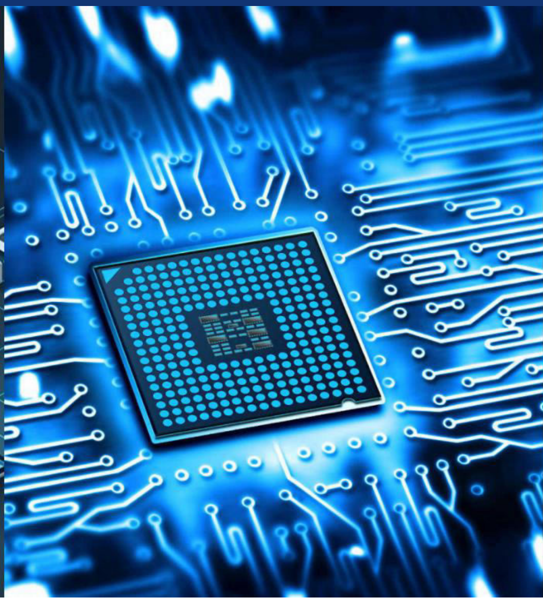
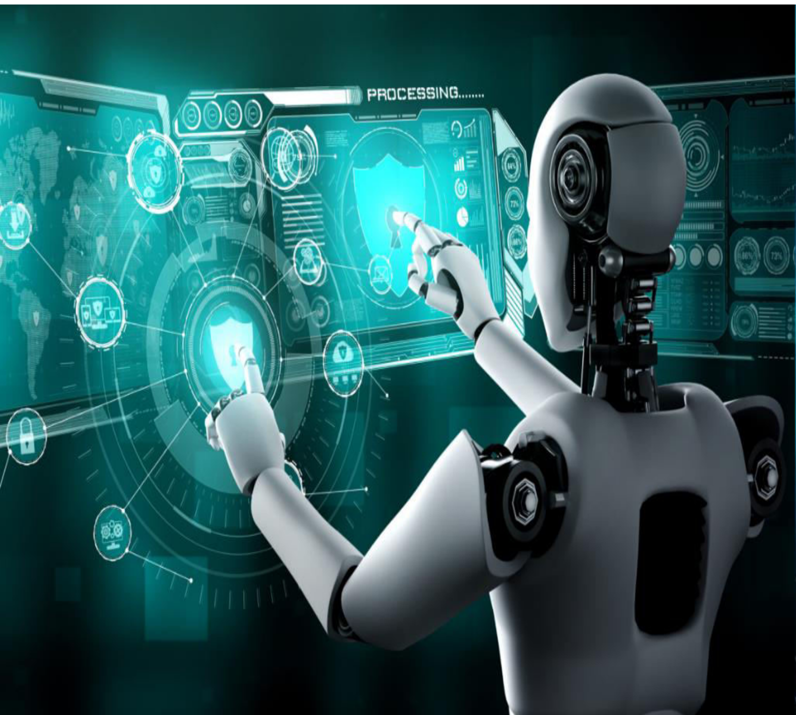
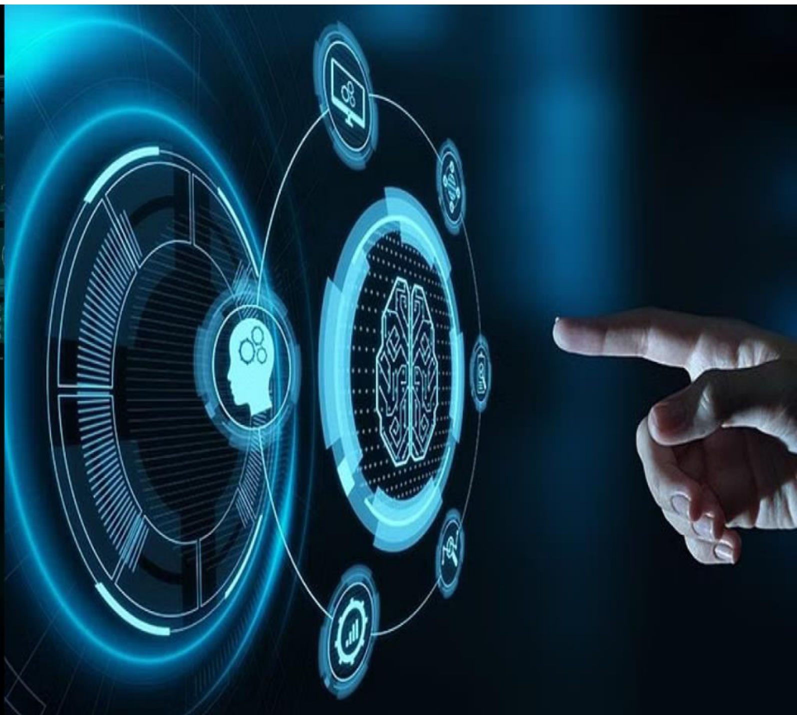
ISSN(O): 2320-9801
ISSN(P): 2320-9798


International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 8.771

Volume 14, Issue 4, April 2026

www.ijircce.com ijircce@gmail.com +91-9940572462 +91 63819 07438

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Plant Disease Identification Through Image Processing Techniques

Ujjwal Sharma, Anish Ranjan Sharma, Mayank Verma, Suyash Kumar Singh

Department of Computer Science, Galgotias University, Greater Noida, India

Department of Computer Science, Galgotias University, Greater Noida, India

Department of Computer Science, Galgotias University, Greater Noida, India

Department of Computer Science, Galgotias University, Greater Noida, India

ABSTRACT: Plant diseases significantly affect agricultural productivity and food security worldwide. They reduce both the quantity and quality of crops. Timely and accurate disease detection is vital for effective crop management and sustainable farming. Traditional disease diagnosis relies heavily on visual checks by agricultural experts. This method can be costly, subjective, and impractical for large-scale farming. With rapid advancements in computing technologies, automated plant disease identification using image processing has become a reliable solution [1], [2].

This research paper presents a thorough study of plant disease identification using image processing techniques. The paper outlines the entire workflow, including image acquisition, preprocessing, segmentation, feature extraction, and classification. It discusses both traditional machine learning methods and recent deep learning approaches in detail [3]–[5]. The paper also addresses current challenges, performance evaluation metrics, and future research directions, especially in precision agriculture and smart farming systems [4].

KEYWORDS: Precision Agriculture, Convolutional Neural Networks (CNNs), Feature Extraction, Image Processing, Machine Learning, Deep Learning, Leaf Disease Detection, Plant Disease Detection, Smart Farming.

I. INTRODUCTION

The agricultural sector is vital for supporting the global population by providing food, raw materials, and jobs. However, agricultural productivity faces serious threats from diseases in plants caused by fungi, bacteria, viruses, and pests [6]. Research shows that plant diseases contribute to annual crop losses of 20 to 40% worldwide, highlighting the need for early and reliable disease detection methods [7].

Conventional disease detection methods include manual inspection and lab testing. Although these methods work, they take a lot of time, cost a lot of money, and are often hard for farmers in rural areas to access [8]. Recent advancements in image processing, computer vision, and artificial intelligence have enabled the development of automated systems that can identify plant diseases based on visual symptoms [9].

Image processing-based plant disease identification systems look at features like color variation, texture abnormalities, and shape distortion on plant leaves. These systems provide scalability, consistency, and high accuracy, making them suitable for today's precision agriculture practices [10]. This paper offers an overview of these systems, focusing on approaches related to computing-oriented conferences, including IC2PCT.

II. RELEVANT WORK AND LITERATURE REVIEW

Early research in plant disease detection mainly used traditional image processing techniques along with statistical classifiers. Color-based analysis with RGB and HSV color spaces was often used to identify disease symptoms like chlorosis and necrosis [11]. Texture-based methods, such as Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP), improved detection accuracy by capturing surface irregularities [12].

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

To improve classification performance, machine learning algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests were introduced [13]. Even with better accuracy, these methods relied a lot on manually crafted feature extraction. They struggled with complex and large-scale datasets.

Recent studies show that deep learning models, especially Convolutional Neural Networks (CNNs), perform much better than traditional methods. They learn important features automatically from raw images [14]. Pretrained architectures like VGG, ResNet, and MobileNet are popular for transfer learning. They achieve significant gains in classification accuracy, even when there is limited training data.

III. PLANT DISEASE IDENTIFICATION SYSTEM ARCHITECTURE

The plant disease identification system uses image processing and has a clear, modular design to ensure accuracy, strength, and scalability. The process starts with image acquisition. Here, images of plant leaves are taken with digital cameras or mobile devices in different environmental conditions.

IoT-enabled devices. Images can be taken under controlled laboratory conditions or directly from agricultural fields [17]. Variations in lighting, background clutter, and image resolution create significant challenges that need to be addressed during preprocessing.

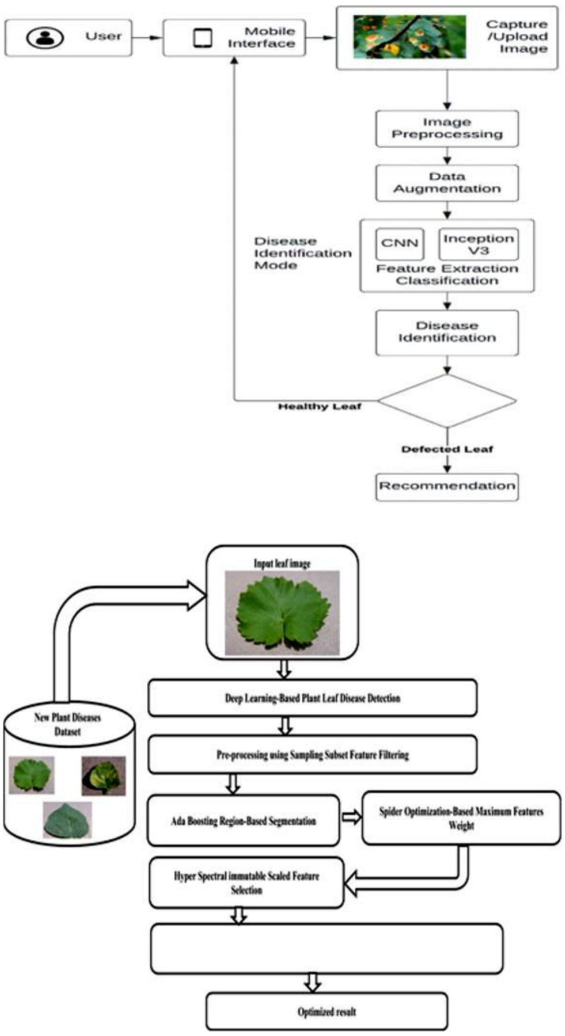


Fig. 1. Plant Disease Identification System Architecture

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The captured images go to the preprocessing unit. This unit reduces noise, improves contrast, resizes images, and converts color spaces to boost image quality. After that, segmentation techniques work to separate diseased areas from healthy parts of the leaf. In the feature extraction stage, we pull out important color, texture, and shape features that show disease symptoms. Finally, we classify the plant diseases using machine learning or deep learning models. This structure enables efficient processing, reliable diagnosis, and easy integration with smart farming systems [16].

IV. IMAGE ACQUISITION

Image acquisition involves capturing high-resolution images of plant leaves using digital cameras, smartphones, drones, or IoT-enabled devices. Images can be taken under controlled laboratory conditions or directly from agricultural fields [17]. Variations in lighting, background clutter, and image resolution create significant challenges that need to be addressed during preprocessing.

V. IMAGE PREPROCESSING

Preprocessing enhances image quality and ensures dataset consistency. Common preprocessing techniques include noise removal using median or Gaussian filters, contrast enhancement through histogram equalization, image resizing, and color space transformation [9]. Effective preprocessing improves the accuracy of segmentation and classification stages.

VI. IMAGE SEGMENTATION

Image segmentation divides diseased regions from healthy leaf areas and the background. Traditional methods like thresholding and K-means clustering are fast but sensitive to changes in lighting [18]. Good segmentation is essential for effective feature extraction and disease classification. Deep learning models, such as U-Net, offer greater accuracy than traditional methods; however, they need more computational power.

TABLE I
STAGES OF PLANT DISEASE DETECTION SYSTEM

Stage	Description	Purpose
Image Acquisition	Capturing leaf images using cameras, smartphones, or drones	Provides raw data
Image Preprocessing	Noise removal, resizing, contrast enhancement, color conversion	Improves image quality
Image Segmentation	Separating diseased regions from background	Focuses analysis
Feature Extraction	Extracting color, texture, and shape features	Numerical representation
Classification	Applying ML/DL algorithms	Disease identification

VII. FEATURE EXTRACTION

Feature extraction turns segmented diseased areas into numerical forms that can be used for classification.
Color Features: RGB and HSV histograms capture discoloration patterns on leaf surfaces [11].
Texture Features: GLCM and LBP methods detect surface irregularities and texture variations [12].
Shape Features: Area, perimeter, and compactness identify structural changes in leaves.
These features are essential for traditional machine learning classifiers.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

VIII. CLASSIFICATION TECHNIQUES

A. Conventional Machine Learning

Conventional machine learning methods mainly rely on decision tree algorithms like ID3. Other popular classifiers are Support Vector Machines (SVM), K Nearest Neighbors (KNN), Random Forest, and Naive Bayes. These classifiers are favored for their simplicity, low computational cost, and effectiveness with small-scale datasets [13].

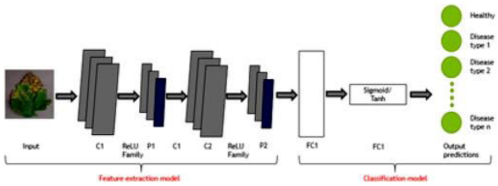


Fig. 2. Classification techniques showing original image, lesion segmentation, and leaf segmentation

B. Deep Learning Approaches

Deep learning methods, especially Convolutional Neural Networks (CNNs), learn various features from raw images on their own. This means there is no need for manual feature extraction. These models show better results in detecting plant diseases. Transfer learning techniques that use pre-trained models improve classification accuracy and lower training time and computing costs [14], [15].

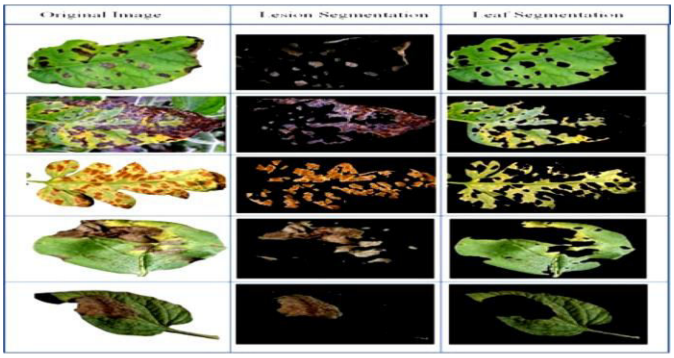


Fig. 3. Deep learning-based classification, object detection, and segmentation of plant diseases

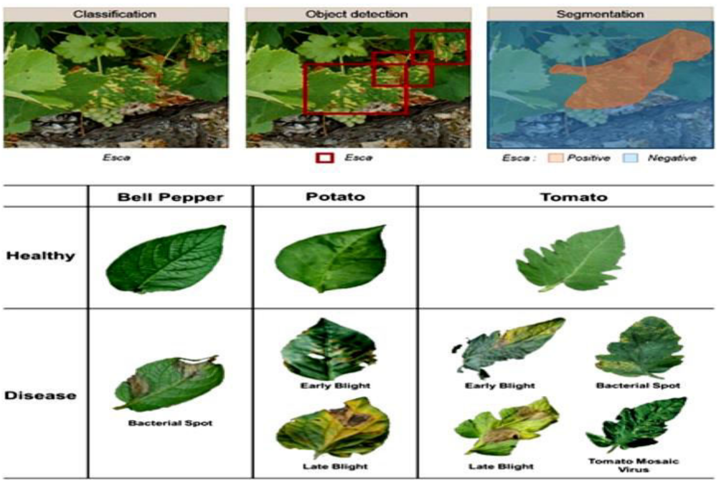


Fig. 4. CNN-based deep learning architecture for plant disease classification showing feature extraction and classification stages

© 2026 IJIRCCE | Volume 14, Issue 4, April 2026 DOI: 10.15680/IJIRCCE.2026.1404047

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

IX. PERFORMANCE EVALUATION MEASURES

Performance evaluation is an important part of plant disease identification systems. It helps measure how effective and reliable the proposed models are. Various quantitative metrics compare traditional machine learning with deep learning approaches. Common evaluation measures include accuracy, precision, recall, F1-score, and loss values over training epochs. Accuracy shows how correct the classification is overall. Precision and recall focus on false positive and false negative rates, respectively. The F1-score balances precision and recall, which is useful for imbalanced datasets. Analyzing loss curves helps us understand how well the model is converging and if it is overfitting during training.

Paper	Dataset			Preprocessing and Augmentation Techniques	Network		Acc [%]	
	Name (Species/Classes)	Number of Images	Number of Images After Preprocessing		(Best) CNN Architecture	Transfer Learning	Overall	Separate Classes
[31]	PlantVillage (1/3)	3700	3700	Re	Modified LeNet	No	92.88	N/A
[9]	PlantVillage (25/58)	54,309	87,848	Cr, Re	VGG	No	99.53	N/A
[33]	Collected (1/9)	5000	43,398	AB, AC, Cr, Fl, NR Re, Ro	R-FCN and ResNet-50	No	85.98	75–95
[36]	Collected (1/3)	299	N/A	NR, Re, Sg	Modified LeNet	Yes	98.60	N/A
[7]	Collected (1/4)	1053	13,689	AB, AC, AS, AT, NR, MS, PCA jittering	Modified AlexNet	No	97.62	91–100
[14]	Collected (14/56)	1567	46,409	BR, Re, Sg	GoogLeNet	Yes	94	75–100
[13]	PlantVillage (14/38)	54,306	N/A	Re, Sg	GoogLeNet	Yes	99.35	N/A
[37]	Collected (6/15)	4483	33,469	AT, Cr, PT, Re, Ro	Modified CaffeNet	Yes	96.30	91–98
[38]	PlantVillage (14/38)	54,323	55,038	Cr, Re, DCGAN	Inception_v3	Yes	99.76	N/A
[39]	PlantVillage (1/4)	2086	N/A	Re, No, Ro, Fl, Zo	VGG16	Yes	90.40	83–100

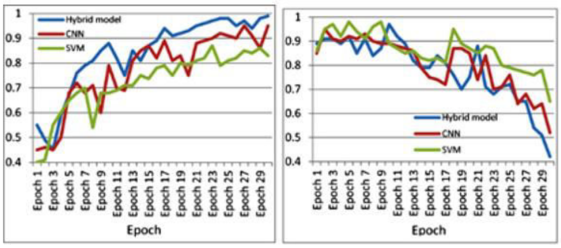


Fig. 5. Performance evaluation comparison of different models using accuracy and loss metrics over training epochs

X. CHALLENGES AND LIMITATIONS

Despite significant progress, plant disease detection systems face several challenges. A major limitation is the lack of large, labeled datasets for training deep learning models. Many plant diseases exhibit similar visual symptoms, leading to class overlap and misclassification. Environmental variability such as lighting conditions, background clutter, and leaf orientation further affects model robustness. Additionally, deep learning models require high computational resources, making real-time deployment difficult in resource-constrained environments [6], [18].

XI. USE IN PRECISION AGRICULTURE

Image processing-based plant disease detection systems play an important role in precision agriculture by enabling:

- Smart farming platforms
- Mobile-based disease diagnosis applications
- Drone-based crop monitoring systems
- IoT-integrated agricultural systems

These applications improve decision-making based on data, boost crop yield, and support sustainable farming practices [10].

XII. FUTURE RESEARCH DIRECTIONS

Future research will focus on creating lightweight deep learning models that can be used on mobile and edge devices. Other promising areas include multispectral and hyperspectral imaging, real-time disease diagnosis, and smooth integration with cloud computing and IoT-based agricultural systems [15], [17].

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

XIII. RESULTS AND ACCURACY COMPARISON

Accuracy was seen as the main way to measure different classification models. Traditional machine learning methods like K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) reached moderate accuracy because they depended on features manually created. In comparison, deep learning CNN models showed better results by automatically learning important features from leaf images. CNN models using transfer learning achieved the highest accuracy, showing their strength in identifying plant diseases.

TABLE II
ACCURACY COMPARISON OF CLASSIFICATION MODELS

Model	Accuracy (%)
K-Nearest Neighbors (KNN)	82.4
Support Vector Machine (SVM)	86.7
Random Forest	89.1
Convolutional Neural Network (CNN)	94.6
CNN with Transfer Learning	97.2

XIV. CONCLUSION

This paper presented a detailed analysis of plant disease detection using image processing techniques. It highlighted the importance of these methods in modern agriculture. The complete workflow included image acquisition, preprocessing, segmentation, feature extraction, and classification. This process demonstrated the effectiveness of automated disease detection systems. We analyzed both traditional machine learning and deep learning approaches, finding that deep learning models showed better accuracy and scalability [6].

Automated plant disease detection reduces reliance on manual inspection. It minimizes human error and allows for early diagnosis, which helps reduce crop losses. While challenges like environmental variability and limited datasets still exist, ongoing advancements in artificial intelligence and computer vision are steadily improving system performance. Overall, image processing-based plant disease detection systems have strong potential to support precision agriculture and sustainable farming practices.

REFERENCES

[1] S. Arivazhagan, R. N. Shebiah, S. Ananthi, and S. Vishnu Varthini, "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features," Agricultural Engineering International: CIGR Journal, vol. 15, no. 1, pp. 211–217, Jan. 2013. [Online]. Available: https://www.researchgate.net/publication/287577015
[2] K. Renugambal and B. Senthilraja, "Application of Image Processing Techniques in Plant Disease Recognition," International Journal of Engineering Research and Technology, vol. 4, no. 3, Mar. 2015, doi: 10.17577/IJERTV4IS030829.
[3] D. P. Hughes and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," arXiv preprint arXiv:1511.08060, Apr. 2016. [Online]. Available: https://arxiv.org/abs/1511.08060
[4] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," Frontiers in Plant Science, vol. 7, Sep. 2016, doi: 10.3389/fpls.2016.01419.
[5] J. G. Arnal Barbedo, "Plant disease identification from individual lesions and spots using deep learning," Biosystems Engineering, vol. 180, pp. 96–107, Apr. 2019, doi: 10.1016/j.biosystemseng.2019.02.002.
[6] Food and Agriculture Organization (FAO), "FAO Knowledge Repository," 2025. [Online]. Available: https://openknowledge.fao.org/items/21407895-8cee-41c0-83ae-4d74b9df8bc5

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[7] R. N. Strange and P. R. Scott, "Plant disease: a threat to global food security," Annual Review of Phytopathology, vol. 43, pp. 83–116, 2005, doi: 10.1146/annurev.phyto.43.113004.133839.
[8] A. Camargo and J. S. Smith, "Image pattern classification for the identification of disease causing agents in plants," Computers and Electronics in Agriculture, vol. 66, no. 2, pp. 121–125, May 2009, doi: 10.1016/j.compag.2009.01.003.
[9] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 4th ed. Pearson, 2018.
[10] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.
[11] M. Karthick, D. Vijayalakshmi, M. K. Nath, and M. Mathumathi, "Machine Learning Approaches for Automatic Disease Detection from Paddy Crops – A Review," International Journal of Engineering Trends and Technology, vol. 70, no. 12, pp. 392–405, Dec. 2022, doi: 10.14445/22315381/IJETTV70I12P237.
[12] R. M. Haralick, "Statistical and structural approaches to texture," Proceedings of the IEEE, vol. 67, no. 5, pp. 786–804, 1979, doi: 10.1109/PROC.1979.11328.
[13] C. Cortes and V. Vapnik, "Support-vector networks," Machine Learning, vol. 20, pp. 273–297, 1995.
[14] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/j.compag.2018.01.009.
[15] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," Computers and Electronics in Agriculture, vol. 161, Mar. 2019, doi: 10.1016/j.compag.2018.03.032.
[16] J. C. Russ and F. B. Neal, The Image Processing Handbook. CRC Press, 2018, doi: 10.1201/b18983.
[17] S. Sladojevic et al., "Deep neural networks based recognition of plant diseases," Computational Intelligence and Neuroscience, 2016, doi: 10.1155/2016/3289801.
[18] N. Otsu, “A threshold selection method from gray-level histograms,” IEEE Transactions on Systems, Man, and Cyber netics, vol. 9, no. 1, pp. 62–66, 1979. [Online]. Available: https://ieeexplore.ieee.org/document/4310076.

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

www.ijircce.com

Scan to save the contact details