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Original Contribution

COMPARISON OF DOUBLE DIGIT INDEX AND DISEASE SEVERITY IN DISEASE PROGRESS OF WHEAT SEPTORIOSIS (*SEPTORIA TRITICI*) USING ARTIFICIAL NEURAL NETWORK

Sh. Mojerlou[1], N. Safaie[1*], A. Alizadeh[1], F. Khelghatibana[2]

[1]Department of Plant Pathology, Faculty of Agriculture, Tarbiat Modares University, Tehran, Iran.
[2]Seed and Plant Certification and Registration Institute, Karaj, Iran

ABSTRACT
Artificial Neural Networks (ANN) provide an alternative or complementary to conventional approaches for model development and have been used in plant pathology to study of dynamics, modeling and forecasting of several disease in recent years. The most conventional type of neural network is Back Propagation Network which is a type of Feed- Forward Networks, used in this study. The disease progress data as double digit disease index and disease severity in five wheat cultivars (Tajan, Zagros, Koohdasht, Shiroodi, Shanghai) and two lines (N-80-16 and N-80-19) were analyzed using Neurosolution 5.0. In this software, one input layer, one hidden layer with four nodes, one output layer and sigmoid function were considered for modeling. The results showed that double digit disease index were more efficient compared to disease severity in all cultivars and lines for describing disease progress in time. All cultivars and lines revealed high efficiency of ANN in the disease progress of wheat Septoriosis, according to high coefficient of correlation and low Root of Mean Square Error and Maximum Absolute Error parameters. This is the first study on using ANN models in temporal progress of wheat Septoriosis.

Key words: wheat; *Septoria tritici*; Artificial Neural Network (ANN), temporal progress.

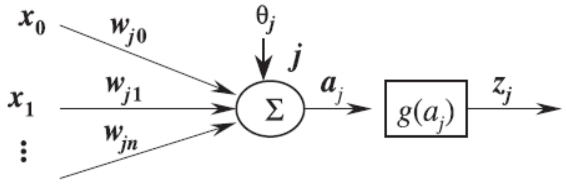
INTRODUCTION

Artificial neural networks (ANN) are complementary approaches for conventional model development (1). ANN technology was developed in the 1940s and 1950s and new architectures interest in this technology, recently (2, 3). According to Francl (4), ANNs are capable to describe relationships among variables even when the system being modeled is poorly understood (1). It provides a flexible way to connect disease outcome with environmental and other determinant variables. Neural networks are similar to regression models in that both develop coefficients that model patterns by evaluation of the relationship between independent and dependent variables. However, neural networks don't require to hypothetical information for modeling, unlike parametric statistical models. In general, neural networks consist of three or more groups of elements that represent sets of equations used by the model. The type of neural network determines interconnection and processing of the various elements and data (5). The network "learns" the relationships between independent and dependent variables through the association of patterns (6). Back propagation neural networks (BPNN), a common type of neural network use an iterative presentation of independent variables, and observed dependent variables to identify the appropriate form of the model (5).

Artificial neural networks are made up of highly interconnected processing elements called nodes or neurons that process information by their dynamic-state response to the external signals and can handle imprecise information. Important features of ANN are a set of processing units; an activation state for each unit equivalent to its output; *wjk* defines connections between the units and determines the effect that unit *j* has on unit *k*; a propagation rule that determines the effective input of the unit, an activation function, a scalar-to-scalar function that transforms inputs to a unit; an external input (bias, offset),

***Correspondence to:** *Naser Safaie , Tel.: +98 2144194912; fax: +98.2144196524*
Email address: nsafaie47@yahoo.com or nsafaie@modares.ac.ir

similar to a parameter estimate for each unit; and a method for information gathering, the so-called learning rule. A processing unit can be simply expressed as follows (7):



$$a_j = \sum_{i=1}^{n} w_{ji} x_i + \theta_j \qquad z_j = g(a_j)$$

Where $x0$, $x1$, … xn are inputs; $wj0$, $wj1$, … wjn are weights; θj is the bias term; j is the unit; $g(aj)$ is the activation function; and zj is the output.

Artificial neural network has been applied for classification, optimization, and prediction problems in the agricultural sciences (8, 9). In the past few years, ANN used for cereal grain classification and identification tasks (10). Its application in plant pathology includes the prediction of leaf wetness duration (11) and soybean rust progress (12). Also, it has been applied to the prediction of disease intensity (13, 14) and leaf wetness duration (15, 16). It has been shown to perform just as well as or better than traditional multivariate approaches at classifying incidence (5) and detecting infection periods of Tan spot of wheat (13) and predicting wheat scab epidemics (6).

The Septoria blotch diseases of wheat are incited by *Septoria tritici* Roberg in Desmaz. (Telemorph: *Mycosphaerella graminicola* (Fuckel) J. Schrot in Cohn) cause major foliar disease of wheat, considerable yield losses in many countries worldwide (17). Disease importance and crop loss were significant when Mexican cultivars with good farm characters like; high yield, toleration to various environments and resistance to rust were used in many countries. It caused significant crop loss in many countries because of their susceptibility to Septoriosis (18, 19).
This disease is second important disease (after yellow rust) in hot and moderate climate of Iran (20). The epidemics of this disease were occurred in most parts of Iran in 1996 (21) and in Golestan province during 2002-2003 (22). Ascospores of *M. graminicola* produced on wheat stubble are an important inoculum source worldwide and play a significant role in disease epidemiology (23). Pycnidiospores are most important as secondary inoculum locally as the crop is growing and are disseminated mainly by rain splash (24). Moisture plays an essential role in all stages of the infection cycle. Inoculum density plays an important role in establishment and lesion extension of *S. tritici* as well (25). The greatest risk to a crop is related to the occurrence of conditions that favor spore dispersal during and shortly after flag leaf emergence. Spore dispersal and infection at this time favors a second generation of pathogens (26).

Septoria leaf blotch of wheat is one of the most important diseases of wheat which reduce yield yearly and temporal analysis is the first step for disease forecasting system. This study was conducted to analyze the temporal progress of wheat septoriosis based on two different indices using ANNs in Iran.

MATERIALS AND METHODS

The study of temporal progress was conducted in greenhouse and field for two consecutive growing seasons in 2006-2007 and 2007-2008.

Greenhouse experiments were carried out in complete randomized block design with four replicates. Five wheat cultivars including Tajan, Zagros, Koohdasht, Shiroodi, Shanghai and two lines named N-80-6, N-80-19 were used in these experiments. Two single-spored isolates of *Septoria tritici* which were collected from Golestan province were used for inoculation. Potato dextrose broth was inoculated with 5-mm plug of each fungal isolate and was shaken for 4-7 days at 25°C. Spore concentration was adjusted to 2×10^6 spores/ ml. Seedlings were inoculated at the two- leaf stage using the quantitative techniques of Eyal *et al.* (27). After inoculation pots were covered with transparent plastic for 72 hours to increase humidity and promote infection. Disease severity was assessed 15 days after inoculation on the first (coleoptilar) and second leaves, using the Saari- Prescott (28) scale. Disease recordings were continued until flowering.

Field experiments were conducted during 2006-2007 and 2007-2008 in Gorgan (Araghi-mahale) research station. Cultivars and lines which were used in greenhouse experiments, were sown at early December in four rows plots, 5 m long with 1.2 m width. A complete randomized block design was used. Inoculum was prepared as above and applied in calm and rainy weather during March at 2×10^7 spores/ ml. Artificial inoculation was performed at three growth stages including; tillering (GSZ, 37), stem elongation (GSZ, 45) and flag leaf opening (GSZ, 53). Disease severity was assessed after symptom appearance. Disease recording was continued until flag leaf infection every other day, using Saari- Prescott (28) method. Double digit index and disease severity were recorded in both experiments.

Data analysis. Disease index and disease severity were evaluated with various ANNs models including one, two or four hidden layer and two and four nodes. Also, sigmoid and tanh functions were compared. The ANNs analyses were done using Neurosolution 5.0 software. Fitness of different models was examined by coefficient of correlation (R^2) and Mean Square Error (MSE) and Maximum Absolute Error (MAE).

RESULTS

Greenhouse study:

Disease symptoms were appeared 15 days after inoculation. Double digit disease index and disease severity data were analyzed using Neurosolution 5.0 software. Epoch 1000, one hidden layer with four nodes and sigmoid function were used in this software. Comparing of one, two, four hidden layers, also, sigmoid and tanh functions revealed that the network with one hidden layer, four nodes and sigmoid function was the most efficient for modeling.

In Tajan cultivar disease severity had high R^2 but it was not suitable for modeling due to high MSE and MAE. In this cultivar disease index was efficient for modeling. Also, in Cvs. Zagros, Shiroodi, Koohdasht and N-80-6 and N-80-19 lines, disease index was suitable for modeling due to high R^2 and low MSE and MAE. In cultivar Shanghai, R^2 was the same in disease severity and disease index models. But comparison of MSE and MAE showed that disease index was more suitable for modeling using ANN.

Field study:

First year (2006-2007):

Disease symptoms were appeared 30 days after inoculation. Double digit disease index and disease severity data were analyzed using Neurosolution 5.0 software. Comparing of one, two, four hidden layers also sigmoid and tanh functions revealed that the network with one hidden layer, four nodes and sigmoid function was the most efficient for modeling. The results showed that disease severity and disease index had the same R^2 (0.91) but the lower MSE and MAE of disease severity revealed that disease severity was more suitable for modeling in Tajan cultivar. Comparing of R^2, MSE and MAE showed that, disease index was more suitable for modeling in Cvs. Zagros, Shiroodi, Shanghai, Koohdasht and N-80-6 and N-80-19 lines. Based on the results, disease index was more suitable for modeling using ANN in all cultivars and lines except Tajan.

Second year (2007- 2008):

In this experiment, disease symptoms were appeared 30 days after inoculation as well and data were analyzed using Neurosolution 5.0 software. Compare of R^2, MSE and MAE showed that using disease index was more efficient for modeling in all cultivars and lines.

Combined data of two years:

All data were analyzed using Neurosolution 5.0 software. In this experiment network was defined like before. The results revealed that model has high efficiency in all cultivars and lines due to R^2, MSE and MAE. It confirmed the high efficiency of ANN in disease progress modeling. R^2 and other parameters of each cultivar and lines using disease index in greenhouse and field experiments were showed at **tables 1, 2, 3 and 4.**

Table 1. *Statistical results of neural network model of Septoria tritici using disease index in seven wheat cultivar and lines in greenhouse*

Cultivar/ line	Input series	Network architecture	Training			Testing			Network type
			R^2	MSE	MAE	R^2	MSE	MAE	
Tajan	1	1-4-1	0.85	15.35	2.99	0.67	19.53	3.30	BPNN
Zagros	1	1-4-1	0.76	23.87	3.81	0.83	31.73	4.70	BPNN
Shiroodi	1	1-4-1	0.66	25.26	3.50	0.73	31.93	4.35	BPNN
Koohdasht	1	1-4-1	0.40	48.09	5.52	0.47	63.96	6.07	BPNN
Shanghai	1	1-4-1	0.76	58.27	6.19	0.85	58.91	5.82	BPNN
N-80-6	1	1-4-1	0.75	29.99	3.90	0.69	44.69	5.09	BPNN
N-80-19	1	1-4-1	0.42	167.99	11.33	0.50	147.67	10.02	BPNN

Table 2. *Statistical results of neural network model of Septoria tritici using disease index in seven wheat cultivar and lines in greenhouse in 2006-2007*

Cultivar/ line	Input series	Network architecture	Training			Testing			Network type
			R^2	MSE	MAE	R^2	MSE	MAE	
Tajan	1	1-4-1	0.95	33.71	4.77	0.90	54.43	6.40	BPNN
Zagros	1	1-4-1	0.93	38.96	4.52	0.91	79.72	7.67	BPNN
Shiroodi	1	1-4-1	0.95	27.57	4.31	0.97	34.40	4.64	BPNN
Koohdasht	1	1-4-1	0.95	34.56	5.02	0.94	30.22	3.78	BPNN
Shanghai	1	1-4-1	0.92	47.06	5.50	0.92	43.37	6.13	BPNN
N-80-6	1	1-4-1	0.95	31.28	4.75	0.94	42.54	5.42	BPNN
N-80-19	1	1-4-1	0.95	29.30	4.31	0.98	37.79	4.62	BPNN

Table 3. *Statistical results of neural network model of Septoria tritici using disease index in seven wheat cultivar and lines in greenhouse in 2007-2008*

Cultivar/ line	Input series	Network architecture	Training			Testing			Network type
			R^2	MSE	MAE	R^2	MSE	MAE	
Tajan	1	1-4-1	0.88	33.95	4.38	0.93	35.76	5.42	BPNN
Zagros	1	1-4-1	0.97	12.80	3.36	0.99	19.86	4.22	BPNN
Shiroodi	1	1-4-1	0.84	27.39	4.35	0.89	69.61	6.41	BPNN
Koohdasht	1	1-4-1	0.89	38.83	5.38	0.95	61.12	6.00	BPNN
Shanghai	1	1-4-1	0.80	20.94	3.27	0.84	76.31	7.91	BPNN
N-80-6	1	1-4-1	0.76	52.25	6.46	0.75	25.56	4.25	BPNN
N-80-19	1	1-4-1	0.76	89.20	7.87	0.84	54.73	6.02	BPNN

Table 4. *Statistical results of neural network model of Septoria tritici using disease index in seven wheat cultivar and lines in greenhouse in2006-2007 and 2007-2008*

Cultivar/ line	Input series	Network architecture	Training			Testing			Network type
			R^2	MSE	MAE	R^2	MSE	MAE	
Tajan	1	1-4-1	0.90	48.75	5.10	0.94	68.98	6.70	BPNN
Zagros	1	1-4-1	0.94	33.67	4.78	0.90	35.42	4.38	BPNN
Shiroodi	1	1-4-1	0.85	69.43	7.25	0.80	91.25	8.57	BPNN
Koohdasht	1	1-4-1	0.87	71.25	7.02	0.94	68.14	6.50	BPNN
Shanghai	1	1-4-1	0.71	141.64	10.33	0.64	173.00	11.85	BPNN
N-80-6	1	1-4-1	0.80	111.35	8.88	0.66	123.76	9.86	BPNN
N-80-19	1	1-4-1	0.88	60.11	6.33	0.91	50.61	5.89	BPNN

DISCUSSION

In plant pathology, ANN was used for prediction of leaf wetness duration (11) and soybean rust progress (12). It has been applied to the prediction of disease intensity (13, 14) and leaf wetness duration (15, 16). Also, it has been shown to perform just as well as or better than traditional multivariate approaches at classifying incidence (5) and detecting infection periods of Tan spot of wheat (13) and predicting wheat scab epidemics (6). Based on the results of our study, disease index was the most efficient for modeling using ANN. The efficiency of disease index was confirmed with epidemiological models too.

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