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Forecasting of powdery mildew in mustard (*Brassica juncea*) crop using artificial neural networks approach

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ABSTRACT

Recently artificial neural networks (ANNs) techniques has become the focus of much attention, largely because of their wide range of applicability and the ease with which they can treat complicated problems even if the data are imprecise and noisy. From statistical perspective, neural networks are interesting because of their potential use in prediction. This methodology have been illustrated by considering various aspects, viz maximum pest disease severity, crop age at first appearance of disease, crop age at maximum disease severity for powdery mildew in mustard crop at S K Nagar (Gujarat) as response variable and weather indices (a technique based on relatively smaller number of manageable variables and at the same time taking care of entire weather distribution) as predictors. In this study, data have been taken from Mission mode project under National Agricultural Technology Project, entitled 'Development of weather-based forewarning system for crop pests and diseases', CRIDA, Hyderabad in which the IASRI was one of the cooperating institutions. Two type of neural network architecture namely Multilayer perceptron (MLP) and Radial basis function (RBF) were attempted and compared with weather indices based regression model and it has been found that a MLP performs best in terms of mean absolute percentage error (MAPE).

Key words: Artificial neural network, Forecasting models, Multilayer perceptron, Powdery mildew, Radial basis function, Weather indices

An agricultural loss constitutes 30–40% in the yield of the crop due to the infestation of various pests and diseases. Such losses can be reduced to a considerable extent if their occurrence is known in advance so that timely remedial measures may be taken. A disease / pest can only progress if the conditions provided by the host plants and weather conditions are favourable and if some inoculum is present. Weather conditions are responsible for infestation of pests and diseases in the crop. It is therefore, usual to make prediction only after certain biological and meteorological conditions favourable to the disease / pest have been fulfilled. Thus there is a need to develop forewarning systems which can provide advance information for outbreak of pests / diseases attack on the basis of weather parameters so that protection measures can be implemented before the actual onset of the damage. Most of the earlier workers have utilized regression models (both linear and non-linear) for pests / diseases forewarning (Agrawal *et al.* 2004, Chattopadhyay *et al.* 2005a,b, Desai *et al.* 2004, Dhar *et al.* 2007). Recently, artificial neural networks (ANNs) techniques have become the focus of much attention, largely because of their wide range of applicability and the ease with which they can treat complicated problems even if the data are imprecise and noisy. These techniques are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology, physics, biology and agriculture. From statistical perspective, neural networks are interesting because of their potential use in prediction. The relationships among host - pathogen - weather are very complex one, therefore, ANNs technique can be utilized for forewarning pests / diseases in advance.

ANNs are data-driven self-adaptive methods in that there are a few prior assumptions about the models for problems under study. A very important feature of these networks is their adaptive nature where 'learning by example' replaces 'programming' in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available. On the basis of examples, subtle functional relationships among the data are captured even if the underlying relationships are unknown or hard to describe.

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ANNs can identify and learn correlated patterns between input data sets and corresponding target values through training. After training, ANNs can be used to predict the outcome of new independent input data and have great capacity in predictive modeling ie all the characters describing the unknown situation can be presented to the trained ANNs, and then prediction of agricultural system may be feasible. Preliminary work on ANNs has been done by many workers, Cheng and Titterington (1994) made a detailed study of ANNs models vis-a-vis traditional statistical models. They have shown that some statistical procedures including regression, principal component analysis, density function and statistical image analysis can be given neural network expressions. Warner and Misra (1996) reviewed the relevant literature on neural networks, explained the learning algorithm and made a comparison between regression and neural network models in terms of notations, terminologies and implementation. Kaastra and Boyd (1996) developed neural network model for forecasting financial and economic time series. Dewolf and Francl (1997, 2000) demonstrated the applicability of neural network technology for plant diseases forecasting. Zhang *et al.* (1998) provided the general summary of the work in ANNs forecasting, providing the guidelines for neural network modeling, general paradigm of the ANNs, especially those used for forecasting. They have reviewed the relative performance of ANNs with the traditional statistical methods, wherein in most of the studies ANNs were found to be better than the latter. Chakraborty *et al.* (2004) utilized the ANNs technique for predicted severity of anthracnose diseases in legume crop. Gaudart *et al.* (2004) compared the performance of Multilayer perceptron (MLP) and that of linear regression for epidemiological data with regard to quality of prediction and robustness to deviation from underlying assumptions of normality, homoscedasticity and independence of errors and it was found that MLP performed better than linear regression.

MATERIALS AND METHODS

In mustard, field trials were sown on 10 dates at weekly intervals (1, 8, 15, 22, 29 October, 5, 12, 19, 26 November and 3 December) at S K Nagar (Gujarat) were laid out in 1999–2000, 2000–01, 2001–02, 2002–03, 2003–04, 2004–05, 2005–06 and 2006–07. Observations for per cent disease severity were recorded every week until harvesting of crop and hence crop age at first appearance of diseases, crop age at peak severity of disease and maximum severity of diseases were obtained. Data for different dates of sowing were taken together for model development. Weekly data on weather parameters starting from week of sowing up to six week of crop were considered for forewarning various characters such as crop age at first appearance of disease, crop age at peak severity of disease and maximum severity of diseases in two varieties, viz Varuna and GM2 of mustard crop for powdery mildew on leaf.

Thus extent of weather influence on crop pests / diseases depends not only on the magnitude but also on the distribution pattern of weather variables over the crop season which, as such, calls for the necessity of dividing the whole crop season into fine intervals. This will increase number of variables in the model and in turn a large number of model parameters will have to be evaluated from the data. This will require a long series of data for precise estimation of parameters which may not be available in practice. Thus, a technique based on relatively smaller number of manageable variables and at the same time taking care of entire weather distribution, weather indices were obtained which were used as predictors for models development. Weather variables on maximum temperature, minimum temperature, morning relative humidity, evening relative humidity and bright sunshine hours (T_{max}, T_{min}, RHI, RHII and BSH) for the period from 1999–2000 to 2005–06 were considered for models development. Models have been validated using data on subsequent years not included in developing the models. Two type of neural network architecture namely Multilayer perceptron (MLP) and Radial basis function (RBF) were attempted and compared with weather indices regression model.

Weather indices-based regression models

In this type of model, for each weather variable two indices have been developed, one as simple total of values of weather parameter in different weeks and the other one as weighsed total, weights being correlation coefficients between variable to forecast and weather variable in respective weeks. The first index represents the total amount of weather parameter received by the crop during the period under consideration, while the other one takes care of distribution of weather parameter with special reference to its importance in different weeks in relation to the variable to forecast. On similar lines, indices were computed with products of weather variables (taken two at a time) for joint effects Agrawal *et al.* (1986) and Agrawal and Mehta (2007).

The form of the model was

$$Y = a_0 + \sum_{i=1}^{p} \sum_{j=0}^{1} a_{ij} Z_{ij} + \sum_{i^{\prime}i^{\prime}}^{p} \sum_{j=0}^{1} b_{ii^{\prime}j} Z_{ii^{\prime}j} + \varepsilon$$

where

$$Z_{ij} = \sum_{w=n_1}^{n_2} r_{iw}^{j} X_{iw}$$

$$Z_{ii^{\prime}j} = \sum_{w=n_1}^{n_2} r_{ii^{\prime}w}^{j} X_{iw} X_{i^{\prime}w}$$

Y variable to forecast

X_{iw} value of ith weather parameter in wth week

r_{iw} correlation coefficient between Y and ith weather parameter in wth week

$r_{ii'w}$ correlation coefficient between Y and product of X_i and $X_{i'}$ in wth week p number of weather parameters

n_1 initial week for which weather data were included in the model

n_2 final week for which weather data were included in the model

e error term

Step-wise regression technique was used for selecting important variables to be included in the model.

Multilayer perceptron artificial neural network

Multilayer perceptron technique is very popular and is used more often than other neural network types. MLP is neural network in which the non-linear elements (neurons) are arranged in successive layers, and the information flows uni-directionally from input layer to output layer through hidden layer(s). MLP architecture can have a number of hidden layers with a variable number of hidden units/layer. The network thus has a simple interpretation as a form of input-output model, with weights and thresholds (biases) as free parameters of the model. Such networks can model functions of almost arbitrary complexity, with the number of layers, and the number of units in each layer, determining the function complexity. For models development, data is divided into three distinct sets called training, validation and testing sets. The training set is the largest set and is used by neural network to learn patterns present in the data. The test set is used to evaluate the generalization ability of a supposedly trained network. A final check on the performance of the trained network is made using validation set. In a training of the network, through learning algorithm, produces its own output and tries to minimize the discrepancies between its own output and the target output. The minimization of discrepancies is done by weight adjustment during the learning phase. The standard back propagation method employs the steepest decent algorithm for weight adjustment. In this study, supervised procedure was used for the learning. In this method, actual output of a neural network is compared to the predicted output. Initially weights were randomly assigned to input variables and output was produced using hyperbolic activation function, ie

$$f(x) = (\exp(x)-\exp(-x))/(\exp(x)+\exp(-x))$$

The learning method tries to minimize the current errors of all processing elements. This global error reduction is created over time by continuously modifying the input weights until acceptable network accuracy is reached. This training will be considered complete when the neural network reaches an user-defined performance level. The graphic representation of this learning procedure is given in Fig 1.

Radial basis functions networks

The RBF neural network has both a supervised and unsupervised component to its learning. It consists of three layers of neurons – input, hidden and output. The hidden layer neurons represent a series of centres in the input data space. These networks are also feedforward, but have only one hidden layer with non-linear units, followed by an output layer with linear units. The non-linear basis function of a hidden unit is function of normalized radial distance. The connection networks are mathematically represented by a basis function u (w,×), where w stands for the weight matrix, and × for the input vector. The net value represents the radial distance to a reference point,

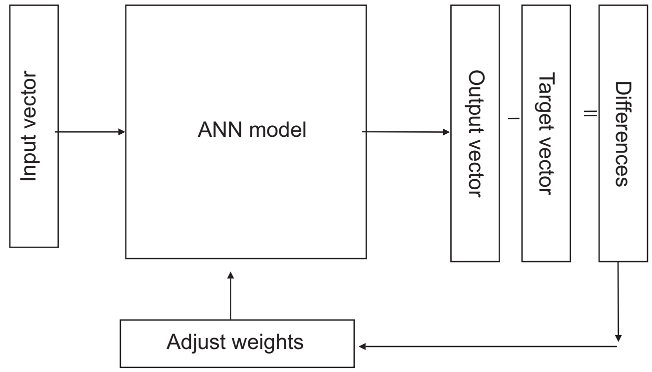

Fig 1 A learning cycle in the ANN model

$$U_i(w,x)=\sqrt{\sum_{j=1}^{n}(x_j-w_{ij})^2}$$

In a radial basis function network units respond (non-linearly) to the distance of points from the center represented by the radial unit. The response surface of a single radial unit is therefore a Gaussian function, peaked at the centre, and descending outwards. Each of these centres has an activation function, typically Gaussian. The activation depends on the distance between the presented input vector and the centre. The aurther the vector is from the centre, the lower is the activation and *vice versa*. The generation of the centres and their widths is done using an unsupervised k-means clustering algorithm. The centres and widths created by this algorithm then form the weights and biases of the hidden layer, which remain unchanged once the clustering has been done. The output layer (which has non-linear activations) is trained by back-propagation.

The forecasting performance of various ANNs models and traditional models (models based on weather indices) were judged by Mean Absolute Percentage Error (MAPE).

$$MAPE=\frac{1}{n}\sum\left|\frac{(Y_t-F_t)}{Y_t}\right|x100$$

where Y_t is actual observation Ft is the forecast form models and n is the total number of tested data.

RESULTS AND DISCUSSION

Weather variables utilizing weekly data from week of sowing up to six weeks of crop, on maximum temperature, minimum temperature, morning relative humidity, evening

Table 1 Number of data points in different sets for various character in different varieties of mustard crop for powdery mildew

Character	Variety	Training set	Validation set	Testing set
Maximum severity (Y_1)	Varuna	45	10	10
Age at first app (Y_2)		45	10	10
Age at peak severity (Y_3)		45	10	10
Maximum severity (Y_1)	GM2	45	10	10
Age at first app (Y_2)		45	10	10
Age at peak severity (Y_3)		45	10	10

relative humidity and bright sunshine hours - [X_1 to X_5] for the period from 1999–2000 to 2005–06 were considered for models development. Weather indices (using weekly data from week of sowing up to six weeks of crop) were obtained and used as input variables and various characters, viz maximum severity of powdery mildew, crop age at first appearance of powdery mildew and crop age at peak severity of powdery mildew were used as output in the neural network models. The available data set was divided into three set namely training, validation and testing sets. The details of data sets are given in Table 1.

The MLP architecture using back-propagation learning is one of the most popular neural networks. In this study, MLP model consists of three layers: an input layer, a hidden layer and an output layer. Neural network models with different hidden layers (one and two) and different number of neurons(4, 5 and 6) in a hidden layer with hyperbolic function as an activation function with varying learning rate (from 0.3 to 0.8), were obtained and selected the best architecture, which having lowest mean absolute percentage error (MAPE). In RBF architecture which consists of three layers of neurons – input, hidden and output. The hidden layer neurons represent a series of centres in the input data space. Each of these centres has an activation function, typically Gaussian. The activation depends on the distance between the presented input vector and the centre. The generation of the centres and their widths is done using an unsupervised k-means clustering algorithm. The centres and widths created by this algorithm then form the weights and biases of the hidden layer, which remain unchanged once the clustering has been done. The output layer (which has non-linear activations) is trained by back-propagation. The analysis has been done by using Statistical Neural Networks Version 6.1 available at Indian Agricultural Statistics Research Institute, New Delhi. Using neural network models with MLP and RBF architecture, forewarning of powdery mildew in mustard crop for different characters, viz maximum severity of disease (Y_1), crop age at first appearance of disease (Y_2), crop age at peak severity of disease (Y_3) for two varieties namely Varuna and GM2 have been obtained. The trained ANN models have been implemented for prediction of forewarning different characters for subsequent cases corresponding to the years not included in the model development. For this, input information pertaining to these years was supplied to the trained models as a test data set.

Model using weather indices (WI)-based regression models were also developed for forewarning crop age at first appearance of disease, crop age at peak severity of disease and maximum severity of diseases in two varieties (Varuna and GM2) of mustard crop for powdery mildew. Models have been validated using data on subsequent years not included in developing the models. The significant variables(*) which are included in models are given in Table 2.

The comparisons (% deviation for forecast) of models developed are presented in Tables 3 to 5 for different characters for powdery mildew in mustard crop in different two varieties. This Table reveals that the deviation in the

Table 2 Models to forecast different character of powdery mildew in mustard crop along with coefficient of determination in different varieties

Varieties	Character	Model	R^2
Varuna	Maximum severity (Y_1)	$Y = 133.40 + 0.11\ Z_{120} + 12.71\ Z_{21}$	0.84
	Age at first app (Y_2)	$Y = 59.52 + 0.02\ Z_{120} - 0.01\ Z_{241} + 0.06\ Z_{351}$	0.84
	Age at peak severity (Y_3)	$Y = 126.35 + 1.17\ Z_{41} - 0.04\ Z_{141}$	0.35
GM 2	Maximum severity (Y_1)	$Y = -52.46 + 0.06\ Z_{121} - 0.08\ Z_{131} + 1.23\ Z_{31}$	0.56
	Age at first app (Y_2)	$Y = 53.12 + 0.16\ Z_{251} - 0.01\ Z_{241} + 0.003\ Z_{130}$	0.85
	Age at peak severity (Y_3)	$Y = 106.27 + 0.22\ Z_{11} + 0.005\ Z_{341}$	0.29

* Z_{120}, Unweighed interaction of maximum temperature and minimum temperature; Z_{21}, weighed minimum temperature; Z_{241}, weighed interaction of minimum temperature evening relative humidity; Z_{351}, weighed interaction of morning relative humidity and bright sun shine hour; Z_{41}, weighed evening relative humidity; Z_{141}, weighed interaction of maximum temperature and evening relative humidity; Z_{121}, weighed interaction of maximum temperature and minimum temperature; Z_{131}, weighed interaction of maximum temperature and morning relative humidity, Z_{31}, weighed morning relative humidity; Z_{251}, weighed interaction of maximum temperature and bright sunshine hour; Z_{130}, unweighed interaction of maximum temperature and morning relative humidity; Z_{341}, weighed interaction of morning and evening relative humidity; Z_{11}, weighed maximum temperature.

Table 3 Deviation (%) of forecasts in different models for maximum severity of powdery mildew (Y_1) on Varuna and GM2 variety in mustard at S K Nagar for 2006–07

Date of sowing	MLP		RBF		WI	
	Varuna	GM2	Varuna	GM2	Varuna	GM2
1 Oct.	64.7	1.0	100.0	76.1	39.5	100.0
8 Oct.	33.9	0.8	87.4	68.4	27.1	91.6
15 Oct.	27.6	33.5	72.6	61.2	34.7	80.3
22 Oct.	45.7	4.3	59.7	57.7	47.5	71.1
29 Oct.	40.8	0.0	61.8	55.9	57.3	69.3
5 Nov.	25.5	0.0	49.4	42.4	44.4	58.5
12 Nov.	17.5	0.0	34.9	31.1	28.4	51.8
19 Nov.	6.3	12.9	29.0	33.1	23.3	46.9
26 Nov.	2.7	14.6	25.6	32.0	16.0	37.9
3 Dec.	1.0	0.0	41.2	44.0	32.9	39.6

Table 4 Deviations (%) of forecasts in different models for crop age at first appearance of powdery mildew (Y_2) on Varuna and GM2 varieties in mustard at S K Nagar for 2006–07

Date of sowing	MLP		RBF		WI	
	Varuna	GM2	Varuna	GM2	Varuna	GM2
1 Oct.	14.8	14.9	17.4	15.3	30.2	27.5
8 Oct.	22.8	21.2	26.2	24.0	34.3	31.7
15 Oct.	17.4	15.3	17.5	17.6	25.6	23.9
22 Oct.	23.6	17.5	19.5	18.8	24.2	22.9
29 Oct.	24.3	10.6	14.3	8.8	20.4	16.5
5 Nov.	20.6	8.7	10.0	5.8	14.6	13.9
12 Nov.	13.0	3.5	4.7	4.4	11.1	8.6
19 Nov.	19.0	8.5	8.9	14.0	16.9	16.6
26 Nov.	28.5	5.4	12.4	19.9	14.7	13.7
3 Dec.	29.7	16.1	21.9	22.7	24.7	27.1

forecast is lowest for neural network models using MLP architecture in most of the cases. The mean absolute per cent

Table 5 Deviation (%) of forecasts in different models for crop age at severity of powdery mildew (Y_3) on Varuna and GM2 varieties in mustard at S K Nagar for 2006–07

Date of sowing	MLP		RBF		WI	
	Varuna	GM2	Varuna	GM2	Varuna	GM2
1 Oct.	5.5	3.3	6.4	4.7	6.5	5.8
8 Oct.	0.2	0.7	0.2	0.6	0.5	0.2
15 Oct.	3.8	3.6	4.1	4.2	4.0	3.8
22 Oct.	5.6	3.7	7.2	3.9	7.2	3.9
29 Oct.	7.4	9.5	9.1	9.4	8.9	9.4
5 Nov.	7.8	12.4	12.3	13.4	10.7	12.1
12 Nov.	10.5	19.0	15.9	20.3	14.2	20.1
19 Nov.	10.9	14.0	16.6	17.2	17.0	17.7
26 Nov.	17.2	23.9	25.8	27.0	24.3	25.8
3 Dec.	26.6	38.3	37.9	40.6	35.0	39.1

error (MAPE) for different data sets and coefficient of determination for various developed models is presented in Table 6.

Based on MAPE for various models, it was found that neural network model using multilayer perceptron (MLP) architecture perform better than other models, i e neural network models based on radial basis function (RBF) architecture and weather indices-based regression models. Thus reliable forewarnings through this approach are possible well in advance.

The ANNs model has non-linear pattern recognition capability which is valuable for modeling and forecasting complex non-linear problems in practice. In this study, it was found that neural network model using multilayer perceptron (MLP) architecture is better than weather indices-based regression models in terms of MAPE. Therefore, reliable forewarning for crop age at first appearance of disease, crop age at peak severity of disease and maximum severity of diseases in two varieties (Varuna and GM2) of mustard crop for powdery mildew are possible well in advance.

Table 6 Mean absolute percentage error (MAPE) for different data sets and coefficient of determination for various models at S K Nagar in mustard crop

Character	Variety	MLP			RBF			WI	
		MAPE (training set)	MAPE (validation sets)	R^2	MAPE (training set)	MAPE (validation sets)	R^2	MAPE	R^2
Maximum severity (Y_1)	Varuna	91.96	26.5	0.80	319.03	56.2	0.62	35.1	0.84
	GM2	168.3	6.7	0.75	233.1	50.2	0.70	64.7	0.56
Crop age at first appearance (Y_2)	Varuna	6.0	12.2	0.81	6.1	15.1	0.81	20.2	0.84
	GM2	5.3	21.4	0.85	6.0	15.3	0.82	21.7	0.85
Crop age at peak severity (Y_3)	Varuna	2.4	9.5	0.46	3.4	13.5	0.35	12.8	0.35
	GM2	2.5	12.8	0.38	2.5	14.1	0.32	13.8	0.29

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