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Back-Propagation Neural Network (BP-NN) model for the detection of borer pest attack

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Abstract: The multi-disciplinary agri-technologies domain have paved a way to the big data technologies, through Machine learning. Pest management is one of the most important problems facing farmers. A normal human monitoring cannot accurately predict the amount and intense of pests attacked. The issue of plant pests and diseases detection of agriculture has been tackled using the various available Neural Network (NN) techniques to process spectral data. In this manuscript, authors have presented a Back propagation Neural Network (BP-NN) model, which was developed on data of the reflectance spectra (in range of 400 to 900 nm) cashew trees leaves infested with a borer pest attack as well as good leaves spectra. With the help of BP-NN model the classification accuracy was found to be 85% which is quite good. However, the accuracy of the model needs to be improved with better training algorithm and larger dataset.

Keywords: Cashew Stem and Root Borer, Back-Propagation Neural Network (BP-NN), Machine Learning, pest detection, Principal Component Analysis (PCA)

1. Introduction

The agricultural sciences undoubtedly have undergone transformational changes with the usage of Information and Computation Technologies (ICT). The booming domain of machine learning (ML) techniques [1-3] have been applied to the phenotyping of plant stress (biotic and abiotic) through identification, classification, quantification, and prediction. One such ML technique that has carved a niche for the biotic stress of the plant disease detection, is Neural Networks (NN). With regards to processing the spectral data, several studies [4] have utilized the NN that use different algorithms through their techniques, structural variety and classifiers. As for disease detection and diagnosis, the combination of NN-spectral approach is commenced as a robust tool.

In this paper, we focus on biotic stress caused by a borer pest to commercial crops of cashews and mangoes. The Cashew Stem and Root Borer (CSRB) *Plocaederus ferrugineus* is one such pest, that is evidently known to infest the crucial trunk regions and leads to the gradual death of yielding plantations [5]. The pest is invisible during day-time and causes sporadic type of damage. The pest density of CSRB increases over the years, resulting in significant loss of tree population. Thus, the cashew produce in a given region gets reduced over the years. Upon wide-spread proliferation, there is significant loss in nut yield causing distress to the farmers. The main issue with the detection is that, there is no indication on leaves (as shown in Fig. 1), until the boring of the trunk by the borer turns the tree dead.



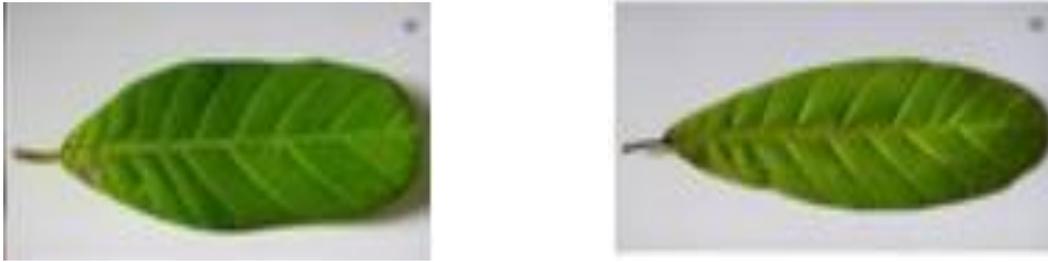


Fig. 1: photographs of the leaf samples for study categories: healthy condition and infested end.

Even worldwide, there is threat to different other trees like pines from borer pests [6-8].

2. History

As per literatures, the detection of borers based on tracking of the symptoms, have resorted to two main technologies: 1) satellite imagery [9, 10] and 2) Image processing [11-18]. Analogously, some studies have been done to trace the flying pest insects, itself [19, 22].

The works of detection CSRB is being ventured using Embedded Systems (through initial analysis via Spectroscopy of the leaves and bark samples) [20]. Also, an image processing technique to develop an RGB model was employed [21], having target on leaves portion of trees, for the early detection of CSRB, although not fruitful.

The different Neural Network (NN) techniques available are Single-Layer Perceptron (SLP), Multi-Layer Perception (MLP) [35,36], Radial-Basis Function (RBF) networks, Learning Vector Quantization(LVQ), Kohonen's Self-Organising Map(SOM) networks, Convolutional Neural Network (CNN) and Probabilistic Neural Network (PNN). These have been exerted thoroughly as per a review [4], for the specific application of plant diseasedetection.

Another review highlights the significance of using PCA, along with ANN, and enlists myriad related works [32]. It also brings out various pre-processing techniques pertaining to spectral data.

3. Methodology

In order to develop a BB-NN model of MLP type, for detecting the existence of borer infestation in early stage, we have followed the procedure formed around pre-processing of data, PCA and ANN. The executed steps are presented using of a flowchart of Fig.3 and implemented using MATLAB 2019b.

Dataacquisition

On-site data was collected in mid-winters of 2018. Altogether 20 trees were selected, 5 each in category of healthy, and infestations - initial, middle and end. A thorough field survey was conducted to recognize individual category, by noticing of dry, boring dust, which had been burrowed out of the bark surfaces during the tunnelling by borer.

Leaves were picked off from the pointed out trees and secured into clean, sanitized and labelled zip-locked bag. All bags were placed in a container of frozen ice-packs so as to deter any effect of temperature rise on the biochemical properties of the leaves, during the day progress while transportation. On arrival at the experimentation location, all the leaves were expunged any water drops and dust, by using clean cotton before beginning the spectra recording.

For every leaf, in each of the categories: Healthy, Infested Start, Infested Middle and Infested End, the database was obtained for reflectance spectra of all of 20 samples, as shown in Fig. 2.

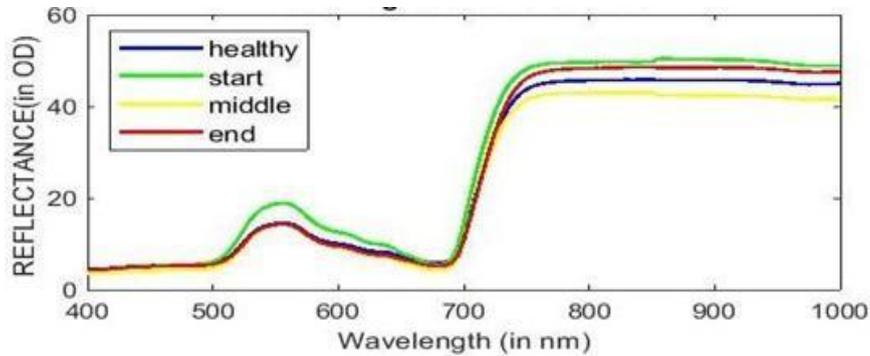


Fig. 2: Reflectance spectra of all of 20 samples, for each of the categories: Healthy, Infested Start, Infested Middle and Infested End.

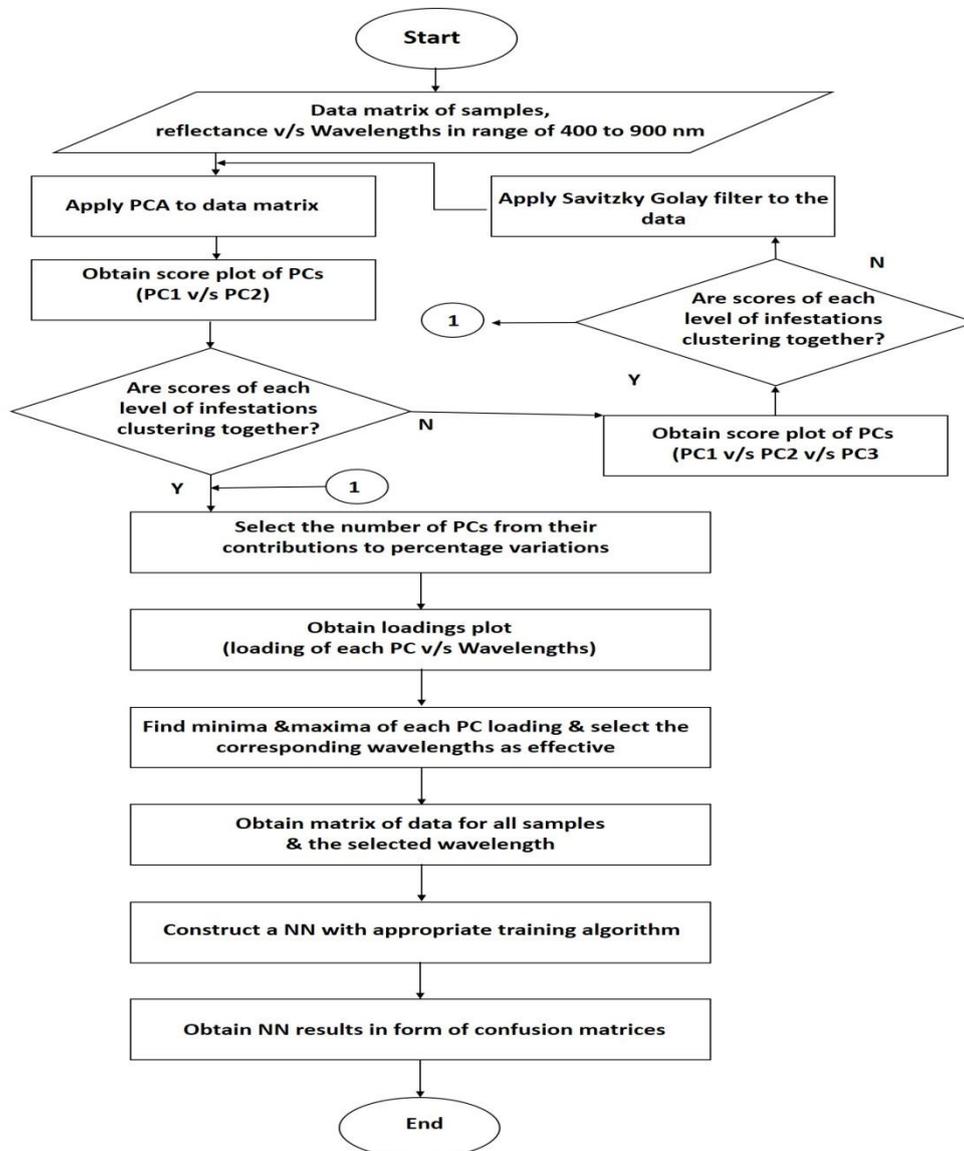


Fig. 3: Flowchart of the method for developing a Machine Learning model for the detection of borer pest attack. PC→Principal Component; NN→Neural Network.

Dataprocessing

The Leaf reflectance being the spectral information data of hundreds of wavelengths for various observations or samples, is bound to information redundancy [30] and multiple collinear variables [30]. Hence, the entire spectra would lead to the complexity of the model, decrease the computation speed, and hamper the model accuracy.

Also, for the purpose of a statistically perfect prediction model with input of leaf reflectance, a huge number of observations would be required, given the existence of large number of wavelengths as inputs to the model. It is an issue particularly with the spectral data, wherein the number of variables is larger than the number of observations. This rules out the possibility of using standard linear multivariate techniques (LMVR) based on the least square criterion, as the solution will not be unique. Moreover, increasing the number of observations (above the number of variables) will not always solve the problem. This is due to the so-called near-multicollinearity which means that some variables can be written approximately as linear functions of other variables. This problem is often found among spectral measurements. Even if the solution will be mathematically unique, it may be unstable and lead to poor prediction performances.

Certainly, it is important to figure out the effective wavelengths (EWs) out of the numerous recorded data. Identification of EWs those are most responsive to plant disease rating, contribute greatly in modelling.

Principal component analysis (PCA) is an unsupervised technique and has a wide application in reducing the dimension of multivariate datasets by removal of linearly correlated or quasi-linearly correlated variables.

Dimensionreduction

Dimension reduction is a phenomenon of extracting the most effective subset of the original features to use in the classification process that should yield higher classification accuracy. In this study, Principle Component Analysis (PCA) was applied as the dimension reduction technique as it is the most utilized means in spectral signal processing. PCA is a linear transformation technique that aims to find a new set of orthogonal axis (principle components) for the input space given by spectral readings.

Consequently, the score plot of principal components (PCs) [21-25, 29, 34] is employed to divulge the features of the variable distribution. Alongside, the loadings plot of PCs brings out the significance of different variables. Principally, the loadings of the first few PCs are used for optimal wavelength selection.

From the score plot of original reflectance data (raw data) in Fig 4(b), it is seen that scores dots corresponding levels of infestations are not found to be clustering together, thus the original data cannot be used to classify the infestation severity. Hence, there is need to apply a suitable pre-processing for the data [26], accordingly Savitzky–Golay smoothing [27, 32, 37] (which is known to remove any sensor noise [28]) was used. As a result, Fig 4(a), it is seen that scores dots corresponding levels of infestations are clustering together. The scores of Healthy cases are grouped as one, and clearly distinct from end cases over the PC1 axis, whereas the start and middle cases are occurring as stretch, however are separable over PC2 axis.

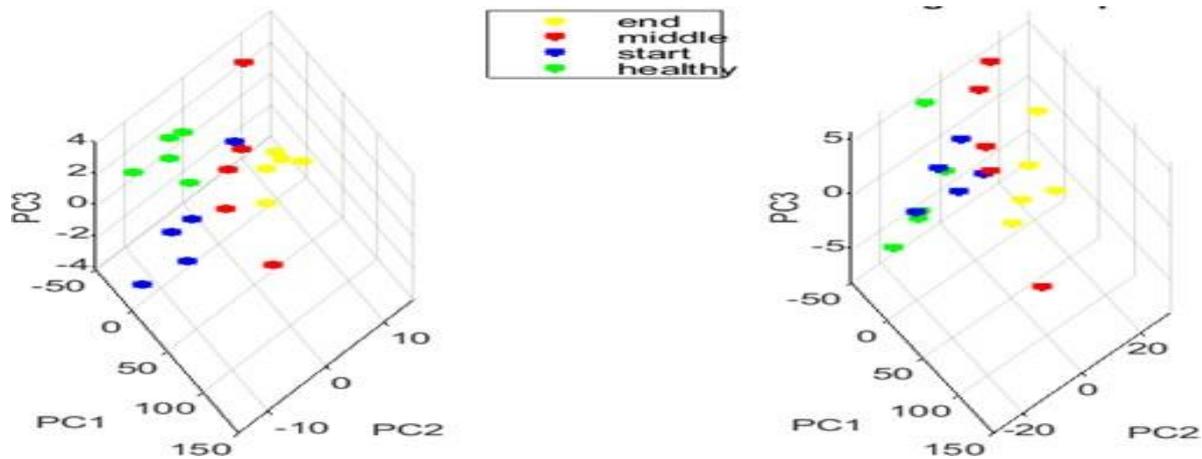


Fig. 4: (a) Score plot of levels of infestations, upon pre-processing by Savitzky–Golay smoothing to raw data; (b) scores plot of levels of infestations of raw data.

Selection of Effective Wavelengths [30]

PCA was utilized to perceive various pertinent wavelengths within 400–900 nm that could eliminate complexities out of the model structure [30] and enhance model accuracy [30]. A total of 99.28% of variation being retained in the first four principal components (PCs), and they had 85.03%, 13.87%, 0.70% and 0.20% of the total variances respectively. Hence, first four PCs were selected. Since each PC score is a linear combination by each spectral point multiplied by the corresponding loading, the wavelengths corresponding to local maximal values (peaks) or minimal values (valleys) of the loadings curve have a more important contribution to the PC score [29-31, 34]. Therefore, the loadings functions of the first four PCs were brought under focus to selecting the EWs. As shown in Figure 5, the loadings at the identified local peaks and valleys were regarded as characteristic loadings and the corresponding wavelengths were considered as key wavelengths for the NN model.

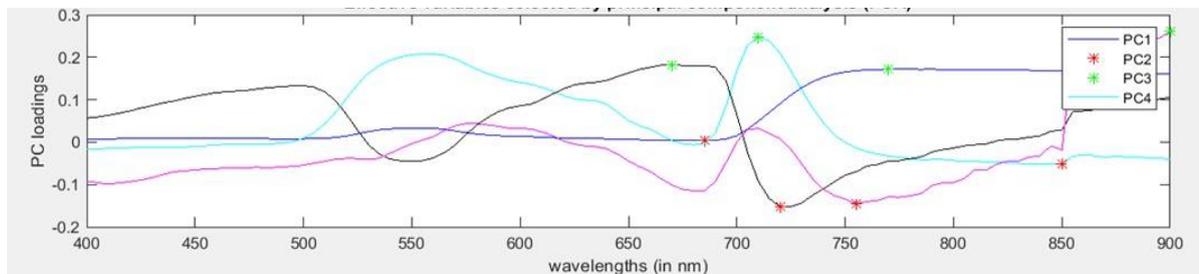


Fig. 5: PC loadings of first 4 components of the PCA, with indication of minima and maxima of each.

Thus, eight effective wavelengths of 670, 685, 710, 720, 755, 770, 850, 900 nm were ideally selected and indicated by an asterisk. The amount of selection comes out to be 8.61% of the total 121 variables of the entire spectra.

Summary

The model is trained to predict the health condition of tree. The model is trained with samples spectral data, containing predictive information i.e. the wavelengths values (EWs), and each tree is labelled with a flag or target of the category of health condition; stating whether the infestation is developed or not. We created a target matrix of dimensions $m \times n$ (where m =number of targets i.e. categories and n =number of samples) is prepared consisting of 0s and 1s. Thus, each row corresponds to health condition of tree and the 1s are placed for those cells against the those samples of that category, and 0s in remaining cells. The input matrix is $o \times n$ (where o =number of EWs and n =number of samples).

Thus two matrices of input data and target was given to Back-Propagation Neural Network for classification.

Following are the specifications of the model architecture:-

- Back-Propagation MLP Neural Network trained with scaled conjugate gradient algorithm. Scaled conjugate gradient algorithm [38] can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance with respect to the weight and bias variables X. The scaled conjugate gradient algorithm is based on conjugate directions, as in Conjugate Gradient with Powell/Beale Restarts, Fletcher-Powell Conjugate Gradient, Polak-Ribière Conjugate Gradient, but this algorithm does not perform a line search at each iteration. Training stops when any of these conditions occurs: The maximum number of epochs (repetitions) is reached, The maximum amount of time is exceeded, Performance is minimized to the goal, The performance gradient falls below min_grad, or Validation performance has increased more than max_fail times since the last time it decreased (when using validation).
- Input: spectra of 20 samples consisting of 8 wavelengths(variables)
- Number neurons of hidden layer:10
- Output: 4 stages or levels of infestations.

The selected data was divided into three sets, one each for training, testing and validation. The NN results of the model were obtained in form of confusion matrices.

4. Results & Discussion

Application of PCA on the dataset is found to be highly nifty, from the score plot (Fig. 4) and loadings plot (Fig. 5).

From Fig.4, it is evident that, Pre-processing using Savitzky-Golay is beneficial in distinguishing healthy and End Infestation cases thoroughly. Also the start and middle stage of Infestation was separable from the former two (however not well from each other on PC1 axis).

We have confusion matrices (for each of datasets, and total data), with each column as the target class i.e.health condition of a tree. Thus, x-axis is denoting actual healthy category. And, each row is output class i.e. the predicted value, and y-axis is denoting predicted healthy category. The sequence of advances of infestation, i.e. healthy to start, middle and end stage of infestation, along x-axis is Left to Right, and along y-axis is Top to Down.

It is known that, a Confusion Matrix [33] is a table organizing the four values; True Positive, True Negative, False Positive and False Negative. When evaluating the performance of a classification model, two terms are crucial, the real outcome (usually called 'y') and the predicted outcome (usually called 'ŷ'). Each prediction from the model can be one of four types with regard to performance: True Positive, True Negative, False Positive or False Negative [33].

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Fig. 6: Example of a confusion matrix for two-class classification. Source: Eugenio Zuccarelli

A confusion matrix for two-class classification as shown in Fig. 6, depicts four key terms: True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN). They are True Positive (TP) [33]: a sample is predicted to be positive ($\hat{y}=1$, e.g. the tree is predicted to belong to a particular health category), whereas its label is actually positive ($y=1$, e.g. the tree is actually

belonging to a health category). False Positive (FP)[33]: a sample is predicted to be positive ($\hat{y}=1$, e.g. the tree is predicted to belong to a particular health category), whereas its label is actually negative ($y=0$, e.g. the tree is actually not belonging to a particular health category). In this case, the sample is “falsely” predicted as positive. False Negative (FN) [33]: a sample is predicted to be negative ($\hat{y}=0$, e.g. the tree is predicted not to belong to a particular health category) and its label is actually positive ($y=1$, e.g. the tree is actually belonging to a particular health category). In this case, the sample is “falsely” predicted as negative. True Negative (TN) [33]: a sample is predicted to be negative ($\hat{y}=0$, e.g. the tree is predicted to belong to various other health category), whereas its label is actually negative ($y=0$, e.g. the tree is actually not belonging to the same other health category).

Since the model is a multi-class, the TN and TP all together does more meaningful as diagonal of a given matrix, which has green colored cells for correct predictions of a particular health category.

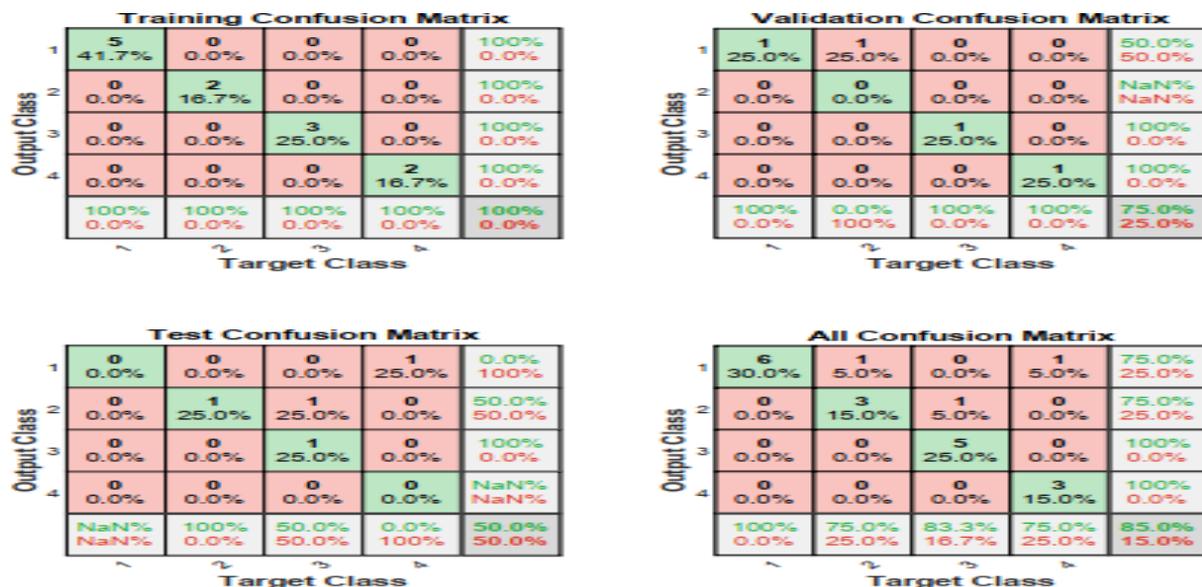


Fig.7: Confusion matrices for training, testing, validation and total data of reflectance spectra of CSR infestation.

The red colored cells are wrongly classified cells.

The percentages in last row and last column are computed for data of individual row and column. The percentages in diagonal green coloured cells are their respective percentages of the cell value (samples) to the total value (samples). Eventually, the percentages in red colored font are the subtractions of their green colored counterparts from 100%.

From Fig.7, the correct classification accuracy at the total confusion matrix for the developed NN model was found to be 85%.

5. Conclusion

The results obtained with a Back-Propagation Neural Network trained with scaled conjugate gradient algorithm, was useful only to fairly classify the levels of infestations with not so impressive accuracy.

For all the wrongly predicted values (red coloured cells, certainly with the non-zero values) of a particular target class have found to fall under output class(es) which is/are previous stages of health category. And never ever, predicted value has fallen under any of stage(s) which are in successions. This point is to be noticed deeply. It means that, a tree which is in certain health condition is predicted to belong to a surpassed health condition(s), by the model. It is a giving a verdict, which is a past thing.

On the contrary, a reverse scenario would be more useful, even if the model is not 100% accurate. A health condition which is yet to be faced by tree (in event of CSRB infestation), if predicted a-priori (although a wrong prediction), would merely call for appropriate treatment procedures. Thus, the (actually unnecessary) correctives measures should not be an issue, compared to the case that tree has reached a further infestation case, but predicted as early infested (or to the bad-luck) healthy.

Hence, to overcome the shortcomings of lesser accuracy and flawed precision, the solution lies in opting for a better training algorithm and a larger abundant dataset.

Future scope

Since the symptoms of the cashew stem and root borer have a location on the trunk of the infestation tree as well, thus the detection of pest should have a capability to track the same. A combination on trunk analysis and leaves analysis would be enhancing and completing the detection in totality.

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