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Application of Hyperspectral Remote Sensing Technology for Plant Disease Forecasting: An Applied Review

Priyadharshini Bhupathi[1*], Prabu Sevugan[2]

[1*]VIT School of Agricultural Innovations and Advanced Learning, Vellore Institute of Technology Vellore, Tamil Nadu, India. E-mail: priyadharshini.b@vit.ac.in

[2]School of Computer Science and Engineering, Vellore Institute of Technology Vellore, Tamil Nadu, India. E-mail: sprabu@vit.ac.in

ABSTRACT

Each plant has distinct behaviour, features, and infections known as pathogens. Plant growth and its life have to be estimated to prevent economic loss in agriculture. Many techniques such as optical techniques, knowledge graph, image processing techniques, remote sensing techniques, DNA based, and serological methods are used to detect the plant diseases from the captured input in the form of images, video frames, and set of characteristics features. Health conditions of a plant are to be recognized accurately in time to avoid disease spread severity. Remote sensing techniques with different types of sensors exemplify extraordinary means which are most helpful to monitor and identify the plant diseases, preventing expensive use of pesticides. Disease forecasting aims to organize control measures before the substance of a plant is likely to infect the crop. A survey on plant disease detection and the applications of remote sensing technology in forecasting the pathogens is presented in this article. Thus it is very significant to predict the diseases by an effective disease warning system that should be reliable to the crop cultivators.

KEYWORDS

Pathogens, Knowledge Graph, Image Processing, Remote Sensing, Plant Diseases.

Introduction

Forecasting plant disease, the process of predicting the severity of diseases affected by plants is the most common analysis in trend. Based on the environmental conditions, season changes in nature, weather conditions, amount of substances in the plant, the pathogen spread varies in plant diseases. Early forecasting gives crop growers sufficient time to rearrange their crop schedules and to avoid susceptible crops in a season when the disease is likely to be severe. Detailed observations over several years may be necessary before forecasting systems based on weather conditions can be prepared. Some diseases originate from inoculum blown in from distant sources and information on the incidence of the disease in such areas if known can be useful in forecasting the date and severity of the disease in the area expected to receive inoculum. Some pathogens are soil-borne, seed-borne and the degree of infection can be estimated in the laboratory. Hence there is a need for remote sensing techniques to forecast the plant diseases. Remote sensing is the acquisition of information about an object or phenomenon without making physical contact with the object and thus in contrast to on-site observation.

In a sensor data fusion approach an early detection of each pathogen was possible by discriminant analysis. To monitor the plants, remote sensing techniques are grouped into two such as imaging and non-imaging approach based on the sensors. RGB cameras, multispectral imaging, hyperspectral imaging, thermal imaging, and fluorescence imaging are the imaging approaches used in detecting plant diseases. Fluorescence spectroscopy, VIS, and IR spectroscopy belong to non-imaging approaches.

Plant disease phenotyping has been summarized in Mutka *et. al.,* [32] accelerating the crop varieties development. Hyperspectral dynamics presented by Wahabzada *et. al.,* [33] to detect the diseases in barley leaves mapping with transport network using a linear time matrix factorization technique. Yu *et. al.,* [67], who pointed out that the hyperspectral narrowband of the red-edge in the near-infrared region, was identified as effective bands for disease discrimination in vegetation. Healthy green plants have high absorption in the visible having high reflectance of IR region except for green band by Nilsson *et. al.,* [79], Barbedo *et. al.,* [95]. Radiometric calibration using a RedEdge camera mounted on a multirotor UAV in multispectral images is performed by Hossein Pourazar *et. al.,*[1] to detect and classify plant diseases. This calibration step converts the digital number into reflectance and generated uniform blocks in normalization. T-test and entropy distances are measured to discriminate against the unhealthy and healthy class of plants from the orthomosaic data of citrus orchard which produced insignificant precision.

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Mrinal Singha *et. al.*,[2] performed a phenological-based classification strategy and textural features were evaluated on the dynamics of paddy rice and presented for MODIS and HJ-1A images. Li *et. al.*, [3] and Pantazi *et. al.*, [93] conducted remote sensing monitoring on wheat scab (WS) in the Yangtze-Huaihe river region. A remote sensing estimation model (Winter wheat Scab Remote sensing Estimating Model, WSREM) of WSI was established based on meteorological factors and spectral information, to conduct the remote sensing evaluation of WSI. Based on the region of interest, Paulina *et. al.*, [4] inspected the crop and barley crops which is greener in the earlier stage of growth. Normalized Difference Vegetation Index (NDVI) relates green biomass during spring growth, Green Difference Vegetation Index (GNDVI) indicating the chlorophyll content and Normalized Difference Red Edge (NDRE) indicates chlorophyll content; are the three vegetation indices applied to multispectral data.

Xiaoxue *et. al.*, [5] constructed the knowledge graph of crop diseases and insect pests promoting the automation and intellectualization of the system. This knowledge graph is the semantic web that exposes the interrelationship between entities which is divided into a schema and data layer. Fernandes *et. al.*, [24] forecasted the plant diseases using a web-based approach. Knowledge representation, extraction, fusion, and reasoning are the methods introduced in its application. Crop conditions are assessed by Ennouri *et. al.*, [6] using remote sensing techniques. Nucleic acid and protein analysis are done in plant disease detection using DNA based and serological methods Martinelli *et. al.*, [8]. To identify the pathogen infections at the asymptomatic stage, biophotonic sensors and remote sensing technologies were used.

Leaf chlorophyll or *Cercospora beticola* disease was assessed by the HyperART system Bergsträsser *et. al.*, [40] to map the leaf transmission, absorption, and reflectance using the properties of Spatio-temporal dynamics. The metabolism of peach leaves affected by PLC is in many ways similar to that of immature sink leaves Moscatello *et. al.*, [21]. That is photosynthetic function is reduced and the leaf imports rather than export sugars. Further, the content of both non-structural carbohydrates and enzymes involved in their metabolism is similar to that of the sink and not source leaves. The chlorophyll content Yu *et. al.*, [56] is monitored to detect the diseased leaf. Late blight disease and early blight disease of the vegetation by using the in-situ spectroscopy of potato are detected by LGold *et. al.*, [7] and tomato leaves are detected by Xie *et. al.*,[100]. Leaf Area Index (LAI), leaf chlorophyll content (LCC), and canopy chlorophyll content (CCC) estimated by vegetation indices in Clevers *et. al.*, [55] using Sentinel-2 satellite images.

Review of Literatures

High-resolution data has been collected from the Hyperspectral images. Biotic and abiotic stress in plants at early onset and the diseases are being detected using hyperspectral imaging analytics Lowe *et. al.*, [11] to mitigate against crop loss and reduced quality. The hhh4 Spatio-temporal endemic-epidemic model Newlands *et. al.*,[16], a multivariate time-series model for disease incidence. It is having spatial dependence assumptions that were selected to compare with the CLR site-specific model predictions, data collected for wheat stripe (yellow) rust (*Puccinia striiformis f.sp. tritici*) (Pst) fungal disease and is tested for the disease. Diseases usually start in a small region on the foliage (e.g. Septoriatritici blotch (STB) of wheat Yu *et. al.*, [67] caused by the fungal pathogen, *Mycosphaerella graminicola*; Apple scab caused by *Venturia inaequalis*), which can be difficult to detect by visual inspection if the crop is large. West *et. al.*, [73] , Yeh *et. al.*, [96] detected Foliar disease using optical sensor technology, Liew [42] under field conditions. However, the ability to identify the disease at this early stage would provide an opportunity for early intervention to control, prevent the spread of infection, or change crop management practices before the whole crop is infected or damaged. Mahlein *et. al.*, [17] has discussed the literature on plant disease detection by imaging sensors. This includes RGB, Multispectral, Hyperspectral, thermal, Chlorophyll Fluorescence, and 3D sensors.

Image analysis techniques shows much potential here as they represent non-invasive and potentially autonomous approaches to detect biotic and abiotic stress in plants. This is illustrated in a recent review by Singh *et. al.*,[98] which examines machine learning for stress phenotyping, exploring literature on high throughput phenotyping Shaloor *et. al.*,[92] for stress identification, classification, quantification and prediction using different sensors. Deep learning techniques have been used to analyse diseases. Wanget *et. al.*,[18] worked on detecting four severity stages of apple black rot disease using the Plant Village dataset. They used CNN architectures with different depths and implemented two different training methods on each of them. Hang *et. al.*,[10] proposed a Convolution Neural network combined with the inception, squeeze-excitation (SE) modules to fuse data as multi scales and global pooling layer to reduce the model parameters in detecting and classifying the plant disease with an accuracy of

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91.7%. This CNN model tried to reduce the time taken for convergence and large parameters involved in the model.

Hyperspectral Image Capture

Hyperspectral data is large, especially when multiple plants are imaged for several days. A scan of a single plant could easily be around a gigabyte in size. If the whole spectrum range is analysed then the process will take considerably longer than several wavelengths to analyse. However, there is a lot of information contained in the data, which could be valuable. Although multi and hyperspectral images can potentially carry more information than normal photographs, they are usually captured by expensive and bulky sensors, while conventional cameras are ubiquitous and present in many consumer-level electronics stores. This has resulted in developing systems based on the visible range, which also leads to a more focused discussion. More information on multi and hyperspectral imaging applied to plant pathology can be found in Sankaran, Mishra *et. al.*,[77]. Spatially reference time series of close-range hyperspectral images presented in Behmann *et. al.*,[61] to track the position of the symptoms automatically.

Flavescence doree is a grapevine disease Albetis *et. al.*,[20] identified from the UAV images (spectral bands, vegetation indices, and biophysical parameters) using univariate and multivariate classification approaches. MicaSense RedEdge sensor includes five independent high precision sensors to capture the vegetation response at five spectral bands (SB): blue, green, red, red-edge, and near-infrared are acquired in UAV images. Pix4D software used to manage and process the UAV images. Univariate and multivariate approaches have been implemented in data acquisition, processing, and analysis of spectral bands. Pinus radiata D. Don trees are simulated Dash *et. al.*,[23] using the targeted application of herbicide. The physiological stress of trees is being monitored by manned aircraft. The crown and needle health representing density and discoloration respectively are assessed time series multi-spectral images of the forest captured. Rededge and near-infrared bands are helpful to detect the stress in plants at an earlier stage.

High-resolution thermal and hyperspectral imagery is captured to predict the *Verticillium* wilt Calderón *et. al.*,[49] using remote sensing at an earlier stage. The classification methods, Linear discriminant analysis (LDA), and support vector machine (SVM) are applied to the images of hyperspectral generating the accuracy of 71.4 % and 75% respectively finding the *Verticillium dahlia* affected in olive plants. This olive wilt is a disease is also assessed by Sancho *et. al.*,[47] using the RGB vegetation indexes measuring normalized green-red difference index (NGRDI), Green Area (GA), and triangular greenness index (TGI) representing the inoculation effect. Multi-scale image matching method Ze *et. al.*,[26] has been developed for producing a complete and accurate Amery ice shelf velocity field from Landsat 8 images. The relationship between the template size and the image entropy is investigated and the high-contrast regions are distinguished preliminary operation improving the matching results over the regions.

Hyperspectral reflectance and multi-spectral imaging techniques based on neural networks were used by Moshou *et. al.*,[27] and Golhani, *et. al.*,[90] to detect the yellow rust plant disease in winter wheat. GPS has been integrated with a multi-sensor platform where calibration of the data processing unit is performed. Normalized vegetation index (NDVI), modified simple ratio index, and soil-adjusted vegetation index Xie *et. al.*, [50], Sabareeswaran *et. al.*,[88] observed on hyperspectral images of winter wheat to estimate disease. These vegetation indices are also estimated in peanut leaves Qi *et. al.*,[62] to quantify the chlorophyll content correlations. Successive projections algorithm (SPA) - multiple linear regression (MLR) was applied in Li *et. al.*,[53] to construct spectral sensitive wavelengths of winter wheat for leaf area index (LAI). PCA-loadings–BPNN model Yao *et. al.*,[60] calculated the chlorophyll content to detect wheat stripe rust early. Krezhova *et. al.*,[28] implemented DAS ELISA techniques to perform serological analysis on the tobacco plant leaves to detect the Bulgaria Tomato spotted wilt virus (TSWV) on the leaf. Statistical analysis, cluster analysis, and derivative analysis are performed on the hyperspectral reflectance data for quick assessment of plant health. Randive *et. al.*,[29] implemented Non-destructive techniques using vegetation indices to identify various diseases on plants. The special signature, light reflectance changes, water content are analyzed using spectroscopic techniques. Maximum reflectance bands of chlorophyll are found to be related to vegetation nitrogen concentrations while comparing spectral reflectance data and ground observations Boegh *et. al.*, [52]. Based on the green leaf area index and nitrogen concentration, the spectral reflectance and vegetation indices are calculated.

Lu *et. al.*, [30], Jones *et. al.*, [76] used a high-resolution portable spectral sensor to detect multi-diseased tomato leaves in different stages, including early or asymptomatic stages. The principal component analysis was conducted to evaluate Fifty-seven spectral vegetation indices (SVIs) to detect late blight, target, and bacterial spots in tomato

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leaves. UAV images are taken from RGB and CIR Canon IXUS/ELPH cameras to map the *Acacia longifolia* flowers present in the coastal and pine forest areas. Random forest techniques were applied to count the presence and absence of flowers with a mapping accuracy of 96% shown by de Sá *et. al.*, [31]. Multispectral images with high resolution are captured using RGB cameras to determine the severity and NDVI of the rice sheath Zhang *et. al.*, [34]. High-end multiSPEC 4C and S110 NIR camera were used by Nebiker *et. al.*, [35] to predict the grains and plant diseases with the use of lightweight multispectral UAV sensors.

Classification Using Spectrum Data

Classification approaches aim to divide the data into several distinct classes. They originate from a family of statistical or machine learning techniques Yang *et. al.*, [85]. One such approach is quadratic discriminant analysis (QDA), which classifies by using a covariance matrix, which compares classes. The QDA method was used in a study with Avocado plants, to examine the fungal disease Laurel wilt (*Raffaelea lauricola*), using plants located both in the field and glasshouse. It is possible of course to use alternative methods at each stage of the analysis pipeline. For example, rather than use QDA, a decision tree approach has been used and reached 95% accuracy Sankaran *et. al.*,[68]. Choosing the correct approach for the data, as well as ensuring sufficient dataset size and quality, is key. Such machine learning approaches represent an increasingly-common set of classification and prediction algorithms. Machine learning approaches train algorithms using a training dataset, intending to analyse and predict results from new, unseen data.

Deep Convolution Neural network model, VGG16 Wang *et. al.*,[18] is used to detect the severity of plant disease from the apple rot images with an accuracy of 90.4%. VGG16, VGG19, Inception-v3, and ResNet50 are the fine-tuned four state of the art deep models trained to perform fine-grained classification where VGG16 shows high accuracy. Wallelign *et. al.*,[22] identified Soyabean plant disease using the CNN based LeNet Architecture and classified with an accuracy of 99.32% achieved from the plant village dataset images. Adaptive moment estimation (Adam) is used to train the model. Filtering the input image followed by applying max pooling, ReLu activation functions in the subsequent output layers, the output is given to the softmax layer to produce probability distribution by this model.

Table 1. Plant disease classification techniques

Plant	**Disease**	**Statistical method or applied technique**	**Classification accuracy**	**Reference**
Mango	*Anthracnose*	Multilayer Convolutional Neural Network (MCNN)	97.13%	Singh *et. al.*, [14]
Olive	*Verticillium dahlia*	Linear discriminant analysis (LDA) and support vector machine (SVM)	71.4% 75%	Calderón *et. al.*, [49]
Avacado	Laurel wilt	Quadratic discriminant analysis (QDA)	94%	Sankaran *et. al.*, [68]
		Decision tree (DT)	95%	
Sugarbeet	*Cerospora* leaf spot	Decision tree (DT)	95 %	Rumpf *et. al.*, [75]
Sugarbeet	Powdery mildew		86 %	
Sugarbeet	Leaf rust		92%	
Sugarbeet	Sugarbeet (cerospora leaf spot)	Spectral angle mapper (SAM)	89.01–98.90%	Mahlein *et. al.*, [41], Leucker *et. al.*, [43]
Sugarbeet	Sugarbeet (powdery mildew)	Support vector machine (SVM)	93%	Behmann *et. al.*, [97]
Citrus	canker-infected immature (green) fruit	Radial Basis Function (RBF)	96%	Abdulridha *et. al.*, [45]
Wheat	Wheat Leaf Rust	scattering pattern of Spectral Vegetation Indices (SVIs)	93%	Ashourloo *et. al.*, [57]
Chestnut	Mildew damage	back propagation neural network (BPNN) and evolutionary neural network (ENN)	99%	Feng *et. al.*, [63]
Banana	*Fusarium* wilt	Binary logistic regression (BLR)	91.7%	Ye *et. al.*, [66]
Oil Palm	*Ganoderma* basal stem rot disease	Lagrangian interpolation technique	84%	Shafri *et. al.*, [78]

Sladojevic [80], Rahman [12] used the deep learning-based approach, Convolution neural network to classify the rice plant disease and pest. Adopted VGG16 and InceptionV3 to recognize diseases and CNN architecture of two-stage. Luo *et. al.*,[9] Predicted crop diseases to warn pest Crop diseases are been identified automatically by using CNN

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Boulent *et. al.*,[19] contributing more sustainable and secure food production. Object detection, which provides identification and location as a bounding box and segmentation, which provides identification for each pixel is performed to identify the disease of a plant.

Vilasini *et. al.*,[13] discussed CNN based approaches for Indian leaf species identification from the white background using smartphones. Variations of CNN models over features like traditional shape, texture, colour, and venation apart from the other miniature features of uniformity of edge patterns, leaf tip, margin, and other statistical features are explored for efficient leaf classification. Singh et al. [14] proposed an innovative model named as multilayer convolutional neural network (MCNN) for the classification of Mango leaves infected from the fungal disease named as Anthracnose. The higher performance of the proposed work is confirmed with an accuracy of 97.13% when compared with other state-of-the-art approaches for its accuracy.

On applying many classification techniques to hyperspectral images, soft independent modeling of class analogy (SIMCA) proved as the strongest in discriminating healthy and unhealthy as non-symptomatic diseased (MS) leaves of peer and apple trees. Nikrooz *et. al.,* [25] before spreading fire blight disease, it is detected at an earlier stage by identifying modified triangular vegetation index1 and modified triangular vegetation index1.

Knowledge graph and case-based reasoning (CBR) has been used to detect the tobacco mosaic disease Gu *et. al.*, [36]. These techniques produced good results compared to PCA and SVM classifiers. Wavelet transformations analysis and SVM combined to forecast cucumber diseases by Wang *et. al.,* [82] with an accuracy of 86%. Zhao *et. al.,* [99] also detected cucumber leaf spot diseases. Rule-based and frame-based knowledge representation expert systems Fajri *et. al.,* [37] developed to detect many types of soybean diseases. Gunawan *et. al.,* [38] proposed Certainty factors to detect disease of plant preventing pest with an accuracy of 90%.

Lopez *et. al.*,[44] detected Red blotch diseases of almond trees by assessing chlorophyll, carotenoid pigment indices, and fluorescence at canopy and leaf level. Healthy and infectious trees are classified using a non-linear SVM technique. The canopy characteristics of maize crops are studied by Xie *et. al.*,[51]. The carotenoids and the vegetation indices can be estimated using Partial Least Square Regression PLSR Yi *et. al.*,[46] which are expressed as mass per unit surface area or leaf area.

Early-stage Detection

Behmann [97] also analysed drought stress in barley using a support vector machine (SVM). This algorithm is supervised and requires labelled training data, which in this case is labelled as drought or healthy. The data is preprocessed with k-means to reduce the size of the dataset before analysis with SVM. The spectral range was 430–890 nm with a spectral resolution of 4 nm. Using this approach, Behmann detected drought stress on day 6, with NDVI detecting a difference on day 16. The spread of Powdery Mildew disease on the barley plant is forecasted by Forster *et. al.*,[84] Cycle-Consistent Generative Adversarial Network using RGB images. Beans plant affected by powdery mildew diseases are studied by Singh *et. al.*,[86] and Zhang *et. al.*,[89] to implement image processing techniques for disease detection. Tijare *et. al.*,[87] and Camargo et al. [94] studied many image recognition techniques to identify crop disease.

There is a disease- centric studies focused on creating disease indices for detecting and quantifying specific diseases, for example, one study used leaf rust disease severity index (LRDSI) with an 87–91% accuracy in detecting the leaf rust (*Puccinia triticina*) in Wheat Ashourloo *et. al.*,[58], however, to our knowledge, it has not been widely tested.

Amara *et. al.*,[15] early detection and diagnosis of these diseases are important. To this end, we propose a deep learning-based approach that automates the process of classifying banana leaves diseases. In particular, we make use of the LeNet architecture as a convolutional neural network to classify image data sets. The preliminary results demonstrate the effectiveness of the proposed approach even under challenging conditions such as illumination, complex background, different resolution, size, pose, and orientation of real scene images.

Disease Identification and Enumerating Sternness

Rumpf *et. al.*,[75] used the same dataset as Mahlein but with different analysis approaches; decision trees (DT), artificial neural networks (ANN) and support vector machine (SVM). All approaches require prior knowledge,

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however once trained have proven to be efficient. For example, with *Cerospora* leaf spot the accuracy for SVM is 97% (compared to DT 95% and ANN 96%); for Sugar beet rust the accuracy is 93% (DT 92%, ANN 95%); and for Powdery mildew the accuracy is 93% (DT 86%, ANN 91%). Measuring the severity with leaf area coverage after the disease has covered 1–2% of the leaf the accuracy is 62–68% and for more than 10% leaf coverage the accuracy is almost 100%. This demonstrates that it is possible to use a variety of analysis methods on the same set of hyperspectral data to elucidate different insights and achieve different levels of accuracy choice of technique is important.

Mahlein *et. al.*,[41] analyzed sugar beet diseases specifically *Cerospora* leaf spot, powdery mildew, and leaf rust. The range is 400–1000 nm with 2.8 nm spectral resolution and 0.19 mm spatial resolution. The plants were analyzed over a while (> 20 days) to monitor the different stages of each disease, and the leaves were classified as healthy or diseased. *Cerospora* leaf spot classification accuracy varied depending on the severity of the disease (89.01–98.90%), powdery mildew accuracy varied between 90.18 and 97.23%, and sugar beet rust reached 61.70%, with no classification before day 20 using SAM.

Applications

Nandris *et. al.*,[39] discussed root rotting fungi of rubber tree detection using remote sensing methods in the Ivory Coast. Cessna 172 airplane with Hasselblad 500 EL/M was used to collect visual pictures, processed, and the trichromatic selection was performed.

Beyyala *et. al.*,[83] detected bud rot and basal stem rot disease in Coconut (*Cocos nuciifera* L), mosaic, and greening in citrus using image processing technology Sabrol *et. al.*,[81] by analysing the size, shape, and colour of the affected region. The immature green fruit of citrus is detected using the Grey Level co-occurrence Matrix (GLCM) Ding *et. al.*,[48] to extract features from hyperspectral images and three supervised classifiers resulting accuracies SVM-86%, logistic regression-79%, and random forest 75%. Kejian *et. al.*,[64] used polymerase chain reaction (PCR) to detect the HLB bacterium (Huanglongbing) Bove *et. al.*,[70] in each leaf of the citrus plant. This disease has also been detected using near IR spectral reflectance by Sankaran *et. al.*,[69] NDVI, Modified RedEdge Simple ratio (MSR), and Vogelmann red-edge index (VOG) indications.

Yellow rust disease, caused by the fungus *Puccinia striiformis*, is a serious threat to wheat production and impacts the yield and quality of wheat Zheng *et. al.*,[59]. The timely detection of crop diseases at different growth stages Bajwa *et. al.*,[65] are critical to the effective management of the economy and agriculture. Moshou *et. al.*,[71], Bravo *et. al.*,[72] discriminated wheat infected by yellow rust from healthy wheat. It was concluded that red-edge wavelengths should be useful in reflectance studies of crop disease throughout the season. used a quadratic discriminating model combined with the sensitive wavebands (at 543 ± 10 nm, 630 ± 10 nm, 750 ± 10 nm, and 861 ± 10 nm) for yellow rust discrimination with the coefficient of determination of 0.96. Self-Organizing Map (SOM) neural network was used by Moshou *et. al.*,[74], Zhang *et. al.*,[91] to perform data fusion on the spectral wavelengths discriminated against with 94.5% of classification accuracy.

RGB vegetation indexes widely used in plant phenotyping Shakoor *et. al.*,[92] and in assessing abiotic stress, showed considerable resolution in detecting changes in plant color that could be attributed to the inoculation factor, especially notable in a context of a lack of wilting symptoms.

Table 2. Vegetation Indexes

Reference	**Vegetation Indexes**	**Equation**
Abdulridha *et. al.*, [45]	Green NDVI (GNDVI)	GNDVI = (NIR850-G580) / (NIR850+G580)
Abdulridha *et. al.*, [45]	Normalized difference vegetation index 780 (NDVI 780)	NDVI 780 = R780-R670 / R780+R670
Xie *et. al.*, [54]	Ratio vegetation Index (RVI)	RVI = R780 / R670

Indian almonds bear fruit during the winter months in India. Almonds display a vibrant spectacle of colours as they ripen: green at first, then changing to yellow, and finally a deep red or sharp magenta. Some greenish varieties go from dark green to brown. Almond has many health benefits such as sickle cell anaemia, boost liver function, treat skin problems, treat liver cancer, and act as an aphrodisiac.

Table 3. Almond Tree Diseases and symptoms

Diseases in Almond tree	**Symptoms**
Almond brownline and decline *Peach yellow leafroll mycoplasma*	Stunted tree growth; drooping/wilting of leaves
Almond kernel shrivel *Peach yellow leafroll phytoplasma*	Late blooming
Almond leaf scorch; golden death *Xylella fastidiosa*	Patches of necrotic tissue with chlorotic margin
Alternaria leaf spot *Alternaria alternata*	Light brown circular lesions on leaves; fruit does not drop from tree
Anthracnose *Colletotrichum acutatum*	Death of foliage

These diseases of almond trees can be monitored using remote sensing techniques and can detect the diseases at an earlier stage with the help of sensors and machine learning techniques for classifying unhealthy parts of it.

Conclusion

Many techniques and its applications are found in this study to perform automatic identification and classification of healthy and unhealthy plants. Hyperspectral remote sensing techniques play a vital role in plant disease forecasting and facilitate pest management in agriculture. The main challenge to be faced in future applications are differentiating between the effects of biotic and abiotic stress, due to complex interactions present between crop physiological status and pathogen infection. Further studies are expected to conduct more research on how to distinguish almond with different varieties of mild species using a hyperspectral imaging system.

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