FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 677-683 | e-ISSN: 2347-470X

Lime Diseases Detection and Classification Using Spectroscopy and Computer Vision

Hardikkumar Sudhirbhai Jayswal[1], Dr. Jitendra Prabhakar Chaudhari[2]

[1]Assistant Professor, Department of Information Technology, Devang Patel Institute of Advance Technology and Research, Charotar University of Science and Technology, Gujarat, India
[2]Associate Professor, V T Patel Department of Electronics and Communication Engineering Chandubhai S Patel Institute College of Technology, Charotar University of Science and Technology, Gujarat, India

***Correspondence:** Hardikkumar S. Jayswal; jayswalhardik300986@gmail.com

ABSTRACT- In the agricultural industry, plant diseases and pests pose the greatest risks. Lime is rich 10 source of vitamin C which works as an immunity booster in human body. Because of the late and manually diseases detection in lime causes a vast loss in crop production worldwide. The most common diseases are found in limes are lime canker, lemon scab, brown rot, sooty mould and Armillaria. In this paper we used imaging and non-imaging (spectral based sensing) methods with the combination of machine learning technique to detect the lime canker and sooty mould diseases. Image acquirement, pre-processing, segmentation and classification are all steps in the imaging methodology, which is then followed by feature extraction. In non-imaging methodology a multispectral sensor (Spectrometer) is used with 400 nm to 1000 nm wavelength to detect the diseases. training set and test set ratio is fixed for both techniques are 75% and 25% respectively. When it comes to identifying and classifying lime disease, spectroscopy has a 99% efficiency rating compared to imaging methodology's 96%.

Keywords: Plant diseases, classification, spectroscopy.

ARTICLE INFORMATION
Author(s): Hardikkumar S. Jayswal and Dr. Jitendra P. Chaudhari;
Received: 16/08/2022 **Accepted**: 13/09/2022; **Published**: 22/09/2022;
e-ISSN: 2347-470X;
Paper Id: IJEER 1608-28;
Citation: 10.37391/IJEER.100343
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-10/ijeer-100343.html

crossref member
CROSSREF.ORG THE CITATION LINKING BACKBONE

Publisher's Note: FOREX Publication stays neutral with regard to Jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

Agricultural is playing an important role in any country's economy. Agriculturalists want to implement latest techniques in farming. However, due to a lack of awareness about new technology, as well as the high cost of technology and resources, they are unable to adopt it. [1]. Day by Day increasing population in the world demanding more agriculture products and agriculture struggles to support the rapidly growing population [2]. Farmers are spending time and cost for controlling diseases manually or without adequate technical support. Use of traditional technique's resulting in poor disease control and pollution and harmful health issues in human being. compare to the other fruits Lime is the popular citrus fruit used by human being because of its multiple use in daily life. Numerous fungal, viral, and a few bacterial pathogens attack citrus fruits, resulting in more than 150 diseases and disorders. The most common disease found on lime plant are lime canker, brown rot, sooty mould [3]. There are mainly three approaches are used to detect and classify the disease are like Molecular Methods, Imaging methods, Non-Imaging (Spectroscopic) Methods [4]. DNA-based techniques, RNA-based techniques, Protein-based techniques are molecular methods which used to detect plant diseases [5]. RGB, multispectral and hyperspectral are popular imaging procedures used to detect the diseases where Machine learning and deep learning models are used to classify the diseases based on image structures [6][7]. For accurate and on time diseases detection spectroscopy method is used where it classifies into Vibrational and Visible and Infrared spectroscopy having a range 400-100000 nm to detect the diseases.

2. MATERIALS AND METHODS

Two approaches implemented in this paper imaging and non-imaging. for both the approaches healthy and disease effected lime data sample collected from Anand agriculture university - Gujarat. For imaging method Mirrorless camera with a zoom range of 16 to 50 mm from Sony, model number ILCE-6400L is used to captured the images [40] and for non-imaging method Multispectral sensor (Pixel sensor) is used with combination of eight different diodes where each of the diode classified the range between 400-1000 nm.

Figure 1 shows the GPS coordinates of the location where sample were collected. Lime canker, sooty mould disease leaf and health leaf shows in *figure 2*. Specification of Multispectral Sensor (Pixelsensor) Spectrometers shows in *table 1*.

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 677-683 | e-ISSN: 2347-470X

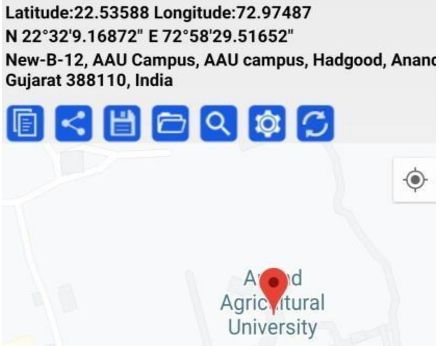

Figure 1

Figure 2

Figure 1: GPS coordinates of the location where sample were collected **Figure 2**: Lime canker, sooty mould disease leaf and health leaf

Table 1: Specification of Multispectral Sensor (Pixelsensor) Spectrometers [39]

Photodiode Performance Characteristics	
Dark current	2nA(Typical),8nA(Max)
Shunt resistance	100MΩ
Range of Spectral	400-1100nm
Break down voltage	75V
Response time	6ns
Absolute Maximum Rating	
Reverse voltage	75V
LCC sensor	
Spectral filters	Standardand custom 10-100 nmFWHM
Photodiodes	Si,1.0x0.8mm
LCCdimensions	9x9mm
OEM Board Specifications	
Integration time	1-1024ms

2.1 Literature Review

Table 2: Machine/Deep Learning and Spectroscopy for Disease Detection and Classification

Image Dataset with diseases name	Technique/model used	Accuracy	Ref.
Down Mildew, Mosaic Virus, Leaf Miner, Early Blight, White Fly with own dataset	K-Mean segmentation; KNN GLCM Algorithm; SVM-Existing	SVM: - 97.6 % KNN:- 98.56%	10
Anthracnose, Areolate or Grey mildew, Wilt with Training dataset	Algorithm Texture, color Decision Tree Classifier Thresholding technique	Increased	11
Kaggle dataset used to detect Melanose, Greening, Citrus Scab Anthracnose, Black spot, Canker,	Model Based segmentation, SVM, ANN Texture, color, Shape, phenotypic Features	SVM: -93.1222% ANN 88.96565%	12
Arkansas Reddit-plant datasets Anthracnose, Leaf Spot, Canker, Alternaria Alternata	k-nearest neighbor KNN, GLCM GLCM algorithm, color, texture	KNN:- 96.76%	13
plant village is used to detect Black- Rot, Esca, Leaf Blight.	Global Thresholding, SVM, RF, Textual, GLCM Algorithm, Ada Boost Threshold,	SVM:- 93.035%	14
Back spread is usedto preparing database	Traditional segmentation with NN, SVM, RF, NB, DT	SVM: -72.9223% RF: -71.88% NB: -70.5745% DT:- 64.005%	15

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 677-683 | e-ISSN: 2347-470X

13 species Plant village using2598 images	Mobile Net, R-CNN	70.53%	16
12 crop species Plant Disease with 79265 images	GAN architecture	93.67%	17
4 crop species Leaf disease Dataset with 61486 images	9-layer deep CNN	96.46%	18
Apple, Peach, Tomato Plant Village with 24000 images	InceptionV3 CNN using hierarchical approach	97.74%	19
Tomato plant with Own dataset of 4923 images	Faster R-CNN, CNN	91.67%	20
Barley plant to detect Powdery Mildew	Linear discriminant analysis (LDA)	VNIR (400 nm-1000 nm)	21
Spinach plant used to detect Bacterial disease	Partial Least Squared- Discrimination Analysis (PLS-DA)	84% VIS-NIR (456-950nm)	22
Wheat plant used to detect Yellow rust	Regression Analysis	90% VIS-NIR (350-2500nm)	23

Table 2 depicts the detection and classification of plant diseases using machine learning and spectroscopy. Researchers use the diverse methodologies to detect and classify the diseases like Leaf Spot, Canker, Alternaria Alternata, Greening, Black spot, Canker, Melanose, Citrus Scab Anthracnose etc.

2.2. Implementation of Imaging Approach for Diseases detection and classification

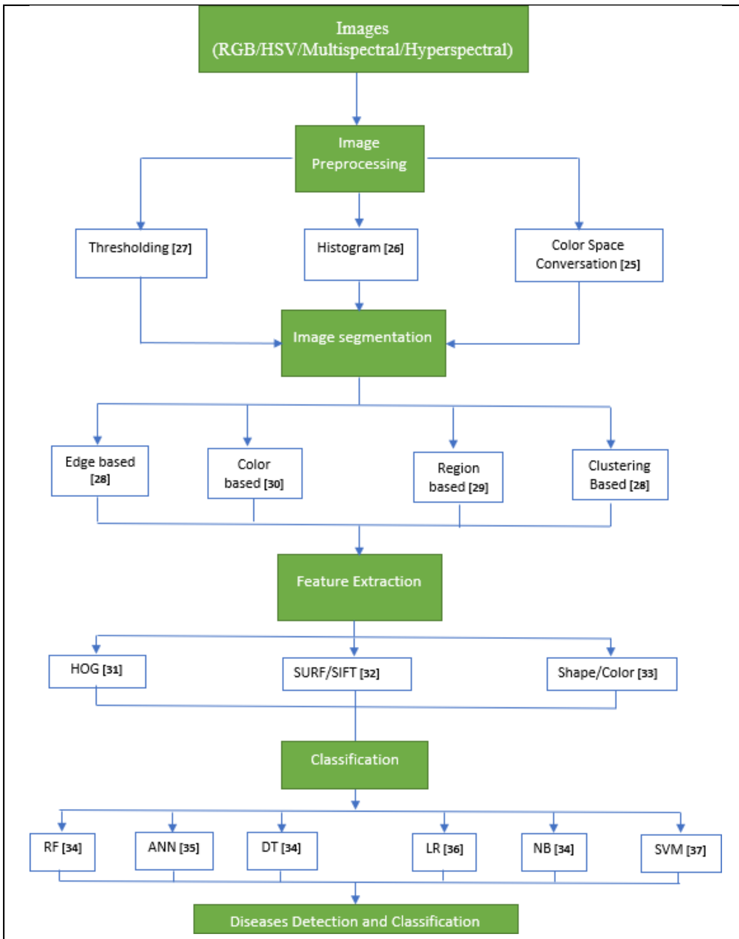

Figure 3: Various approaches for disease detection

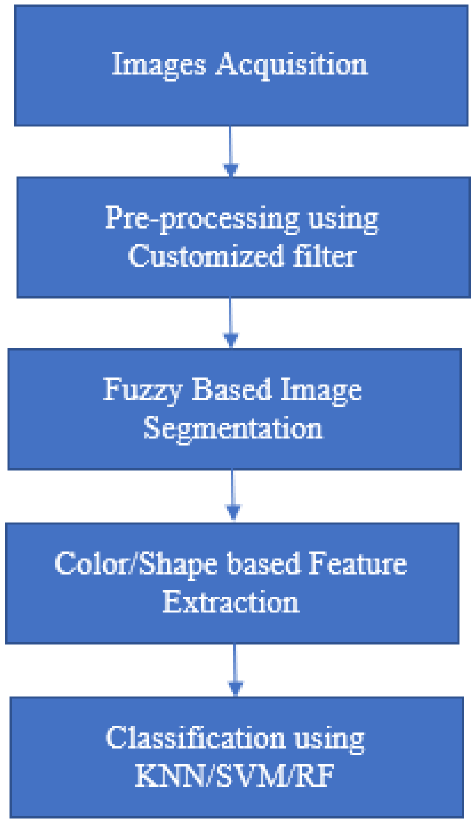

Figure 4: Optimize approach for detection

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 677-683 | e-ISSN: 2347-470X

Figure 3 show the various approaches can possible to detect and classify the disease. From the various approaches the optimize approach selected shown in *figure 4* [25]. In image acquisition part there are total 200 Image sample of healthy, sooty mold and canker are collected from Anand agriculture university using ONY Alpha ILCE-6400L Mirrorless Camera. Real time image capturing having noise, to overcome it customized filter has been applied to make image more informative. The motive to apply segmentation technique is to divide an image into several segments so it can help to detect the Objects and bounding line of images. Fuzzy based segmentation is applied which combines both region and edge features of the image using triangular membership function. Color and shape-based Feature extraction is applied to reduce the amount of redundant data from the data set without losing any significant information. To classify the canker and sooty mold diseases SVM, KNN, RF has been applied.

3. RESULTS

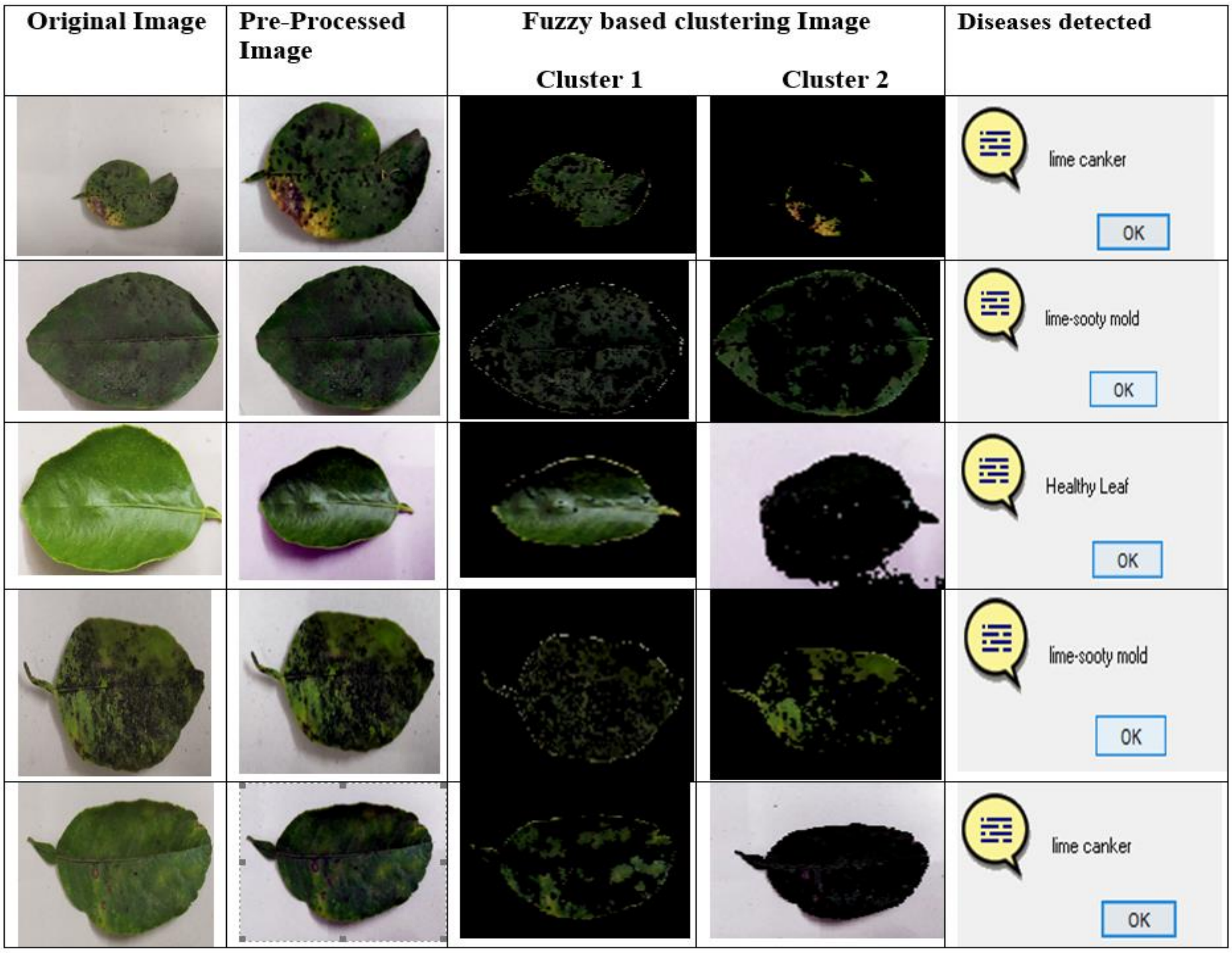

Figure 5: Result images

3.1 Implementation of Non-Imaging Approach (Spectroscopy) for Diseases detection and classification

To detect the sooty mold, canker in lime a multispectral sensor (Spectrometer) is used. A multi spectral spectrometer divided the spectrum into eight separate color bands with selectivity (400-1000 nm). Total 150 diseased sample and 50 healthy sample were measured using spectrometer. *Figure 6* shows the experiment's carried out at university. After the collection of datasets, we pre-processed the data and defined the target and feature variables. To make a prediction we build a model and train it using train and test split target variables. *Figure 7* shows 16000 sample were taken with eight different features and labels. *Figure 8* shows the distribution of various band for disease like canker, sooty mold and health leaf among the eight different diodes.

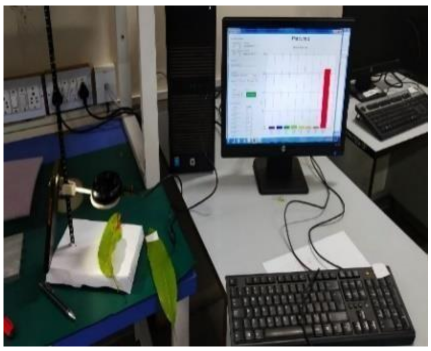

Figure 6: Practical Centre

	Diode 1	Diode 2	Diode 3	Diode 4	Diode 5	Diode 6	Diode 7	Diode 8	label
0	580	466	449	497	324	308	263	8190	2
1	591	466	447	489	318	303	257	8191	2
2	586	471	451	499	326	309	263	8190	2
3	582	467	449	495	323	306	261	8191	2
4	590	466	447	489	319	303	257	8191	2
...	...	...	...	...	...	...	...	...	...
1995	544	398	368	399	258	258	209	8190	3
1996	543	398	367	396	252	254	204	8190	3
1997	553	404	371	401	261	262	212	8190	3
1998	538	393	365	394	256	256	207	8190	3
1999	546	393	364	390	253	254	203	8190	3

16000 rows × 9 columns

Figure 7: 16000 sample were taken with eight different features and labels

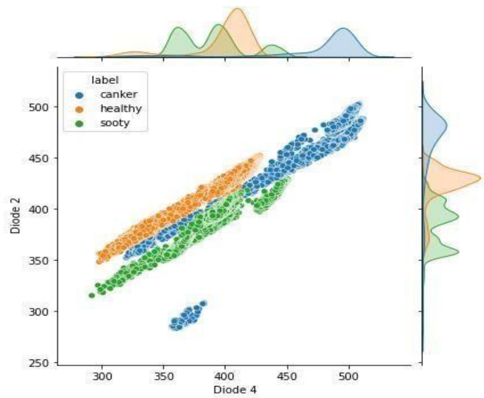

Figure 8: Distribution of various band for disease among the eight different diodes

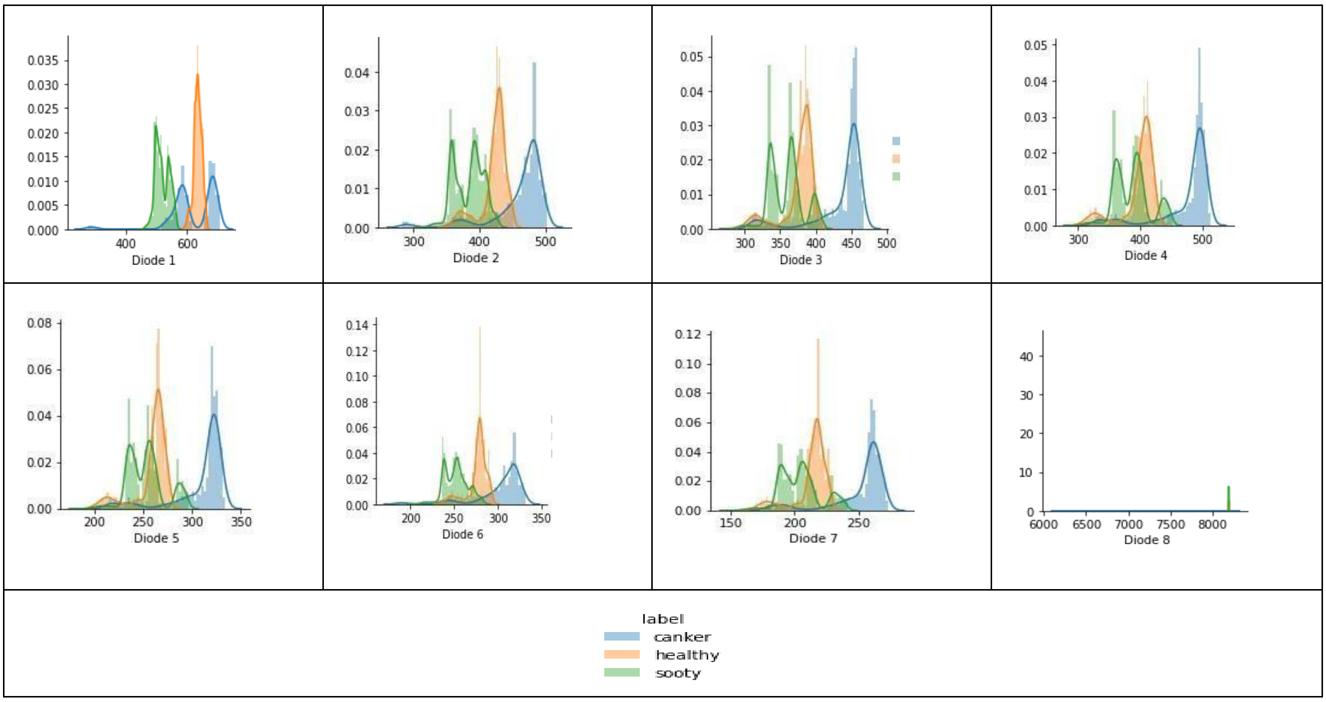

Figure 9:

Accuracy, precision, recall, and f1-score are the parameter which is used to evaluate the performance of classifier for imaging and non-imaging approach. They are measured by determining the number of true false positives and negatives from the confusion matrix. In comparison of classifier precision is taken as evaluation to check effectiveness of algorithm and recall is to check coverage of algorithm.

Table 3 and 4 shows that KNN is performance is finest among the other classifier with having 96.552% accuracy in imaging approach where 99.99696% accuracy achieved in non-imaging approach.

$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$	$\text{Precision} = \frac{TP}{TP+FP}$
$\text{Recall} = \frac{TP}{TP+FN}$	$\text{F1-Score} = 2 * \frac{Precision*Recall}{Precision+Recall}$

Table 3: Classification using Imaging Approach

Classifier	Precision	Recall	F1-Score	Accuracy
NB	0.85	0.69	0.76	80.256%
SVM	0.85	0.82	0.83	83.136%
RF	0.86	0.96	0.91	85.653%
KNN	0.96	0.95	0.97	96.552%

Table 3: Classification using Spectroscopy

Classifier	Precision	Recall	F1-Score	Accuracy
NB	0.94	0.93	0.93	93.08333%
SVM	0.95	0.92	0.93	92.29523%
RF	1.00	1.00	1.00	99.99593%
KNN	1.00	1.00	1.00	99.99696%

4. DISCUSSION

Imaging and non-imaging approach were implemented to detect and classify the lime diseases. The research results show the non-imaging approach having great accuracy for classification of lime diseases. In imaging approach highest accuracy achieved is 96% using KNN where in non-imaging approach spectral data in the range of 400 nm-1000 nm to proceed the sample leaves and achieved 99% accuracy with KNN. Future work would involve the stage wise early, mid and late disease detection and classification in infected lime leaves.

Funding: This research received no external funding.

Acknowledgments: We would like to thank the Charotar University of Science and Technology -CHARUSAT for carried out this Research. We would also like to thanks Dr. S.H Akbari Associate Professor, Anand Agriculture University to help the collection of data and his support during the study. We would like to express our gratitude to Prof. Rikin Nayak, Prof. Axat Patel (Charusat Space Research Center - CHARUSAT) for their continuous support during the study.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations: **RS,** Remote sensing; **IR,** Infrared; **VNIR, visible** and near-infrared; **QDA,** Quadratic discriminant analysis; **PCA,** Principal Component Analysis; **HLB,** Huanglongbing; **NB**, naive bays; **RF**, Random Forest; **KNN,** k-nearest neighbors; **SVM**, Support Vector Machine; **TP**, True Positive; **TN**, True Negative; **FP**, False Positive; **DNA**, Deoxyribonucleic acid; **RNA**, Ribonucleic acid; **GAN**, Generative Adversarial Network.

REFERENCES

[1] 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.

[2] Couture, J. J., Singh, A., Charkowski, A. O., Groves, R. L., Gray, S. M., Bethke, P. C., & Townsend, P. A. (2018). Integrating spectroscopy with potato disease management. Plant disease, 102(11), 2233-2240.

[3] Lakshmi, T. N., Gopi, V., Sankar, T. G., Sarada, G., Lakshmi, L. M., Ramana, K. T. V., & Gopal, K. (2014). Status of diseases in sweet orange and acid lime orchards in Andhra Pradesh, India. International Journal of Current Microbiology and Applied Sciences, 3(5), 513-518.

[4] Farber, C., Mahnke, M., Sanchez, L., & Kurouski, D. (2019). Advanced spectroscopic techniques for plant disease diagnostics. A review. TrAC Trends in Analytical Chemistry, 118, 43-49.

[5] Swapnil Sapre, Iti Gontia-Mishra, Vishwa Vijay Thakur, Sumana Sikdar, Sharad Tiwari (2021). Chapter 20 - Molecular techniques used in plant disease diagnosis. Food Security and Plant Disease Management, Woodhead Publishing, 405-421.

[6] 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), 130 11(2), 41-58.

[7] Prajapati, H. B., Shah, J. P., & Dabhi, V. K. (2017). Detection and classification of rice plant diseases. Intelligent Decision Technologies, 11(3), 357-373.

[8] Farber, C., Mahnke, M., Sanchez, L., & Kurouski, D. (2019). Advanced spectroscopic techniques for plant disease diagnostics. A review. TrAC Trends in Analytical Chemistry, 118, 43-49.

[9] Khaled, A. Y., Abd Aziz, S., Bejo, S. K., Nawi, N. M., Seman, I. A., & Onwude, D. I. (2018). Early detection of diseases in plant tissue using spectroscopy–applications and limitations. Applied Spectroscopy Reviews, 137 53(1), 36-64.

[10] 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.

[11] Chopda, J., Raveshiya, H., Nakum, S. and 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.

[12] Doh, B., Zhang, D., Shen, Y., Hussain, F., Doh, R.F. and 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.

[13] Hossain, E., Hossain, M.F. and 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.

[14] 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.

[15] Sehgal, A. and 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.

[16] Singh, D., Jain, N., Jain, P., Kayal, P., Kumawat, S. and Batra, N., 2020. Plant Doc: a dataset for visual plant disease detection. In Proceedings of the 7th ACM IKDD CoDS and 25th COMAD (pp. 249-253).

[17] Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A. and Stefanovic, D., 2019. Solving current limitations of deep learning based approaches for plant disease detection. Symmetry, 11(7), p.939.

[18] Geetharamani, G. and Pandian, A., 2019. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Computers & Electrical Engineering, 76, pp.323-338.

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

[20] de Luna, R.G., Dadios, E.P. and 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.

[21] Kuska, M. T., Behmann, J., Namini, M., Oerke, E. C., Steiner, U., & Mahlein, A. K. (2019). Discovering coherency of specific gene expression and optical reflectance properties of barley genotypes differing for resistance reactions against powdery mildew. PloS one, 14(3), e0213291.

[22] Teena, M., et al. "Potential of machine vision techniques for detecting fecal and microbial contamination of food products: a review." Food and Bioprocess Technology 6.7 (2013): 1621-1634.

[23] Everard, C. D., Kim, M. S., & Lee, H. (2014). A comparison of hyperspectral reflectance and fluorescence imaging techniques for detection of contaminants on spinach leaves. Journal of Food Engineering, 143, 139- 174 145.

[24] Li, X. L., Ma, Z. H., Zhao, L. L., Li, J. H., & Wang, H. G. (2014). Application of near infrared spectroscopy to qualitative identification and quantitative determination of Puccinia strii formis f. sp. tritici and P. recondita f. sp. tritici. Guang pu xue yu guang pu fen xi= Guang pu, 34(3), 643-647.

[25] Jayswal, H. S., & Chaudhari, J. P. Plant Leaf Disease Detection and Classification using Conventional Machine Learning and Deep Learning.

[26] Gavhale, K.R., Gawande, U. and 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

[27] Thangadurai, K. and 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.

[28] Jhuria, M., Kumar, A. and 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 88 (ICIIP-2013) (pp. 521-526). IEEE.

[29] Kumari, C.U., Prasad, S.J. and 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.

[30] Ratnasari, E.K., Mentari, M., Dewi, R.K. and 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

[31] Schikora, M., Schikora, A., Kogel, K.H., Koch, W. and Cremers, D., 2010. Probabilistic classification of disease symptoms caused by Salmonella on Arabidopsis plants. INFORMATIK 2010. Service Science–Neue Perspektiven für die Informatik. Band 2.

[32] 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.

[33] Albayati, J.S.H. and Üstündağ, B.B., 2020. Evolutionary Feature Optimization for Plant Leaf Disease Detection by Deep Neural Networks for Apple Leaf. International Journal of Computational Intelligence Systems.

[34] Doh, B., Zhang, D., Shen, Y., Hussain, F., Doh, R.F. and 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.

[35] Sehgal, A. and 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.

[36] Shah, N. and 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.

[37] Sun, G., Jia, X. and Geng, T., 2018. Plant diseases recognition based on image processing technology. Journal of Electrical and Computer Engineering, 2018.

[38] Alias, N., Nashat, S., Zakaria, L., Najimudin, N. and 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.

[39] https://www.idil-fibres-optiques.com/product/multispectral-sensor-pixelsensor/

[40] https://www.sony.co.in/electronics/interchangeable-lens-cameras/ilce-6400/specifications

[41] R Gomathi, S Selvankumaran (2022), A Novel Medical Image Segmentation Model with Domain Generalization Approach. IJEER 10(2), 312-319. DOI: 10.37391/IJEER.100242.