Artificial Intelligence in Agriculture 4 (2020) 229–242

Contents lists available at ScienceDirect

Artificial Intelligence in Agriculture

journal homepage: http://www.keaipublishing.com/en/journals/artificial-intelligence-in-agriculture/

A review of imaging techniques for plant disease detection

Vijai Singh *, Namita Sharma, Shikha Singh

GL Bajaj Institute of Technology and Management, Gr. Noida, Uttar Pradesh, India

ARTICLE INFO

Article history:
Received 20 May 2020
Received in revised form 2 October 2020
Accepted 2 October 2020
Available online 6 October 2020

Keywords:
Plant disease detection
Machine learning
Imaging sensors and systems
Plant disease classification
Image processing

ABSTRACT

Agriculture is the basis of every economy worldwide. Crop production is one of the major factors affecting domestic market condition in any country. Agricultural production is also a major prerequisite of economic development, be it any part of any country. It plays a crucial role as it even provides raw material, employment and food to different citizens. A lot of issues are responsible for estimated crop production varying in different parts of the world. Some of these include overutilization of chemical fertilizers, presence of chemicals in water supply, uneven distribution of rainfall, different soil fertility and others. Other than these issues one of the commonly faced challenges across the globe equally includes destruction of the major part of production due to diseases. After providing effective resources to the fields, major section of the production is diminished by the presence of diseases in the plants grown. This leads to focus on effective ways of detection of disease in plants. Presence of various diseases in plant is a major concern among farmers. Plant diseases acts as a major threat to small scale farmers as they lead to major destruction in overall food supply. To provide effective measures for detection and avoidance of the destruction requires an early identification of type of plant disease present. In recent time major work is being done for the identification of plant disease presents in varied parts of the world affection varied crops. Major work is being done in the domain of identification of causing factors of these diseases. Some of the diseases are marked by the presence of viruses while some are resultant of fungal infection. This becomes a major issue when the causing factor is not traceable before it has already spread to major production section. This paper brings a review on effective use of different imaging techniques and computer vision approaches for the identification and classification of plant diseases. Detection of Plant disease is initiated with image acquisition followed by pre-processing while using the process of segmentation. It is further accompanied by different techniques used for feature extraction along with classification. In this Paper we present the Current Trends and Challenges for detection of plant disease using computer vision and advance imaging technique.

Contents

* Corresponding author.
E-mail address: vijai.cs@gmail.com (V. Singh).

https://doi.org/10.1016/j.aiia.2020.10.002

1. Introduction

Agricultural products are used to cater the dietary needs of animals as well as human beings. Agriculture has been a part of everyone's life directly or indirectly. It is the way of crop production which results in providing food, the building block of every human being. Whether a human resides in a metro city or lives in a village everyone survives on this crop production one or the other way. With the advent of civilization humans have started cultivating crops like wheat, cotton and others. With the development in every area of life there has been some vast development in the domain of agriculture also. Along with the variation in the types of crops being grown other activities were also started such as farming, raising cattle etc.

But today also crop production largely contributes to the agricultural output. There have been major changes in crop production also. With the raising knowledge technology has brought some modernization in the area of crop production also. Modern agronomy makes the use of best technological devices and techniques for the increase in the yield. There has been an increased use of modern tools for easy identification of the suitable conditions for larger crop production. Various types of fertilizers and pesticides are being used to bring an increase. Even genetically modified seeds are being tested on a larger scale to pump up the overall production in any area.

Crop production involves taking care of all the activities for the better yield across all the seasons. It involves complete analysis of the soil being used, the type of seeds used, the major nutrient requirement of the particular crop and many others. Yields obtained from the crops, and other sources are being used to meet the daily needs of not only the farmers, but for others also. But as every field suffers from some form of issues agriculture or crop production also faces major challenge in the form of crop diseases. With the huge demand of food around the world, it becomes necessary to focus on the crop production. It is aimed to protect the overall yield from any type of loss before reaching to the market. Besides calamities caused by nature such as draught, earthquakes, diseases also accounts to major crop yield losses.

In context of quality or in the context of quality, yields are reduced due to various types of plant diseases. Plant disease can be described as some form of modification that hampers the normal processes in it. Crop production can be majorly affected by these diseases which may reduce the quality and quantity of the overall produced yield. Management of large amount of crop yield involves various timely activities such as keeping a watch for diseases, which reduces it to undesirable stuff. It also involves finding immediate cure for various challenges faced. Disease can affect the overall functional capacity of the plant. It may result in reduced growth, less fruit production, more leaf falls and many other ailments also. Sometimes the disease may spread from crop to crop or may be spread by some pathogen or other means. Sometimes they may be caused by some fungi or some bacteria. Sometimes even viruses get transferred with seeds from one place to another.

Main reasons of crop diseases are the infections such as insect pests, bacteria, fungi and viruses. These diseases are found and can spread in all parts of the plants like in stem, vegetables, fruits and others can be detected by one of the listed below:

- Discerning the affected area
- Retrieving the features set of the affected area
- Identifying and categorizing the diseases

From a long time, identifying the crop disease is done by the experts through their naked eyes based on their knowledge and experience. Find an expert and contact them is not only a tedious and time consuming task but also a very long and expensive method. Therefore, the complete process sometimes takes so much time which become time taking for the disease to be eradicated and also very tedious in case of large areas (Liu et al., 2020), (Mishra et al. (2020)).

Modern techniques available, for plant disease detection, like processing, similarity identification and deep learning based classification techniques better in respect of time saving than the old methods used (Nagaraju and Chawla, 2020), (Nagasubramanian et al., 2019), (Kulkarni and Ashwin Patil, 2012), (Jasim and Tuwaijari, 2020), (Sun et al., 2020). They help farmers to improve the quality of crops, also bringing a reduction of disease occurrence by early detection and timely curing them (Sinha and Shekhawat, 2020).

In the process of detection of disease, number of imaging techniques is being used. One of the imaging techniques being used id photo acoustic imaging, which makes the use of light absorption in case of tissues. It makes the use of property of light's absorption by tissues and its conversion into heat further resulting in the generation of photo acoustic signals. Here the pressure distribution radiated by tissues further being mapped and used for imaging purposes. Considering various imaging techniques one of the important techniques is magnetic resonance imaging. It can be described as imaging technique that gives detailed images that are mostly used for knowing different types of diseases. In this method strong magnets are being deployed generating strong magnetic field resulting in proper alignment of the protons. Later application of electric field makes the movement in these protons. Finally turning off of the rf filed sensors help in the detection of energy being released from movement.

Among the various spectroscopies one of the recent methods is of fluorescence spectroscopy. It makes the use of fluorescence measurement, being released after the excitation of light with area of interest. Mostly for vegetative studies or plant disease detection laser induced fluorescence are often used on a large scale. These are mostly needed for identification of various physiological states of different plants. Majorly the green leaves are being tested for chlorophyll fluorescence or blue green fluorescence. These help in early identification of any type of impairment resulting from major nutrients deficiencies. (Sankaran et al., 2010).

Among the recent techniques being used one of the effective imaging methodology is using hyper spectral imaging. In this technique electromagnetic spectrum of an image's pixel is being used for the detection of plant disease present. In this technique wide spectrum of light is being used for the analysis of each image's pixel. It helps in the detection of various diseases in more reasonable manner among the variety of plants being considered. Hyper spectral imaging is further extended when used with microscopy for higher resolution clear images. It helps in microscopic studies at the genotypic level of varied plant leaves. (Rumf et al., 2010).

2. Imaging sensors and systems for plant disease detection

Digital Image Analysis has evolved over many years. It firstly began with the era of 2D image analysis came. Secondly, knowledge based approaches using MRI and CT changed the developmental procedures. Lastly, analysis of fully 3D images was brought to the light. Digital model driven approaches were introduced in the beginning and then after 1999 till today advanced imaging and computing technologies are used for better and more realistic visualization as per requirements. Machine Learning methods have also evolved eventually.

For identification of different plant disease, sensors for imaging system are deployed to accumulate the data for study of leaves from different aspect. Various useful imaging techniques include thermal imaging, multispectral imaging, fluorescence imaging, hyper spectral imaging, visible imaging, MRT. Also 3D imaging methods are also tested along various other methods. In next sections we present a state of survey on these techniques along with their applications in different ways.

3. Literature survey

3.1. Magnetic resonance imaging

Also termed as NMR, meaning nuclear magnetic resonance scanner, it is mostly known as magnetic resonance imaging device, is usually identified for its powerful magnets. These magnets are good as they efficiently polarize and further excites the focused proton singly included in water molecules present in the tissue, helping in a detectable signal spatially encoded giving various images of the body. Radio Frequency (RF) pulses are emitted by MRI machines that bind only to oxygen. This system works by initially generating the pulse and transferring it to the examined area of the body. Later they are made to spin in a different orientation by absorption of the send energy. This is called the resonance process involved in the MRI.

3.2. Photo acoustic imaging

Photo acoustic imaging is a technique that has been derived using hybrid biomedical imaging that is originated around the photo acoustic effect. It involves the amalgamation of different benefits such as optical absorption contrast along ultrasonic spatial resolution involved in deep imaging of diffusive and other regime. The studies bring the fact that photo acoustic imaging can be used for various purposes such as tumor analyzing, mapping of the level of blood oxygen, imaging of the brain activity, and other disease detection, etc.

3.3. Tomography

Tomography is one of the techniques that involve imaging of a single plane, or an object giving a tomogram. There are different types of tomography such as linear, poly tomography, zonagraphy, computed type or computed axial and Positron Emission type of tomography.

3.4. Thermography

One of the most common applications of it is breast imaging. Usually one of the three approaches are being used commonly, the tele- thermography, the dynamic angio-thermography and the contact thermography type. The imaging thermographic digital methods involve the advantage of the principle derived from metabolic activity. Also vascular circulation with the area surrounding a developing breast cancer is studied to detect the higher value.

The paper (Anne -Katrin Mahlein et al., 2012) brings the use of noninvasive sensors for detection of plant diseases. Sensors types like thermography, chlorophyll fluorescence and hyper spectral sensors are being studied and compared. It is observed that hyper spectral systems record very large amount of data and hence require different approaches to obtain result. In thermography, temperature is the crucial parameter. The challenge is that the potential of these technologies have not yet been fully explored. Another challenge is the interpretation of sensor data.

This paper (Fang and Ramasamy, 2015) gives the various methods of disease classifications in plants. Direct method includes PCR (polymerase chain reaction), IF (Immuno Fluorescence), (Fluorescence in situ hybridization), FCM (Flow cytometry) and ELISA (Enzyme linked immunosorbent assay) etc. Types of indirect method includes Fluorescence imaging, also discusses the hyper spectral imaging. The direct method is widely available but is difficult to operate, time consuming for data analysis and require expert technicians. Also they are not much apt for different type of testing. Indirect method can be used in on field disease detection but lack specification of different disease types with the advent of nanotechnology, there is vast advancement of sensitive biosensor whose specify can be further improved using enzymes, DNA, antibiotics as the detection element.

3.5. Spectroscopic and imaging technologies

The paper compares the technologies like imaging technologies using spectroscopy along profiling based techniques used to asset in looking the usual health and disease in leaves. The advantage of using these technologies is that they are accurate in detecting pant disease. The challenges which are faced in these techniques is to find the optimize solution for a definite disease of plant and also automating the techniques for continuous checking of the plant disease. (Sankaran et al., 2010).

Major oil content makes peanut an important agricultural product. This paper (EwisOmran, 2016) presents a method for early identification of plant disease. It basically focuses on the study of effect of fungal disease as leaf spots in peanut plant leaves. Early and late leaf indices were identified with the help of in situ spectroscopy. It further involved thermal and spectral calculations for differentiating healthy and infected plant leaves. Later plant chlorophyll decrease is also being identified as a stress detection factor among the infected leaves.

This paper (Federico Martinelli et al., 2015) describes modern method of identification of disease in plants based on nucleic acid and protein analysis. This paper describes different mobility spectrometer and lateral flow devices which will detect early infections directly on fluid. It also summarizes that remote sensing technologies coupled with spectroscopy based methods results in high spatialization and hence help in early identification of any infections in plants. The paper discusses all these tools and how they are helpful in looking for different plant disease and also nucleic acid based methods and serological methods.

3.6. Multispectral imaging

Multispectral imaging techniques use different types of wavebands such as of green, as of red, or near infrared wavebands to capture all types of images rather it be invisible or being it visible images of fruits or crops or it being vegetation. For plant diseases detection the multispectral images integrate with machine learning and classification algorithms which give the information into meaningful data.

3.7. Hyperspectral imaging

Hyper-spectral imaging makes the use of much traditional imaging technique along with the spectroscopy to aggregate different spectral information simultaneously. The objective of this technique is to find the spectrum for involved pixel contributing to the image being considered. In Hyper spectral imaging device is deployed for a wavelength dispersion and also a transportation stage are present in addition different from the traditional computer vision system. (Li et al., 2017) (Rumf et al., 2010).

The human eye has a capacity of vision for a definite range from the electromagnetic spectrum that belongs 400 to 700 nm (Fig. 1) (Amy Lowe et al., 2017). Hyperspectral imaging typically contains number of restricted wavelength bands across a spectral range. This brings a color dataset with useful information, also containing huge spatial resolution which contains thousands of data pixels per leaf (Amy Lowe et al., 2017). (See Tables 1 and 2.)

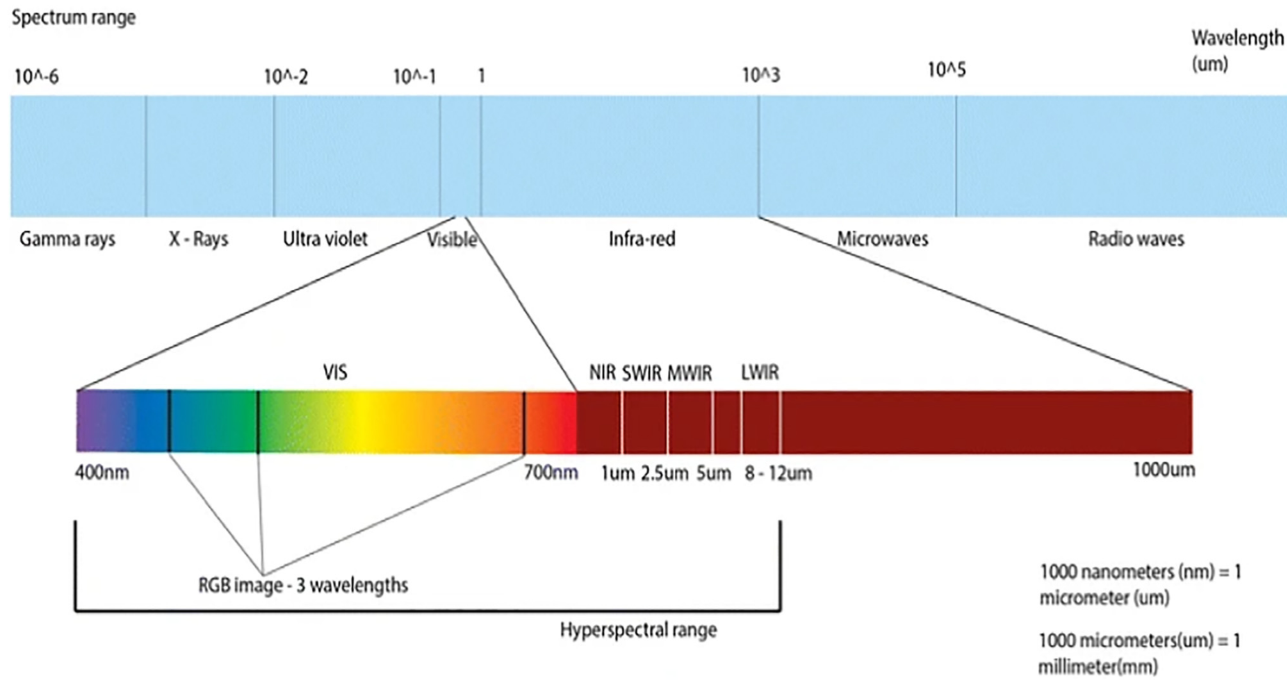

Fig. 1. Hyperspectralrange in Electromagnetic spectrum (Amy Lowe et al., 2017).

In plants stresses can be classified as biotic and non-biotic where biotic are being induced by beings as viruses, fungi and others. In paper (Baranowski et al., 2015) hyper spectral imaging and the thermal imaging identifies plant stress due to fungi in oilseed rape. Initially the thermal images of oilseed rape were being analyzed for temperature distributions. Also hyper spectral images were also recorded. Further distributions temperatures were compared using kernel density curves. Spectral analysis of the leaves with different reflectance was again analyzed.

Paper (Calderón et al., 2015) gives a description about a method for automatic classification of Verticillium Wilt in olive plants considering techniques useful for large scale. Initially thermal and hyper spectral.

Images were acquired over large scale olive orchid. Various vegetation indices as optimized soil adjusted vegetation indices were taken into account while modeling for this study. Correlation coefficient for completer canopy was also used for determining the level of disease spread. Later SVM classification was done for the bifurcating levels of disease. Almond production depends on major environmental factors as climate, sites, resistance to diseases and others.

Paper (López-López et al., 2016) detects early onset of red leaf blotch using thermal and hyper spectral imagery while studying the infection spread subjected to different factors. Here Spectral reflectance across visible regions was used for measurement along with near infrared region also. Later indices as pigment concentration of chlorophyll, chlorophyll fluorescence were considered for comparison. Finally amalgamated information from the different parameters was used for analyzing while developing model to quantify disease seriousness. Further the information gained from the analysis was again passed to multiple classification methods as linear discriminate analysis, support vector machine for proper analysis. Also it is found that linear SVM method is more efficient in early detection of red leaf blotch.

The paper (Cao et al., 2015a) demonstrated that for wheat powdery mildew detection, canopy hyperspectral reflectance can be used while analyzing the unhealthy symptoms. It being observed that wheat cultivators responded more sensitively to canopy reflectance in which wheat cultivars were more susceptible to powdery mildew. The challenge faced here included discriminating the wheat powdery mildew from other ailments. This paper (Kamlesh Golhani et al., 2018) discusses various techniques for the processing and detailing of the data used for hyper spectral analysis, giving special emphasis on detection of plant disease. This paper introduces NN techniques for the development of spectral disease index (SDI). Data being different from camera images, results in difficulty of linearity detection of hyperspectral image. The various challenged faced in NN are like detection of the diseases of three categories such as pre symptomatic and asymptomatic for a single plant.

The paper (Lowe et al., 2017) summarizes the techniques to detect different stress in plants and it focuses on hyperspectral imaging method to detect the early beginning of disease and to predict about the health of the plant. Various indices are increasing day by day and they are important to detect specific criteria for vegetation. For example, vegetation index can be used identify the normal health of the plant but the challenge is we cannot use the index set for one plant and use it for the data of another plant.

The paper (Mahlein et al., 2013) discusses development of different disease index (SDIs) for the identification of diseases in crop plants of sugar beet and the leaf diseases as leaf spot, sugar beet and others. At different stages of development, hyper spectral signatures were assessed for both healthy and diseased leaves. For differentiating between diseased and healthy leaves, several optimized indices of disease were tested. The advantage of SDI is that SDI disease can be easily distinguished which is difficult using vegetative indices. The challenge is to send the generated SDI and to specify its usability for disease monitoring on canopy with different sensors.

This paper (Mahlein et al., 2017) discusses hyperspectral imaging and data analysis routines to identify and quantify relevant plant diseases. Hyperspectral imaging can be helpful in giving new insight into data of different plant at different level. This paper (Moghadam et al., 2017) discuses imaging methods (VNIR and SWIR) along ml technologies for the identification of TSWW, i.e. Tomato Spotted Wilt Virusin capsicum in plants.

The paper (Ochoa et al., 2016) discusses about building a hyperspectral imaging system for identification of Black Sigatoke (BS) disease found in plant and its pre-symptomatic responses in banana leaves. To

Table 1
Analysis of various algorithms.

Species	Optical technique	Application	Method	Accuracy	Reference
Apple	Multispectral Imaging	Identifying defects in images	Rotating in front of camera	90%	(Sankaran et al., 2010)
Sugar Beet leaves	Support Vector Machine	Comparison between healthy and diseased sugar beet leaves	Plants inoculated with pathogens	97%	(Rumf et al., 2010)
Pear Plants	Near infrared Based technique	To identify fire blight disease	Spectroscopy based imaging technique		(Sankaran et al., 2010)
Grapevines	Leaf spectral reflectance	To identify leaf roll disease	Spectroscopy Used	75%	(Sankaran et al., 2010)
Blue Berries	Electric nose system	To detect post harvest fungal disease	Series of gas sensors used		(Sankaran et al., 2010)
Onion	To identify fungi	Molecular Technique (PCR)	DNA of disease causing microorganism is extracted and purified.		(Sankaran et al., 2010)
Citrus	To identify virus	Molecular Techniques(PCR)	DNA of disease causing microorganism is extracted and purified		(Sankaran et al., 2010)
Potato	To identify bacteria	Molecular Techniques (PCR)	DNA of disease causing microorganism is extracted and purified		(Sankaran et al., 2010)
Tomato	To identify virus	Molecular Techniques (PCR)	DNA of disease causing microorganism is extracted and purified		(Sankaran et al., 2010)
Almond	To identify bacteria	Molecular Techniques (PCR)	DNA of disease causing microorganism is extracted and purified		(Sankaran et al., 2010)
Rice	To identify bacteria	Molecular Techniques (FluoroscenesPCR)	DNA of disease causing microorganism is extracted and purified		(Sankaran et al., 2010)
Sugarcane	PLS based method	To identify disease rating	For classification of post harvest		(Sankaran et al., 2010)
Winter wheat	Fluorescence Imaging	To identify yellow rust	Fluorescence images are obtained using camera		(Sankaran et al., 2010)
Iris leaf	Color transform method	To identify heterosporium leaf spot	Otsu threshold is applied to identify disease spot		(Chaudhary et al., 2012b)
Rice Leaf	Color transform method	To identify brown spot	Otsu threshold is applied to identify disesae spot		(Chaudhary et al., 2012a)
Blueberry	Color transform method	To identify bacterial canker	Otsu threshold is applied to identify disesae spot		(Chaudhary et al., 2012a)
Cotton	Particle Sworm Optimization	To identify injured leaf spot	Feature extraction by PSO and forward Neural Network	95	(Sladojevic et al., 2016)
Tea Leaf	Neural Network Ensemble	To identify plant disease	Feature Extraction and neural network ensemble	91%	(Sladojevic et al., 2016)
Wheat	Hyperspectral imaging	Identifying fusarium	Rotating in front of camera		(Bauriegel and Herppich, 2014b)
Barley	Support Vector Machine	Hyperspectral imaging	To identify drought stress on barley		(Behmann and JorgSteinrucken, 2014)
Wheat	Hyperspectral reflectance	To identify wheat powdery mildew	Rotating camera		(Cao et al., 2015b)
Sugar beet plant	Spectral disease indices	To identify leaf spot, sugar beet rust, powdery mildew	Hyperspectral signatures were assessed		(Mahlein et al., 2013)
Capsicum plant	Hyperspectral imaging(VNIR and SWIR)	To detect TSWW(Tomato Spotted Wilt Virus)	Collect hypercubes of capsicum plant leaves in VNIR and SWIR range	90%	(Moghadam et al., 2017)
Winter Wheat	Fusion of hyperspectral andfluorescence imaging	To detect yellow rust disease	Ground based real time remote system		(Moshou et al., 2005)
Banana plant	Hyperspectral imaging	To identify Black Sigatoke	Rotating camera		(Ochoa et al., 2016)
Weed	Hyperspectral imaging	To control weed production	Capturing images		(Okamoto et al., 2007)
Potato	Hyperspectral imaging	To identify late blight disease	Rotating camera		(Ray et al., 2011)
Cucumber leaves	Hyperspectral imaging	To identify Chlorophyll and cartenoid content in cucumber leaves	Finding the pigment distribution in cucumber leaves		(Zhao et al., 2016)
Almond orchards	Hyperspectral imaging and thermal imagery	To identify red leaf blotch in almond orchards	Use of canopy temperature and vegetation indices		(Zhao et al., 2016)
Wheat	MLP, SOM	To identify yellow rust		99%	(Moshou et al., 2004)
Avocado	Hyperspectral sensing, RBF, MLP	To identify Laurel wilt disease		98%	(Abdulridha et al., 2016)
Cotton	NN- SOM	To identify disease Reniform Nematode		97%	(Lawrence et al., 2004)
Egg Plant	Hyperspectral sensor	To identify gray mould			(Wu et al., 2008)
Maize	Portable Hyperspectral imaging system	Fungal infections			(Del Fiore et al., 2010)
Wheat	QDA	Yellow rust		92%	(Bravo et al., 2003)
Sugarbeet	Decision tree (DT)	cerospora leaf spot		95%	(Cao et al., 2015a)
Sugarbeet	Decision tree (DT)	powdery mildew		86%	(Cao et al., 2015b)
Sugarbeet	Decision tree (DT)	leaf rust		92%	(Cao et al., 2015a)
Grapefruit	Spectral Information Divergence	cankerous, normal, greasy spot. Insect damage, melanose, scab, wind scar)		95.2%	(Qin et al., 2009)

capture images, a highly sensitive VIS-NIR camera is used the HS cube images with reduce motion blur. After the step of capturing of images another step is performed for enhancement of the quality of HS images. The paper (Okamoto et al., 2007) proposes to develop a weed detection method using hyperspectral imaging to control weed detection. According to the species, plants can be categorized as crops and weeds. Using hyper spectral imaging, first of all the plants is segmented from the soil surface. Then image pixel of crop and weed are classified with the help of species other characteristics. Various classes of variables are generated which are then used for data compression, followed by the process of extraction of features and then on it linear discrimination is applied. Among other advantages one of the major advantages is that this classification method can be practically applied.

Table 2
Challenges and future trends.

Title	Sample plant	Method	Accuracy	Type of disease detected	Future work	References
Identification of Plant Disease using Image Processing Technique	Fruit leaves	K-mean clustering and random forest classifier	–	*Alternaria alternata*, Antracnose, Bacterial Blight along with Cercospora Leaf Spot	Work could be extended to other type of fungal disease detection	(Jhuria et al., 2013)
Diagnosis of pomegranate plant diseases using neural network	Pomegranate	K-mean clustering and Gray level co-occurrence matrix (GLCM) method, Back propagation algorithm	90%	Bacterial blight, fruit rot and leaf spot in pomegranate plant	Work could be extended to other fruit disease detection	(Dhakate and Ingole, 2015)
An Application of image processing techniques for Detection of Diseases on Brinjal Leaves Using K-Means Clustering Method	Brinjal leaf	Kmeans clustering algorithm along with Neural-network for classification.	–	Cercospora Leaf Spot, Tobacco mosaic virus and Bacterial Wilt.	Work can be extended to identify all possible diseases	(Anand et al., 2016)
Detection of Potato Diseases Using Image Segmentation and Multiclass Support Vector Machine	Potato	Multiclass support vector machine classifier, Gray level Co occurrence Matrix	95%	*Phytophthora infestans* (Late blight), Alternaria solani (Early blight).	Automatic detection of severity of disease	(Islam et al., 2017)
Wheat Disease Detection Using Image Processing	Wheat	K-means clustering, Neural network	80.2%	Fungal disease of wheat plant	Improve the proposed algorithm for reduction of error due to classification	(Gaikwad and Musande, 2017)
Diseases Detection of Cotton Leaf Spot using Image Processing and SVM Classifier	Cotton leaves	K-means clustering, Gray Level Co-occurrence Matrix, Support Vector Machine classifier	98.46%.	Bacterial blight and Magnesium Deficiency	Work can be done to develop a more efficient, and robust system for early automatic tracing	(Bhimte and Thool, 2018)
Plant Leaf Disease Diagnosis from Color Imagery Using Co-Occurrence Matrix and Artificial Intelligence System	Grape leaves	Gray-level co-occurrence matrix, simplified fuzzy Artmap(SFAM)	–	Scab disease,downy mildew disease, rust disease	Work can be done to consider other diseases also.	(Khitthuk et al., 2018)
Detection and Classification of Groundnut Leaf Diseases using KNN classifier	Groundnut Leaf	Fast Feature extraction method and k-NN algorithm	–	Early leaf spot, Late leaf spot, Rust,Bud Necrosis	Can be done for other groundnut plant disease	(Vaishnnave et al., 2019)
Tea diseases detection based on fast infrared thermal image processing technology	Tea Leaves	Infrared thermal imaging technology	–	Tea leaf blight	Work could be extended to other type of disease detection	(Yang et al., 2019)
Early detection of plant disease using infrared thermal imaging	Tomatoes leaves	Digital infrared thermal imaging	–	Tobacco mosaic virus	Work could be extended to other viral disease detection on many more species of tomatoes	(Xu et al., 2006)
Automatic Detection of Diseased Tomato Plants Using Thermal and Stereo Visible Light Images	Tomato plants leaves	Color, depth, and temperature using thermal and stereo visible light images along with SVM Classifier	90%	Fungus Oidiumneolycopersi giving powdery mildew	Work can be extended to study complete canopy scanning on larger scale.	(Raza et al., 2015c)
Detection of the dynamic response of cucumber leaves to fusaric acid using thermal imaging	Cucumber	Digital infrared thermograph, stomata aperture measurement	–	Fusarium wilt	Work can be extended by consideration of other features also	(Wang et al., 2013)
Huanglongbing (Citrus Greening) Detection Using Visible, Near Infrared and Thermal Imaging Techniques	Orange Leaves	Thermal Imaging and Visible-near infrared techniques	87%	Huanglongbi ng (HLB) disease	Work can be done on a larger set of canopy.	(Sankaran et al., 2013)
Registration of thermal and visible light images of diseased plants using silhouette extraction in the wavelet domain	Tomato plants	Thermal and visible imaging with stationary wavelet transform	–	Fungus Oidiumneolycopersici which causes powdery mildew disease	Work can be further extended to stereo images for 3D information	(Raza et al., 2015b)
Early sensing of peanut leaf spot using spectroscopy and thermal imaging	Peanut leaves	Image Spectroscopy, reflectance factor calculation	89.3%	Fungal disease causing early leaf spot and late leaf spot	Work can be done for other fungal disease infections	(EwisOmran, 2016)
Thermal imaging of cucumber leaves affected by downy mildew and environmental conditions	cucumber leaves	Digital infrared thermograph, Measurement of stomata conductance	–	downy mildew	Work can be extended by including more factors	(Oerke et al., 2006)
Plant disease detection based on data fusion of hyper-spectral and multi-spectral fluorescence imaging using Kohonen maps	Wheat Plant	Fluorescence induction and spectral reflection method	–	Yellow Rust	Work can be extended over larger canopy study.	(Moshou et al., 2005)
Thermal and Chlorophyll-Fluorescence Imaging Distinguish Plant-Pathogen Interactions at an Early Stage	Tobacco plants, Sugar beet plants	Chlorophyll fluorescence imaging, thermograph	–	Tobacco mosaic virus and C. beticola infection	Measurement can further be extended to more varied samples.	(LauryChaerle et al., 2004)
Hyper spectral and Chlorophyll Fluorescence Imaging for Early Detection of Plant Diseases, with Special Reference to Fusarium spec. Infections on Wheat	Wheat plant	Chlorophyll Fluorescence along with Hyper spectral Imaging	–	Fusarium resulting Head Blight	Work can be extended to involve various other plant diseases.	(Bauriegel and Herppich, 2014b)
Hyper spectral and Thermal Imaging of Oilseed Rape (*Brassica napus*) Response to Fungal Species of the Genus Alternaria	Oilseed rape	thermograph and hyper spectral imaging	80.5%	Alternaria fungal disease	Work further requires involvement of genetic data.	(Baranowski et al., 2015)
Early Detection of Powdery Mildew Disease in Wheat (*Triticum aestivum* L.) Using Thermal Imaging Technique	Wheat Plant	thermal imaging, temperature monitoring before and after inoculation	–	Erysiphe graminis fungus causing Powdery mildew disease	.Work can be used for developing an expert system	(Awad et al., 2014)
Early Detection and Quantification of Verticillium Wilt in Olive Using Hyper spectral and Thermal Imagery over Large Areas	Olive plant	Hyper spectral imaging linear discriminate analysis, support vector machine	92.7%	Verticillium wilt	Work further requires analysis using different variation in surrounding conditions	(Calderón et al., 2015)

Table 2 (*continued*)

Title	Sample plant	Method	Accuracy	Type of disease detected	Future work	References
Early Detection and Quantification of Almond Red Leaf Blotch Using High-Resolution Hyper spectral and Thermal Imagery	Almond Plant	Hyper spectral imaging, thermal imaging, linear discriminate analysis,support vector machine,	96.2%	Red leaf blotch	Work can be further extended using other classification methods	(López-López et al., 2016)
Robust fitting of fluorescence spectra for pre-symptomatic wheat leaf rust detection with Support Vector Machines	Wheat plant	Fluorescence measurements, support vector machine classification	93%	Wheat leaf rust	Work can be extended for other disease detection at early stages	(Römer et al., 2011)

The paper (Ray et al., 2011) discusses late blight disease detection in potato using hyper spectral reflectance data using spectro radiometer over specific spectral range. It was observed that in 770–860, also 920–1050 nm range there can be noticeable difference found between healthy and diseased plants of potatoes. This paper discusses the advantage of spectral data for identification of disease.

The paper (Zhang et al., 2012) discusses the use of hyperspectral reflectance of normal in comparison to infected leaves. This is checked with a spectro radiometer is a lab 32 spectral features were extracted, and then they are examined with *t*-test, correlation analysis, fisher linear discriminant analysis. It was observed that PLSR performed well as compared to MLR model. Also FLDA gave accuracy of 90% for heavily damaged leaves. The challenge is to use these methods on fields i.e. at canopy level.

The paper (Zhao et al., 2016) discusses the technique of hyperspectral imaging to identify chlorophyll and carotenoid contents in cucumber plant leaves with major infection cases of angular leaf spot (ALS). It was observed that PLSR models results with coefficient correlation predicting 0.871 and 0.876 for Chlorophyll and Carotenoids. The outcomes showed that hyperspectral imaging with chemometrics is a feasible approach to find the presence of disease leaf spot in cucumber leaves. The paper (Lopez-Lopez et al., 2016) discusses the application of hyperspectral imagery and high resolution imagery to detect the presence of leaf blotch in almond studied. The paper discusses the use of canopy temperature and vegetation indices to early identify presence of disease. It was observed that all three including chlorophyll fluorescence are prominent in early identification of detection in almond plants.

3.8. Fluorescence techniques

Fluorescence techniques (Fig. 2.) have been widely used for investigation of the photosynthetic performance in plants. This technique is very useful for crop monitoring which allow us to alleviate stress at an early stage and thus substantially reducing yield losses.

In this (Pérez-Bueno et al., 2016) paper the proposed work highlights the useful benefits of imaging systems based on multicolor fluorescence, making use of thermograph for zucchini plants affected by disorder, caused by *Dickeyadadantii*. Different machine learning technique has been applied which classify the input samples as healthy or infected samples. (Pérez-Bueno et al., 2016). In paper (Moshoua et al., 2005) the detection of Wheat plant disease is being identified with the data fusion techniques. It also shows the use of self-organizing map neural network on reflectance data. It reflects the method of identification of yellow rust using wheat plant spread over farm area. Later multi-spectral fluorescence imaging systems was done on sampled canopy. Further leaf disease detection is done using indices as normalized vegetation and others. This paper shows the use of fluorescence induction and spectral reflection for the disease presence detection.

Paper (LauryChaerle et al., 2004) makes use of chlorophyll fluorescence imaging and thermograph for knowing and comparison of infection by fungus and viral infection in plant leaves. Here both the imaging techniques are used comparatively under different growth scenarios for pathogen plant interaction study. Firstly, the imaging of tobacco leaf is analyzed for the lesion presence resulting from TVM. Also the usage of salicylic acid application on tobacco leaves is further checked by color reflectance. Secondly beet root is again sprayed with Cercosporabeticola spore solution. Here the different response of different temperatures resulting in varied fluorescence effects is being characterized. This paper briefs about the combined usage of multiple types of imaging for plant and various pathogen combination for early symptoms detection.

Crop quality is also a great factor taken into consideration while estimation of agricultural overall production. Paper (Bauriegel and

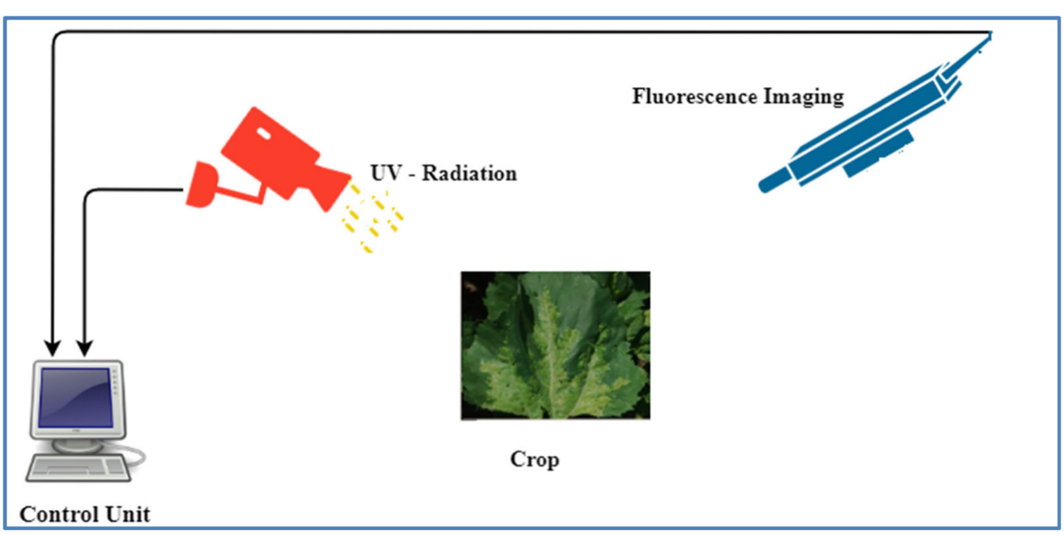

Fig. 2. Fluorescence Imaging Techniques.

Herppich, 2014a) presents the detection of head blight disease in wheat plants using chlorophyll fluorescence and also with hyper spectral imaging. It signifies the ways in which hyper spectral imaging is being useful for higher information density extraction. In this paper the different imaging techniques are being further highlighted as better methods of early bight disease detection.

Timely identification of disease among the plants may result in better procurement and agricultural productions. Paper (Römer et al., 2011) presents a method for differentiating leaf rust wheat leaf from healthy leaf at early level. This paper presents pre symptomatic detection and further classification using support vector machine method. It also presents use of Fluorescence detection using fluorescence spectrometer for collection of various parameters. Further support vector machine was being used classification for healthy and inoculated leaves. Finally, fluorescence signatures used during polynomial fitting presents a technique for detection of disease.

The paper (Bauriegel and Herppich, 2014b) discuss about how chlorophyll fluorescence and hyper spectral imaging, can help in identifying fusarium head blight in wheat both in laboratory and field. Also two methods hyperspectral imaging and CFI analysis are compared seeking their usage in detecting fusarium. The CFI methodology is helpful during the initial phase of inspection whereas hyperspectral imaging involves various wavelengths in image analysis and thus helps in meaningful monitoring of the disease. Hyperspectral imaging is effective while dealing with the visibility of infection symptoms. The challenges are that for any image based methodology on field recording of head blight will require two passages over crop whether the imaging system are used single or being combined.

The paper (Moshou et al., 2005) discusses about combination of imaging techniques using hyper spectral reflection with fluorescence for distinguishing yellow rust disease with wheat of the increasing disease, hence the paper discusses about the formation of a real time remote sensing system for disease detection. The images from hyper and multi spectral fluorescence reflection, are used to find the of disease present. It is found that fusing the measurements from the two methods gave discrimination of 94.5% by using QDA. The methodology used for date fusion is SOM (self-organizing map) NN. The advantage of using fusion of measurements from different optical sensors is that they identify disease is field with more accuracy. This methodology shows potential for implementing in field also.

3.9. Thermal imaging

This (Fig. 3) is a process that convert the various radiation identified from an object to different types of images for extraction of varied features, analysis along with classifying them. It was firstly used for defense needs but later gained a major use in different fields such as engineering techniques used in agriculture.

Several instruments and methods have been developed for thermal imaging of plant. The thermal imaging method is very useful for many different operations of agriculture before and after harvesting. For this site specific Crop management and precision farming, Thermal imaging is an important phenomenon where Plant, soil, and water relationship has been studied in detail by several researchers. (Vadivambal and Digvir, 2011).

In paper (Yang et al., 2019) a method has been described for fast determination of disease in tea leaves using a method making use of application of infrared thermal imaging technology. In paper (Xu et al., 2006) the comparison of different temperature distribution under the effect of virus strain-TMV on three species of tomato plant leaves are shown. Here thermal images are being used for the determination of changes in pathogen related proteins and salicylic acid in infected leaves and normal leaves. It is also highlighted how the transpiration is affected by pathogen infection.

This Paper (Raza et al., 2015a) focus on the involvement of thermal depth data with visible light image for automatic identification of disease in tomato plant leaves. It shows the way of initial setup done for the acquisition of visual and thermal images. Here a technique for disparity detection has also been proposed.

This paper (Wang et al., 2013) gives a way of using digital infrared thermography for detection of the changes as water loss further affecting the temperature also. It also shows the importance of identification and prevention of fungal toxin for agricultural needs. In this paper the leaf temperature is observed under variant conditions. It also estimated stomata apertures by nail varnish method. Later on leaves with

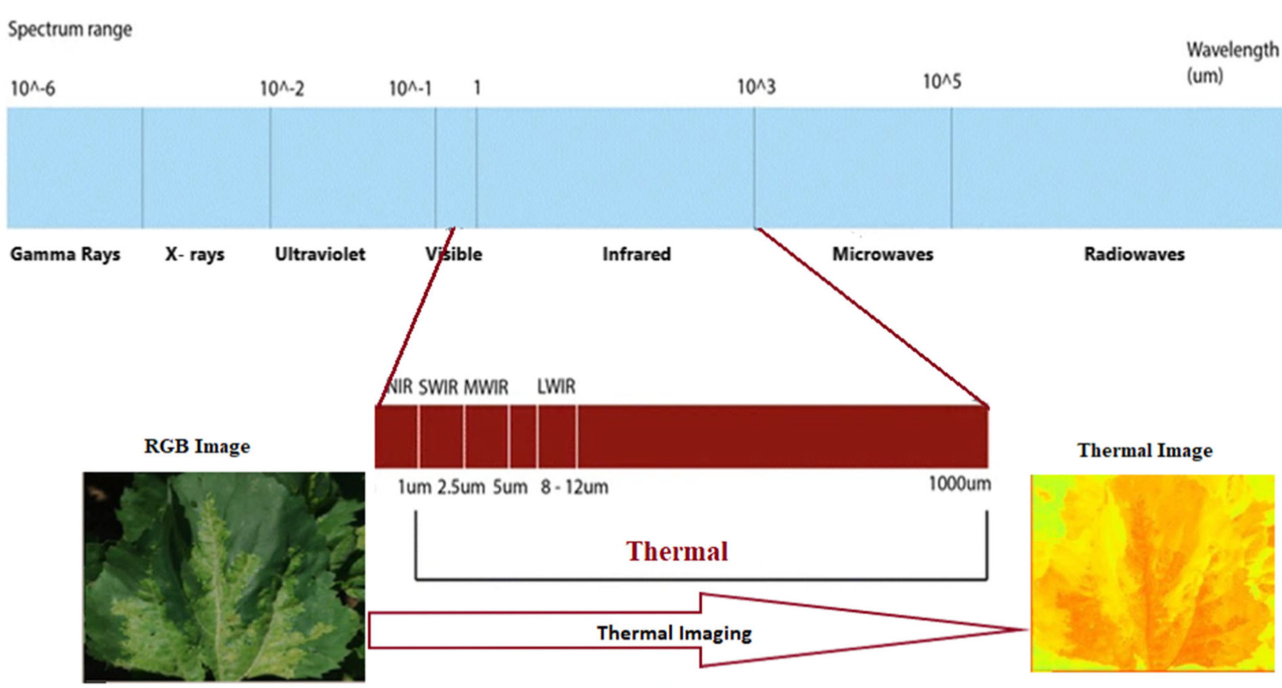

Fig. 3. Thermal imaging.

membrane injury were identified along with FA content being measured in different temperatures.

Here paper (Sankaran et al., 2013) shows the requirement of a sensor efficient of determining HLB for overall complete cover. Here infrared along with thermal images are used for detected HLB-infected citrus trees. This paper briefs about the evaluation of the use of multispectral images for HLB detection, by the medium of a mobile ground-based sensor. It initially used two multispectral cameras and one thermal camera for capturing images from the head of the citrus canopies. It further shows the method of using various indices as the average spectral reflectance, structure insensitive pigment and many others. It also uses thermal imaging for identification of stress due to pathogens in plants. Later on different classifiers were used including LDA, BDT, SVM and QDA for classification study for many features.

Thermal imaging of plant leaves result in early identification of disease thus reducing large agricultural losses. In paper (Raza et al., 2015b) an algorithm is proposed for the identification of disease in plants using silhouette registration through visible images. Initially the algorithm detects silhouette through visible light images. It also employs stationary wavelet transform for thermal images for the same. It makes use of gradient-based method in this multi scale approach. This paper also shows that another method that can be further used for different sample using silhouette presence while registering the images.

Detection of Plant Disease is possible by digital infrared thermograph as temperature measurement is directly related to water quantity decrease by stomata aperture openings. This paper (Oerke et al., 2006) shows the study of irregularities presence in plant affected by *P. cubensis*. It also describes detection of downy mildew through temperature difference. Initially the leaves were analyzed for the presence of disease by visual inspection various lesions were recorded for sensitizing disease presence. Later spectral images were used to study the presence of disease on basis of various factors including transpiration rate, stomata apertures and others. Finally, the relation established between electrolyte leakage and transpiration rate for the disease presence d is analyzed.

Paper (Awad et al., 2014) gives a study for early identification of disease such as powdery mildew in plants using thermal images of wheat samples. Firstly, wheat leaves were artificially infected with Erysiphe graminis fungus for experimental purpose. It also made use of greenhouse conditions for complete experimental study. Further the difference in the temperature was measured in normal and was compared with the infected leaves under various conditions. It also shows the various monitoring process after artificial infection. Further changes in temperatures were analyzed. This paper describes the need for recommended expert system for the detection of different disease.

3.10. 3D imaging

In 2D Imaging data is taken from two different dimensions which differentiate given some denominations of plants such as development, overall height, and yield estimation. Thus, the need of 3D imaging appears as an essential for automatic plant diseases detection. There are various techniques for 3-D image acquisition (Bellmann et al., 2007) (Jarvis, 1983) (Blais, 2004) and 2-D together with 3-D machinery in applications pertaining to agriculture (Grift, 2008) (McCarthy et al., 2010). Block diagram of 3-D imaging system is given below in Fig. 4.

There are two main 3D representations i.e. one concerned with the surface and other with the volume presentations. The first one involves the depth details, the surface element and the different points given by their dimension coordinates. The volume is also given defining the volumetric component and a frequency component of the model's coordinates. In now a day different types of affordable sensors are available. They also exhibhits technologically advanced to a great extent for various domains like nutrient content, growth level, crop presence, biomass estimation, and height and health status. Plant leaf diseases being further analyzed using these sensors because the gathered data can be used for quantifying the previously identified various production characters. (Vázquez-Arellano et al., 2016).

Sensors including various types of LIDARs and TOF cameras with their sensors, determine the depth using the light velocity (Fig. 5) (Underwood et al., 2013) (Lachat et al., 2015).

4. Image classification methods for plant disease detection

Most important step of Leaf image analysis is segmentation. Image Segmentation is the process which takes an image as a single input and further partition that particular image into different sub segments. In the area of imaging for classification (Fig. 6.) purpose, these segments often constitute various classes of tissues, organs or biologically important structures. Here image segmentation becomes challenging due to various factors including low contrast and other imaging ambiguities along with noise.

4.1. Interactive segmentation

It can be described as one of the techniques that are beneficial where expert can give certain useful information about the seed region or a brief description about the region used to perform segmentation. Further an algorithm works fine for the refinement including the segmentation. There can be other methods also some including manual intervention for providing the different classes of the tissue using pixel information. Along with all lastly, feedback control principle is also being involved with segmentation, which adds to other benefits for the users such as flexibility, the automatic removal of issues.

There can be numerous methods that have been brought to application by researchers in last many years; some of them are reviewed as following.

Yan Cheng Zhang et al. (2007) brought one of the Selection methods to light, that makes use of fuzzy curves for the identification of presence of disease in cotton plant leaves. The given technique has been found to be better in terms of the speed of the execution. It yields a better classification result without being affected by the local minima issues that are otherwise usually prominent in the nonlinear methods. Savita N Ghaiwat also gave a survey of the different types of the classification methods feasible for detection of various diseases in plant leaves (Ghaiwat and Arora, 2014).

Al Bashish et al. (2010) discussed one of the segmentation method based on K-mean. Here different disease such as cottony meld, tiny

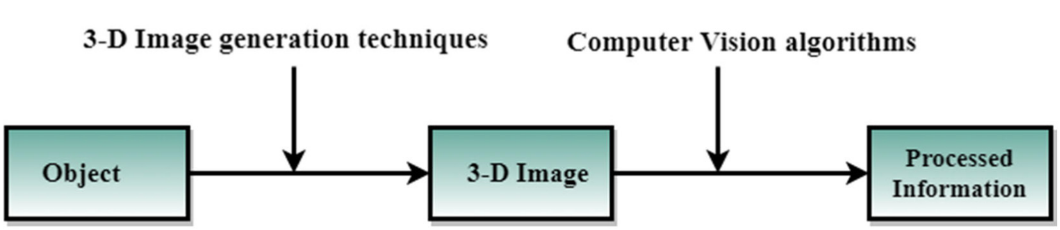

Fig. 4. Block diagram of 3-D imaging.

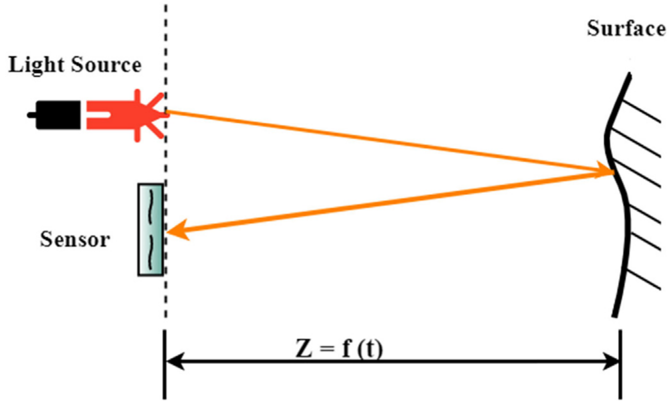

Fig. 5. Imaging through TOF Sensors.

whiteness is being detected using this. It also shows the use of ANN for further identification of disease as early scorch and ashen meld present in various plants. In this paper the results giving accuracy rate of 93% has been discussed. A. Meunkaewjinda et al. (2008), also has given a technique for the early identification of disease present in specifically grape leaves. It also exhibits classification using support vector machine. Jaware et al. (2012) has proposed a faster classification algorithm. Here different types of diseases such as Early Scorch, Cottony meld and tiny whiteness have been identified easily using this technique. This method has been shown as an optimum method for detection of the varied diseases in shorter span of time.

Gurjar and Gulhane (2012) briefed about the regularization method. Here a technique has been discussed that involves the use of Eigen features. It has been highlighted how it is being better than some of the other techniques with respect to accuracy. For the identification of some of the disease caused by fungus such as red spot, it is able to work with an accuracy of 90%.

Revathi and Hemalatha (2012) have given disease identification method that makes use of detection of edges based on uniform Segmentation. One of the disease commonly found in cotton leaves such as Fusarium wilt gets easily identified using this technique. Other types of diseases as Root rot, Gray mildew, Leaf blight, Bacterial blight, Boll rot, and Leaf curl have also been detected through neural networks. Here application of this method beneficial in smart farming has also been discussed. Madhogaria et al. (2011) have given technique of classification using individual information of each pixel for classifying diseases of plants. It has also shown use of svm. Tian et al. (2010) discussed a technique using different classifier such as support vector for the early detection of disease present in wheat plant. The disease detected here includes leaf blight and powdery mildew.

Sannakki et al. (2011) has given the detection of disease profoundly present in pomegranate leaves. The technique shown also helps in the identification of the specific detoriation stage of the disease discussed. Here the use of decision tree learning, fuzzy logic along with Bayesian network has been discussed.

Arivazhagan et al. (2013) discussed a technique involving four stages of early disease detection. It also shows the use of software for the automatic identification. The various stages discussed here include formation of a color transformation for the given image that is followed by masking of the green pixels. These are further followed by removal of definite threshold values along with segmenting them. Feature extraction and computation of texture information has also been discussed. It is being shown on a data of 500 plant samples including lemon, tomato, beans, banana and others resulting in an accurate rate of 94%.

Anand et al. (2016) have given a technique for the presence of plant diseases. This work brings about the use of different techniques of image processing for disease detection. It also makes use of artificial neural network while identifying these. One of the filters as Gabor filter has been deployed for filtering purpose before complete segmentation. Various features are later trained that helps in differentiating between healthy and unhealthy leaves. Naikwadi and Amoda (2013) also gave a software solution for early disease detection in different plants. Only after the stage of segmentation, green pixels are detected. These are further being masked for definite threshold found using Otsu's method. The technique used provides a precision ranges from 83% to 94%. Patil and Bodhe (2011) makes use of threshold method for segmentation of the leaf region. Later in categorization it shows an accuracy of 98.60%.

Beyyala and Beyyala (2012) discussed different methods of early identification of plant diseases making use of image Processing. Piyush Chaudhary et al. (2012b) have given an algorithm for disease detection. It involves the segmentation of spot using varied processing methods in plants. Also a systematic comparison among HIS, cielab and ycbcr color has been derived while spot identification.

The paper (Mohanty et al., 2016) proposes to train a deep neural network by using 54,306 images having healthy unhealthy leaves both to identify 26 diseases and 14 crop species. It proposes the use of Smartphone for diagnosing crop diseases. The model proposes both classifying the crop species and identifying the disease on images of the plant thus making use of Smartphone for detection of crop disease

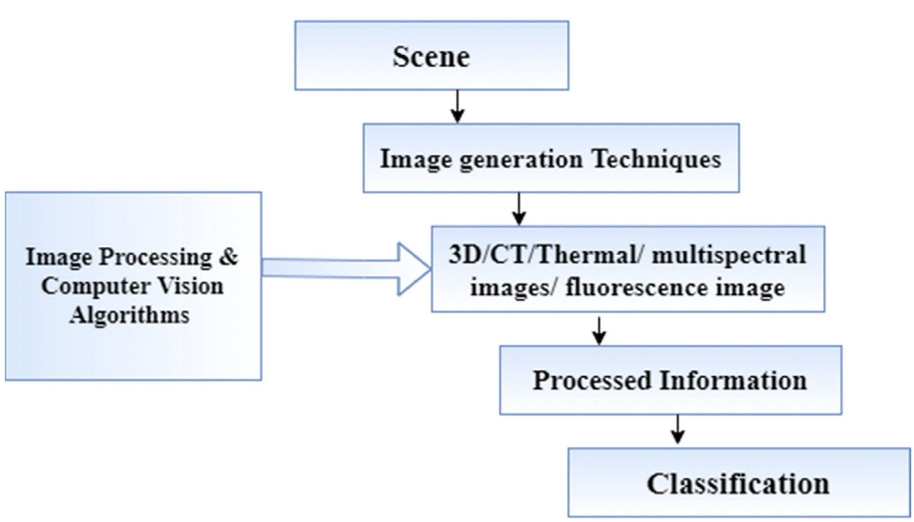

Fig. 6. Plant disease detection and classification.

feasible. The shortcoming of this paper is that this model gives higher accuracy for the dataset for which model is trained. However, if the data set is collected from different condition, the accuracy of model would be reduced. Also the image collected is more focused on only upper side of leaves which needs to be elaborated.

The paper (Konstantinos P. Ferentinos, 2018) proposes the development of convolution neural network models for detecting and diagnosing diseases in different leaves making use of deep learning methodologies. In paper Sladojevic et al., 2016, proposes the method of deep neural networks for leaf image classification to recognize plant diseases. The model which is developed helps in identification of plant diseases. Further a method for differentiating them has also been shown. Caffe is used to give the training in deep CNN. The final accuracy of the trained model was 96.3%. The challenge highlighted here includes the collection of images for better accuracy of the model, having apt augmented done.

This paper (Rumf et al., 2010) proposes a procedure for detecting and differentiating between healthy and diseases plant leaves using support vector machines with vegetative indice. This paper also differentiates between the different diseases like lercospora, powdery mildew and leaf rust also identifying the diseases at an initial stage. The leaves are inoculated with the different pathogens like lercosporapeticola, uromycesbetac or E rysiphebetac causing lercospora leaf spot, and powdery mildew and hyperspectral data are recorded from these diseases leaves and healthy leaves. In this paper diseased leaves and healthy leaves. This paper shows use of 9 vegetation indices for automatic classification. The classification accuracy has been drastically improved to 97%. The advantage of using SVMs method based on Vis is that this procedure can also applied to other plant pathogen systems.

This paper (Chaudhary et al., 2012b) proposes a technique for disease spot detection in affected area since the disease spots in plants are different in color; this paper proposes color transformation of RGB image to get better segmentation of disease spots. Various color models like YCbCr and CIELAB are differentiated from 'A' component of CIELAB model. Then the image which is color transformed is passed through median filter and the spots includes segmentation by OTSU threshold. The advantage of this method is that the noise introduced by background, vein and camera flash are wiped out using CIELAB model. The only challenge left is differentiating the same colored veins from spots.

The paper (Behmann and JorgSteinrucken, 2014) proposes an approach combining supervised and unsupervised methods to identify drought stress on barely. The methodology is applied on both polled plants found in drought stress condition or properly watered. Ordinal classification with support vector machine has been brought to use for visualizing the division of different sections. It also differentiates between both easily. Paper shows that drought stress is detected 10 days earlier than NDVI. The advantages of this method are that it is an optimum technique for early identification of drought.

In now a day's Deep Learning (DL) have an edge over accuracy. A huge amount of work has been done for improving the varied DL architecture that is useful in early classification of different types of diseases found in plants. They provide an effective way of many different benefits related to agricultural processes. In paper (Hall et al., 2015), classification has been carried out by hybrid CNN. It also makes the use of Random Forest (RF) classifier for experimentation giving accurate results. Paper (Kamilaris and Prenafeta-Boldú, 2018) shows its drawback for identification of occluded objects. Counting of fruits and leaf were also done using CNN in (Itzhaky et al., 2018) (Ubbens et al., 2018). For classification among different plants, (Raza et al., 2015b) (Kussul et al., 2017) used modified CNN. Plant recognition has been done by the different Deep Learning algorithm in (Kussul et al., 2017) (Grinblat et al., 2016) (Singh et al., 2015). For detection and classification of Crop different experiments was performed in (Pound et al., 2017) (Milioto et al., 2017).

5. Challenges and future trends

Major research done in the last few years discussing various types of techniques have been shown earlier in this paper. The state of art survey with current challenges on Plant diseases detection has been done and given below-

This paper (Khitthuk et al., 2018) mainly involves analyzing the different plant features based on varied statistics. It also includes the process of classification. Here firstly the image is processed using Gaussian low pass filter. This paper (Vaishnnave et al., 2019) discusses the technique for the early determination of disease such as in groundnut plant leaves.

In paper (Jhuria et al., 2013) images of leaf is first captured and preprocessed for noise filtering. It also involved image enhancement and application of morphological operation. Later on Kmean clustering has been shown for cluster formation. Finally, random forest classifier enabled the classification of different fungal disease as Bacterial blight, Cercospora Leaf spot and as *Alternaria alternata*.

In paper (Dhakate and Ingole, 2015) a system is being shown for the determination of presence of disease in pomegranate plant. Here different way has been highlighted for training purpose using back propagation method. Bacterial blight, fruit rot were among the major identified. It also described the use of k mean clustering for cluster formation of the images used.

This paper (Anand et al., 2016) focus on the identification of brinjal plant leaves disease. It showcases the process of pre-processing of the plant leave images. Further K mean clustering has been used, followed by the feature extraction step that is accomplished by using the color Co-occurrence Method. This highlights the various parameters used for the identification as Area, perimeter, centroid, and diameter for showing presence of disease.

This paper (Islam et al., 2017) gives a method that involves machine learning technique along with image processing for detection of presence of disease in potato plant leaves. It shows the importance of early detection of disease. Firstly, the region of interest has been extracted by masking the background. Further a multicast support vector classifier is being for differentiating between the absence and presence of disease using color and texture characteristics. Later Gray Level Co-occurrence method is also being placed for extracting specific features including homogeneity, correlation contrast, and energy.

Detection of disease in plant is the most important step for reduction of agricultural yield losses. Here paper (Gaikwad and Musande, 2017) involves development of early detection methods for different plant disease. Initially the wheat plant leaves image taken were undergone the process of preprocessing. This is further followed by K mean clustering partitioning method. Here the basic features extracted include texture, shape and color. It highlights the neural network classification method for the detection of fungal disease presence wheat plant leaves.

The challenge in this approach is that it is required to use sensors also for practical use in future. In paper (Padol and Yadav, 2016) the detection and further classification of grape leaf disease is processed using SVM classification technique. The fungal diseases occurring in grape leaves being discussed here includes Downy Mildew and Powdery Mildew. It also includes the classification done through training and testing phases.

Increasing huge losses in cotton yield due to various diseases is a crucial reason for developing an early disease detection system for cotton plant. In paper (Bhimte and Thool, 2018) a method is proposed for early detection of disease among cotton leaves through Support vector machine. This paper (Pawar and Jadhav, 2017) proposes a novel method for identifying disease and classification. It highlights this process involving acquisition. Here k mean clustering algorithm is being used for pomegranate plant leaves analysis. Various features as. Color, morphology, edges, texture have been extracted and classified using ANN method.

Following are the research gaps which are observed and they still exist in research on Plant diseases detection and classification:

a. Automatic cluster centre initialization is lacking.
b. improves the proposed algorithm for reduction of error due to classification
c. Can be done for other groundnut plant disease
d. To integrates advance imaging technique and Computer vision algorithms
e. For automatically detection of plant leaf disease algorithms are still required.
f. Work further requires analysis using different variation in surrounding conditions.
g. Need an expert System for plant diseases detection.

6. Conclusions

This paper gives an overall review for the various techniques of disease identification. It also presents brief summary of different imaging methods useful for early detection of plant diseases. We present the Current Trends and Challenges for detection of plant disease using computer vision and advance imaging technique. These techniques include thermal, hyperspectral, fluorescence, Multispectral, and 3D imaging.

We have also presented different techniques for early determination of plant diseases and classification. The major techniques are SVM, K-means clustering, Deep learning, and K-NN. This review concludes that there is a need for efficient method with comparison to the cost incurred. Also a reliable and efficient sensor deployed for looking fulfillment of proper criteria of plant health would facilitate advancements in agriculture. In future, work can be done to develop a more efficient, and robust system for early automatic tracing and can be extended to identify all possible diseases.

References

Abdulridha, J., Ehsani, R., Castro, A., 2016. Detection and differentiation between laurel wilt disease, phytophthora disease, and salinity damage using a hyperspectral sensing technique. Agriculture 6 (4), 56.

Al Bashish, Dheeb, Braik, Malik, Bani-Ahmad, Sulieman, 2010. A framework for detection and classification of plant leaf and stem diseases. International Conference on Signal and Image Processing, pp. 113–118.

Anand, R., Veni, S., Aravinth, J., 2016. An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method. International Conference on Recent Trends in Information Technology (ICRTIT).

Arivazhagan, S., Newlin, Shebiah R., Ananthi, S., Vishnu, Varthini S., 2013. Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features. Agric. Eng. Int. CIGR J. 15 (1), 211–217.

Awad, Yasser Mahmoud, Abdullah, Ahmed Ameen, Bayoumi, Tarek Youssef, Abd-Elsalam, Kamel, Hassanien, Aboul Ella, 2014. Early detection of powdery mildew disease in wheat (Triticum aestivum L.) using thermal imaging technique, intelligent systems. Adv. Intell. Syst. Comput. 323. https://doi.org/10.1007/978-3-319-11310-4_66.

Baranowski, P., Jedryczka, M., Mazurek, W., Babula-Skowronska, D., Siedliska, A., Kaczmarek, J., 2015. Hyperspectral and thermal imaging of oilseed rape (Brassica napus) response to fungal species of the genus Alternaria. PLoS One 10 (3), e0122913. https://doi.org/10.1371/journal.pone.0122913.

Bauriegel, E., Herppich, W.B., 2014a. Hyperspectral and chlorophyll fluorescence imaging for early detection of plant diseases, with special reference to Fusarium spec. Infect. Wheat Agric. 2014 (4), 32–57.

Bauriegel, Elke, Herppich, Werner B., 2014b. Hyperspectral and chlorophyll fluorescence imaging for early detection of plant diseases, with special reference to Fusarium spec. Infect. Wheat Agric. 4 (1), 32–57.

Behmann, Jan, JorgSteinrucken, Lutz Plumer, 2014. Detection of early plant stress responses in hyperspectral images. ISPRS J. Photogramm. Remote Sens. 93, 98–111.

Bellmann, A., Hellwich, O., Rodehorst, V., Yilmaz, U., 2007. IEEE Conference on Computer Vision and Pattern Recognition. A Benchmarking Dataset for Performance Evaluation of Automatic Surface Reconstruction AlgorithmsIEEE, Minneapolis, MN, USA, pp. 1–8.

Beyyala, Arun Kumar, Beyyala, Sai Priya, 2012. Application for diagnosis of diseases. In crops using image processing. Int. J. Life Sci. Bt. Pharm. Res. 1 (2), 171–176 2012. ISSN 2250–3137. www.ijlbpr.com.

Bhimte, Namrata R., Thool, V.R., 2018. Diseases detection of cotton leaf spot using image processing and SVM classifier. Second International Conference on Intelligent Computing and Control Systems (ICICCS).

Blais, F., 2004. Review of 20 years of range sensor development. J. Electron. Imaging. 13, 231–240. https://doi.org/10.1117/1.1631921.

Bravo, C., Moshou, D., West, J., McCartney, A., Ramon, H., 2003. Early disease detection in wheat fields using spectral reflectance. Biosyst. Eng. 84 (2), 137–145 01 Feb 2003.

Calderón, R., Navas-Cortés, J.A., Zarco-Tejada, P.J., 2015. Early detection and quantification of Verticillium wilt in olive using hyperspectral and thermal imagery over large areas. Remote Sens. 2015 (7), 5584–5610.

Cao, X., Luo, Y., Zhou, Y., Fan Xu, X., West, J.S., et al., 2015a. Detection of powdery mildew in two winter wheat plant densities and prediction of grain yield using canopy hyperspectral reflectance. PLoS One 10 (3), e0121462. https://doi.org/10.1371/journal.pone.0121462.

Cao, X., Luo, Y., Zhou, Y., Fan, J., Xu, X., West, J.S., et al., 2015b. Detection of powdery mildew in two winter wheat plant densities and prediction of grain yield using canopy hyperspectral reflectance. PLoS One 10 (3), e0121462. https://doi.org/10.1371/journal.pone.0121462.

Chaudhary, Piyush, Chaudhari, Anand K., Cheeran, A.N., Godara, Sharda, 2012a. Color transform based approach for disease spot detection on plant leaf. Int. J. Comput. Sci. Telecomm. 3 (6) (June 2012).

Chaudhary, Piyush, Chaudhari, Anand K., Cheeran, A.N., Godara, Sharada, 2012b. Color transform based approach for disease spot detection on plant leaf. Int. J. Comput. Sci. Telecommun. 3 (6), 65–70.

Del Fiore, A., Reverberi, M., Ricelli, A., Pinzari, F., Serranti, S., Fabbri, A.A., 2010. Early detection of toxic fungi on maize by hyperspectral imaging analysis. Int. J. Food Microbiol. 144 (1), 64–71 2010 Nov 15.

Dhakate, Mrunmayee, Ingole, A.B., 2015. Diagnosis of Pomegranate Plant Diseases Using Neural Network. Fifth National Conference on Computer Vision. Pattern Recognition, Image Processing and Graphics (NCVPRIPG).

EwisOmran, El-Sayed, 2016. Early sensing of peanut leaf spot using spectroscopy and thermal imaging. Arch. Agron. Soil Sci. https://doi.org/10.1080/03650340.2016.1247952.

Fang, Yi, Ramasamy, Ramaraja P., 2015. Current and prospective methods for plant disease detection. Biosensors https://doi.org/10.3390/bios5030537.

Ferentinos, Konstantinos P., 2018. Deep learning models for plant disease detection and diagnosis. Comput. Electron. Agric. 145 (2018), 311–318.

Gaikwad, Varsha P., Musande, Vijaya, 2017. Wheat disease detection using image processing. First International Conference on Intelligent Systems and Information Management (ICISIM).

Ghaiwat, Savita N., Arora, Parul, 2014. Detection and classification of plant leaf diseases using image processing techniques: a review. Int. J. Rec. Adv. Eng. Technol. (IJRAET) 2 (3), 1–7 ISSN (Online): 2347–2812.

Golhani, Kamlesh, Balasundaram, Siva K., Vadamalai, Ganesan, Pradhan, Biswajeet, 2018. A review of neural netwoks in plant disease detection using hyperspectral data. Inform. Proc. Agric. 5 (3), 354–371 September 2018.

Grift, T., 2008. A review of automation and robotics for the bioindustry. J. Biomech. Eng. 1, 37–54.

Grinblat, G.L., Uzal, L.C., Larese, M.G., Granitto, P.M., 2016. Deep learning for plant identification using vein morphological patterns. Comput. Electron. Agric. 127, 418–424.

Gurjar, Ajay A., Gulhane, Viraj A., 2012. Disease detection on cotton leaves by Eigen feature regularization and extraction technique. Int. J. Electr. Commun. Soft Comput. Sci. Eng. 1 (1), 1–4.

Hall, D., McCool, C., Dayoub, F., Sunderhauf, N., Upcroft, B., 2015. Evaluation of features for leaf classification in challenging conditions. Proceedings of the 2015 IEEE Winter Conference on Applications of Computer Vision, Waikoloa Beach, HI, USA, 6–8 January, pp. 797–804.

Islam, Monzurul, Dinh, Anh, Wahid, Khan, Bhowmik, Pankaj, 2017. Detection of potato diseases using image segmentation and multiclass support vector machine. IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE).

Itzhaky, Y., Farjon, G., Khoroshevsky, F., Shpigler, A., Bar-Hillel, A., 2018. Leaf counting: multiple scale regression and detection using deep CNNs. Proceedings of the BMVC, North East, UK, p. 328.

Jarvis, R., 1983. A perspective on range finding techniques for computer vision 1983. IEEE Trans. Patt. Anal. Mach. Intell. 1983 (PAMI-5), 122–139. https://doi.org/10.1109/TPAMI.1983.4767365.

Jasim, M.A., Tuwaijari, J.M.A.L., 2020. Plant leaf diseases detection and classification using image processing and deep learning techniques. International Conference on Computer Science and Software Engineering (CSASE), Duhok, Iraq, 2020, pp. 259–265 https://doi.org/10.1109/CSASE48920.2020.9142097.

Jaware, Tushar H., Badgujar, Ravindra D., Patil, Prashant G., 2012. Crop disease detection using image segmentation. Proceedings of Conference on Advances in Communication and Computing (NCACC'12).

Jhuria, Monika, Kumar, Ashwani, Borse, Rushikesh, 2013. Image processing for smart farming: detection of disease and fruit grading. IEEE Second International Conference on Image Information Processing (ICIIP-2013).

Kamilaris, A., Prenafeta-Boldú, F.X., 2018. Deep learning in agriculture, a survey. Comput. Electron. Agric. 147, 70–90.

Khitthuk, Chaowalit, Srikaew, Arthit, Attakitmongcol, Kitti, Kumsawat, Prayoth, 2018. Plant leaf disease diagnosis from color imagery using co-occurrence matrix and artificial intelligence system. International Electrical Engineering Congress (iEECON).

Kulkarni, Anand H., Ashwin Patil, R.K., 2012. Applying image processing technique to detect plant diseases. Int. J. Mod. Eng. Res. 2 (5), 3661–3664.

Kussul, N., Lavreniuk, M., Skakun, S., Shelestov, A., 2017. Deep learning classification of land cover and crop types using remote sensing data. IEEE Geosci. Remote Sens. Lett. 14, 778–782.

Lachat, E., Macher, H., Mittet, M., Landes, T., Grussenmeyer, P., 2015. First experiences with Kinect v2 sensor for close range 3D modeling. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. ISPRS, Avila, Spain, pp. 93–100 Vol. XL-5/W4.

LauryChaerle, DikHagenbeek, De Bruyne, Erik, Valcke, Roland, Van Der Straeten, Dominique, 2004. Thermal and chlorophyll-fluorescence imaging distinguish plant-pathogen interactions at an early stage. Plant Cell Physiol. 45 (7), 887–896.

Lawrence, G.W., Kelly, A.T., King, R.L., Vickery, J., Lee, H.K., McLean, K.S., 2004. Remote Sensing and Precision Nematicide Applications for Rotylenchulus Reniformis Management in Cotton.

Li, Xiaona, Li, Ruolan, Wang, Mengyu, Liu, Yaru, Zhang, Baohua, Zhou, Jun, 2017. Hyperspectral Imaging and their Applications in the Nondestructive Quality Assessment of Fruits and Vegetables. https://doi.org/10.5772/intechopen.72250.

Liu, Linyi, Dong, Yingying, Huang, Wenjiang, Xiaoping, Du, Ren, Binyuan, Huang, Linsheng, Zheng, Qiong, Ma, Huiqin, 2020. A Disease Index for Efficiently Detecting Wheat Fusarium Head Blight Using Sentinel-2 Multispectral Imagery. 8. IEEE Access, pp. 52181–52191. https://doi.org/10.1109/ACCESS.2020.2980310.

López-López, M., Calderón, R., González-Dugo, V., Zarco-Tejada, P.J., Fereres, E., 2016. Early detection and quantification of almond red leaf blotch using high-resolution Hyperspectral and thermal imagery. Remote Sens. 2016 (8), 276.

Lopez-Lopez, Manuel, Calderon, Rocio, Gonzalez-Dugo, Victoria, Zarco-Tejada, Pablo J., Fereres, Elias, 2016. Early detection and quantification of almond red leaf blotch using high resolution hyperspectral and thermal imagery. Remote Sens. 8, 276.

Lowe, Amy, Harrison, Nicola, French, Andrew P., 2017. Hyperspectral Image Analysis techniques for the detection and classification of the early onset of plant disease and stress. Plant Methods 13, 80.

Madhogaria, Satish, Schikora, Marek, Koch, Wolfgang, Cremers, Daniel, 2011. Pixel-based classification method for detecting unhealthy regions in leaf images. Informatikschafft Communities 41. Jahrestagung der Gesellschaft fürInformatik, 4.-7.10.2011, Berlin.

Mahlein, A., Kuska, M., Thomas, S., Bohnenkamp, D., Alisaac, E., Behmann, J., Kersting, K., 2017. Plant disease detection by hyperspectral imaging: from the lab to the field. Adv. Anim. Biosci. 8 (2), 238–243. https://doi.org/10.1017/S2040470017001248.

Mahlein, A.K., Rumpf, T., Welke, P., Dehne, H.-W., Plumer, L., Steiner, U., Oerke, E.-C., 2013. Developments of spectral indices for detecting and identifying plant diseases. Remote Sens. Environ. 128 (21), 21–30.

Mahlein, Anne-Katrin, Oerke, Erich-Christian, Steiner, Ulrike, Dehne, Heinz Wilhelm, 2012. Recent advances in sensing plant diseases for precision crop protection. Eur. J. Plant Pathol. 133, 197–209.

Martinelli, Federico, Scalenghe, Riccardo, Davino, Salvatore, Panno, Stefano, Scuderi, Giuseppe, Ruisi, Paolo, Villa, Paolo, Stroppiana, Daniela, MircoBoschtti, Luiz, Goulart, R., Davis, Cristina E., Dandekar, Abhaya M., 2015. Advanced methods of plant disease detection. Agron. Sustain. Dev. 35 (1), 1–25 Springer Verlag/EDP Sciences/INRA, 2015.

McCarthy, C.L., Hancock, N.H., Raine, S.R., 2010. Applied machine vision of plants. 2010. A review with implications for field deployment in automated farming operations. Intell. Serv. Robot. 3, 209–217. https://doi.org/10.1007/s11370-010-0075-2.

Meunkaewjinda, A., Kumsawat, P., Attakitmongcol, K., Kaew, Sri, 2008. Grape leaf disease detection from color imagery using hybrid intelligent system. Proceedings of ECTI-CON 2008. 1. Krabi, pp. 513–516.

Milioto, A., Lottes, P., Stachniss, C., 2017. Real-time blob-wise sugar beets vs weeds classification for monitoring fields using convolutional neural networks. Isprs Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 4, 41.

Mishra, P., Polder, G., Vilfan, N., 2020. Close range spectral imaging for disease detection in plants using autonomous platforms: a review on recent studies. Curr. Robot. Rep. 1, 43–48.

Moghadam, Peyman, Ward, Daniel, Goan, Ethan, Jayawardena, Srimal, Sikka, Pavan, Hernandez, Emili, 2017. International Conference on Digital Image Computing: Techniques and Applications (DICTA). 2017. Plant Disease Detection using Hyperspectral Imaging, Sydney, NSW, pp. 1–8.

Mohanty, Sharada P., Hughes, David P., Salathe, Marcel, 2016. Using deep learning for image based plant disease detection. Front. Plant Sci. 7, 1419. https://doi.org/10.3389/fpls.2016.01419.

Moshou, D., Bravo, C., West, J., Wahlem, S., McCartney, A., Ramon, H., 2004. Automatic detection of “yellow rust” in wheat using reflectance measurement and neural networks. Comput. Electron. Agric. 44 (3), 173–188.

Moshou, D., Bravo, C., Oberti, R., West, J., Bodria, L., McCartney, A., Ramon, H., 2005. Plant disease detection based on data fusion of hyper spectral and multi spectral fluorescence imaging using Kohonen maps. Real-Time Imag. 11 (2), 75–83.

Moshoua, D., Bravoa, C., Obertib, R., Westc, J., Bodriab, L., McCartney, L., Ramona, H., 2005. Plant disease detection based on data fusion of hyper-spectral and multi-spectral fluorescence imaging using Kohonen maps. Real-Time Imag. 11 (2), 75–83. https://doi.org/10.1016/j.rti.2005.03.003.

Nagaraju, M., Chawla, P., 2020. Systematic review of deep learning techniques in plant disease detection. Int. J. Syst. Assur. Eng. Manag. 11, 547–560.

Nagasubramanian, K., Jones, S., Singh, A.K., et al., 2019. Plant disease identification using explainable 3D deep learning on hyperspectral images. Plant Methods 15, 98.

Naikwadi, Smita, Amoda, Niket, 2013. Advances in image processing for detection of plant diseases. Int. J. Appl. Innov. Eng. Manag. 2 (11), 168–175.

Ochoa, Daniel, Cevallos, Juan, Vergas, German, Criollo, Ronald, Romero, Dennis, Castro, Rodrigo, Bayona, Oswaldo, 2016. Hyperspectral imaging system for disease scanning on banana plants. Proc. SPIE 9864, Sensing for Agriculture and Food Quality and Safety VIII, 98640M.

Oerke, E.-C., Steiner, Dehne H.-W., Lindenthal, M., 2006. Thermal imaging of cucumber leaves affected by downy mildew and environmental conditions. J. Exp. Bot. 57 (9), 2121–2132. https://doi.org/10.1093/jxb/erj170 June 2006.

Okamoto, Hiroshi, Murata, Tetsuro, Kataoka, Takashi, Hata, Shun-Ichi, 2007. Plant Classification for Weed Detection using Hyperspectral Imaging with Wavelet Analysis. https://doi.org/10.1111/j.1445-6664.2006.00234.x.

Padol, Pranjali B., Yadav, Anjali A., 2016. SVM classifier based grape leaf disease detection. Conference on Advances in Signal Processing (CASP).

Patil, Sanjay B., Bodhe, Shrikant K., 2011. Leaf disease severity measurement using image processing. Int. J. Eng. Technol. 3 (5), 297–301.

Pawar, Rashmi, Jadhav, Ambaji, 2017. Pomogranite disease detection and classification. IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI).

Pérez-Bueno, M.L., Pineda, M., Cabeza, F.M., Barón, M., 2016. Multicolor fluorescence imaging as a candidate for disease detection in plant Phenotyping. Front. Plant Sci. 7, 1790. https://doi.org/10.3389/fpls.2016.01790.

Pound, M.P., Atkinson, J.A., Townsend, A.J., Wilson, M.H., Griffiths, M., Jackson, A.S., Bulat, A., Tzimiropoulos, G., Wells, D.M., Murchie, E.H., 2017. Deep machine learning provides state-of-the-art performance in image-based plant phenotyping. Gigascience 6, gix083.

Qin, J., Burks, T.F., Ritenour, M.A., Bonn, W.G., 2009. Detection of Citrus Canker Using Hyperspectral Reflectance Imaging with Spectral Information Divergence.

Ray, Shibendu Shankar, Jain, Namrata, Arora, R.K., Chavan, S., Panigrahy, Sushma, 2011. Utility of hyperspectral data for potato late blight disease detection. J. Indian Soc. Remote Sens. (June 2011) 39 (2), 161.

Raza, S.-A., Prince, G., Clarkson, J.P., Rajpoot, N.M., et al., 2015b. Automatic detection of diseased tomato plants using thermal and stereo visible light images. PLoS One 10, e0123262. https://doi.org/10.1371/journal.pone.0123262.

Raza, Shan-e-Ahmed, Prince, Gillian, Clarkson, John P., Rajpoot, Nasir M., 2015a. Automatic detection of diseased tomato plants using thermal and stereo visible light images. PLoS One https://doi.org/10.1371/journal.pone.0123262.

Raza, Shan-e-Ahmed, Sanchez, Victor, Prince, Gillian, Clarkson, John P., Rajpoot, Nasir M., 2015c. Registration of Thermal and Visible Light Images of Diseased Plants Using Silhouette Extraction in the Wavelet Domain. https://doi.org/10.1016/j.patcog.2015.01.027.

Revathi, P., Hemalatha, M., 2012. Homogenous segmentation based edge detection techniques for proficient identification of the cotton leaf spot diseases. Int. J. Comput. Appl. 47 (2) (0975 – 888). June 2012.

Römer, Christoph, Bürling, Kathrin, Hunsche, Mauricio, Rumpf, Till, Noga, Georg, Plümer, Lutz, 2011. Robust fitting of fluorescence spectra for pre-symptomatic wheat leaf rust detection with Support Vector Machines. Comput. Electron. Agric. 79 (2), 180–188 November 2011.

Rumf, T., Mahlein, A.K., Steiner, U., Oerte, E.-C., Dehne, H.-W., Plumer, L., 2010. Early detection and classification of plant disease with support vector machine based on hyperspectral reflectance. Comput. Electron. Agric. 74 (2010), 91–99.

Sankaran, Sindhuja, Mishra, Ashish, Ehsani, Reza, Davis, Cristina, 2010. A review of advance techniques for detecting plant diseases. Comput. Electron. Agric. 72 (1), 1–13.

Sankaran, Sindhuja, Maja, Joe Mari, Buchanon, Sherrie, Ehsani, Reza, 2013. Huanglongbing (Citrus Greening) Detection Using Visible, Near Infrared and Thermal Imaging Techniques. ISSN 1424-8220. www.mdpi.com/journal/sensors.

Sannakki, S.S., Rajpurohit, V.S., Nargund, V.B., Arun Kumar, R., Yallur, P.S., 2011. A hybrid intelligent system for automated pomegranate disease detection and grading. Int. J. Mach. Intell. 3 (2), 36–44 ISSN: 0975–2927 & E-ISSN: 0975–9166.

Singh, A., Ganapathysubramanian, B., Singh, A.K., Sarkar, S., 2015. Machine learning for highthroughput stress phenotyping in plants. Trends Plant Sci. 21, 110–124. https://doi.org/10.1016/j.tplants.2015.10.015.

Sinha, Shekhawat, R.S., 2020. Review of image processing approaches for detecting plant diseases in. IET Image Process. 14 (8), 1427–1439 196. https://doi.org/10.1049/iet-ipr.2018.6210.

Sladojevic, Srdjan, Arsenovic, Marko, Anderla, Andras, Culibrk, Dubravko, Stefanovic, Darko, 2016. Deep neural networks based recognition of plant diseases by leaf image classification. Comput. Intell. Neurosci. 2016, 3289801.

Sun, J., Yang, Y., He, X., Wu, X., 2020. Northern maize leaf blight detection under complex field environment based on deep learning. IEEE Access 8, 33679–33688 2020. https://doi.org/10.1109/ACCESS.2020.2973658.

Tian, Yuan, Zhao, Chunjiang, Lu, Shenglian, Guo, Xinyu, 2010. SVM-based multiple classifier system for recognition of wheat leaf diseases. Proceedings of 2010 Conference on Dependable Computing (CDC'2010), Yichang, China.

Ubbens, J., Cieslak, M., Prusinkiewicz, P., Stavness, I., 2018. The use of plant models in deep learning: an application to leaf counting in rosette plants. Plant Methods 14, 6. https://doi.org/10.1186/s13007-018-0273.

Underwood, J., Calleija, M., Nieto, J., Sukkarieh, S., 2013. A robot amongst the herd: remote detection and tracking of cows. In: Ingram, L., Cronin, G., Sutton, L. (Eds.), Proceedings of the 4th Australian and New Zealand Spatially Enabled Livestock Management Symposium. The University of Sydney, Camden, Australia, p. 52.

Vadivambal, R., Digvir, Jayas, 2011. Applications of thermal imaging in agriculture and food industry—a review. Food Bioprocess Technol. 4, 186–199. https://doi.org/10.1007/s11947-010-0333-5.

Vaishnnave, M.P., Suganya, Devi K., Srinivasan, P., ArutPerum, Jothi G., 2019. Detection and classification of groundnut leaf diseases using KNN classifier. IEEE International Conference on System, Computation, Automation and Networking (ICSCAN).

Vázquez-Arellano, M., Griepentrog, H.W., Reiser, D., Paraforos, D.S., 2016. 3-D imaging systems for agricultural applications-a review. Sensors (Basel, Switzerland) 16 (5), 618. https://doi.org/10.3390/s16050618.

Wang, Min, Xiong, Yinfeng, Ling, Ning, Feng, Xumeng, Zhong, Zengtao, Shen, Qirong, Guo, Shiwei, 2013. Detection of the Dynamic Response of Cucumber Leaves to Fusaric Acid Using Thermal Imaging. https://doi.org/10.1016/j.plaphy.2013.02.004.

Wu, D., Feng, L., Zhang, C., He, Y., 2008. Early detection of Botrytis cinerea on eggplant leaves based on near and infrared spectroscopy. Trans. ASABE 51 (3), 1133–1139.

Xu, Huirong, Zhu, Shengpan, Ying, Yibin, Jiang, Huanyu, 2006. Early detection of plant disease using infrared thermal imaging. Proc. SPIE 6381, 638110.

Yang, Ning, Yuan, Minfeng, Pan, Wang, Zhang, Rongbiao, Suna, Jun, Mao, Hanping, 2019. Tea Diseases Detection Based on Fast Infrared Thermal Image Processing Technology, (wileyonlinelibrary.com). https://doi.org/10.1002/jsfa.9564.
Zhang, Jing-Cheng, Pu, Rui-Liang, Wang, JI-Hua, Huang, Wen-Jiang, Yuan, Lin, Luo, Ju-Hua, 2012. Detecting powdery mildew of winter wheat using leaf level hyperspectral measurements. Comput. Electron. Agric. 85, 13–23.
Zhang, Yan Cheng, Mao, Han Ping, Hu, Bo, Xili, Ming, 2007. Features selection of Cotton disease leaves image based on fuzzy feature selection techniques. IEEE Proceedings of the 2007 International Conference on Wavelet Analysis and Pattern Recognition, Beijing, China, 2–4 Nov.
Zhao, Yan-Ru, Li, Xiaoli, Yu, Ke-Qiang, Cheng, Fan, He, Yong, 2016. Hyperspectral imaging for determining pigment contents in cucumber leaves in response to angular Leasf spot disease. Sci. Rep. 6, 27790 (2016). https://doi.org/10.1038/srep27790.