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A Systematic Review on the Detection and Classification of Plant Diseases Using Machine Learning

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ABSTRACT

The occurrence of disease in plants might affect the crop production at a large scale, resulting into decline of the economic growth rate of the country. The disease in plants can be detected and treated at an early stage. Machine learning (ML), deep learning (DL), and computer vision-based techniques could play a pivotal role in detecting and classifying the diseases at an early stage. These approaches have even surpassed the human performance, as well as image processing based traditional approaches in the analysis and classification of plant diseases. Over the years, numerous authors have applied various image processing ML and DL techniques for the diagnosis of different ailments in plants that gives great hope to the farmers and landlords to cure the disease at an early stage. In this study, the authors addressed and evaluated the various currently existing state of art methods and techniques based on machine and deep learning. Besides, the authors have also focused on various limitations and challenges of these approaches that can explore greater possibly of these methods about their usability for disease detection in plants.

KEYWORDS

Agriculture, classification, Deep learning, Image Processing, Machine learning, segmented image

1. INTRODUCTION

Crops and plants suffering from disease can have a major influence on crop quality and measure. This can adversely affect the country's economy, especially if agriculture is the primary source of income and occupation (Jiawei et al., 2016). Hence, detection and identification of disease in the crops at an early stage is crucial to avoid crop damage and improve its quality. As per the reports, about 70% of

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India's population is dependent on agriculture, either directly or indirectly, and contributes around 17% of the country's GDP.

Diseases and infections among crops are caused by a variety of reasons; some of them are based on environment and aging such as a lack of quality land manures, the selection of inappropriate crops, climatic fluctuations, and rodents etc. Pest infections alone account for roughly 30-33% of the overall output loss in India. Infections in plants are caused by fungus, viruses, and bacteria. Owning to these numerous diseases and variables, farmers face significant hurdles in transition from one infection control method to another to prevent these infections, which has high impact on total output and crop quality.

Agriculturalists are still using the traditional and ancient methods to discern crop diseases and substantially studying the crops with their judgments, even in this technologically advanced era, where high tech instruments are available to discern any disease prevailing in the plant at any point of time. This age-old method of monitoring and analyzing crops with the naked eye based on the farmer's experience has several flaws and drawbacks. An agriculturalist may be intelligent to detect some crop contagions and diseases with this method, however it is not effective in detecting new or unknown crop infections. As a result, the crop's infection is usually ignored, or sometimes inappropriate control plan is used to detect them.

Advanced and in-depth investigation is required in such circumstances. To avoid contagions in the crops, farmers must be an expert and have a thorough understanding of all the crop diseases, and their corresponding solutions of diagnosis particularly in current scenario, when new contaminations are venting due to current climatic disruptions. Easy and precise detection of plant ailments is known as the pillar of the productive and effective agriculture strategies.

Detection of diseases from the plant images is considered most critical research field due to high similarity of diseases in appearance, however they need the different treatment and care. Hence, different image processing, machine learning, and computer vision algorithms are needed to outline and identify the disease in plant leaves.

Over the centuries, the basic stages in farming, such as identifying diseases and selecting effective medicines for controlling such diseases, have been practiced by farmers to avoid crop loss and to maintain crop quality. However, owning to the global climatic changes, dramatic rise in many crop diseases may take place. Farmers must be familiar with these crop diseases to recognize and control them. However, due to vast number of diseases, it's difficult for farmers to be familiar with all of them. In addition, it is both economically and physically impossible for a farmer to monitor large-scale production.

As a result, different plant diseases and infections often go unnoticed, affecting total crop output and quality. As a result, automatic identification and classification of crop disease is required and is the need of the hour to cope with such difficulties. Farmers and researchers all around the world are already using Machine Learning and Computer Vision in agriculture for a variety of applications. Machine Learning-based techniques can be used to detect and classify diseases in crops in real time, increasing crop yield and quality while reducing labor, expense, and improving farmer accuracy in crop cultivation.

To prevent crop loss due to disease, a variety of strategies have been devised. Integrated pest management (IPM) slants have progressively complemented historical ways of extensive pesticide application in the last decade (Ehler et al., 2006). Regardless of the method used, correctly identifying an illness on first sight is vital for optimal disease management. Farmers have started using mobile phone-based tools nowadays across the globe.

2. CATEGORIES OF PLANT DISEASES

Plants might be caught by many diseases, which can affect the whole crop. These diseases can be further categorized into different classes. In general, plant diseases are categorized into abiotic and biotic diseases. Pugoy et al., (2015) in their research, proved that abiotic diseases are those diseases, which arises due to environmental conditions like temperature rise, derisory minerals, bad soil pH, bad mild, extreme moisture, or greenhouse effect, whereas the biotic diseases are generated from the living mortals (i.e. fungi, insects, viruses, and bacteria). The plants may have fungal, bacterial, or viral diseases. Mohanty et al., (2016) and Sanyal et al., (2008) explained the various strategies and techniques for detection of molds, rust, mildew, rots, wilts, and spot diseases, however, distortion and dwarfing diseases have not been covered in considerable detail in these studies. Various categories of fungal, bacterial, and viral diseases are revealed in Fig.1.

3. GENERAL FRAMEWORK OF PLANT DISEASE DETECTION SYSTEM

Plant disease is the major hazard that might cause a great decline in image quality resulting into a heavy loss of crop production. Numerous researchers have made countless exertions for controlling the plant diseases in the last decade. Over the ten years, machine and deep learning algorithms have widely been cast-off for the detection of various plant diseases.

Plant disease detection general framework using machine / deep learning is shown below in Fig. 2.

Prepossessing and segmentation steps are the pre-requisite steps of machine learning algorithms. Hence, in this section, we have briefly explained the pre-processing and segmentation steps. Machine learning method basically rely upon the hand-crafted features. The general framework for disease detection in plants involves the various steps viz., image acquisition, prepossessing, feature extraction, and classification as illustrated in Fig 2. All the steps are described one by one in considerable details in the following sections.

Image acquisition: - In general, the leaves images are collected from the open field. In India, Rice crops are grown in hot season (i.e., July-September). In hot weather, there are more chances of fungi, bacteria, or virus in the rice crops, which might adversely affect the crop in this season.

Numerous researchers have used their own collected data sets, like IPM images, APS image database, and plant village images, which were generally grown underneath precise environmental conditions. Numerous authors such as Anthonys et al., (2009); Pydipati el al., (2006); Bauer et al., (2011) showed the acquisition of sample plant images in sampling box or laboratories under operative control of intensity, radiance, and illumination. In case of soyabean leaves, the diseased leaves of soybean are placed on clear base to eliminate background complexity.

Figure 1. Categories of biotic disease in plant (Kruse et al., 2014; Barbedo et al., 2019)

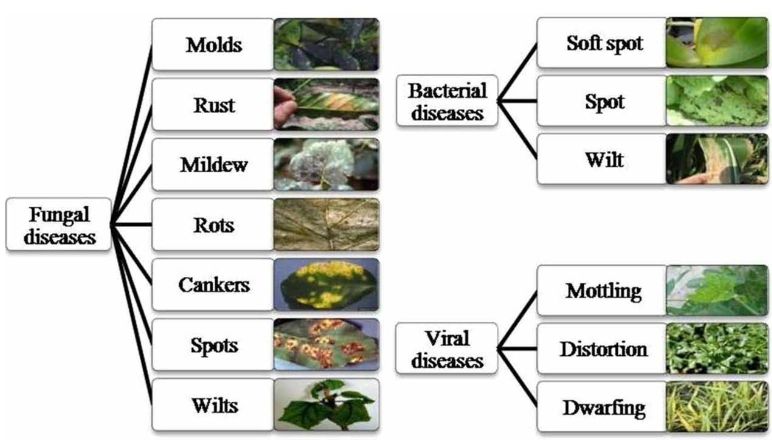
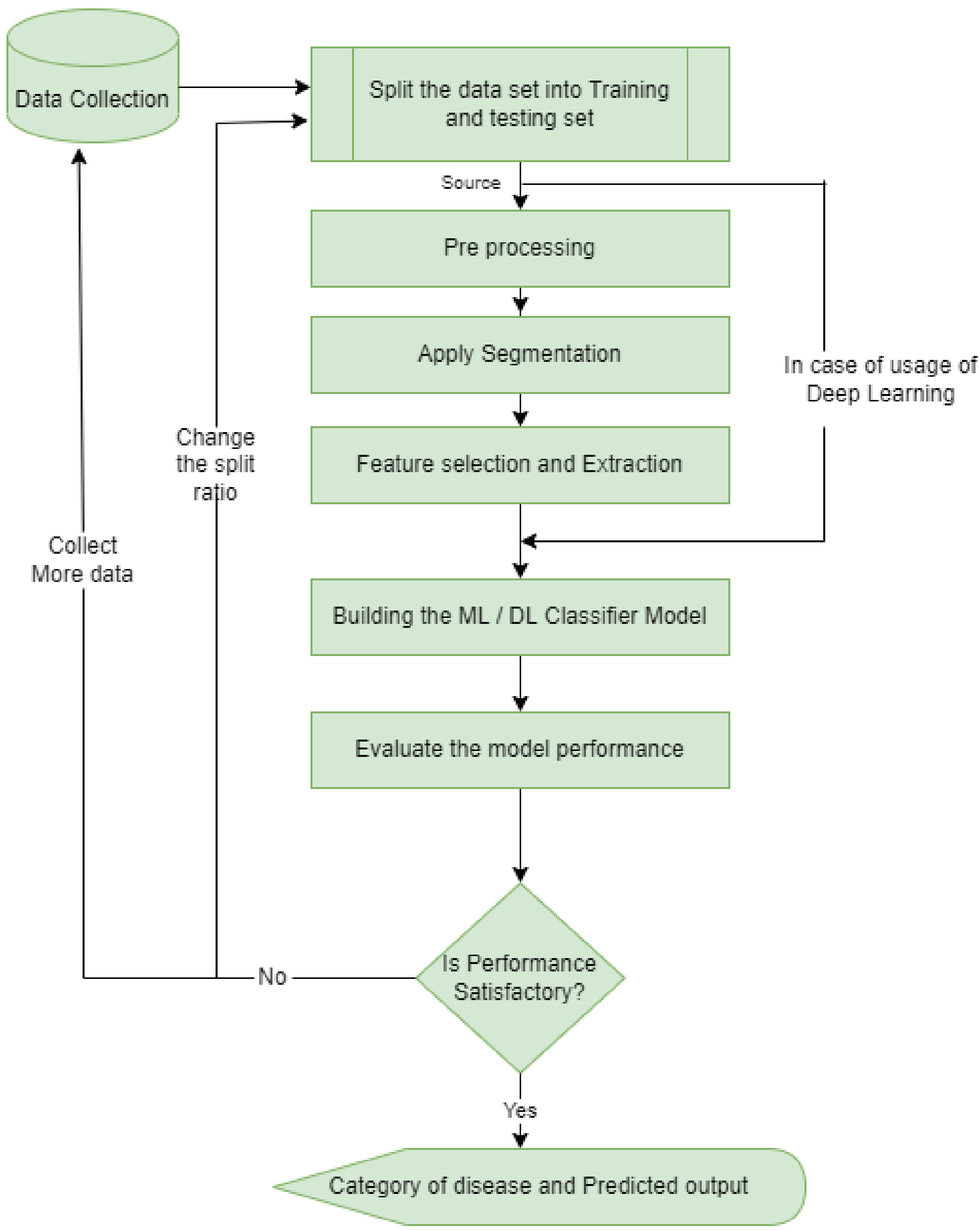


Figure 2. General Framework for Plant disease detection



Other authors such as Barbedo et al., (2019); Oppenheim et al., (2019) in their work, have seized images with compound background in the arena. Some of the acquisition techniques that have been used by different authors in previous studies are listed in Table 1.

In this review, some sample images were procured from plant village. The sample images taken from Plant Village data set are shown in Figure 3.

Image Pre-processing: This step is essentially required to improve the quality of the collected images to make them suitable for subsequent processing. In general, the plant images are acquired from the open field, therefore might contain several artifacts and noise, which need to be eliminated

Table 1. Different Techniques for Image Acquisition and data collection

Reference	Technique	Summary
Comar et al., (2012)	Mono RGB vision	This technique used the additional brands and filters resulting into segmenting of spectrum of specific regions.
Nguyen et al., (2016)	Stereo-vision	Discovered a place in plant phenotyping and Multi view stereo (MSV) was also evolved by Stereo vision.
Wahabzada el al., (2016)	Multi- hyperspectral-cameras	Increased phenotyping by use of hyperspectral cameras, with identification of pathologies, or pests, or physiological responses in a non-invasive way. A system was developed by using probabilistic topic models, for the identification of pathogens in barley leaves.
Paulus et al. (2014)	Time -of- Flight-cameras (ToF cameras)	Low-cost image acquisition system i.e., Microsoft Kinect designed for video gaming, was used for tracking of phenological parameters
Wallace et al., (2013)	LIDAR- technology	Was used for measurement of multiple wavelengths and obtained arboreal parameters
Cui et al., (2018)	Thermography -fluorescence- imaging	Act as a venerable tool for detection and monitoring of genotypes of disease in plants.
Brodersen et al., (2016)	Tomography -imaging	Resolution of images was increased as well as the devices' portability and the size of the fields-view was also increased.
Singh A K et al., (2022)	Hybrid Approach	Different size images were obtained and more sensor power observed.

Figure 3. Visualization of sample images taken from Plant Village dataset

before applying any segmentation techniques. In previous studies (Zhang, M et al., 2011; Alenya, G et al., 2013; Wang, J et al., 2013; Kruse, Ole Mathis Opstad, et al., 2014), authors have applied numerous prepossessing techniques successfully to enhance the visual features of an image. For instance, Barbedo and J.G Arnal., (2016) proposed an efficient preprocessing technique to improve the image quality under light varying conditions that led to enhanced visual features of an image.

In addition, Prasad et al., (2015) have demonstrated the importance of preprocessing in reducing the overall computational power and memory space requirements.

Table 2 shown below presents the summary of some important preprocessing techniques.

Zhang and Meng et al., (2011) employed two-step hierarchical matching procedure to filter out lesions from leaf and background, directly. Alenya et al., (2013) used the depth information to localize and extract the leaves from plant images. Wang et al., (2013) used local minima as control

Figure 4. Factors affecting the images

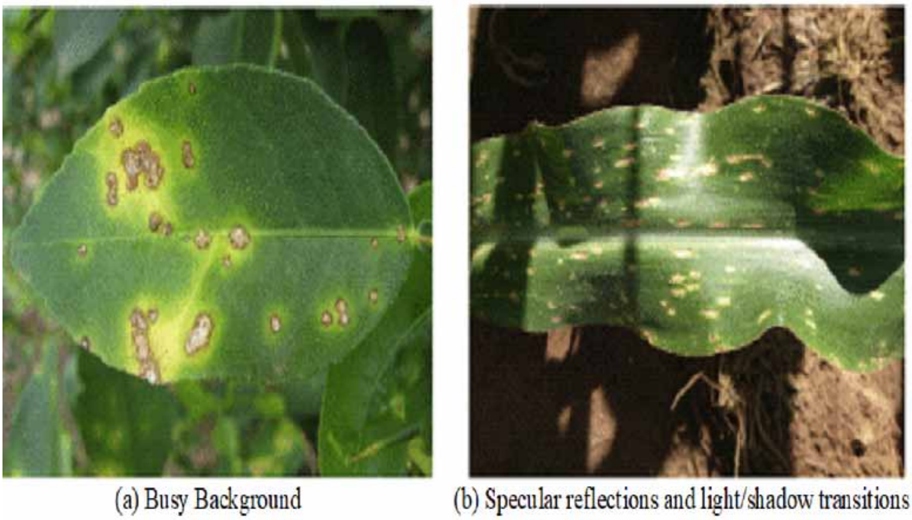


Table 2. Techniques employed for pre-processing of plant leaves

Reference	Technique used	Summary
Zang et al., (2011)	Two step Hierarchical Matching Procedure	To filter out lesions from leaf and background, directly.
Alenva et al., (2013)	Depth-Information	DI is used to extract the leaves as a ROI from the image. Used the approach to localize the leaves.
Wang et al., (2013)	Local minima selection in certain plants from the image's gradient as control markers	This technique was used to unscramble the leaves from the rest of the image.
Kruse et al., (2014)	Manually	Removed background

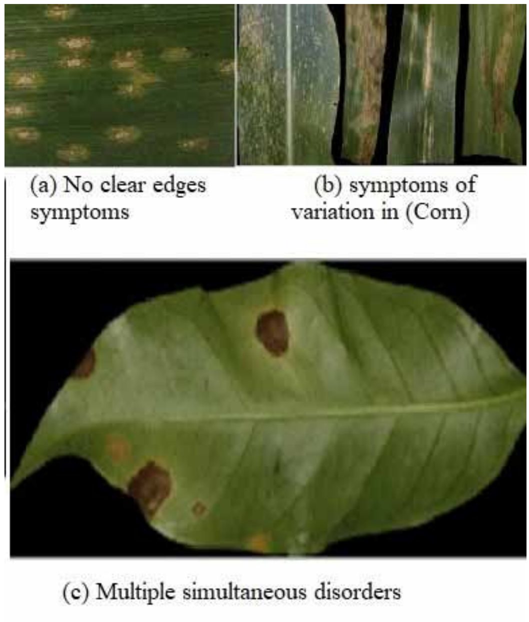
markers to separate leaves from rest of the image. In this study, certain local minima were obtained from the gradient image. Cui et al., (2014) in their research utilized the manual approach to remove the background.

Plant Image Segmentation: Most of the image processing-based techniques for leaf analysis resume with leaf segmentation. Segmenting the leaf is predominantly difficult, when the background has excessive number of green elements and shadow transitions as shown in Fig. 4(a) and 4(b). To improve and enhance the image quality, the pre-processing is usually adopted in most of the image processing and computer vision tasks.

Segmentation technique is applied to excerpt diseased portion from the input image (fig. 5). In some research, authors have widely used clustering approach such as K-means and Fuzzy C-means, for plant disease detection in which authors generally divided the input image into three clusters: one for background, second for diseased portion, and third for green healthy portion.

Feature Extraction: it plays a pivotal role to differentiate among the different classes of a disease. Before feature extraction, feature selection process is carried out, wherein appropriate features are chosen based on the geometry and visual characteristics of an object of interest. Jaffery et al., (2009) explained optimal selection of features that requires in-depth domain knowledge and expertise of the field and sometimes is decided based on optimal search technique or an efficient optimization algorithm.

Figure 5. Segmentation of disease symptoms



Feature extraction is the subsequent step of segmentation that is needed for development of an efficient classifier. In literature (Zaheeruddin et al., 2012; Jaffery et al., 2013), researchers have utilized numerous features such as texture, geometrical, morphological, and grey level features to design object detection system. Some of the authors have used texture, color, and shape features. In various research, shape features such as mean, median, average brightness and standard deviation of RGB color images have been used to build an effective plant disease detection system. It was observed that the model performance can be improved by using the combination of features, for instance, Anthonys et al., (2009) used combination of texture and color features and obtained the better results in comparison to the results, which were obtained using independent features.

Classification: Generally, the object classification can be done either by machine learning or deep learning techniques. However, deep learning algorithms

are more preferred to build classifiers due to automatic extraction of features, which makes them more efficient and flexible as compared to machine learning algorithms. However, machine learning algorithms requires less amount of data to build model. Machine learning and deep learning algorithms have their own advantages and limitation, which are summarized in this paper with respect to plant disease detection. In the present study, authors tried to include all the latest algorithms, which have been used by authors in recent years, their advantages, and limitations along with their respective outcomes.

Detection of disease in plants started long back manually using traditional approaches. However, these approaches are time consuming, error prone and idiosyncratic. Advancement in computer technology and software engineering has made the use of machine and deep learning approaches possible for the early detection of diseases in plants. Nowadays, usage of machine learning and deep learning techniques are on rise in current scenario for the development of plant disease detection system. Besides application of plant disease detection, image processing, ML and DL techniques have also been widely used for the different types of applications such as cancer detection (Singh et al., 2009; Dafni et al., 2022; Singh et al., 2017; Singh et al., 2018), retinopathy detection (Mishra et al., 2022), unstructured road detection and classification (Alam et al., 2021), fault diagnosis (Singh et al., 2021) including solving the problems of robotic path planning too (Kumar et al., 2021). In this study, we primarily analysed the work of other authors, from the perspective of easy implementation, latest architecture, and improved efficiency with regards to detection of a disease in plant images.

In classification of plant diseases, the leaves are classified into different categories based on identified disease as healthy and infected leaves. The various methods and approaches used so far for the disease classification are elaborated in detail in subsequent section as follows:

4. CLASSIFIERS

Various machine learning approaches, which are currently being used at larger scale for various application in computer vision are Logistic Regression, Random Forest (RF), Support Vector Machine (SVM), Naïve- Bayes Method, Stochastic Gradient Descent (SGD), While, Convolutional Neural Network, Long Short-Term Memory and Gated recurrent Unit, VGG-19, VGG-16, INCEPTION V3 are some of the deep learning techniques, which are being widely used for image analysis and object classification.

4.1 Classifiers based on Machine Learning Techniques

4.1.1 Support Vector Machine

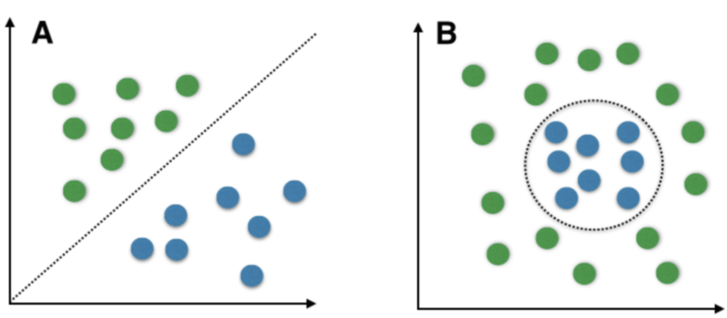
Support Vector Machine (SVM) is one of the most popular classification techniques that employs machine learning theory to enhance predicted accuracy while avoiding overfitting to the data. Soman et al., (2009) concluded that support vector machine is a discriminative technique defined by an unscrambling hyper plane that boosts the boundary between two classes. In their research, they also suggested that, for more than two class data, classification can be done by multi class SVM classifier.

Linear SVM and Non-Linear SVM are the two types of Support Vector Machine. Linear SVM is used for linear data. That means; data should have two categories & be linearly separable. As seen in Fig. 6A, the hyper-plane is an orthodox line. When there are only two classifications as output, such as a healthy and hostile leaf, linear SVM could be effectively utilized.

Non-linear SVM is used to classify the data, which have mixed cluster-groups. This is not easily separable data. As illustrated in Fig. 6B, presented data cannot be categorized using a single straight line, they can be represented by a curvy line. However, in a higher dimension, the data can be converted to linearly separable data. To classify data with more than two classes, a multi-class Support Vector Machine classifier is utilized.

Padol et al. (2016) devised classifier based grape leaf disease detection system (DDS). V. Singh et al. (2017) worked on the development of DDS using 100 image dataset achieving accuracy of 95.71%. Masazhar et al. (2017) has worked on palm oil leaf disease detection using multiclass classifier.

Figure 6. (A) Graph representing linear data for SVM (B) Graph representing Non-linear data for SVM



4.1.2 K-Nearest Neighbors

K-Nearest Neighbors is the one of oldest classification algorithm that does not make any fundamental assumptions around data distribution. Amara et al., (2017) in their research explained data classification using stored and labelled instances according to a distance or similarity function in instance-based learning. An automated technique was developed for leaf disease verdict by using GLCM features and Gabor Wavelet (GWF) features. Prasad et al., (2015), in their research, explained weighted KNN that was used for training these multi-resolution features. Euclidean equation has been used for calculating distance function in K-NN.

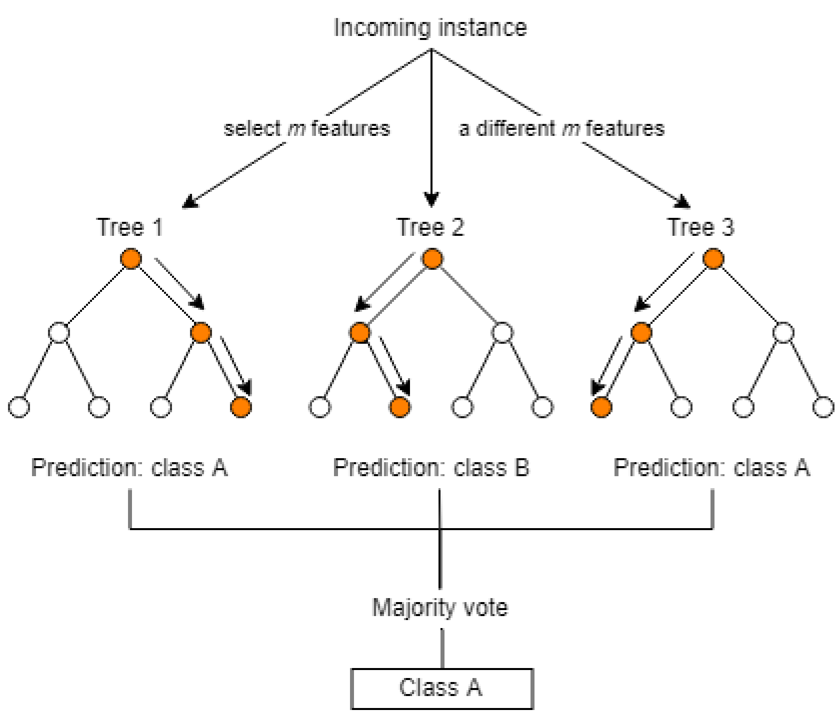
$$E\left(x,y\right)=\sqrt{\sum_{i=1}^{n}\left(x_{i}-y_{i}\right)^{2}} \tag{1}$$

Here, E (x, y) is distance measure between vector x and y, whereas i and n are the participation of significant and quantity of highlight vectors respectively.

4.1.3 Random Forest

Random forest overcome outcome limitations of all the decision trees in classification problem. The Ensemble learning method is known as Random Forest. Breiman et al., (1996) constructs a cluster of decision-trees using a random subgroup of the data. Owomugisha al., (2018) used nearest neighbors, random forest for classification by curve analysis. The functioning of Random Forest is elaborated in Fig 7.

Figure 7. Random Forest classification method



4.1.4 Naive Bayes

Friedman et al., (1998) proposed supervised learning algorithm based upon Bayes theorem. He assumed independence among each pair of features as naive. The graphical plot for Naïve bayes Classification algorithm is shown in Fig 8. Sandhu et al., (2019) compared the SVM classifier and Naïve bayes classification in terms of accuracy and execution time.

4.1.5 Decision tree

Decision tree falls under the category of supervised learning algorithm that plays a pivotal role for classification problems. Quinlan et al., (1986) assesses the relevance of a target variable using many input variables. Owomugisha et al., (2018), in their research, used the decision tree for perceiving a high score and flexibility to application.

4.1.6 Linear models

J Kim et al., (2000) used analysis of variance (ANOVA) for ANN model analysis. It comprises of neural net-based backpropagation algorithm. Jagtap et al., (2014) proposed framework that comprised of an image analyzer supported with design credit without an indicative leading framework demonstration.

4.1.7 Fuzzy

Annabel et al., (2019) shows that a fuzzy classifier can be constructed by specifying classification rules or use distances to the neighbors as well as their soft labels. Besides him, Many other authors as stated above have also worked on unsupervised fuzzy clustering, which helped in achieving more optimal results with relatively few data sets. The fuzzy classifier model is shown in Fig 9.

4.1.8 AdaBoost

When numerous weak classifiers are tangled to make a strong classifier. Bartlett et al.,2007 worked on the Boosting approach. Karoda et al., 2012 concluded as the number of reiterations rises the miss-classification error values is reduced in Ada-Boost algorithm than pure Naïve-Bayesian classifier algorithm.

4.2 Classifiers based on Deep Learning Techniques

4.2.1 Convolution Neural Network (CNN)

Lee et al., (2015) used deep learning for diagnosis of disease in plant leaves using CNN. The developed model produced the consistent and good results with regards to classification disease in plants. Mohanty et al., (2016) also employed deep learning model on the public dataset of 54K images of

Figure 8. Naïve Bayes classification method

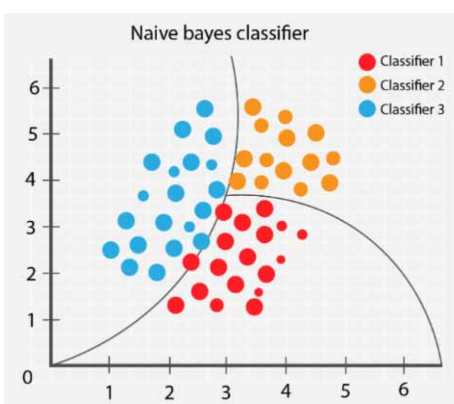
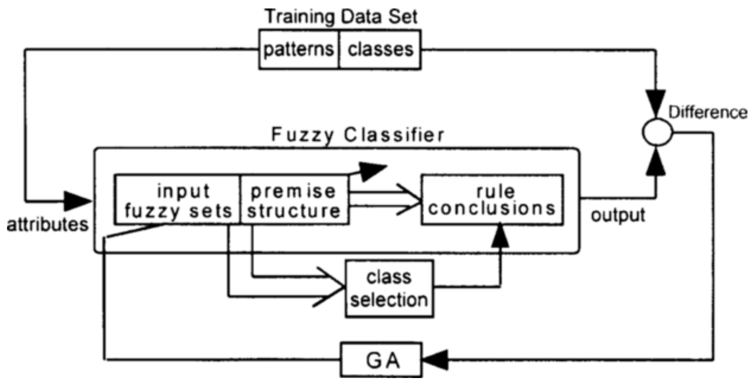


Figure 9. Fuzzy classifier Model



diseased and healthy plant leaves and got success in identify 14 categories of crop diseases. Table 3 summarizes the CNN with their respective architectures used for detection of diseases in plant leaves.

4.2.2 Inception–V3

Inception – V3 is a deep convolution neural network model that comprises of 48-layers. It is refereed as a architecture with an extended Google Net. Convolution is part of a constructed model that includes symmetric and asymmetric pieces. – creating a feature map by smearing a filter to the image-input, avg pooling and computing the average from the feature map for each maximum pooling – max- pixel, patch, and that helps in reducing the computation rate by reducing the number of parameters for learning purposes, concerts – merging the same size inputs, dropouts – usually placed after pooling that helps in increasing accuracy and reducing over-fitting, each layer's neuron is entirely coupled to the neuron of the next layer. Batch norm is utilized for activation norm, and loss is calculated using soft-max. (Liu et al., 2017).

Summary of some research papers that are surveyed for the classification using various Machine / Deep learning techniques is shown in Table 4

R. Sujatha et al., (2021) discussed the performance comparison of machine learning and deep learning classification techniques in plant disease detection. The disease classification accuracy (CA) they received by research was notable as deep learning approaches achieve better than that of machine learning methods in disease detection of plant leaves as shown in Figure 10.

As discussed above the common methodology for disease detection system are image acquisition, prepossessing, segmentation, feature extraction and classification. Each step is elaborated here under using Fig. 11.

The block diagram shown in Figure 11 demonstrate the methodology describing each phase of machine learning approach. Whereas the detailed methodology is illustrated through the flow diagram shown in Figure 12.

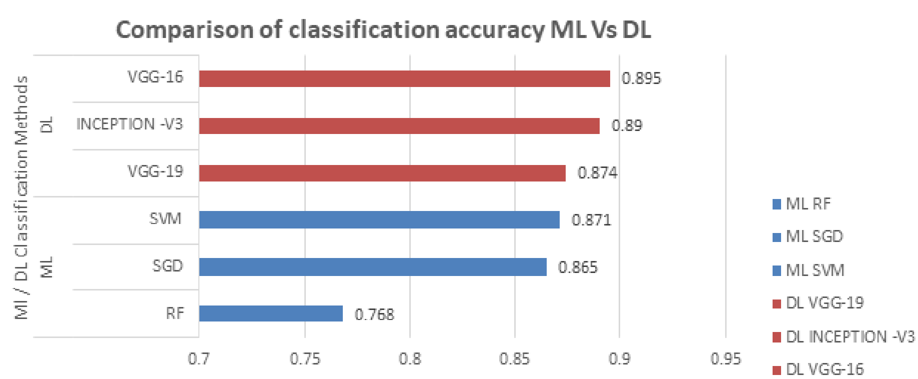
Table 3. CNN with different Networks

References	Deep Learning Network	Accuracy	DataSet
Ferentinos et al., (2018)	CNN with several Networks	99%	Plant Village dataset of 14,903 images
Liu, Zhang et al., (2017)	CNN with AlexNet	98%	2486 Apple Images from Apple Data-image augmentation
Brahimi et al., (2017)	CNN with AlexNet and GoogleNet	99%	Plant Village
Lu,Yi,et al., (2018)	CNN with AlexNet inspired	95%	From rice field 1800 image samples collected

Table 4. Accuracy of various classification techniques on plant disease

Classifiers	Accuracy	References
CNN	99.5% on 25 plants	Chuanlei, Zhang, et al., (2017)
	99% 14 crops	Mohanty et al., (2016)
	99.3% on soyebean	Wallelign, Polceanu et al., (2018)
	96.3% on 5 plants	Sladojevic, Srdjan, et al., (2016)
SVM	97% on oil palm	Masazhar et al. (2017)
	95% on citrus	Gavhale, Gawande et al., (2014)
	93% on tea	Hossain, Selim, et al., (2018)
	90% 0n soyebean	Kaur, S. et al., (2018)
	90% on potato	Islam, Monzurul, et al., (2017)
	88.89% on grape	Padol, Pranjali, et al., (2016)
ANN	96.41% ground nut	Ramakrishnan et al., (2015)
	93% on various plant with 5 diseases	Al Bashish et al., (2010)
	90%cucumber	Vakilian et al., (2013)
	90% pomengranate	Dhakate et al., (2015)
KNN	95% on sugarcane	Umapathy Eaganathan et al., (2016)
	82% on cotton	Parikh, Aditya, et al., (2016)
	96.76% on 5 plants	Kalaivani et al., (2020)
FUZZY	88% wheat	Sukhvir et al., (2019)

Figure 10. Comparison of Classification Accuracy Machine Learning and Deep Learning



	ML			DL		
	RF	SGD	SVM	VGG-19	INCEPTION -V3	VGG-16
Classification Accuracy	0.768	0.865	0.871	0.874	0.89	0.895

5. LITERATURE SURVEY PLANT DISEASE DETECTION SYSTEM

Some of the work is explained further to shed the light on the recent approaches available in this field.

Barbedo et al., (2019) used classification approach based on Boolean operations to analyse the abnormal leaf images. In the developed approach, Boolean operations were used to change the colour of a diseased leaf. The effectiveness of the proposed strategy was evaluated using a database that contain 77 different diseases of 11 plant species.

Figure 11. Common Methodology for disease detection system

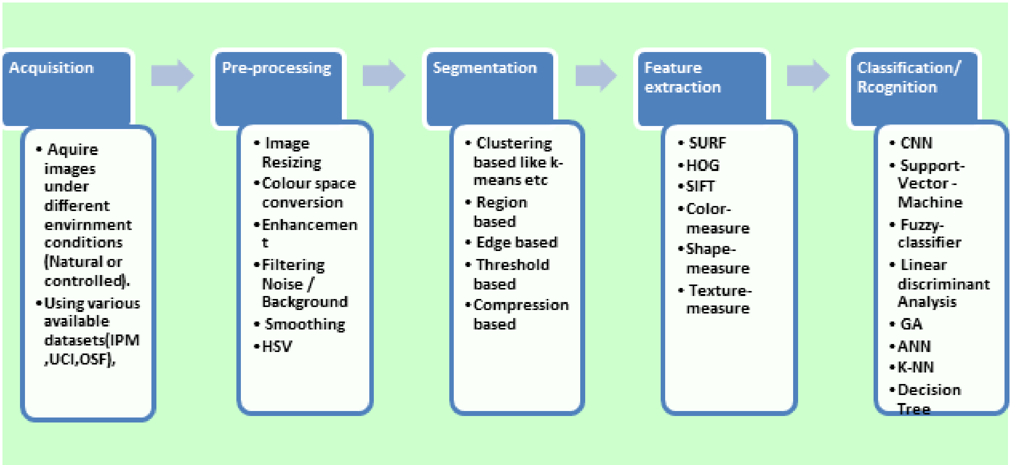
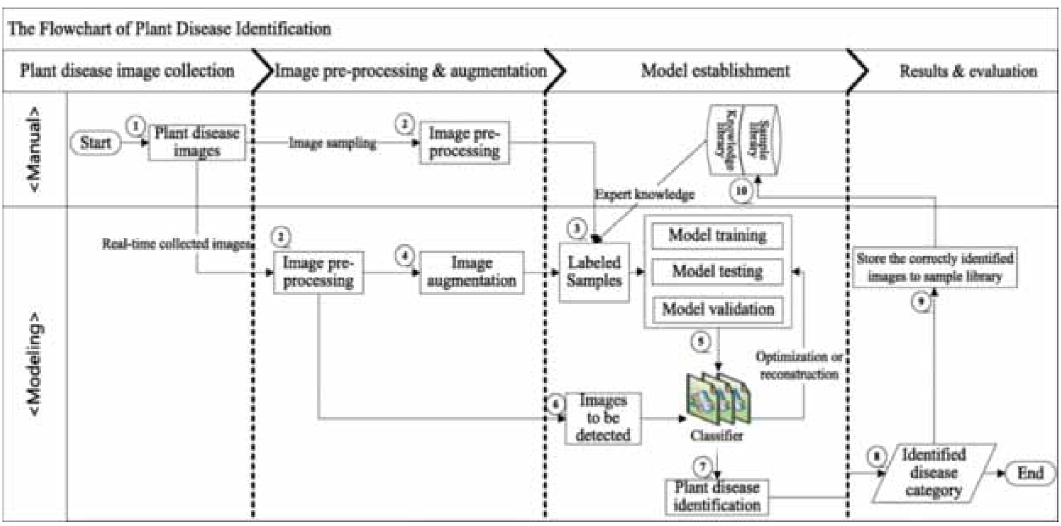


Figure 12. Detailed flow chart of plant disease detection system



Kalaivani et al., (2020) developed an effective disease prediction system based on image histogram to identify ROI containing various diseases such as rust, rot and foiler. The developed approach achieved the satisfactory results with the detection accuracy of 98%.

It involves the extraction image features like textures, shape, colour, and motion attributes.

Sukhvir Kaur et al., (2018) worked on automated plant leaf classification systems. So that, more research can be supported through this work order to assist researchers to find more information in this field of computer applications.

Chouhan et al., (2020) protected the plant leaves from various diseases to enrich plant growth. In his research, digital image processing techniques were used to monitor the plants. This developed system monitored the plant's heath and helped in discovering the concerned area which, protects it from a variety of diseases. Several articles have been evaluated in this work to evade and monitor the plants in order to boost productivity.

For identification of image various techniques are researched to obtain the accuracy. The identification focused on the classification system to train images and building a high-grade classification system.

Golhani et al., (2018) presented an approach in which authors applied the advanced Neural Network (NN) on the hyperspectral data that focus on identification of plant diseases. In their work, approach was used to detect the plant's disease at an early stage. Hybridization method was also utilized to link hyperspectral data to the NN process.

Salazar-Reque et al., (2019) suggested a new crop protection method based on artificial neural networks (ANNs) to classify super pixels as healthy or unhealthy using the colour attributes of super pixel clusters. To group the same region as super pixels, the proposed approach used the Simple Linear Iterative Clustering (SLIC) algorithm. By using the proposed methodology, the authors obtained the mean error and the average F-score about 11%, and 0.67, respectively.

Zhang et al., (2019) have proposed a novel segmentation based on a hybrid clustering. The super pixels clustering technique divides the image into multiple compacts, each with its own clustering cues. The proposed method then proceeds to picture segmentation in order to speed up the convergence of the expectation maximization (EM) algorithm, after which the lesion pixels are quickly and reliably segregated from each super pixel using the EM algorithm. The effectiveness of proposed methos show experimental results and the comparative results positive.

Lucas G. Nachtigall et al., (2016) have deliberate for inevitably classifying and detecting the diseases, nutritional deficiencies by the usage of CNN. The researchers have shown that the 97.3% of accuracy is achieved by trained CNN that was out-performed through the research.

Liu Bin et al., (2017) have projected a precise identification method based on deep neural network for leaf disease in apple fruit. It entails generating enough problematic data, as well as designing a new structure to detect disease in apple leaf based on AlexNet CNN. The study demonstrated that the proposed DNN model provides a better resolution for disease control of disease in apple leaf, with higher rate and accuracy.

Cruz A et al., (2017) have anticipated an image-processing technology and pattern recognition system and identification of disease in plant leaves. DCNN classifiers are used for detecting these diseases. In the proposed method, the selected subset of features is globally optimal and produced the 90% accuracy rate for identification.

Pugoy et al., (2019) Proposed colour image analysis on automated rice leaf disease detection. In 3rd International Conference on DIP, International Society for Optics and Photonics. In this they used detection method for detection of leaf scald rice disease. In the proposed algorithm firstly, healthy, and diseased images are prepared by using HS extraction of histogram and extraction of colour, respectively. Secondly, the test images are used for detection of disease.

A research work in (International Telecommunication Union. 2015) to quote the leaves diseased parts, they used fermi energy-based segmentation. Coloured features such as SD and mean were extracted.

Sanyal et al., (2008) analysed through pattern recognition method on the texture of 400 rice leaf pictures. As a result, early and proper detection of leaf spot are observed. A farmer can detect the diseases if the recommended technology is embedded into camera phones, and these diseases show their destructive symptoms earlier without any help from a plant pathologist.

(Saheer, et al., (2017), In their research they introduced smart irrigation system. And explained water requirements for plant growth. The research also focused on the various types of plant diseases caused by water requirement and soil needs. Deepkiran et al. (2022), used 3 plant species with 15 dissimilar classes including some healthy leaves of plants and concluded that CNN achieved the highest classification accuracy among CNN, LDA and KNN.

In this study, in order to provide the proper research summary about the research work carried out by different authors, Table 5 presents the details about the research year, data sets, network and accuracy, respectively .

Table 5. Summary of the research papers in plant disease detection

Plant Species Name	Authors & Year	Total Images	Data Source	Network	Accuracy
10 different crops	(Barbedo et al., 2019)	46135	Self + Plant Village	GoogleNet, CNN	Near about 85%
14 variants	(Mohanty, S. Pugoy et al., 2016)	52306	Plant Village	GoogleNet	99.34%
14 Variants	(Ramcharan, Amanda, et al., 2018)	54300	Plant Village	50, 101 and 152 layers (ResNet), 121 layers (DenseNet), VGG-16 and Inception V4	99.59%, 99.66%, 99.59%, 99.75%, 81.83%, and 98.08%
4 crops	(Too, Edna Chebet, et al., 2017)	100	Self -Captured	SVM Classifier K-means clustering+ proposed algo	95.71%
5 species	(Nguyen, Thuy Tuong, et al., 2016)	2589	Stanford background dataset, OpenCV library, Internet	CaffeNet(Deep CNN)	Achieved precision between 91-98%, for separate class tests, achieved about average of 96.3%
Apple	(Nachtigall, Lucas G et al., 2016)	2086	Plant Village	VGG-16, ResNet-50, VGG-19, Inception-v3	With VGG-16 90.4%
Banana	(Cruz, Albert C., et al., 2017)	3700	Plant Village	With different train and test ratio of LeNet Model	99.72% with the ration of 50% tarin and test split
Casava	(Ramcharan, Amanda, et al., 2017)	2756	Self- captured from different locations	Softmax, KNN and SVM as final layer with Inception -3	Max 93% when with SVM
	(Too, Edna Chebet, et al., 2019)	760	Disease Existence and Severity and Measurements from Leaf Images	KNN, Linear SVC	93%, 95%
Chili	(Yun, Shi, et al., 2015)	150	Self	PNN	92% for Blight disease & 90% for Downy mildew
Corn	(Khaki, Saeed, et al., 2020)	800	Self-taken by Label me software	CNN and Sliding window approach	95.86
Cucumber	(Ma, Juncheng, et al., 2018)	14208	Self + Plant Village	AlexNet, Deep convolutional neural network (DCNN) with Random forest and SVM	DCNN with an accuracy of 93.4%
	(Gandhi, Rutu, et al., 2018)	1184	Self + Plant Village	Pre-trained AlexNet, Custom DCNN	94%, 93.2%
	(Kawasaki, Yusuke, et al., 2015)	800	Clicked by own	Custom CNN	94.90%
	(Fujita, Erika, et al., 2016)	7200	Self-taken	CNN1 -good CNN2-Bad	83.20%
Maize	(Zhang, Xihai, et al., 2018)	500	Plant Village	GoogleNet, Cifar10	98.9%-GoogleNet, 98.8%-Cifar10
	(DeChant, Chad, et al., 2017)	1796	Taken from fields	CNN	96.70%
	(Lin, Zhongqi, et al., 2018)	50,000	Imagenet.org	KNN, Multichannel-CNN	Augmented database accuracy-96.17% general data base accuracy-93.01%
	(Sena Jr, D. G., et al., 2005)	40	Self-captured by Digital camera MS3100	Iterative method	94.70%
Olive	(Wang, Guan, et al., (2017)	300	Self + Plant Village	LeNet	98.60%

continued on following page

Table 5. Continued

Plant Species Name	Authors & Year	Total Images	Data Source	Network	Accuracy
Pomegranate	(Sharath, D. M., et al., 2019)	400	Self-captured through camera	Gaussian Mixture Model Canny Edge detection	98.34%
Potato	(Oppenheim, Dor, et al., 2019)	2465	Self-Captured	CNN	90%
Rice	(Kalaivani, S et al., 2020)	400	UCI Machine Learning Repository	Residual Neural Network	95.83%
	(Prajapati et al., 2017)	500	Self- captured	Deep CNN	95.48%
	(Too, Edna Chebet, et al., 2019)	120	Self- captured	K-means clustering SVM Classifier	Training accuracy of 93.33% and testing accuracy of 73.33%
Soyabean	(Wallelign, Serawork et al., 2018)	1200	Plant Village + Self Captured	SVM	98%
Sugarcane	(Huang, Tisen, et al., 2018)	537	Self-data (CCD camera captured)	SVM Classifier	95.83%
	(Ratnasari, Evy Kamilah, et al., Umapathy Eaganathan et al.., 2014)	30	From the sugarcane field of Indonesia using colored digital camera	SVM	80%
Tomato	(Agarwal, Mohit, et al., 2020)	1000	Plant Village	ResNet101, Chan- Vese for feature extraction	83.75%
	(Ashqar A M et al., 2018)	14828	Plant village	KNN- Classification AlexNet	91.8% GoogleNet
	(Fuentes, Alvaro, et al., 2017)	5000	Self -taken	ResNet-101, ResNet-50, AlexNet, VGG-16	Max 86% with ResNet-50
	(Brahimi, Mohammed et al., 2017)	18000	Plant Village	SqueezeNet, AlexNet	94.3%,95.65%resp
	(Ashqar, Belal AM et al., 2018)	About 56000	Plant Village	MobileNet, InceptionV3	92%, 88.6% resp
	(Lu, Jinzhu, et al., 2017)	166	166 hyperspectral leaves images by the experimental system fused on an array CCD camera (C8484-05G01	Hyperspectral imaging system with SVM Classifier	100% Threshold value achieved.
	(Sabrol, H et al., 2016)	13262	Plant village	AlexNet,Transfer learning VGG16	97.49%, 97.29%
Wheat	(Majumdar, Diptesh, et al., 2015)	8170	Self- clicked	ResNet50	87%
	(Lu, Jiang, et al., 2017)	9320	Self by camera on various locations	CNN, DMIL-WDD	93.7%, 97.95%

6. CONCLUSION

In this study, the elementary acquaintance of machine / deep learning has been introduced and performed an extensive literature survey of recent research work done in plant leaf disease recognition using machine / deep learning.

In this survey, we covered the various latest ML techniques which have been used in past years for plant disease detection. Before explaining the techniques, we elaborated the general framework of plant disease detection system as follows:

As a very first step, researchers gathered information, common material, and tools for acquiring the image of plant leaves through which disease can be identified. In this study, it has been observed that most of the researchers focused on village dataset for their study and in the reviewed papers, some researchers have taken their own image through camera for data collection, or some researchers collect data images from the available data source like plant village, internet etc. Various cameras were used for taking picture based on their resolution factors etc. while some images are taken through Data set available on the sources like plant village.

For further processing preprocessing done by using various techniques for pre-processing and discussed the best pre-processing technique. By the literature survey and summary collected, we find mainly classifiers which are used for detection of plant disease to evaluate their efficiency and accuracies. Then to choose the best one among them all.

Based on literature, it has been observed that most of the disease detection system uses above discussed segmentation and classification techniques. As per our observation, the following chart describes methodologies used in various reviewed papers. In most of the research papers, the SVM classification methodology was most frequently applied for plant disease detection system & it obtained promising results too. However, in deep learning models, ResNet-50 obtained the highest accuracy of 99.7% followed by Google Net architecture, which obtained detection accuracy of 99.3%.

The chart shown in Fig. 14 illustrate the comparison of several classifiers which are castoff for classification in plant disease detection system with their accuracy rate in finding the diseases in plant.

In this survey, we have done a review based on the classification methods and Model architecture used for plant disease detection. We have gone through about 100 research papers that are applying various machine learning or deep learning techniques and identified the best suited methodology.

Figure 13. Chart showing the comparison of various architecture in plant disease detection

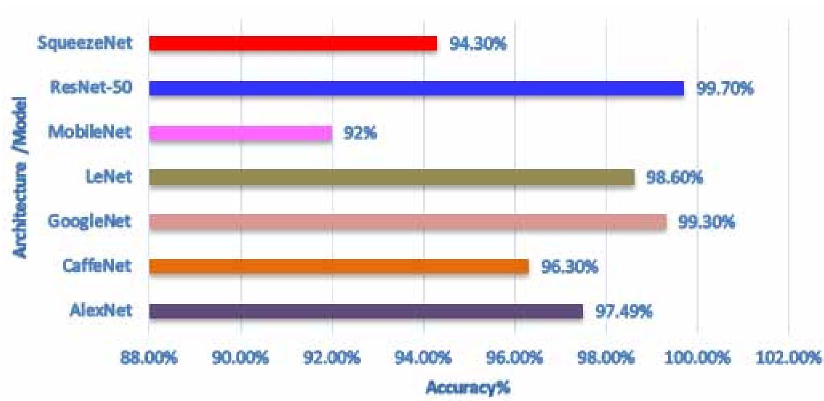
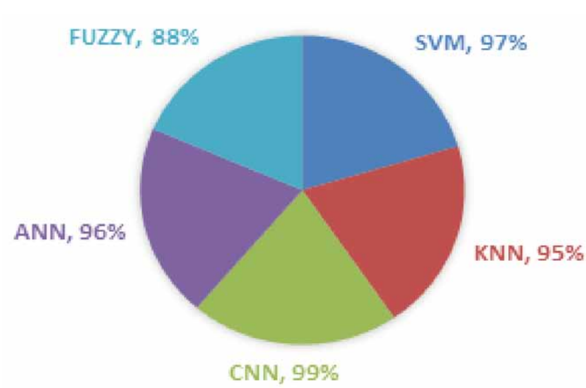


Figure 14. Comparative usage of reviewed methods for plant disease detection



With this survey, CNN gives a good result in classification accuracy and Google Net and ResNet-50 is considered as best architecture Model for the plant disease detection.

7. FUTURE WORK

Despite the numerous advantages afforded by various image-processing, machine-learning and deep-learning techniques for identification and classification of diseases in plant leaves, these systems still have a huge number of drawbacks.

Image processing algorithms have the capability to detect and detach infected segments from a plant leaf image. On the other hand, new approaches and techniques are required to solve a variety of existing challenges, such as noise handling, the existence of irrelevant background objects, and so forth. A variety of computer-vision approaches and techniques, that have formed a new hotspot of study in this sector, and this publication acknowledges them.

It's crucial to detect plant sickness at an early stage so that proper precautions can be taken to avoid crop loss. For the general use, there are only insufficient websites and mobile-based applications available. In the literature, there are several highly efficient and precise models. That should be deployed and tested in open fields by real-time mobile-apps and web-services so that farmers can utilize these advanced automatic disease diagnostic approaches in their farming by taking a sample photo of dubious plant leaf . For almost all plant diseases, leaf is the index. Nutrient deficits in the plant and crops can also be determined using leaf images. Similarly, water scarcity in plants can be sensed through changes in form, color, and collapsing of leaves.

In future we will use a different approach with enhanced color, shape, and texture and with a greater number of crops to attain the more accuracy. We will also study the latest and advanced architectures of deep learning techniques for classification and identification of plant disease. The overall purpose of this survey is to find the elegant, hybrid, automatic systems that can overcome all the aforementioned problems.

DATA AVAILABILITY

Data shall be made available on request.

CONFLICTS OF INTEREST

There are no conflicts of Interest among authors.

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REFERENCES

Agarwal, M., Singh, A., Arjaria, S., Sinha, A., & Gupta, S. (2020). ToLeD: Tomato leaf disease detection using convolution neural network. *Procedia Computer Science*, *167*, 293–301. doi:10.1016/j.procs.2020.03.225

Al Bashish, D., & Braik, M. (2010). AFramework for Detection and Classification of Plant Leaf and StemDiseases. In *International Conference on Signal and ImageProcessing*. IEEE.

Alam, A., & Singh, L. (2021). Distance-based confidence generation and aggregation of classifier for unstructured road detection. *Journal of King Saud University - Computer and Information Sciences*. 10.1016/j.jksuci.2021.09.020

Alenya, G., Dellen, B., Foix, S., & Torras, C. (2013). Robotized plant probing: Leaf segmentation utilizing time-of-flight data. *IEEE Robotics & Automation Magazine*, *20*(3), 50–59. doi:10.1109/MRA.2012.2230118

Amara, J., Bouaziz, B., & Algergawy, A. (2017). A Deep Learning-based Approach for Banana Leaf Diseases Classification. *Proceedings of the BTW* (pp. 79–88). Academic Press.

Anas, S., Badhusha, I., Zaheema, O. T., Faseela, K., & Shelly, M. (2017, April). Cloud based automated irrigation and plant leaf disease detection system using an android application. In *International conference of Electronics, Communication and Aerospace Technology (ICECA)* (Vol. 2, pp. 211-214). IEEE.

Annabel, L. S. P., Annapoorani, T., & Deepalakshmi, P. (2019, April). Machine Learning for Plant Leaf Disease Detection and Classification–A Review. In *International Conference on Communication and Signal Processing (ICCSP)* (pp. 0538-0542). IEEE. doi:10.1109/ICCSP.2019.8698004

Anthonys, G., & Wickramarachchi, N. (2009) An image recognition system for crop disease identification of paddy fields in Sri Lanka. In International conference on industrial and information systems ICIIS, (pp 403–407). IEEE. doi:10.1109/ICIINFS.2009.5429828

Asefpour Vakilian, K., & Massah, J. (2013). An artificial neural network approach to identify fungal diseases of cucumber (Cucumis sativus L.) plants using digital image processing. *Archiv für Phytopathologie und Pflanzenschutz*, *46*(13), 1580–1588. doi:10.1080/03235408.2013.772321

Ashqar, B. A., & Abu-Naser, S. S. (2018). Image-based tomato leaves diseases detection using deep learning.

Barbedo, J. G. A. (2016). A review on the main challenges in automatic plant disease identification based on visible range images. *Biosystems Engineering*, *144*, 52–60. doi:10.1016/j.biosystemseng.2016.01.017

Barbedo, J. G. A. (2019). Plant disease identification from individual lesions and spots using deep learning. *Biosystems Engineering*, *180*, 96–107. doi:10.1016/j.biosystemseng.2019.02.002

Bartlett, P. L., & Traskin, M. (2007). AdaBoost is consistent. *Journal of Machine Learning Research*, *8*, 2347–2368.

Bauer, S. D., Korč, F., & Förstner, W. (2011). The potential of automatic methods of classification to identify leaf diseases from multispectral images. *Precision Agriculture*, *12*(3), 361–377. doi:10.1007/s11119-011-9217-6

Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: Classification and symptoms visualization. *Applied Artificial Intelligence*, *31*(4), 299–315. doi:10.1080/08839514.2017.1315516

Breiman, L. (1996). Bagging predictors. *Machine Learning*, *24*(2), 123–140. doi:10.1007/BF00058655

Brodersen, C. R., & Roddy, A. B. (2016). New frontiers in the three-dimensional visualization of plant structure and function. *American Journal of Botany*, *103*(2), 184–188. doi:10.3732/ajb.1500532 PMID:26865119

Chouhan, S. S., Singh, U. P., & Jain, S. (2020). Applications of computer vision in plant pathology: A survey. *Archives of Computational Methods in Engineering*, *27*(2), 611–632. doi:10.1007/s11831-019-09324-0

Chuanlei, Z., Shanwen, Z., Jucheng, Y., Yancui, S., & Jia, C. (2017). Apple leaf disease identification using genetic algorithm and correlation-based feature selection method. *International Journal of Agricultural and Biological Engineering*, *10*(2), 74–83.

Comar, A., Burger, P., de Solan, B., Baret, F., Daumard, F., & Hanocq, J. F. (2012). A semi-automatic system for high throughput phenotyping wheat cultivars in-field conditions: Description and first results. *Functional Plant Biology*, *39*(11), 914–924. doi:10.1071/FP12065 PMID:32480841

Cruz, A. C., Luvisi, A., De Bellis, L., & Ampatzidis, Y. (2017). Vision-based plant disease detection system using transfer and deep learning. In *Asabe annual international meeting* (p. 1). American Society of Agricultural and Biological Engineers.

Cui, S., Ling, P., Zhu, H., & Keener, H. M. (2018). Plant pest detection using an artificial nose system: A review. *Sensors (Basel)*, *18*(2), 378. doi:10.3390/s18020378 PMID:29382093

Dafni, R. J. (2022). VijayaKumar, K; Singh, L, Sharma, SK. (2022). Computer-aided diagnosis for breast cancer detection and classification using optimal region growing segmentation with MobileNet model. *Concurrent Engineering*, *30*(2), 181–189. doi:10.1177/1063293X221080518

DeChant, C., Wiesner-Hanks, T., Chen, S., Stewart, E. L., Yosinski, J., Gore, M. A., Nelson, R. J., & Lipson, H. (2017). Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning. *Phytopathology*, *107*(11), 1426–1432. doi:10.1094/PHYTO-11-16-0417-R PMID:28653579

Deepkiran, Singh, L., Pandey, M., & Lakra, S. (2022, May). Automated Disease Detection in Plant Images using Convolution Neural Network. International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES) (pp. 487-492). IEEE. doi:10.1109/CISES54857.2022.9844338

Dhakate, M., & Ingole, A. B. (2015, December). Diagnosis of pomegranate plant diseases using neural network. In *Fifth national conference on computer vision, pattern recognition, image processing and graphics (NCVPRIPG)* (pp. 1-4). IEEE. doi:10.1109/NCVPRIPG.2015.7490056

Eaganathan, U., Sophia, J., Luckose, V., & Benjamin, F. J. (2014). Identification of sugarcane leaf scorch diseases using K-means clustering segmentation and K-NN based classification. *Int. J. Adv. Comput. Sci. Technol. (IJACST)*, 11-16.

Ehler, L. E. (2006). Integrated pest management (ipm): Definition, historical development and implementation, and the other ipm. *Pest Management Science*, *62*(9), 787–789. doi:10.1002/ps.1247 PMID:16786545

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, *145*, 311–318. doi:10.1016/j.compag.2018.01.009

Friedman, N., Geiger, D., & Goldszmidt, M. (1997). Bayesian network classifiers. *Machine Learning*, *29*(2–3), 131–163. doi:10.1023/A:1007465528199

Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *Sensors (Basel)*, *17*(9), 2022. doi:10.3390/s17092022 PMID:28869539

Fujita, E., Kawasaki, Y., Uga, H., Kagiwada, S., & Iyatomi, H. (2017). Basic investigation on a robust and practical plant diagnostic system. *Proceedings of the 15th IEEE International Conference on Machine Learning and Applications, ICMLA 2016* (pp. 989–992). IEEE Press.

Gandhi, R., Nimbalkar, S., Yelamanchili, N., & Ponkshe, S. (2018, May). Plant disease detection using CNNs and GANs as an augmentative approach. In *IEEE International Conference on Innovative Research and Development (ICIRD)* (pp. 1-5). IEEE. doi:10.1109/ICIRD.2018.8376321

Gavhale, K. R., Gawande, U., & Hajari, K. O. (2014, April). Unhealthy region of citrus leaf detection using image processing techniques. In *International Conference for Convergence for Technology* (pp. 1-6). IEEE. doi:10.1109/I2CT.2014.7092035

Golhani, K., Balasundram, S. K., Vadamalai, G., & Pradhan, B. (2018). A review of neural networks in plant disease detection using hyperspectral data. *Information Processing in Agriculture*, *5*(3), 354–371. doi:10.1016/j.inpa.2018.05.002

Hossain, S., Mou, R. M., Hasan, M. M., Chakraborty, S., & Razzak, M. A. (2018, March). Recognition and detection of tea leaf's diseases using support vector machine. In *14th International Colloquium on Signal Processing & Its Applications (CSPA)* (pp. 150-154). IEEE. doi:10.1109/CSPA.2018.8368703

Huang, T., Yang, R., Huang, W., Huang, Y., & Qiao, X. (2018). Detecting sugarcane borer diseases using support vector machine. *Information Processing in Agriculture*, *5*(1), 74–82. doi:10.1016/j.inpa.2017.11.001

IPM Images. (2018). *About IPM Images.* IPM Images. https://www.ipmimages.org/about/.

Islam, M., Dinh, A., Wahid, K., & Bhowmik, P. (2017, April). Detection of potato diseases using image segmentation and multiclass support vector machine. In *30th Canadian conference on electrical and computer engineering (CCECE)* (pp. 1-4). IEEE. doi:10.1109/CCECE.2017.7946594

ITU. (2015). *ICT Facts and Figures – the World in 2015*. International Telecommunication Union.

Jadhav, S. B., & Patil, S. B. (2015). Grading of soybean leaf disease based on segmented image using k-means clustering. *Int J Adv Res Electr Commun Eng*, *4*(6), 1816–1822.

Jaffery, Z., Zaheeruddin, A., & Singh., L. (2013). Performance Analysis of Image Segmentation Methods for the Detection of Masses in Mammograms. *International Journal of Computer Applications, 82*(2), 44-50.

Jagtap, MSB and Hambarde (2014). Agricultural Plant Leaf Disease Detection and Diagnosis Using Image Processing Based on Morphological Feature Extraction. *IOSR J. VLSI Signal Process, 4* (5), 24–30.

Jiawei, H., Micheline, K., & Jian, P. (2016). *Data mining concepts and techniques.* Morgan Kaufmann.

Kalaivani, S., Shantharajah, S. P., & Padma, T. (2020). Agricultural leaf blight disease segmentation using indices-based histogram intensity segmentation approach. *Multimedia Tools and Applications*, *79*(13), 9145–9159. doi:10.1007/s11042-018-7126-7

Kaur, S., Pandey, S., & Goel, S. (2018). Semi-automatic leaf disease detection and classification system for soybean culture. *IET Image Processing*, *12*(6), 1038–1048. doi:10.1049/iet-ipr.2017.0822

Kaur, S., Pandey, S., & Goel, S. (2019). Plants disease identification and classification through leaf images: A survey. *Archives of Computational Methods in Engineering*, *26*(2), 507–530. doi:10.1007/s11831-018-9255-6

Kawasaki, Y., Uga, H., Kagiwada, S., & Iyatomi, H. (2015, December). Basic study of automated diagnosis of viral plant diseases using convolutional neural networks. In *International symposium on visual computing* (pp. 638-645). Springer. doi:10.1007/978-3-319-27863-6_59

Khaki, S., Pham, H., Han, Y., Kuhl, A., Kent, W., & Wang, L. (2020). Convolutional Neural Networks for Image-Based Corn Kernel Detection and Counting. *Sensors (Basel)*, *20*(9), 2721. doi:10.3390/s20092721 PMID:32397598

Kim, A., Mowat, A., Poole, P., & Kasabov, N. (2000). Linear and non-linear pattern recognition models for classification of fruit from visible-near infrared spectra. *Chemometrics and Intelligent Laboratory Systems*, *51*(2), 201–216. doi:10.1016/S0169-7439(00)00070-8

Korada, N. K., Kuma, N., & Deekshitulu, Y. V. N. H. (2012). Implementation of naïve Bayesian classifier and ada-boost algorithm using maize expert system. *International Journal of Information Sciences and techniques (IJIST), 2*.

Kruse, O. M. O., Prats-Montalbán, J. M., Indahl, U. G., Kvaal, K., Ferrer, A., & Futsaether, C. M. (2014). Pixel classification methods for identifying and quantifying leaf surface injury from digital images. *Computers and Electronics in Agriculture*, *108*, 155–165. doi:10.1016/j.compag.2014.07.010

Kumar, R., Singh, L., Tiwari, R. (2021). Path Planning for the Autonomous Robots Using Modified Grey Wolf Optimization Approach. *Journal of Intelligent and Fuzzy Systems, 40* (2021), 94-53-9470.

Lee, S. H., Chan, C. S., Wilkin, P., & Remagnino, P. (2015, September). Deep plant: Plant identification with convolutional neural networks. In International conference on image processing (ICIP) (pp. 452-456). IEEE.

Li, L., Zhang, S., & Wang, B. (2021). Plant disease detection and classification by deep learning—A review. *IEEE Access: Practical Innovations, Open Solutions*, *9*, 56683–56698. doi:10.1109/ACCESS.2021.3069646

Lin, Z., Mu, S., Shi, A., Pang, C., & Sun, X. (2018). A novel method of maize leaf disease image identification based on a multichannel convolutional neural network. *Transactions of the ASABE*, *61*(5), 1461–1474. doi:10.13031/trans.12440

Liu, B., Zhang, Y., He, D., & Li, Y. (2017). Identification of apple leaf diseases based on deep convolutional neural networks. *Symmetry*, *10*(1), 11. doi:10.3390/sym10010011

Lu, J., Hu, J., Zhao, G., Mei, F., & Zhang, C. (2017). An in-field automatic wheat disease diagnosis system. *Computers and Electronics in Agriculture*, *142*, 369–379. doi:10.1016/j.compag.2017.09.012

Lu, J., Zhou, M., Gao, Y., & Jiang, H. (2018). Using hyperspectral imaging to discriminate yellow leaf curl disease in tomato leaves. *Precision Agriculture*, *19*(3), 379–394. doi:10.1007/s11119-017-9524-7

Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., & Sun, Z. (2018). A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. *Computers and Electronics in Agriculture*, *154*, 18–24. doi:10.1016/j.compag.2018.08.048

Majumdar, D., Ghosh, A., Kole, D. K., Chakraborty, A., & Majumder, D. D. (2015). Application of fuzzy c-means clustering method to classify wheat leaf images based on the presence of rust disease. In *Proceedings of the 3rd International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2014* (pp. 277-284). Springer. doi:10.1007/978-3-319-11933-5_30

Masazhar, A. N. I., & Kamal, M. M. (2017, November). Digital image processing technique for palm oil leaf disease detection using multiclass SVM classifier. In *4th International conference on smart instrumentation, measurement, and application (ICSIMA)* (pp. 1-6). doi:10.1109/ICSIMA.2017.8311978

Mishra, A., Singh, L., Pandey, M., & Lakra, S. (2022). Image based early detection of diabetic retinopathy: A systematic review on Artificial Intelligence (AI) based recent trends and approaches. *Journal of Intelligent & Fuzzy Systems*, *43*(5), 6709–6741. doi:10.3233/JIFS-220772

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, *7*, 1419. doi:10.3389/fpls.2016.01419 PMID:27713752

Nachtigall, L. G., Araujo, R. M., & Nachtigall, G. R. (2016, November). Classification of apple tree disorders using convolutional neural networks. In *28th International Conference on Tools with Artificial Intelligence (ICTAI)* (pp. 472-476). IEEE. doi:10.1109/ICTAI.2016.0078

Nguyen, T. T., Slaughter, D. C., Maloof, J. N., & Sinha, N. (2016, May). Plant phenotyping using multi-view stereo vision with structured lights. In *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping* (Vol. 9866, pp. 22–30). SPIE.

Oppenheim, D., Shani, G., Erlich, O., & Tsror, L. (2019). Using deep learning for image-based potato tuber disease detection. *Phytopathology*, *109*(6), 1083–1087. doi:10.1094/PHYTO-08-18-0288-R PMID:30543489

Oppenheim, D., Shani, G., Erlich, O., & Tsror, L. (2019). Using deep learning for image-based potato tuber disease detection. *Phytopathology*, *109*(6), 1083–1087. doi:10.1094/PHYTO-08-18-0288-R PMID:30543489

Owomugisha, G., Melchert, F., Mwebaze, E., Quinn, J. A., & Biehl, M. (2018, July). Machine Learning for diagnosis of disease in plants using spectral data. In *International Conference on Artificial Intelligence (ICAI)* (pp. 9-15).

Padol, P. B., & Yadav, A. A. (2016, June). SVM classifier based grape leaf disease detection. In *Conference on advances in signal processing (CASP)* (pp. 175-179). IEEE. doi:10.1109/CASP.2016.7746160

Parikh, A., Raval, M. S., Parmar, C., & Chaudhary, S. (2016, October). Disease detection and severity estimation in cotton plant from unconstrained images. In *International Conference on Data Science and Advanced Analytics (DSAA)* (pp. 594-601). IEEE doi:10.1109/DSAA.2016.81

Paulus, S., Behmann, J., Mahlein, A. K., Plümer, L., & Kuhlmann, H. (2014). Low-cost 3D systems: Suitable tools for plant phenotyping. *Sensors (Basel)*, *14*(2), 3001–3018. doi:10.3390/s140203001 PMID:24534920

Prajapati, H. B., Shah, J. P., & Dabhi, V. K. (2017). Detection and classification of rice plant diseases. *Intelligent Decision Technologies*, *11*(3), 357–373. doi:10.3233/IDT-170301

Prasad, S., Peddoju, S. K., & Ghosh, D. (2015). Multi-resolution mobile vision system for plant leaf disease diagnosis. *Signal, Image and Video Processing*, *10*(2), 379–388. doi:10.1007/s11760-015-0751-y

Pydipati, R., Burks, T. F., & Lee, W. S. (2006). Identification of citrus disease using color texture features and discriminant analysis. *Computers and Electronics in Agriculture*, *52*(1), 49–59. doi:10.1016/j.compag.2006.01.004

Quinlan, J. R. (1986). Induction of decision trees. *Machine Learning*, *1*(1), 81–106. doi:10.1007/BF00116251

Ramakrishnan, M. (2015, April). Groundnut leaf disease detection and classification by using back probagation algorithm. In *International Conference on Communications and Signal Processing (ICCSP)* (pp. 0964-0968). IEEE. doi:10.1109/ICCSP.2015.7322641

Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J., & Hughes, D. P. (2017). Deep learning for image-based cassava disease detection. *Frontiers in Plant Science*, *8*, 1852. doi:10.3389/fpls.2017.01852 PMID:29163582

Ratnasari, E. K., Mentari, M., Dewi, R. K., & Ginardi, R. H. (2014, September). Sugarcane leaf disease detection and severity estimation based on segmented spots image. In *Proceedings of International Conference on Information, Communication Technology and System (ICTS)* (pp. 93-98). IEEE. doi:10.1109/ICTS.2014.7010564

Sabrol, H., & Satish, K. (2016, April). Tomato plant disease classification in digital images using classification tree. In *International Conference on Communication and Signal Processing (ICCSP)* (pp. 1242-1246). IEEE. doi:10.1109/ICCSP.2016.7754351

Salazar-Reque, I. F., Huamán, S. G., Kemper, G., Telles, J., & Diaz, D. (2019). An algorithm for plant disease visual symptom detection in digital images based on superpixels. *International Journal on Advanced Science, Engineering and Information Technology*, *9*(1), 194–203. doi:10.18517/ijaseit.9.1.5322

Salazar-Reque, I. F., Huamán, S. G., Kemper, G., Telles, J., & Diaz, D. (2019). An algorithm for plant disease visual symptom detection in digital images based on superpixels. *International Journal on Advanced Science, Engineering and Information Technology*, *9*(1), 194–203. doi:10.18517/ijaseit.9.1.5322

Sandhu, G. K., & Kaur, R. (2019, April). Plant disease detection techniques: a review. In international conference on automation, computational and technology management (ICACTM) (pp. 34-38). IEEE. doi:10.1109/ICACTM.2019.8776827

Sanyal, P., & Patel, S. C. (2008). Pattern recognition method to detect two diseases in rice plants. *Imaging Science Journal*, *56*(6), 319–325. doi:10.1179/174313108X319397

Sena, D. G. Jr, Pinto, F. A. C., Queiroz, D. M., & Viana, P. A. (2003). Fall armyworm damaged maize plant identification using digital images. *Biosystems Engineering*, *85*(4), 449–454. doi:10.1016/S1537-5110(03)00098-9

Sharath, D. M., Kumar, S. A., Rohan, M. G., & Prathap, C. (2019, April). Image based plant disease detection in pomegranate plant for bacterial blight. In International Conference On Communication And Signal Processing (ICCSP) (pp. 0645-0649). IEEE.

Singh, A. K., Sreenivasan, S. V. N., Mahalaxmi, U. S. B. K., Sharma, H., Patil, D. D., & Asenso, E. (2022). Hybrid Feature-Based Disease Detection in Plant Leaf Using Convolutional Neural Network, Bayesian Optimized SVM, and Random Forest Classifier. *Journal of Food Quality*. doi:10.1155/2022/2845320

Singh, L., Alam, A., & Kumar, K. V. (2021). Kumar, D., Kumar., P., Jaffery, Z.A. (2021). Design of thermal based health condition monitoring and early fault detection technique for porcelain insulators using machine learning. *Environmental Technology and Innovation.*, *24*, 102000. doi:10.1016/j.eti.2021.102000

Singh, L., & Jaffery, Z. A. (2009). Segmentation and Characterization of Brain Tumor from Medical Imaging. *International Conference on Advances in Recent Technologies in Communication and Computing*. IEEE.

Singh, L., & Jaffery, Z. A. (2017). Computerized segmentation of suspicious lesions in digital mammograms. *Computer Methods in Biomechanics and Biomedical Engineering. Imaging & Visualization*, *5*(2), 77–86. doi:10.1080/21681163.2014.982304

Singh, L., & Jaffery, Z. A. (2018). Computerized detection of breast cancer in digital mammograms. *International Journal of Computers and Applications*, *40*(2), 98–109. doi:10.1080/1206212X.2017.1395131

Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. *Information Processing in Agriculture*, *4*(1), 41–49. doi:10.1016/j.inpa.2016.10.005

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*. doi:10.1155/2016/3289801 PMID:27418923

Soman, K. P., Loganathan, R., & Ajay, V. (2009). *Machine learning with SVM and other kernel methods*. PHI Learning.

Sujatha, R., Chatterjee, J. M., Jhanjhi, N. Z., & Brohi, S. N. (2021). Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocessors and Microsystems*, *80*, 103615. doi:10.1016/j.micpro.2020.103615

Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, *161*, 272–279. doi:10.1016/j.compag.2018.03.032

Umapathy Eaganathan, D., Lackose, V., & Benjamin, F. J. (2014). Identification of sugarcane leaf scorch diseases using K-means clustering segmentation and K-NN based classification. [IJACST]. *International Journal of Advances in Computer Science and Technology*, *3*(12), 11–16.

Wahabzada, M., Mahlein, A. K., Bauckhage, C., Steiner, U., Oerke, E. C., & Kersting, K. (2016). Plant phenotyping using probabilistic topic models: Uncovering the hyperspectral language of plants. *Scientific Reports*, *6*(1), 1–11. doi:10.1038/srep22482 PMID:26957018

Wallace, A. M., McCarthy, A., Nichol, C. J., Ren, X., Morak, S., Martinez-Ramirez, D., & Buller, G. S. (2013). Design and evaluation of multispectral lidar for the recovery of arboreal parameters. *IEEE Transactions on Geoscience and Remote Sensing*, *52*(8), 4942–4954. doi:10.1109/TGRS.2013.2285942

Wallelign, S., Polceanu, M., & Buche, C. (2018, May). Soybean plant disease identification using convolutional neural network. In FLAIRS conference (pp. 146-151).

Wang, G., Sun, Y., & Wang, J. (2017). Automatic image-based plant disease severity estimation using deep learning. *Computational Intelligence and Neuroscience*, *2017*, 2017. doi:10.1155/2017/2917536 PMID:28757863

Wang, J., He, J., Han, Y., Ouyang, C., & Li, D. (2013). An adaptive thresholding algorithm of field leaf image. *Computers and Electronics in Agriculture*, *96*, 23–39. doi:10.1016/j.compag.2013.04.014

Xu, G., Zhang, F., Shah, S. G., Ye, Y., & Mao, H. (2011). Use of leaf color images to identify nitrogen and potassium deficient tomatoes. *Pattern Recognition Letters*, *32*(11), 1584–1590. doi:10.1016/j.patrec.2011.04.020

Yun, S, Xianfeng, W, & Shanwen, Z, Chuanlei. (2015). PNN based crop disease recognition with leaf image features and meteorological data. *International Journal of Agricultural and Biological Engineering*, *8*(4), 60–68.

Zaheeruddin, Z., Jaffery, Z. A., & Singh, L. (2012). Detection and shape feature extraction of breast tumor in mammograms. In *Proceedings of the world congress on engineering*, (pp. 719-724). WCE.

Zhang, M., & Meng, Q. (2011). Automatic citrus canker detection from leaf images captured in field. *Pattern Recognition Letters*, *32*(15), 2036–2046. doi:10.1016/j.patrec.2011.08.003

Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2018). Identification of maize leaf diseases using improved deep convolutional neural networks. *IEEE Access: Practical Innovations, Open Solutions*, *6*, 30370–30377. doi:10.1109/ACCESS.2018.2844405

Zhang, Z., You, Z., & Wu, X. (2019). Plant disease leaf image segmentation based on superpixel clustering and EM algorithm. *Neural Computing & Applications*, *31*(S2), 1225–1232. doi:10.1007/s00521-017-3067-8

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