A Review on Artificial Intelligence Techniques for Disease Recognition in Plants

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Abstract. Disease detection in crops is one of major task that every farmer practice and takes necessary action for eradicating them as they are harmful to not only crops but also to farmers, consumers, and environment too. Quality and safety of agricultural products is one of major concern in today’s scenario. In earlier times farmers consults experts or use their own experience for identification of diseases in their crops but now days intelligent techniques are slowly replacing the monitoring of crops as they are more reliable, accurate, fast and economical in comparison to earlier techniques. This paper discusses few techniques based on machine learning and image processing that were presented by researchers all over the world for recognition of diseases in crops, later discussions are presented that can be helpful for improvements in this domain. This study would help other researchers and practitioners to survey various techniques used for the process of disease detection in plants and limitations of current systems.

Keywords: Artificial Intelligence, classification, feature extraction, disease detection, Image processing

1. Introduction
Advancements in agricultural practices have made things very easy as farmers have started applying smart farming techniques which had resulted in improved yield of crops. Earlier techniques were time consuming, costly, and required more labor but now in no time several tasks can be done quite easily. Smart farming technique which is being applied to several agriculture applications such as plants disease detection, weed detection, land cover classification, fruit grading etc. But still there is very little progress is made in the adaptation of these techniques as majority of farmers still relay on tradition techniques of agriculture especially in Asian and African countries, as around 50% of their population is dependent on this agriculture for employment but this sector pays heavily as 30 to 40% of yearly production is lost due to diseases consequently which has great economic effect [1].

Earlier disease detection was completely dependent on manual methods as farmers use their own experience or hire expert for the detecting symptoms so that disease could be identified, and some necessary preventive action can be taken. There were drawbacks of traditional method as it totally depends on eyesight of the expert, was very time consuming, cumbersome, labor intensive and lacks accuracy [8]. So, there is a need of an hour to replace manual disease detection techniques with an automated one as quality and safety of agricultural goods is one of major concern. It is very important to detect diseases at their earlier stages, as their spread could be controlled easily without hampering
quality and productivity of crops. This survey provides various disease recognition techniques which are proposed by researchers from all around the globe. Starting with survey of different literatures (Section 2), then architecture of plant disease recognition systems is presented (Section 3). Next section provides survey of few systems that were proposed by different researchers for several crops.

2. Related Work

Based on image processing techniques Dhingra et al. [1] provides extensive survey on disease detection and classification for leaf diseases of different cultures. Researchers surveyed techniques from year 1997 to 2016, consequently categorized disease detection techniques in the basis of color, texture, thresholding etc. and disease classification techniques were categorized as ANN, Naive Byes Classifier, PSO etc. They agree that image processing is a very effective tool used for identifying and classifying plant diseases but are dissatisfied with the advances achieved in last 25 years of research in this domain and lists several limitations of present systems.

Different kinds of diseases in rice plant and their identification using image processing and data mining techniques were presented by Bera et al.[3].Image processing techniques are used for segmenting disease portion of image and then extracting different features of each disease while data mining is used for gathering hidden information which will be used for detection of disease. Researchers concluded that numerous disease detection algorithms have already been researched but still improvement is required for accurate detection of plant diseases.

Auzzi et al. [4] researched on identifying four major paddy diseases (leaf blast, bacterial leaf blight, brown spot and tungro) using fractal descriptors for analyzing texture of lesions present on paddy leaves. After manual acquisition images were cropped and converted into HSV color space and saturation component was extracted. Feature extraction process was carried out for each lesion using fractal descriptors and these values worked as input for the Probabilistic Neural Networks classifier. Author validated that this model gives at least 80% accuracy.

Majumdar et al. [6] developed image processing and analysis system for automatic infection of wheat leaf diseases. More than 300 images were captured from research station in West Bengal using high resolution cameras for identifying rust disease in wheat leaves. To detect certain abnormalities defected images were transformed to HSI space and Fuzzy C-means clustering algorithm was applied for the segmentation of infected area. Various features were extracted from segmented images and later BPNN was used for classification of images. The success rate of proposed system was 84.8%. Author concluded that proposed system can be modified, and web-based interface can be provided to farmers with the help of government.

Tian et al. [7] proposed a system which combines three kind of SVM classifiers rather than single classifier for identification of diseases present on wheat leaves. In Image Acquisition phase 800 wheat leaves images with Powdery mildew, Leaf Blight, Rust Puccinia Triticina, Puccinia Striiformis were captured form fields with black background. For segmentation phase simple threshold method was used as a result color, texture and shape features were extracted. Later features were classified by three classifiers i.e. low level, mid-level, and high-level classifiers. Author concluded that Multiple classifier system provides accuracy of 95.16% and has better success rate in comparison to other wheat leaf disease reorganization systems.

Dey et al. [8] proposed algorithm for detection of rot diseases of Betel vine. Author described three stages of the algorithm (Image Acquisition, Image Preprocessing, and Image Segmentation). In first stage 12 diseased images of betel vine were collected using flatbed scanner. In second stage size of images was reduced for removing redundant background for saving disk space and improving CPU processing speed. In Image Segmentation stage the diseased portion was separated from the leaves. Firstly, color analysis was done on leaves samples where HVS color modal was selected. Author assured that H component of HVS modal is best as it displays rotted area very clearly. Finally rotted area is calculated by applying Otsu threshold method. Author concluded that proposed modal is very promising and can help for disease detection and diagnosing leaf diseases in betel vine.
Vijay kumar et al. [9] conducted two experiments on betel vine plant for detection of powdery mildew diseases using image processing techniques. Firstly, image acquisition was done using high resolution digital camera and images were stored in jpeg format. In the preprocessing phase Photoshop 7 was used for making background of images as white. The image processing task was divided into three phases i.e. normal leaf phase, fully infected phase, and test leaves phase. The difference between fully infected and test leaves phase was that test leaves phase contains samples of visually unidentifiable infected leaves while fully infected phase consists of visually identifiable leaves samples. Then first experiment was conducted where RGB components were separated of normal and fully infected leaves and mean values were calculated of front end and back of leaves and stored in system then RGB components of test leaves were taken and mean values are calculated of both upper and lower parts of leaves and stored in system. Now author compares both the results to recognize that test leaves are infected with disease or not. The second experiment was like first the only difference was that median was calculated in place of mean. Author concluded that this method of detection was very cost effective, its efficiency can be improved by modifying camera parameters.

Shrivastava et al. [10] proposed a method for identification and estimation of soybean plant disease severity levels. Firstly 1000 leaves samples were collected using Samsung mobile phone camera and were stored in jpeg format. These RGB images were converted into YCbCr color space, Segmentation was done using threshold method. Various novel parameters were used for detecting severity levels of soybean plant, these parameters were Infection Per Region, Disease Level Parameter and Diseases Severity Index. Author considered six soybean leaf diseases namely frog eye, rust, bacterial blight, sudden death syndrome, brown spot, and powdery mildew. Author pointed that this method was cost effective and it can be used in distinct filed conditions and advance background separation methods can also be used in future for improving this method.

Mokhtar et al. [12] discussed a method for detection of powdery mildew and early blight from tomato leaves using SVM. Firstly 200 infected tomato leaves were captured manually from several farms. then in image preprocessing phase leaves were isolated, resized and background was removed using background subtraction technique. Gabor welvet transform was applied for extracting several features of tomato leaf diseases. for image classification SVM was used with several kernel functions namely Laplacian kernel, Caunchy kernel and Invmult kernel. Author concluded that using Laplacian kernel function accuracy is high.

Ratnasari et al. [13] proposed a model for detecting sugarcane leaf diseases and recognizing severity of several spot diseases using segmented spot. Diseases are identified using Otsu method using a* channel of L*a*b color space. Severity estimation was done on sample data which consist of regular sized leaves. For feature Extraction color feature were extracted using L*a*b color space and texture features were extracted using GLCM. Finally, SVM classifier was used for classifying sugar cane leaf diseases namely ring, rust and yellow spot. Author concluded that proposed model has high accuracy for disease identification.

Revathi and Hemalatha [14] proposed algorithm named Homogenous Pixel Counting Technique for Cotton Disease Detection (HPCCDD) for detecting spot diseases in cotton leaves using Edge detection methods. Firstly, mobile camera was used for capturing images of cotton leaves, then image enhancement was carried out. After enhancement color image segmentation was performed for detecting diseased parts and leaves. Finally, Canny and Sobel filters are used for identifying edges and features of these edges were used for recognizing disease spots. Author compared HPCCDD with other existing algorithms and testified that accuracy of this algorithm is better than existing algorithms.

Meumkaewginda et al. [15] presented technique for detection of grape's scab and rust diseases using Artificial intelligence. System has mainly three parts i.e. color segmentation part, disease segmentation part and analysis and classification part. Color segmentation part removes any unnecessary information from background, then a self-organizing feature map and BPNN algorithms were used together for recognizing color of leaves. for maintaining information about affected pixels Anisotropic diffusion method was used. Disease segmentation was performed with the help of Genetic
Algorithm and Feature map which are self-organizing. In Image analysis phase Gabor wavelet filter was applied and for classification of diseases SVM method was applied. Author concluded that propose system provides very efficient results but has some restriction particularly about background of the image for extracting color pixels which are ambiguous.

Sannakki et al. [16] discussed a model for classifying grape leaf diseases using Feed forward BPNN. Initially images were collected using digital camera and some were taken from internet. Green color masking was used for background removal and Anisotropic Diffusion for noise removal image segmentation was done using K means clustering method and texture features were extracted using GLCM. Finally, for classification purpose BPNN was used. According to author Hue feature provides maximum accuracy and proposed modal can be useful for classifying other diseases of grapes.

Zhang et al. [17] presented an improved PSO algorithm for identifying and diagnosing maize leaf diseases based on Neural Networks. Image Acquisition was done from Hebei Agricultural university in 2013, preproccessing of image was performed by median filtering and histogram equalization. Features based on shape, color and texture were extracted. Finally, classification was done using Particle Swarm Optimization algorithm based on Neural Networks. Author concluded that proposed algorithm is better than traditional Neural Network methods, as Neural Networks have limitations of local optimum and slow convergent speed.

Pixia et al. [18] introduced novel technique for identifying leaf diseases of cucumber based on minimum distance methods. Firstly 25 samples of each disease (Downey mildew, powdery mildew, and anthracnose) were collected, then image preprocessing was applied using median filter. Image segmentation was done using different color ranges of diseases for attaining lesion segment. Then shape, color and texture features were extracted, finally disease identification was performed using shortest distance classification. Author concluded that this novel method was very effective and provides more than 96% accuracy. Next subsections present understanding of plant diseases, their types and causes.

### Table 1. Different disease detection and classification techniques

| Reference | Culture | Diseases Covered | Image Acquisition | Number of Samples | Feature Extraction | Classifier | Performance (%) |
|-----------|---------|------------------|-------------------|-------------------|-------------------|------------|-----------------|
| [4]       | Paddy   | 1. Brown Spot    | Paddy Fields of Indoneisa using Digital Camera and Internet | 40 images | Fractal Descriptors | PNN | 83% |
|           |         | 2. Bacterial Blight |                             |                  |                   |            |                 |
|           |         | 3. Leaf Blast 4. Tungro |                             |                  |                   |            |                 |
| [5]       | Paddy   | 1. Brown Spot    | Paddy Fields of Indonesia using Digital Mobile Phone | Not Specified | Fuzzy Entropy | PNN | 91.46% |
|           |         | 2. Bacterial Blight |                             |                  |                   |            |                 |
|           |         | 3. Leaf Blast 4. Tungro |                             |                  |                   |            |                 |
| [6]       | Wheat   | Leaf Rust        | Fields using High Resolution Camera | 342 images | 1. Color 2. Shape 3. Texture | BPNN | 84.8% |
|           |         |                  |                             |                  |                   |            |                 |
| [7]       | Wheat   | 1. Powdery mildew| China fields using Nikon D80 Camera | 800 images | 1. Color 2. Shape 3. Texture | Multi Classifier | 95.16% |
|           |         | 2. Leaf rust 3. Leaf blight |                             |                  |                   |            |                 |
| [8]       | Betel vine | Rot             | Chhattisgarh fields using Flatbed Digital Scanner | 12 images | Color | Otsu Method | Not Specified |
|           |         |                  |                             |                  |                   |            |                 |
| Plant     | Disease Types                                                                 | Image Acquisition       | Image Samples | Feature Extraction    | Classification Techniques | Performance |
|-----------|--------------------------------------------------------------------------------|-------------------------|---------------|-----------------------|---------------------------|-------------|
| Betel Vine| Powdery Mildew                                                                  | High Resolution Camera  | 30 images     | Color                 | Not Specified             |             |
| Soybean   | Frog eye, Rust, Bacterial Blight, Downy Mildew, Sudden Death Syndrome           | Mobile Phone Camera     | 1000 images   | Color, Shape          | Bi Level Thresholding     |             |
| Tomato    | Early Blight                                                                     | Captured at greenhouse, Columbia | 190 ROI images | Color                | Color Based Structure Descriptor |             |
| Tomato    | Powdery Mildew, Early Blight                                                    | From farms using High Resolution Camera | 200 images | Texture              | SVM                       | 99.5%       |
| Sugarcane | Sugarcane Ring, Rust, Yellow spots                                              | Fields in Indonesia using Digital Camera | 30 Images    | 1. Texture, 2. Color | SVM                       | 80%         |
| Cotton    | Leaf Spot                                                                        | Digital Mobile Phone Camera | Not Specified | Color                | Neural Network Classifier | 98.1%       |
| Grape     | Scab, Rust                                                                       | Training-1478 images    | Color         | SVM                   | 97.8%                    |
| Grape     | Downy Mildew, Powdery Mildew                                                     | Digital Camera and Internet | 33 images    | Texture              | BPNN                      | 100%        |
| Maize     | Leaf Blight, GreyLeaf Spot, Brown Spot                                           | Experimental Station of Hebei Agricultural University, China | Traning-400 images, Testing-180 images | 1. Shape, 2. Color, 3. Texture | PSO and Neural Networks       | 93.3% and 87.8% |
| Cucumber  | Downy mildew, Powdery mildew, Anthracnose                                       | Digital Color Camera    | Not Specified | 1. Shape, 2. Color, 3. Texture | MDC                      | Greater than 96% |

Table 1 Displays research on different plants diseases covered by researchers, image acquisition and number of image samples gathered, feature extraction and classification techniques used and finally the performance of proposed model.

3. **AI based techniques for Plant Disease Detection and Recognition**

In earlier disease detection process experience of farmers was used or expert was hired by farmers for manual inspection of diseases. But this process had several drawbacks like, it was very time-consuming process as person needs to inspect plant at each stage, this method lacks accuracy as several diseases have almost similar symptoms and It was totally dependent on eyesight of person or
expert [8][16]. Machine learning and Image processing techniques have been widely used for disease detection and recognition. Such system may have five modules i.e. Image Acquisition, Image Preprocessing, Image Segmentation, Feature Extraction and Classification or Recognition [2]. Figure 1 displays generic structure of a disease recognition system with different techniques used in each module.

### 3.1. Image Acquisition

The accuracy of the system totally depends upon this module for training, several researchers used datasets (Plant Village, IPM Images, and APS image database), some used scanned images which were taken under controlled conditions of environment [2]. Captured images samples quality can be degraded due to droplets of dew, insects’ excrements, dust etc. present on the parts of plant which may lead to shadow or noise effect, these effects can be removed using several filters and contrast enhancement algorithms [3]. 40 image samples of diseased paddy leaves were captured by [4] using digital camera and internet, later were stored in JPEG format. 3-CCD color camera was placed in the height of 60mm over the wheat leaves for their acquisition and over 300 image samples were collected [6]. 640*480 resolution Nikon D80 camera was used by [7] for collection of 800 image samples of four wheat leaves keeping background as black in natural lightening conditions. [8] used flatbed scanner for acquisition of 12 images of betel vine plant’s leaves, to produce RGB image, acquired images were digitized at 300 dpi resolution. Using mobile phone camera (Samsung GT-S3770) images were captured of various development stages of soybean plant [10], mobile phone camera was chosen as it is cheap, easily available, and easily accessed by farmers. Sonny digital color camera (16 mega pixel resolution) was used for collection of image samples under natural conditions, later these images were stored in jpeg format [12]. [14] used digital mobile camera for collection of image samples which will be used detection and classification of cotton leaves spot diseases. With the aid of digital camera (Nikon Coolpix P510,16.1 Megapixel) and internet image acquisition was performed, and the samples were stored in jpeg format [16].

### 3.2. Image Preprocessing

The collected samples of images may contain noise and may not be suitable for processing directly so preprocessing techniques are applied to samples. These techniques are cropping, enhancement, filtering, smoothing, color conversion etc. [2]. This step enhances the quality of optical inspection of the image samples. Auzi et al. [4] converted the image samples to HSV color space, extracted S component from them, they also performed histogram equalization and used Laplacian filters for sharpening images. Diseased area in image samples was cropped then images were converted into their corresponding gray levels and finally Laplacian filter was applied by [5] for image enhancement. According to [6] infected regions of plant leaves have higher intensity values in comparison to other parts so collected image samples were converted HIS color space. Acquired images were cropped by [8] for high utilization of CPU, faster processing time and efficient disk storage consequently 30% of storage space was saved, CPU performance was improved 1.4 times and there was no loss of region of interest. RGB image samples were converted into YCbCr color space, extracting Y, Cb and Cr component later background was separated from the captured images [10]. Figure 1 displays generic structure of a disease recognition system with different techniques used in each module.

### 3.3. Image Segmentation

It is applied for obtaining region of interest and can be helpful for differentiating between diseased and healthy regions of the image samples [3], as they are divided into clusters where infected portions lies under one cluster and healthy portions falls under another cluster [6]. In this module preprocessed images are subdivided into several smaller regions such that features can be extracted easily. Fuzzy C-Means clustering algorithm was applied by [6] for segmentation of wheat leaves using the set of intensity values of the image samples. [7] used simple threshold segmentation for obtaining region of interest from the image samples. Otsu thresholding algorithm was applied by [8] for segmentation of
betel vine leaves, firstly RGB image was converted into HSV color space and later Otsu method was applied to “H” component for segmentation purpose. Color filtering operation was applied for segmentation as a result the image formed was of bi level, white regions of image indicates diseased region and black region indicates healthy or background region later several morphological operations were applied [10].

![Image of a diagram showing the structure of a leaf disease recognition system.](image)

**Figure 1.** Structure of Leaf Disease Recognition System [1,2]

Otsu method was applied for extracting region of interest using a* channel in L*a*b by [13], in this method gray levels of image are used for separation of background and foreground pixels. Homogeneous edge detection techniques namely Canny and Sobel were used by [14] for segmentation. SOFM (Self Organizing Maps) and BPNN method was used for clustering grape leaf color from other background color while for segmenting diseased region from healthy MSOFM and SVM were used [15]. K-means clustering algorithm was used by [16] and six clusters were formed for extracting lesions from the preprocessed images. Several segmentation techniques are Threshold based, Clustering based, Region based etc. Each of the techniques have their porn and corns as described briefly below [1].

3.3.1. **Region based techniques.** They are immune to noise, better for homogeneous regions but are complex and slow.

3.3.2. **Watershed segmentation.** These techniques are computationally sound but sometimes does over segmentation.

3.3.3. **Edge based techniques.** They work well for good contrast images, but are more immune to noise, are inaccurate and complex.

3.3.4. **K-means approaches.** They are faster, provides tighter segments but it is difficult to predict k-value.
3.3.5. **Histogram based thresholding techniques.** These techniques are less complex but spatial details are not considered.

3.3.6. **Neural Networks based approaches.** These approaches are fast, less complex but they have long training time.

3.4. **Feature Extraction**

In this module different features can be extracted from the segmented image and these features will distinguish object from the other objects. Its objective is to reduce the image data by performing measurement on certain properties of segmented image samples. [6]. Three types of features are considered for this phase namely color, texture, and shape. Color is usually defined by moments and histogram, texture can be attached to several attributes like homogeneity, entropy, variance, contrast etc. and for shape features like roundness, concavity, area, and eccentricity can be defined [2]. Fractal descriptors were used by [4] for extracting features like texture, color and shape from the image samples. [6] extracted multiple features from the segmented image samples, using co-occurrence matrix texture based features (inertia, energy, correlation and homogeneity) values were obtained other features extracted were color (hue moments, saturation moments, intensity moments etc.) and shape (entropy, median, mode, variance, number of 0’s in binary image, standard deviation etc.) . Firstly, Color features (Average, Correlation, Entropy, Variance, Deviation, Energy of color histogram etc.) were extracted by using two color spaces (RGB and HIS), secondly, GLCM was used to extract texture features (Energy, Entropy, Moment of Inertia, Local Smooth, Correlation etc.) in four directions after converting RGB spot image to Gray and finally using edge detection shape features were extracted (spot area ratio, compactness, invariant moments etc.) and PCA was used for feature selection [7]. For extracting texture features Gabor filters were used on each image sample [12]. L*a*b color channel was used for extracting color features while GLCM was used for extraction of texture features like energy, correlation, contrast, and homogeneity [13]. Using Gabor filter texture features were extracted and by using H, S (HSI color space) and Cr (YCbCr) components color features were extracted [15]. With the help of GLCM nine texture features were extracted namely contrast, uniformity, max probability, homogeneity, inverse difference moment of order 2, difference variation diagonal variance, entropy, and correlation [16]. For extraction of shape features complexity, roundness, long axis ratio and degree of rectangle attributes were used, for texture features were extracted using energy, entropy and contrast parameters using GLCM and color features were extracted by calculating average of RGB components of lesion area [18].

3.5. **Image Classification**

It is also known as Image Recognition. Based on the extracted features labels are assigned to the objects based on the descriptions and this will be helpful for identification of a particular property of the object [1]. Classifier is firstly trained using training set after that classifiers is used for recognizing images from the test set. Auzi et al. [4] used PNN (Probablistic Neural Networks) for recognition of diseases in paddy crop, 5-cross fold validation was used for segregating training and test data and finally confusion matrix was used for further result analysis. PNN was used for disease recognition by [5], It has four layers namely input layer, pattern layer, summation layer and output layer, moreover this neural network has faster training speed in comparison with BPNN. [6] used three layered Back Propagation Artificial Neural Network for image classification, first layer contained 22 neurons describing the features of image samples extracted during feature extraction phase, third layer is output layer which consisted of only one neuron during
training its output is 0 or 1 in case of image sample healthy or diseased and hidden layer contains four neurons. [7] used multiple kinds of SVM for image recognition, these SVM’s were Color SVMs, Shape SVMs, Texture SVMs and Meta level SVM’s, Final decision of classification was by Meta level SVMs which improved performance of the proposed system to great extent. SVM was employed for classification of tomato leaves and performance was evaluated using k-fold cross validation method [12]. After the extraction texture and color features [13] used four kinds of SVM kernels (linear, polynomial, radial basis function and quadratic), linear kernel was recommended due to its accuracy in detection of sugarcane diseases Multiclass SVMs were deployed by [15] for recognition of grape leaves diseases. [16] used Back propagation neural networks for recognition of powdery and downy mildew disease in grape leaves, input layer consisted of nine neurons (nine texture features) while output layer consisted of two neurons (downy mildew and powdery mildew). An improved PSO based algorithm was applied by [17] on traditional neural networks, input layer of neural networks consisted of 20 neurons (extracted features), output layer contains three neurons (diseases that were to be recognized) and hidden layer contains 19 neurons (combined with Kolmogorov algorithm). Minimum Distance classifier was used by [18] for three diseases of cucumber.

4. Conclusion
Digital images are more reliable for disease recognition in comparison to human eyes, many diseases have similar features at times it is difficult for human eyes for identifying them moreover recognition is totally dependent on eyesight of human expert. This work discussed several Machine Learning and Image Processing techniques which are useful in identifying and classifying diseases of different crops but still there is lot of scope of improvement in this domain so that manual disease identification methods can be replaced for benefit of all. For future work large and high-quality image samples can be used for proposing a robust and reliable technique which can overcome limitations of existing techniques.

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