Enhanced Back Propagation Neural Network For Fruit Disease Prediction And Classification

P. Kanjana Devi
Research Scholar , Dept of master of computer applications, N.G.M. College of arts and science, Pollachi , Tamilnadu , India.
Dr. M. Rathamani
Associate professor Dept of master of computer applications, N.G.M. College of arts and science, Pollachi , TamilNadu , India

Abstract

Data mining assumes an essential part in the dynamic cycle in numerous application territories. Information mining is essential for data handling and the executives. Plant sicknesses bargain efficiency which impacts public activity and economy of the country. The viable utilization of horticulture information mining can upgrade yield creation and give monetary advantage to the rancher and the country. The acknowledgment of the disease is done truly by noticing and recognizing the microorganisms, are which is for the most part take additional time and is likewise much expensive with lower precision. In this way, to defeat that there is most ideal decision this is fast and errorless determination by utilizing a few methods. We can see the side effects of contaminations or illnesses on the various pieces of the natural products in the plant, leaf, injuries. The point of this article is to recognize and distinguish the sickness precisely from the picture dataset. In this paper we proposed Enhanced Back Propagation Neural Network to distinguish the sickness on the natural products dataset. Our exploratory outcomes express that the proposed arrangement can essentially uphold exact discovery and programmed distinguishing proof of natural product illnesses.

Keywords [Data mining, Recognition, Back Propagation, accurate detection]

1. INTRODUCTION

India is non-industrial country. In this progression commitment of horticultural field is major. Sharp developing is connected to drawing in the current farmers with the decision instruments and robotization propels that reliably facilitates things, learning and organization for better productivity, quality and advantage. In this front line age another thoughts of keen developing has been introduced Where the field condition are controlled and checked using oneself working systems instead of using the standard methodologies, for instance ,conventional techniques, for example, extraordinary picture handling strategies. Surely, even in the wake of paying a solitary sum aggregate customers are disillusioned with the things they buy. One of such things is the foods grown from the ground. To a natural eye may appear to be solid and new yet just in the wake of cutting or eating it, the customers know its quality. This moreover impacts the advantage for the creators. Thusly, there is need applications which recognize the quality, disfigurements of foods grown from the ground so the customers get only the best quality thing for the money they pay. The quality, flaws of organic products are checked using developments like MRI, x-beam imaging and so forth which are extravagant for ranchers to bear, burn-through broad space, customers need to logical information to use and break down the results, and have destructive effect

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on the example utilized for research and the set up approach for discovery and recognizable proof of natural product illnesses relies upon the stripped eye insight by the subject matter experts. In some agricultural country, counseling experts are exorbitant and drawn-out as a result of the furthest spaces of their availability. Along these lines, they can't be used by everyone and on each and every thing. Some infection in like manner pollutes various zones of the tree causing sickness of twigs, leaves, and branches. Each sickness occurring in organic products makes a particular surface or unequivocal concealed spot. We can use these features for ID of illness in the organic product. Organic product sickness recognition requires gigantic proportion of work, information in the organic product illness.

Information mining is the way toward choosing, finding and demonstrating colossal measures of information. This cycle has become an inexorably deceptive movement in every aspect of clinical science research. Information mining has brought about the disclosure of valuable concealed examples from immense data sets. Information mining issues are regularly settled utilizing various methodologies from both PC sciences, for example, multi-dimensional data sets, AI, delicate registering and information representation; and incorporates order and relapse procedures. A portion of the examination works are done in this side, however every one of them are zeroing in on a couple of strategies for investigation, conclusion or forecast of this sickness by utilizing various devices and procedures, this work is centered around the early expectation of different infections by utilizing WEKA apparatus.

Checking of wellbeing and discovery of sicknesses is basic in foods grown from the ground for manageable agribusiness. As far as we could possibly know, no sensor is accessible industrially for the continuous appraisal of trees medical issue. Exploring is the most broadly utilized strategy for observing pressure in trees, yet it is costly, tedious and work serious cycle. Polymerase chain response which is a sub-atomic strategy utilized for the distinguishing proof of natural product sicknesses yet it requires nitty gritty inspecting and preparing. The different sorts of sicknesses on organic products decide the quality, amount, and security of yield. The infections in natural products decrease the yield as well as weaken the assortment and its withdrawal from the development. Early recognition of infection and yield wellbeing can work with the control of organic product illnesses through appropriate administration approaches, for example, vector control through fungicide applications, sickness explicit substance applications and pesticide applications; and improved efficiency. The old style approach for location and distinguishing proof of organic product illnesses depends on the unaided eye perception by specialists. In a portion of the non-industrial nations, discussion with specialists is a tedious and expensive undertaking because of the inaccessible areas of their accessibility. Organic product infections can cause critical misfortunes in yield and quality showed up in gathering. For instance, soybean rust (a contagious illness in soybeans) has caused a huge financial misfortune and just by eliminating 20% of the contamination, the ranchers may profit with an around 11 million-dollar benefit. Some organic product sicknesses likewise contaminate different spaces of the tree causing illnesses of twigs, leaves and branches. An early discovery of natural product illnesses can help in diminishing such misfortunes and can stop additionally spread of sicknesses.

Sicknesses show up as spots on the foods grown from the ground not treated on schedule, cause serious misfortunes. Over the top employments of pesticide for organic product infection treatment expands the peril of harmful buildup level on rural items and has been distinguished as a significant supporter of the ground water tainting. Pesticides are likewise among the most elevated parts in the creation cost in this way their utilization should be limited. In this manner, we have endeavored to give a methodology which can distinguish the infections

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in the organic products when they produce their manifestations on the developing organic products to such an extent that a legitimate administration application can be applied.

1.1 Fruit Diseases:

(a) Apple Scab:

This apple contamination causes generally pulverizing from all diseases. Apple-developing zones are influenced by this kind contamination. Apple scab is more extreme when its sprout time in cool and wet climate however in huge dry or warm environments it isn't sensibly. Leaves, petals, blossoms, husk, natural product, youthful shoots and bud sizes of apple tree shows the side effect of apple scab. The normal and clear contamination is on foods grown from the ground. Proper temperatures and dampness increment the arrival of v. In a equalisa scospores in organic product. This pivot of auxiliary illness proceeds all through the mid year, until the leaves and natural product tumble from the tree at the beginning of winter.

(b) Bitter Rot:

Botryosphaeriaobtusa named parasite causes the harsh decay in organic product. The leaves, bark and products of apple tree are principle part where its effect. After the 1 to 3 weeks the main side effects of apple decay shows up on external surfaces of leaves, petiole fall as little, and purple smear after which community become earthy colored tan and yellowish earthy colored. After that second phase of apple decay happens following not many weeks. In this stage optional augmentation of leaf spots happens. Leaf tumble from the tree which are profoundly influenced by these diseases.

(c) Black Rot:

This issue is brought about by a disease that spread on numerous woody plants and trees and its microorganisms are spread by wind. Leaves may have numerous large earthy colored denotes that start adjust and become patches as they become together. The spots are dry and like paper. Spots on organic product may show up any time during the season and tainted natural product decay and hold tight the tree. The organism likewise causes ulcers on branches.

(d) Apple Blotch:

It is generally normal "summer infection" of apples in the northwest. Apple smear is caused because of two unique organic entities. The barbarous consequence of this contamination is prudent disappointment and business quality damage. Dim greenish-blue spots on the outside of contaminated natural product are indications of infection. One to numerous almost roundabout settlements is grown separately. These signs happen three to about a month after once pamphlet falls.

(e) Scooty Blotch:

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On surface of the organic product earthy colored to dull dark tone, dirty blotches with an inconclusive diagram are singing of this disease. Blotches are ¼ inch in measurement or might be bigger. The opening natural product is cover by the blotches basically. Thepycnidia on have plants assemble numerous quantities of spores that emerge from infection and gather in a tacky mass.

(f) Bacterial Blight:

In the year 1952, it was first recorded in Delhi .till 1998 bacterial scourge was take as a low financial danger. However, presently days this contamination record generally and has been seen all over the place. This disease emerges in all pomegranate-developing states like Maharashtra, Karnataka, and Andhra Pradesh. Sepals, twigs and pomegranate are contaminated by bacterial curse. Fundamentally finishes paperwork for the contamination can be dark hued spots covered by bacterial ooze. 90% yield of pomegranate drains as a result of bacterial curse. Because of this sort of illness organic product crack.

(g) Aspergillums Fruit Rot:

Moniker of alternaria natural product decay. Disease saved in inner piece of organic product when it's open in stormy season. Little change in shade of skin and low weight because of interior rot are a portion of the indications of illness. Be that as it may, this contamination for the most part isn't showed up until gathering or during natural product arranging. With no outside indications of parasite might be developing inside the organic product. More often than not, contaminated organic product show little yellowish to caramel red staining and are little crude, for example, a pale red.

(h) Gray Mold:

Dark shape is otherwise called botrytis cinetea. During the hour of post-reap wash and spread and kept in room temperature this contamination is more successful and as often as possible seen. Bloom a piece of natural product take harm in dim form disease and influences the harvest until its aging. At the point when the natural product is washed or put away in high stickiness, buildup or water on the bloom tissues initiates the contagious mycelium to start developing. The regular grayish covering of spores and microbe sporulats on the bloom parts are created. At last the parasite will fan out inside organic product tissue the crown tissue will be involved. We need to store abandoned organic product in high moisture.

In this paper, we proposed Enhanced Back Propagation Neural Network to distinguish the sickness on the natural products dataset.

2. EXISTING METHODOLOGY

Three different data mining classification techniques namely KNN, Naive Bayes and Support Vector Machine are used to analyse the dataset.

2.1 K-Nearest Neighbor (KNN) Algorithm

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Let (xi, ci) where i= 1,2………..,n be data points. Xi denotes feature values & ci denotes labels for xi for each i. Assuming the number of classes as ‘c’.

$C_i \in$ {1,2,3,………, c} for all values of i

Let x be a fact for which label is not identified, and we would like to discover the label class using knearest neighbor algorithms.

Pseudo Code

- Calculate “d(x, x_i)” i=1,2,……, n; where d denotes the Euclidean distance between the points is calculated as follows
- Distance = $\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$
- Organise the premeditated n Eucledian distances in increasing order.
- Let k be a+ve number, take the leading k distances from this sorted list.
- Find those k-points corresponding to these k-distances.
- Let k_i denotes the quantity of facts fitting to the i^{th} class among k points i.e. k≥ 0
- If $k_i > k_j$ ∀ i ≠ j then put x in class i.

2.2 Naive Bayes Algorithm

Bayesian normal is valuable to dynamic. The portrayal for Naive Bayes is probabilities. It deals with Bayes hypothesis of likelihood to foresee the class of obscure informational index. A rundown of probabilities is put away to petition for a learned gullible Bayes model. This incorporates: • Class Likelihoods: The probabilities of each class in the preparation dataset. • Conditional Likelihoods: The contingent probabilities of each info esteem given each class esteem.

Pseudo Code

Learning Phase: Learning a naive Bayes model from your training data is fast. Given a training set S and F features and L classes, For each target value of $c_i(c_i = c_1, \ldots, c_1)$

P(C_i) ← estimation P(C_i) with examples in S;

For all feature value X_{jk} of each feature X_i (j= 1,……F; K=1,….., N_j)

P($X_j = X_{jk}| C_i$) ← estimate P($X_{jk}| C_i$) with examples in S;

Output: F*L condition probabilistic models

Testing Phase: Training is fast because only the probability of each class and the probability of each class given different input (X) values need to be calculated. Given an unknown instance X' =(a' 1,….., a'_n)

Look up tables to assign the label c* to X' if

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$[P(a'_1|\ C^*)\ldots\ldots P(a'_n|C^*)>[P(a'_n|\ C_i)]\ p(C_i),\ C_1 = C_1,\ldots\ldots, C_1.$

2.3 Support Vector Machine

A Support Vector Machine (SVM) is a directed AI calculation utilized for arrangement reason. SVMs have been widely investigated in the information mining and AI field and applied to applications in different spaces. SVMs are all the more normally utilized in grouping issues. Two exceptional properties of SVMs are that SVMs accomplish (1) high speculation by augmenting the edge and (2) support an effective learning of nonlinear capacities by part stunt.

SVM Classification

The essential strategy for SVMs is a twofold classifier where the yield of refined undertaking is either obvious or bogus. Twofold SVMs are classifiers which recognize information points of two classes. Every information focuses is addressed by a n-dimensional vector. A straight classifier for the most part isolates the two classes with a hyper plane, there are numerous direct classifiers that accurately arrange the two gatherings of information. In course to achieve outrageous partition between the two classes, SVM picks the hyper plane which has the greatest limit. The limit is the summation of the briefest separation from the isolating hyper plane to the closest information point of the two classes. A particularly hyper plane is feasible to improve on well, ramifications that the hyper plane appropriately sorts "undetectable" or testing information focuses.

Pseudo Code

Algorithm 1 Pseudo-code of SVM algorithm

Inputs: *Determine the various training and test data.*

Outputs: *Determine the calculated accuracy.*

Select the optimal value of cost and gamma for SVM.

While*(stopping condition is not met)* ***do***

Implement SVM train step for each data point

Implement SVM classify for testing data points.

end while

Return *accuracy*

3. PROPOSED METHODOLOGY

3.1 Fruits Data Set Preparation

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To set up the organic products informational index the pictures were gotten by shooting the organic products while they are turned by an engine and afterward removing outlines. A short film of 20 seconds was recorded by planting the natural products in the shaft of a low speed engine (3 rpm) by putting a white piece of paper as foundation. At that point organic product picture was downsized to 100x100 pixels.

Figure 1: Banana Image

The below figures are some of the example of the defected fruits.

(a) Mango	(b) Apple	(c) Guava	(d) Orange

Figure 2: Disease affected Fruits

The primary parameters that play vital role while classifying a fruit include the machine learning algorithm that is being used, quality of images in the fruit database, fruit's images' shape and size and fruit's color. Secondary parameters that affect the classification are similar characters of fruits like color, shape, size, etc. If both primary and secondary parameters are not analyzed properly in the beginning then it may cause problem during classification and may lead to less accuracy and unexpected results. Many related works have been conducted in fruit classification using different classification algorithms but those approaches still lack in some aspects. A research in fruit classification has been carried out by just taking only three fruits into consideration with 100% accuracy. However, considering only three fruit in the sample is not enough because the trained model

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may not recognize the fruit's images' that are out of the training sample. Similarly, proper implementation of machine learning algorithm should also be taken into consideration while performing classification.

A data mining tool named Weka 3.6.11 was used for the experiment. Additionally, multilayer perceptron neural network (MLPNN) with backpropagation (BP) was used as the training algorithm.

3.2 Multilayer Perceptron Neural Network (MLPNN)

It was introduced by Frank Rosenblatt in 1958 based on the model of Mc-Culloch & Pitts and the error correction learning rule. His intention was to illustrate some fundamental properties of intelligent systems in general, without going into further details regarding specific and unknown conditions for specific biological organisms. The first Perceptron model was developed in a biological environment mimicking how the human eye works, hence its name perceptron. In this type of neural networks, the number of inputs is discrete and the activation function for each neuron corresponds to a step type.

MLPNN is one of the most significant models in artificial neural network. The MLPNN consists of one input layer, one or more hidden layers and one output layer. In MLPNN, the input nodes pass values to the first hidden layer, and then nodes of first hidden layer pass values to the second and so on till producing outputs as shown in Figure 3.

One of the most common Neural Networks is Multiple Layer Perceptron Neural Network (MLPNN). The architecture of MLPNN may contain two or more layers. Input layer is the first layer which its number of neurons is equal to the number of selected specific features. Output layer is the last layer which determines the desired output classes. The number of neuron in the output layer depends on the number of desired classes and design. The intermediate layers may be added to increase the ability of MLPNN mostly useful for nonlinear systems. Although each MLPNN could include multiple hidden layers, it is typical to use just one hidden layer with a try and-error based number of neurons. Unlike the input and output layers, we have no prior knowledge of the number of neurons needed in the hidden layer. Large number of neurons in the hidden layer would definitely increase the computational complexity and the processing time, however, small amount would increase the classification errors. Therefore, determining the appropriate number of neurons in the hidden layer is one of the most critical tasks in a neural network design.

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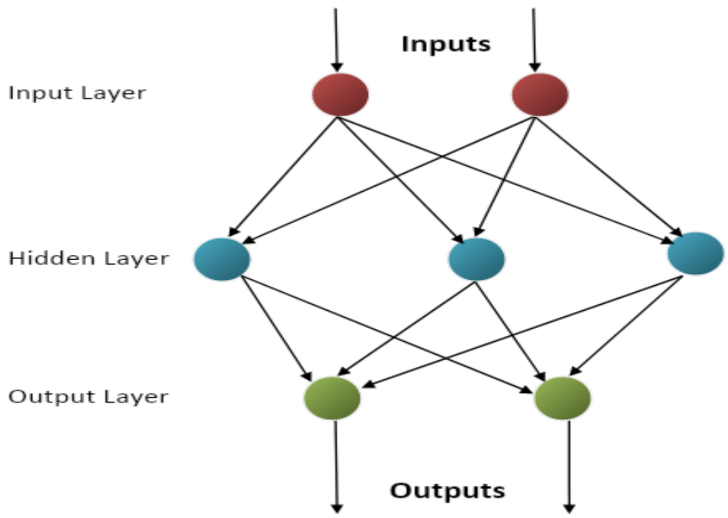

Figure 3. Multi Layer Perceptron Neural Network

Algorithm MLPNN
Data: *The existence of a W arrangement representing ANN.*
Result: *Neural network trained with the data from the training examples;*
Neurons = W.size() //The size of the arrangement that represents the neural network is obtained;
for *i = 0; i< neurons; i++* ***do***
W[i] = *random(−1,1) //Each neuron is covered and is started with a random number between −1 and 1;*
end *i< neurons; i++ do*
bias = 0.5// Approximation to the obtained output;
inputs = readInputs() //Reading of the inputs used for the training;
Outputs = readOutputs() //Storing of the size of training examples;
Size = inputs.size() // storing of the size of the training examples;
for i= 0; i< size; i++ ***do***
Sum = 0;
for *j = 0; j < neurons; j++* ***do***
*Sum = Sum + W[j] * inputs[i] [j] // The ANN output is calculated for each one of the outputs;*
end
output = hardlims (Sum + bias) //The output is approximated using hardlims;
if *output ! = outputs[i]* ***then***
error = *output[i] –output // The ANN output error is calculated with respect to the expected output, in case they are different;*
for *j = 0; j <neurons ; j++* ***do***
*W[j]= W[j] + inputs[i][j]*e //each neuron is corrected and its weights corrected with respect to the calculated error;*
end
bias = 0.5+ error// Correction of approximation
end

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end

3.3 Back Propagation Neural network

The BP algorithm has filled in as a helpful philosophy to prepare multi-facet Perceptron for a wide scope of utilizations. The BP network computes the distinction among genuine and anticipated qualities, which is circled from yield hubs in reverse to hubs in past layer. The Back-propagation neural network can be separated into two stages, engendering and weight update.

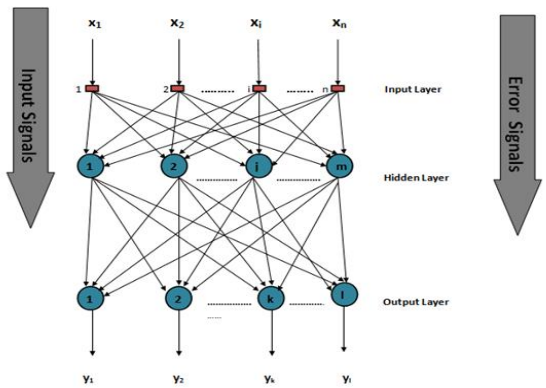

Fig. 2 Back-propagation neural network

In a Back-propagation neural network, the learning calculation has two stages. Initial, a preparation input design is introduced to the organization input layer. The organization spreads the information design from one layer to another until the yield design is produced by the yield layer.

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$$x_{i,j}^{l} = \sum_{m}\sum_{n} w_{m,n}^{l} o_{i+m,j+n}^{l-1} + b_{i,j}^{l}$$

$$o_{i,j}^{l} = f(x_{i,j}^{l})$$

$$\delta_{i,j}^{l} = \frac{\partial E}{\partial x_{i,j}^{l}}$$

$$\frac{\partial E}{\partial x_{i',j'}^{l}} = \sum_{m=0}^{k_1-1}\sum_{n=0}^{k_2-1} \delta_{i'-m,j'-n}^{l+1} w_{m,n}^{l+1} f'\left(x_{i',j'}^{l}\right)$$

$$\frac{\partial E}{\partial w_{m',n'}^{l}} = \sum_{i=0}^{H-k_1}\sum_{j=0}^{W-k_2} \delta_{i,j}^{l} o_{i+m',j+n'}^{l-1}$$

Notation

To help us explore the forward and backpropagation, we shall make use of the following notation:

1. l is the l^{th} layer where $l = 1$ is the first layer and $l = L$ is the last layer.
2. Input x is of dimension $H \times W$ and has i by j as the iterators
3. Filter or kernel w is of dimension $k_1 \times k_2$ has m by n as the iterators
4. $w_{m,n}^{l}$ is the weight matrix connecting neurons of layer l with neurons of layer $l-1$.
5. b^{l} is the bias unit at layer l.
6. $x_{i,j}^{l}$ is the convolved input vector at layer l plus the bias represented as

$$x_{i,j}^{l} = \sum_{m}\sum_{n} w_{m,n}^{l} o_{i+m,j+n}^{l-1} + b^{l}$$

7. $o_{i,j}^{l}$ is the output vector at layer l given by

$$o_{i,j}^{l} = f(x_{i,j}^{l})$$

8. $f(\cdot)$ is the activation function. Application of the activation layer to the convolved input vector at layer l is given by $f(x_{i,j}^{l})$

On the off chance that this example is unique in relation to the ideal yield, a mistake is determined and afterward engendered in reverse through the organization from the yield layer to the information layer. The loads are changed as the blunder is engendered. As per the Richard P. Lippmann, he addresses step of the back-

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proliferation preparing calculation and clarification. The back-spread preparing calculation is an iterative slope intended to limit the mean square mistake between the real yield of multi-facet feed forward Perceptron and the ideal yield. It requires consistent differentiable non-linearity. The accompanying accepts a sigmoid calculated nonlinearity.

Step 1: *Initialize loads and balances*

Set all loads and hub balance to little arbitrary qualities.

Step 2: *Present input and desired outputs*

Present a nonstop esteemed information vector $X_{0,}X_{1,}\ldots\ldots\ldots X_{N-1}$ *and specify the desired output* $d_{0,}d_{1,}\ldots..d_{M-1}$. *In the event that the net is utilized as a classifier them all ideal yields are normally set to zero except for that relating to the class the info is from. That ideal yield is 1. The information could be new on every preliminary or tests from a preparation set could be introduced consistently until balance out.*

Step 3: *Calculate Actual Output*

Utilize the sigmoid non linearity from a higher place and equations to figure output y0, y1…..YM-1

Step 4: *Adapt loads*

Utilize a recursive calculation beginning at the yield hubs and working back to the primary secret layer by $W_{ij}(t+1) = W_{ij}(t) + n\delta_j X_i$ *(3)*

n this condition Wig(t) is the load from covered up hub I or from a contribution to hub j at time t, is either the yield of hub I or is an info, ℵ is an addition term, and δ_j, is a blunder term for hub j, on the off chance that hub j is a yield hub,

$\delta_j = y_j (1- y_j (1 - y_j)(d_j - y_j)$ *(4)*

Where d_j *is the desired output of node j and* y_j *is the actual output.*

If node j is an internal hidden node, then

$\delta_j = x_j (1 - x_j) \sum_k \delta_j^m W_{jk}$ *(5)*

Where k is over all nodes in the layers above node j.

Inner hub edges are adjusted likewise by expecting they are association loads on joins from helper steady esteemed data sources. Union is once in a while quicker if a force term is added and weight change are smoothened by

$w_{ij}(t+1) = w_{ij}(t) + n\,\delta_j x_i + \alpha(W_{ij}(t) - W_{ij}(t-1))$, *where* $0<\alpha < 1$ *(6)*

$\delta_j = y_j(1 - y_j) (d_j - y_j)$ *()*

Step 5: *Repeat by going to step 2*

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To begin with, this learning calculation gives preparing information to the organization and thinks about the real and wanted yields. At that point, it ascertains the blunder in every neuron. In view of this, the calculation computes what yield ought to be for every neuron and how much sequential yield should be adapted to want yield lastly changes the loads. The general interaction is done to improve loads during handling.

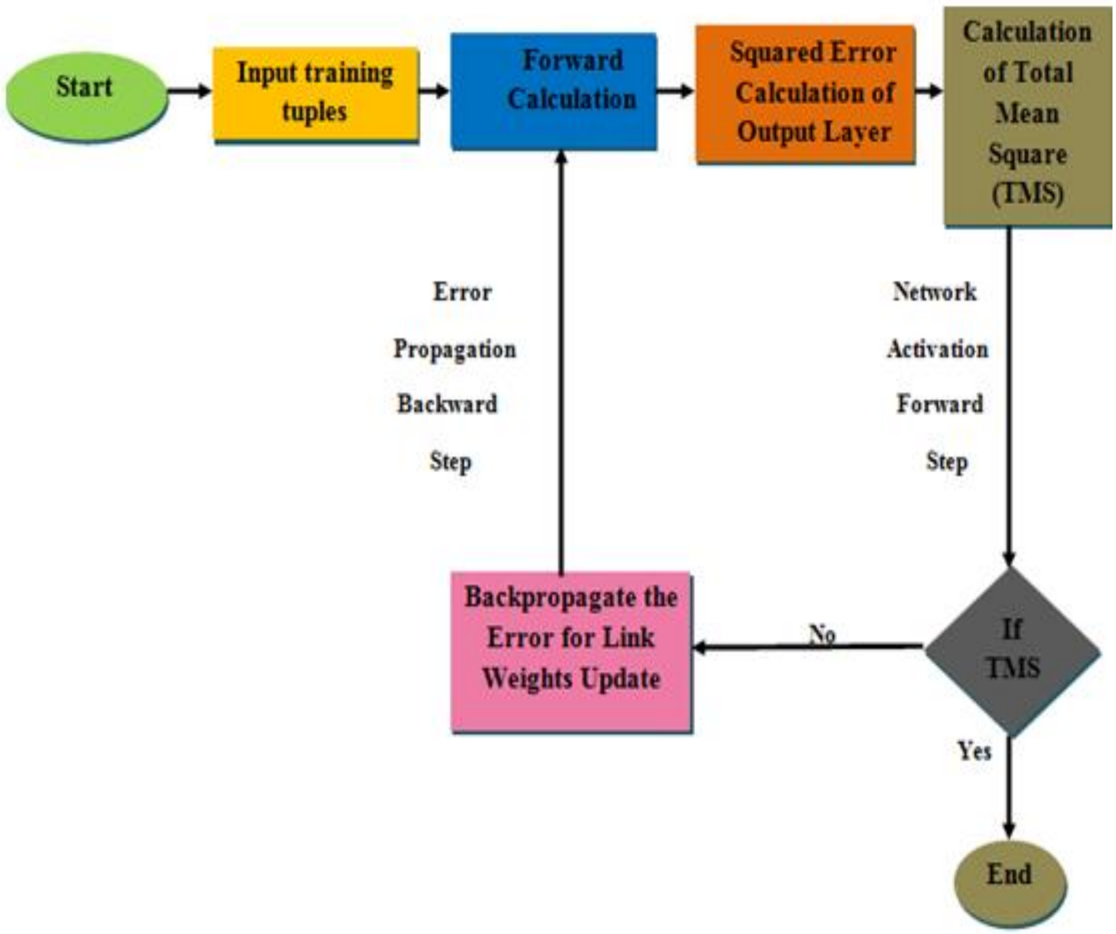

Figure 5: Working procedure of MLPNN using BP algorithm

A disarray network contains data about genuine and anticipated orders done by an arrangement framework. The information in the grid are assessed to know the presentation of such frameworks.

The confusion matrix contains the accompanying four passages:

- TP (genuine positive): The quantity of records delegated valid while they were in actually true.
- FP (bogus positive): The quantity of records named valid while they were in actually false.
- FN (bogus negative): The quantity of records delegated bogus while they were in actually true.
- TN (genuine negative): The quantity of records named bogus while they were in actually false.

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4. Experimental Result

1. Sensitivity

$$\boldsymbol{SENSITIVITY} = \frac{\boldsymbol{TRUE\ POSITIVE}}{\boldsymbol{TRUE\ POSITIVE + FALSE\ POSITIVE}} \ldots \ldots \ldots \ldots \textbf{(10)}$$

	KNN (%)	NB (%)	EBTNN (%)
TP	75.4	78.4	80.3
TN	83.1	85.3	90.1
FP	87.2	90.6	95.7
FN	92.4	94.5	97.5

Table 1.Sensitivity

The Comparison table 1 of Sensitivity Values explains the different values of existing algorithms and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN). While comparing the Existing algorithm and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN), provides the better results. The existing algorithm values start from 75.4 to 92.4, 78.4 to 94.5 and proposed back propagation algorithm values starts from 80.3 to 97.5. So the proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) provides the great results.

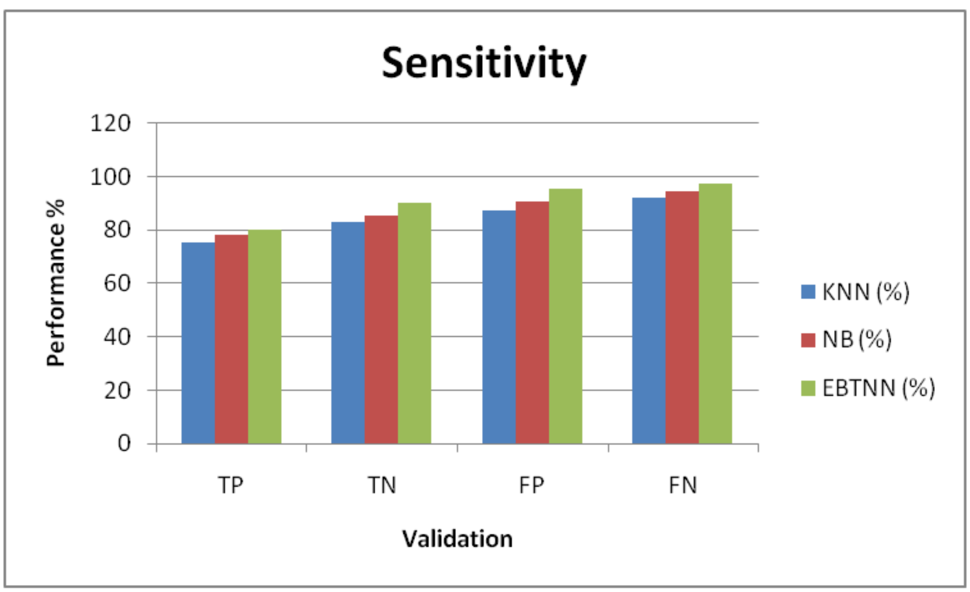

Figure 6.Comparison of Sensitivity Chart

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The Figure 6 Shows the comparison chart of Sensitivity demonstrates the existing1, existing 2 and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) values. X axis denote the Validation of the Algorithm and y axis denotes the performance values in Sensitivity. The proposed values are better than the existing algorithm. The existing algorithm values from 75.4 to 92.4, 78.4 to 94.5 and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) values starts from 80.3 to 97.5. So the proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) provides the great results.

2. Specificity

$$\boldsymbol{SPECIFICITY = \frac{TRUE\ NAGATIVE}{TRUE\ FALSE+FALSE\ POSITIVE}} \dots\dots\dots\dots(11)$$

	KNN (%)	NB (%)	EBTNN (%)
TP	51.2	54.4	65.8
TN	70.6	79.3	80.2
FP	53.2	63.9	84.4
FN	89.4	76.5	94.7

Table 2.Specificity

The Comparison table 2 of Specificity Values explains the different values of existing algorithms and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN). While comparing the Existing algorithm and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN), provides the better results. The existing algorithm values start from 51.2 to89.4, 54.4 to 76.5 and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) values starts from 65.8 to 94.7. So the proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) provides the great results.

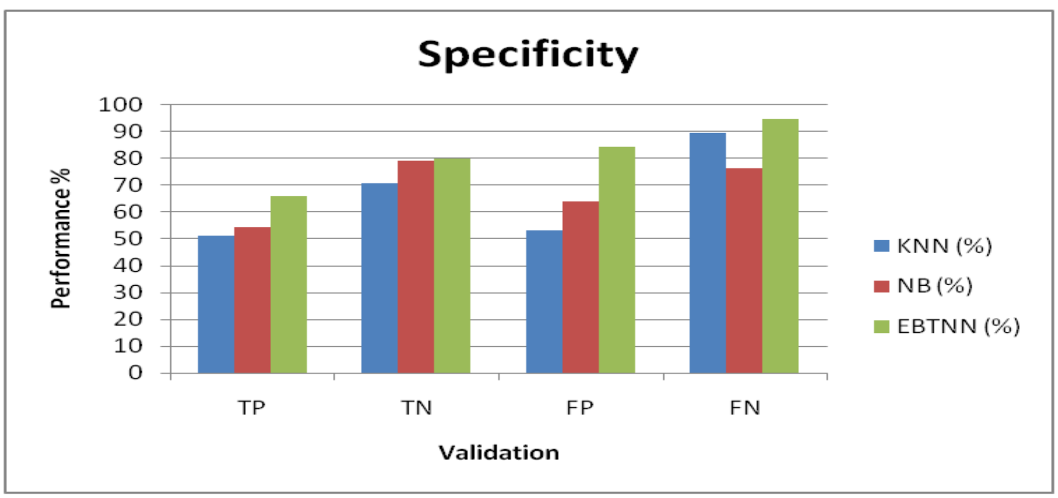

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Figure 7.Comparision of Specificity chart

The Figure 7 Shows the comparison chart of Specificity demonstrates the existing1, existing 2 and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) values. X axis denote the Validation of the Algorithm and y axis denotes the performance values in Specificity. The proposed values are better than the existing algorithm. The existing algorithm values from51.2 to 89.4, 54.4 to 76.5 and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) values starts from 65.8 to 94.7. So the proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) provides the great results.

3. Accuracy

$$ACCURACY = \frac{TRUE\ NEGATIVE + TRUE\ POSITIVE}{TRUE\ NEGATIVE + TRUE\ POSITIVE + FALSE\ POSITIVE + TRUE\ POSITIVE} \ldots\ldots\ldots(12)$$

	KNN (%)	NB (%)	EBTNN (%)
TP	76.4	79.4	81.3
TN	84.1	86.3	89.9
FP	90.7	90.6	93.1
FN	94.2	96.4	97.6

Table 3. Accuracy

The Comparison table 3 of Accuracy Values explains the different values of existing algorithms and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN). While comparing the Existing algorithm and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN), provides the better results. The existing algorithm values start from 76.4 to 94.2, 79.4 to 96.4 and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) values starts from 81.3 to 97.6. So the proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) provides the great results.

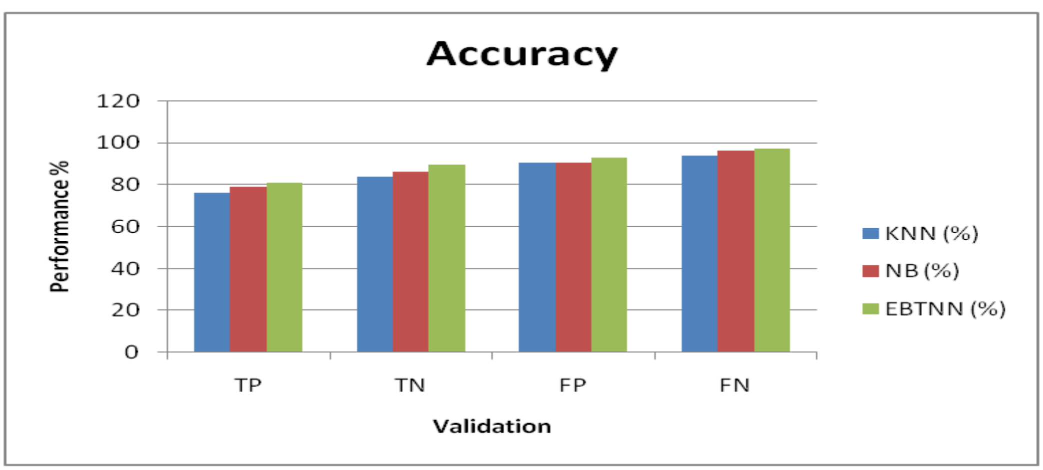

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Figure 8.Comparison of Accuracy chart

The Figure 8 Shows the comparison chart of Accuracy demonstrates the existing1, existing 2 and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) values. X axis denote the Validation of the Algorithm and y axis denotes the performance values in Accuracy. The proposed values are better than the existing algorithm. The existing algorithm values from 76.4 to 94.2, 79.4 to 96.4 and proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) values starts from 81.3 to 97.6. So the proposed Enhanced Back Propagation Neural Network Algorithm (EBPNN) provides the great results.

Conclusion

The convenient finding of organic product sicknesses is fundamental to lessen creation misfortune and nuisance the board. Natural product sickness recognition has been an intense errand to accomplish utilizing PCs. A wide range of types of organic product will require the model to perceive the kind of natural products expanding the calculation cost. In this paper we proposed Enhanced Back Propagation Neural Network to recognize the sickness on the natural products dataset. Rather making separate models permits the model to get explicit and increment precision in one area, this will by and large permit better outcomes. Our exploratory outcomes express that the proposed arrangement can fundamentally uphold precise location and programmed distinguishing proof of natural product infections.

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