AUTHORS PROFILE

Akruti Naik: Assistant Professor,

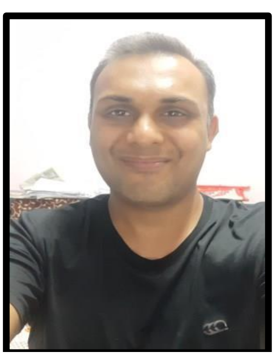
DUIAS And DSIM&C, Department Of Computer Science, MCA, (Web Technology), Valsad –Gujarat.

Email: akrutinaikdesai@gmail.com

Dr. Hetal R. Thaker: Associate Professor, Faculty of Science, Department of M.C.A., Atmiya University, M.C.A. (Gold Medalist), Ph.D. (Computer Science), IBM DB2 and RAD Certified Developer, Rajkot - Gujarat.

Email: hrt.research@gmail.com

ORCID ID: https://orcid.org/0000-0002-1327-003X



Dr. Dhaval Vyas: Assistant Professor, DUIAS And DSIM&C, Department Of Microbiology, Awarded D.S Kothari post-doctoral fellow by UGC in 2012. Specialization in image processing and Hyperspectral remote sensing.

Email: vyasdhaval84@gmail.com

A SURVEY ON VARIOUS IMAGE PROCESSING TECHNIQUES AND MACHINE LEARNING MODELS TO DETECT, QUANTIFY AND CLASSIFY FOLIAR PLANT DISEASE

Akruti Naik *[a], Dr. Hetal Thaker [b], Dhaval Vyas [a]
[a] Dolat-Usha Institute of Applied Sciences, Valsad
[b] Associate Professor, Department of Computer Application, Atmiya University, Rajkot
*Corresponding Author
akrutinaikdesai@gmail.com

ABSTRACT

Agriculture is one of the significant factors that drive India's economy. A decrease in the yield of agricultural food crops due to plant diseases results in great loss to the economy of the developing country. Detection of plant disease at an early stage will decrease the chance of loss on the overall economy. Nowadays, ICT (Information And Communication Technology) plays a major role in all sectors including agriculture. Classical agriculture has been reformed using ICT. Farmers are getting the correct information on time. ICT is necessary for agriculture, it may increase productivity using data generation, storage, and analysis. This paper presents a survey of various image processing techniques and machine learning tools to detect, quantify, and classify plant diseases. Methods that explore visible symptoms in leaves and stems were considered. This paper aims on exploring this wide research area and possible scope of further researcher there by looking at various aspects of review such as accuracy, image processing techniques, machine learning models, and plants on which work has been carried out. This survey is likely to be useful to researchers working both on disease detection on the leaf and pattern recognition, providing a quick overview of this important field of research.

Keywords: Image Processing, Plant Disease, K-Means, Neural Network, SVM.

1. INTRODUCTION

Food security is a major concern in modern society. Plant disease is greatly affecting the yield of agricultural crops and it is an immense threat to food security. Early identification of plant disease can decrease the effect of disease on crop yield. Agriculture has become much more than simply a means to feed ever-growing populations. Plants have become an important source of energy, and are a fundamental piece in the puzzle to solve the problem of global warming (Barbedo, 2013). Several diseases distress plants with the latent to cause devastating economical, social, and ecological losses. Therefore, detecting diseases in an accurate and timely way is the most important task. In tropical countries like India, yields of agricultural crops are immensely affected by various plant diseases. Early identification of these diseases can be useful to abolish the effect of disease on crop yield. Empirical techniques of identification are time consuming and lengthy. It is noteworthy that most plant diseases produce different symptoms on the surface of the leaves. Most diseases, however, generate some kind of manifestation in the visible spectrum. In the vast majority of the cases, the diagnosis, or at least a first guess about the disease, is performed visually by humans. Farmers can take and upload an image using smartphones. Trained raters may be efficient in recognizing and quantifying diseases, however, they have associated some disadvantages that may harm the efforts in many cases (Barbedo, 2013). (Bock CH, 2010) et al. list some of those disadvantages. However, these symptoms can be identified using various digital image analysis techniques. Image analysis techniques can be useful to resolve this problem. A relationship between digital numbers in various pixels can be identified from the image. Pixel-wise classification techniques can be applied to identify disease symptoms on the leaves of the plant.

2. LITERATURE REVIEW

Methods are exploring visual cues present in almost all of those parts, like roots (Smith SE, 1991), kernels (Ahmad IS, 1999), fruits (Aleixos N, 2002) (Corkidi G, 2005) (López-García F, 2010), stems and leaves. However, the present work concentrates, particularly on plant leaves.
Pujari (2013) et al. have projected statistical tool for sensing and classifying fungal disease. The classification is constructed on infection severity. Images of fruits affected by diverse fungal infection signs are collected and characterized based on infection severity as partly affected, soberly affected, harshly affected, and standard. (M. Malathi, 2015) et al. provided a review of plant foliage disease recognition using image processing methods. With the help of programmed image processing methods that can sense diseased foliage using pigment data of leaves. The technique projected by Sena DG Jr (2003) et al. aims to distinguish amongst maize plants affected by fall armyworm from healthy ones using digital images. They separated their procedure into two main stages: image processing and image analysis. In the image processing stage, the image is altered to a greyscale, threshold, and sieved to eliminate false objects. In the image analysis stage, the entire image is separated into 12 blocks. Slabs whose foliage area is fewer than 5% of the total area are discarded. For each residual block, the number of linked objects, representing the unhealthy regions, is counted. The plant is considered infected if this number is above a threshold, which, after empirical evaluation, was set to ten. The method proposed by Tucker CC (1997) et al. objects to enumerate and recognize infections in sunflower and oat foliage. The first step of the system is a separation whose threshold differs rendering to the disease being considered. The subsequent pixels are associated with gatherings, representing the unhealthy regions. Martin DP (1998) et al. suggested a technique to enumerate the indications caused by the maize streak virus. The scheme projected by Skaloudova B (2006) et al. measures the mutilation produced in the foliage by spider mites. The final assessment is given by the ratio amongst the quantities of pixels in affected regions divided by the total amount of pixels of the leaf. However, most of the fruitful study is focused on three Methods K – Mean, Neural Networks, and Support Vector Machines. Therefore, in the present study, we tried to review these three methods in detail.

3. K – Mean

K-Means unsupervised classification calculates initial class means evenly distributed in the data space then iteratively clusters the pixels into the nearest class using a minimum distance technique. Each iteration recalculates class means and reclassifies pixels concerning the new means. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached.

3.1 K-Means Clustering

There are multiple ways to cluster the data but the K-Means algorithm is the most used algorithm. Which tries to improve the intergroup similarity while keeping the groups as far as possible from each other.
Basically, K-Means runs on distance calculations, which again uses "Euclidean Distance" for this purpose. Euclidean distance calculates the distance between two given points using the following formula:

$$\text{Euclidean Distance} = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2}$$

The above formula captures the distance in 2-Dimensional space but the same is applicable in multi-dimensional space as well with the increase in the number of terms getting added. "K" in K-Means represents the number of clusters in which we want our data to divide. The basic restriction for the K-Means algorithm is that your data should be continuous in nature. It won't work if data is categorical in nature (ENVI, 2009) (Unscrambler Users Guide, 1997).

3.2. Review of K-Means method

H. Al-Hiary (2011) et al. developed a software solution for instinctive recognition and classification of plant leaf diseases. The dispensation scheme contains four main stages. The applications of K-means clustering and Neural Networks (NNs) were articulated for the classification of diseases on plant leaves. Al Bashish D (2010) et al. suggested an image-processing-based attitude, used for leaf and stem disease recognition using K – Mean classification. Wang et al., (2012) concluded that K – Mean classification is better for image recognition of two kinds of wheat and grape diseases. Narmadha and Arulvadivu (2017) Sensed Paddy Leaf Disease Indications by means of Image Processing and K-means techniques. Suresha et al., (2017) attained an accuracy of 77 % for the detection of Diseases in Paddy Leaves with the help of a kNN Classifier. Dr. Sridhathan et al. (2018) established an algorithm for recognition of disease using image processing. For color separation K – Mean is suitable while GLCM classification achieved 98.27% accuracy.

One can infer concerning K-Mean from the above literature review that this classification method performs well with less complex classes. The application of K-mean to separate less complex variables, features, or classes always worked well. It is noteworthy that the K-means method is active in constructing decent clustering results for many applied applications. However, k-means has trouble clustering data where clusters are of fluctuating sizes and compactness. Moreover, the K-mean classification mechanism yielded comparatively less accuracy (<80 %).

4. <u>Neural networks</u>

Use Neural Net to apply a layered feed-forward neural network classification technique. The Neural Net technique uses standard backpropagation for supervised learning. You can select the number of hidden layers to use and you can choose between a logistic or hyperbolic activation function. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back-propagated through the network and weight adjustment is made using a recursive method. You can use the Neural Net classification to perform non-linear classification (Figure 1) (ENVI, 2009) (Unscrambler Users Guide, 1997).

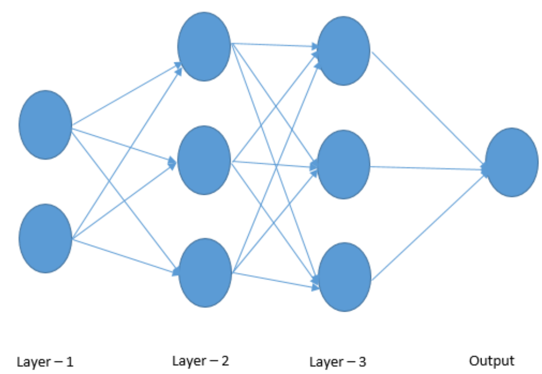


Figure 1: Graphic representation of Neural Network method

4.1 Review of Neural networks method

An initial effort to monitor plant health was supported by Hetzroni et al. (1994). Their scheme tried to recognize iron, zinc, and nitrogen deficits by monitoring lettuce leaves. Those strictures are finally nourished to neural networks and statistical classifiers, which are used to recognize the plant condition. Pydipati et al. (2005) likened two dissimilar methods to sense and classify three types of citrus ailments. The primary method was based on a Mahalanobis minimum distance classifier, using the nearest neighbor value. The second tactic castoff radial basis functions (RBF) neural network classifiers skilled with the backpropagation algorithm. Conferring to the authors, both the classification methods performed alike, by means of the finest of the four subsets, which contained ten hue and saturation texture features. Huang (2007) projected a system to sense and classify three kinds of diseases that affect Phalaenopsis orchid seedlings. Earlier, Linderman (2004) et al. have reported that the neural network is probably more proficient for the classification of minor and complex features.

The ANN classifier was able to classify correctly even those quadrats which are having a lesser percentage of occupancy (Vyas, 2011) et al. Kulkarni and Patil (2012) projected a methodology for detecting plant diseases, using image processing procedures and Artificial Neural Network (ANN). An ANN-based classifier is approved which uses the mixture of color and texture features to distinguish and classify diverse plant diseases. The scheme projected by Abdullah et al. (2007) attempted to discriminate a plant disease of rubber tree leaves, Principal Component Analysis (PCA) is applied straight to the RGB values of a low-resolution image of the leaves. The first two principal components are then nourished to a Multilayer Perceptron (MLP) Neural Network with one hidden layer, whose output reveals if the sample is diseased or not. Singh and Misra, (2017) developed an algorithm for image division method Which is used for automatic detection and classification of plant leaf diseases with the help of Artificial Neural Network, Bayes classifier, Fuzzy Logic, and hybrid algorithms. Hidayatuloh et al. (2018) effectively detected tomato plant disease through its leaf image automatically with an accuracy of identification of 86.92% using Neural Network (CNN).

We can infer that Neural Network works well for complex clustering of variables or classes. Very high accuracy was obtained (>80%) for the classification of various classes with the help of Neural Network. NN worked fared better with the higher complexity of the data set.

5. <u>Support vector machines (SVM)</u>

SVM is a classification method based on statistical learning wherein a function that describes a hyperplane for optimal separation of classes is determined. As the linear function is not always able to model such a separation, data are mapped into a new feature space and a dual representation is used with the data objects represented by their dot product. A kernel function is used to map from the original space to the feature space and can be of many forms, thus providing the ability to handle nonlinear classification cases. The kernels can be viewed as a mapping of nonlinear data to a higher dimensional feature space while providing a computation shortcut by allowing linear algorithms to work with higher dimensional feature space. The support vector is defined as the reduced training data from the kernel. The figure below illustrates the principle of applying a kernel function to achieve separability (Figure 2).

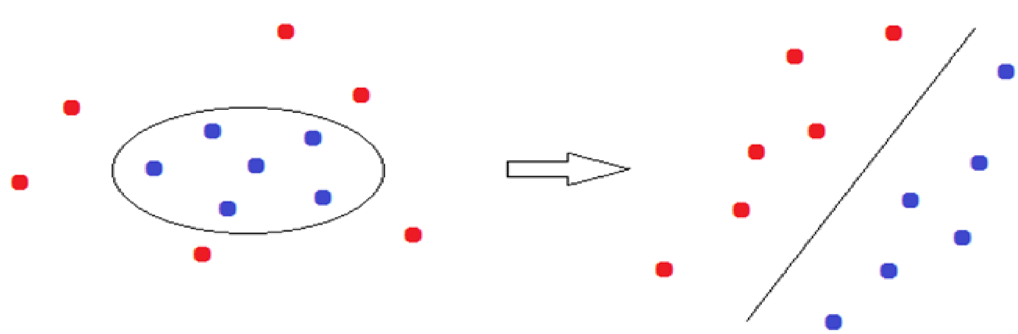


Figure 2: Graphic representation of the SVM method (CAMO unscramble ®)

In this new space, SVM will search for the samples that lie on the marginal amongst the classes, i.e. to find the samples that are ideal for unraveling the classes; these samples are named support vectors. The figure below exemplifies this in that only the samples marked with positive for the two classes are used to produce the rule for classifying new samples (ENVI, 2009) (Unscrambler Users Guide, 1997).

5.1 Review of SVM

Meunkaewjinda et al. (2008) proposed a technique to identify and classify diseases that affect grape-vines. The colors present on the leaves are then clustered by means of an unsupervised and untrained self-organizing map, diseased and healthy regions are then separated by a Support Vector Machine (SVM). Youwen et al. (2008) proposed a technique to recognize two diseases that can appear in cucumber leaves, some color, shape, and texture features are extracted. Those features feed an SVM, which performs the final classification. The authors stated that the results provided by the SVM are far better than those achieved using neural networks. The system proposed by Yao et al. (Yao Q, 2009) aimed to identify and classify three types of diseases that affect rice crops. Color, shape, and texture features are extracted, the latter one from the HSV color space. Finally, the features are submitted to a Support Vector Machine, which performs the final classification. Jian and Wei (2010) proposed a technique to identify three types of cucumber leaf diseases. As in most approaches, the separation between healthy and diseased regions is made by a simple thresholding procedure (Barbedo, 2013). In the following, a variety of color, shape, and texture features are extracted. Those features are submitted to an SVM with Radial Basis Function (RBF) as the kernel, which performs the final classification. Jagadeesh D. Pujari et al. (2013) proposed a technique for quantitative detection and classifying disease on Mango, Pomegranate, and Grape and achieved 76.6% accuracy (ENVI 4.7 User guide ®).

The Support Vector Machine (SVM) is an effective distribution-free classifier that has been extensively used in the current decade for solving various image classification problems. We can infer that SVM achieved moderate accuracy in classifying complex clusters of pixels.

6. Detection

Detection helps to identify whether the plant leaves is affected by some disease or not. There are many image processing techniques and machine learning tools to detect plant leave disease. In the following table, a detailed survey of various research papers is given based on Detection.

Table1: Detailed Survey Of Research Papers based on Detection

AUTHOR	CORE ANALYSIS TOOL	PLANT	ACCURACY
(Sena DG Jr, 2003) et al.	Thresholding	Maize	94.72%
(Pydipati R, 2005) et al.	NN	Citrus Plant	95%
(Abdullah NE, 2007) et al.	Neural networks	Rubber tree	70%
(Story D, 2010) et al.	Dual-segmented regression analysis	Lettuce	N/A
(Wang H, 2012) et al.	K-MEAN	Wheat Plant	97.14%
(R.P.Narmadha, 2017) et al.	K-MEAN	Paddy Plant	N/A
(Akbar Hidayatuloh, 2018) et al.	CNN	Tomato	86.92%

7. Quantification

Quantification helps to quantify the symptoms and measures the damage caused in leaves to identify whether the plant leaves are affected by some disease or not. In the following table, a detailed survey of various research papers is given based on Quantification.

Table 2: Detailed Survey Of Research Papers based on Quantification

AUTHOR	CORE ANALYSIS TOOL	PLANT	ACCURACY
(Lindow SE, 1983) et al.	Thresholding	Sycamore, fern, tomato, buckeye	Better accuracy and precision
(Price TV, 1993) et al.	Thresholding	Coffee	
(Olmstead JW, 2001) et al.	3rd party package	Cherry	N/A
(Skaloudova B, 2006) et al.	Thresholding	Bean	N/A
(Camargo A, 2009) et al.	Thresholding	Banana, maize, soy, alfalfa, cotton	69.0%
(Pagola M, 2009) et al.	Color analysis	Barley	N/A
(Macedo-Cruz A, 2011) et al.	Thresholding	Oat	92%
(Martin DP, 1998) et al.	Thresholding		96.4%
(Pang J, 2011) et al.	Region growing	Maize	92%
(Patil SB, 2011) et al.	Thresholding	Sugar cane	98.60%
(Lloret J, 2011) et al.	Thresholding		N/A
(Peressotti E, 2011) et al.	3rd party package	Grapes	N/A
(Sannakki SS, 2011) et al.	Fuzzy logic	Pomegranate	Accurate & Satisfactory
(Coninck BMA, 2012) et al.	3rd party package	Sugar beet	N/A
(Contreras-Medina LM, 2012) et al.	Color analysis	Pumpkin, pepper, bean	N/A
(Jagadeesh D. Pujari, 2013) et al.	Thresholding	Mango, Pomegranate, Grape	94.085%

8. Classification

Classification helps to categorize the data into various classes like disease or severity wise. The detailed survey of research papers based on classification is given in the following table.

Table3: Detailed Survey Of Research Papers based on Classification

AUTHOR	CORE ANALYSIS TOOL	PLANT	ACCURACY
(Pydipati R, 2005) et al.	Neural networks	Citrus	95%
(Pydipati, 2006) et al.	Self-organizing maps	Orange	96%
(KY, 2007) et al.	Neural networks	Orchid	89.6%
(Camargo, 2009) et al.	SVM	Cotton	90%
(Anthonys G, 2009) et al.	Membership function		70%
(Kawcher Ahmed, 2019) et al.	KNN		97%
(Kurniawati NN, 2009) et al.	Feature-based rules		94.7%
(Kurniawati NN, 2009) et al.	Feature-based rules		87.5%
(Rakesh Kaundal, 2006) et al.	SVM	Rice	97.2%
(Al Bashish D, 2010) et al.	Neural networks	N/A	93%
(Kai S, 2011) et al.	Neural networks		98%
(V. N. T. Le, 2019) et al.	SVM	Maize	91.85%
(Suresha M, 2017) et al.	KNN		76.59%
(Kholis Majid, 2013) et al.	Fuzzy Logic and PNN	Padddy Plant	91.46%
(Dr. Sridhathan C, 2018) et al.	K-Mean	N/A	98.27%

(G. Dhingra, Mar-2019) et al.	SVM	Basil	98%
(G. Saleem, Feb - 2019) et al.	KNN	N/A	96%
(Y. Sun, 2019) et al.	SVM	Tea Plant	98.5%
(Sanjeev S Sannakki, 2013) et al.	NN	Grape	100% for Downy affected region and Powdery affected region
(S.Sivasakthi, 2020)	SVM & ANN	Greenhouse Crop	92% (SVM) 87% (ANN)

9. Comparative Analysis of Various Methodologies

The following table compares various methods represented in the reviewed papers. The comparison shows that SVM performs better than other methods and provide better accuracy.

AUTHOR	CORE ANALYSIS TOOL	Task	ACCURACY
Plant : Rice / Paddy Plants			
(Kholis Majid, 2013) et al.	Fuzzy Logic and PNN		91.46%
(Suresha M, 2017) et al.	KNN		76.59%
(Rakesh Kaundal, 2006) et al.	SVM		97.2%
(Kawcher Ahmed, 2019) et al.	KNN		97%
(Kurniawati NN, 2009)	Feature-based rules		94.7%
(Kurniawati NN, 2009)	Feature-based rules	Classification	87.5%
Greenhouse Crops			
(S.Sivasakthi, 2020)	SVM & ANN	Classification	92% (SVM) 87% (ANN)
Maize			
(Martin DP, 1998)	Thresholding	Quantification	96.4%
(Pang J, 2011)	Region growing	Quantification	92%

10. CONCLUSION:

The extensive diversity of applications on the subject of identifying objects in digital images makes it hard for someone to outlook all possible treasured ideas present in the literature. In this context, this paper tried to present a short review on the subject, pointing at being a starting point for those researching the issue. The present survey paper gives a squat survey on leaf disease detection and classification techniques using image processing. There are many methods in automated or computer vision for disease detection and classification but still, there is a lack of this research topic. All diseases cannot be identified using a single method. From the study of the above classification techniques, we come up with the following conclusion.

The present study concludes, that the K-Mean classification method performs well with less complex classes. However, the K-mean classification mechanism yielded comparatively less accuracy (<80 %). Moreover, Neural Network works well for complex clustering of variables or classes. Very high accuracy was obtained (>80%) for the classification of various classes with the help of Neural Network. NN worked fared better with the higher complexity of the data set. It is noteworthy that The Support Vector Machine (SVM) is an operative distribution-free classifier that has been widely used and SVM achieved moderate accuracy in classifying composite clusters of pixels.

Different authors used different algorithms for accurate detection of diseases. The advantage of using the image processing method is that the leaf diseases can be identified at its early stage. For improving the recognition rate, most researchers used artificial neural networks and classifiers like Bayes classifier, Fuzzy Logic, K-means clustering, etc.

References

Abdullah NE, R. A. (2007). Classification of rubber tree leaf diseases using multilayer perceptron neural network. *5th student conference on research and development. IEEE.* Selangor.

Ahmad IS, R. J. (1999). Color classifier for symptomatic soyabean seeds using image processing. *Plant Disease, 83*(4), 320-327.

Akbar Hidayatuloh, M. N. (October 22-25, 2018). Identification of Tomato Plant Diseases by Leaf Image Using Squeezenet Model. *International Conference on Information Technology Systems and Innovation (ICITSI) Bandung - Padang.*

Al Bashish D, B. M.-A. (2010). A framework for detection and classification of plant leaf and stem diseases. *international conference on signal and image processing. IEEE, Chennai*, 113–118.

Aleixos N, B. J. (2002). Multispectral inspection of citrus in real time using machine vision and digital signal processors. *Comput Electron Agric, 33*(2), 121-137.

Anand.H.Kulkarni1, A. P. (SEP/OCT – 2012). Applying image processing technique to detect plant diseases. *International Journal of Modern Engineering Research* .

Anthonys G, W. N. (2009). An image recognition system for crop disease identification of paddy fields in Sri Lanka. *International Conference on Industrial and Information Systems (ICIIS). IEEE.* Sri Lanka.

Barbedo, J. G. (2013). Digital image processing techniques for detecting, quantifying and classifying plant diseases. *SpringerPlus, 2*(1), 660.

Bock CH, P. G. (2010). Plant disease saverity estimated visually, by digital photography and image analysis and by hyperspectral imaging. *Critical Rev Plant Science, 29*(2), 59-107.

Boese BL, C. P. (2008). Digital image analysis of Zostera marina leaf injury. . *Aquat Bot, 88*, 87–90.

Boissard P, M. V. (2008). A cognitive vision approach to early pest detection in greenhouse crops. *Comput Electron Agric, 62*(2), 81-93.

Camargo A, S. J. (2009). An image-processing based algorithm to automatically identify plant disease visual symptoms. *Biosyst Eng, 102*, 9-21.

Camargo, A. S. (2009). Image pattern classification for the identification of disease causing agents in plants. *Comput Electron Agric, 66*(2), 121–125.

Coninck BMA, A. O. (2012). The use of digital image analysis and real-time PCR fine-tunes bioassays for quantification of Cercospora leaf spot disease in sugar beet breeding. *Plant PathoL, 61*, 76–84.

Contreras-Medina LM, O.-R. R.-P.-T.-G.-A. (2012). Smart sensor for real-time quantification of common symptoms present in unhealthy plants. . *Sensors (Basel, Switzerland), 12*, 784–805.

Corkidi G, B.-R. K.-C. (2005). Assessing mango anthracnose using a new three-dimensional image-analysis technique to quantify lesions on fuit. *Plant Pathol, 55*(2), 250-257.

Dr. Sridhathan C, D. M. (2018). Plant Infection Detection Using Image Processing. *Interntional Journal of Modern Engineering Research (IJMER), 8*(7), 13-16.

ENVI. (2009). ENVI 4.7. User Guide.

G. Dhingra, V. K. (Mar-2019). A novel computer vision based neutrosophic approach for leaf disease identification and classification. *Measurement, 135*, 782-794.

G. Saleem, M. A. (Feb - 2019). Automated analysis of visual leaf shape features for plant classification. *Comput. Electron. Agricult., 157*, 270-280.

Goodwin PH, H. T. (2010). Quantification of fungal infection of leaves with digital images and Scion Image software. . *Methods Mol Biol, 638*, 125–135.

H. Al-Hiary, S. B.-A. (March 2011). Fast and Accurate Detection and Classification of Plant Diseases. . *International Journal of Computer Applications (0975 – 8887), 17*(1).

Hairuddin MA, T. N. (2011). Overview of image processing approach for nutrient deficiencies detection in Elaeis Guineensis. *IEEE international conference on system engineering and technology. IEEE.* Shah Alam.

Hetzroni A, M. G. (1994). Machine vision monitoring of plant health. *Adv Space Res, 14*(11), 203–212.

Jagadeesh D. Pujari, R. A. (2013, Dec). Statistical Methods for Quantitatively Detecting Fungal Disease from Fruits. *Images International Journal of Intelligent Systems and Applications in Engineering*.

Jagadeesh D. Pujari, R. A. (Dec- 2013). Statistical Methods for Quantitatively Detecting Fungal Disease from Fruits' Images. *International Journal of Intelligent Systems and Applications in Engineering, 1*(4), 60-67.

Jagadeesh D. Pujari, R. A. (Dec- 2013). Statistical Methods for Quantitatively Detecting Fungal Disease from Fruits' Images . *International Journal of Intelligent Systems and Applications in Engineering* .

Jian Z, W. Z. (2010). Support vector machine for recognition of cucumber leaf diseases. *2nd international conference on advanced computer control. IEEE.* Shenyang.

Kai S, Z. L. (2011). A research of maize disease image recognition of corn based on BP networks. *third international conference on measuring technology and mechatronics automation. IEEE.* Shangshai.

Kawcher Ahmed, T. R. (2019). Rice leaf disease detection using machine learning techniques. *International Conference on Sustainable Technologies for Industry 4.0 (STI), IEEE,* (pp. 1-5). Dhaka, Bangladesh: IEEE.

Kholis Majid, Y. H. (28-29 Sep, 2013). "I-PEDIA: Mobile Application for Paddy Disease Identification using Fuzzy Entropy and Probabilistic Neural Network". *ICACSIS* (pp. 403-406). IEEE.

Kurniawati NN, A. S. (2009). Texture analysis for diagnosing paddy disease. *International conference on electrical engineering and informatics. IEEE.* Selangor.

Kurniawati NN, A. S. (2009). Investigation on image processing techniques for diagnosing paddy diseases. *international conference of soft computing and pattern recognition. IEEE*, (pp. 272–277). Malacca.

KY, H. (2007). Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features. *Comput Electron Agric , 57*, 3–11.

KY, H. (2007). Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features. . *Comput Electron Agric, 57*, 3–11.

Linderman, M. L. (2004). Using artificial neural networks to map the spatial distribution of under storey bamboo from remote sensing data. *International Journal of Remote Sensing, 25*, 1685–1700.

Lindow SE, W. R. (1983). Quantification of foliar plant disease symptoms by microcomputer-digitized video image analysis. *Phytopathology , 73*(4), 520–524.

Lloret J, B. I. (2011). A wireless sensor network for vineyard monitoring that uses image processing. *Sensors, 11*(6), 6165–6196.

López-García F, A.-G. G. (2010). Automatic detection of skin defects in citrus fruits using a multivariate image analysis approach. *Comput Electron Agric, 71*(2), 189–197.

M.Malathi, K. (Dec – 2015). A survey on plant leaf disease detection using image processing technique. *International Journal of engineering and technology (IRJET – Dec – 2015)*.

Macedo-Cruz A, P. G.-R. (2011). Digital image sensor-based assessment of the status of oat (Avena sativa L.) crops after frost damage. *Sensors , 11*(6), 6015–6036.

Martin DP, R. E. (1998). Microcomputer-based quantification of maize streak virus symptoms in zea mays. *Phytopathology, 88*(5), 422–427.

Meunkaewjinda A, K. P. (2008). Grape leaf disease detection from color imagery using hybrid intelligent system. *5th international conference on electrical engineering/electronics, computer, telecommunications and information technology. IEEE.* Krabi.

Moya EA, B. L. (2005). Assessment of the disease severity of squash powdery mildew through visual analysis, digital image analysis and validation of these methodologies. *Crop Protect, 24*(9), 785–789.

Olmstead JW, L. G. (2001). Assessment of severity of powdery mildew infection of sweet cherry leaves by digital image analysis. *Hortscience, 36*, 107–111.

Pagola M, O. R.-T. (2009). New method to assess barley nitrogen nutrition status based on image colour analysis. *Comput Electron Agric, 65*(2), 213-218.

Pang J, B. Z. (2011). Automatic segmentation of crop leaf spot disease images by integrating local threshold and seeded region growing. *international conference on image analysis and signal processing. IEEE.* Hubei.

Patil SB, B. S. (2011). Leaf disease severity measyrement using image processing. *Int J Eng Technol, 3*(5), 297-301.

Peressotti E, D. E. (2011). A semi-automatic non-destructive method to quantify grapevine downy mildew sporulation. *J Microbiol Methods , 84*(2), 265–271.

Phadikar S, S. J. (2008). Rice disease identification using pattern recognition techniques. *11th International conference on Computer and information technology. IEEE.* Khulna.

Price TV, G. R. (1993). A comparison of visual and digital image-processing methods in quantifying the severity of coffee leaf rust (Hemileia vastatrix). *Aust J Exp Agric, 33*, 97–101.

Pugoy RADL, M. V. (2011). Automated rice leaf disease detection using color image analysis. *international conference on digital image processing, volume 8009. SPIE.* Chengdu.

Pydipati R, B. T. (2005). Statistical and neural network classifiers for citrus disease detection using machine vision. *Trans ASAE , 48*(5), 2007–2014.

Pydipati, R. B. (2006). Identification of citrus disease using color texture features and discriminant analysis. *Comput Electron Agric , 52*(1-2), 49-59.

R.P.Narmadha, G. (Jan. 05 – 07, 2017). Detection and Measurement of Paddy Leaf Disease Symptoms using Image Processing. *International Conference on Computer Communication and Informatics (ICCCI -2017).* Coimbatore, INDIA.

R.P.Narmadha, G. (Jan. 05 – 07, 2017). Detection and Measurement of Paddy Leaf Disease Symptoms using Image Processing. . *International Conference on Computer Communication and Informatics (ICCCI -2017), Coimbatore, INDIA*.

Rakesh Kaundal, A. S. (2006). Machine learning technique in disease forecasting: a case study on rice blast prediction. *BMC Bioinformatics*.

S.Sivasakthi, M. (n.d.). PLANT LEAF DISEASE IDENTIFICATION USING IMAGE PROCESSING AND SVM, ANN CLASSIFIER METHODS. *International Conference on Artificial Intelligence and Machine learning.* Journal of Analysis and Computation (JAC).

Sanjeev S Sannakki, V. S. (Jul 4-6, 2013). Diagnosis and Classification of Grape Leaf Diseases using Neural Networks. *ICCCNT.* Tiruchengode, India.

Sannakki SS, R. V. (2011). Leaf disease grading by machine vision and fuzzy logic. *Int J , 2*(5), 1709–1716.

Sanyal P, B. U. (2007). Color texture analysis of rice leaves diagnosing deficiency in the balance of mineral levels towards improvement of crop productivity. . *10th International Conference on Information Technology (ICIT 2007). IEEE.* Orissa.

Sanyal P, P. S. (2008). Pattern recognition method to detect two diseases in rice plants. *Imaging Sci J, 56(6)*(7).

Sekulska-Nalewajko J, G. J. (11-14 May 2011). A semi-automatic method for the discrimination of diseased regions in detached leaf images using fuzzy c-means clustering. *MEMSTECH'2011*, (pp. 172-175). Polyana-Svalyava (Zakarpattaya), UKRAINE.

Sena DG Jr, P. F. (2003). Fall armyworm damaged maize plant identification using digital images. *Biosyst Eng , 85*(4), 449–454.

Skaloudova B, K. V. (2006). Computer-assisted estimation of leaf damage caused by spider mites. *Comput Electron Agric, 53*(2), 81–91.

Smith SE, D. S. (1991). Quantification of active vascular-arbuscular mycorrhizal infection using image analysis and other techniques. *Australian journal of plant physiology, 18*(6), 637-648.

Story D, K. M. (2010). Lettuce calcium deficiency detection with machine vision computed plant features in controlled environment. *Computer and electronics in agriculture, 74*, 238-243.

Suresha M, S. K. (2017). Recognition of diseases in paddy leaves using KNN classifier. . *2017 2nd International Conference for Convergence in Technology (I2CT)*.

Tucker CC, C. S. (1997). Quantitative assessment of lesion characteristics and disease severity using digital image processing. . *J Phytopathol, 145*(7), 273–278.

Unscrambler Users Guide, v. 6. (1997). Programme Package for multivariate Calibration. Trondheim, Norway: Camo, A. S. A. .

V. N. T. Le, B. A. (2019). Effective plant discrimination based on the combination of local binary pattern operators and multi-class support vector machine methods. *Inf. Process. Agricult., 6*, 116-131.

Vijai Singh, A. M. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. . *INFORMATION PROCESSING IN AGRICULTURE, 4*, 41-49.

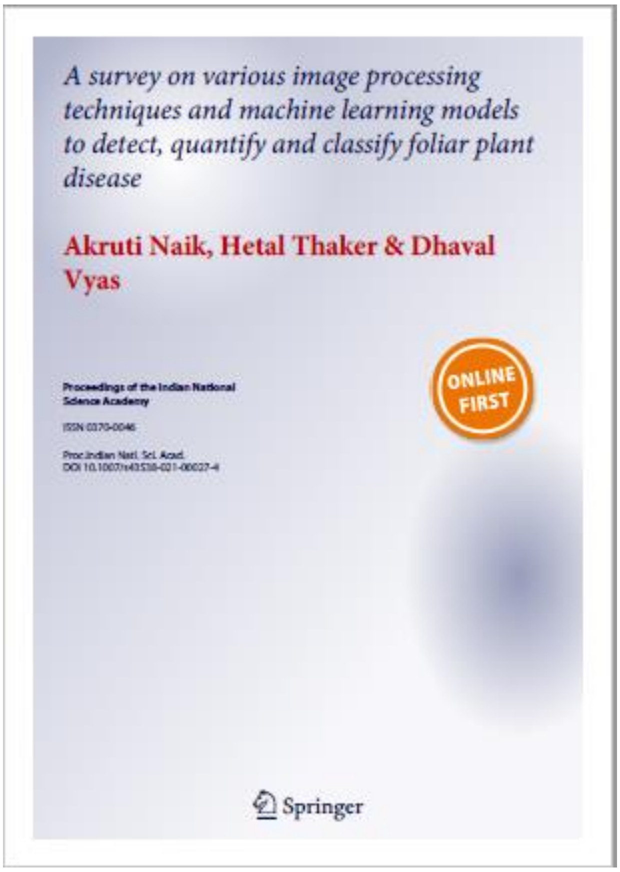
Vyas, D. K. (2011). Evaluation of classifiers for processing Hyperion (EO-1) data of tropical vegetation. *International Journal of Applied Earth Observation and Geoinformation, 13*(2), 228-232.

Wang H, L. G. (2012). Application of neural networks to image recognition of plant diseases. *International Conference on Systems and Informatics (ICSAI). IEEE, Yantai*, 2159–2164.

Y. Sun, Z. J. (2019). SLIC_SVM based leaf diseases saliency map extraction of tea plant. *Cpmput. Electron. Agricult, 157*, 102-109.

Yao Q, G. Z. (2009). Application of support vector machine for detecting rice diseases using shape and color texture features. *international conference on engineering computation. IEEE.* Hong Kong.

Youwen T, T. L. (2008). The recognition of cucumber disease based on image processing and support vector machine. *congress on image and signal processing. IEEE.* Sanya.



Author's personal copy

Proceedings of the Indian National Science Academy
https://doi.org/10.1007/s43538-021-00027-4

REVIEW ARTICLE

A survey on various image processing techniques and machine learning models to detect, quantify and classify foliar plant disease

Akruti Naik[1] · Hetal Thaker[2] · Dhaval Vyas[1]

Received: 3 December 2019 / Accepted: 18 January 2021
© Indian National Science Academy 2021

Abstract
Agriculture is one of the significant factors that drive India's economy. A decrease in the yield of agricultural food crops due to plant diseases results in great loss to the economy of the developing country. Detection of plant disease at an early stage can decrease the chance of loss on the overall economy. Nowadays, ICT (Information And Communication Technology) plays a major role in all sectors including agriculture. Classical agriculture has been reformed using ICT. Farmers are getting the correct information on time. ICT is necessary for agronomy, it may increase productivity using data generation, storage, and analysis. This paper presents a survey of various image processing techniques and machine learning tools to detect, quantify, and classify plant diseases. Methods that explore visible symptoms in leaves and stems were considered. This paper aims on exploring this wide research area and possible scope of further researcher there by looking at various aspects of review such as accuracy, image processing techniques, machine learning models, and plants on which work has been carried out. This survey is likely to be useful to researchers working both on disease detection on the leaf and pattern recognition, providing a quick overview of this important field of research.

Keywords Image Processing · Plant Disease · K-Means · Neural Network · SVM

Introduction

Food security is a major concern in modern society. Plant disease is greatly affecting the yield of agricultural crops and it is an immense threat to food security. Early identification of plant disease can decrease the effect of disease on crop yield. Agriculture has become much more than simply a means to feed ever-growing populations. Plants have become an important source of energy, and are a fundamental piece in the puzzle to solve the problem of global warming (Barbedo 2013). Several diseases distress plants with the latent to cause devastating economical, social, and ecological losses. Therefore, detecting diseases in an accurate and timely way is the most important task. In tropical countries like India, yields of agricultural crops are immensely affected by various plant diseases. Early identification of these diseases can be useful to abolish the effect of disease on crop yield. Empirical techniques of identification are time consuming and lengthy. It is noteworthy that most plant diseases produce different symptoms on the surface of the leaves. Most diseases, however, generate some kind of manifestation in the visible spectrum. In the vast majority of the cases, the diagnosis, or at least a first guess about the disease, is performed visually by humans. Farmers can take and upload an image using smartphones. Trained raters may be efficient in recognizing and quantifying diseases, however, they have associated some disadvantages that may harm the efforts in many cases (Barbedo 2013). (Bock 2010) et al. list some of those disadvantages. However, these symptoms can be identified using various digital image analysis techniques. Image analysis techniques can be useful to resolve this problem. A relationship between digital numbers in various pixels can be identified from the image. Pixel-wise classification techniques can be applied to identify disease symptoms on the leaves of the plant.

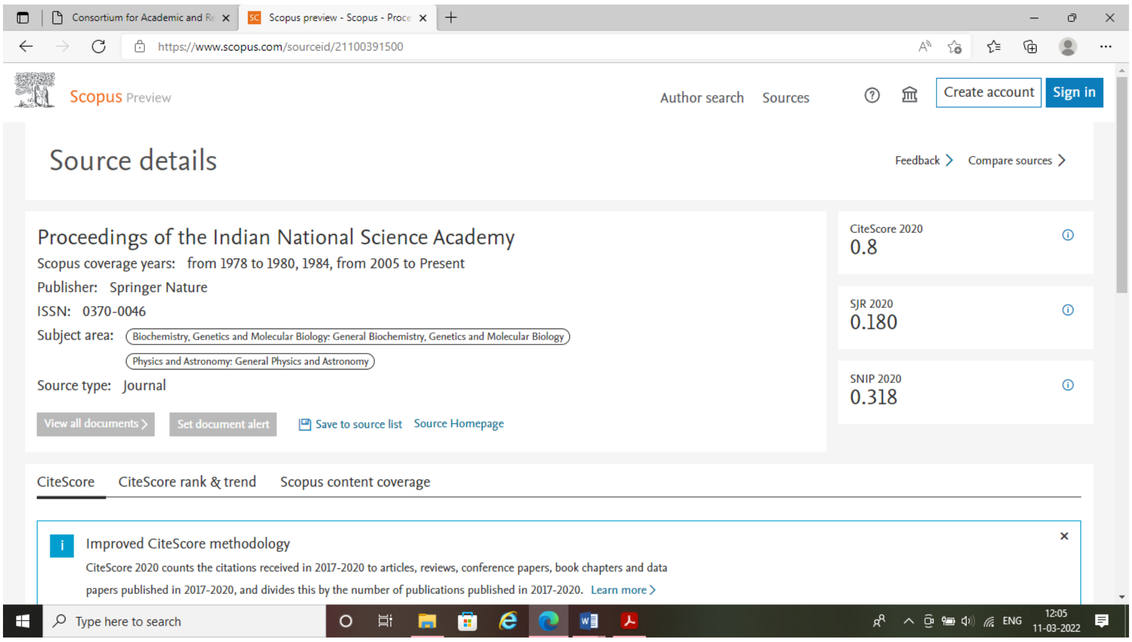
✉ Akruti Naik
akrutinaikdesai@gmail.com

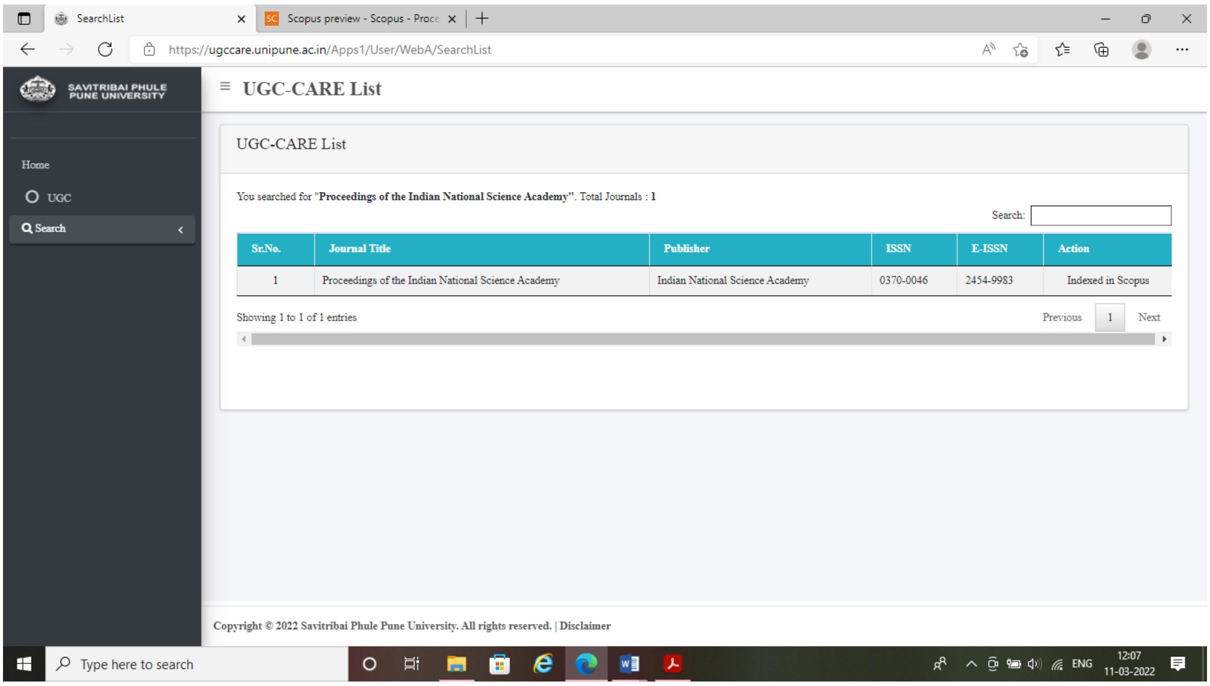
Hetal Thaker
hrt.research@gmail.com

Dhaval Vyas
vyasdhaval84@gmail.com

[1] Dolat-Usha Institute of Applied Sciences, Valsad, India
[2] Department of Computer Application, Atmiya University, Rajkot, India

Published online: 28 June 2021


Consortium for Academic and Re
Scopus preview - Scopus - Proce
https://www.scopus.com/sourceid/21100391500
Scopus Preview
Author search
Sources
Create account
Sign in
Source details
Feedback
Compare sources
Proceedings of the Indian National Science Academy
Scopus coverage years: from 1978 to 1980, 1984, from 2005 to Present
Publisher: Springer Nature
ISSN: 0370-0046
Subject area: Biochemistry, Genetics and Molecular Biology: General Biochemistry, Genetics and Molecular Biology
Physics and Astronomy: General Physics and Astronomy
Source type: Journal
View all documents
Set document alert
Save to source list
Source Homepage
CiteScore 2020
0.8
SJR 2020
0.180
SNIP 2020
0.318
CiteScore
CiteScore rank & trend
Scopus content coverage
Improved CiteScore methodology
CiteScore 2020 counts the citations received in 2017-2020 to articles, reviews, conference papers, book chapters and data papers published in 2017-2020, and divides this by the number of publications published in 2017-2020. Learn more
Type here to search
ENG
12:05
11-03-2022


SearchList
Scopus preview - Scopus - Proce
https://ugccare.unipune.ac.in/Apps1/User/WebA/SearchList
SAVITRIBAI PHULE PUNE UNIVERSITY
UGC-CARE List
Home
UGC
Search
UGC-CARE List
You searched for "Proceedings of the Indian National Science Academy". Total Journals : 1
Search:
Sr.No.
Journal Title
Publisher
ISSN
E-ISSN
Action
1
Proceedings of the Indian National Science Academy
Indian National Science Academy
0370-0046
2454-9983
Indexed in Scopus
Showing 1 to 1 of 1 entries
Previous
1
Next
Copyright © 2022 Savitribai Phule Pune University. All rights reserved. | Disclaimer
Type here to search
ENG
12:07
11-03-2022