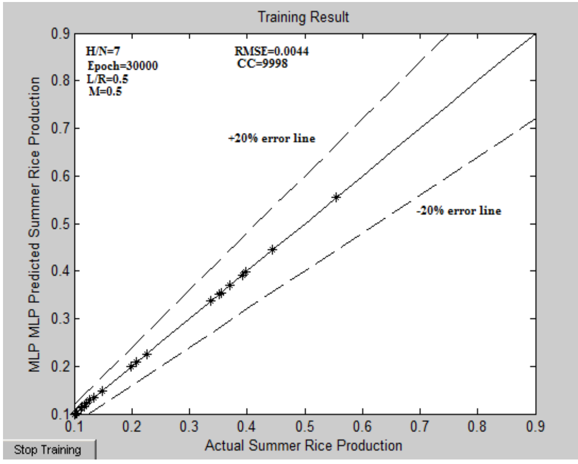


Figure 5: Comparison of actual and MLP Predicted Rice Production (Training)

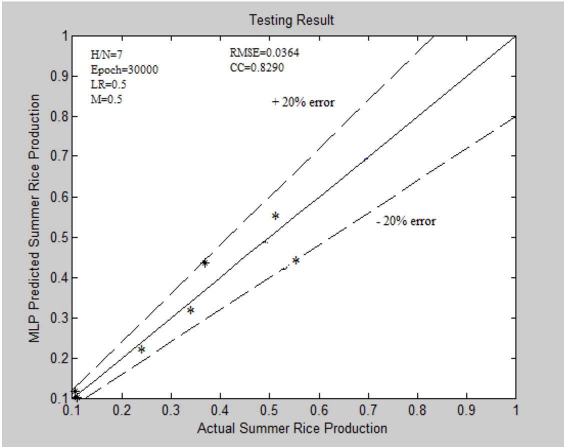


Figure 6: Comparison of actual and MLP Predicted Rice Production (Testing)

CONCLUSION

In the present study, MLP network has been tested with different type of activation functions to predict the maximum crop area and crop production of NBP Zone of Assam. From Table 1, it can be concluded that MLP with Log-sigmoid activation function in the hidden and output layer provides better result than the other activation functions for the prediction of crop area and crop production of NBP Zone of Assam. From the figures from Fig.3 – Fig.6, it is observed that the predicted values are within ±20% error from the observed values.

The present study has been carried out with MLP network with different transfer functions in the hidden as well as output layer. Further experimentation needs to be carried out with other neural network models *viz.* radial basis function network and Bayesian network with different transfer functions. Further research efforts should be conducted towards the issues that may influence the performance of the developed models, *viz.* the network architecture, optimization of the connection weights and model validation for prediction of crop area and crop production.

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