ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/352787124

Plant Leaf Disease Detection and Classification using Conventional Machine Learning and Deep Learning

Article · January 2020

CITATIONS
15

READS
2,652

2 authors:

Hardikkumar Jayswal
Charotar University of Science and Technology
8 PUBLICATIONS 86 CITATIONS

SEE PROFILE

Jitendra Chaudhari
Charotar University of Science and Technology
68 PUBLICATIONS 192 CITATIONS

SEE PROFILE

All content following this page was uploaded by Hardikkumar Jayswal on 28 June 2021.

The user has requested enhancement of the downloaded file.

International Journal on Emerging Technologies 11(3): 1094-1102(2020)

ISSN No. (Print): 0975-8364
ISSN No. (Online): 2249-3255

Plant Leaf Disease Detection and Classification using Conventional Machine Learning and Deep Learning

Hardikkumar S. Jayswal[1] and Jitendra P. Chaudhari[2]
[1]Assistant Professor, Department of Information Technology, Charotar University of Science and Technology Anand (Gujarat), India.
[2]Associate Professor,Charusat Space Research and Technology Center Anand (Gujarat), India.

(Corresponding author: Hardikkumar S. Jayswal)
(Received 24 March 2020, Revised 21 May 2020, Accepted 23 May 2020)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: Agricultural field plays an important role for Gross Domestic Product (GDP) of any country. Plants are very important as they are supply source to human being. In Most of developing countries farmers use manual methods for farming. Sometimes late identifications of diseases in plants cause economic losses to the farmer which affects the economy of the state and the country at a large scale. There are some challenges in disease identification and classification are uneven background during image acquisition, segmentation and classification of an images. Once diseases are identified as per the symptoms, and its characteristics, control mechanisms can be applied. This survey presents detail discussions on plant diseases, disease detection and its classification using traditional methods, machine learning and deep learning. The survey revealed that the adoption of traditional methods, machine learning techniques are still inefficient. While deep learning methods delivered superior results for disease identification and classification, compare to traditional methods.

Keywords: Classification, Decision tree, Deep learning, Disease detection, Machine learning, Neural network, Random forest, Support vector machine.

Abbreviations: SVM, Support Vector Machine; SIFT, Scale-invariant feature transform ; ANN, Artificial Neural Network; SURF, Speeded Up Robust Features; NN, Neural Network; HOG, Histogram of an Oriented Gradient; KNN, K-Nearest Neighbors; BOVW, Bag of Visual Word; DT, Decision Tree; BPNN, Back Propagation Neural Network; RF, Random Forest; GLCM, Gray-Level Co-Occurrence Matrix; NB, Naïve Bayes; PNN, Probabilistic Neural Network; ML, Machine Learning; RGB, Red Green Blue; DL, Deep Learning; HIS, Hue, Saturation and Intensity; LR, Linear Regression; HSV, Hue, Saturation, and Value; SOM, Self-Organizing Map; DNN, Deep Neural Network; CNN, Convolutional Neural Network; RBF, Radial Basis Function Network.

I. INTRODUCTION

Agricultural is the backbone of any country's economy. Many farmers want to adopt modern agriculture but they can't due to the several reasons like lack of awareness about latest technology, high cost of the technology etc. [7]. In recent years, Machine learning based techniques have good performance in many image processing applications [43]. Learning based on artificial Intelligence applications has achieved productive output. Machine learning techniques which train the system in the way it can learn automatically and improve the results with its own experiences [8]. It has been observed many times that plant diseases are difficult to control as its population is varied according to environmental condition. There are different types of diseases which exist in the plants like fungal, bacterial, viral etc. It has been found 85% plants are affected by fungal like organisms [52]. Farmers of developing countries use traditional method which requires more labour work and is more time consuming. It is also possible that manual detection or naked eye observation cannot give fruitful results. It is also observed that many farmers use pesticides to remove the effect of disease without confirming the specific diseases, farmers use pesticides unlimitedly which can affect to plant quality as well as human health. Detection and classifications of plant diseases using machine learning and deep learning can help the famer to identify the diseases and they can take necessary action to control it. Machine learning and deep learning techniques used to detect plant diseases are more accurate and less time consuming compared to the traditional image processing techniques. Researchers are facing major issues in the field of plant disease like unavailability of data set for each and every disease, background noise in captured images, low resolution images, sometimes texture property of plant leaf varies during the change of environment.

II. PLANT DISEASES AND ITS SYMPTOMS

Following are the some basic information on bacterial, viral, fungal diseases.
Bacterial diseases: bacterial diseases named as bacteria causes different kinds of symptoms that include overgrowths of plants, leaf spots, scabs and cankers. Bacterial infection symptoms are nearly about similar like fungal disease. The most common type of symptoms found in bacterial disease is leaf spot [60].
Viral diseases: In the case of viral diseases it is little hard to identify and analyze. Symptoms of viral disease are Mosaic leaf pattern, Crinkled leaves, Yellowed leaves, Plant stunting. Some of the major viral disease

are Tobacco mosaic and Tomato spotted virus, Potato virus , Cauliflower mosaic virus etc. [20].

Fungal diseases: these are the diseases which are commonly found on wide range of vegetables. Fungal diseases are responsible for a enormous damage on plant. Some of major fungal diseases are Anthracnose, Downy mildews, Powdery mildews, Rusts, Rhizoctonia rots, Sclerotinia rots, Sclerotium rots [50].

Bacterial diseases
Fig. 1.

Viral diseases
Fig. 2.

Fungal diseases
Fig. 3.

Conventional Techniques for Diseases Detection: Plant disease detection and classification is process which is consist of two major parts, Digital Image processing and machine learning. Image processing include capture of an images, noise removal, image segmentation, manual feature extraction while machine learning techniques include feature selection and classification. Machine learning models are used to categorize the diseases based on image features [47].

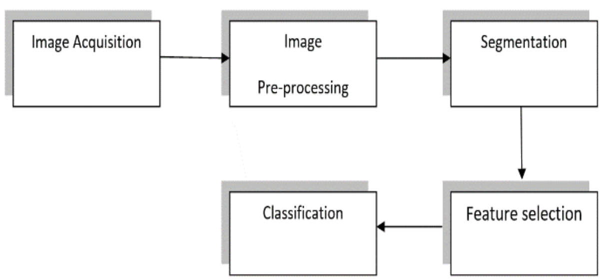

Fig. 4. Approach for diseases detection and classification.

As above figure shown the general approach to detect and classify the plant diseases. each phase of general approach will consist of different part like image pre-processing include operations like image filtering , noise removal, image resizing etc. similarly image segmentation can be perform with the help of different methods like edge detection (sobel, canny etc.) , k-means clustering, otsu thresholding etc. feature extraction can be implement using Histogram of oriented gradients, Speeded-up robust features, color and texture features, Local binary patterns (LBP) etc., for classification purpose different methods can be used like NB Classifier, Nearest Neighbor, SVM, DT, Boosted Trees, RF, NN, Logistic Regression, etc [29].

Difference between Machine Learning and Deep Learning

Deep Learning is a part of machine learning but major difference is how to present the data into system .Machine learning models and techniques dealing with structured data where deep learning depends on the layer of ANN. In detection of plant diseases and its classification, conventional machine learning techniques is focusing on manual feature extraction where in the case of deep learning it is preparing automatically [36].

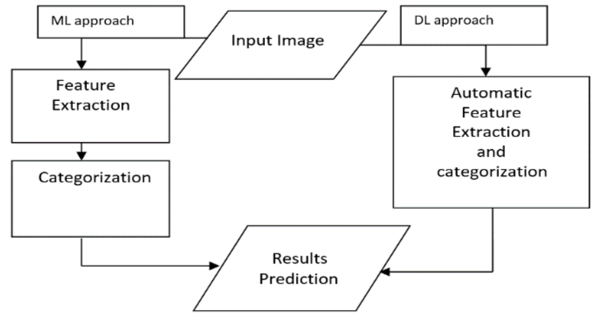

Fig. 5. shows two different approaches for disease detection and classification.

III. SURVEY OF MACHINE LEARNING TECHNIQUES FOR DISEASES DETECTION

Nikos Petrellis developed a mobile application to detect Downy Mildew, Powdery, Mildewn in plant [49]. Xanthoula Eirini Pantazi was used One Class Support Vector Machines and it were trained with a training set of 8 pictures to detect the Powdery Mildew , Black Rot and Downy Mildew [48]. Trimi Neha Tete were used K-means clustering and Neural Networks to detect the plant diseases [68]. Sourabh Shrivastavaused the concept of image retrieval to detect the plant diseases. Punnarai Siricharoen worked on plant disease monitoring using texture and shape attribute. In his research SVM and shape normalization were used to monitoring the diseases [62]. Noa Schor made a robotic application to control the pesticides and improve the diseases control mechanism ,The principal component analysis (PCA) based algorithm achieved 95% accuracy while the coefficient of variation (CV) based algorithm and achieved 85% accuracy. VijaiSingh identified early disease detection with the help of soft computing techniques[57]. Jobin Francis has performed experiment on HSV images of pepper plant and classify the healthy and unhealthy plant leaf using K-Means Clustering Method [19], An experiment performed on Brinjal Leaves to detect the leaf spot [3]. Otsu Threshold Algorithm and Back propagation Network used by Sachin D. Khirade to detect diseases [34]. A research on cotton leaf was carried out by P. R. Rothe [55]. To detect a diseases on cotton leaf researcher used the Pattern Recognition Techniques. Unhealthy Region of Citrus Leaf Detected by Ms. Kiran R. Gavhale [23]. To detect a diseases on Orchid Leaf Wan MohdFadzil used Border Segmentation Techniques [21]. John William Orillo used Back Propagation Artificial Neural Network for the identification of rise plant diseases [45]. Haiguang Wang used PCA,RBF,SVM to detect greap and wheat diseases [73]. A Statistical Approach adopted by Nurul Hidayah Tuhid to identify orchid disease using RGB color [71]. Jayme Garcia presented a detailed survey on plant disease detection. With the help of K-means clustering and Back Propagation Neural Network Sanjeev S Sannakki classified the grape leaf diseases [63]. Thi-Lan Le [37] Proposed a fully automatic leaf-based plant identification method. Noor Ezan Abdullah proposed a work on watermelon leaf diseases using Fuzzy logic [12].

Role of deep learning for computer vision

Table 1: Comparisons of Various Machine Learning Techniques.

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. Jaisakthi (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 global features can give better result
SumitNema (2018)	self dataset creation	powdery mildew, tan Spot, pink snow mold,	for other plants this method can be 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

Gone are the days of the conventional machine learning techniques were used for computer vision, now that deep learning has revolutionized the process, producing far better results. Deep learning is part of machine learning that uses a neural network, which is, an interconnected web of nodes called the neurons, similar to the neuron in our brain, which receive input, compute complex calculation and produce output. Neural nets are capable of extracting patterns form an unlabeled dataset by optimizing the relevant input parameters and making predictions by classifying the output into befitting classes. This feature of 'learning' from the given input is what gives deep learning an upper hand. CNN can automatically extract the features that are important from the provided input and pass it on to the further layers for classification. This has proven to be the most significant improvement in the field of computer vision. A CNN is typically a combination of multiple convolutional, RELU, pooling layers followed by a fully connected layer that enables classification. The convolutional layer interacts with the image input, extracting features based on the weights and biases. RELU stands for rectified linear units and pooling layer is used for dimensionality reduction. In the field of agriculture, deep learning can be utilized on a large scale for various purposes like plant disease detection, weed detection, fruit detection, etc. As a matter of fact, many researchers have taken place in aforementioned domains. Using a large dataset, deep learning can produce results to match up to right standards and the insights drawn from these results can significantly aid the agricultural sector.

Functioning of deep learning in plant disease detection and classification: Deep Learning can play a vital role to detect and classify the plant diseases. There are various kind of deep learning models are available which can be give very excellent results to solve agricultural problems. Deep learning models used in research papers to classify the diseases are 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 hierarchical approach, Faster R-CNN, CNN, Dense NetsCNN (VGG), Alex Net,ResNet50 with R-FCN, GoogleNet Cifar10 ,CNN (CaffeNet) etc. it has been found that except few researchers , most of the researchers used plant village dataset to perform an experiment. GoogleNet, Cifar 10, Multi channel CNN Models are giving good accuracy result compare to other deep learning models. Various research paper comparisons based on Dataset, number of classes and accuracy is shown in Table 3.
After Survey hundreds of research papers we found that in different research paper each of researchers used a different way to detect and classify the diseases.

Fig. 6 shown the possible number of approaches to detect and classify the plant diseases. Each of different combination approach shown in different color. We also found research issues like Proper segmentation [27], Accuracy [27], Designing issues [65], Classification [17], Time consuming [49], Noise removal [57], Uneven Background [19], Reliability [30], Factors affecting image acquisition [23].

Table 2: Detail of ML technique to Diseases 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-Supervised technique	SVM, Random Forest, AdaBoost	Threshold, Textual,GLCM Algorithm	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: Summarizes various researches conducted for plant disease detection.

Authors	Year	Dataset				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%
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%
Sladojevic *et al.,*	2016	5 crop species	Internet	13	2589	CNN (CaffeNet)	96.3%

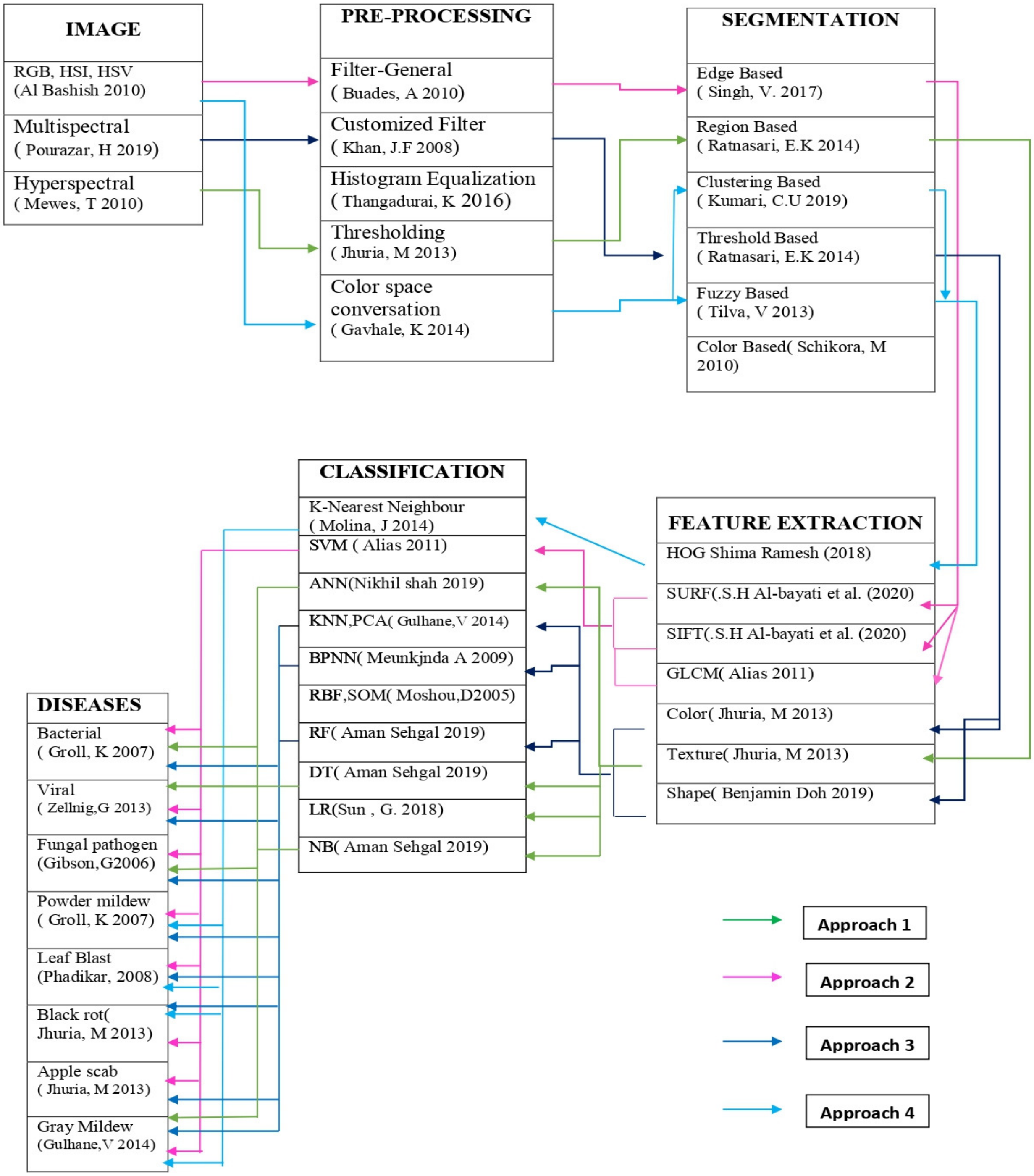

Fig. 6. Different approaches to detect and classify plant diseases.

IV. CONCLUSION

In this Survey we discussed traditional methodology, machine learning and deep learning techniques for plant disease detection and classification. We discussed four major phases to detect and classify the diseases which are Image Pre-processing, Segmentation, Feature selection and classification. From the above survey it can be concluded that K-means for segmentation, SVM and ANN are the most efficient methods to detect and classify the infected plant. After surveying different research papers on deep learning it can be concluded that CNN gives the best performance in the field of plant diseases detection and classification. All the comparisons made between traditional machine learning methods and deep learning methods, it can be clearly seen that deep learning is far better than the traditional methods. Some of dataset has been captured in standard situation means the absence of noise so while noise comes in a picture, it might be possible that the performance of an algorithm will be degraded. After surveying hundreds of paper one major limitation was found that many researchers came up with their own dataset which are not available to other researchers so new algorithm development form other researcher cannot test the dataset which is not available publicly. Future direction is hardware development of an algorithm which can help famers to detect and classify diseases.

V. DISCUSSION AND FUTURE SCOPE

We discussed the basics of plant diseases, different methodology of plant disease detection, classification and comparisons of various techniques. In the field of plant agriculture, hundreds of diseases are exist. Among all those diseases we can be classified into three main categories: bacterial, viral, fungal. Fig 1, 2, 3 shows the texture of diseases. Plant disease is a major issue for researcher, in this survey we present the traditional methodology (as shown in Fig. 4) which consist of existing image processing techniques to detect the diseases. How machine learning can be helpful to detect and classify the disease we have shown in Table 1 with comparisons of different researcher's work. Table 2 shows the detail comparisons of image segmentation, feature extraction, classification methods with the accuracy achieved by each researcher. In Table 1 we showed the future research direction given by each researcher. From comparison in Table 1 it can be noticed that the researcher came up with kaggle, plant village and own dataset. In Table 2 we observed that for segmentation mostly researchers used k-means segmentation and Hue Based segmentation, while for classification purpose, researchers used different machine learning classification algorithm like SVM, ANN, Decision Tree Classifier, Random Forest, Decision tree, Naive bayes, PNN, BPNN. The SVM and NN are mostly used for classification and these algorithms produce maximum accuracy as shown in Table 2. Fig. 6 shown the proposed four different approaches to detect and classify the plant diseases. Each of combination approach shown in different color. The comparison of various deep learning techniques is shown in Table 3. The researcher performed experiments on various crops like tomato, maize, apple etc. and came up with plant village dataset consist of thousands of images. From Table 3 we noticed that GoogleNet, Cifar10, Mutichannel CNN, R-CNN, CNN (CaffeNet) models are used to obtained accuracy.

Conflict of Interest. There is no conflict of interests Regarding the publication of this paper.

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.

[11]. Costa, J., Silva, C. and Ribeiro, B., (2019). Hierarchical Deep Learning Approach for Plant Disease Detection. In Iberian Conference on Pattern Recognition and Image Analysis (pp. 383-393). Springer, Cham.

[12]. Chopda, J., Raveshiya, H., Nakum, S., & Nakrani, V. (2018, January). Cotton Crop Disease Detection using Decision Tree Classifier. In *2018 International Conference on Smart City and Emerging Technology (ICSCET)* (pp. 1-5). IEEE.

[13]. da Silva Abade, A., de Almeida, A.P.G. and de Barros Vidal, F., 2019. Plant Diseases Recognition from Digital Images using Multichannel Convolutional Neural Networks.

[14]. de Luna, R. G., Dadios, E. P., & Bandala, A. A. (2018, October). Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition. In TENCON 2018-2018 *IEEE Region 10 Conference* (pp. 1414-1419). IEEE.

[15]. Doh, B., Zhang, D., Shen, Y., Hussain, F., Doh, R. F., &Ayepah, K. (2019, September). Automatic Citrus Fruit Disease Detection by Phenotyping Using Machine Learning. In *2019 25th International Conference on Automation and Computing* (ICAC) (pp. 1-5). IEEE.

[16]. Durmuş, H., Güneş, E. O., &Kırcı, M. (2017, August). Disease detection on the leaves of the tomato plants by using deep learning. In *2017 6th International Conference on Agro-Geoinformatics* (pp. 1-5). IEEE.

[17]. Ferentinos, K.P., 2018. Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture,* 145, pp.311-318.

[18]. Fuentes, A., Yoon, S., Kim, S.C. and Park, D.S., 2017. A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors.

[19]. Francis, J., & Anoop, B. K. (2016, March). Identification of leaf diseases in pepper plants using soft computing techniques. In *2016 conference on emerging devices and smart systems (ICEDSS)* (pp. 168-173). IEEE.

[20]. Fang, Y., & Ramasamy, R. P. (2015). Current and prospective methods for plant disease detection. *Biosensors, 5*(3), 537-561.

[21]. Fadzil, W. N. W. M., Rizam, M. B. S., Jailani, R., & Nooritawati, M. T. (2014). Orchid leaf disease detection using border segmentation techniques. In *2014 IEEE Conference on Systems, Process and Control (ICSPC 2014)* (pp. 168-173). IEEE.
[22]. Geetharamani, G., & Pandian, A. (2019). Identification of plant leaf diseases using a nine-layer deep convolutional neural network. *Computers & Electrical Engineering,* 76, 323-338.
[23]. 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-2014* (pp. 1-6). IEEE.
[24]. Gulhane, V. A., &Kolekar, M. H. (2014, December). Diagnosis of diseases on cotton leaves using principal component analysis classifier. In *2014 Annual IEEE India Conference (INDICON)* (pp. 1-5). IEEE.
[25]. Gröll, K., Graeff, S. and Claupein, W., (2007). Use of Vegetation indices to detect plant diseases. Agrarinformatikim Spannungsfeldzwischen Regionalisierung und globalen Wertschöpfungsketten–Referate der 27. GIL Jahrestagung.
[26]. Gibson, G. J., Otten, W., Filipe, J. A., Cook, A., Marion, G., & Gilligan, C. A. (2006). Bayesian estimation for percolation models of disease spread in plant populations. *Statistics and Computing, 16*(4), 391-402.
[27]. Huang, S., Liu, W., Qi, F. and Yang, K., 2019, August. Development and Validation of a Deep Learning Algorithm for the Recognition of Plant Disease. In *2019 IEEE 21st International Conference on High Performance Computing and Communications; IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS)* (pp. 1951-1957). IEEE.
[28]. Hossain, E., Hossain, M. F., & Rahaman, M. A. (2019, February). A color and texture based approach for the detection and classification of plant leaf disease using KNN classifier. In *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)* (pp. 1-6). IEEE.
[29]. Iqbal, Z., Khan, M. A., Sharif, M., Shah, J. H., urRehman, M. H., & Javed, K. (2018). An automated detection and classification of citrus plant diseases using image processing techniques: A review. *Computers and electronics in agriculture, 153*, 12-32.
[30]. Jaisakthi, S.M., Mirunalini, P. and Thenmozhi, D., 2019, February. Grape Leaf Disease Identification using Machine Learning Techniques. In *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)* (pp. 1-6). IEEE.
[31]. Jhuria, M., Kumar, A., & Borse, R. (2013, December). Image processing for smart farming: Detection of disease and fruit grading. In *2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013)* (pp. 521-526). IEEE.
[32]. Kumari, C. U., Prasad, S. J., & Mounika, G. (2019, March). Leaf Disease Detection: Feature Extraction with K-means clustering and Classification with ANN. In *2019 3rd International Conference on Computing Methodologies and Communication* (ICCMC) (pp. 1095-1098). IEEE.
[33]. Kusumo, B. S., Heryana, A., Mahendra, O., & Pardede, H. F. (2018). Machine learning-based for automatic detection of corn-plant diseases using image processing. In *2018 International Conference on Computer, Control, Informatics and its Applications (IC3INA)* (pp. 93-97). IEEE.
[34]. Khirade, S. D., & Patil, A. B. (2015). Plant disease detection using image processing. In *2015 International conference on computing communication control and automation* (pp. 768-771). IEEE.
[35]. Khan, J. F., Adhami, R. R., & Bhuiyan, S. M. (2008). Color image segmentation utilizing a customized Gabor filter. *In IEEE SoutheastCon 2008* (pp. 539-544). IEEE.
[36]. Loey, M., ElSawy, A., & Afify, M. (2020). Deep Learning in Plant Diseases Detection for Agricultural Crops: A Survey. *International Journal of Service Science, Management, Engineering, and Technology (IJSSMET), 11*(2), 41-58.
[37]. Le, T. L., Tran, D. T., & Hoang, V. N. (2014, December). Fully automatic leaf-based plant identification, application for Vietnamese medicinal plant search. In Proceedings of the fifth symposium on information and communication technology (pp. 146-154).
[38]. Maniyath, S.R., Vinod, P.V., Niveditha, M., Pooja, R., Shashank, N. and Hebbar, R., 2018, April. Plant disease detection using machine learning. In 2018 International Conference on Design Innovations for 3Cs *Compute Communicate Control (ICDI3C)* (pp. 41-45). IEEE.
[39]. Molina, J. F., Gil, R., Bojacá, C., Gómez, F., & Franco, H. (2014). Automatic detection of early blight infection on tomato crops using a color based classification strategy. In 2014 XIX Symposium on Image, *Signal Processing and Artificial Vision* (pp. 1-5). IEEE.
[40]. Mewes, T., Waske, B., Franke, J., & Menz, G. (2010, June). Derivation of stress severities in wheat from hyperspectral data using support vector regression. In 2010 2nd Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (pp. 1-4). IEEE.
[41]. Meunkaewjinda, A., Kumsawat, P., Attakitmongcol, K., & Srikaew, A. (2008). Grape leaf disease detection from color imagery using hybrid intelligent system. In 2008 5th international conference on electrical engineering/electronics, computer, telecommunications and information technology (Vol. *1*, pp. 513-516). IEEE.
[42]. Moshou, D., Bravo, C., Oberti, R., West, J., Bodria, L., McCartney, A., & Ramon, H. (2005). Plant disease detection based on data fusion of hyper-spectral and multi-spectral fluorescence imaging using Kohonen maps. *Real-Time Imaging, 11*(2), 75-83.
[43]. Nazki, H., Yoon, S., Fuentes, A., & Park, D. S. (2020). Unsupervised image translation using adversarial networks for improved plant disease recognition. *Computers and Electronics in Agriculture, 168*, 105117.
[44]. Nema, S., & Dixit, A. (2018). Wheat Leaf Detection and Prevention Using Support Vector Machine. In *2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET)* (pp. 1-5). IEEE.
[45]. Orillo, J. W., Cruz, J. D., Agapito, L., Satimbre, P. J., & Valenzuela, I. (2014, November). Identification of diseases in rice plant (oryza sativa) using back propagation Artificial Neural Network. In *2014 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)* (pp. 1-6). IEEE.

[46]. Pourazar, H., Samadzadegan, F., & DadrassJ avan, F. (2019). Aerial multispectral imagery for plant disease detection: radiometric calibration necessity assessment. *European Journal of Remote Sensing, 52*(sup3), 17-31.
[47]. Prajapati, H. B., Shah, J. P., & Dabhi, V. K. (2017). Detection and classification of rice plant diseases. *Intelligent Decision Technologies, 11*(3), 357-373.
[48]. Pantazi, X. E., Moshou, D., Tamouridou, A. A., &Kasderidis, S. (2016, September). Leaf disease recognition in vine plants based on local binary patterns and one class support vector machines. In *IFIP International Conference on Artificial Intelligence Applications and Innovations* (pp. 319-327). Springer, Cham.
[49]. Petrellis, N. (2017, May). A smart phone image processing application for plant disease diagnosis. In *2017 6th International Conference on Modern Circuits and Systems Technologies (MOCAST)* (pp. 1-4). IEEE.
[50]. Pujari, J. D., Yakkundimath, R., & Byadgi, A. S. (2015). Image processing based detection of fungal diseases in plants. *Procedia Computer Science*, *46*, 1802-1808.
[51]. Phadikar, S., &Sil, J. (2008, December). Rice disease identification using pattern recognition techniques. In *2008 11th International Conference on Computer and Information Technology* (pp. 420-423). IEEE.
[52]. Rezende, V.C., Costa, M., Santos, A. and de Oliveira, R.C., 2019, October. Image Processing with Convolutional Neural Networks for Classification of Plant Diseases. In *2019 8th Brazilian Conference on Intelligent Systems (BRACIS)* (pp. 705-710). IEEE.
[53]. Ramesh, S. (2018, September). Rice Blast Disease Detection and Classification Using Machine Learning Algorithm. In *2018 2nd International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE)* (pp. 255-259). IEEE.
[54]. Reza, Z. N., Nuzhat, F., Mahsa, N. A., & Ali, M. H. (2016, September). Detecting jute plant disease using image processing and machine learning. In *2016 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT)* (pp. 1-6). IEEE.
[55]. Rothe, P. R., & Kshirsagar, R. V. (2015, January). Cotton leaf disease identification using pattern recognition techniques. In *2015 International Conference on Pervasive Computing (ICPC)* (pp. 1-6). IEEE.
[56]. 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) 2014* (pp. 93-98). IEEE.
[57]. Singh, D., Jain, N., Jain, P., Kayal, P., Kumawat, S., & Batra, N. (2020). PlantDoc: a dataset for visual plant disease detection. In *Proceedings of the 7th ACM IKDD CoDS and 25th COMAD* (pp. 249-253).
[58]. Sehgal, A., &Mathur, S. (2019, June). Plant Disease Classification Using SOFT COMPUTING Supervised Machine Learning. In *2019 3rd International conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 75-80). IEEE.
[59]. Shah, N., & Jain, S. (2019, February). Detection of Disease in Cotton Leaf using Artificial Neural Network. In *2019 Amity International Conference on Artificial Intelligence (AICAI)* (pp. 473-476). IEEE.
[60]. Saradhambal, G., Dhivya, R., Latha, S. and Rajesh, R., 2018. Plant disease detection and its solution using image classification*. International Journal of Pure and Applied Mathematics, 119*(14), pp.879-884.
[61]. Sun, G., Jia, X., & Geng, T. (2018). Plant diseases recognition based on image processing technology. *Journal of Electrical and Computer Engineering*, *2018*.
[62]. Siricharoen, P., Scotney, B., Morrow, P., & Parr, G. (2016, September). Texture and shape attribute selection for plant disease monitoring in a mobile cloud-based environment. In *2016 IEEE International Conference on Image Processing (ICIP)* (pp. 489-493). IEEE.
[63]. Sannakki, S. S., Rajpurohit, V. S., Nargund, V. B., & Kulkarni, P. (2013, July). Diagnosis and classification of grape leaf diseases using neural networks. In *2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT)* (pp. 1-5). IEEE.
[64]. Schikora, M., Schikora, A., Kogel, K. H., Koch, W., &Cremers, D. (2010). Probabilistic classification of disease symptoms caused by Salmonella on Arabidopsis plants. *INFORMATIK 2010. Service Science–NeuePerspektivenfür die Informatik. Band 2*.
[65]. Thomas, S., Kuska, M. T., Bohnenkamp, D., Brugger, A., Alisaac, E., Wahabzada, M., & Mahlein, A. K. (2018). Benefits of hyperspectral imaging for plant disease detection and plant protection: a technical perspective. *Journal of Plant Diseases and Protection*, *125*(1), 5-20.
[66]. 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.
[67]. Tulshan, A.S. and Raul, N., 2019, July. Plant Leaf Disease Detection using Machine Learning. In *2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)* (pp. 1-6). IEEE.
[68]. Tete, T.N. and Kamlu, S., 2017, September. Plant disease detection using different algorithms. In *Proceedings of the Second International Conference on Research in Intelligent and Computing in Engineering, 10,* 103-106).
[69]. Thangadurai, K., & Padmavathi, K. (2014, February). Computer visionimage enhancement for plant leaves disease detection. In *2014 world congress on computing and communication technologies* (pp. 173-175). IEEE.
[70]. Tilva, V., Patel, J., & Bhatt, C. (2013). Weather based plant diseases forecasting using fuzzy logic. In *2013 Nirma University International Conference on Engineering (NUiCONE)* (pp. 1-5). IEEE.
[71]. Tuhid, N. H., Abdullah, N. E., Khairi, N. M., Saaid, M. F., Shahrizam, M. S. B., & Hashim, H. (2012). A statistical approach for orchid disease identification using RGB color. In *2012 IEEE Control and System Graduate Research Colloquium* (pp. 382-385). IEEE.
[72]. Wang, G., Sun, Y., & Wang, J. (2017). Automatic image-based plant disease severity estimation using deep learning. *Computational intelligence and neuroscience*.
[73]. Wang, H., Li, G., Ma, Z., & Li, X. (2012, October). Image recognition of plant diseases based on backpropagation networks. In *2012 5th International*

Congress on Image and Signal Processing (pp. 894-900). IEEE.
[74]. Yadav, R., Rana, Y.K. and Nagpal, S., 2018, November. Plant Leaf Disease Detection and Classification Using Particle Swarm Optimization. In International Conference on Machine Learning for Networking (pp. 294-306). Springer, Cham.
[75]. Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2018). Identification of maize leaf diseases using improved deep convolutional neural networks. *IEEE Access*, *6*, 30370-30377.
[76]. Zellnig, G., Möstl, S., & Zechmann, B. (2013). Rapid immunohistochemical diagnosis of tobacco mosaic virus disease by microwave-assisted plant sample preparation. *Microscopy*, *62*(5), 547-553.

How to cite this article: Jayswal, H. S. and Chaudhari, J. P. (2020). Plant Leaf Disease Detection and Classification using Conventional Machine Learning and Deep Learning. *International Journal on Emerging Technologies*, *11*(3): 1094–1102.

View publication stats