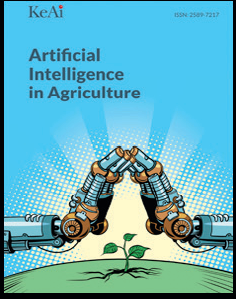
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[](http://crossmark.crossref.org/dialog/?doi=10.1016/j.aiia.2020.10.002&domain=pdf)A review of imaging techniques for plant disease detection

Vijai Singh [⁎](#_bookmark0), Namita Sharma, Shikha Singh

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

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a b s t r a c t

Agriculture is the basis of every economy worldwide. Crop production is one of the major factors affecting do- mestic market condition in any country. Agricultural production is also a major prerequisite of economic devel- opment, 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 com- monly faced challenges across the globe equally includes destruction of the major part of production due to dis- eases. 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 de- tection 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 tech- niques used for feature extraction along with classification. In this Paper we present the Current Trends and Chal- lenges for detection of plant disease using computer vision and advance imaging technique.

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\* Corresponding author.

*E-mail address:* [vijai.cs@gmail.com](mailto:vijai.cs@gmail.com) (V. Singh).

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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 civili- zation 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 ge- netically 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 re- quirement 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 ca- lamities 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 re- duced due to various types of plant diseases. Plant disease can be de- scribed as some form of modification that hampers the normal processes in it. Crop production can be majorly affected by these dis- eases which may reduce the quality and quantity of the overall pro- duced 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 imme- diate 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. Some- times 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 consum- ing task but also a very long and expensive method. Therefore, the com- plete 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](#_bookmark34)), ([Mishra et al. (2020)](#_bookmark36)).

Modern techniques available, for plant disease detection, like pro- cessing, similarity identification and deep learning based classification techniques better in respect of time saving than the old methods used ([Nagaraju and Chawla, 2020](#_bookmark46)), ([Nagasubramanian et al., 2019](#_bookmark48)), ([Kulkarni and Ashwin Patil, 2012](#_bookmark28)), ([Jasim and Tuwaijari, 2020](#_bookmark20)), ([Sun](#_bookmark38) [et al., 2020](#_bookmark38)). 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](#_bookmark36)).

In the process of detection of disease, number of imaging techniques is being used. One of the imaging techniques being used id photo acous- tic 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 conver- sion into heat further resulting in the generation of photo acoustic sig- nals. 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 im- aging. It can be described as imaging technique that gives detailed im- ages that are mostly used for knowing different types of diseases. In this method strong magnets are being deployed generating strong mag- netic 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 measure- ment, 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. Ma- jorly 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](#_bookmark34) [et al., 2010](#_bookmark34)).

Among the recent techniques being used one of the effective imag- ing methodology is using hyper spectral imaging. In this technique elec- tromagnetic 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](#_bookmark34)).

1. 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 ap- proaches 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 sys- tem are deployed to accumulate the data for study of leaves from differ- ent 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.

1. Literature survey
   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 ef- ficiently 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 differ- ent orientation by absorption of the send energy. This is called the res- onance process involved in the MRI.

* 1. *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.

* 1. *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 to- mography such as linear, poly tomography, zonagraphy, computed type or computed axial and Positron Emission type of tomography.

* 1. *Thermography*

One of the most common applications of it is breast imaging. Usually one of the three approaches are being used commonly, the tele- ther- mography, the dynamic angio-thermography and the contact thermog- raphy 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](#_bookmark34)) brings the use of nonin- vasive sensors for detection of plant diseases. Sensors types like thermog- raphy, 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 ob- tain 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](#_bookmark8)) gives the various methods of disease classifications in plants. Direct method includes PCR (polymer- ase chain reaction), IF (Immuno Fluorescence), (Fluorescence in situ

hybridization), FCM (Flow cytometry) and ELISA (Enzyme linked im- munosorbent assay) etc. Types of indirect method includes Fluores- cence 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 en- zymes, DNA, antibiotics as the detection element.

* 1. *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 opti- mize solution for a definite disease of plant and also automating the techniques for continuous checking of the plant disease. ([Sankaran](#_bookmark34) [et al., 2010](#_bookmark34)).

Major oil content makes peanut an important agricultural product. This paper ([EwisOmran, 2016](#_bookmark8)) presents a method for early identifica- tion 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 in- fected plant leaves. Later plant chlorophyll decrease is also being identi- fied as a stress detection factor among the infected leaves.

This paper (Federico [Martinelli et al., 2015](#_bookmark34)) 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.

* 1. *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 multi- spectral images integrate with machine learning and classification algo- rithms which give the information into meaningful data.

* 1. *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 consid- ered. In Hyper spectral imaging device is deployed for a wavelength dis- persion and also a transportation stage are present in addition different from the traditional computer vision system. ([Li et al., 2017](#_bookmark34)) ([Rumf](#_bookmark34) [et al., 2010](#_bookmark34)).

The human eye has a capacity of vision for a definite range from the electromagnetic spectrum that belongs 400 to 700 nm ([Fig. 1](#_bookmark1)) (Amy [Lowe et al., 2017](#_bookmark34)). 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 reso- lution which contains thousands of data pixels per leaf (Amy [Lowe et al.,](#_bookmark34) [2017](#_bookmark34)). (See [Tables 1 and 2](#_bookmark2).)

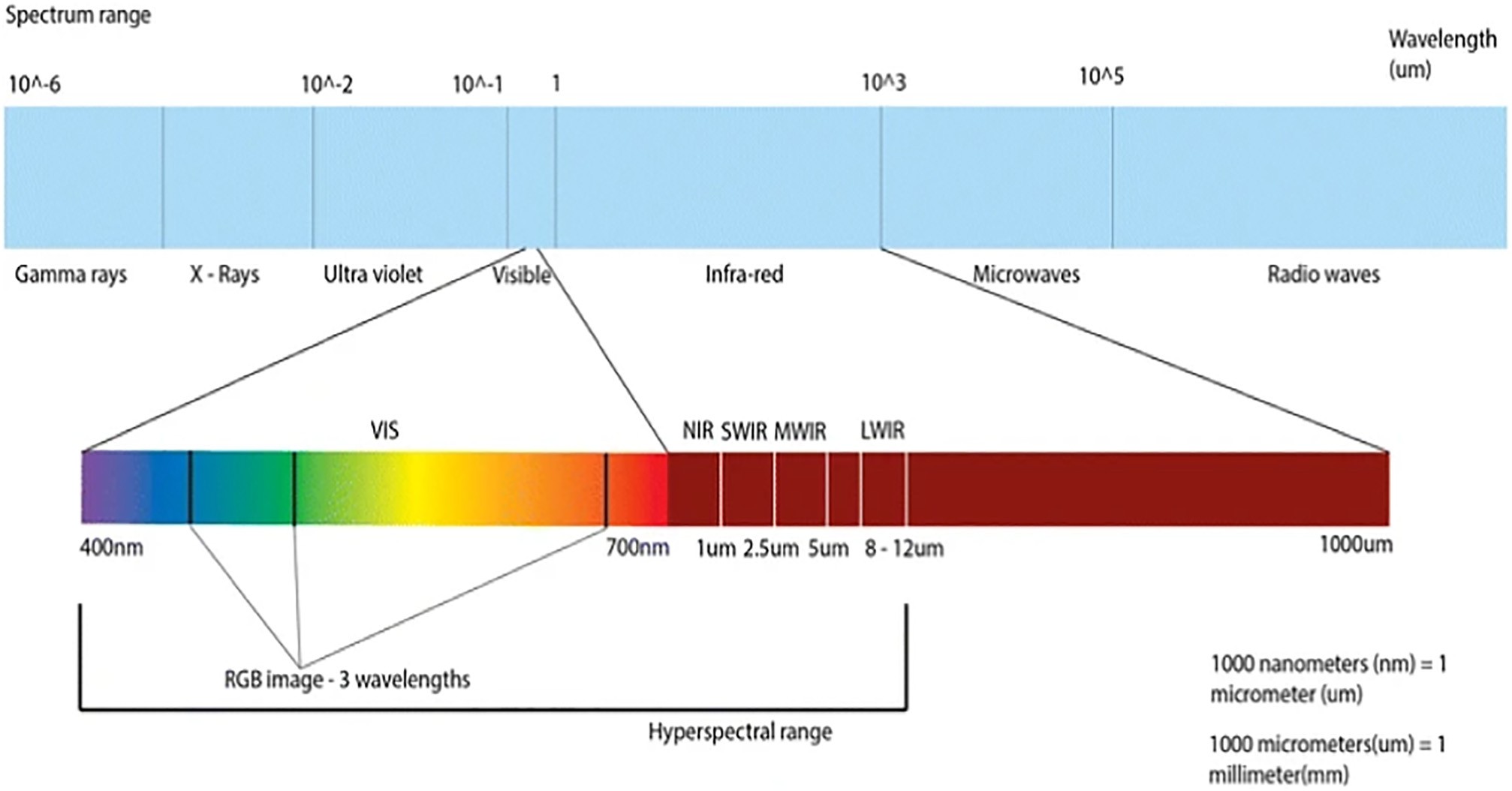
[](Image%20of%20Fig.%201)

Fig. 1. Hyperspectralrange in Electromagnetic spectrum (Amy [Lowe et al., 2017](#_bookmark34)).

In plants stresses can be classified as biotic and non-biotic where bi- otic are being induced by beings as viruses, fungi and others. In paper ([Baranowski et al., 2015](#_bookmark21)) hyper spectral imaging and the thermal imag- ing identifies plant stress due to fungi in oilseed rape. Initially the ther- mal 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](#_bookmark8)) 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 vegeta- tion 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](#_bookmark34)) 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 vis- ible 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 in- formation from the different parameters was used for analyzing while developing model to quantify disease seriousness. Further the informa- tion 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](#_bookmark8)) demonstrated that for wheat powdery mildew detection, canopy hyperspectral reflectance can be used while analyzing the unhealthy symptoms. It being observed that wheat culti- vators responded more sensitively to canopy reflectance in which wheat cultivars were more susceptible to powdery mildew. The chal- lenge faced here included discriminating the wheat powdery mildew

from other ailments. This paper (Kamlesh [Golhani et al., 2018](#_bookmark8)) 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](#_bookmark34)) 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](#_bookmark34)) 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 be- tween diseased and healthy leaves, several optimized indices of disease were tested. The advantage of SDI is that SDI disease can be easily distin- guished which is difficult using vegetative indices. The challenge is to send the generated SDI and to specify its usability for disease monitor- ing on canopy with different sensors.

This paper ([Mahlein et al., 2017](#_bookmark34)) discusses hyperspectral imaging and data analysis routines to identify and quantify relevant plant dis- eases. Hyperspectral imaging can be helpful in giving new insight into data of different plant at different level. This paper ([Moghadam et al.,](#_bookmark37) [2017](#_bookmark37)) discuses imaging methods (VNIR and SWIR) along ml technolo- gies for the identification of TSWW, i.e. Tomato Spotted Wilt Virusin capsicum in plants.

The paper ([Ochoa et al., 2016](#_bookmark51)) discusses about building a hyper- spectral imaging system for identification of Black Sigatoke (BS) disease found in plant and its pre-symptomatic responses in banana leaves. To

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](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) |
| Sugar Beet | Support Vector Machine | Comparison between healthy and diseased | Plants inoculated with pathogens | 97% | ([Rumf](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) |
| leaves |  | sugar beet leaves |  |  |  |
| Pear Plants | Near infrared Based technique | To identify fire blight disease | Spectroscopy based imaging technique |  | ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) |
| Grapevines | Leaf spectral reflectance | To identify leaf roll disease | Spectroscopy Used | 75% | ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) |
| Blue | Electric nose system | To detect post harvest fungal disease | Series of gas sensors used |  | ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) |

Berries

Onion To identify fungi Molecular Technique (PCR) DNA of disease causing microorganism is

extracted and purified.

Citrus To identify virus Molecular Techniques(PCR) DNA of disease causing microorganism is

extracted and purified

Potato To identify bacteria Molecular Techniques (PCR) DNA of disease causing microorganism is

extracted and purified

Tomato To identify virus Molecular Techniques (PCR) DNA of disease causing microorganism is

extracted and purified

Almond To identify bacteria Molecular Techniques (PCR) DNA of disease causing microorganism is

extracted and purified

Rice To identify bacteria Molecular Techniques (FluoroscenesPCR) DNA of disease causing microorganism is

extracted and purified

([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34)) ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34))

Sugarcane PLS based method To identify disease rating For classification of post harvest ([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34))

Winter wheat

Fluorescence Imaging To identify yellow rust Fluorescence images are obtained using camera

([Sankaran](#_bookmark34) [et](#_bookmark34) [al., 2010](#_bookmark34))

Iris leaf Color transform method To identify heterosporium leaf spot Otsu threshold is applied to identify

disease spot

Rice Leaf Color transform method To identify brown spot Otsu threshold is applied to identify

disesae spot

Blueberry Color transform method To identify bacterial canker Otsu threshold is applied to identify

disesae spot

Cotton Particle Sworm Optimization To identify injured leaf spot Feature extraction by PSO and forward

Neural Network

Tea Leaf Neural Network Ensemble To identify plant disease Feature Extraction and neural network

ensemble

([Chaudhary](#_bookmark8) [et](#_bookmark8) [al.,](#_bookmark8) [2012b](#_bookmark8))

([Chaudhary](#_bookmark8) [et](#_bookmark8) [al.,](#_bookmark8) [2012a](#_bookmark8))

([Chaudhary](#_bookmark8) [et](#_bookmark8) [al.,](#_bookmark8) [2012a](#_bookmark8))

95 ([Sladojevic](#_bookmark37) [et](#_bookmark37) [al., 2016](#_bookmark37))

91% ([Sladojevic](#_bookmark37) [et](#_bookmark37) [al., 2016](#_bookmark37))

Wheat Hyperspectral imaging Identifying fusarium Rotating in front of camera ([Bauriegel and](#_bookmark25)

[Herppich, 2014b](#_bookmark25)) Barley Support Vector Machine Hyperspectral imaging To identify drought stress on barley ([Behmann and](#_bookmark27)

[JorgSteinrucken, 2014](#_bookmark27))

Wheat Hyperspectral reflectance To identify wheat powdery mildew Rotating camera ([Cao](#_bookmark8) [et](#_bookmark8) [al., 2015b](#_bookmark8))

Sugar beet plant

Spectral disease indices To identify leaf spot, sugar beet rust, powdery

mildew

Hyperspectral signatures were assessed ([Mahlein](#_bookmark34) [et](#_bookmark34) [al., 2013](#_bookmark34))

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](#_bookmark37) [et](#_bookmark37) [al.,](#_bookmark37) [2017](#_bookmark37))

Winter Wheat

Fusion of hyperspectral andfluorescence imaging

To detect yellow rust disease Ground based real time remote system ([Moshou](#_bookmark42) [et](#_bookmark42) [al., 2005](#_bookmark42))

Banana plant

Hyperspectral imaging To identify Black Sigatoke Rotating camera ([Ochoa](#_bookmark51) [et](#_bookmark51) [al., 2016](#_bookmark51))

Weed Hyperspectral imaging To control weed production Capturing images ([Okamoto](#_bookmark55) [et](#_bookmark55) [al., 2007](#_bookmark55))

Potato Hyperspectral imaging To identify late blight disease Rotating camera ([Ray](#_bookmark34) [et](#_bookmark34) [al., 2011](#_bookmark34))

Cucumber leaves

Hyperspectral imaging To identify Chlorophyll and cartenoid content

in cucumber leaves

Finding the pigment distribution in cucumber leaves

([Zhao](#_bookmark56) [et](#_bookmark56) [al., 2016](#_bookmark56))

Almond orchards

Hyperspectral imaging and thermal imagery

To identify red leaf blotch in almond orchards Use of canopy temperature and vegetation

indices

([Zhao](#_bookmark56) [et](#_bookmark56) [al., 2016](#_bookmark56))

Wheat MLP, SOM To identify yellow rust 99% ([Moshou](#_bookmark40) [et](#_bookmark40) [al., 2004](#_bookmark40))

Avocado Hyperspectral sensing, RBF,

MLP

To identify Laurel wilt disease 98% ([Abdulridha](#_bookmark11) [et](#_bookmark11) [al.,](#_bookmark11)

[2016](#_bookmark11))

Cotton NN- SOM To identify disease Reniform Nematode 97% ([Lawrence](#_bookmark34) [et](#_bookmark34) [al., 2004](#_bookmark34)) Egg Plant Hyperspectral sensor To identify gray mould ([Wu](#_bookmark52) [et](#_bookmark52) [al., 2008](#_bookmark52))

Maize Portable Hyperspectral imaging system

Fungal infections ([Del](#_bookmark8) [Fiore et](#_bookmark8) [al., 2010](#_bookmark8))

Wheat QDA Yellow rust 92% ([Bravo](#_bookmark8) [et](#_bookmark8) [al., 2003](#_bookmark8))

Sugarbeet Decision tree (DT) cerospora leaf spot 95% ([Cao](#_bookmark8) [et](#_bookmark8) [al., 2015a](#_bookmark8))

Sugarbeet Decision tree (DT) powdery mildew 86% ([Cao](#_bookmark8) [et](#_bookmark8) [al., 2015b](#_bookmark8))

Sugarbeet Decision tree (DT) leaf rust 92% ([Cao](#_bookmark8) [et](#_bookmark8) [al., 2015a](#_bookmark8))

Grapefruit Spectral Information

Divergence

cankerous, normal, greasy spot. Insect damage, melanose, scab, wind scar)

95.2% ([Qin](#_bookmark34) [et](#_bookmark34) [al., 2009](#_bookmark34))

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](#_bookmark55)) 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 advan- tages 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](#_bookmark22) [et](#_bookmark22) [al.,](#_bookmark22) [2013](#_bookmark22)) |
| Diagnosis of pomegranate plant diseases using neural network  An Application of image processing | Pomegranate  Brinjal leaf | K-mean clustering and Gray level co-occurrence matrix (GLCM) method, Back propagation algorithm  Kmeans clustering algorithm | 90%  – | Bacterial blight, fruit rot and leaf spot in pomegranate plant  Cercospora Leaf Spot, | Work could be extended to other fruit disease detection  Work can be extended to | ([Dhakate and](#_bookmark8) [Ingole, 2015](#_bookmark8))  ([Anand](#_bookmark14) [et](#_bookmark14) [al.,](#_bookmark14) |
| techniques for Detection of Diseases on Brinjal Leaves Using K-Means Clustering  Method |  | along with Neural-network for classification. |  | Tobacco mosaic virus and Bacterial Wilt. | identify all possible diseases | [2016](#_bookmark14)) |
| Detection of Potato Diseases Using Image Segmentation and Multiclass Support Vector Machine  Wheat Disease Detection Using Image | Potato  Wheat | Multiclass support vector machine classifier, Gray level Co occurrence Matrix  K-means clustering, Neural | 95%  80.2% | *Phytophthora infestans* (Late blight), Alternaria solani (Early blight).  Fungal disease of wheat | Automatic detection of severity of disease  Improve the proposed | ([Islam](#_bookmark15) [et](#_bookmark15) [al.,](#_bookmark15) [2017](#_bookmark15))  ([Gaikwad and](#_bookmark8) |
| Processing  Diseases Detection of Cotton Leaf Spot using | Cotton | network  K-means clustering, Gray | 98.46%. | plant  Bacterial blight and | algorithm for reduction of  error due to classification Work can be done to | [Musande,](#_bookmark8) [2017](#_bookmark8))  ([Bhimte and](#_bookmark32) |
| Image Processing and SVM Classifier  Plant Leaf Disease Diagnosis from Color | leaves  Grape leaves | Level Co-occurrence Matrix, Support Vector Machine classifier  Gray-level co-occurrence | – | Magnesium Deficiency  Scab disease,downy | develop a more efficient, and robust system for early automatic tracing  Work can be done to | [Thool, 2018](#_bookmark32))  ([Khitthuk](#_bookmark27) |
| Imagery Using Co-Occurrence Matrix and Artificial Intelligence System  Detection and Classification of Groundnut Leaf | Groundnut | matrix, simplified fuzzy Artmap(SFAM)  Fast Feature extraction | – | mildew disease, rust disease  Early leaf spot, Late leaf | consider other diseases also.  Can be done for other | [et al., 2018](#_bookmark27))  ([Vaishnnave](#_bookmark48) |
| Diseases using KNN classifier | Leaf | method and k-NN algorithm |  | spot, Rust,Bud Necrosis | groundnut plant disease | [et al., 2019](#_bookmark48)) |
| Tea diseases detection based on fast infrared | Tea Leaves | Infrared thermal imaging | – | Tea leaf blight | Work could be extended | ([Yang](#_bookmark56) [et](#_bookmark56) [al.,](#_bookmark56) |

thermal image processing technology

Early detection of plant disease using infrared thermal imaging

Tomatoes leaves

technology

Digital infrared thermal imaging

to other type of disease detection

– Tobacco mosaic virus Work could be extended

to other viral disease detection on many more species of tomatoes

[2019](#_bookmark56))

([Xu](#_bookmark55) [et](#_bookmark55) [al.,](#_bookmark55) [2006](#_bookmark55))

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](#_bookmark34) [et](#_bookmark34) [al.,](#_bookmark34) [2015c](#_bookmark34))

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](#_bookmark53) [et](#_bookmark53) [al.,](#_bookmark53) [2013](#_bookmark53))

Huanglongbing (Citrus Greening) Detection Using Visible, Near Infrared and Thermal Imaging Techniques

Registration of thermal and visible light images of diseased plants using silhouette extraction in the wavelet domain

Early sensing of peanut leaf spot using spectroscopy and thermal imaging

Orange Leaves

Tomato plants

Peanut leaves

Thermal Imaging and Visible-near infrared techniques

Thermal and visible imaging with stationary wavelet transform

Image Spectroscopy, reflectance factor calculation

87% Huanglongbi ng (HLB) disease

– Fungus

Oidiumneolycopersici which causes powdery mildew disease

89.3% Fungal disease causing

early leaf spot and late leaf spot

Work can be done on a larger set of canopy.

Work can be further extended to stereo images for 3D information

Work can be done for other fungal disease infections

([Sankaran](#_bookmark34) [et al., 2013](#_bookmark34))

([Raza](#_bookmark34) [et](#_bookmark34) [al.,](#_bookmark34) [2015b](#_bookmark34))

([EwisOmran,](#_bookmark8) [2016](#_bookmark8))

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](#_bookmark54) [et](#_bookmark54) [al.,](#_bookmark54) [2006](#_bookmark54))

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](#_bookmark42)

[et al., 2005](#_bookmark42))

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](#_bookmark34) [et al., 2004](#_bookmark34))

Hyper spectral and Chlorophyll Fluorescence Imaging for Early Detection of Plant Diseases, with Special Reference to Fusarium spec. Infections on Wheat

Hyper spectral and Thermal Imaging of Oilseed Rape (*Brassica napus*) Response to Fungal Species of the Genus Alternaria

Early Detection of Powdery Mildew Disease in Wheat (*Triticum aestivum* L.) Using Thermal Imaging Technique

Wheat plant Chlorophyll Fluorescence

along with Hyper spectral Imaging

Oilseed rape thermograph and hyper

spectral imaging

Wheat Plant thermal imaging,

temperature monitoring before and after inoculation

* Fusarium resulting

Head Blight

80.5% Alternaria fungal disease

* Erysiphe graminis fungus causing Powdery mildew disease

Work can be extended to involve various other plant diseases.

Work further requires involvement of genetic data.

.Work can be used for developing an expert system

([Bauriegel and](#_bookmark25) [Herppich,](#_bookmark25) [2014b](#_bookmark25))

([Baranowski](#_bookmark21) [et al., 2015](#_bookmark21))

([Awad](#_bookmark18) [et](#_bookmark18) [al.,](#_bookmark18) [2014](#_bookmark18))

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](#_bookmark8)

[et al., 2015](#_bookmark8))

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](#_bookmark34) [et al., 2016](#_bookmark34)) |
| 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](#_bookmark34) [et](#_bookmark34) [al.,](#_bookmark34) [2011](#_bookmark34)) |

The paper ([Ray et al., 2011](#_bookmark34)) 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 advan- tage of spectral data for identification of disease.

The paper ([Zhang et al., 2012](#_bookmark56)) discusses the use of hyperspectral re- flectance 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 com- pared 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](#_bookmark56)) 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 out- comes showed that hyperspectral imaging with chemometrics is a feasi- ble approach to find the presence of disease leaf spot in cucumber leaves. The paper ([Lopez-Lopez et al., 2016](#_bookmark34)) discusses the application of hyperspectral imagery and high resolution imagery to detect the pres- ence of leaf blotch in almond studied. The paper discusses the use of can- opy 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.

* 1. *Fluorescence techniques*

Fluorescence techniques ([Fig. 2](#_bookmark3).) have been widely used for investi- gation 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](#_bookmark34)) paper the proposed work high- lights the useful benefits of imaging systems based on multicolor fluo- rescence, making use of thermograph for zucchini plants affected by disorder, caused by *Dickeyadadantii*. Different machine learning tech- nique has been applied which classify the input samples as healthy or infected samples. ([Pérez-Bueno et al., 2016](#_bookmark34)). In paper ([Moshoua et al.,](#_bookmark44) [2005](#_bookmark44)) 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 iden- tification of yellow rust using wheat plant spread over farm area. Later multi-spectral fluorescence imaging systems was done on sampled can- opy. Further leaf disease detection is done using indices as normalized vegetation and others. This paper shows the use of fluorescence induc- tion and spectral reflection for the disease presence detection.

Paper ([LauryChaerle et al., 2004](#_bookmark34)) makes use of chlorophyll fluores- cence imaging and thermograph for knowing and comparison of infec- tion 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 es- timation of agricultural overall production. Paper ([Bauriegel and](#_bookmark23)

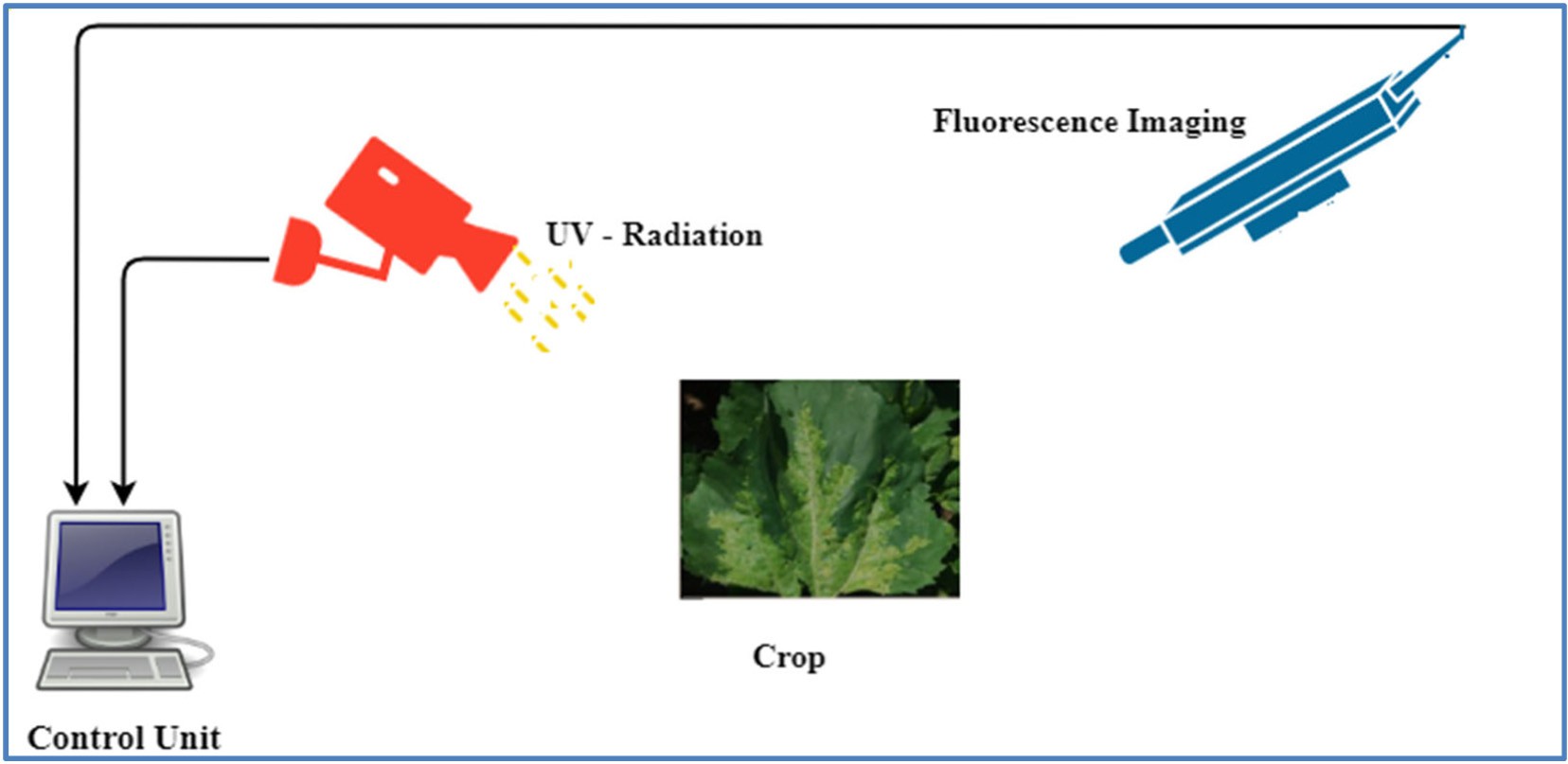
[](Image%20of%20Fig.%202)

Fig. 2. Fluorescence Imaging Techniques.

[Herppich, 2014a](#_bookmark23)) presents the detection of head blight disease in wheat plants using chlorophyll fluorescence and also with hyper spectral im- aging. It signifies the ways in which hyper spectral imaging is being use- ful 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 bet- ter procurement and agricultural productions. Paper ([Römer et al.,](#_bookmark34) [2011](#_bookmark34)) presents a method for differentiating leaf rust wheat leaf from healthy leaf at early level. This paper presents pre symptomatic detec- tion and further classification using support vector machine method. It also presents use of Fluorescence detection using fluorescence spec- trometer 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](#_bookmark25)) discuss about how chlo- rophyll 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 deal- ing with the visibility of infection symptoms. The challenges are that for any image based methodology on field recording of head blight will re- quire two passages over crop whether the imaging system are used sin- gle or being combined.

The paper ([Moshou et al., 2005](#_bookmark42)) discusses about combination of im- aging 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 fu- sion 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.

* 1. *Thermal imaging*

This ([Fig. 3](#_bookmark4)) is a process that convert the various radiation identified from an object to different types of images for extraction of varied fea- tures, 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](#_bookmark47) [Digvir, 2011](#_bookmark47)).

In paper ([Yang et al., 2019](#_bookmark56)) a method has been described for fast de- termination of disease in tea leaves using a method making use of appli- cation of infrared thermal imaging technology. In paper ([Xu et al., 2006](#_bookmark55)) 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](#_bookmark34)) focus on the involvement of thermal depth data with visible light image for automatic identification of dis- ease in tomato plant leaves. It shows the way of initial setup done for the acquisition of visual and thermal images. Here a technique for dis- parity detection has also been proposed.

This paper ([Wang et al., 2013](#_bookmark53)) gives a way of using digital infrared thermography for detection of the changes as water loss further affect- ing 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

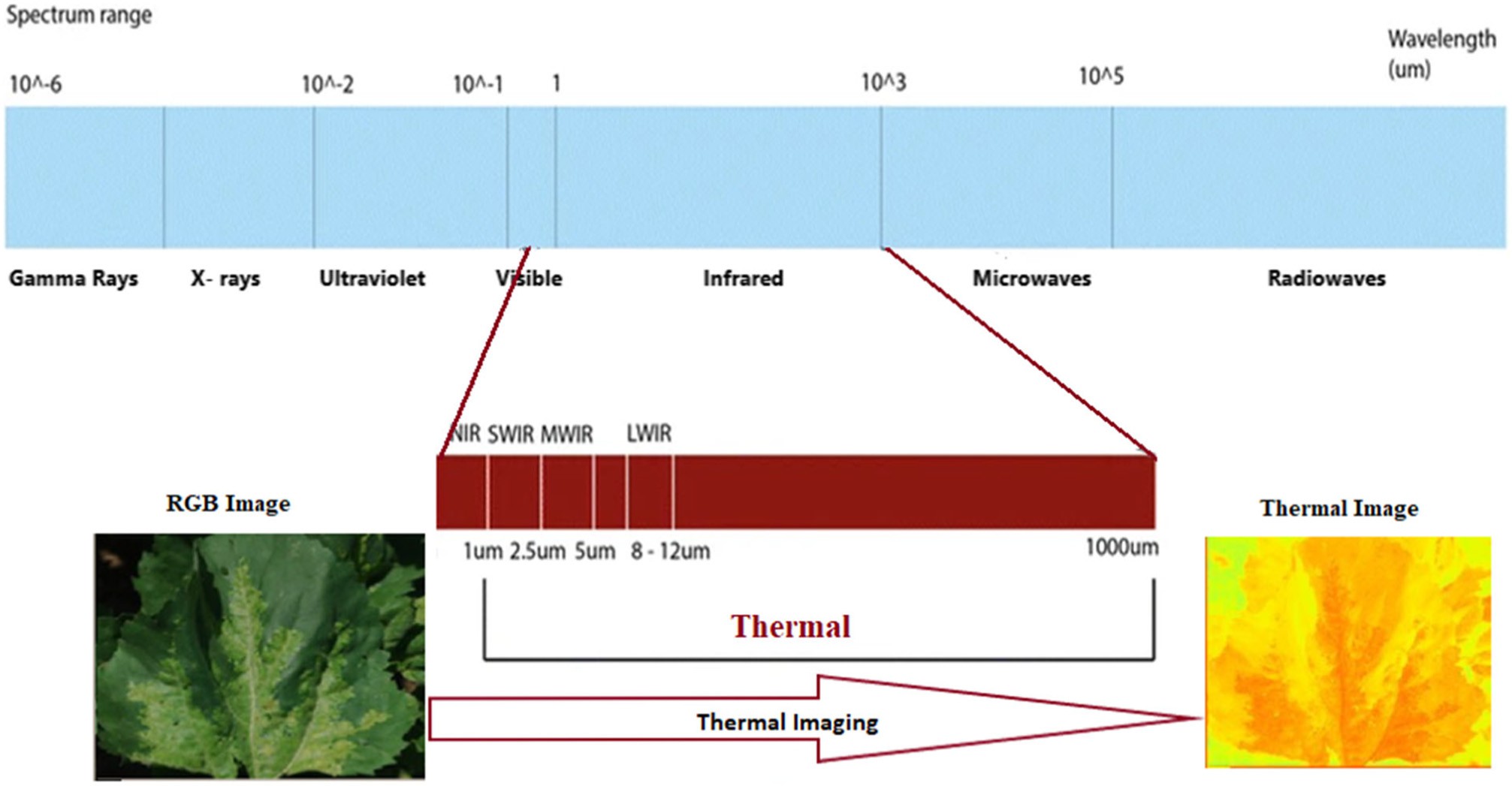
[](Image%20of%20Fig.%203)

Fig. 3. Thermal imaging.

membrane injury were identified along with FA content being mea- sured in different temperatures.

Here paper ([Sankaran et al., 2013](#_bookmark34)) shows the requirement of a sen- sor efficient of determining HLB for overall complete cover. Here infra- red along with thermal images are used for detected HLB-infected citrus trees. This paper briefs about the evaluation of the use of multi- spectral images for HLB detection, by the medium of a mobile ground- based sensor. It initially used two multispectral cameras and one ther- mal 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 dis- ease thus reducing large agricultural losses. In paper ([Raza et al.,](#_bookmark34) [2015b](#_bookmark34)) 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 em- ploys 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 dif- ferent 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](#_bookmark54)) shows the study of irregularities presence in plant affected by

*P. cubensis*. It also describes detection of downy mildew through temper- ature 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 electro- lyte leakage and transpiration rate for the disease presence d is analyzed. Paper ([Awad et al., 2014](#_bookmark18)) 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. Fur- ther 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 de- scribes the need for recommended expert system for the detection

of different disease.

* 1. *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 ap- pears as an essential for automatic plant diseases detection. There are various techniques for 3-D image acquisition ([Bellmann et al., 2007](#_bookmark29)) ([Jarvis, 1983](#_bookmark19)) ([Blais, 2004](#_bookmark8)) and 2-D together with 3-D machinery in

applications pertaining to agriculture ([Grift, 2008](#_bookmark8)) ([McCarthy et al.,](#_bookmark34) [2010](#_bookmark34)). Block diagram of 3-D imaging system is given below in [Fig. 4](#_bookmark5).

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 vol- umetric component and a frequency component of the model's coordi- nates. In now a day different types of affordable sensors are available. They also exhibhits technologically advanced to a great extent for vari- ous domains like nutrient content, growth level, crop presence, biomass estimation, and height and health status. Plant leaf diseases being fur- ther analyzed using these sensors because the gathered data can be used for quantifying the previously identified various production char- acters. ([Vázquez-Arellano et al., 2016](#_bookmark49)).

Sensors including various types of LIDARs and TOF cameras with their sensors, determine the depth using the light velocity ([Fig. 5](#_bookmark6)) ([Underwood et al., 2013](#_bookmark45)) ([Lachat et al., 2015](#_bookmark33)).

1. 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](#_bookmark7).) purpose, these segments often constitute various classes of tissues, organs or biologically impor- tant structures. Here image segmentation becomes challenging due to various factors including low contrast and other imaging ambiguities along with noise.

* 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. Fur- ther an algorithm works fine for the refinement including the segmen- tation. 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 applica- tion by researchers in last many years; some of them are reviewed as following.

[Yan Cheng Zhang et al. (2007)](#_bookmark56) 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 classi- fication 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](#_bookmark8)).

[Al Bashish et al. (2010)](#_bookmark12) discussed one of the segmentation method based on K-mean. Here different disease such as cottony meld, tiny

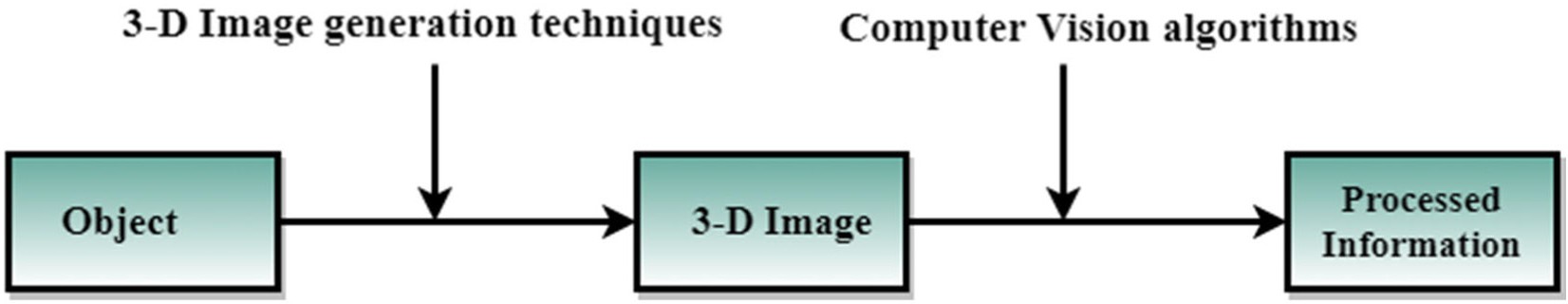
[](Image%20of%20Fig.%204)

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

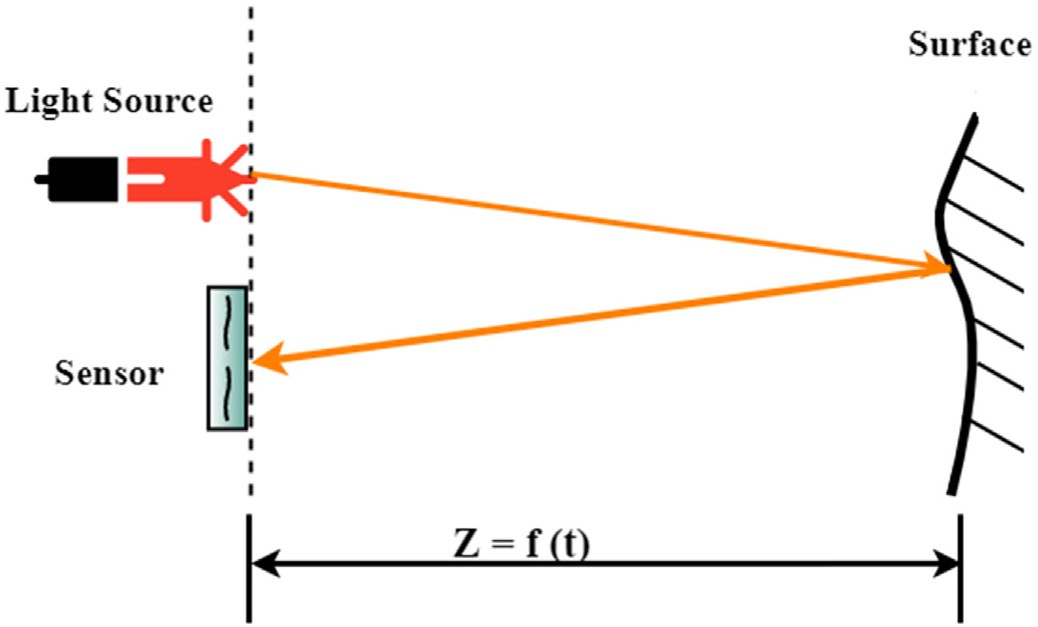
[](Image%20of%20Fig.%205)

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)](#_bookmark34), also has given a tech- nique for the early identification of disease present in specifically grape leaves. It also exhibits classification using support vector machine. [Jaware et al. (2012)](#_bookmark24) 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 dis- eases in shorter span of time.

[Gurjar and Gulhane (2012)](#_bookmark9) briefed about the regularization method. Here a technique has been discussed that involves the use of Eigen fea- tures. 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)](#_bookmark34) have given disease identification method that makes use of detection of edges based on uniform Segmen- tation. 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)](#_bookmark34) 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)](#_bookmark41) discussed a technique using different classifier such as support vector for the early detection of disease present in wheat plant. The disease de- tected here includes leaf blight and powdery mildew.

[Sannakki et al. (2011)](#_bookmark34) 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)](#_bookmark16) 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 extrac- tion and computation of texture information has also been discussed. It is being shown on a data of 500 plant samples including lemon, to- mato, beans, banana and others resulting in an accurate rate of 94%.

[Anand et al. (2016)](#_bookmark14) 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. Var- ious features are later trained that helps in differentiating between healthy and unhealthy leaves. [Naikwadi and Amoda (2013)](#_bookmark50) also gave a software solution for early disease detection in different plants. Only after the stage of segmentation, green pixels are detected. These are fur- ther being masked for definite threshold found using Otsu's method. The technique used provides a precision ranges from 83% to 94%. [Patil](#_bookmark34) [and Bodhe (2011)](#_bookmark34) 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)](#_bookmark30) discussed different methods of early

identification of plant diseases making use of image Processing. Piyush [Chaudhary et al. (2012b)](#_bookmark8) 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](#_bookmark39)) 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

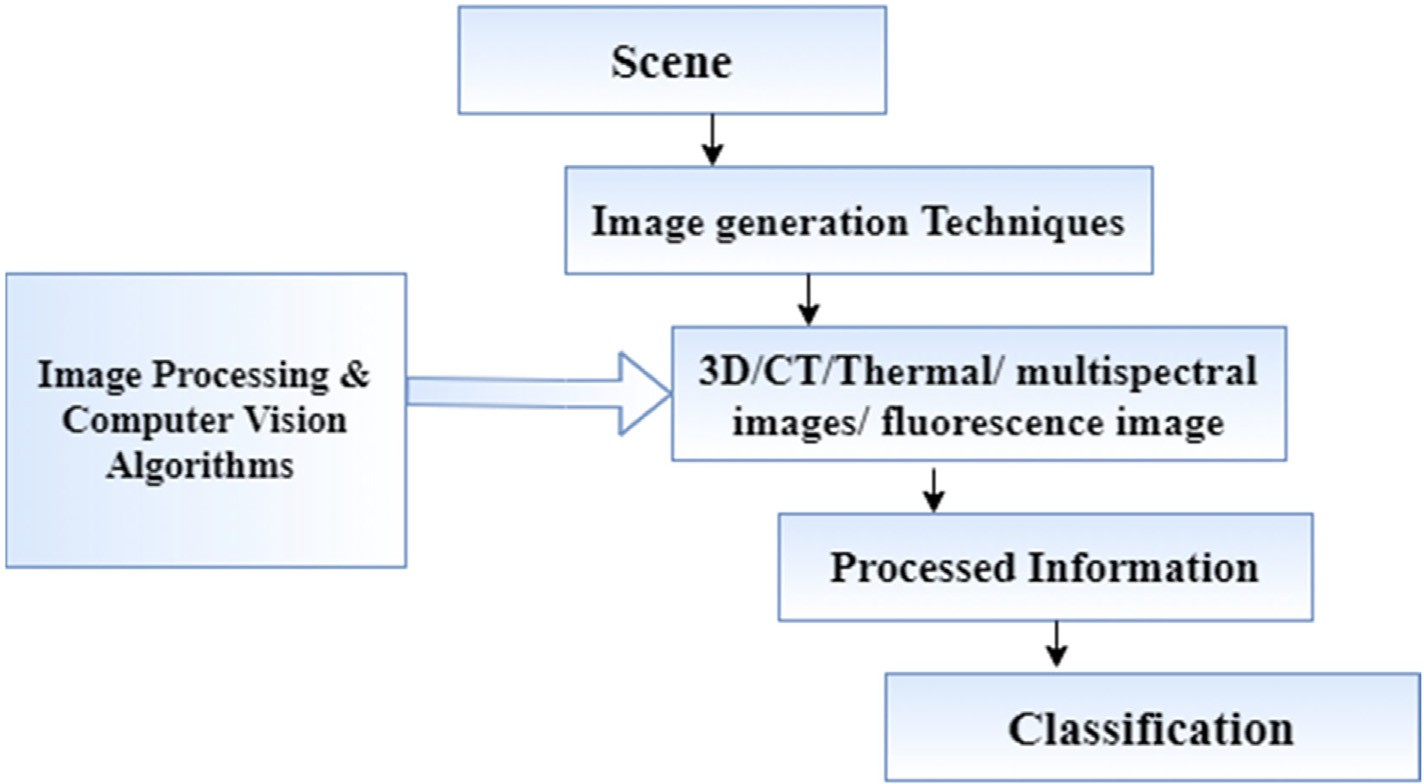
[](Image%20of%20Fig.%206)

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](#_bookmark8)) proposes the develop- ment 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](#_bookmark37), proposes the method of deep neural net- works 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 im- ages for better accuracy of the model, having apt augmented done.

This paper ([Rumf et al., 2010](#_bookmark34)) proposesa procedure for detecting and differentiating between healthy and diseases plant leaves using support vector machines with vegetative indice. This paper also differentiates be- tween the different diseases like lercospora, powdery mildew and leaf rust also identifying the diseases at an initial stage. The leaves are inocu- lated 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 classi- fication 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](#_bookmark8)) proposes a technique for disease spot detection in affected area since the disease spots in plants are different in color; this paper proposes color transforma- tion of RGB image to get better segmentation of disease spots. Vari- ous color models like YCbCr and CIELAB are differentiated from ‘A' component of CIELAB model. Then the image which is color trans- formed is passed through median filter and the spots includes seg- mentation 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 differenti- ating the same colored veins from spots.

The paper ([Behmann and JorgSteinrucken, 2014](#_bookmark27)) proposes an ap- proach 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. Ordi- nal classification with support vector machine has been brought to use for visualizing the division of different sections. It also differen- tiates between both easily. Paper shows that drought stress is de- tected 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 ar- chitecture that is useful in early classification of different types of diseases found in plants. They provide an effective way of many dif- ferent benefits related to agricultural processes. In paper ([Hall et al.,](#_bookmark13) [2015](#_bookmark13)), 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,](#_bookmark26) [2018](#_bookmark26)) shows its drawback for identification of occluded objects. Counting of fruits and leaf were also done using CNN in ([Itzhaky](#_bookmark17) [et al., 2018](#_bookmark17)) ([Ubbens et al., 2018](#_bookmark43)). For classification among different plants, ([Raza et al., 2015b](#_bookmark34)) ([Kussul et al., 2017](#_bookmark31)) used modified CNN. Plant recognition has been done by the different Deep Learning algo- rithm in ([Kussul et al., 2017](#_bookmark31)) ([Grinblat et al., 2016](#_bookmark10)) ([Singh et al.,](#_bookmark35) [2015](#_bookmark35)). For detection and classification of Crop different experiments was performed in ([Pound et al., 2017](#_bookmark34)) ([Milioto et al., 2017](#_bookmark35)).

1. 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](#_bookmark27)) mainly involves analyzing the dif- ferent plant features based on varied statistics. It also includes the pro- cess of classification. Here firstly the image is processed using Gaussian low pass filter. This paper ([Vaishnnave et al., 2019](#_bookmark48)) discusses the technique for the early determination of disease such as in ground- nut plant leaves.

In paper ([Jhuria et al., 2013](#_bookmark22)) 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](#_bookmark8)) a system is being shown for the determination of presence of disease in pomegranate plant. Here differ- ent way has been highlighted for training purpose using back propaga- tion 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](#_bookmark14)) 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](#_bookmark15)) gives a method that involves machine learning technique along with image processing for detection of pres- ence 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 ho- mogeneity, 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](#_bookmark8)) involves development of early detection methods for different plant dis- ease. 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](#_bookmark34)) the de- tection 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 Mil- dew. It also includes the classification done through training and testing phases.

Increasing huge losses in cotton yield due to various diseases is a cru- cial reason for developing an early disease detection system for cotton plant. In paper ([Bhimte and Thool, 2018](#_bookmark32)) a method is proposed for early detection of disease among cotton leaves through Support vector machine. This paper ([Pawar and Jadhav, 2017](#_bookmark34)) proposes a novel method for identifying disease and classification. It highlights this process in- volving acquisition. Here k mean clustering algorithm is being used for pomegranate plant leaves analysis. Various features as. Color, morphol- ogy, 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:

1. Automatic cluster centre initialization is lacking.
2. improves the proposed algorithm for reduction of error due to clas- sification
3. Can be done for other groundnut plant disease
4. To integrates advance imaging technique and Computer vision algo- rithms
5. For automatically detection of plant leaf disease algorithms are still required.
6. Work further requires analysis using different variation in surround- ing conditions.
7. Need an expert System for plant diseases detection.
8. Conclusions

This paper gives an overall review for the various techniques of dis- ease 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 com- puter 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 in- curred. Also a reliable and efficient sensor deployed for looking fulfill- ment 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.

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