International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

Plant Leaf Disease Detection and Control Measures

Shaik Razeena Begum[1] – Assistant Professor, Department of Computer Science and Engineering, Andhra Loyola Institute of Engineering and Technology, Vijayawada, India.
Thatha. Hairsh[2], Department of Computer Science and Engineering, Andhra Loyola Institute of Engineering and Technology, Vijayawada, India. (19HP1A05A3).
Ganga Eswar[3], Department of Computer Science and Engineering, Andhra Loyola Institute of Engineering and Technology, Vijayawada, India. (19HP1A05A2).
Yannam. Durga Dinesh[4], Department of Computer Science and Engineering, Andhra Loyola Institute of Engineering and Technology, Vijayawada, India. (19HP1A05A1).

ABSTRACT:
The agricultural sector is crucial to a nation's overall Economy. Trees are crucial to humanity's survival because they provide food and other necessities. Many farms in the world's poorest nations still rely on time-honored physical labor. The state and national economy can take a hit if plant illnesses aren't discovered in time to prevent economic damages for farmers. Background irregularities during picture capture, segmentation, and categorization pose difficulties in illness detection and classification. It is only possible to implement measures of control after an illness has been properly diagnosed based on the signs and traits of that disease. This study provides in-depth talks on the nature of plant illnesses, how to identify and categorize plant diseases, and the role that machine learning and deep learning play in this process. Based on the results of the poll, it seems that despite their popularity, machine learning techniques have not yet achieved widespread usage. For illness detection and categorization, deep learning approaches have proven more effective than conventional ones.
Keywords: Machine Learning, Data Analysis, Classification, Decision Tree, Deep Learning, Disease Detection, Machine Learning, Neural Network, Random Forest, and Support Vector Machine.

Abbreviations: Scale-invariant feature transform (SIFT) and Support Vector Machine (SVM) Speeded Up Robust Features (SURF) and Artificial Neural Networks (ANN) K-Nearest Neighbors (KNN), Histogram of Oriented Gradient (HOG), and Neural Network (NN). Bundle of Visible Words (BOVW), Decision Tree (DT), etc. Neural Network Trained with Back Propagation (BPNN); Random Forest; Gray-Level Co-Occurrence Matrix; Naive Bayes Probabilistic Neural Network, or PNN for short; Machine Learning; Color Spaces (RGB); Neural Networks (DL); Red, Green, Blue Color, Lightness, and Brightness; HIS Color, Saturation, and Value; LR; Linear Regression; Chart that organizes itself; In this context, we use the abbreviations DNN, CNN, and RBF to refer to Deep Neural Networks, Convolutional Neural Networks, and Radial Basis Function

I. INTRODUCTION

A nation's agricultural sector is its economic bedrock. Though many farmers would like to switch to more contemporary farming methods, they often are unable to because of factors such as a dearth of knowledge about the most recent advancements in the field, the high cost of the necessary equipment, etc. [7]. Many image processing apps have seen improved efficiency in recent years thanks to the use of machine learning based methods [43]. The results of AI-based learning apps have proven fruitful. Methods of machine learning [8] teach the computer to learn naturally and better its performance based on its own observations. It has been noted on numerous occasions that the number of plant illnesses varies according to climatic state, making them challenging to manage. Plants are subject to a wide variety of pathogens, including

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

those of the fungus, bacterial, viral, and parasitic varieties. The prevalence of fungal-like creatures on plants has been estimated at 85% [52]. Traditional methods, which farmers in poor countries still use despite their increased labor and time costs, are generally inferior. It's also conceivable that using your own two eyes won't yield any useful results when it comes to unaided identification. It has likewise been noticed that many ranches use herbicides to neutralize the impacts of illness without first recognizing the particular illnesses at play, a practice that poses risks to both the quality of the crops and the people who eat them. Farmers can benefit from machine learning and deep learning for illness detection and categorization in plants so they can take preventative measures. The use of machine learning and deep learning to identify plant illnesses is more efficient and precise than using conventional picture processing methods. Scholars in the field of plant disease face significant challenges, including a lack of data sets for individual diseases, background noise in recorded pictures, low resolution images, and variations in the material property of plant leaves brought on by environmental shifts.

II. PLANT DISEASES AND ITS SYMPTOMS

The following is some fundamental data about microbial pathogens (bacteria, viruses, fungi).

Bacterial diseases: Overgrowths, leaf blotches, scabs, and cankers are just a few of the signs caused by bacterial illnesses. The signs and symptoms of a bacterial illness are very similar to those of a fungus infection. In the case of bacterial illness, leaf blotch is the most typical sign.[60].

Viral diseases: Isolating and analyzing the cause of a virus illness can be a challenging task. Mosaic leaf design, crinkled foliage, yellow leaves, and plant wilting are all signs of a virus illness. Diseases caused by viruses include tobacco mosaic virus, tomato spotted virus, potato virus, cauliflower mosaic virus, and many others.[20].

Fungal diseases: Diseases like these are prevalent on many different types of veggies. Plants can suffer significant losses due to fungal illnesses. Anthracnose, downy mildews, powdery mildews, rusts, rhizoctonia rots, sclerotinia rots, and sclerotium rots are all significant fungus illnesses.[50].


Bacterial diseases Fig. 1. Viral diseases Fig. 2. Fungal diseases Fig. 3.

Traditional Methods of Disease Detection Classifying and identifying plant diseases is a process that relies heavily on digital image processing and machine learning. Catching an image, taking out clamor, portioning a picture, and physically removing highlights are instances of picture handling; include choice and order are instances of AI. Based on the characteristics of the images, machine learning algorithms are used to classify the illnesses. [47].

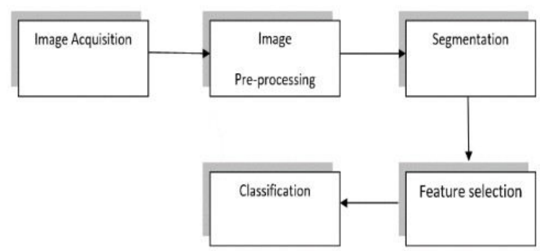


Fig. 4. Approach for diseases detection and classification.

The above diagram depicts the standard procedure for diagnosing plant illnesses and categorizing them. Image pre-processing includes tasks like picture filtration, noise elimination, scaling, and so on; this is just one example of the many sub-steps that make up the overall method. In the same vein, various techniques, such as edge recognition (Sobel, Canny, etc.), k-means clustering, otsu thresholding, etc., can be used to carry out picture segmentation. Histogram of directed gradients, Faster Robust Features, Color and Texture Features, Local Binary Patterns (LBP), etc., can all be used for feature extraction, while NB Classifier, Nearest Neighbor, SVM, DT, Boosted Trees, RF, NN, Logistic Regression, etc., can all be used for classification.[29].

Difference between Machine Learning and Deep Learning

While both Profound Learning and customary machine learning use information, the way that data is presented to the system is where the two diverge significantly. Deep learning in machine learning models and methods for organized data, where the number of ANN layers makes a difference. While traditional machine learning approaches to plant disease identification and categorization rely heavily on human-executed feature extraction, deep learning takes care of this step autonomously.[36].

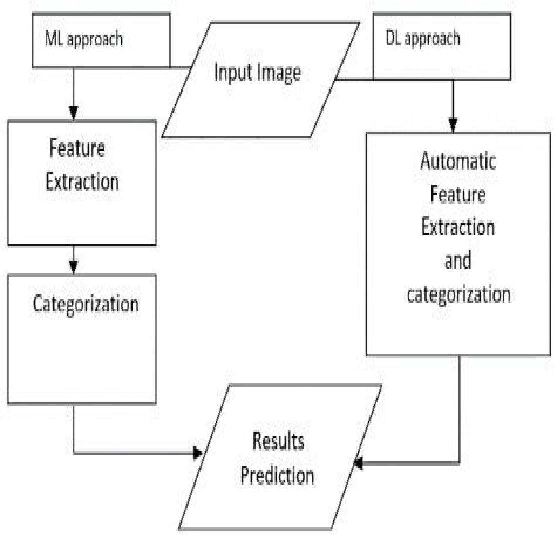


Fig. 5. shows two different approaches for disease detection and classification.

III. SURVEY OF MACHINE LEARNING TECHNIQUES FOR DISASES PREDICTION

[49] Nikos Petrellis made a cell phone program to recognize Wool Mold, Fine Buildup, and Mildewn in plants. Fine mold, dark decay, and fleece buildup were totally distinguished utilizing One Class Backing Vector Machines learned on a collection of eight images by Xanthoula Eirini Pantazi [48]. K-means clustering and Neural Networks were utilized by Trimi Neha Tete to identify plant illnesses [68]. Using the idea of picture extraction, Sourabh Shrivastava was able to identify the afflictions affecting the plants. Plant disease tracking with texture and form characteristic was the focus of Punnarai Siricharoen's research. For his study, he utilized SVM and shape normalization for disease monitoring [62]. Noa Schor developed a droid software to regulate chemicals and enhance the system for monitoring and combating illness. Compared to the 85% accuracy achieved by the algorithm based on the coefficient of variation (CV), the 95% accuracy achieved by the algorithm based on the principal component analysis (PCA) was striking. Using fuzzy computing methods, VijaiSingh found a way to identify diseases early on[57]. Experiments on HSV pictures of pepper plants were conducted by Jobin Francis, who used the K-Means Clustering Technique to categorize the leaves into healthy and ill groups [19] and wherein experiments were conducted on Brinjal leaves to identify leaf spots [3]. Sachin D. Khirade developed a method for early illness detection based on the Otsu Threshold Algorithm and the Back Propagation Network [34]. P. R. Rothe [55] studied cotton leaf. The Pattern Detection Methods were used to identify the illness on the cotton leaves. Ms. Kiran R. Gavhale Identified a Toxic Area on an Orange Foliage [23]. In order to diagnose Orchid Leaf Disease With Boundary Segmentation Methods [21], Wan MohdFadzil was able to divide up the image. John William Orillo identified rising plant illnesses using a Back Propagation Artificial Neural Network [45]. In order to identify greap and wheat diseases, Haiguang Wang utilised PCA,RBF,SVM [73]. Nurul Hidayah Tuhid used a statistical method involving colour space and the RGB colour model to diagnose orchid illness [71]. In her talk, Jayme Garcia provided a comprehensive overview of methods for diagnosing plant diseases. By utilising K-means grouping and a Back Propagation Neural Network Grape foliage illnesses were categorised by Sanjeev S. Sannakki [63]. Le Thi-Lan [37] recommended a framework for the robotized acknowledgment of plants in view of their leaves. The use of Fuzzy logic in a study of cantaloupe foliage illnesses was suggested by Noor Ezan Abdullah. [12].

Role of deep learning for computer vision

Table 1: Analysis of the Differences Between Several Machine Learning Methods.

Name of the author	Image dataset name	Types of disease detected	Future research direction
Amrita S.Tulsham (2019)	Own Dataset	DownMildew, Early Blight, Mosaic Virus, Leaf Miner, White Fly	this research algorithm may apply on huge dataset
JayrajChopda (2018)	Training dataset	Anthracnose , Areolate or Greymildew , Wilt	Future work on building an Android Application
Benjamin Doh (2019)	Kaggle dataset	Anthracnose, Black spot, Canker, Melanose, Greening, Citrus Scab	Up gradation within the classification precision
Eftekhar Hossain (2019)	Arkansas Reddit-plant datasets	Anthracnose, Bacterial Blight, Leaf Spot, Canker, Alternaria Alternata	For perfection of classification NN can be used.
S.M. Jaisakt hi (2019)	plant village	Balck-Rot, Esca, Leaf Blight.	Accuracy may increase with deep learning .
BudiariantoSuryoKusumo (2018)	PlantVillage	Corn Gray Leaf Spot, Corn Common Rust , Corn Nothern Leaf Blight	To study hybrid features
Shima Ramesh (2018)	Own training Dataset	Papaya leaf diseases	Combination of local and globalfeatures can give better result
SumitNema (2018)	self dataset creation	powdery mildew, tan Spot, pink snow mold,	for other plants this method canbe applied
Nikhil Shah(2019)	Own dataset	Cotton leaf diseases	Adding more hidden layer
Aman Sehgal (2019)	Back spread is used to preparing database	General plant disease	back propagation calculations may added for further accuracy
Sarangdhar, A.A (2017)	Collected form Buldhana district appx. 900 images	Bacterial Blight ,Alternaria Cerespora ,Grey Mildew Fusarium Wilt	Accuracy may increase with deep learning .
Ramesh, S.,2018	data set consists of 300 images	Rice Blast Disease	Performance will check with large database
Sandika, B. (2016)	Collected Dindori in Nashik district 900 appx.	Antharcnose, Powdery Mildew and Downy Mildew.	RF is best accuracy for GLCM features others techniques can be tested in future
Reza, Z.N. (2016)	Own dataset	Stem diseases	Disease detection in jute plant

Traditional machine learning methods have been replaced by deep learning as the dominant approach to improving PC vision. Profound learning is a subfield of AI that utilizes brain organizations. These organizations comprise of a snare of hubs called neurons that process data in a manner analogous to how neurons in the human brain process information, taking in data, performing complex calculations, and then outputting the results. By maximizing the appropriate input parameters and categorizing the output into appropriate categories, neural networks can derive patterns from an unstructured dataset and make forecasts. The ability to "learn" from existing data is what sets deep learning apart. To facilitate categorization in subsequent levels, CNN can instantly identify and send along the most relevant characteristics from the input. There has been no greater advancement in machine perception than this. To perform categorization, a CNN usually employs a completely linked layer after several convolutional, RELU, pooling layers. The convolutional layer engages the incoming picture and, using the weights and biases, extracts features. To accomplish this, a pooling layer is used in conjunction with corrected linear units (RELU) for dimensionality reduction. In agriculture, deep learning has a wide range of potential applications, including the identification of plant diseases, weeds, and even fruits. Indeed, a great deal of study has been done in the aforementioned fields. Deep learning trained on a big dataset can yield results that are up to par, and the insights gained from these results can greatly benefit the farming industry.

The Role of Deep Learning in Identifying and Categorizing Plant Diseases: In order to identify and categorise plant illnesses, Deep Learning can play an important part. Different deep learning algorithms can provide very effective solutions to a wide range of farming issues. MobileNet, R-CNN, DNN GAN architecture, GoogleNet Inception structure, Mutichannel CNN, AlexNet, SVM, 9- layer deep CNN, Two-head network using pre-trained model, InceptionV3 CNN using hierarchy method, and many more deep learning models have been used in scientific publications to identify illnesses. Quicker R-CNN, CNN, and Dense Networks Except for a select few researchers, it has been discovered that the

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

majority of academics used the plant village dataset to conduct their experiments with various CNNs, including CNN (VGG), Alex Net, RessNet50 with R-FCN, GoogleNet Cifar10, and CNN (Caffe2). When compared to other deep learning models, the precision results from GoogleNet, Cifar 10, and Multi channel CNN Models are quite promising. Figure 3 displays a contrast of a selection of study papers with respect to Collection, number of classes, and precision.

After analysing the methods used to identify and categorise illnesses in hundreds of studies, we discovered that researchers did so in a wide variety of ways. The variety of methods for identifying and categorising plant illnesses is depicted in Fig. 6. A unique hue represents each possible strategy for combining elements. Issues like proper segmentation [27], accuracy [27], design challenges [65], classification [17], slowness [49], noise [57] elimination, uneven backgrounds [19] reliability [30], and factors influencing picture capture [all] were also discovered in the course of our study. [23]

Table 2: Details of the ML approach to disease detection and classification

Author Name	**Segmentation technique**	**Classification Algorithm**	**Extracted Features**	**Classifier Accuracy**
Amrita S. Tulsham (2019)	region based k-mean segmentation	SVM-Existing KNN- Proposed	GLCM Algorithm	SVM 97.6 % KNN 98.56%
Jayraj Chopda (2018)	Thresholding technique	Decision Tree Classifier Algorithm	Texture, color	Increased but not specified
Benjamin Doh (2019)	K-mean ,Model-Based segmentation	SVM, ANN	Texture, color, Shape, phenotypic Features	SVM93. 12% ANN 88.96%
Eftekhar Hossain (2019)	k-nearest neighbor	KNN,GLCM	GLCM algorithm, color, texture	KNN 96.76%
S.M. Jaisakthi (2019)	Grab cut, Global Thresholding, Semi-	SVM, Random Forest, AdaBoost	Threshold, Textual,GLCM	SVM 93.035%
Budiarianto Suryo Kusumo (2018)	Not Specified	K-means, DT, NB and Nearest Neighbor	Complex genetic features,	RF may improve if number of tree larger
Shima Ramesh (2018)	Not Specified	RF	HOG	RF - 70.14%
SumitNema (2018)	k-means clustering	SVM	color, texture and edge	Given in the form of Standard Deviation
Nikhil Shah (2019)	Traditional	BPNN	Texture	relative error 0.051
Aman Sehgal (2019)	Traditional segmentation	NN,SVM,RF,NB, DT	Color and texture	SVM - 72.92% RF- 71.88% NB- 70.57% DT-64%
Sarangdhar, A.A (2017)	Color transform and thresholding	SVM	Color moment , texture Gabor filter	SVM 83.26%
Ramesh, S., 2018	K-Means Clustering	ANN	Color and texture	ANN Training 99% Testing 90%
Sandika, B. (2016)	Traditional	RF,PNN,BPNN,SVM	thresholding and image filling	RF 86%
Reza, Z.N. (2016)	Hue Based Segmentation	SVM	Color and texture	SVM 86%

Table 3 summarises different studies carried out to identify plant diseases

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362
IJARST

Authors	Year	Data set				Model	Accuracy
		Name of Crop	Data set name	No. of Classes	No. of Images		
Davinder Singh	2020	13 speices	Plant village	27	2598	MobileNet ,R-CNN	70.53 %
J.S.H. Al-bayati *et al.,*	2020	Apple	Plant village	6	2539	DNN, SURF, GOA	98.28 %
AndrasAnderla *et al.,*	2019	12 crop species	Plant Disease	42	79265	GAN architecture	93.67 %
Peng Jiang	2019	Apple	Real World (ALDD)	5	26377	INAR-SSD	78.80 %
Andre Abade *et al.,*	2019	14 crop species	Plant Village	38	54000	Mutichannel CNN	99.59 %
Rishabh Yadav *et al.,*	2019	7 crop species	Plant Village	23	8750	AlexNet, PSO, SVM	97.39 %

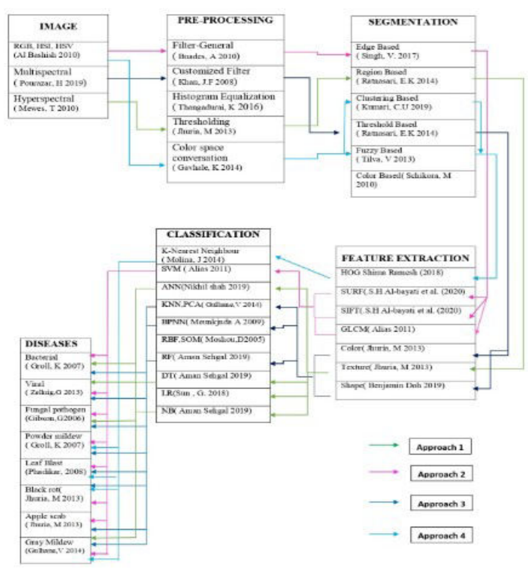


Fig. 6. Alternative methods for identifying and categorising plant illnesses.

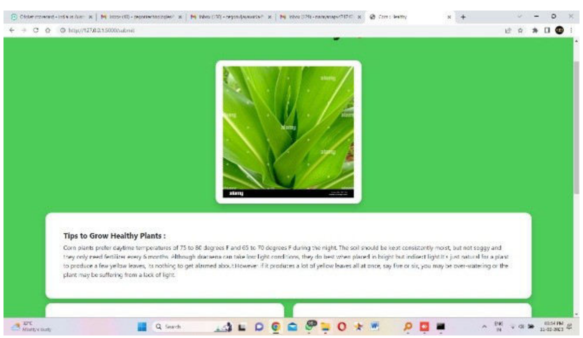
IV. CONCLUSION

In this research, we analysed the strengths and weaknesses of traditional techniques, machine learning, and deep learning when it comes to classifying plant illnesses and making diagnoses. We talked about four key steps—Image Pre-processing, Segmentation, Feature selection, and Classification—in the process of detecting and categorising illnesses. K-means for segmentation, support vector machines, and artificial neural networks are the most effective methods for detecting and classifying sick plants, as evidenced by the aforementioned review. Comparing CNN's performance to that of more conventional machine detection and categorization methods for plant illnesses, the results are clear from a review of the literature on deep learning. It is evident that, when comparing all of the various learning techniques, deep learning is by far the most effective. Some of the dataset was recorded under ideal conditions, which means there was no background noise. If noise is introduced to the image, the algorithm's effectiveness could suffer. After looking at a large number of papers, one significant shortcoming was identified: many researchers created their own dataset, which isn't available to different specialists. Thus, new calculation improvement from different specialists can't assess the dataset, which isn't straightforwardly accessible. The next step is to implement a programmed that will aid farmers in illness detection and classification in hardware.

Sladojevic *et al.,*	2016	5 crop species	Internet	13	2589	CNN (CaffeNet)	96.3 %
Geetharamani *et al.,*	2019	14 crop species	Leaf disease dataset	39	61486	9-layer deep CNN	96.46 %
Sijiang Huang *et al.,*	2019	8 crop species	Plant Disease	19	40000	U-Net, Two-head network using pre-trained model	98.07%, 87.45%
Joana Costa *et al.,*	2019	Apple, Peach, Tomato	Plant Village	16	24000	InceptionV3 CNN using hierarchical approach	97.74 %
Robert Luna *et al.,*	2018	Tomato	Own	4	4923	Faster R-CNN, CNN	91.67 %
Edna Too *et al.,*	2017	14 crop species	Plant Village	38	54000	DenseNets	99.75 %
Ferentinos	2018	25 crop species	Open Dataset	58	87848	CNN (VGG)	99.53 %
HalilDurmus *et al.,*	2017	Tomato Plant leaf	Plant Village	10	18000	Alex Net	95.65 %
Wang *et al.,*	2017	Apple black rot	Plant Village	4	2086	VGG 16	90.4 %
Fuentes *et al.,*	2017	Tomato	Own	9	5000	ResNet50 with R-FCN	85.98 %
XihaiZang	2017	Maize	Plant Village	9	500	GoogleNet Cifar10	98.9% 98.8%

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

V. OUTPUT RESULTS



VI .DISCUSSION AND FUTURE SCOPE

In this lesson, we covered the fundamentals of plant illnesses, as well as numerous methods for identifying and categorising them. There are a plethora of different plant-related illnesses that need to be dealt with. Bacterial, virus, and fungus infections are the three major types of illnesses that affect humans. The structure of various illnesses is depicted in Figures 1, 2, and 3. Scientists face many challenges when trying to study plant illnesses; in this overview, we present the conventional approach, which relies on already-developed image processing methods (as depicted in Fig. 4). Figure 1 compares the results of various researchers in order to demonstrate how machine learning can be used to identify and categorize illness. The precision of various picture segmentation, feature extraction, and categorization techniques are compared and contrasted in Table 2. Each researcher's suggested path forward for the field is outlined in Table 1. Researcher created Kaggle, Plant Village, and their own dataset, as shown in Table 1. It is clear from Table 2 that k-means segmentation and Hue Based segmentation were the most popular methods for researchers to use when attempting to segment data, while various machine learning classification algorithms such as SVM, ANN, Decision Tree Classifier, Random Forest, Decision tree, Naive bayes, PNN, and BPNN were used when attempting to classify the data. Figure 2 shows that the SVM and NN are the most popular categorization algorithms because they achieve the highest levels of precision. The four methods for diagnosing plant illnesses are depicted in Fig. 6. The various hue codes represent the various possible combinations. Figure 3 displays a summary of the different deep learning approaches. The study's author conducted tests on tomato, corn, apple, and other products to generate the plant community collection, which includes thousands of pictures. The models used to achieve precision are listed in Table 3, and they include GoogleNet, Cifar10, Mutichannel CNN, R-CNN, and CNN (CaffeNet). Controversy arising from competing interests. Interests are not in competition. In regards to the release of this article.

VII. REFERENCES

[1]. Al-bayati, J. S. H., & Üstündağ, B. B. (2020). Evolutionary Feature Optimization for Plant Leaf Disease Detection by Deep Neural

Networks. International Journal of Computational Intelligence Systems, 13(1), 12-23.
[2]. Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., & Stefanovic, D. (2019). Solving current limitations of deep learning based approaches for plant disease detection. Symmetry, 11(7), 939.
[3]. Anand, R., Veni, S., &Aravinth, J. (2016). An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method. In 2016 international conference on recent trends in information technology (ICRTIT) (pp. 1-6). IEEE.
[4]. Abdullah, N. E., Hashim, H., Yusof, Y. W. M.,Osman, F. N., Kusim, A. S., & Adam, M. S. (2012, September). A characterization of watermelon leaf diseases using Fuzzy Logic. In 2012 IEEE Symposium on Business, Engineering and Industrial Applications (pp. 1-6). IEEE.
[5]. Alias, N., Nashat, S., Zakaria, L., Najimudin, N., & Abdullah, M. Z. (2011, November). Classification gel electrophoretic image of DNA Fusarium graminearum featuring support vector machine. In 2011 IEEE International Conference on Signal and Image Processing Applications (ICSIPA) (pp. 109-114). IEEE. [6]. Al Bashish, D., Braik, M., &Bani-Ahmad, S. (2010, December). A framework for detection and classification of plant leaf and stem diseases. In 2010 international conference on signal and image processing (pp. 113- 118). IEEE.
[7]. Balakrishna, K., & Rao, M. (2019). Tomato plant leaves disease classification using KNN and PNN. International Journal of Computer Vision and Image Processing (IJCVIP), 9(1), 51-63.
[8]. Bajpai, G., Gupta, A., & Chauhan, N. (2019, July). Real Time Implementation of Convolutional Neural Network to Detect Plant Diseases Using Internet of Things. In International Symposium on VLSI Design and Test (pp. 510-522). Springer, Singapore.
[9]. Barbedo, J. G. A. (2013). Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus, 2(1), 660.
[10]. Buades, A., Le, T. M., Morel, J. M., & Vese, L. A. (2010). Fast cartoon+ texture image filters. IEEE Transactions on Image Processing, 19(8), 1978-1986.