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Determination of the Disease of Plants by Calculating the Leaf Wetness Hour based on the Relative Humidity

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ABSTRACT

Connections between splint stuffiness and factory conditions have been studied for centuries. The progress and threat of numerous bacterial, fungal, and oomycete conditions on a variety of crops have been linked to the presence of free water on leafage and fruit under temperatures favorable to infection. Whereas the rate parameters for infection or epidemic models have constantly been linked with temperature during the wet ages, splint stuffiness ages of specific time duration are necessary for the propagule germination of utmost phytopathogenic fungi and for their penetration of factory napkins. Using these types of connections, complaint-advising systems were developed and are now being used by farmer communities for a variety of crops. As an element of Integrated Pest Management, complaint-warning systems give farmers information regarding the optimum timing for chemical or natural operation practices grounded on rainfall variables most suitable for pathogen disbandment or host infection. The need for largely accurate splint stuffiness duration data remains precedence to achieve the most effective complaint operation. To prognosticate splint stuffiness, several biases have been used, where the design and perpetration have changed with time, with no extensively accepted standard[4]. These days, electronic splint stuffiness detectors are used where the circuit is depicted in the form of an artificial splint placed within the foliage and is able of measuring the splint stuffiness through a change in impedance due to the drop of water over the splint face. The total electronic circuit depends on the charge transfer of the capacitive seeing process through the artificial emulation of the leaves. But the stuffiness of the splint stuffiness detector gives confusing results. The confusion substantially revolves around the idea that whether the dimension of splint stuffiness duration is that of a splint, cover, or complete foliage. The offer of the "Estimation of LWD" algorithm helps in calculating the splint stuffiness by using relative moisture and temperature as a metric without the intervention of any kind of detectors curtails the nebulosity in dimension. The factual vapor pressure and achromatism vapor pressure help in generating the relative moisture of that area, and grounded on that, splint stuffiness hour is calculated, reflective of the presence of pathogens in the separate area. However, pathogen dissipation is verified, followed by infection spreading, If the splint stuffiness duration crosses a particular time period.

Keywords: Leaf wetness, oomycete disease, herbage

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The relationship between splint factor conditions and leaves has been studied for centuries till moment's date. In 1853, DeBary was one of the first experimenters to associate the infection of potatoes by Phytophthora infestans with the circumstance of free water on the factory cover[4]. Since also, and onwards the progress and threat of numerous bacterial, oomycete, and fungal conditions on a variety of crops have been linked to the presence of free water on fruit and leafage under temperatures favorable to infection[5]. The rate parameters for infection or epidemic models have constantly been linked with temperature during the splint stuffiness ages and wet ages, of specific time duration, are necessary for the propagule germination of utmost phytopathogenic fungi and for their penetration of factory apkins[17]. There are connections between air temperature and splint stuffiness duration needed for the infection of several hosts by three different phytopathogenic fungi. Using these types of connections, complaint- advising systems were developed and are now being used by farmers for a variety of crops. As a element of Integrated Pest Management (IPM), complaint-warning systems give farmers the information regarding the optimum timing for chemical or natural operation practices grounded on rainfall variables (e.g., downfall, moisture, LWD, air temperature) most suitable for pathogen disbandment or host infection[12]. This approach contrasts with traditional timetable- grounded systems, which recommend operation sprays grounded on fixed metable dates or phenological stages, rather than dates determined by measures of environmental variables on infection and the situations of omplaint threat. Disease-advising systems can reduce the number of recommended sprays during ages when complaint threat is low, but may also recommend more sprays than a timetable-grounded system when conditions are exceptionally complaint-conducive[10]. Though these systems are robust enough to permit some crimes in the estimates or measures of LWD, the need for largely accurate LWD data remains precedence to achieve the most effective complaint operation.

OBJECTIVE

Identifying varieties of diseases caused due to leaf wetness and also keeping a record of the relative humidity of various plans for future use.

LEAF WETNESS

Leaf stuffiness is the presence of free water on the face of a crop cover. It results primarily from three sources of water that have been interdicted by the cover during a downfall or fog event; overhead irrigation; or dew, which can form on any face of the crop cover, substantially on leaves, on both their top and ether most sides. There are two sources of water vapor. The first source, and utmost generally appertained to, is water vapor forming from the atmosphere above the cover (Fig. 1). Dew that forms from atmospheric water vapor is appertained to as 'dewfall'. The alternate source of water vapor is the soil face and profile; this commensurate donation to the dew quantum is appertained to as 'distillation' (distillation is also called 'dew rise' in the literature[9].

Fig. 1: Wet leaf of potato plant

RELATIVE HUMIDITY

Relative Moisture (RH) is the rate between (expressed in percent) the quantum of atmospheric humidity present relative to the quantum that would be present if the air were impregnated (also refer Table 1).

Table 1: Showing disease warning system and parameters

Disease warning system	Pathogen	Group	Reference Range
Apple scab	Fungi		39
Cedar apple rust	Fungi		44
Late blight (potato)	Oomycetes		15
Tomato early blight	Fungi		48.20
Strawberry anthracnose fruit rot	Fungi		33

LEAF WETNESS AND DISEASES

Almost 50% of the variation in leaf wetness duration can be explained by maximum and minimum temperatures, rainfall, and hours with relative humidity above 90% on a daily basis. All of these parameters can be estimated from a standard weather station. If variables related to wind are added the level of explanation increases to 69-76%.

Leaf wetness duration explained up to 42% of the rate of disease increase (RDI). Leaf wetness duration was accumulated over a 5-day 'window' period and correlated with the rate of disease increase after a 7-day 'lag' period. Standard weather variables could explain 20-34% of the disease increase.

Some of the sensors are used to sense the leaf wetness of a variety of leaves (Fig. 2 and 3).

Fig. 2: Mechanical sensors

Fig. 3: Electrical Sensors

Day by day sensors is getting evolved to receive the most efficient result so that measures can be taken immediately as per requirement.

OVERVIEW OF THE PROBLEM

The problems associated with LWD dimension are generally not attributable to the detectors themselves, but rather to how the detectors are used, when water is present on the face of the detector, the detector will descry it. The question is what does that detector reading represent? Is it representative of LWD for a splint, cover, field, or region? Is the onset of splint stuffiness said to do when the first drop of water is seen on the crop cover or when some portions of the leaves are wet? Dalla Marta *et al.* indicated stuffiness began when 10 of the face of a splint was wet, whereas Lau *et al.*[3] assumed that it began when 50 of the tried leaves displayed stuffiness. numerous of the problems associated with the accurate determination of LWD stem from the supposition — infrequently vindicated — that the information attained by a detector is representative of the spatial scale at which the exploration or marketable spray timing is applied, whether at a single splint, an apple cover, a field of tomatoes, or an entire croft.

OBJECTIVE

There are so many electronic leaf wetness sensors (LWS) already on the market, but none of themare automatic. In each case, sensors take the reading, and then it has to be calculated to determine the relative humidity through which percentage we can evaluate the percentage of wellness or theprobability of early plant disease[11]. By implementing an Artificial Neural Network, we will try to develop such a code that will be able to connect all the component nodes and through which directly we will be able to evaluate the relative humidity of the weather and the leaf wetness percentage too in early cases.

METHODOLOGY

An artificial neural network(ANN) is a reproduction of the mortal brain. A natural brain has the capability to learn new effects and acclimatize to a new and changing terrain. The brain has the most amazing capability to dissect deficient and unclear, fuzzy information, and make its own judgment out of it (Fig. 4).

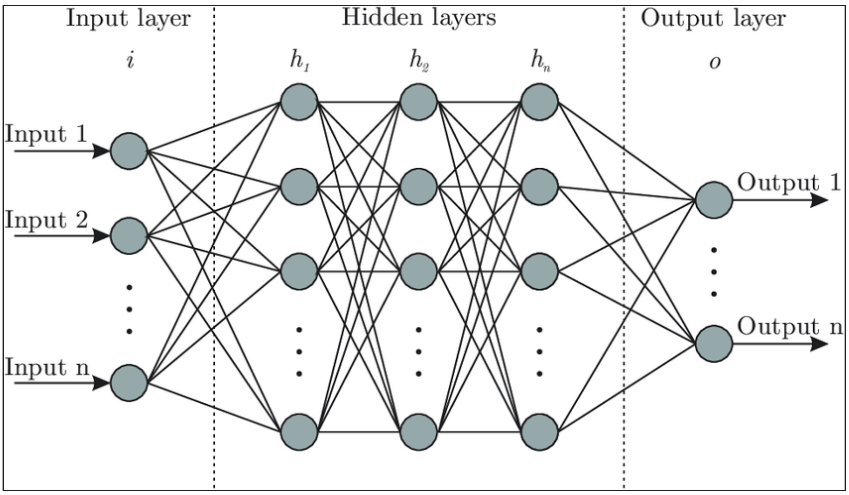

Fig. 4: Artificial Neural Network

ANN Architecture consists of- Input Layer, a Hidden Layer, and an Output layer (multiple output layers can be present). Through the input, layer inputs are sensed, and multiple hidden layers are present between the Input and Output Layers the final output layer is used for the ultimate outcome[6].

(a) Activation Function: In artificial neural networks, the activation function of a knot defines the affair of that knot depending on a set of inputs. A standard intertwined circuit can be seen as a digital network of activation functions that can be "ON" (1) or "OFF" (0), depending on the input. This is analogous to the geste of the direct perceptron in neural networks. Still, only nonlinear activation functions allow similar networks to cipher nontrivial problems using only a small number of bumps.

(b)Training Process: Orders of ANN are grounded on supervised and unsupervised literacy styles. The simplest form of ANN armature is Perception, which consists of one neuron with two inputs and one affair. The activation function used is the stepped function or ramp function.. comprehensions are used for the bracket of data into two separate classes. For further complex operations, multilayer comprehensions (MLP) are used, which contain one input subcaste, one affair subcaste, and one or further retired layers[15]. The backpropagation algorithm is the most generally used system in training the neural network.

(c) Backpropagation: Backpropagation is a short form for "backward propagation of errors." It is a standard method of training artificial neural networks (Fig. 5).

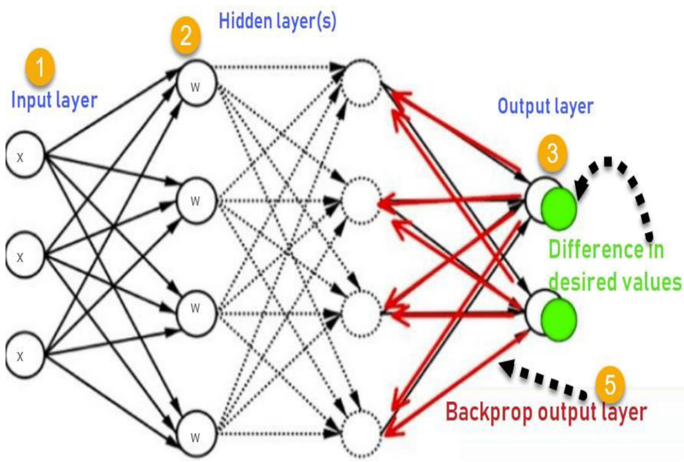

Fig. 5: Backpropagation

1. Inputs X, arrive through the preconnected path
2. Input is modeled using real weights W. The weights are usually randomly selected.
3. Calculate the output for every neuron from the input layer, to the hidden layers, to theoutput layer.
4. Calculate the error in the output-- Error=Actual Output-Desired Output
5. Travel back from the output layer to the hidden layer to adjust the weights such that theerror is decreased.

Keep repeating the process until the desired output is achieved.

ALGORITHM

In this algorithm, five consecutive steps are present, and we have calculated the hourly percentage of relative humidity (RH). In order to do that, as inputs, particular air temperature, dew point temperature, hourly actual vapor pressure, and hourly saturated vapor pressure have been taken (Refer Fig. 6).

- ❖ Step-1: Conversion of daily max-min temperature into an hourly air temperature
- ❖ Step-2: Estimation of hourly dew point temperature
- ❖ Step:3 Calculation of actual Vapour Pressure (Hourly)
- ❖ Step-4: Calculation of Saturated Vapour Pressure (Hourly)
- ❖ Step-5: Calculation of hourly relative humidity of the surface adjacent (here leaf)

IMPLEMENTATION OF THE ABOVE ALGORITHM THROUGH THE FLOWCHART

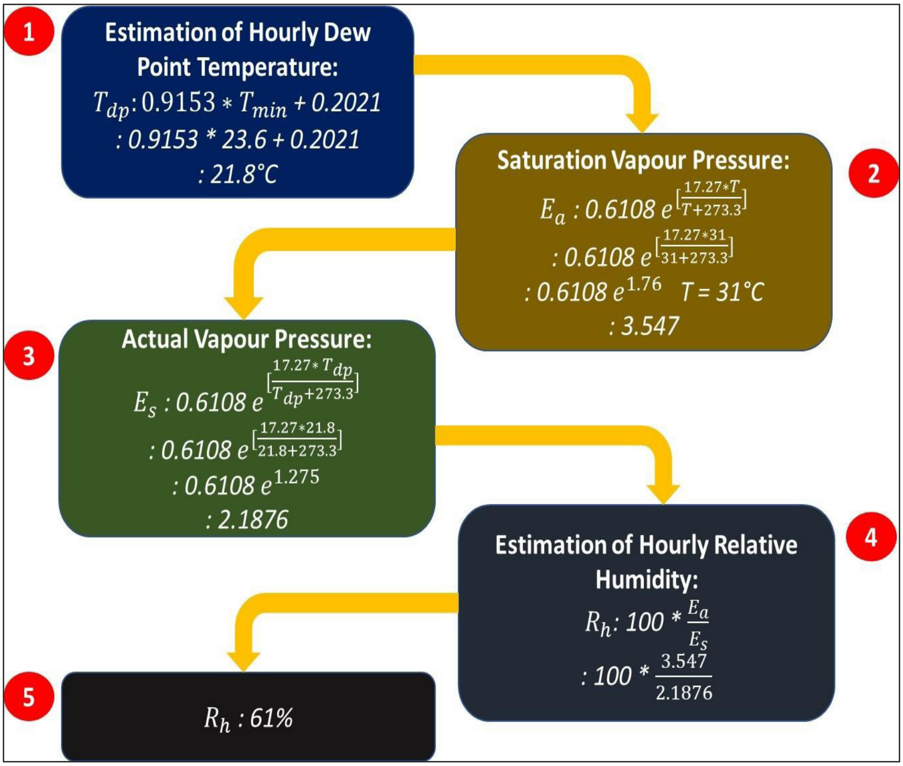

Fig. 6: Algorithm Flow Chart

All input layer attributes will be given via standardized data sets and the relative humidity will be taken from the above-mentioned algorithm. After implementing the neural network, the output layer will give the leaf wetness duration. Now, there will be a standard threshold value If the output of leaf wetness duration exceeds that threshold value then we will be able to say whether thereis any possibility of early disease or not.

RESULT (FINAL OUTCOME) AND FUTURE SCOPE

If Rh (Calculated) > 90%, count it as leaf wetness hour and if leaf wetness hour perceives for consistently 7-8 hours, we can conclude that the disease is the pointof arrival[13].

There are some other aspects too which can be explored. Such as, attempting to quantify the variability of dew in two crop canopies infields of similar topography and soil texture for the same dew periods to see if the variability in dew amount is seen for both canopies.

CONCLUSION

Through Max temperature and min temperature, we have got Actual vapor pressure, Saturation vapor pressure, and Relative humidity of a plant which is nearly around 61%.Now according to experts, if the relative humidity is more than 90% and the leaf wetness preserves for v7 to 8 hours then we can say that the plant is affected. Now, this system is giving LWD (leaf wetness duration) as output. To know something more about this leaf wetness we have to recreate this algorithm and also have to study the relative humidity of each leaf at different situation in various point of time.

SUGGESTION

To protect plants and also leaves of varieties of plants detail study on leaf wetness is required and also the study on relative humidity is mandatory. If detail analysis happens on these topics then definitely multiple count of plants can be saved from varieties of diseases.This detaction can be very helpful for varieties of business owners specially plant based and plant product based businesss owners.

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