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Detection and Classification of Grain Crops and Legumes Disease: A Survey

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Abstract

The agriculture plays very important role as it helps to accomplish the need of food among people. The production in agriculture consequentially contributes to the economy of every country. The grain crops rice, wheat, maize, and legumes are suffering a lot due to some viral, bacterial, and fungal diseases. The pest and variety of diseases can bring a heavy loss to the global economy. The monitoring of crops health and identification of diseases at early days is very challenging and emerging task in agriculture. So, it is very important to prevent crops from fatal diseases in the early stage, but the manual process of disease discovery can lead to erroneous magnitude of pesticides. The trouble is figure out by automate discovery of diseases and supplication of relevant medication on time. It is very necessary to find out accurate disease to overcome heavy loss to economy. From the few decades, to detect disease correctly, the process of detection become automate using emerging technologies and techniques using computer vision, machine learning and image processing. This article presents the extensive literature on existing methodologies utilized for recognition and classification of leaves diseases. The studies addresses that there is still many limitations and challenges find in different phases in plant disease detection system. The presented research also highlights the pros and cons of different techniques that help out the researchers for contribution in future.

Keywords: Detection, Classification, Grain Crops, Legumes Disease, Fungal diseases, leaves diseases, Classification.

1. Introduction

Agriculture address an active role as it is associated with production of essential crops. From some recent decades the research in the Agriculture sector allow to initiate effective approaches to increase the production with quality to meet the needs of economy [1] as the United Nations Food and Agriculture Organization (UN FAO) alarming report give the recommendation of increasing food supply up to 70% to meet the future requirements [2]. The field of agriculture builds giant contribution towards the GPD in Pakistan which show the developing progress in the country. The farmer's uses grains to produce the major grain crops and legumes. These grain crops and legumes having rich source of nutrients, minerals, dietary fibers that directly related to the humans heath and prevent from health disorders. But due to pandemic situation like COVID-19 it cause the instability in the economy; in such situation food security becomes the important concern of the modern world to secure the future supply, as according to United Nations (UN) report the population of the world increase by 8 billion people in 2023 and 10 billion in 2050 [3]. Due to some factors like non-identification and late detection of diseases can waste up to 40% of agriculture products [4]. The development of agriculture sector is very important for the prosperity of the nation. But the developing countries are facing a lot of trouble in agriculture due to the attack of different diseases on plants. The formers are not train and also not aware with the modern techniques used to cure plants. The strategy to prevent plant from diseases in the past is to uprooting the plant and the use of insects killer andpesticides.

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The formers were trained to detect and cure diseases in traditional manner that is not so efficient and the result is loss of crops that bring heavy loss to the formers as well as the economy. With the passage of time there is a need of efficient system for accurate disease detection in plants with less amount of time to minimize the economic loss and improve productivity. In order to overcome all climate, weather and soil consequence, the modern technologies must be utilized to detect the plant diseases in early stages to get good quality and high productivity of crops [5]. For recognition of diseases in crops at the early stage and production of crops with high quantity and quantity is become necessitate task but the farmers examine crops manually by naked eye that is not accurate so the automation of system is require for solution [6]. To overcome regarding problems a variety of different techniques and methods are used. The diseased images show the abnormalities like spots [7] the infected area of image may have different variation in color that are difficult to differentiate so that computer vision and image processing techniques helps to evaluate diseases in effective, fast and efficient manner. From some recent years researchers used different method to analyze the plant diseases. Different researcher's presented review to discuss the techniques used for detection of various diseases. Shaopeng Jia et al. [8] presented review on pest image and crop disease recognition.

The researcher describes literature on the traditional approach such as handcrafted method and deep learning to find diseases as well as classify them. The comparison also performed between these two methods by using their advantages and disadvantages. Prabira Kumar Sethy et al. [9] presented a review on different rice diseases discovery like False Smut, Shealth Blight, Brown Spot Rice Blast, Leaf Scald, Bacterial leaf blight and Bakane. Moreover they describe identification process containing different steps in image processing. Zahid Iqbal et al. [10] presented a survey on the various techniques for discovery along with the classification of citrus diseases. Lawrence C. Ngugi et al. [11] published an article on image processing techniques that automate leaf pest and disease detection. The researcher presented different techniques like hand crafted features extraction method, deep learning and hybrid leaf condition recognition system that used both deep learning and hand crafted features. The research also include the unresolved challenges that should be resolved by researchers in future. Nilay Ganatra et al. [12] presented review on detection and classification of different agriculture products and highlight the pros and cons of different segmentation techniques, features extraction techniques based on color and texture and classifiers. Jitesh P. Shah et al. [13] presented a review based on various rice diseases detection and classification including the general process to find them with image processing and machine learning for recognition of leaves diseases efficiently. Anup Vibhute et al. [14] described about the application of different image processing approaches in the agriculture sector. The article is divided into two applications; one application is on weed detection by using algorithms of image processing and second application is about fruits and food grading.

The arrangement of the remaining review paper provide the comprehensive literature that is arrange as follow: Section 2 depicts different types of plants diseases. Section 3 presented the techniques utilized for plants diseases detection. Section 4 provides the extensive review on grain crops and legumes diseases. Section 5 describes the performance metrics that determines the efficiency or correctness of crop disease detection and its classification. Section 6 depicts future directions, which helps researcher to contribute infuture. Section 7 describes discussion and conclusion.

2. Types of plants diseases

The plants are called diseased when it shows some abnormalities in growth and production. There are different types of diseases that make effect on growth and production of plant. Plant's diseases are grouped according to the behavior and manner of their primary agents, some of them infectious and some were noninfectious. The infectious diseases are caused due to variety of pathogenic organisms like bacteria, fungus, and virus and it reproduce into host and spread over the whole crops. The diseases can cause by the living organisms and sometimes due to climate change, chemicals burning etc. But the biotic diseases are most dangerous and caused heavy loss to crop. More than 19,000 parasitic fungi that produce plant diseases in crops [18]. The fungal organisms that cause plant disease are very small in size and can travel through the air from one plant to another. The fungal disease symptom is leaf turns yellow and few of them diseases are stem rust, powdery mildew, and leaf rust. The diseases can also cause by many types of bacterial insects.The sign of bacterial diseases are bacterial ooze out from the infected tissues and on the surface of leaf it creates sticky material [19]. The symptoms are leaf spot with yellow halo. If once plant infected with viral disease, there is no sign as it cannot be seen Different insects are the carrier of these diseases. The symptoms of viral diseases are plant stunting, yellowed and crinkled leaves.

3. Plant disease detection system

This portion describes the framework of the disease detection and classification system which includes the step by step process. The whole process consists of training and testing of sample images. The training starts from image acquisition. Image may capture through camera or get from publically available datasets. After then image should be clear and clean to get better results for this purpose image preprocessing is performed that enhance the image, remove noise from image and may resize the image. Then segmentation makes separation of image effected region from background. In feature extraction different types of attributes from diseased image extracted to train classifier. At the testing step the classifier make decision by using the training experience that the image is healthy or infected and extend their class.

3.1 Image acqusition

It is a process to get the digital presentation of a scene called image and its composition elements called pixels. The image can be in different form, so the image acquisition system is classified into 7 classes Mono- RGB vision, Stereo vision, Multi- and hyperspectral cameras, Time of Flight cameras (ToF), LIDAR technology, Thermography and fluorescence imaging included [20]. The use of appropriate technique is initial and also very essential step for making any machine vision system. Shveta Mahajan et al. [21] presented different image acquisition techniques for the estimation of legume quality. The researchers described different acquisition techniques also describing their nature, sensor and quality parameters based on Electromagnetic Spectrum including Visual Imaging, X-Ray Imaging, Multi spectrum Imaging, NMR Imaging, NIR Imaging and Thermal Imaging. Some researcher utilized the publically available datasets and some build their local datasets that gathered manually. The publically dataset Plant village contained 38 categories and 54303 healthy and disease images available to performed experiment [22]. A dataset of citrus fruits leaves is presented to recognized and find the class of citrus diseases. The dataset is captured by single camera and images presented in JPG and Raw format. It contains total 759 images out of which 609 presented citrus diseased leaves images and 150 of them citrus fruits diseases images. These images were captured from Orchards in Sargodha region of Pakistan in December, when fruits are ripen and diseases show maximum symptoms [23]. The performance of the plant diseases detection system is highly depended on the capture images, as the influence of background complications and bad capturing conditions may degrade the achievement of the system.

3.2 Preprocessing

The aim is to refine the quality of image than original image. The preprocessing techniques includes image enhancement, noise removal, cropping/resizing and smoothing of the image. These techniques apply on the image according to the condition and requirement. As per literature filtering and enhancement is done by the color space conversion. The researchers described the image processing based system to detect Betel Vine, for this purpose scanned rotted leaves images were used. The sample images of rotten leave contain 30% leaf area and rest of 70% area presented background area, which consumed storage space on disk as well as utilize CPU processing time. To resolve this issue image cropping technique is used to preprocessed the image and make the processing speed fast and does not loss any information about Region of Interest (ROI) [24]. The leaf disease discovery and its classification are performed with a variety of techniques using Plant Village dataset with 20636 images. The training of large dataset consumed a large amount of time, to make this process optimized image resizing is performed by the researchers to scale the image up to 128 X128 for achieve fastness in training and also preserve the integrity of valuable data [25]. The identification of unhealthy regions in plant leaves performed with the utilization of texture attributes. To preprocess the images Hue, Saturation, Value (HSV) is applied as color space that resembles the properties of human color sensing [26]. The preprocessing is performed to discover the leaves diseases by bring up RGB image to Hue, Saturation, Intensity (HSI) color space transformation that facilitates specification of variety of colors after that H component is picked and S, I dropped as these components contain no information [27]. Noise is the important factors as it creates the unwanted changes in image like make variation in the colors and brightness, produce unwanted artifacts and make the image blur. The researchers proposed system to detect diseases in rice leaves by color and texture attributes. The images were taken using CCD color camera from a rice field where insects, dewdrops and dust appear in the image as noise that may degrade segmentation process. For the sake of noise removal median filter with the size of 3*3 mask is used to the original image [28]. Paddy leave disease detection is performed, lesions were cropped manually from collected images and then conversion is performed into Hue, Saturation, and Value (HSV) to extract Saturation. To overcome the difference of lightning Histogram equalization is used and for sharpening Laplacian filter is utilized [29]. The preprocessing of sample images was performed to removing background, undesired distortions and noise. The RGB images were resized and the conversion is performed in the format of Hue, Saturation and Value (HSV). For the purpose of subtracting noise, smoothing and make the information clear, median filter is applied to original image. Moreover the histogram equalization is used that distribute the intensities for image enhancement [30]. Preprocessing is very important step as it refines the image by removing degradation that helps to predict the best outcome.

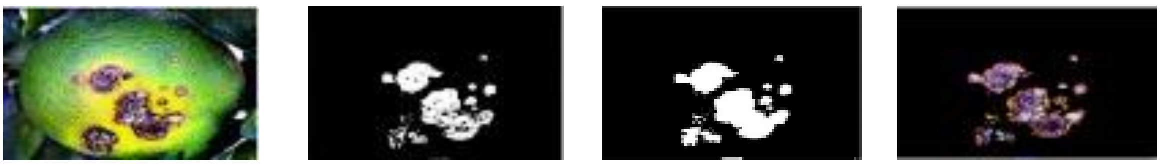
Limitations and challenges: the plant disease detection is become automate using advance tools but still there are some limitations in agriculture field. According to researchers for the improvement of disease identification the input should be large number of training samples should increase with optimal features that predict better [26]. The other researchers also think to increase their database, as the number of sample increase the accuracy should also be increase for the recognition of more plant diseases and also classify them [30].

(A) (B)

Fig.1. Preprocessing results, (A) Original image, (B) Enhanced image [30]

3.3 Segmentation

Image segmentation divides the single image into different meaningful parts. The purpose is to highlight the infected part called Region of interest (ROI). The matching pixels are group together for segmentation in input image. In agriculture it is important to identify the infected part or Region of Interest (ROI) in diseased image. Muhammad sharif et al. [31] proposed optimized weighted segmentation technique to find citrus diseases. Nida M. Zaitoun et al. [32] presented an article on different segmentation methodologies like region based segmentation techniques and edge or boundary based segmentation methods. Some researchers used different segmentation techniques to segment the image for calculating the area of disease part on the leaf. In Plant disease detection to segment the image, segmentation is performed by Edge based segmentation called canny edge detector that does not apply directly on RGB image so image is converted into grayscale moreover background edges are removed and only preserve leaf edge details and compute edge histogram for comparison of healthy or infected sample [33]. For the separation of background and foreground and make the image segmented, a threshold segmentation Otsu's segmentation is performed on dataset of tomato plant leaves [34]. To increase the accuracy of crop disease segmentation an algorithm is proposed by integrating the local threshold with seed region growing segmentation named LTSRG used for corn leaf disease detection thus result of LTSRG is highly satisfactory as compared with Clustering-based EM and threshold based Otsu method [35]. A system is proposed for improvement in classifying grape leaf diseases, the images were segmented by K-mean clustering that break the image into number of clusters, at number three best results were observed but cluster select manually that show diseased part [36]. In the segmentation process the threshold value is very important, incorrect threshold value can cause poor segmentation that affect the accuracy of the system. The summary of some segmentation approaches described in Table 2.



(a) (b) (c) (d)

Fig.2. Segmentation results, (a) enhanced image, (b) weighted segmentation, (c) fusion image, (d) infected part identification [31].

Limitation and challenges: with modern technologies segmentation is become accurate but still there is need of improvement is such domain. The researchers overcome the issue of manual selection of cluster in K-means clustering from number of clusters by using extracted feature knowledge each cluster present [36].

3.4 Features extraction

The features of disease obtained from the highlighted part of image during segmentation. It usually extracts and gain color, texture, and shape attributes from infected part in the image. A system proposed in which color co-occurrence method is utilized and extract texture attributes like Local Homogeneity Contrast, Energy, and Cluster Shade that help to calculate some statistical measures of diseased part [37]. The researchers proposed system for plant leaf diseases detection using Local Tri-directional Pattern for Features extraction that is used as variant of Local Binary Pattern (LBP) features descriptors and extracts discriminant information for each class, at the end three histograms are formed and serially fused to build final feature vector thus after classification the achieved accuracy is 94% [38]. The researchers proposed Artificial Neural Network (ANN) to specify Phalaenopsis seedling recognition. The GLCM gain features of lesion area moreover mixture of Gray Level Co-occurrence Matrix and 3 color features utilized for recognize the disease class. The system achieved 89.6% average accuracy and detection ability without the classification of disease is 97.2% [39]. The researchers described a system for correctly point out of paddy diseases. The texture features for color image were extracted based on CIE XYZ color space and, color features extracted with the help of CIE L*a*b and shape features based on area, roundness etc. [40]. Palm oil an agriculture commodity makes contribution in production of vegetable oil. A system is proposed for palm oil disease including Anthracnose, Hawar Leaf and Leaf Spot detection and classification on Mobile Device. The researcher's extracted Shape features, median of RGB, quartile 1, quartile 3, average brightness and standard deviation. After classification with Neural Network the system obtained accuracy is 87.75% [41]. A system is described to recognize cotton leaves diseases Bacterial Blight, Alternaria, Gray Mildew, Fusarium wilt and cercospora. The color features were extracted by Color moment with standard deviation and mean. To extract the texture features 2D Gabor filter is used with mean and standard deviation of magnitude of Gabor wavelet transform coefficient after classification the system achieved 83.26% [42]. The researchers proposed method to detect fungal diseases in commercial crops. The features were extracted from segmented image using Discrete Wavelet Transform (DWT). To reduce number of features Principle Component Analysis (PCA) applied after that classification is performed [43]. Another system is proposed for plant disease identification and classification. The researcher's extracted texture, color and the morphological features etc. but morphological features gives better results over color and texture features [44]. A system is proposed to discover citrus diseases based on symptoms with the help of textural descriptors LBP and color histogram, HSV histogram features with the accuracy of 99.9% [45]. The summary of features extraction techniques presented in Table 3.

Limitations and challenges: the focus should be on developing of the new advance algorithm for accurate and fast detection of leaves diseases [37]. The researcher proposed method for leaves disease detection but the proposed method work only for texture attribute so the color based features and shape feature along with texture features were remain un explored for the better performance [38]. The system proposed to find out Phalaenopsis seedling diseases but the researcher only focus on the find and classify the lesion area using CDD camera but not able to examine affected area on cover blades for growth observation [39]. A system is designed to find Palm oil diseases on the mobile devices; there is still need of improvement for increase in accuracy rate [41]. The system proposed to find citrus diseases and researchers suggest that there is still demand required in availability of standard dataset for the improvement in performance of system [45].

3.4.1 Classification

Identify the correct disease class is most important step in leaf disease detection system. The classification distinguished the healthy and unhealthy leaves and further class of the disease. The first step is to pick up the image from training dataset for the learning purpose of classifier to detect disease correctly on test dataset. The researchers explored and evaluate performance of number of statistical classifiers that find diseases in citrus leaves successfully and differentiate between the classses [46]. The summary of differentclassifiers described in table 4.

Limitations and challenges: the proposed system's results evaluate that the classifier Linear Discriminant Analysis is robust and remaining three in which KNN has less classification rate so there is need of evaluatethe classifier for increase accuracy [46].

3.5 Deep learning

Now a day the most adopted method to recognized diseases is deep learning approach that brings image processing to new heights. Deep learning is widely used and serving a lot in smart agriculture. There is the variety of deep learning algorithms used due to their strong grip on image processing [47]. The researchers describe approach for plant disease detection named as transfer learning and depicts the basic architecture of CNN for successful classification of diseases [48]. The most common algorithms of deep learning are Convolutional Neural Network, Generative Adversarial Network, Recurrent Neural Network and Feedforward Neural Network and Backpropagation Neural Network [49]. The architecture of basic deep learning model presented in figure 5. *Limitations and challenges:* some researchers utilized publically available datasets with plain background so that in some practical scenario there is need of practical environment.

4. Review on Grain Crops and Legumes diseases

4.1 Rice

Rice is the one of the most important grain crops and considers as the extensively consuming staple food inhumans. Rice is among highly consumed cereals so that it produces on large scale. The researchers proposed manymethods that recognized and classify different rice diseases by utilizing the approaches of image processingto analyze the leaf images. The system proposed to find the nine classes of diseases in rice plant includingfalse smut, blast brown spot, tungro virus leaf scald, bacterial leaf blight, red stripe, leaf smut, shealth blight.The diseased images preprocessed by cropping, resizing, random flipping and translation of image without affecting its quality and also enhance the image to remove distortions. The features extraction performed by Deep Convolutional Neural Network and classification with SVM classifier. The hybrid system provideaccuracy of 97.5% and classify 270 images [51]. An automate system proposed to classify the rice diseasesLeaf brown spot, leaf blast with the help of morphological change that cause due to disease attack. To reduce the difference between intensities as the image bring up in gray scale and quality of image enhancedby applying Mean Filter.

(a) (b) (c) (d) (e)

Fig. 3. Rice diseases symptoms (a) : Brown Spot;(b) : False Smut;(c) : Leaf Blast;
(d) : Bacterial blight; and (e): Leaf Strake [50]

After that the segmentation is performed by using Otsu's threshold and features were extracted. The classification of infected and uninfected leaves done by histogram and classification between the diseased images were performed by Support Vector Machine (SVM), Bayes reports accuracy of 68.1% and 79.5% respectively [52]. The quantity as well as the quality of the rice plants should increase by accurate disease detection at the early stage. An automate system proposed to identify the brown spot, Rice blast diseases and healthy samples. First image preprocessed to get the image into appropriate form by conversion in L*a*b color space and Median filter utilized for subtraction of noise. After preprocessing segmentation achieve by K-means clustering approach and different Area, GLCM, Color Moment and Fuzzy LBP features extracted and features selected by Genetic algorithm. Then classifier SVM and ANN separates healthy leaves images and diseased image and report the accuracy of 92.5% and 87.5% respectively [53].The visual identification of diseases by human is very difficult and challenging as the symptoms are very similar. To identify the rice disease efficiently a system is proposed that classify the four diseases. In preprocessing the images resized and normalized then the images were segmented using YCbCr space and different shape and color features extracted to classify the diseases using K-nearest neighbor (KNN) and Minimum Distance Classifier (MDC) with the accuracy of 87.02% and 89.23% respectively [54]. To examine and evaluate the disease by naked eye is time consuming and not very accurate so automate disease detection method is described that detect rice diseases like leaf blast, bacterial leaf blight and brown spot. These samples were preprocessed by resizing, noise removal is done by Median filter and Contrast enhancement is performed. The samples get segmented by utilizing clustering approach K-means clustering moreover number of attributes extracted. The Support Vector Machine recognized class of disease with 92.06% and system also suggested pesticides that help the farmers [55]. A system is introduced to discover the rice leaf diseases leaf smut, brown spot and bacterial leaf blight using leaf images. The images resized in preprocessing step and segmented by Otsu's threshold approach. The features extraction is done through LBP and HOG. The Support Vector Machine polynomial with HOG gained the best accuracy of 94.6% [56]. The system is designed to detect three disease class of paddy leaf that was bacterial leaf blight, leaf blast disease and bacterial shealth Blight. The preprocessing contains crop and resized function. The disease identification is perform by Neuro-Fuzzy expert system which is the combine the capabilities of Artificial Neural Network with rule base expert system and fuzzy logic system. The system obtained the accuracy of 74.21% [57]. The early disease detection and classification helps in cure recommendation. Using image processing approaches a system is designed to detect paddy leaf disorders brown spot, bacterial leaf blight and false smut. The whole process is split, where first phase is to learn andsecond is to predict.

The image conversion is performed in gray scale and Scale Invariant Feature Transform approach applied to gain the attributes after that classification process done by SVM. The system achieved accuracy is 94.16%, recall rate is 91.6% and precision is 90.9% [58]. The discovery of disease knowing its class is very important and necessitate task in agriculture. The paddy disease blast and brown spot detected and classify by K-Nearest Neighbor (KNN). Otsu threshold is used with global threshold for segmentation and geometric features are extracted. The 76.59% result is gain from proposed system [59]. A system is proposed to detect Paddy Blast and Brown Spot disease with image processing approaches. The features extraction performed through Scale Invariant Feature Transform. Two classifiers K-Nearest Neighbor and Support Vector Machine applied to detect class of specific disease with result of 92.2%, 95.5% respectively [60]. As grain production is increases but the quantity and quality production of rice become insufficient so that there is need to detect diseases at early stage for sufficient supply of quality grain products. For this purpose a system is proposed to detect rice leaves diseases with deep learning. The redundant pixel of image removed that do not contain any information using compression technique. The feature extraction and classification is automatically done with Sequential Convolutional Neural Network. The deep learning model achieved the prediction accuracy of 99.61% [61]. The rice diseases affect the production of rice and bring heavy loss to economy as well as to farmers. To reduce this loss an automatic system proposed to discover four rice diseases, for segmentation mean shift image segmentation technique is applied that remove noise from background of lesion image and also boost the characteristics of image for better prediction. Different features of diseased images were automatically extracted through CNN model but to enhance robustness model and accuracy the Softmax classification function is replaced with Support Vector Machine. The system obtained the accuracy of 96.8% that is greater than the traditional back propagation deep learning models [62]. For high quality of rice production and to detect disease in early stage a system is proposed to detect the five rice diseases that were brown spot, blast, bacterial blight, bacterial leaf streak and narrow brown spot using effective deep learning models. There are number of deep learning models used to evaluate the experiment such as ResNet101, ResNet50, DenseNet169 and DenseNet161. After performing the experiments on all DNN models the DenseNet161 achieved best results with the accuracy95.74% [63]. The summary of proposed methods describe in Table 1.

Table 1: Summary of rice disease detection techniques

Number	Year	Disease	Classifier	Dataset	Accuracy
[51]	2019	Tungro virus, false smut, brown spot , leaf scald, leaf smut, bacterial leaf blight, shealth blight, , blast, red stripe.	SVM	BRKB,BRRI, IRRI, Plantix andOwn.	97.5%
[52]	2009	Leaf brown spot, leaf blast, healthy	Bayes, SVM, Histogram	Local	79.5%, 68.1%
[53]	2017	Rice blast, healthy, brown spot	ANN, SVM	Rice research center	87.5%,92.5%
[54]	2016	Rice shealth rot, rice bacterial blight, rice brown spot, rice blast,	Minimum distance classifier MDC, KNN	Agricultural research station, Lonavala, Maharashtra and internet resources	89.23%,87.20%
[55]	2017	Leaf blast, brown spot, bacterial leaf blight	SVM	Own, internet resource	92.06%
[56]	2020	Bacterial leaf blight,brown spot, leaf smut	SVM polynomialwith HOG	UC Irvine Machine Learning Repository	94.6%
[57]	2015	Bacterial leaf blight, leafblast disease, bacterial shealth blight	Neuro-Fuzzy	MARDI	74.21%
[58]	2019	Brown pot, false smut, bacterial leaf blight	SVM	RKB,APS,SS and RRI	94.16%
[59]	2017	Blast and brown spot	KNN	Local	76.59%
[60]	2015	Paddy blast, brown spot	SVM KNN	Local	95.5%, 92.2%
[61]	2020	Healthy, leaf blast	Sequential Convolutional Neural Network	Kaggle	99.61%
[62]	2020	Shealth blight , red blight, rice blast, stripe blight, and healthy	ConvolutionalNeural Network with SVM	Local	96.8%
[63]	2020	Bacterial blight, brown spot, bacterial leaf streak, narrow brown spot and blast	DenseNet161	K5RD	95.74%

4.2 Maize

Maize is an important and worldwide consumed cereal grain crop. Maize crop grateful source ofcarbohydrates, minerals like magnesium, iron, copper, zinc etc

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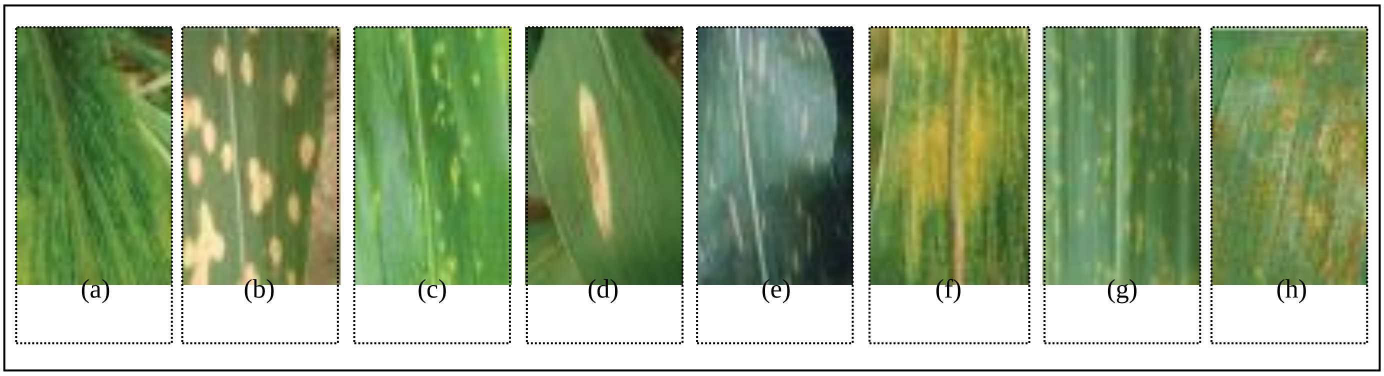

Fig.4. Maize diseases (a): dwarf mosaic; (b): gray leaf spot; (c): round spot; (d): northern leaf blight; (e):southern leaf blight; (f):

brown spot; (g): curvularia leaf spot; (h): rust [64]

The corn cob is utilized in manufacturing of industrial products like insecticides, fertilizers and making ethanol. It is known as Queen of crops as it produces in all around the world. But the grain crop production is affected due to different diseases. The Researchers proposed many systems to discover and for classify diseased leaf to save crop and to increase the crop production for the global economy. A system proposed to detect 8 classes of maize diseases using Improved Deep learning models. For better learning process the original dataset expand by data augmentation. The Convolutional Neural Networks models including GOOGLENET Model and CIFAR10 Model were used for experiment. Both models provide the accuracy of 98.9%, 98.8% [64]. Maize crop is infected due to harmful diseases that cause loss. A system is described to detect and classify maize diseases that were recognized 3 diseases and healthy class. The publically available Plant Village dataset used for classification that not sufficient so that data augmentation performed and preprocessed by Principle Component Analysis (PCA) techniques. The Deep CNN model LeNet architecture is designed for experiment. To train the LeNet model gradient-descent algorithm is utilized that obtained the accuracy of 97.89% [65]. Maize is the important grain crop and source of food for human a system is proposed by researchers for detection of corn disorders common rust, cercospora leaf spot and leaf blight. The system performed two experiments for feature extraction, in the first experiment the bag of features extracted with the help of Speeded up Robust Features (SURF) approach and in second experiment the textural features extracted through Histogram and GLCM. The Multiclass SVM utilized to discover class of disease, with bag of feature the achieved accuracy is 83.7% and the statistical based features obtained accuracy of 81.3% [66]. Another system proposed for discovery of the class of disease in maize leaves. The dataset include leaf blight, healthy leaf, leaf spot and common rust. The image is preprocessed for subtraction of noise using median filter and Gaussian filter but in this experiment Gaussian filter is more accurate. The Contrast enhancement is used to make better quality of image after that image segmented with K-means clustering approach. Different features were extracted in which seven were texture features, six color feature and nine morphological features. The process of classification performed through Support Vector Machine (SVM) that report the accuracy 95.63% [67]. The plant diseases create negative impact to overcome this negative impact the detection of disease at early stage can prevent that loss so the researchers proposed an automated system to recognize the corn leaf disorders that were northern leaf blight, gray leaf spot, healthy and common rust images. The proposed Convolutional Neural Network (CNN) architecture compared with three other Convolutional Neural Network (CNN) frameworks ResNet50, Inception V3 and MobileNet. The result of proposed model is 97.09% that less than the other 3models but the achievement is that it reduce the parameters up to fourth times less parameters than MobileNet [68]. An approach named as Optimized Dense Convolutional Neural Network proposed to recognized and classifyvarious maize disorder.

The Convolutional Neural Network models required huge time in training that is costly and time consuming. So the researchers proposed an optimized architecture of DenseNet with less number of parameters. This architecture is compared with the different models EfficientNet, VGG19Net, XceptionNet and NASNet. The proposed architecture achieved the accuracy of 98.06% that is very close to the existing models but it used small number of parameters so it became time and cost effective [69]. An ensemble model is proposed using ensemble learning approach that combines two or more models for better optimal and predictive model. The two Convolutional Neural Network (CNN) models VGG16 and VGG19 combined for final classification. The CNN models contained number of hyper parameters for reduction number of hyper parameters, the algorithm named as Orthogonal Learning Particle Swarm Optimization (OLPSO) that optimize the process and find optimal values. The optimized trained model VGG16, VGG19 gained the accuracy of 97.9%, 97.7% and the proposed ensemble model AE achieved 98.2% [70]. The attack of diseases can decrease the supply of grains to prevent grain crop maize from these diseases a system is proposed that detect three classes of diseased and one healthy using Convolutional Neural Network model. The dataset of 600 images out of which 70% is to train the Convolutional Neural Network model and 30% to test that model. The model can detect and distinguish the different diseased and healthy images with the average accuracy of 92.85% [71]. Corn is important grain crop to save crop from diseases a system is proposed that recognize different corn diseases brown spot, leaf blight, curvularia leaf spot,gray leaf spot, rust spot and small foot. The image segmented with the help of Seeded Regional Growing (SRG) after that Curvelet Modulus Correlation (CMC) utilized that gain the effective contour of diseased leaves. The Curvelet Modulus Correlation (CMC) combined with SC algorithm to gain Histogram features. with the accuracy of 94.446% [72]. By the passage of time the corn crop production is become reducing to stop this reduction a system is proposed to recognized corn leaf diseases southern leaf blight, shealth blight, corn leaf blight, small leaf spot and round leaf spot. To extract attribute YCbCr color space utilized for spot segmentation after GLCM to gained texture of spot. Further BP Neural Network classify diseases with the accuracy of 98% [73]. Another approach is used to find turcicum leaf blight diseases. The image conversion is performed to get gray scale image. After that sample image get segmented to using K-means clustering and moreover background is removed. To check the sample is infected with disease or not histogram based approach is used. The histogram based classifier detect downy mildew, powdery mildew and normal samples images [74]. Hence the researchers contribute a lot by their proposed systems to recognize the maize diseases. The table 2 describes the summary about the different techniques utilized for maize disease detection and recognition with their classifiers and obtained accuracy.

Table 2: Summary of maize diseases detection methods

Number	Year	Disease	Classifier	Dataset	Accuracy

[64]	2018	Brown spot, southern leaf blight, curvularia leaf spot, gray leaf spot, dwarf mosaic, round spot and northern leaf blight	GOOGLENET,CIFAR10	Plant Village and other internetresources	98.9% 98.8%
[65]	2019	Gray leaf spot, northern leaf blight, common rust andhealthy	LeNet	Plant Village	97.89%
[66]	2018	Cercospora leaf Spot,common rust and leaf blight	Bag of featuresclassification, Histogram basedfeatures classification	Plant Village	83.7% 81.3%
[67]	2019	leaf spot, common rust, leaf blight, healthy leaf	SVM	Local	95.63%
[68]	2017	Healthy, northern leaf blight, common rust, gray leaf spot	CNN	Plant Village	97.09%
[69]	2020	Healthy crop, cercospora leaf spot gray leaf spot, commonrust, and northern leaf blight	DenseNet	Local	98.06%
[70]	2020	Healthy , northern leaf Blight , gray leaf spot, common rust	AE ensemble model	Kaggle	98.2%
[71]	2019	Gray leaf spot, northern corn leaf blight, common rust and healthy	CNN model	Local	92.85%
[72]	2015	Leaf blight, brown spot, gray leaf spot, rust spot, curvularia leaf spot and small foot	Curvelet Modulus Correlation (CMC) with SC descriptor	Institute of cropscience	94.446%
[73]	2011	Southern leaf blight, shealth blight, corn leaf blight, smallleaf spot and round leaf spot.	BP neuralnetwork	Local	98%
[74]	2012	Normal Powdery mildew Downy mildew	Histogram basedclassification	Local	96.7% 95.2% 83.5%

4.3 Wheat

It is one to the most grown and major staple crop in world wide. It is the most consumed crop in Asian countries but due to environmental changes and attack of diseases can reduce wheat production that creates a heavy loss. To save the wheat crop from diseases a novel approach is used to recognized eight classes of wheat diseases.

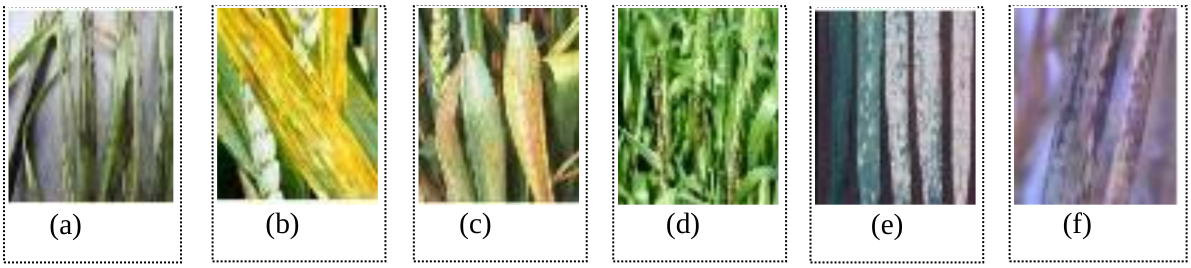

Fig. 5. Wheat diseases (a): flag smut; (b): stripe rust; (c): brown rust; (d): loose smut; (e): powdery mildew; (f): black rust [75]

The deep learning model Differential Amplification Convolutional Neural Network (DACNN) proposed to recognize these diseases by combined capabilities of four classifiers Support Vector Machine, Random forest, Softmax and K- Nearest Neighbor (KNN). The proposed model accuracy is 95.18% which is highest among Inception v3, ZFNet, LeNet and Alexnet models [76]. The diagnosis and recognition of the leaves diseases portray the status of the crop. The researchers proposed Convolutional Neural Network to contribute in wheat diseases recognition. The dataset consist of three classes of healthy, stem rust and leaf rust and number of these samples images expanded by data augmentation. The data is trained on the multiple deep learning models like VGG-16, VGG-19, AlexNet, ResNet-18, ResNet-38, ResNet-50 but ResNet-101 showed best performance and obtained the accuracy of 98.6% [77]. The disease recognition is suffered due to different factors like illumination, equipment jitter and dew etc. According to complex situation a Matrix-based Convolutional Neural Network (M-bCNN) proposed for fine grain classification for wheat diseases. The dataset have different classes mechanical damage leaf, normal leaf , two classes of spore parasitism, two classes of leaf rust and two classes of bacterial diseases. The proposed model provides the accuracy of 91% that is higher than VGG-16 and AlexNet models [78]. An automate system is proposed to different between healthy and diseased image. For noise free images median filter is applied. The histogram is used to recognize healthy and non-healthy images. The diseased were converted into gray scale image and segmented through K-means clustering moreover different features were extracted. For classification two classifiers Neural Network and SVM give the accuracy of 80.21% and 89.23% respectively [79]. The Convolutional Neural Network applies for the improvement in recognition process. Thus a deep learning model used to discover diseases and the benefit is that it can work on raw data directly and automatically extract features from samples. Thus a

Convolutional Neural Network is purposed to recognize wheat diseases like yellow rust, powderly, stem rust and normal images. The proposed architecture AlexNet 84.54% correctly recognized and classifies the given classes [80]. To discover wheat diseases another approach utilized Otsu segmentation technique for separation of lesion part. The researcher's proposed two features extraction approaches in their research. In first approach the features from segmented image extracted with the help of Improved Rotation Kernel Transformation (IRKT) that gain directional statistics information. The second method to extract features is Edge Orientation Histogram (EOH). The IRKT and EOH achieved the accuracy of 97.5% and 95% respectively [81]. The researchers introduced a new classifier to detect fungal wheat diseases. The goal is to downscale the dimensionality of the selected attributes using minimal- Redundancy-Maximal-Relevance criterion (mRMR). The dataset contained sample images of tan spot, stem rust, leaf rust, stripe rust, septoria, powdery mildew and pink snow mold. The median filter applied to preprocess them and segmented using Otsu threshold approach after conversion of RGB to CIELAB. Then different features were extracted and Radial Basis Function (RBF) Neural Network obtained the accuracy of 98.3% in fungal disease recognition [82]. An approach is proposed to detect the wheat diseases rust puccinia triticina, powdery mildew, puccinia striiformis and leaf blight. A blend of three different attributes contains texture, color and shape created for the analysis of classification. The shape, color and texture attributes extracted for learning of classifier. The Multiple Classifier System (MCS) using multiple Support Vector Machine (SVM) based classifiers is proposed. The described system obtained the accuracy of 95.16% that is highest among single classifiers [83]. A system is proposed to detect three diseases to extract the lesion from disease sample that pretreated to gray scale image using Otsu threshold. To identify the diseases some morphological attributes were extracted after that Principle Component Analysis (PCA) utilized moreover system classify images according to their diseases [84]. The researchers proposed methodology to detect stripe rust, leaf rust and powdery mildew by automatic segmentation approach and the benefit is that it do not required the manual setting to gain threshold value. Firstly samples get preprocessed by median filter. The conversion performed and the converted into Lab color space from RGB and K-means clustering adapted which provided accuracy is greater than 90% [85]. Table 3 presents the summary of wheat diseases recognition.

4.4 Legumes

Soybean present as the most important grain legume. To prevent soybean from different diseases, the researchers introduces many techniques to identify these diseases. To produce accurate Diagnosis accuracies different researchers considered automated soybean diseases diagnosis systems with the combination of computer vision, machine learning and image processing. A system is proposed to recognized soybean diseases through two transfer learning models. The researchers choose deep learning models that give the facility to use the raw images without handcrafted features. For deep learning models AlexNet and GoogleNet dataset consist same three infected and healthy samples but number were different. To train the data the both network models has two stages one of them is backward stage the other one is forward stage. Both models GoogleNet and AlexNet achieved the accuracy of 96.25% and 98.75% respectively [88]. To detect soybean diseases a system is proposed to detect 8 classes of soybean diseases. The initial image samples is presented in L*a*b after the samples get segmented with K-means clustering.

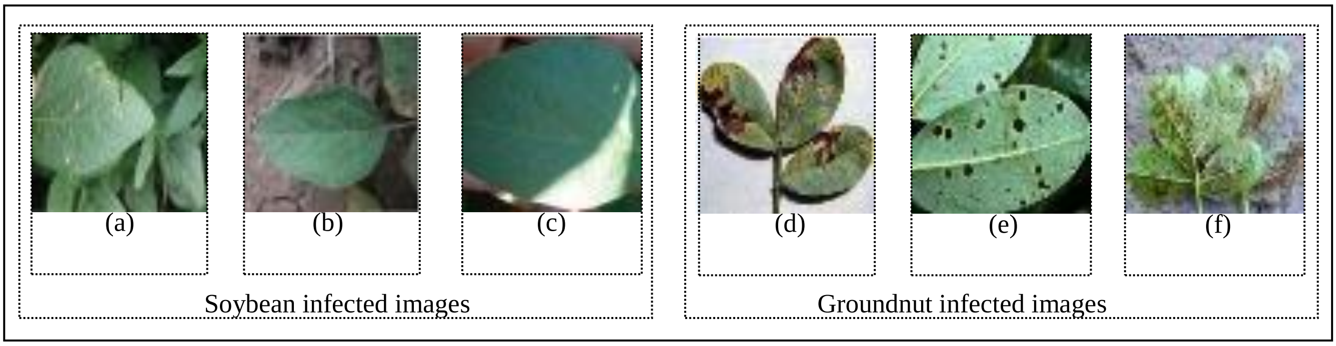

Fig.6. Legumes diseased images (a): frogeye leaf spot; (b): septorial leaf spot; (c): downy mildew; (d): pestalotiopsis; (e): late leaf spot; (f): rust [86],[87]

The textural attributes gain with the help of Local Binary Patterns (LBP), local features extracted using Bag of Words (BoVW) algorithm and Speeded up Robust features (SURF), color features extracted using color moment technique. The final step is classification that is performed through supervised leaning classifier Support Vector Machine (SVM) that obtained the accuracy of 75.8% [89]. An algorithm learning vector quantization neural network purposed to detect three classes of soybean diseases and Healthy class. The learning vector quantization is a neural network approach which merges supervised learning with competitive learning utilized for classification problems. To achieved better accuracy two types of features textural and color extracted. The standard deviation and mean of RGB color channels compute color attributes and Gray Level Co-Occurrence Matrix extracts eight textural attributes thus, the approach gain the accuracy of 93% [90]. Thus another solution is proposed by detecting the diseases in soybean crops using automate system. The researchers proposed a deep learning model to detect 5 disease classes. Preprocessing is performed by transformation in Gray scale image. Moreover these preprocessed images enhanced and segmented through Fuzzy c-means clustering approach. The features extraction and classification done using CNN model. The operation is performed on VGG16, Deep CNN model and SVM but VGG16 achieved best accuracy 93.54% [91]. A deep Convolutional Neural Network model named SoyNet proposed to detect 16 classes of soybean diseases from publically available dataset PDDB with healthy diseased and unknown classes moreover data augmentation is performed. The background removal important to process only leaf part.

Table 3: Summary of wheat disease detection approaches

Number	Year	Disease	Classifier	Dataset	Accuracy
[76]	2020	Bacterial blight, leaf rust, cochliobolus heterostrophus, stripe rust, bacterial leaf streak, mechanical damage leaf, powdery mildew and healthy.	DACNN	Wheat plantingbases of Shandong	95.18%
[77]	2020	Healthy, stem rust and leaf rust	VGG-16 VGG-19 AlexNet ResNet-18 ResNet-34 ResNet-50 ResNet-101	Internet resource(international maize and wheat improvement center)	93.2% 96% 92.6% 96% 93.9% 97.9% 98%
[78]	2019	Leaf rust, bacterial leaf streak, stripe rust, mechanical damage leaf, powdery mildew, bacterial blight cochliobolus, heterostrophus and healthy.	M-Bcnn	Wheat plantingbases of Shandong	90.1%
[79]	2017	Healthy and non-healthy	HistogramNN SVM	Local	- 80.21% 89.23%
[80]	2018	Yellow rust, powderly, stem rust and normal	AlexNet	Local	84.54%
[81]	2014	Powdery mildew and wheat striperust	IRKT, EOH (features based)	Beijing PrecisionAgriculture Experimental Base and Local	97.5% 95%
[82]	2015	Tan spot, stem rust, leaf rust, stripe rust, septoria, powdery mildew and pink snow mold	radial basisfunction (RBF) neural network	Local	98.3%
[83]	2011	Rust puccinia triticina, powderymildew, Puccinia striiformis and leaf blight	SVM-based (MCS)	Local	95.16%
[84]	2010	Powdery mildew Wheat sharp eyespotWheat stripe rust	PCA based	Local	96.7% 93.3% 86.7%
[85]	2014	Stripe rust, leaf rust and powdery mildew	Segmentation based	Internet and literature	90%

Firstly the background is subtracting to gain only leaf area of these images. Then these images were train on CNN model SoyNet architecture, as compared to existing models the proposed model provide higher F1 score (97), precision (97), recall (97) and accuracy of 98.14% in soybean diseases recognition [92]. Soybean leaf disease present the a verity of characteristics that are local outbreaks and large impact, large variety thus an automate system is required to discover these diseases, to conduct the experiment the 1470 sample images were collected from a farm but these samples were not sufficient and led the model to overfitting. The purpose solution to this problem is expanding the data samples by data augmentation. To identify the different diseases the experiment performed on three deep learning models ResNet, AlexNet and GoogLeNet. Out of these three models RestNet obtained the 94.26% [93]. The Convolutional Neural Network is utilized that is very powerful in recognition and classification problems so that a large dataset taken from plant village. The training samples were not enough so that data augmentation is performed. The CNN model LeNet is utilized to identify soybean leaves diseases with accuracy of 99.23% [86]. Another legume is pea that suffers a lot due to leaves diseases thus; a system is proposed to detect pea rust. The images converted into gray scale so that images smoothing performed by Gaussian filter that provide the best performance and image is get enhanced by log transform approach. The binary threshold applied on preprocessed image for the sake of segmentation. The features were selected through Discrete Wavelet Transform and finally SVM that classifies the samples and accuracy is 89.60% [94]. To find the bean disease samples were images preprocessed by scaling, linear contrast enhancement and transformed from RGB to HIS. The enhanced image segmented through K-means clustering after that converted in grayscale to extract through GLCM. The system to recognize beans diseases automate system is proposed for two diseases powdery mildew and bacterial brown spot in leaves. 100% correctly recognized these two diseases [95]. Another approach is used to detect diseases in different specimen out of which one is common bean. To deal with diseases the leaf is segmented after that color transformation is performed. Moreover the detection system process intensity histogram and for classification pairwise based approach is used. The result obtained the overall accuracy of 50% to identify 12 classes [96]. Another grain legume is groundnut that suffers a lot due to a verity of diseases. So deep convolution neural network model (DCNN) utilized to discover the classes of diseases. For this purpose a large dataset of 10 diseased classes collected. The model delivers different accuracies at different steps but overall provide 99.88% accuracy for each class [97]. The summary of legumes (Soybean, Pea, Common Bean and Groundnut) disease detection along with technique and accuracy presented in table 4.

Table 4: Summary of grain and legumes disease detection approaches

No	Year	Disease	Classifier	Dataset	Accuracy
[88]	2020	Bacterial Blight, frogeye leaf spot, brown spot and healthy images	GoogleNet AlexNet	Local	96.25% 98.75%
[89]	2019	Powdery mildew, soybean rust, copper phytotoxicity, soybean mosaic, target spot, downy mildew, bacterial blight and septoria brown spot	SVM	Digipathos	75.8%
[90]	-	Septoria brown spot,blight, frogeyeleaf spot, and healthy	learning vector quantization neural network	Local	93%
[91]	-	Alternaria leaf Spot, phyllosticta leafspot, bacterial blight, frogeye feaf spot, and target leaf spot.	VGG16, Deep CNN model SVM	Plant village andother internet databases	94.45% 89.84% 83.23%
[92]	2020	Septoria/brown spot, southern blight, rust, phytophora rot, oidio/powdery mildew, anthracnose, bacterial blight, charcoal rot, carijo rot, copper phytotoxicity, mela/ rhizoctoni aerialblight, leaf cercopora, mildio/downy and murcha sclerocio	SoyNet	PDDB	98.14% 97% (Precision)97% (Recall) 97% (F1 score)
[93]	2019	Virus disease, Pesticide, spider mite,pest, bacterial health and downy mildew	ResNet	Local	94.29%
[86]	2018	Healthy, septorial, frogeye and downy mildew	LeNet	Plant village	99.32%
[94]	2019	Pea rust	SVM	Hill agriculture research and extension center	89.60%
[95]	2018	Powdery mildew and bacterial brownspot	SVM	Plant Village andsome other resources	100%
[96]	2016	Phytotoxicity, bean golden mosaic, powdery mildew, web blight, bacterial brown spot, target leaf spot, hedylepta indicate, rust, common bacterial blight, anthracnose, cercospora leaf spot and angular mosaic	Pairwise-based classification	Local	50%
[97]	2020	Alternaria leaf, early leafspot, pestalotiopsis, pepper spot, bud necrosis, late leaf spot, choanephora, tikka, phyllosticta and rust diseases	DCCN	Plant village	99.88%

5. Discussion and conclusion

Agriculture is the oldest activity in the world and with the passage of time developments are held to make it more progressive. The plant diseases tear down the ecosystem and may become cause to complicate the environment. The millions of dollars are spending by the farmers just to control pests and diseases in fields. In every year a large amount of crop is wasted due to poor management and lack of technical support. So that it become necessary to discover these diseases by use of latest technologies. Hence, all the articles in this survey paper present different computational techniques to detect the grain crop diseases. This paper depicts a variety of different processing approaches to recognize, analyze and classify the grain diseases. This survey paper presents the literature review on the grain crops rice, maize, wheat, and some grain legumes. We have concluded that the deep learning models are somehow more accurate in disease recognition. There are number of techniques used to detect the diseases but still there is need of efficient computational techniques for the solution of agriculture problems more efficiently with in less complexityand time.

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