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Artificial Neural Network Assisted Weather Based Plant Disease Forecasting System

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Abstract— An interactive plant disease forecasting system was developed using Artificial Neural Network model with multilayer perceptron architecture having two hidden layers. When data from the same site are used for both training and testing, the prediction accuracy of the model was found to be between 81-87% for rice blast disease. Being a multivariate non-linear non-parametric data driven self adaptive statistical method, it shows significantly higher accuracy then the conventional regression based models.

Keywords-*Artificial Neural Network, Forecasting, Plant Disease, Multi-layer Perceptron.*

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I. INTRODUCTION

Disease forecasting is integral part of integrated disease management system. It is in fact a support system for decision making and provides an indication when the disease is likely to appear and when it go critical. The prediction of disease outbreak, combined with knowledge of disease epidemiology, allows control measures to be applied in time when they are most effective, reducing cost of production and the impact of fungicides/pesticides on environment. Reliable and well timed disease forecast are of vital importance for appropriate, foresighted and up-to-date planning. The impacts of plant pathogens are mostly not consistent or predictable due to very unpredictable and important factor in the disease triangle: the weather that dictates the intensity or severity of an epidemic. Disease prediction is based on weather conditions under which a pathogen, when in contact with a susceptible host, can infect and become established [I].

The forecasting of plant disease, based on weather data, requires simultaneous study of lot of weather parameters and their complex correlation with disease for a significant time period (minimum 10-15 years). The complexity of many plant disease process and dependence on several factors is such that our understandings, and thus the forecasting skill of many mathematical/statistical techniques, are inherently limited. Also, there felt a wide gap of understanding the mathematical relationships between the environmental conditions and the specific stages of disease infection cycle. Artificial Neural network (ANN), with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to analyze or notice. A well trained ANN, with proper algorithm selection, has ability to learn from the past data and events to predict the future probability of occurrence or non-occurrence of the event based on the conducive condition. ANN is a multivariate non-linear non-parametric data driven self-adaptive statistical method. The main advantage of neural network is its flexible functional form and universal functional approximator [II]. This model does not forecast disease outbreak, but analyze the ambient environmental conditions to predict disease risk. It determines the conditions conducive to disease development and uses this information to forecast potential outbreak. The objective was to develop an interactive disease risk forecasting system that receive data from the users, analyze it using the ANN based model developed and output disease risk.

II. MATERIALS AND METHODS

The forecasting system consists of four modules: (i) End User, (ii) Administrator, (iii) ANN model and (iv) Database system as shown in Fig. 1.

Administrator: The administrator determines the flow of application, managing the interaction of the end user, request/retrieval to/from ANN model, and request/retrieval from Database System (DBS).

Artificial Neural Network Model: The core of this forecasting system is the ANN based forecasting model that acts as job processing system. ANNs have been developed as generalizations of mathematical models on biological nervous system to mimic human learning process [III]. They are parallel computing systems made up of a large number of simple, 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. A typical artificial neuron is illustrated in Fig 2.

Referring to the Fig 2, the signal flow from inputs X_0, X_1, ……, X_N is considered to be unidirectional, which are indicated by arrows, as is a neuron’s output signal flow (O).

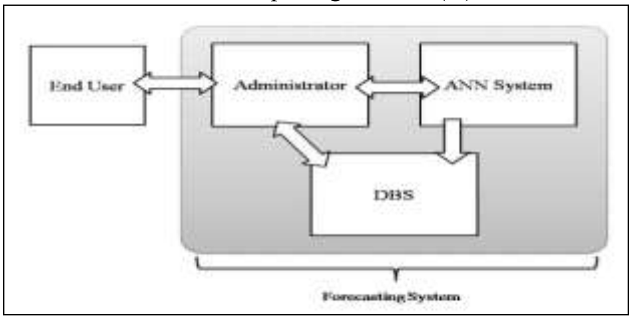

Figure 1. The forecasting system with different modules

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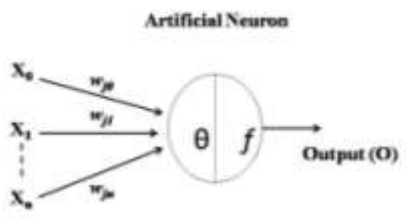

Figure 2. Typical artificial neuron

The neuron output signal O is given by following equation:

$$O = f(\text{net}) = f\left(\sum_{i=1}^{n} w_{ji}X_i\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where, the connection between the units, generally defined by a weight w_{ji} that determines the effect that unit *j* has on unit *k*; a propagation rule that determines the effective input of the unit, the function *f* (*net*) is referred to as an activation (transfer) function. The variable *net* is defined as a scalar product of the weight and input vectors,

$$net = w^T x = w_{j1}x_1 + w_{j2}x_2 \ldots\ldots\ldots\ldots\ldots + w_{jn}x_n \quad \ldots\ldots\ldots\ldots(2)$$

where T is the transpose of a matrix, and, in the simplest case, the output value O is computed as

$$O = f(\text{net}) = \begin{cases} 1, & if\ w^T x \geq \theta \\ 0, & otherwise \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

where θ is called the threshold level.

Architecture used: The most commonly applied ANN architecture in forecasting is the multilayer perception (MLP). An MLP consist of set of neurons or nodes organized into an input layer, a number of “hidden layers” and an output layer. The hidden layers that connect the input and output layers strengthen ANN, as their addition allows for the MLP to approximate nonlinear functions. General model of MLP is depicted in Fig. 3.

The architecture chosen in this model was feedforward MLP with two hidden layers. It uses the Levenberg-Marquardt training (trainlm function in MATLAB) algorithm [IV]. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm. Training basically involves feeding training samples as input vectors through a neural network calculating the error of the output layer, and then adjusting the weights of the network to minimize the error. The best training

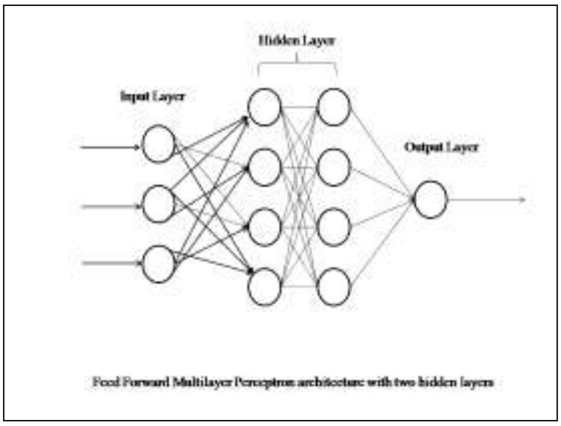

Figure 3. Feed Forward Multilayer Perceptron Architecture with two hidden layers

procedure is to compile a wide range of examples (for more complex problems, more examples are required), which exhibit all the different characteristics of the problem.

Input nodes: The number of input nodes corresponds to the number of variables in the input vector used to forecast future values. The input variables were determined according to three main selection criteria [V]: (i) statistical inferences- each potential input parameters for disease forecasting were compared; if significant differences were found, the parameter was considered as it has potential to provide some discriminatory ability to final ANN; (ii) domain knowledge and (iii) availability of data. The four major influencing weather parameters selected on the basis of above criteria for MLP that greatly influence plant diseases were as follows: (a) Temperature, (b) Relative Humidity, (c) Rainfall and (d) Wind speed.

Hidden layers and nodes: Though single hidden layer is sufficient for ANNs to approximate any complex non-linear function with any desired accuracy [VI], but two hidden layers results in a more compact architecture which achieves a higher efficiency in the training process compared to one hidden layer [VII]. Optimum numbers of nodes in the hidden layers were decided by incrementally increasing their number without leading to over-fitting and compromising MLP performance. Larger network generally able to simulate more complex functions, but beyond a limit it leads to over parameterization [VIII].

Activation function: Activation function determines the relationship between the inputs and outputs of a node and a network introducing a degree of nonlinearity that is valuable for most ANN applications. The most popular activation function is sigmoid (logistic) function given by

$$f(x) = (1 + \exp(-x))^{-1} \quad \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Training: The training was supervised one in that desired response of the network (target value) for each input pattern is always available. On scaling of all inputs to the same range, the inputs with larger mean magnitude are biased resulting in

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low efficiency of MLP training [IX]. Thus all input data were normalized to fit the range [-1, 1] as the transfer function is sigmoid (logistic). Randomization of inputs and their associated target (outputs) was done as per pseudo-randomization technique [X] in order to remove inter-seasonal variability form training, testing and validation sets. Through this practice, the correlation present between inputs and outputs presented is removed improving MLP skill [IX]. Any possibility of bias in the result that could have been obtained had the network been trained on older observations and validated on more recent data was removed by randomization [V]. It also ensures that the testing and validation sets conform to the same limits as the training set. Regularization and early stopping were employed to improve generalization [X]. The skill of the MLP had been assessed by using separate testing set that had not been used at all during the training phase. Relative characteristics of the training and validation sets are one of the determining factors of performance of any MLP-based forecasting aid.

Database System: The DBS stores data as database tables or files. It stores the disease forecasting data resulted from the ANN model for future assessment and training of ANN. It also stores the tables of detailed information on diagnosis and control of the disease. DBS was implemented using conventional Microsoft Access Database.

The system is a general model, based on the disease selection and training data it will forecast the risk of that very disease.

III. RESULTS

The front end (user interface) of the forecasting system is shown in Fig. 4. The user can either select interactive mode or form based mode. On entering the current weather data for the day of disease assessment and previous 24 hours, gave the prediction of the disease for the site the ANN was trained for. The detail data available can also be uploaded into the system. The users need to register to the system to use the system. The registration window is shown in Fig. 5. The registered user can also obtain detail precautionary and remedial measures from the system database. The training window is shown in Fig. 6. It is password protected and only authorized administrator is allowed to enter into the training window. Detail database is shown in Fig 7. As stated it contains information about the disease for which the system was trained for, geographic data of the site for which the system was trained for and weather data of the site. The database administrator is entitled to modify the database. The system can be trained for disease severity or for just information about disease or no disease. When trained for Rice Blast forecasting on the data from a field site, the accuracy of prediction of the model was found to be 81-87%.

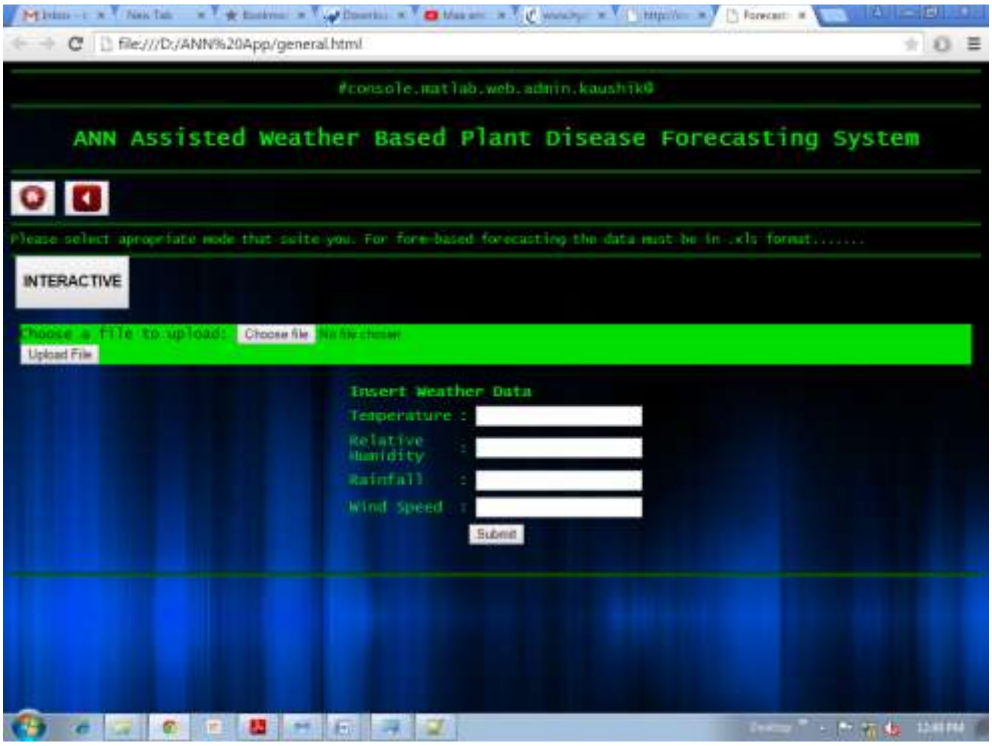

Figure 4. User interface on the forecasting system

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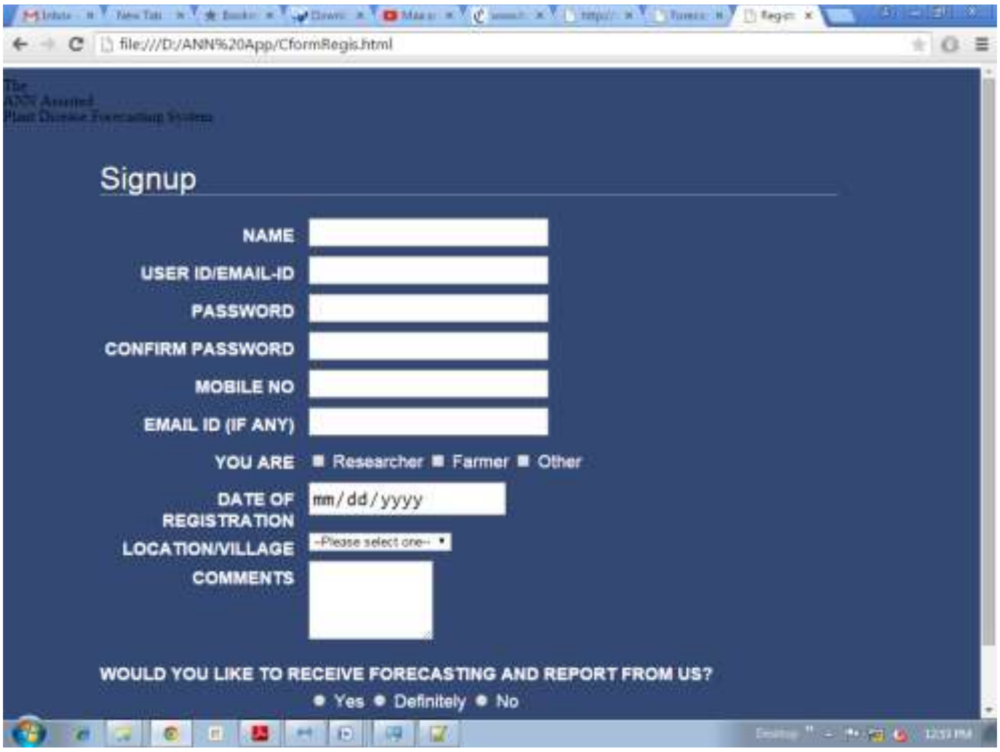

Figure 5. User information window

Figure 6. The ANN Training window

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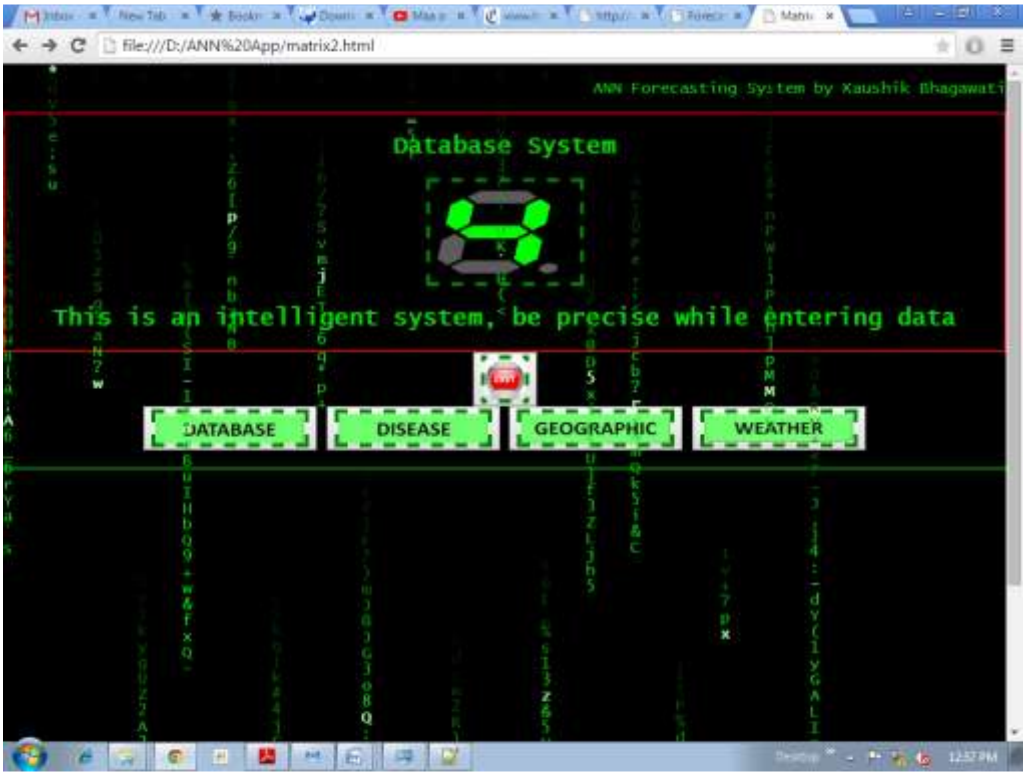

Figure 7. The Database System

IV. DISCUSSION

The major useful characteristics of the model are: i) Accuracy, 2) its site-specific nature, 3) interactive nature and 4) flexibility.

Accuracy: The most remarkable characteristic of ANN is its capability to handle non-linear relationships due to hidden layers. The number of hidden neurons in most of the applications was found to be often greater than the number of important input weather variables in the model. This suggests that the relationship between the disease and ambient weather parameters are not non-linear, and hence could not be fitted in the conventional regression model [XI]. But the hidden neurons in the ANN models intrinsically capture the nonlinearity.

Site-specific nature: If the data from the same site are used for both training and testing, the prediction accuracy of the model increases above 90% depending on training algorithm selected [XII]. Though the model can be trained and tested by using pooled data from different site, but the accuracy of the general model decreases.

Interactive nature: The model has an interactive module that guides the user the steps of entering data for proper use of the system. This factor lowers the discrepancy in the forecasting result due to false data entry.

Flexibility: This system is a prototype for general disease forecasting model. The model can be trained for any plant disease that depends on weather for its inoculum survival, Liberation & dispersal, infection, latency, lesion expansion and spore formation.

The application of ANN models for plant disease prediction shown in this and other work [XIII] makes them a useful tool for future forecasting models, and combining aspects of ANN and well established statistical tools [XIV] may offer a more flexible option for the future.

ANNs do have some limitations that restrict its use in all forecasting problems. It is mainly ideal for (i) large data sets; (ii) problems with non-linear structure; and (iii) the multivariate time series forecasting problems [XV]. The major limitations are [VII]:

i. The relationship between the input and output cannot be explicitly explained and analyzed
ii. It is prone to have overfitting problems
iii. No structured method till date to identify what network structure can best approximate the function, mapping the inputs to outputs
iv. ANNs usually require more data and computer time for training.

There may be discrepancy on what the networks can learn from the data and make predictions. This is due to non-parametric property of ANN [XVI]. Thus ANNs cannot do everything well every time.

V. ACKNOWLEDGEMENTS

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