CHAPTER 2

Literature Survey

2.1 Introduction

Agriculture crop have become an beneficial resource of power energy, and are a primary piece in the mystery to resolve the difficulty of global warming. There are numerous diseases that influence agriculture, plants with the prospective to cause disturbing cost-effective, communal and environmental losses. There are numerous ways to identify plant disease. In those cases, generally some kind of complicated laboratory analysis, usually by way of powerful and accurate microscopes, is compulsory. In other cases, the symptoms can only be identified by the electromagnetic spectrums that are not noticeable to human beings. With the help of remote sensing techniques that survey multi-hyperspectral digital image captures. The procedures that acquire this method often utilize digital image processing tools to accomplish their goals. Digital image processing helps to solve many problems or reduce by use of pattern recognition and statistical analysis tools. In chapter two different dimensions taken to identify and detect the soybean plant diseases are reported. The first move towards to involve with spectroscopic apparatus and digital imaging techniques for soybean plant disease detection, whereas the second move towards to describe soybean disease detection, cataloguing and retrieval. These two techniques were carried as they could be straightforwardly incorporated with an agricultural soybean plant disease.
monitoring service for disease control and cure in early stage. The timely recognition of soybean plant infection by insect and diseases could be a helpful and valuable source of information for performing the exact pest management with cure and infection, manage measures to avoid the growth and the spread of soybean harmful diseases. The chapter is divided into six sections e.g. Plant foliar disease, Disease sensing, Disease detection method, Disease classification method, Fungicides for plant foliar disease and problem identification

2.2 Plant foliar diseases:

All the plant foliar diseases come under the category of biotic stress, which is mainly caused by biological factors like weeds, insects and diseases [Dorrance et al. (2007)]. Various soybean plant foliar diseases, which are responsible for the major portion of yield loss as discussed in the following subsection. Figure 2.1 shows the images of agriculture field survey with different day intervals.

![Figure 2.1 Field Analysis of Soybean Leaves](image)
(a) Soybean Rust (SBR)

The figure-2.2 shows the typical picture of Soya leaf infected by rust, which is the most accountable foliar disease causing a significant reduction in yield, mainly in Asian countries like India. The disease is caused by pathogen named Phakopsora Pachyrhizi and effects soybean yield losses of up to 80%. The reported yield loss is up-to 80% in the geographical areas where this pathogen is active. Environment optimal circumstance for infection include moderately hot temperatures (60 to 75 F) and at least 6 hours of free moisture is needed for infection, which includes dew and/or rain, on leaves.

Phakopsora Pachyrhizi can grow rapidly and that makes it a potential agent for severe yield losses affecting the soya plants by the most destructive foliar disease. The appearances of 2-5mm² russet to dark-brown polygonal lesions starting from the lower canopy of leaves are the most common symptoms of soybean rust as shown in figure-2.2 (Miles et al. 2003). Leaves of soybean plant are susceptible to Phakopsora pachyrhizi at any phase, but disease and lesion severity depends on developmental phase of the plant at the moment of infectivity. The fast spread of soybean rust and responsible for severe soybean yield losses makes this the most destructive foliar disease. [Hartman et al. (1991)]
Figure 2.2 Soybean Rust\(^1\)

(b) Bacterial Blight (BB)

Bacterial blights which stem from Pseudomonas syringae pv. Glycinea bacteria and is a very frequent soya-plant foliar disease, which usually transpires in early growth stages and develops mainly in rainy and wet weather. The bacterial blight produces the symptoms of angular lesions with color varying from yellow to light brown spot. Angular lesions elaborate in aplomb, showery, rainy and cool weather and may combine to produce big, irregular dead areas. This disease dies the plant tissues while the lesion color turns from a darker shade of red and brown to black; it's encapsulated by a halo that is yellowish green in color. Distinctive infected water-soaked lesions can be seen 5 to 7 days after cultivation. The indications of the pustule disease are somewhat standardized and similar to those of bacterial blight. Bacterial Blight tissue in more previous lesions may drop out, giving infected leaves a bothered appearance. Frequently, the leaves are badly shredded after heavy rains and moisture wind. The typical picture of soya leaf infected with bacterial blight has been shown in figure-2.3. The infection spreads to the seeds through the pods during the sessions for cleaning and harvesting. The early infections observed in the cotyledons could potentially become a large source of inoculum, which create secondary lesions. At the time of cultivation when the foliage becomes wet, and during windy rainstorms, the bacterium spreads throughout the field with great ease [Park and Lim (1986)].
Figure 2.3 Bacterial Blight

[2 http://www.extension.umn.edu/agriculture/crop-diseases/soybean/BacterialBlight]
(c) Sudden-Death-Syndromes (SDS)

Sudden Death Syndrome (SDS) of soybeans as shown in figure-2.4 is mainly caused by a soil borne fungi known as Fusarium Solani. SDS is supported by the cool temperatures and rainy circumstances throughout the early flowering period. Yield loss commonly ranges between 10 and 15%, but in extreme cases it may go up-to 70% of the yield loss. The favorable conditions for the development of contamination by Fusarium Solani (a type of fungi) are the soaked soils and continuous temperature range of 55° to 65°F [Roy et al.(1997), Westphal et al. (2006)]. The first detectable indications of SDS are yellowing color and biological and organic process of upper leaves of soybean. Lesion symptoms first occur in a field, they may be limited to a tiny area in the field, often in surfactant or compressed areas. Over the tracing two weeks, involved areas may elaborate and plant areas in the field may identify symptoms. The yield losses by SDS depend on the timing and severity of disease reflection proportional to plant development in regards to yield. If the SDS occurs early in the season, flowers and pods. The name SDS is rather confusing; since the infection may occur time up to 14 days to completely build up. The indication may not be eagerly obvious until the infection is well sophisticated and plants have in fact begun to defoliate. Time from infection and defoliation to demise is less and may account for the "suddenness" SDS. The infection may transmit a disease to roots as early as one week after harvest appearance, but aboveground symptoms of SDS rarely become visible until mid-July, when soybean plants start to flower. Heavy showery conditions throughout reproductive stages often are crucial for SDS indication growth. Wet soil produces the fungus toxins in the roots that are trans allocated to the leaves. Toxins are what happens foliar disease indication; the fungus does not assault the stems
beyond a little few distance in inches of the soil. It does not assault flowers, pods, leaves or seeds.
Figure 2.4 Sudden Death Syndrome[^3]

[^3]: [http://www.extension.unl.edu/agriculture/crop-diseases/soybean/SDS](http://www.extension.unl.edu/agriculture/crop-diseases/soybean/SDS)
(d) Downy Mildew (DM)

The fungus known as *Peronospora Manschurica* mainly causes downy mildew as shown in figure-2.5. Downy mildew usually infects all the green and dynamically emergent parts of the vine containing active stomata being used for air exchange on plant leaf tissues and develops yellowish-green to dark brown irregular lesion on their upper surface within 15-days after contamination. The fungus sporulates under the leaf, when it becomes humid. It produces gray, chocolate, white or violet lesion spot growth. Air currents and splashing water are very much responsible for dislodging these sporangia which starts infecting in proximity of healthy plants. [Sweets et al.(2008), Beckerman (Bp-68-w)]. Powdery mildew always appears on both surface of leaves but in primarily condition downy mildew appears on the underside of the leaves. Lesions are enlarging slowly in size and shape and color changes pale to bright yellow. Infection ration occurs in younger leaves compare to older leaves. The infection starts from the canopy of the leaves. DM infection occurs in three phases a) initial wetting stage in other words the temperature remains minimum in 16 hours b) Release of zoospores c) leaves wet continuously 2-3 hours.
Figure 2.5 Downy Mildew

[http://www.extension.umn.edu/agriculture/crop-diseases/soybean/Downymoldew]
(e) Brown Spot (BS)

The fungus Septoria glycines cause brown spot. A typical picture of a leaf infected by brown spot is shown in figure-2.6 [Lee et al. (1996)]. Lesion size of brown spot varies from pinpoint in size up to 5 mm. Leaf spots are angular or somewhat circular with irregular edges, and they can have different sizes, from just a tiny speck of something as large as 1/4 inch in diameter. They are observed on the lower and upper leaf surfaces [Dorrance et al. (2010)]. Brown spots are surrounded by yellowish color. The infection and the development of the disease are helped by the warmth and moistness of the weather, which in turn augments the spore production in the first lesion. The optimum temperature for developing brown spot is 59°-86°F. Brown spot is easily confused with soybean rust, but it can be differentiated with the help of shape, size and color of the lesion. The disease development usually starts at the beginning of the pod to beginning to seed. Abundant brown spots caused to become the leaves yellow and drops from the plants [Loren (2011)]. Brown spot expanded right through the soybean farming season, and on extremely vulnerable lines, indication can build up when the first pair of true soybean leaves have formed. The lesions of brown spot on the first true leaves are noticeable on both leaf surfaces. Tissue neighbouring the lesions turn into chlorotic and if circumstances are constructive for the growth of the fungus, the infection development up the soybean leaves from the lower leaves, connecting the trifoliate soybean leaves, leading which uneven lesions are produced by coalescence of adjacent spots.
Figure 2.6 Brown Spot\textsuperscript{5}

\footnotesize{\textsuperscript{5} \url{http://www.extension.umn.edu/agriculture/crop-diseases/soybean/Brownspot} }
(f) Frog's Eye (FE)

Frogeye leaf spot [Dorrance et al.(2010), Mian et al.(2008), Westphal et al. (BP-131-W)] is a significant disease (foliar in nature) found in regions that are humid and hot and is caused by Cercospora sojina. The frogeye leaf spot is a disease which is polycyclic in nature. As the weather continues to improve for the bug, the number of lesions also continues to increase. This illness can be recognized by small, gray acne with reddish-brown and purple boundaries on the upper leaves in the month of August. On the underneath part of soybean leaf, the lesion appears with brown, and small dark hair and the color of elder lesion turns usually brown to dark shade with border. Any stage of the development of the soybean can suffer an infection. However, the probability of infection is higher after flowering. Symptoms include yellow spots on the leaves that are small in size. The first symptom is detected on the growth stage of at or after R5 stage. Eventually the size of the spots grows to a 1.4 inch diameter. It takes 7 to 12 days after inoculation for symptom development depending on the temperature and other environmental conditions. As the number of lesions grows, the green leaf area suffers a similar reduction; as a consequence the yield also suffers reduction. If the infection is able to find favorable conditions for growth till the later part of the season, the fungus then infects the seeds and the pods. Significant yield loss from frog eye disease is 10-60% under hot and humid growing conditions. Symptoms of FE happen on immature leaves more readily than that of older leaves. If appropriate wetness is stable other soybean leaves of a plant may turn into spoiled, and if waterless periods are interspersed with wet periods, layered patterns of lightly and heavily FE soybean leaves can happen in the similar plant.
Figure 2.7 Frog Eye

[http://www.extension.umn.edu/agriculture/crop-diseases/soybean/Brownspot]
2.3 Disease Sensing Methods

(a) Remote Sensing: Remote sensing technology was used in agriculture for yield crop estimation. It depends on the spatial resolution of the digital image and it is affected in growing crops estimation. This method is more robust because it’s established the relation between yield monitor data and remotely sensed images. Hyper spectral image contains ten to hundred narrow bands and it’s also provide the missing data with additional information [Lee et al. (2010)]. Mainly instrument design is the limitation for image based application. Fixed spectral band sensors are not more accurate in the field analysis.

Aircraft based sensor avoid this limitation, but it is not suitable for large land coverage. The remote sense multispectral imaging is used for soil wetness substance, crop phenologic stage, and yield production, crop disease, weed infestation and insect infestation information. In remote sensing broad observable and near infrared band may be helpful to differentiate between healthy and infected plant. Diseased area changes the visible spectrum and helps to identify the disease. The present restrictions for digital image based remote sensing techniques are essentially due to remote sensor attributes, such as limited spectral range, spatial resolution, time, and area coverage.

(b) Thermograph Techniques: Thermograph techniques are depending upon the biomass of the fruit or disease. This technique refers to identifying and classifying between fruit and shrubs and trees. Biomass is heavily dependent of water contains in fruit, vegetables, leaves and stems of trees so it help to differentiate between fruit and leaves. Thermography techniques convert the visible image to invisible radiation pattern and it has successfully adopted in agriculture. Various researches used thermographs to recognitions of fruits [Stajnko and Hoevar (2004), Wang et al. (2009), Bulanon et al. (2008)]. The temperature of fruit and leaves are also helpful to differentiate by using
thermography but it fluctuate occasion by occasion in a day [Bulanon et al. (2008)]. Thermal infrared region varies between 3 to 14 µm with different wavelength and it is useful in heat imaging signatures [Gonzalez et al. (2009)]

(c) Laser Sensing – laser sensors are used for fruit recognitions technique. Image processing and laser based application systems are used for navigating a tractor through the alleyway of a citrus grove. Proportional-integral-derivative controller is developed to test in tractor using the information from the image and laser radar. Laser sensor gives the 3D information on agriculture crop and forage swaths, together with expert system which can identify the these features and overcome interference caused by sensible amounts of airborne dust. Mostly laser technology applies in the agriculture vehicles to identification of weed, dust, crop and disease [Lee et al. (2010), Noushath et al. (2006), Specht (1990), Ludeker et al. (1996)].

(d) Visible Spectroscopy – Visible spectroscopy techniques applied in soil testing and characterization. There are various methods like NIR reflectance spectroscopy, Raman spectroscopy, VIS, VV, etc. Which are applied in agriculture sector [Lee et al. (2010)]. Xing et al. (2013) used a visible spectroscopy for quality classification of intact pork meat. In this method the visible spectral analysis is not satisfactory to classify in groups, but accuracy classification by using the reflectance spectra is better than using the L*, a* and b* values [Pernkopf (2005)].

(e) Light Reflectance – Light reflect work on law of reflection, and the result shows the reflection occurs off a curved surface or off a flat surface. Light always never passes through the virtual actual image location it only appears to investigate as though the light is emanating from the virtual image location. Light reflectance is used for disease classification. Each disease has own fundamental color properties and light reflectance works on the bases of wave length and spectrum. The result shows that each
disease has own bandwidth, wave length and spectrum which help to classify the disease. The value of all these properties shows the classification validity of the disease. Result analysis by a different range of the spectrum and the best results for the identify of diseases shows in the VIS and NIR range of the spectrum. [Barbedo (2013), Lee et al. (2010)]

2.4 Plant Foliar Disease Detection Methods

Zhang and Quingand (2010) developed an image processing based citrus canker disease detection method on citrus fruit. They used local binary pattern histogram and boost algorithm to identify the citrus canker. Lili ma et al. (2010) developed the color based image processing method to detect an excess nitrogen content in soybean leaves. They used the RGB and HSI color based model to analysis the nitrogen content in soybean leaves. Powbun Thom et al. (2012) developed an image processing based method for finding the severity of brown spot in Cassara leaves. They had counted the number of spot and severity level on the bases of the digital image processing method. Xiang Dong et al. (2013) studied about the disease in the cucumber leaves and find the infection with the help of digital image processing. They applied the median filter, color, texture parameter, shape and texture parameter to extract the feature.

Yuzhu et al. (2011) investigated the suitable diagnosis index to estimate and quantify the effect of nitrogen in pepper plant leaves with the help of color image processing. Sanyal et al. (2007) analyzed the change of minerals in rice plant leaves and make a prototype system using mobile camera and image processing based method. Pang et al. (2011) studied that color of leaves and disease spots are uneven, so it is difficult to apply the fixed threshold method. They developed the integrating local threshold based region
growing method for identification of the disease spots. Meunkaewjinda et al. (2008) developed an automatic grape leaf infection conclusion system with multiple artificial intelligent techniques. The method consists three main parts: a) grape leaf infection segmentation b) analysis and classification of diseases c) grape leaf color segmentation. In this method segmentation is used for subtraction of the background from the leaf area and color of the grape leaf is recognized by self-organizing characteristic with a BPNN. The Gabor wavelet filter was allowed the system to analyze leaf disease color features more efficiently.

Kurniawati et al. (2009) developed an identification and classification system to distinguish the paddy infection and that is Blast Disease. The first step of Algorithm is red, green, blue images are changed into a binary image using global, automatic and variable Otsu segmentation techniques and is applied the morphological region filling operation to remove noise. The second step of the algorithm is description consisting of lesion percentage, color, and paddy leaf color is removed from infected leaf images.

Perrissiotti et al. (2011) developed a digital image processing based semi-automatic procedure for quantification of downy mildew and grapevine disease; involvement of an open source software Image J and compact digital camera. Rath (2005) developed an image processing based automatic analyzer for fall army worm disease in maize crop. In this method image is captured in three different light intensities. Author divided this algorithm in two stages, first for segmentation and second for subdivision into blocks. The efficiency of digital image analysis evaluated with simple visual scale, for quantitative and quantity of disease severity and its appliance in quantitative genetic studies, and the result of guessimate genetic limit was observed by Bock et al. (2009a).
Digital image analysis was more susceptible in identifying of quantitative variation between bean genotypes. The comparative study of visual scale of infection severity is helpful and practical tools for detailed choice in reproduction programs and digital image analysis may be new appropriate for phenotypic measurement in quantitative genetic studies. Bock et al. (2009b) studied about the reproducibility of digital image examination for calculating the severity of disease warning sign and evaluate this to visual estimation made by visual for a variety of indication category and to assess inter and intra-VR reproducibility. The result shows the linear group between actual disease by digital image analysis and visual ratters. Image processing becomes visible to offer a highly reproduceable way to measure infected leaves.

Bock et al. (2009c) developed automatic severity estimation method for citrus canker disease. They used a threshold based pre-processing method and color analysis method for healthy leaf identification. The HISI based color model was used for identification of color. The value of healthy color range in RGB be is near about R:7, G:28 and B:194 in Photoshop. Patil and Bodhe (2011) measured the disease severity in the sugar cane with the help of digital image processing. In this method simple threshold method is used for calculating the leaf area, the triangle threshold method is used for segmentation the lesion area. Samnakkki et al. (2011) developed an image processing and fuzzy logic based disease grading method. In this method total leaf area and total disease area were calculated. Fuzzy logic is used for calculating the percentage infection information.

Sun et al. (2014) developed the image processing based method for measuring the disease severity of bacterial spot in tomato and genetic algorithm is used for disease level parameters. The result shows P1 1282216 not significant, P1 114490 showed the least severity disease and OH88119 showed the most severity disease level. Oberti et al. (2014)
developed the method for identifying the powdery mildew disease on grapevine leaves using image processing and proximal optical sensing techniques. The result obtains by image analysis of infected disease at five view angle from 0 to 75 degrees. Roscher et al. (2014) developed a method for high throughput digital image analysis framework which non-invasively detect the grape wine berries and estimated the size of berries in mm. This framework detects the circular structure of berries automatically and no barriers using one classification method. Garcia et al. (2010) developed an automatic recognition of skin imperfection in fruit by digital image processing. Color and texture feature are used to PCA classification as an input.

Font et al. (2014) developed the image processing technique for in-line automatic and individual nectarine variety verification in a fruit-packing line based on the use of feature histogram vectors. In this method calculated and concatenating color layer histograms of Nectarines skin circular central area. Luis et al. (2012) premeditated about the elegant sensor competent of providing that robust, exact and accurate quantification of worldwide indication in leaves of diseased plants. The indication are: mosaics, deformation, white spots, necrosis and chlorosis. The authors used FPGA support smart sensor capable to perform non destructive, real-time analysis of infected and healthy leaf images to quantify multiple symptoms and this methodology used in serving as an indicator of the health and nutrition in plants.

Heald et al. (1979) used a remote sensing method for detecting the Rotylenchulus reniformis Infestations by photography using aerial infrared. Liefer et al. (1979) developed a thermography based observation technique to identify and classify the green portion of the plant leaves of sugar beets infected with Pythium aphanidermatum and cotton infected with Phymatotrichum omnivorum had midday radiant leaf temperatures 3°
to 5° heater than adjacent plants with no symptom of disease. Chaerle et al. (2001) developed the srobotized thermal image techniques without a doubt allows in planta apparition of the initial phase of cell death. The method utilized to imagine generalized amend in transpiration simultaneous with cell death, not counting the complexity of probable set-up property during gas swap measurements.

Yuzhu et al. (2011) examined the appropriate index of the identification of pepper nitrogen significance by color image analysis. In this laboratorial experiment six levels of nitrogen fertilization were established at the flowering to fruiting stages. The color image is analyzed in order to determine the averages of the red (R), green (G) and blue (B) colors. The out put of the result indicated the considerable negative relations between G/(R+G+B) ratio of coverage image and the indexes of pepper nitrogen status. Blackmer et al. (1994) developed a light reflectance method for measurement of nitrogen stress in corn leaves and result show the reflectance mean 550 pm is the promising technique to detect the N deficiencies in the corn leaves. Wavelength near about 550nm is the beast wavelength to analysis the N treatment difference.

Edner et al. (1995) developed a fluorescence radar system for remote sensing of vegetation using spectral resolution and multi spectral imaging mode. Moya et al. (2005) developed the method for squash powdery mildew disease severity method. They used Arc View GIS 3.2 software for image assessment on the basis of scanner and digital segment, but in visual segment they used five evaluators.

2.5 Disease Classification Methods

Rumpf et al. (2010) produces a method for near the beginning stage detection diseases based on Support Vector Machines, Digital Image Processing and Spectral
Vegetation Indices. Relationship between disease severity and spectral vegetation indices is the Pearson correlation coefficient using SPSS. Author contributes on categorize healthy component and region of sugar beet leaves, categorize involving powdery mildew disease, Cercospora leaf spot and rust, and recognize diseases even before precise symptoms became noticeable. Piotr and Piotr (2012) developed the algorithm to examine barley kernel images to estimate cereal grain feature and execute grain classification. The method predictable personality kernels soft and crumpled regions. The algorithm was also capable to conclude the dimension of the crumpled and the soft region on a grain’s outside, which authorized automatic categorization and kernel excellence evaluation. The methodology was experienced and evaluate using barley images, and authenticate by association with the valuation results of a specialized appraiser.

Atas et al. (2012) investigated and detected aflatoxin contaminated chili pepper with the help of Halogen illuminations and UV. Authors have proposed complete differentiation of successive spectral energy features. In each spectral band applied the quantized histogram matrix for feature extraction. Finally results summary shows the reduced spectral bands and that will be probable to assemble an uncomplicated machine vision organization for aflatoxin recognition in chili pepper. Philipp and Rath (2003) method aim to separate plants with background and foreground in color images taken by a digital camera by canonical transformation, and color model, discriminant analysis, and Lab. The method relies heavily on the Logarithmic discriminant analysis because the mis-classification of plant background and foreground pixels of about 2%.

Moshou et al.(2001) proposed a Self-Organizing Map (SOM) neural network(NN) and utilized in a organize way for a categorization assignment and tested result shows the categorization of reflectance spectra from field weeds from the crops, and provided improved results evaluated with other neural network and statistical classifiers. Zhao et al.
(2012) proposed a method for identifying the wormholes on the prospect in open and closed infection in oilseed rape leaves reason by caterpillars in vegetable i.e. cabbage. Author composed the method in unclosed wormhole location, identification and reconstruction. Calibration models and validation models were recognized based on genetic-neural-network (GNN), wavelet neural network (WNN), genetic-wavelet-neural-network (GWNN), genetic-wavelet-neural-network-reconstruction-algorithm (G-WNNRA) and Back-propagation neural-network BPNN algorithms. Huang Y. K. (2007) developed an application based system of image processing and neural network for classifying and identifying three Phalaenopsis seedling diseases. The texture feature lesion was evaluated by gray level co-occurrence matrix (GLCM). GLCM and mean gray level of lesion area on the R, G, and B bands were used as a feature vector and it classify with the help of back-propagation neural network.

Hiary et al. (2011) developed the software solution for automatic detection and classification of plant leaf diseases. In this method applications of K-means clustering and Neural Networks (NNs) have been formulated for classification of diseases. An algorithm is divided into three steps a) identify the mostly green color pixels b) masking applied only green pixel specific threshold values that are computed using Otsu’s method, c) pixels with zeros R, G and B values and the pixels on the diseased boundaries of the lesion cluster (object) were totally isolated. The software effectiveness can effectively distinguish and categorize the infected lesion with an accuracy between 83% and 94%.

Yao et al. (2009) developed an application of image processing techniques and Support Vector Machine (SVM) for detecting rice disease early and accurately. Lesion areas were binaries and their texture and shape features were extracted. The results showed accuracy of 97.2% in disease detection and classification. Jian and Wei (2010)
developed a method for recognizing cucumber leaf diseases using Support vector machine (SVM). This method takes each spot of leaves as a sample instead of taking each leaf as a sample. Radial Basis Function (RBF), polynomial and sigmoid kernel experimental function were also used to carry out qualified tests. The experimental results showed that, the SVM method based on RBF kernel function and taking each spot as a sample made the best presentation for categorization diseases. The method proposed by Camargo and Smith (2009) reported image pattern recognitions, identification and classification of infection reason by agents. Infected lesions were segmented, enhanced and a set of features were extracted. The extracted features are used as input in SVM. The results suggested that, texture features, might be used as discriminators.

Hu et al. (2013) developed a smart phone based classification method for species of fish. This method is based on color and texture features using a multi-class support vector machine (MSVM). The results confirm best categorization model for fish species recognition is composed of a wavelet domain feature extractor. Onyango and Marchant (2003) developed an image processing method for differentiating the crops and weeds. The segmentation is based on hue which is infrequently doing well because there is significant overlie stuck between the classes in any one measurement of the usually utilized color spaces. The average result indicates over 12 images, the highest and lowest crop categorization rate was 96% and 82% respectively. The highest and lowest weed categorization rate was 92% and 68% respectively.

Tian et al. (2008) developed a computer image processing and support vector machine (SVM) based method for recognizing cucumber leaf disease based and studied to improve efficiency and recognition. They applied the median to remove the noise of cucumber disease leaf and then mathematics morphology and statistic pattern recognition was
introduced to segment images of cucumber disease leaf. At last color, texture and shape features of the cucumber color disease spot were extracted, and SVM classifier is used for recognition of cucumber disease. The results show that the classification rate of SVM is better than neural networks.

Wang et al. (2012) developed a technique to recognize digital image and pattern detection of plant infection. In this method various neural network methods are used, i.e. radial basis function (RBF) neural networks, back-propagation (BP) networks, probabilistic neural networks (PNNs) and generalized regression networks (GRNNs) to differentiate between rust from wheat leaf and to discriminate downy mildew infection from powdery mildew infection. All classification is based on three basic features texture, color and shape which are extracted from the infected lesion image. The result indicated two types of wheat diseases, the best calculation precision was 100% with the fitting precision equal to 100%, while GRNNs, BP networks, or PNNs were used, and the best estimate precision was 97.50% with the fitting precision equal to 100% while RBF neural networks were used. Ahmed et al. (1999) characterized the symptoms associated with fungal damage, immature soybean (Glycine max) seeds and viral diseases using Digital image processing methods. The RGB color model was used for categorization between asymptomatic and symptomatic seeds for inspection and grading and classification result shows accuracy of 88% was achieved using a linear discriminant function.

Gui et al. (2013) developed unsupervised color image segmentation method based on fuzzy clustering and applied for classification of three types of soybean disease infection. The results indicate that this method can precisely segment the lesion area from the color image. Payne et al. (2013) developed a machine vision system for count up mango fruit from daytime colored images of individual trees for the purpose of estimation the mango
crop yield. All these fruit images, pixels were segmented into fruit and background pixels using color segmentation in the RGB and YCbCr color ranges and a texture segmentation based on adjacent pixel variability. Liu et. Al. (2010) developed a neural network based application method for discriminate fungal infection levels in rice panicles using principal components analysis and hyper-spectral reflectance. Rice panicles were measured through the Hyper-spectral reflectance on the wavelength range from 350 to 2500nm with a portable spectro-radiometer. The spectral response characteristics of rice panicles were analyzed, and PCA was executed to achieve the principal components (PCs) derived from different spectra methods.

Moshouet al. (2004) developed an automatic method for recognition of yellow rust by reflectance measurement and neural network in wheat. Huang Y. K. (2012) developed an application of image processing and neural network methods for classifying and identifying the supremacy of Areca nuts. Author used the segmentation by a detection line method for defects in diseases or insects of Areca nuts. Various geometric feature parameters are used in the classification method. A BPNN classifier was used to classify the superiority of Areca nuts with 90.9% accuracy.

The method developed by Bravo et al. (2004) recognize and classify the plant stress caused by yellow rust disease in the field using the combination of fluorescence imaging and hyper-spectral reflection information between 450 and 900 NM. This method is used in tractor mounted cost-effective optical device for site-specific pesticide application. All hyper-spectral reflection images are taken by imaging spectrograph. Quadratic discrimination classifier is used for selected group of wavebands to discriminate diseased from healthy plants and the result shows 10% error in classification. Leaf recognition and spectral normalization comparison of 550 and 690 NM fluorescence images, the
recognition of infected plant stress was clearly possible. Omrani et al. (2014) studied about the automated, seeking quick, fast, cost-effective, exact and precise methods of apple fruit infection discovery. Author developed a continuous monitoring image processing based system to identify and classify the three dissimilar apple infection become visible on leaves, namely black spot, leaf miner pest and Alternaria. Classification is based on three soft-computing methods for disease cataloguing, of continuous monitoring SVM and ANN. The comparative results shows the support vertor machine (SVM) affords improved results than the artificial neural network (ANN) for apple fruit infection categorization.

Barnrdes et al. (2013) studied and discussed about the pathogens in cultivated area. The result indicated the yield losses in field crop by pathogens and represents less income to the farmers due to the inferior product superiority as well as higher prices to the consumer due to the lesser offering of goods. Author developed a method for the automatic cotton diseases classification on the feature extraction of foliar cotton diseased images. Wavelet transform and SVM classifier is used for feature extraction and classification respectively. The disease is classified into five classes Healthy, Ramularia, Bacterial Blight, Ascochyta Blight and Unknown disease.

Abdullah et al. (2007) proposed a method for categorizing the infection in rubber leaf through utilizing and automation RGB model. Many rubber tree disease leaf images are being designed for RGB channel extraction on the basis of color. All the three sets of disease leaf image are digitally sensing under manage and benchmark situation. The ANN model in this worked on the central pixel mean of RGB and applying principal component analysis of the pixel gradation values of each tree disease leaf image. The
result shows the 70% in diagnostic precision with more than 80% realization for sensitivity.

In their two papers, Dubey and Jalal (2012a, 2013) presented a framework to classify the fruits and vegetables from images. They considered images of 15 different types of fruit and vegetable collected from a supermarket. Their approach was first segment the image to extract the region of interest and then calculate image features from that segmented region, which is further used in training and classification by a multi-class SVM. They first calculated sum and difference with neighbouring pixel in x-direction and then simulated these output in y-direction by calculating sum and difference in y-direction. By considering x and y direction separately, the algorithm is able to encode the relation of any pixel with its neighbouring pixels in both x and y direction very efficiently. In their three papers,

Dubey and Jalal (2012b, 2012c, and 2014a) have also proposed a method to detect and classify the fruit diseases using image processing techniques. They have used the three diseases of Apple namely Blotch, Rot and Scab under consideration. First of all, they detected the defected region by k-means clustering based image segmentation technique, then extracted the features from that segmented defected region which is used by a multi-class support vector machine for training and classification purpose. They also used ISADH feature descriptor developed to classify the Apple fruit diseases in Dubey and Jalal (2014b). In Singh et al. (2012), color, texture and shape based descriptors are used for content based image retrieval. They proposed two phase retrieval approach one without feature fusion and another one is with feature fusion to improve the retrieval performance.
2.6 Fungicides for Soybean Foliar Disease

Table 2.1 shows various fungicides which can use for curing or treating the foliar infection. As per the table the effectiveness of various classes of fungicides against various plant foliar disease is given as Excellent (E), very good(VG), good(G), fair(F), not recommended(NE), No data(-)
<table>
<thead>
<tr>
<th>Product</th>
<th>Fungicides Class</th>
<th>Fungicide Active Ingredient</th>
<th>Rate/A</th>
<th>Brown Spot</th>
<th>Bacterial Blight</th>
<th>Frog Eye</th>
<th>Soybean Rust</th>
<th>Sudden Death Syndrome</th>
<th>Downy Mildew</th>
</tr>
</thead>
<tbody>
<tr>
<td>Headline 2EC</td>
<td>Strobilurin</td>
<td>Pyaclostrobin</td>
<td>6 fl oz.</td>
<td>G</td>
<td>VG</td>
<td>E</td>
<td>VG</td>
<td>E</td>
<td>G</td>
</tr>
<tr>
<td>Quadris 2 SC</td>
<td>Strobilurin</td>
<td>Azoxystrobin</td>
<td>6.9 fl oz.</td>
<td>F</td>
<td>G</td>
<td>VG</td>
<td>E</td>
<td>VG</td>
<td>F</td>
</tr>
<tr>
<td>Domark 230 ME</td>
<td>Triazole</td>
<td>Tetracazolate</td>
<td>4.5 fl oz.</td>
<td>NR</td>
<td>-</td>
<td>VG</td>
<td>E</td>
<td>VG</td>
<td>NR</td>
</tr>
<tr>
<td>Foliar 3, 6 F</td>
<td>Triazole</td>
<td>Tebuconazole</td>
<td>4 fl oz.</td>
<td>F</td>
<td>G</td>
<td>G</td>
<td>VG</td>
<td>G</td>
<td>F</td>
</tr>
<tr>
<td>Laredo 2 EC</td>
<td>Triazole</td>
<td>Myclobutanil</td>
<td>7.8 fl oz.</td>
<td>NR</td>
<td>F</td>
<td>F</td>
<td>E</td>
<td>F</td>
<td>NR</td>
</tr>
<tr>
<td>Pounce BC</td>
<td>Triazole</td>
<td>Flusilazole</td>
<td>4 fl oz.</td>
<td>NR</td>
<td>G</td>
<td>VG</td>
<td>E</td>
<td>VG</td>
<td>NR</td>
</tr>
<tr>
<td>Topguard 1.25 SC</td>
<td>Triazole</td>
<td>Flusilazole</td>
<td>7 fl oz.</td>
<td>F</td>
<td>VG</td>
<td>G</td>
<td>E</td>
<td>G</td>
<td>F</td>
</tr>
<tr>
<td>Quilt</td>
<td>Strobilurin + Triazole</td>
<td>Azoxystrobin + Pyaclostrobin</td>
<td>14 fl oz.</td>
<td>G</td>
<td>G</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>G</td>
</tr>
<tr>
<td>Stratego 2 EC</td>
<td>Strobilurin + Triazole</td>
<td>Triloxystrobin + Pyaclostrobin</td>
<td>7-10 fl oz.</td>
<td>NR</td>
<td>F</td>
<td>VG</td>
<td>VG</td>
<td>VG</td>
<td>NR</td>
</tr>
</tbody>
</table>
2.7 Formulation of Research Problems

On the basis of the detailed literature survey, it is evident that various methods can be developed for soybean plant foliar disease detection, classification, quantification, etc. using an image processing method along with the latest pattern recognition tools. So the objective of the research is to develop an expert system for early and timely detection, estimation, prevention and cure of foliar disease. Thus the objective of the research is divided into the following problems

- Automatic Soybean Plant Foliar Disease Detection
- Soybean Plant Foliar Infection Cataloguing
- Soybean Plant Disease Identification using Retrieval and Classification Methods
- Soybean Plant Disease Quantification and Expert System