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Forecasting of Productivity and Pod Damage by *Helicoverpa armigera* using Artificial Neural Network Model in Pigeonpea (*Cajanus cajan*)

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Abstract

Pigeonpea (*Cajanus cajan*) is one of the most important food legume, making it an ideal supplement to traditional cereals, which are generally protein-deficient. So, due to its high nutritional value and enormous losses caused by insect pests, it is very important to forecast the damage caused by major insect-pests and the yield of this crop. In this paper, Artificial Neural Network (ANN) model was developed to forecast productivity (Kg/ha) and percent pod damage by a key insect pest *Helicoverpa armigera* of long duration pigeonpea in North East Plain Zone (NEPZ) of India. The forecasted values of percent pod damage by this pest and productivity of Pigeonpea during 2012-13 were obtained as 26.29% and 1137.40 kg/ha, respectively. The performance of the model was assessed by values of the mean squared error, and the model was found suitable for the problem under study.

Highlights

Artificial Neural Network (ANN) model was developed to forecast productivity and percent pod damage by *Helicoverpa armigera* for NEPZ in India. The forecasted values of percent pod damage and productivity of Pigeonpea by this pest were obtained as 26.29% and 1137.40 kg/ha, respectively.

Keywords: Forecasting, artificial neural network, mean squared error, pigeonpea, *Helicoverpa armigera* and productivity.

Agriculture is one of the most important activities in both developed and developing countries, which provide basic raw materials to human beings and various agro-based industries. India is one of the world's largest agrarian economies. Indian farming community is facing multitude of problems. Insect pests are supposed to be a major constraint to the crop productivity. The main problem in addressing the issue of pest management is inadequate knowledge about the pest dynamics. India is the largest producer and consumer of pulses throughout the world in India, pigeonpea (*Cajanus cajan*) is considered as second most important pulse crop after chickpea (*Cicer aritinum L.*), accounting for 15.8% of total pulse production during 2010-2011 (Ministry of Agriculture, Government of India, 2010-11). India's pigeonpea production stands at around 2.86 million tons, which is 4/5th share in the world total pigeonpea produced. About 90% of the global pigeonpea area falls in India (FAOSTAT, 2012). In India alone *Helicoverpa armigera* feed on at least 181 plant species spread across 45 botanical families. *Helicoverpa armigera* is a key pest inflicting 80 to 90 percent of loss caused by pod borers (Kooner *et al.* 2006). It causes considerable yield loss of 2,50,000 tones of grain per annum worth more than 3750 million rupees per year. Heavy losses caused by *Helicoverpa armigera* are mainly due to feeding preference of the larva for plant parts that are high in protein content, particularly the reproductive structures and growing points, e.g. flowers and pods of long duration pigeonpea resulting in a direct reduction in the crop yield (Srivastava 1980; Srivastava *et al.,* 2010). Hence, there is a need to provide timely and reliable forecast so that protection measures can be implemented in time. Time series forecasting is used to provide an aid to decision-making and in planning for the future effectively and efficiently.

The best suitable technique to forecast complex relationship in agriculture is Artificial Neural Networks (ANNs) which are one of the most accurate and widely used forecasting models because of its various features. First, ANNs are nonlinear data-driven (Zhang *et al.,* 1998). They are capable to perform nonlinear modeling without *apriori* knowledge about the relationships between input and output variables. Second, ANNs are of the kind of universal functions approximation. It has been shown that a neural network can approximate any continuous function to any desire accuracy. Third, its generalizing ability (Zhang *et al,*. 1998). After learning the data presented to structure, ANNs can often correctly infer the unseen part of a population even if the sample data contain noisy information. (Marquardt 1963; Hagan *et al,* 1994; Haykin 2001, Ho *et al.,* 2002 and Mishra *et al.,* 2013).

The objective of present study was to develop the artificial neural network model for forecasting percent pod damage by *Helicoverpa armigera* and productivity of long duration pigeonpea for North East Plain Zone (NEPZ) of India.

Materials and methods

In the present study, time series secondary data on percent pod damage due to *Helicoverpa armigera* and on productivity (kg/ha) were collected for the period 1985-86 to 2011-12 from All India Coordinated Research Project on Pigeonpea (Indian Council of Agricultural Research) from four centers, *viz.*, Varanasi, Kanpur, Faizabad and Dholi in North East Plain Zone (NEPZ) of India , which is shown in Figure 1.

Then Neural Network architectures were developed by using Levenberg Marquardt (LM) Algorithm as a training algorithm of weight matrix. The LM algorithm blends the steepest descent method and the Gauss–Newton algorithm. In the artificial neural-network field, this algorithm is suitable for training small and medium-sized problems. LM algorithm is an iterative technique that finds a local minimum of a function that is expressed as the sum of squares of nonlinear functions. (Hao *et al.* 2011, Ranganathan Ananth, 2004).

Algorithm for ANN

Levenberg–Marquardt algorithm is an improvement over Steepest descent algorithm, Newton's method and Gauss–Newton's algorithm as speed of convergence of step size is increased as well as it is more robust than other algorithms.

If Sum square due to error (SSE) for the training process is

$$E\ (x,w)=\frac{1}{2}\sum_{p=1}^{P}\ \sum_{m=1}^{M}e^2\,p.m$$

Where,

- P is the number of patterns, M is the number of outputs.
- $e_{p,m}$ is the training error at output m when applying pattern p and it is $e_{p,m} = d_{p,m} - o_{p,m,}$ d is the desired output vector and o is the actual output vector

In the Steepest Descent Algorithm, update rule of weights is: $\boldsymbol{w}_{k+1} = \boldsymbol{w}_k - \alpha\, \mathbf{g}_{k,}$ where k is the index of iterations, $\boldsymbol{x}$ is the input vector and $\boldsymbol{w}$ is the weight vector, á is the learning constant (step size) and $\boldsymbol{g}$ is gradient. Whereas, in the Newton's Method, update rule for Newton's method is: $w_{k+1} = w_k - H_k^{-1} g_k$, where H (square matrix) is the Hessian matrix given as:

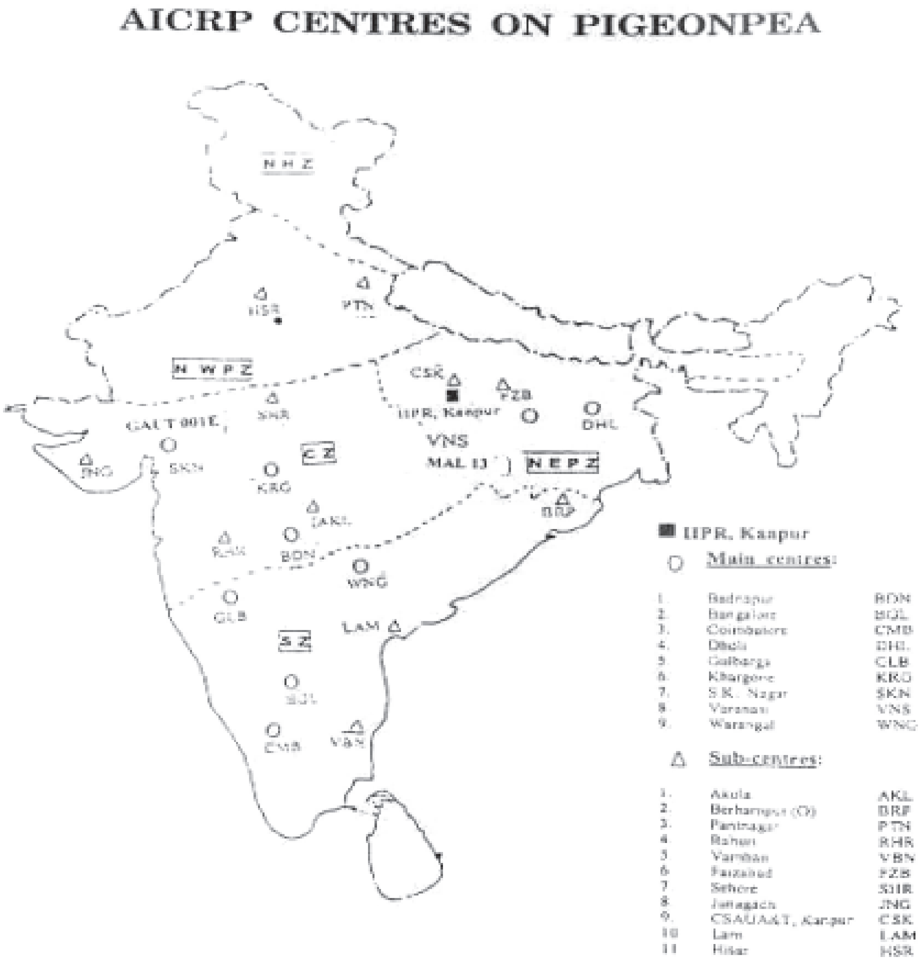

Figure 1: Different Centres of All India Coordinated Research Project on Pigeonpea

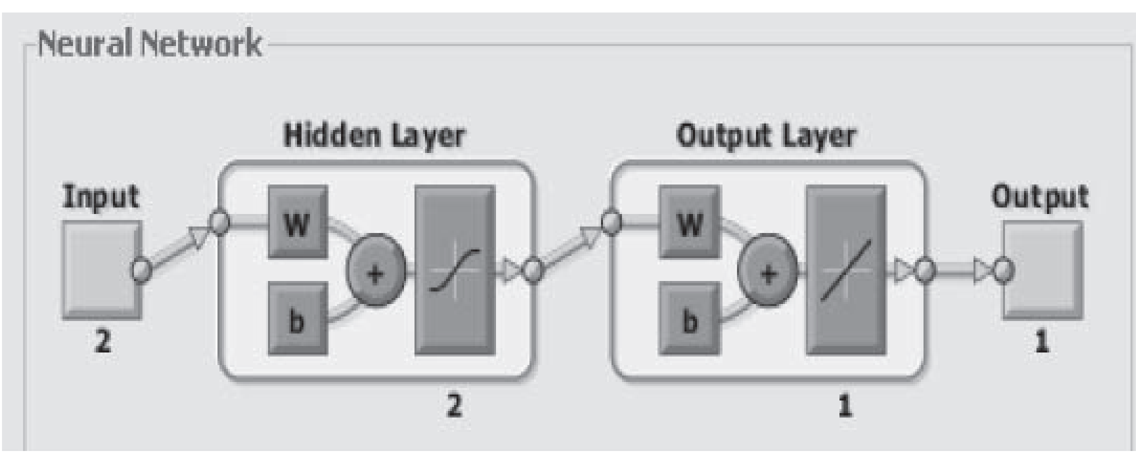

Figure 2 Two-layer feed-forward network

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$$H = \begin{bmatrix} \frac{\partial^2 E}{\partial w_1^2} & \frac{\partial^2 E}{\partial w_1 \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_N} \\ \frac{\partial^2 E}{\partial w_2 \partial w_1} & \frac{\partial^2 E}{\partial w_2^2} & \cdots & \frac{\partial^2 E}{\partial w_2 \partial w_N} \\ \cdots & \cdots \quad \cdots & & \cdots \\ \frac{\partial^2 E}{\partial w_N \partial w_1} & \frac{\partial^2 E}{\partial w_N \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_2 \partial w_N^2} \end{bmatrix}$$

In Gauss–Newton Algorithm, update rule of weights is :

$$w_{k+1} = w_k - \left(J_k^T J_k\right)^{-1} J_k e_k$$

Where, ***J*** is Jacobian matrix, defined as;

$$J = \begin{bmatrix} \frac{\partial^2 e_{1.1}}{\partial w_1} & \frac{\partial^2 e_{1.1}}{\partial w_2} & \cdots & \frac{\partial^2 e_{1.1}}{\partial w_N} \\ \frac{\partial^2 e_{1.2}}{\partial w_1} & \frac{\partial^2 e_{1.2}}{\partial w_2} & \cdots & \frac{\partial^2 e_{1.2}}{\partial w_N} \\ \cdots & \cdots \quad \cdots & & \cdots \\ \frac{\partial^2 e_{1.M}}{\partial w_1} & \frac{\partial^2 e_{1.M}}{\partial w_2} & \cdots & \frac{\partial^2 e_{1.M}}{\partial w_N} \\ \cdots & \cdots \quad \cdots & & \cdots \\ \frac{\partial^2 e_{P.1}}{\partial w_1} & \frac{\partial^2 e_{P.1}}{\partial w_2} & \cdots & \frac{\partial^2 e_{P.1}}{\partial w_N} \\ \frac{\partial^2 e_{P.2}}{\partial w_1} & \frac{\partial^2 e_{P.2}}{\partial w_2} & \cdots & \frac{\partial^2 e_{P.2}}{\partial w_N} \\ \cdots & \cdots \quad \cdots & & \cdots \\ \frac{\partial^2 e_{P.M}}{\partial w_1} & \frac{\partial^2 e_{P.M}}{\partial w_2} & \cdots & \frac{\partial^2 e_{P.M}}{\partial w_N} \end{bmatrix}$$

where error vector ***e*** has the form

$e^T = [e_{1,1}\ \ e_{1,2}\ \ldots\ e_{1,M}\ \ldots\ldots\ e_{P,1}\ \ e_{P,2}\ \ldots\ e_{P,M}]$

In order to make sure that the approximated Hessian matrix $\boldsymbol{J^T J}$ is invertible, Levenberg–Marquardt algorithm introduced another approximation to Hessian matrix:

$$H = J^t J + \mu I$$

Where ì is called combination coefficient, which is always positive and ***I*** is the identity matrix.

So the update rule of weights in this algorithm is :

$$w_{k+1} = w_k - \left(J_k^T J_k + \mu I\right)^{-1} J_k e_k$$

[Hao *et al,* 2011].

Artificial Neural Network Architecture

Neural Network architecture was developed with the help of MATLAB Neural Network Toolbox 2010. The network used was a two-layer feed-forward network as given in Figure 2.

Out of various architecture of Neural Network, the best architecture was chosen, which was made up of two-layer feed-forward network having input as two lag value of time series with predicting one output. There were two nodes in hidden layer with sigmoid function [g (netinput) = $1/(1+e^{-netiput})$] as an activation function of hidden neurons and linear function [g (netinput) = netinput] as an activation function for output neurons. Therefore, four weights for input to hidden neurons and two weights for hidden to output neurons and three bias values were chosen. For training 70%, for each of validation and testing 15 % data were used by using Random Data Division Process. The weights of two input lag value in input layer were denoted by notation I_i (i=1,2), weights of two hidden node of hidden layer were denoted as H_j (j=1,2) and weight of output node is denoted as O, indicating only one output in output node. Similarly, bias values of three nodes (two hidden nodes and one output node) were denoted as $B_{H1,}$ B_{H2} and $B_{O.}$ The performance of the proposed network when trained with Levenberg-Marquardt back propagation algorithm was accessed by their Mean Squared Error (MSE) value along with multiple correlation coefficient (R) between observed and predicted outputs.

Results and Discussions

Forecast for damage (%) in pods by *Helicoverpa armigera* in pigeonpea (*Cajanus cajan*) in NEPZ of India:

Weights between input and hidden nodes, and weights between hidden and output nodes were given in Table 1

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where I_1 and I_2 are input values, H_1 and H_2 are hidden nodes and O is output node. Bias values of hidden nodes H_1, H_2 and output node O were given in Table 2.

Figure 3. demonstrated that mean squared errors of training, validation and testing all decreased until epoch 3. This iteration stopped when the errors increased or remain constant. In this study, the result was reasonable because of the fact that the final mean-squared error was small (2.3248), the test set and validation set errors had similar characteristics and no over fitting had been occurred at epoch 3 (where the best validation performance occurred). The Regression analysis plot shown in Figure 4., displayed a linear regression between network outputs and the corresponding targets with the R value as 0.9806 showing the fit was reasonably good for all data sets.

The forecasted value of pod damage by *Helicoverpa armigera* in Pigeonpea for the year 2012-13 was found as 26.29% in NEPZ. Whereas, similar level damage was obtained as 25.19 % and 26.67 % in 2010-11 and 2011-12, respectively.

Table 1

Weights	H_1	H_2
I_1	1.5051	-0.2608
I_2	0.0180	0.9858
O	0.5325	0.8887

Table 2

Bias values	H_1	H_2	O
	-1.1503	0.3443	0.1800

Table 3

Weights	H_1	H_2
I_1	-2.0144	0.9275
I_2	0.8174	2.7642
O	1.2762	0.7321

Forecast for productivity (kg/ha) of Pigeonpea in NEPZ of India

Weights between input and hidden nodes, and weights between hidden and output nodes were given in Table 3. Bias values of hidden nodes H_1, H_2 and output node O were given in Table 4.

Table 4

Bias values	H_1	H_2	O
	1.8439	-0.7103	-1.0150

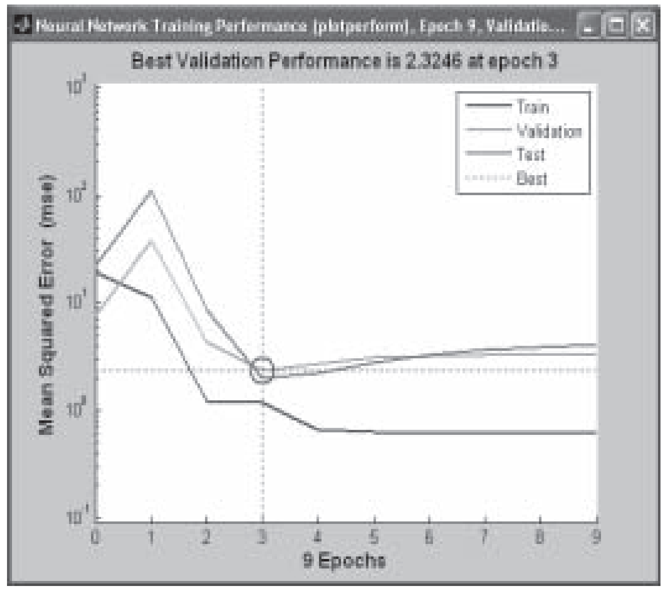

Figure 3: Performance of Levenberg-Marquardt Backpropagation Algorithm

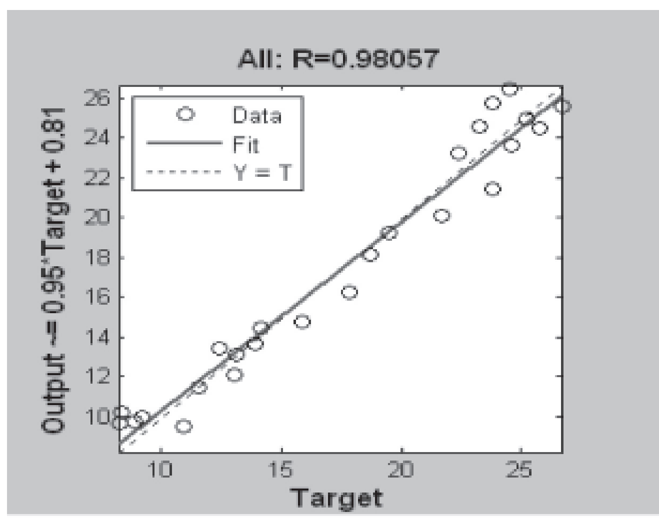

Figure 4. Regression Analysis Plot- LM Backpropagation Algorithm

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From Figure 5., it was observed that the best validation performance 29836.36 at epoch 7 was obtained. The Regression analysis plot shown in Figure 6, displayed a linear regression between network outputs and the corresponding targets with the R value as 0.8359 showing the fit was reasonably good for all data sets.

The forecasted value of productivity of pigeonpea for the year 2012-13 was found as 1137.40 kg/ha in NEPZ. Whereas, productivity was obtained as 1372.00 kg/ha and 1002.80 kg/ha in 2010-11 and 2011-12, respectively.

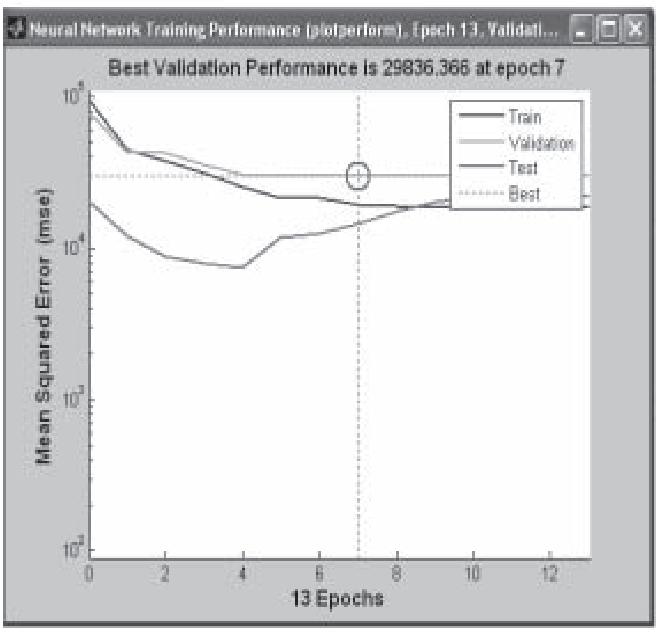

Figure 5. Performance of Levenberg-Marquardt Backpropagation (LM) Algorithm

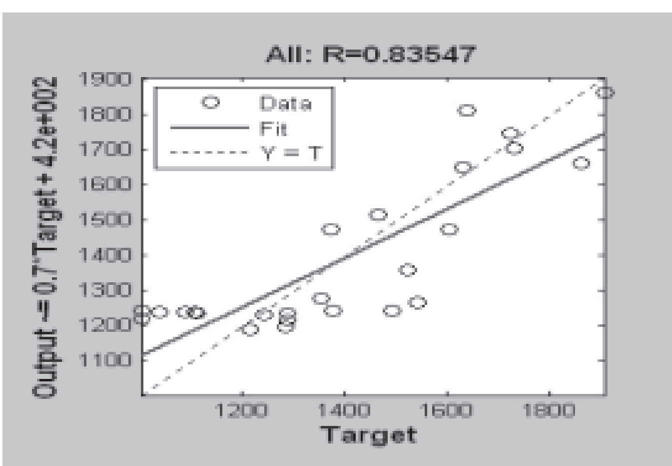

Figure 6: Regression Analysis Plot-LM Backpropagation Algorithm

Conclusion

This paper aimed to evaluate the artificial neural network to predict the damage on pods of pigeonpea by key insect pest i.e. Pod Borer *Helicoverpa armigera.* The feedforward neural network with supervised learning is proposed to forecast the damage. It has been inferred that Levenberg-Marquardt algorithm gave the best performance in the prediction of damage (26.29%) and productivity (1137.40 kg/ha) of long duration pigeonpea for NEPZ in India for the year 2012-13.

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