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Weather based forecast models for diseases in mustard crop

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सार – पूर्व चेतावनी प्रणालियाँ फसलों पर नाशक जीवों / बीमारियों के हमले होने की पूर्व सूचना प्रदान कर सकती हैं। इससे पहले के अधिकांश कामगार नाशक जीवों / बीमारियों की पूर्व चेतावनी के लिए समाश्रयण मॉडल्स (रैखिक और अरैखिक दोनों) का उपयोग करते रहे हैं। इनकी उपयुक्तता की व्यापकता के कारण वर्तमान में कृत्रिम तंत्रिकीय संजाल (ANNs) तकनीक प्रचलन में है और इस तकनीक के सुगम होने के कारण अस्पष्ट और दोषपूर्ण आंकड़ों के होने पर भी इससे जटिल समस्याओं का इलाज किया जा सकता है। इस पद्धति की खोज सरसों की फसल में होने वाली अधिकतम गंभीर बीमारियों एल्टरनेरिया ब्लाइट और पाउडरी मिल्ड्यू की पूर्व चेतावनी देने के लिए की गई है। बीमारी की आरंभिक अवस्था में और बीमारी के गंभीर हो जाने की अवस्था में फसल पर इनके प्रभाव अलग–अलग होते हैं जैसा कि पूर्वानुमानकर्त्तओं द्वारा भरतपुर, ढोली और बेरहामपुर नामक तीन स्थानों के मौसम तालिकाओं द्वारा बताया गया है । इस शोधपत्र में दो प्रकार के तंत्रिकीय संजाल संरचनाओं नामतः मल्टीलेअर परसेप्ट्रॉन (MLP) और रेडिअल बेसिस फंक्शन (RBF) को लिया गया है और इसकी तुलना मौसम तालिकाओं पर आधारित समाश्रयण मॉडल से की गई है और पाया गया है कि MLP के परिणाम औसत निरपेक्ष प्रतिशत त्रुटि (MAPE) के अर्थ में सबसे अच्छे रहे हैं।

ABSTRACT. Forewarning systems can provide advance information for outbreak of pests / diseases attack. Most of the earlier workers have utilised regression models (both linear and non-linear) for pests / diseases forewarning. Artificial Neural Network (ANNs) techniques are in vogue due to their wide range of applicability and the ease with which they can treat complicated problems even if the data are imprecise and noisy. This methodology has been explored for forewarning Alternaria Blight and Powdery mildew in mustard for maximum disease severity, crop age at first appearance of disease and crop age at maximum disease severity as response variables and weather indices as predictors for three locations namely Bharatpur, Dholi and Berhampur. In this study, two types of neural network architectures 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 – Forecasting models, Alternaria blight, Powdery mildew, Artificial neural network, Multilayer perceptron, Radial basis function and weather indices.

1. Introduction

Rapeseed-mustard is one of the major oilseed crops cultivated in India and around the world. Out of 36217 thousand tonnes of rapeseed-mustard seed produced from 23961 thousand ha in the world, India produces 4088 thousand tonnes from 4626 thousand ha (Damodaram and Hegde, 2002). Alternaria Blight and Powdery mildew affects all above-ground parts of the plant, which is considered an important constraint in husbandry of oilseed Brassicas in India as well as world. Though total destruction of the crop due to the disease is rare and usually yield losses at harvest are 5-15%, they can reach up to 47% (Kolte *et al*., 1987). Therefore, there is a need to develop forewarning systems, which can provide advance information for outbreak of the disease. Any disease can only progress if the conditions provided by the host plants as well as weather conditions are favourable. Weather is one of the major factors responsible for infestation of diseases in the crop. A weather-based model can be an effective scientific tool for forewarning diseases in advance so that protection measures can be implemented before the actual onset of the damage. Most of the earlier workers have utilised regression models (both linear and non linear) for pests / diseases forewarning [Agrawal *et al*. (2004); Chattopadhyay *et al*. (2005a & 2005b); Desai *et al*. (2004) and Dhar *et al*. (2007)]. Recently Artificial Neural Network (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, 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. Preliminary work on ANNs has been done by many workers, Cheng and Titterington (1994) made a detailed study of ANN 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 (2000) demonstrated the applicability of neural network technology for plant diseases forecasting. Zhang *et al.* (1998) provided the general summary of the work in ANN 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 ANN technique for predicting 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.

2. Materials and methods

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", at CRIDA, Hyderabad. Models were developed for forecasting different aspects relating to diseases for Alternaria Blight and Powdery mildew in Mustard crop. The field trials were sown on 10 dates at weekly intervals (01, 08, 15, 22, 29 October, 05, 12, 19, 26 November and 03 December) at each of the locations, *viz*., Bharatpur, Dholi and Berhampur for Alternaria Blight and at S. K. Nagar for Powdery Mildew. Data for different dates of sowing were taken together for model development. Weekly data on weather variables starting from week of sowing up to six weeks of crop growth were considered for forewarning time (crop age) of first appearance of disease, time (crop age) of peak severity of disease and maximum severity of diseases in two varieties of mustard crop for Alternaria Blight on leaf and pod (Varuna and Rohini - Bharatpur, Varuna and Binoy - Behrampur and Varuna and Pusabold - Dholi) and Powdery Mildew on leaf (Varuna and GM2 - S. K. Nagar). Weather variables on maximum temperature, minimum temperature, morning relative humidity and evening relative humidity (MAXT, MINT, RHI and RHII) for the period from 2001-02 to 2005-06, 2000-01 to 2003-04 and 2001-02 to 2003-04 for Bharatpur, Berhampur and Dholi respectively were considered for Alternaria Blight. For Powdery Mildew, weather variables on maximum temperature, minimum temperature, morning relative humidity, evening relative humidity and bright sunshine hours (MAXT, MINT, RHI, RHII and BSH) for the period from 1999-2000 to 2006-07 were considered. Models have been validated using data on subsequent years not included in developing the models. Observations for per cent disease severity were recorded every week until harvesting of crop and hence maximum severity of disease, crop age at first appearance of disease and crop age at peak severity of disease were obtained for different locations in two varieties (Varuna and Rohini - Bharatpur, Varuna and Binoy - Berhampur and Varuna and Pusabold - Dholi) for Alternaria Blight on leaf and pod portion of plant. Weather data on maximum temperature, minimum temperature, morning relative humidity and evening relative humidity (MAXT, MINT, RHI and RHII) were considered as explanatory variables.

Two types of indices were developed, one as simple total of values of weather variables in different weeks and the other one as weighted total, weights being correlation coefficients between variable to forecast and weather variable in respective weeks. The first index represents the total amount of weather variable received by the crop during the period under consideration while the other one takes care of distribution of weather variable 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. The forms of two indices

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

TABLE 1

Number of data points in different sets for various character in different varieties of mustard crop for various locations in different diseases

Disease	Location	Character	Variety	Training set	Validation set	Testing set
Alternaria Blight	Bharatpur	Maximum severity (Y_1)	Varuna	40	10	10
		Age at First app (Y_2)		40	10	10
		Age at Peak Severity (Y_3)		40	10	10
		Maximum severity (Y_1)	Rohini	40	10	10
		Age at First app (Y_2)		40	10	10
		Age at Peak Severity (Y_3)		40	10	10
	Berhampur	Maximum severity (Y_1)	Varuna	35	10	10
		Age at First app (Y_2)		35	10	10
		Age at Peak Severity (Y_3)		35	10	10
		Maximum severity (Y_1)	Binoy	35	10	10
		Age at First app (Y_2)		35	10	10
		Age at Peak Severity (Y_3)		35	10	10
	Dholi	Maximum severity (Y_1)	Varuna	30	10	10
		Age at First app (Y_2)		30	10	10
		Age at Peak Severity (Y_3)		30	10	10
		Maximum severity (Y_1)	Pusa bold	30	10	10
		Age at First app (Y_2)		30	10	10
		Age at Peak Severity (Y_3)		30	10	10
Powdery mildew	S. K. Nagar	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

TABLE 2

Models to forecast different character of Alternaria Blight in mustard crop along with coefficient of determination in different varieties

Disease	Location	Variety	Character	Model	R^2
Alternaria Blight	Bharatpur	Rohini (on Leaf)	Y_1	$81.16 - 1.38\ Z_{20} + 0.06\ Z_{121} + 0.001\ Z_{341}$	0.75
			Y_2	$2.95 + 0.75\ Z_{11}$	0.82
			Y_3	$7.59 + 0.006\ Z_{231}$	0.40
		Rohini (on Pod)	Y_1	$11.42 + 0.0012\ Z_{340} + 0.026\ Z_{231}$	0.29
			Y_2	$87.10 - 0.01\ Z_{240} + 0.01\ Z_{231} + 0.08\ Z_{241}$	0.40
			Y_3	$26.94 + 0.06\ Z_{31} + 0.001\ Z_{241}$	0.63
		Varuna (on Leaf)	Y_1	$60.65 + 0.002\ Z_{340} + 0.01\ Z_{121} + 0.006\ Z_{341}$	0.78
			Y_2	$7.82 + 0.54\ Z_{11} + 0.005\ Z_{231}$	0.83
			Y_3	$-4.68 + 0.34\ Z_{11}$	0.58
		Varuna (on Pod)	Y_1	$36.11 + 0.08\ Z31$	0.60
			Y_2	$-222.95 + 4.43\ Z_{20} - 0.14\ Z_{120} + 3.61\ Z_{11} + 2.38\ Z_{31}$	0.63
			Y_3	$68.41 - 0.02\ Z_{130} + 0.66\ Z_{21} + 0.04\ Z_{131}$	0.71
	Dholi	Pusa Bold (on Leaf)	Y_1	$28.79 - 0.01\ Z_{240} + 0.04\ Z_{121} + 0.002\ Z_{131}$	0.96
			Y_2	$24.29 - 0.001\ Z_{140} + 0.01\ Z_{131}$	0.72
			Y_3	$-87.90 + 17.56\ Z_{20} + 31.64\ Z_{21} + 2.32\ Z_{31}$	0.52
		Pusa Bold (on Pod)	Y_1	$68.95 + 0.39\ Z_{41} + 0.01\ Z_{121} + 0.007\ Z_{131}$	0.83
			Y_2	$81.10 - 0.003\ Z_{240} + 0.01\ Z_{121} + 0.005\ Z_{141}$	0.87
			Y_3	$144.65 + 1.87\ Z_{31} + 0.33\ Z_{41} + 0.01\ Z_{131}$	0.77
		Varuna (on Leaf)	Y_1	$72.89 - 2.11\ Z_{21} + 3.35\ Z_{41} + 0.07\ Z_{121} - 0.02\ Z_{341}$	0.93
			Y_2	$-17.86 - 0.05\ Z_{240} + 0.01\ Z_{131} - 0.007\ Z_{231} + 0.10\ Z_{241}$	0.84
			Y_3	$-59.10 + 1.72\ Z_{31} + 0.015\ Z_{121}$	0.55
		Varuna (on Pod)	Y_1	$-206.31 + 0.61\ Z_{30} + 0.02\ Z_{121} + 0.005\ Z_{341}$	0.79
			Y_2	$106.97 - 0.03\ Z_{230} + 0.029\ Z_{121} + 0.03\ Z_{231}$	0.87
			Y_3	$121.89 + 0.02\ Z_{130} + 0.045\ Z_{131} - 0.01\ Z_{141}$	0.87
	Berhampur	Binoy (on Leaf)	Y_1	$57.38 - 0.025\ Z_{141} + 0.03\ Z_{241}$	0.54
			Y_2	$92.84 + 5.17\ Z_{21} + 3.94\ Z_{31} - 0.11\ Z_{121}$	0.61
			Y_3	$-93.70 + 4.91\ Z_{10} + 0.06\ Z_{230} + 0.31\ Z_{121}$	0.62
		Binoy (on Pod)	Y_1	$-99.41 + 0.021\ Z_{131}$	0.62
			Y_2	$93.91 - 0.04\ Z_{240} + 0.09\ Z_{241} - 0.004\ Z_{341}$	0.61
			Y_3	$170.01 + 0.01\ Z_{131} + 0.005\ Z_{231}$	0.50
		Varuna (on Leaf)	Y_1	$59.21 + 0.56\ Z_{30} + 5.67\ Z_{31} + 0.03\ Z_{121}$	0.57
			Y_2	$213.53 - 0.01\ Z_{130} - 0.003\ Z_{140} + 0.09\ Z_{121}$	0.67
			Y_3	$125.08 + 9.19\ Z_{10} + 27.51\ Z_{11}$	0.46
		Varuna (on Pod)	Y_1	$188.16 + 1.55\ Z_{31} + 1.15\ Z_{41} + 0.03\ Z_{121}$	0.56
			Y_2	$148.25 + 1.66\ Z_{31} + 0.02\ Z_{121}$	0.60
			Y_3	$-31.168 - 0.007\ Z_{240} + 0.01\ Z_{341}$	0.53
Powdery mildew	S. K. Nagar	Varuna	Y_1	$Y = 133.40 + 0.11\ Z_{120} + 12.71\ Z_{21}$	0.84
			Y_2	$Y = 59.52 + 0.02\ Z_{120} - 0.01\ Z_{241} + 0.06\ Z_{351}$	0.84
			Y_3	$Y = 126.35 + 1.17\ Z_{41} - 0.04\ Z_{141}$	0.65
		GM - 2	Y_1	$Y = -52.46 + 0.06\ Z_{121} - 0.08\ Z_{131} + 1.23\ Z_{31}$	0.56
			Y_2	$Y = 53.12 + 0.16\ Z_{251} - 0.01\ Z_{241} + 0.003\ Z_{130}$	0.85
			Y_3	$Y = 106.27 + 0.22\ Z_{11} + 0.005\ Z_{341}$	0.69

TABLE 3

Mean Absolute Percentage Error (MAPE) of various models for Alternaria Blight in mustard

Character	Variety	MLP	RBF	WI
	Alternaria Blight (Bharatpur) for 2006-07			
Maximum severity (Y_1)	Varuna (on Leaf)	111.0	153.8	150.1
Age at First app (Y_2)		14.0	15.1	14.7
Age at Peak Severity (Y_3)		14.1	27.3	22.3
Maximum severity (Y_1)	Varuna (on Pod)	113.7	143.6	132.6
Age at First app (Y_2)		15.7	9.2	14.2
Age at Peak Severity (Y_3)		3.9	6.4	5.4
Maximum severity (Y_1)	Rohini (on Leaf)	184.0	200.6	196.3
Age at First app (Y_2)		12.0	15.5	8.9
Age at Peak Severity (Y_3)		28.3	27.8	26.2
Maximum severity (Y_1)	Rohini (on Pod)	174.8	220.4	229.6
Age at First app (Y_2)		29.3	28.2	24.7
Age at Peak Severity (Y_3)		19.2	20.7	17.6
	Alternaria Blight (Dholi) for 2004-05			
Maximum Severity (Y_1)	Varuna (on Leaf)	38.1	29.9	51.9
Age at First app. (Y_2)		15.6	9.9	8.4
Age at Peak severity (Y_3)		5.0	9.6	9.3
Maximum Severity (Y_1)	Pusa bold (on Leaf)	32.0	45.9	48.5
Age at First app. (Y_2)		7.2	10.9	10.4
Age at Peak severity (Y_3)		5.9	5.1	7.0
Maximum Severity (Y_1)	Varuna (on Pod)	88.1	75.4	88.9
Age at First app (Y_2)		7.6	12.8	3.9
Age at Peak severity (Y_3)		4.0	4.9	3.0
Maximum Severity (Y_1)	Pusa bold (on Pod)	65.5	82.5	91.8
Age at First app (Y_2)		6.4	11.1	6.9
Age at Peak severity (Y_3)		3.5	3.3	3.3

TABLE 3 (*Contd.*)

Character	Variety	MLP	RBF	WI
Alternaria Blight (Berhampur) for 2004-05				
Maximum Severity (Y_1)	Varuna (on Leaf)	60.1	64.4	61.9
Age at First app (Y_2)		18.8	20.1	22.3
Age at Peak severity (Y_3)		13.8	10.3	9.7
Maximum Severity (Y_1)	Varuna (on Pod)	107.2	81.8	68.1
Age at First app (Y_2)		21.9	19.3	23.3
Age at Peak severity (Y_3)		6.9	7.8	7.4
Maximum Severity (Y_1)	Binoy (on Leaf)	50.3	40.1	61.0
Age at First app (Y_2)		12.1	12.4	12.4
Age at Peak severity (Y_3)		10.5	11.9	9.7
Maximum Severity (Y_1)	Binoy (on Pod)	120.4	194.4	182.7
Age at First app (Y_2)		22.3	18.4	12.6
Age at Peak severity (Y_3)		3.8	3.0	2.9
Powdery mildew (S. K. Nagar) for 2006-07				
Maximum Severity (Y_1)	Varuna	26.5	56.2	35.1
Age at First app (Y_2)		12.2	15.1	20.2
Age at Peak severity (Y_3)		9.5	13.5	12.8
Maximum Severity (Y_1)	GM2	6.7	50.2	64.7
Age at First app (Y_2)		21.4	15.3	21.7
Age at Peak severity (Y_3)		12.8	14.1	13.8

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

X_{iw} is value of i^{th} weather variable in w^{th} week,

r_{iw} is correlation coefficient between variable to forecast and i^{th} weather variable in w^{th} week,

$r_{ii'w}$ is correlation coefficient between variable to forecast and product of X_i and $X_{i'}$ in w^{th} week,

p is number of weather variables,

n_1 is initial week for which weather data are included in the model and

n_2 is final week for which weather data are included in the model.

Using these weather indices as independent variables and variable to forecast as dependent variable, two types of neural network architecture namely Multilayer perceptron (MLP) and Radial basis function (RBF) were attempted and compared with weather indices based regression model.

Forewarning of Alternaria Blight and Powdery mildew in mustard crop for different characters, *viz.*, maximum severity of disease (Y_1), crop age at first appearance of disease (Y_2) and crop age at peak severity of disease (Y_3) for two varieties in different locations has been obtained, using neural network models with MLP and RBF architectures. Weather data for the period from 2001-02 to 2005-06, 1999-2000 to 2003-04 and 2000-01 to 2003-04 for Bharatpur, Berhampur and Dholi respectively were considered for model development in Alternaria Blight while weather data from 1999-2000 to 2005-06 were considered for models development in Powdery mildew. The data for subsequent years were used for testing the models. The developed weather indices were used as input variables and various characters were used as output in the neural network models. The available data set was divided into three sets namely training, validation and testing set. The details of data sets are given in Table 1 for different locations.

2.1. *Weather indices based regression models*

The developed indices were used in developing forecast models through regression approach. The form of the model was [Agrawal and Mehta (2007)]

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

where Y is variable to forecast; a_0, a_{ij}, $b_{ii'j}$ are constants; ε is error term and other symbols have same meaning as explained earlier. Stepwise regression technique was used for selecting important variables to be included in the model.

2.2. *MLP and RBF architecture based neural network models*

Neural network models using MLP architecture with different hidden layers and different number of neurons in a hidden layer with hyperbolic function as an activation function with varying learning rates and RBF architecture, were obtained and best architecture was selected having lowest Mean Absolute Percentage Error (MAPE).

3. Performance measure

The forecasting performance of various ANN models and regression models was judged by Mean Absolute Percentage Error (MAPE).

$$\text{MAPE} = \frac{1}{n}\sum \left| \frac{(Y_t - F_t)}{Y_t} \right| \times 100$$

where Y_t is actual observation, F_t is the forecast from model and n is the total number of test data point.

4. Results and discussion

Weather Indices (WI) based regression models were developed for various characters and models have been validated using data on subsequent years not included in developing the models. The analysis has been done by using SAS (Statistical Analysis System) Version 9.2 software package available at Indian Agricultural Statistics Research Institute, New Delhi. The models are given in Table 2.

Neural network models using MLP architecture with different hidden layers (one & two) and different number of neurons (4, 5 and 6) in a hidden layer with hyperbolic function as an activation function with varying learning rates (from 0.3 to 0.8) and RBF architecture, were obtained and best architecture was selected having lowest Mean Absolute Percentage Error (MAPE). The analysis has been done by using Statistica Neural Networks Version 6.1 available at Indian Agricultural Statistics Research Institute, New Delhi. The Mean Absolute Percent Error (MAPE) for different characters of Alternaria Blight and Powdery mildew in mustard crop in two varieties for various developed models is presented in Table 3. This table reveals that the neural network models using MLP have lowest MAPE as compared to other developed models in most of the cases.

5. Conclusion

The ANN 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 RBF and weather indices based regression models in terms of MAPE. Therefore, reliable forewarning for maximum severity of disease, crop age at first appearance of disease, crop age at peak severity of disease in two different varieties of mustard crop for Alternaria Blight and powdery mildew is possible well in advance.

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