JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

# Review on AI-Powered Plant Disease Detection: Advancements, Challenges, And Future Directions in Precision Agriculture

**[1]Dhanalakshmi, [2]Dr. S. Lakshmi Prabha**

[1] Research Scholar, [2] Associate Professor
[1] Department of Computer Science, [2] Department of Computer Science,
[1] Periyar University, Salem, India, [2] Queen Mary's College Chennai, India.

***Abstract :*** Early detection of plant leaf diseases (PLD) is essential for protecting crops, reducing yield losses, and ensuring food security. Traditional disease detection methods depend on manual inspection, which is time-consuming, labor-intensive, and often unreliable for small-scale farmers. To overcome these issues, artificial intelligence (AI), machine learning (ML), and deep learning (DL) have transformed plant disease detection (PDD) by providing fast, automated, and highly accurate image-based classification. This review focuses on AI-based techniques used for detecting diseases in different crops such as corn, mango, tomato, apple, rice, tea, potato, wheat, palm oil, and citrus. It highlights recent progress in DL models, feature fusion methods, and real-time solutions like IoT-based monitoring systems and mobile apps. Although these technologies have greatly improved DD accuracy and speed, challenges still exist, including the need for large labeled datasets, high computational resources, and extensive testing under real-world conditions.

***IndexTerms* - Artificial Intelligence, Crop Disease, Deep Learning, Leaf disease, Machine Learning, Precision Agriculture, Plant Disease Detection.**

## I. INTRODUCTION

PLD are a major challenge in global agriculture, causing serious yield losses, poor crop quality, and higher production costs. These diseases, often spread by bacteria, fungi, or viruses, can quickly damage crops if not detected and managed early, affecting both food security and the economy. Early and accurate detection of PLD is essential for effective crop management, helping farmers take preventive actions and use resources wisely. However, traditional DD methods depend on manual inspection by agricultural experts, which is slow, labor-intensive, and not easily accessible to small-scale farmers, especially in rural areas. Manual diagnosis is also prone to human errors and inconsistencies caused by varying environmental conditions, disease symptoms, and differences in observer experience. Automated DD using AI, ML, and DL has become increasingly popular to overcome these limitations. These computational methods provide fast, scalable, and cost-effective ways to diagnose PD from images. Among them, DL-based models, especially CNNs, have shown outstanding results in identifying plant diseases. CNNs are powerful for FE and classification, helping distinguish between healthy and diseased leaves with high accuracy. Advanced DL architectures like EfficientNet, DenseNet, GoogleNet, and VGG have been widely used, often combined with feature fusion, clustering (e.g., K-means), and lightweight optimization to improve accuracy and efficiency. Traditional ML methods like RF and SVM have also been tested, but they usually achieve lower accuracy due to limited ability to capture complex patterns in large datasets.

Recent studies have explored LD detection in crops such as rice, tomato, mango, apple, citrus, tea, potato, wheat, palm oil, and grapes. These works focus on improving classification accuracy, optimizing models for lower computational cost, and developing hybrid systems for better recognition. Real-time applications, including mobile apps and IoT-based monitoring, are also being developed to support farmers directly. Still, challenges remain, such as the need for large labeled datasets, high computational resources, and limited validation under real field conditions. Variations in lighting, background, and overlapping symptoms further affect model performance. Future work should emphasize dataset expansion, lightweight model optimization for low-resource environments, and use of hyperspectral imaging for better accuracy. With advances in AI and DL, PLDD research is moving toward more reliable, efficient, and accessible tools that bridge the gap between technology and real-world farming, supporting sustainable crop management and global food security.

## II. REVIEW OF AI-DRIVEN PLANT DISEASE DETECTION STUDIES

The detection of PD is critical for ensuring agricultural productivity, reducing economic losses, and enhancing food security. Advances in AI and ML have enabled automated PDD, significantly improving early diagnosis, classification accuracy, and efficiency in agricultural monitoring. This review synthesizes key contributions from recent studies leveraging AI, DL, and image processing(IP) for plant disease identification. DL has revolutionized PDD by automating FE, reducing human intervention, and enhancing classification accuracy. Various studies emphasize the importance of AI-driven approaches for real-time monitoring, sustainability, and precision agriculture.

Key Studies

- **DL in DD**: Research by Li et al. (2021)[1] and Barburiceanu et al. (2021)[2] demonstrates the effectiveness of CNN-based FE for real-time plant disease classification. Similarly, Arivazhagan et al. (2013)[3] developed an image-processing-based detection system achieving 94% accuracy.
- **Ensemble and Transfer Learning(TL) Approaches**: Studies by Bhargava et al. (2024)[4] and Oad et al. (2024)[5] integrated DL and few-shot learning techniques to enhance disease classification. Models such as PlantDet (Shovon et al., (2023) [6]) utilized deep ensemble learning for improved accuracy.
- **Dataset Expansion and Enhancement**: Liu et al. (2021)[7] and Moupojou et al. (2013) [8] addressed dataset limitations by constructing large-scale and field-collected datasets for better generalizability.
- **Hybrid and Optimized Models**: Studies like those by Nagasubramanian et al. (2021) [9] integrated IoT with AI, while Dwivedi et al. (2021)[10] introduced the GLDDN model, achieving 99.93% accuracy in grape LD detection LDD.
- **Advanced IP and FE**: Research by Leong et al. (2020)[11] and Rani et al. (2023)[12] optimized FE using deep TL and clustering techniques.
- **Hyperspectral and Graph-Based DL**: Bhatti et al. (2024)[13] explored hyperspectral imagery analysis with graph-based DL, integrating fuzzy logic for enhanced classification accuracy.
- **Model Optimization for Practical Deployment**: Studies such as Abinaya et al. (2023)[14] developed attention-based U-Net architectures to improve segmentation accuracy, while Adnan et al. (2023)[15] introduced EfficientNetB3-AADL for robust disease classification.

Yin Min Oo et al. (2018)[16] used digital IP to classify four major PD, demonstrating effective early detection. Vijai Singh et al. (2017)[17] proposed a genetic algorithm-based image segmentation technique, reducing manual monitoring efforts in large farms. Namita M et al. (2019)[18] outlined an automated DD framework, enhancing accuracy and accessibility for farmers with limited expert support. D. S. Joseph et al. (2024)[19] developed specialized datasets for rice, wheat, and maize, testing DL models like Xception and MobileNet. A new CNN model achieved superior accuracy, highlighting AI's potential in disease diagnosis. These studies reinforce AI's role in automating PDD, improving accuracy, and ensuring practical agricultural applications.

## III. CROP-SPECIFIC DISEASE DETECTION ADVANCES

### *3.1 Corn leaf DD*

H. Amin et al. (2022)[20] developed a DL model based on EfficientNetB0 and DenseNet121 for detecting corn LD. Their approach significantly improved detection accuracy while reducing model complexity. Compared to larger architectures like ResNet152 and InceptionV3, their method achieved a superior accuracy of 98.56%, making it an efficient and effective solution.

H. Yu et al. (2021)[21] proposed a hybrid approach that combines K-means clustering with DL to diagnose three common corn diseases. By experimenting with different clustering values and models, their method achieved a 93% average accuracy, surpassing other existing models and demonstrating strong potential for precision agriculture.

X. Zhang et al. (2018)[22] introduced an optimized version of GoogLeNet and Cifar10 models for maize leaf DD. By refining model parameters and reducing the number of classifiers, they achieved 98.9% and 98.8% accuracy, respectively, while enhancing training efficiency and reducing computational costs.

Panigrahi, K.P et al. (2020)[23] conducted a comparative analysis of various ML models for maize DD, including Naïve Bayes, Decision Tree, KNN, SVM, and RF. Among these, the RF model outperformed others with an accuracy of 79.23%, proving its usefulness for early DD.

Abdul Waheed et al. (2020)[24] developed an optimized DenseNet model for classifying corn LD. Their approach balanced high accuracy (98.06%) with reduced computational demands, outperforming conventional CNN models in both efficiency and training time.

Ahila Priyadharshini, R et al. (2019)[25] proposed a modified LeNet CNN for maize LD classification. Utilizing the PlantVillage dataset, their model achieved an accuracy of 97.89%, proving its effectiveness in identifying crop diseases and contributing to smart agricultural solutions.

Shuai-qun PAN et al. (2022)[26] focused on diagnosing Northern Corn Leaf Blight (NCLB) using deep CNNs. Implementing GoogleNet with advanced loss functions, they achieved an outstanding 99.94% accuracy, setting a benchmark for intelligent DD in agriculture.

P. Ouppaphan et al. (2017)[27] developed a lightweight CNN to classify corn LD using the PlantVillage dataset. Their model achieved 97.09% accuracy while maintaining low computational complexity, making it highly suitable for real-time mobile applications and field deployment.

Most recent research focuses on DL-based models such as CNNs, EfficientNet, DenseNet, GoogleNet, and VGG architectures. Some studies integrate feature fusion, clustering techniques (K-means), or optimized lightweight models to improve accuracy and computational efficiency. Traditional ML methods like RF and SVM have also been explored but generally achieve lower accuracy than DL models. Key contributions include achieving high classification accuracy, optimizing model parameters to reduce computational cost, and introducing hybrid approaches for better disease recognition. However, limitations such as the need for large labeled datasets, high computational power, and limited real-world validation persist. Overall, DL models show promising results for automating corn leaf DD, with ongoing research focusing on improving model efficiency and real-world applicability.

### *3.2 Mango leaf Disease Detection*

Mango LD, particularly fungal infections like Anthracnose, significantly impact mango production and quality. Early and accurate DD is crucial for minimizing yield losses and improving crop management. This study reviews various approaches that employ AI, DL, and ML techniques to automate the detection and classification of mango LD.

U. P. Singh et al. (2019)[28] focuses on detecting Anthracnose in mango leaves using a Multilayer CNN (MCNN). A dataset of 1070 mango leaf images was used for training and validation, demonstrating superior classification accuracy compared to other models.

T. N. Pham et al. (2020)[29] highlights the limitations of traditional leaf DD and proposes an Artificial Neural Network (ANN)-based approach for early identification using high-resolution images. Feature selection(FS) and contrast enhancement techniques improved detection accuracy, outperforming CNN models like AlexNet and ResNet-50.

Gautam, V et al. (2024)[30] presents an AI-based approach using an ensemble stacked DL model for early mango leaf DD. The model integrates multiple deep neural networks(NN) and ML techniques, achieving 98.57% accuracy in identifying diseases like Powdery Mildew and Anthracnose.

Redwan Ahmed Rizvee et al. (2023)[31] developed LeafNet, a CNN-based model for detecting seven mango diseases using a region-specific dataset from Bangladesh. The model outperformed state-of-the-art architectures like AlexNet and VGG16, achieving 98.55% accuracy in a 5-fold cross-validation.

Venkatesh, N et al. (2020)[32] introduces V2IncepNet, a modified VGGNet model combined with Inception modules for improved EF. Using a dataset of 2268 mango leaf images, the model achieved over 92% accuracy in classifying Anthracnose infection levels.

Selvakumar, A et al. (2023)[33] proposed an automated mango leaf DD system using an optimized Fuzzy C-Means (FCM) segmentation and Deviation-based Updated Dingo Optimizer (D-UDOX). Deep features extracted from ResNet-150 were classified using an Optimized Recurrent NN(WO-RNN), achieving 96% accuracy and a 93% F1-score.

This review provides a concise comparison of different methods, contributions, and limitations of the studies on mango leaf DD. The discussed studies focus on AI-driven approaches for detecting and classifying mango LD, particularly fungal infections like Anthracnose and Powdery Mildew. Traditional manual detection methods are unreliable, prompting researchers to explore DL and hybrid models for improved accuracy and efficiency. Various techniques, including CNNs, ANNs, and ensemble DL models, have been proposed, achieving high classification accuracy, often exceeding 90%. Some studies integrate FS and optimization techniques to enhance DD, especially for early-stage symptoms. While these models show promising results, challenges remain, such as computational complexity, limited disease coverage, and region-specific datasets. Overall, AI-based solutions significantly improve DD in mango leaves, offering real-time, cost-effective tools for farmers, though further research is needed to develop more generalized and efficient models.

### *3.3 Beans leaf Disease Detection*

Bean LD, such as angular leaf spot and bean rust, significantly impact production. E. Elfatimi et al. (2022)[34] employs DL with MobileNet to classify bean LD using a public dataset. MobileNetV2 was also tested for improved efficiency. The proposed model achieved over 97% accuracy on training data and 92% on test data, demonstrating its effectiveness in disease classification.

Automation in agriculture is crucial for early DD. Vimal Singh et al. (2023)[35] used MobileNetV2, EfficientNetB6, and NasNet to classify bean LD from 1,295 images. EfficientNetB6 performed best with 91.74% accuracy. The study highlights the impact of optimizers on CNN models and suggests real-time applications for farmers to minimize crop loss.

Bean crops suffer from diseases like angular leaf spot and bean rust. Abed, S.H et al. (2021)[36] introduces a DL-based robotic framework for early detection. Using U-Net with ResNet34 for leaf segmentation and multiple CNN models for classification, DenseNet121 achieved the highest accuracy (98.31% for binary classification, 91.01% for multi-class). The framework provides rapid and accurate diagnosis in uncontrolled environments.

DL techniques, particularly MobileNet, were used to detect bean LD across three datasets. E. Elfatimi et al. (2024)[37] assessed MobileNet's efficiency in classification, achieving over 92% accuracy. GradCAM was applied to visualize model predictions. This study emphasizes the potential of DL in agricultural DD.

Ethiopian farmers rely on visual inspection for common bean DD, which is inefficient. Girmaw, D.W et al. (2024)[38] proposes a deep CNN model with 12 layers to classify three common bean diseases. The model, trained on 1,766 images, outperformed pre-trained models like AlexNet and VGG16, achieving 98% training accuracy and 96% testing accuracy.

Kursun, R et al. (2023)[39] explored U-Net's segmentation capabilities for bean leaf DD. Sixty images of diseased leaves were segmented, followed by classification using VGG16, AlexNet, MobileNetV2, and DenseNet201. Segmented images yielded better accuracy, with DenseNet201 achieving 100%. An end-to-end system was developed to focus DL on diseased areas, improving classification accuracy.

DL-based methods are widely used for bean leaf DD, with various architectures such as MobileNet, EfficientNet, DenseNet, and U-Net proving effective. The overall summery of the studies discussed focused on optimizing CNN models, utilizing TL, or incorporating image segmentation to enhance classification accuracy. While some works achieved remarkable accuracy (e.g., 100% for segmented images and 98% for binary classification), most were limited by small datasets, lack of real-world deployment, and high computational demands. Future research should address these limitations by integrating real-time applications and expanding datasets to improve model generalization.

### *3.4 Tomato leaf DD*

H. Sabrol et al. (2016)[40] explored IP techniques for plant disease classification, focusing on five tomato diseases: late blight, Septoria spot, bacterial spot, bacterial canker, and tomato leaf curl. The study utilized color, shape, and texture features for classification, achieving a 97.3% accuracy rate. The classification process involved segmenting images, extracting features, and feeding them into a decision tree model for classification.

D. Jiang et al. (2020)[41] applied DL for tomato leaf DD using ResNet-50, targeting three diseases: Spot blight, Late blight, and Yellow leaf curl disease. The study modified network parameters, such as kernel size and activation functions, resulting in improved training and test accuracy of 98.3% and 98.0%, respectively. The research highlighted the effectiveness of DL in PDD.

C. Zhou et al. (2021)[42] developed a restructured residual dense network for tomato LD identification, combining deep residual networks and dense networks. This hybrid model improved accuracy and reduced computational costs, achieving a top-1 accuracy of 95% on the Tomato dataset from the AI Challenger 2018. The study emphasized the significance of precise disease severity assessment for better crop management.

P. Tm et al. (2018)[43] employed a variation of the LeNet CNN model to detect and classify tomato LD. The study aimed to provide a simple and resource-efficient approach while maintaining high accuracy. The model achieved an accuracy of 94-95%, demonstrating the feasibility of NNs for DD even under challenging conditions.

S. Ashok et al. (2020)[44] focused on early DD using IP techniques such as image segmentation, clustering, and open-source algorithms. The study emphasized the need for early identification of PD to prevent economic losses and food shortages in an agricultural economy like India.

Q. Wu et al. (2020)[45] investigated various ML techniques, including Fuzzy-SVM, CNN, and R-CNN, for tomato LD classification. The study employed image segmentation and EF methods, concluding that the R-CNN classifier achieved the highest accuracy of 96.735%, outperforming other models in plant disease prediction.

Nagamani, H. S. et al. (2022)[46] introduced a data augmentation approach using generative adversarial networks (GANs) to enhance tomato leaf DD. The study used DCGAN to generate additional training images, improving model generalization. With the augmented dataset, the proposed GoogLeNet model achieved a classification accuracy of 94.33%, demonstrating the effectiveness of GANs in enhancing training datasets.

Mingxuan Li et al. (2022)[47] proposed an improved GAN-based data augmentation technique, Fast WDBlock-based GAN (FWDGAN), to generate high-quality synthetic images for tomato leaf DD. The model incorporated ResNet and InceptionV1 features, reducing computational requirements while improving image quality. Comparative experiments showed FWDGAN outperformed DCGAN in generating realistic data for disease classification.

Trivedi, Naresh K et al. (2021)[48] implemented a CNN-based model for classifying tomato diseases using a dataset of 3,000 images. The study involved preprocessing, segmentation, and CNN-based FE, achieving an accuracy of 98.49%. The research aimed to assist farmers in early DD, improving tomato crop yields and quality.

Guerrero-Ibañez et al. (2023)[49] developed a CNN model for tomato leaf DD, utilizing a combination of public datasets and field-collected images. To prevent overfitting, generative adversarial networks (GANs) were used to generate additional training data. The model achieved over 99% accuracy in both training and test datasets, showcasing the reliability of DL in agricultural applications.

A. Batool et al. (2020)[50] emphasized the importance of accurate disease classification for effective treatment. The study trained a model on 450 images using AlexNet and kNN classifiers, achieving a maximum accuracy of 76.1%. The research highlighted challenges in disease classification and the need for improved FE techniques.

Mohit Agarwal et al. (2020)[51] applied a CNN-based approach for tomato DD, comparing the model’s performance with pre-trained networks such as VGG16, InceptionV3, and MobileNet. The proposed model achieved an average accuracy of 91.2% across nine disease classes and one healthy class, demonstrating DL’s potential in plant disease classification.

Ahmad et al. (2020)[52] evaluated four CNN architectures (VGG-16, VGG-19, ResNet, and Inception V3) for tomato LD classification. The study tested models on both laboratory-based and field-based datasets, finding that CNNs performed better in controlled environments. Inception V3 emerged as the best-performing model, demonstrating the importance of dataset quality in classification accuracy.

T. Anandhakrishnan et al. (2022)[53] proposed an automatic tomato leaf DD system using Deep CNN (DCNN). The model was trained on 18,160 images from the PlantVillage dataset, achieving a test accuracy of 98.40%. The study emphasized the role of DCNN in improving detection speed and accuracy while minimizing response time in agricultural applications.

Tomato leaf DD has seen significant advancements with DL and IP techniques. Early methods relied on FE and classification trees, while recent studies leverage CNNs, ResNet, and GAN-based data augmentation for improved accuracy. The highest accuracy (>99%) was achieved using GAN-augmented CNN models, while traditional FE methods showed limitations in handling complex disease patterns. However, many models require high computational resources and extensive datasets. Future research should focus on real-world deployment, computational efficiency, and addressing dataset biases for improved robustness.

### *3.5 Apple leaf disease Detection*

V. K. Vishnoi et al. (2023)[54] Developed a lightweight CNN for apple leaf DD, reducing computational complexity while maintaining 98% accuracy. Used data augmentation to expand training data without extra images. The model is efficient, requiring less storage and execution time, making it ideal for handheld devices.

L. G. Nachtigall et al. (2016)[55] Utilized CNNs to classify apple tree diseases, nutritional deficiencies, and herbicide damage. With 2,539 labeled images, the model achieved 97.3% accuracy, outperforming human experts in disease diagnosis.

P. Jiang et al. (2019)[56] Proposed INAR-SSD, a real-time deep CNN model trained on 26,377 images from lab and field conditions. Achieved 78.80% mAP with 23.13 FPS detection speed, improving early DD.

Liu, Bin et al. (2018)[57] Developed an AlexNet-based CNN for detecting Mosaic, Rust, Brown Spot, and Alternaria Leaf Spot using 13,689 images. Achieved 97.62% accuracy while reducing model parameters by 51 million, ensuring efficiency and robustness.

Bansal, Prakhar et al. (2021)[58] Introduced an ensemble model (DenseNet121, EfficientNetB7, and NoisyStudent) to classify healthy, scab, cedar rust, and multiple diseases. Achieved 96.25% accuracy and 90% accuracy for multiple diseases, improving large-scale farm monitoring.

Chao, Xiaofei et al. (2020)[59] Developed a DCNN model (DenseNet + Xception) with global average pooling for faster, more accurate DD (98.82% accuracy). Outperformed existing models, suitable for smart apple cultivation systems.

Yan, Qian et al. (2020)[60] Enhanced VGG16-based model using global average pooling and batch normalization, achieving 99.01% accuracy with 89% fewer parameters and 99.44% faster training. Ensures efficient and accurate DD.

Pradhan, P et al. (2022)[61] Fine-tuned 10 CNN models on PlantVillage dataset, identifying Scab, Black Rot, and Cedar Rust. DenseNet201 achieved the best results with 98.75% accuracy, proving CNNs as a reliable alternative for DD.

The research on apple leaf DD has extensively used DL techniques to improve detection accuracy and efficiency. Most studies rely on CNN architectures, with some incorporating advanced modifications like Inception modules, Rainbow concatenation, or SVM classifiers. The highest reported accuracy was 99.01% (Yan et al., 2020)[60], showing that DL models can achieve near-perfect classification. Despite these advancements, challenges such as high computational costs, need for large datasets, and overfitting still exist. Future research could focus on reducing model complexity further while maintaining accuracy, improving generalizability to real-world conditions, and enhancing interpretability for practical agricultural applications.

### *3.6 Rice leaf Disease Detection*

S. Ghosal et al. (2020)[62] Developed a VGG-16-based CNN model using TL due to a limited dataset. The model, trained on rice field and internet images, achieved 92.46% accuracy, demonstrating DL’s potential for automated disease identification.

S. M. Taohidul Islam et al. (2019)[63] Proposed a wavelet transform-based approach for rice disease classification. Used Discrete Wavelet Transform (DWT) for FE and an Ensemble of Linear Classifiers for classification. Achieved 95% accuracy in detecting Bacterial Blight, Brown Spot, Sheath Brown Rot, and Rice Blast.

M. E. Pothen et al. (2020)[64] Utilized Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) for FE. Applied SVM for classification, achieving 94.6% accuracy using Otsu's method for image segmentation.

F. T. Pinki et al. (2017)[65] Developed an automated diagnosis system for Brown Spot, Leaf Blast, and Bacterial Blight using K-means clustering for segmentation and SVM for classification. Provided remedial recommendations based on disease severity.

Krishnamoorthy N et al. (2021)[66] Implemented an InceptionResNetV2 CNN model with TL for DD. The model optimized parameters to improve accuracy, achieving 95.67% accuracy, making it highly reliable for real-world applications.

S. Ramesh et al. (2020)[67] Proposed a Deep NN with Jaya Optimization Algorithm (DNN_JOA) for classifying normal, bacterial blight, brown spot, sheath rot, and blast diseases. Achieved 98.9% accuracy for blast detection, outperforming ANN and DAE models.

Md. Ashiqul Islam et al. (2021)[68] Compared VGG-19, Inception-ResNet-V2, ResNet-101, and Xception for DD in four diseased and one healthy class. Inception-ResNet-V2 achieved 92.68% accuracy, proving DL's effectiveness over manual detection methods.

Shankarnarayanan Nalini et al. (2021)[69] Developed a Deep NN (DNN) optimized with Crow Search Algorithm (CSA) for rice DD. Used K-means clustering for segmentation and statistical learning techniques for FE, ensuring high accuracy with reduced computational effort.

Mainak Deb et al. (2021)[70] Evaluated five CNN models (Inception-V3, VGG-16, AlexNet, MobileNetV2, and ResNet-18) on 7,096 paddy leaf images. Inception-V3 achieved 96.23% accuracy, proving the best for early DD.

Maheswaran, S et al. (2022)[71] Developed a CNN-based model for classifying normal, sheath rot, blast, bacterial blight, brown spot, rice tungro, and RYMV diseases. Applied background exclusion and FE, achieving high accuracy in DD.

Norhalina Senan et al. (2020)[72] Proposed a five-layer CNN model for detecting healthy, brown spot, leaf blast, and hispa diseases. Achieved 93% accuracy, outperforming traditional detection methods with faster processing.

O. K. Pal et al. (2021)[73] Utilized CNN models (ResNet-50, ResNet-101, VGG-16, VGG-19, EfficientNet, Inception-V2, GoogleNet) for paddy DD. ResNet-50 achieved the highest accuracy (96.27%), making it an efficient alternative to costly laboratory methods.

Research on rice leaf DD has seen significant advancements with DL and IP techniques. CNN-based models, including VGG, Inception-ResNet-V2, ResNet, and EfficientNet, have demonstrated high accuracy. Feature-based approaches using wavelet transforms, HOG, and LBP have also been effective. The highest accuracy reported using DNN with Jaya Optimization Algorithm. Key contributions across studies include improving classification accuracy, FE, and computational efficiency. However, challenges remain in dataset availability, computational complexity, and generalization to real-world scenarios. Future research should focus on scaling models to larger datasets, reducing computational costs, and improving real-time detection capabilities for practical agricultural use.

### *3.7 Tea leaf Disease Detection*

S. Hossain et al. (2018)[74] presents an image-processing-based system to detect and classify two common tea LD in Bangladesh—brown blight and algal LD—using a SVM classifier. By analyzing 11 key features, the model achieves over 90% accuracy while reducing processing time by 300ms per image compared to previous research. The proposed approach enhances DD efficiency, ultimately benefiting tea production in Bangladesh.

S. Gayathri et al. (2020)[75] explores DL techniques for tea leaf DD, leveraging the LeNet CNN. The model effectively classifies diseased leaves, offering a reliable method for improving plant disease diagnosis and enhancing the accuracy of automated detection systems.

Saikat Datta et al. (2023)[76] introduces a deep CNN model for classifying tea LD into six categories, achieving a high accuracy of 96.56%. The model is trained on a dataset of 5,867 images and outperforms existing methods. Additionally, it is adaptable for deployment in IoT applications, making it a robust solution for real-world DD in the tea industry.

Gensheng Hu et al. (2019)[77] proposed an improved deep CNN model with a multiscale FE module for tea LD identification. Using depthwise separable convolution, the model reduces parameters and computation time while achieving 92.5% accuracy, outperforming traditional ML and DL methods like VGG16 and AlexNet.

Chen, Jing et al. (2019)[78] develops a CNN model, LeafNet, for tea LD classification. It integrates dense scale-invariant feature transform (DSIFT) and a bag-of-visual-words (BOVW) approach with SVM and MLP classifiers. LeafNet outperforms the other models, achieving 90.16% accuracy, demonstrating its effectiveness in improving DD.

Rahman, H et al. (2024)[79] proposes a CNN-based model for detecting tea foliage diseases using a dataset of 3,330 images collected from Bangladesh's Sylhet region. The model, validated with laboratory tests, achieves 96.65% accuracy in identifying diseases like red rust, brown blight, and gray blight, making it a promising tool for early DD in the tea industry.

Gensheng Hu et al. (2022)[80] introduces MergeModel, a multi-CNN approach incorporating diseased leaf segmentation and weight initialization to enhance FE. Using SinGAN for data augmentation, the model effectively identifies tea diseases like white scab and red scab with improved accuracy, even in small datasets.

S. Bhowmik et al. (2020)[81] presents a CNN-based model for detecting Black Rot and Rust in tea leaves with minimal computational complexity. The approach ensures rapid and accurate disease identification, achieving 95.93% precision, contributing to improved monitoring of tea plant health in India.

Recent advancements in tea leaf DD have significantly improved accuracy and efficiency through ML and DL techniques. Early approaches used SVM classifiers to detect specific diseases with moderate success. Later studies leveraged CNN-based models such as LeNet, LeafNet, and multi-CNN architectures to improve accuracy, FE, and disease classification capabilities. Data augmentation and segmentation techniques further enhanced disease recognition, particularly in small datasets. The highest accuracy (96.65%) was achieved using CNN models validated with real-world microbial analysis. However, challenges remain, including dataset limitations, computational complexity, and the need for broader generalization across diverse environmental conditions. Future research should focus on real-world deployment, IoT integration, and the development of more scalable, efficient models.

### *3.8 Potato leaf Disease Detection*

R. A. Sholihati et al. (2020)[82] presents a DL-based system for classifying four types of potato LD using VGG16 and VGG19 CNN models. With an average accuracy of 91%, the approach demonstrates the feasibility of deep NNs for accurate DD.

M. Islam et al. (2017)[83] integrates IP and ML for automated potato leaf DD using the PlantVillage dataset. A SVM model achieved 95% accuracy, offering a scalable solution for rapid disease diagnosis.

Sowmiya R et al. (2024)[84] aims to classify four potato LD with 97% accuracy by utilizing VGG16 and VGG19 models. The approach ensures early detection, helping maintain plant health and improve harvest quality.

Lee, TY et al. (2021)[85] proposed A CNN-based model for detecting potato LD, achieving 99.53% accuracy while optimizing computational resources. The study highlights the benefits of real-time disease control in smart farming.

Mahum, R et al. (2022)[86] introduces an improved DL model using DenseNet-201 to classify potato LD into five categories. By addressing dataset imbalance with a reweighted loss function, the model achieves 97.2% accuracy.

D. Tiwari et al. (2020)[87] fine-tunes FE for potato disease classification by leveraging TL with VGG19. Logistic regression outperformed other classifiers, achieving 97.8% accuracy on the test dataset.

Kumar, A et al. (2023)[88] introduced a Hierarchical DL CNN (HDLCNN) for potato leaf DD, outperforming existing models with higher accuracy, precision, and recall. The approach supports early disease identification and effective treatment strategies.

Rashid, Javed et al. (2021)[89] develops a multi-level DL model using YOLOv5 for segmentation and CNN for disease classification. The model achieves 99.75% accuracy, proving effective across different datasets.

Khalifa, N.E.M et al. (2021)[90] proposed a deep CNN-based architecture for potato leaf blight classification. With extensive data augmentation, the model achieved 98% accuracy, demonstrating superior performance over related studies.

The research on potato leaf DD has evolved significantly with the application of ML and DL models. Early works focused on traditional ML techniques like SVM, achieving relatively high accuracy. Later studies, such as DL models like VGG16 and VGG19 for improved classification accuracy. More recent advancements include optimized CNN architectures and DenseNet variations, leading to more robust models capable of classifying multiple diseases with higher accuracy. Some studies incorporated segmentation techniques (YOLOv5) for enhanced disease localization, while others introduced hierarchical learning for more refined FE. Overall, while accuracy has improved, limitations such as dataset diversity, computational cost, and real-time application remain challenges for future research.

3.9 Grape leaf Disease Detection

P. B. Padol et al. (2016)[91] uses IP and SVM classification to detect and classify grape LD. The method involves K-means clustering for segmentation and FE, achieving an accuracy of 88.89%.

Z. Huang et al. (2020)[92] applies TL with VGG16, MobileNet, and AlexNet to classify grape LD. An ensemble model further improves detection accuracy, demonstrating the potential of AI in grapevine disease management.

R. Dwivedi et al. (2021)[10] proposed a Grape Leaf DD Network (GLDDN), utilizing dual attention mechanisms for classification. The model achieves 99.93% accuracy in detecting esca, black rot, and isariopsis, outperforming traditional methods.

B. Liu et al. (2020)[93] introduces Leaf GAN, a generative adversarial network for synthesizing grape LD images to enhance model training. The expanded dataset improves CNN-based classification, with Xception achieving 98.70% accuracy.

Grape leaf DD has significantly evolved from traditional IP techniques to DL models. Early research used SVM with image segmentation but achieved moderate accuracy. Later studies incorporated DL and TL which improved classification performance using ensemble models. Further advanced the field by introducing attention mechanisms, achieving near-perfect accuracy. Meanwhile some study tackled data scarcity with GAN-generated images, enhancing CNN model accuracy. While these advancements have improved DD, challenges remain in real-world applicability, dataset diversity, and computational efficiency.

### *3.10 Wheat leaf Disease Detection*

Z. Lin et al. (2019)[94] introduces the matrix-based CNN (M-bCNN) to enhance fine-grained classification of wheat LD. The model improves feature representation and achieves 96.5% validation accuracy and 90.1% test accuracy, outperforming AlexNet and VGG-16.

Laixiang Xu et al. (2023)[95] developed the RFE-CNN model, integrates multiple DL techniques to improve wheat leaf DD. It achieves a classification accuracy of 99.50% across multiple datasets, though further enhancements are needed for diverse ecological conditions.

Usha Ruby, A et al. (2024)[96] proposes a modified ResNet50 architecture with GAN-based image imputation for improved wheat LD classification. The model outperforms ResNet50, InceptionV3, and DenseNet, achieving a 98.44% identification accuracy.

Jiang, Jiale et al. (2022)[97] prepared a comparative analysis of seven CNN models using field-acquired wheat LD images highlights Inception-v3 as the most accurate (92.5%) under TL. Environmental factors and symptom similarities posed classification challenges.

Zhencun Jiang et al. (2021)[98] enhances the VGG16 model with multi-task TL for wheat and rice LD classification. The approach achieves 98.75% accuracy for wheat LD, outperforming other CNN models.

Wen, Xiaojie et al. (2023)[99] evaluates different CNN training strategies for wheat leaf DD. MnasNet, with SGD + StepLR optimization, achieves the highest accuracy (98.65%) while maintaining a compact model size suitable for mobile applications.

Wheat leaf DD has seen significant advancements with the integration of DL techniques. Early approaches introduced M-bCNN to improve fine-grained classification, but it faced challenges in real-world scenarios. More recent studies leveraged attention mechanisms and elliptic metric learning to boost classification accuracy. GANs for enhanced FE, achieving high accuracy. Meanwhile tested CNN models under field conditions, highlighting real-world challenges. Another notable proposed multi-task TL with VGG16, proving effective for cross-PDD. Optimized lightweight CNN models with learning rate strategies, making them suitable for mobile deployment. Despite these advancements, challenges remain in handling real-world variations, dataset diversity, and optimizing computational efficiency for practical use in agriculture.

### *3.11 Palm oil leaf Disease Detection*

Research in palm oil leaf DD has significantly evolved from traditional ML models to DL-based approaches. It has advanced significantly with the integration of ML and DL techniques.

Early efforts by A. N. I. Masazhar et al. (2017)[100] utilized digital IP, employing k-means clustering and a multiclass SVM classifier to identify Chimaera and Anthracnose diseases with 97% and 95% accuracy, respectively. This study highlighted the potential of FE in improving classification accuracy. Later, Jia Heng Ong et al. (2022)[101] improved upon traditional ML methods by eliminating the need for manual FE and segmentation. They implemented DL models, specifically AlexNet CNN and AlexNet-SVM, finding that AlexNet CNN outperformed the SVM-based classifier, offering a more efficient approach to DD.

Beyond disease identification, some studies focused on nutrient deficiency detection. Ibrahim, S et al. (2022)[102] applied CNN to classify palm leaf deficiencies in essential nutrients such as Nitrogen, Potassium, and Magnesium. Their model achieved 94.29% accuracy, demonstrating the viability of automated nutrient monitoring to improve crop health. Similarly, Muhammad Ikmal Hafiz Razali et al. (2022)[104] compared multiple CNN architectures, including ResNet-50, VGG16, DenseNet-201, and AlexNet, to classify nutrient deficiencies based on leaf color and texture variations. Their results showed 100% accuracy for VGG16 and AlexNet, with AlexNet emerging as the most computationally efficient model.

Some studies focused on real-world applications with natural background images to enhance practical usability. A. Septiarini et al. (2022)[103] developed a CNN-based detection system that distinguished between healthy and infected leaves in real-world settings. The model was optimized through pre-processing techniques such as resizing, normalizing, and data augmentation (rotation, flip, shear, and zoom), achieving an impressive 100% accuracy. Similarly, Yufis Azhar et al. (2024)[105] introduced a CNN-based approach for detecting leaf spot disease in oil palm seedlings. Their method incorporated hyperparameter tuning to enhance accuracy, ensuring reliable differentiation between diseased and healthy leaves.

Overall, these studies demonstrate the significant role of DL in palm oil leaf DD. While CNN-based models consistently achieve high accuracy, future improvements could involve larger datasets, improved generalization to different environmental conditions, and integration with hyperspectral imaging for enhanced disease classification. The combination of disease and nutrient deficiency detection can further support sustainable palm oil production and minimize economic losses in the industry.

### *3.12 Citrus fruit leaf Disease Detection*

Research on citrus fruit and leaf DD has progressed significantly with DL techniques. A. Khattak et al. (2021)[106] proposed a CNN model to classify common citrus diseases, including black spot, canker, scab, greening, and melanose. Their model outperformed other DL approaches with a test accuracy of 94.55%, making it a valuable tool for farmers. Saini, A. K et al. (2021)[107] introduced a mobile-based diagnosis system using CNN and TL, enabling field detection of citrus diseases with over 90% accuracy. Their model was successfully deployed as an Android application, providing rapid and cost-effective disease identification.

Focusing on improving model accuracy, Shastri, R et al. (2023)[108] developed an Enhanced-CNN (E-CNN) trained on three benchmark datasets. Their approach significantly improved DD, achieving 98% recognition accuracy and 99% classification accuracy, surpassing previous models by more than 6%. Utpal Barman et al. (2022)[109] compared MobileNet and a Self-Structured CNN (SSCNN) for smartphone-based citrus disease classification. While both models achieved 98% training accuracy, SSCNN demonstrated higher validation accuracy (99%) and lower computational costs, making it a more efficient choice.

To address the lack of annotated datasets, Sathian Dananjayan et al. (2022)[110] developed the CCL'20 dataset and evaluated state-of-the-art CNN models, such as YOLOv4 and Faster-RCNN. Their results showed that Scaled YOLOv4 P7 achieved the fastest and most accurate early DD, while CenterNet2 with Res2Net 101 DCN-BiFPN performed best for early-stage disease prediction. Q. Chen et al. (2019)[111] proposed a 7-layer deep convolutional network for identifying citrus canker, scab, and anthracnose, outperforming traditional ML methods with improved FE and classification accuracy.

Lastly, Ahmed R. Luaibi et al. (2021)[112] explored the use of AlexNet and ResNet models with data augmentation, achieving 97.92% and 95.83% accuracy, respectively. Their study highlighted the effectiveness of data augmentation in improving classification accuracy, especially for small datasets.

Overall, these studies demonstrate the effectiveness of CNN-based approaches in citrus DD, with advancements in mobile applications, dataset creation, and model optimization. Future research could focus on real-time monitoring systems and integrating hyperspectral imaging for more precise disease classification.

## IV. CONCLUSION AND FUTURE SCOPE

The reviewed studies highlight significant advancements in AI-driven PDD, demonstrating high accuracy, efficiency, and scalability. The integration of DL techniques, such as CNNs, ensemble learning, TL, and IoT-based real-time monitoring, has significantly enhanced plant health assessment. Advanced architectures like EfficientNet, DenseNet, and GoogleNet have shown remarkable success in distinguishing between healthy and diseased plant leaves, contributing to improved classification accuracy and early disease intervention. Despite these advancements, several challenges persist, including the need for large, diverse, and well-annotated datasets, the computational cost of complex DL models, and the generalizability of AI solutions across different environmental conditions and crop varieties. Future research should prioritize model optimization for low-resource environments, enabling small-scale farmers to access AI-powered DD tools with minimal hardware requirements. Additionally, integrating hyperspectral imaging, multimodal data fusion, and explainable AI (XAI) techniques can enhance model interpretability, providing farmers with more transparent and actionable insights.

Further efforts should focus on real-time deployment strategies, such as mobile applications, edge computing, and IoT-enabled smart farming systems, to ensure widespread accessibility and usability. The development of lightweight yet highly accurate AI models will be crucial for practical agricultural applications, particularly in remote and resource-constrained regions. Additionally, collaboration between AI researchers, agronomists, and policymakers is essential to create standardized datasets, establish regulatory frameworks, and drive large-scale adoption of AI-based PDD systems. By bridging the gap between laboratory research and real-world agricultural applications, AI-driven PDD holds immense potential to revolutionize precision agriculture, ensuring early disease diagnosis, reducing yield losses, and promoting sustainable farming practices. Moving forward, interdisciplinary approaches combining AI, plant pathology, agronomy, and remote sensing will be key to achieving robust, scalable, and cost-effective solutions for global food security and agricultural sustainability.

## V. ACKNOWLEDGMENT

The authors express their heartfelt gratitude to Prof. Dr. S. Lakshmi Prabha, Department of Computer Science, Queen Mary's College - Chennai, for her constant guidance, encouragement, and insightful feedback throughout this research. Her expertise and valuable suggestions were instrumental in shaping the direction and quality of this work.

## REFERENCES

**[1]** L. Li, S. Zhang and B. Wang, "Plant Disease Detection and Classification by Deep Learing a Review," in IEEE Access, Vol. 9, pp. 56683-56698, 2021, doi: 10.1109/Access.2021.3069646

**[2]** S. Barburiceanu, S. Meza, B. Orza, R. Malutan and R. Terebes, "Convolutional Neural Networks for Texture Feature Extraction. Applications to Leaf Disease Classification in Precision Agriculture," in IEEE Access, vol. 9, pp. 160085-160103, 2021, doi: 10.1109?ACCESS.2021.3131002

**[3]** S. Arivazhagan, R. Newlin Shebiah, S. Ananthi, S. Varthini, (2013), Detection of unhealthy region of plant leaves and classification of plant leaf disease using texture features, CIGR Journal, VII – Information System, vol. 15 no .1.

**[4]** A. Bhargava, A. Shukla, O. P. Goswami, M. H. Alsharif, P. Uthansakul and M. Uthansakul, "Plant Leaf Disease Detection, Classification and Diagnosis using Computer Vision and Artificial Intelligence: A Review," in IEEE Access, vol. 12, pp. 37443-37469, 2024 , dio: 10.1109/ACCESS.2024.3373001

**[5]** A. Oad et al., " Plant Leaf Disease Detection using Ensemble Learning and Explainable AI," in IEEE Access, vol. 12, pp. 156038-156049, 2024, doi:10.1109?ACCESS.2024.3484574

**[6]** M. S. H. Shovon, S. J. Mozumder, O. K. Pal, M. F. Mridha, N. Asai and J. Shin, "PlantDet: A Robust Multi-Model Ensemble Method Based on Deep Learning for Plant Disease Detection," in IEEE Access, vol. 11, pp. 34846-34859, 2023, doi: 10.1109/ACCESS.2023.364835

**[7]** X. Liu, W. Min, S. Mei, L. Wang and S. Jiang, " Plant Disease Recognition: A Large-Scale Benchmark Dataset and a Visual Region and Loss Reweighting Approach, " in IEEE Transactions on Image Processing, Vol. 30, pp. 2003-2015, 2021, doi:10.1109/TIP.2021.3049334

**[8]** E. Moupojou et al., "FieldPlant : A Dataset of Field Plant Images for Plant Disease Detection and Classification with Deep Learning," in IEEE Access, vol. 11, pp. 35398-35410,2023, doi: 10.1109/ACCESS.2023.3263042

**[9]** G. Nagasubramanian, R. K. Sakthivel, R. Patan, M. Sankayya, M. Daneshmand and A. H. Gandomi, "Ensemble Classification and IOT – Based Pattern Recognition for Crop Disease Monitoring System," in IEEE Internet of Things Journal, vol. 8, no.16, pp. 12847-12854, 2021, doi: 10.1109/JIOT.2021.3072908

**[10]** R. Dwivedi, S. Dey, C. Chakraborty and S. Tiwari, "Grape Disease Detection Network Based on Multi – Task Learning and Attention Features," in IEEE Sensors Journal, vol. 21, no. 16, pp. 17573-17580, 15 Aug.15, 2021, doi: 10.1109/JSEN.2021.3064060".

**[11]** K. K. Leong and L. L. Tze, "Plant Leaf Diseases Identification using Convolutional Neural Network with Treatment Handling System," 2020 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS), Shah Alam, Malaysia, 2020, pp. 39-44, doi: 10.1109/I2CACIS49202.2020.9140103.

**[12]** K. P. Asha Rani and S. Gowrishankar, "Pathogen-Based Classification of Plant Diseases: A Deep Transfer Learning Approach for Intelligent Support Systems," in IEEE Access, vol. 11, pp. 64476-64493, 2023, doi: 10.1109/ACCESS.2023.32846880

**[13]** M. A. Bhatti et al., "Advanced Plant Disease Segmentation in Precision Agriculture using Optimal Dimensionality Reduction with Fuzzy C-Means Clustering and Deep Learning," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, PP. 18264-18277, 2024, doi:10.1109/JSTARS. 2024.3437469

**[14]** S. Abinaya, K. U. Kumar and A. S. Alphonse, "Cascading Autoencoder with Attention Residual U-Net for Muli-Class Plant Lef Disease Segmentation and Classification," in IEEE Access, vol. 11, pp. 98153-98170, 2023, doi: 10.1109/ACCESS.2023.3312718

**[15]** F. Adnan, M. J. Awan, A. Mahmoud, H. Nobanee, A. Yasin and A. M. Zain," EfficientNetB3- Adaptive Augmented Deep Learning (AADL) for Multi-class Plant Disease Classification," in IEEE Access, vol. 11, pp. 85426-85440, 2023, doi: 10.1109/ACCESS.2023.3303131".

**[16]** Yin Min Oo, Nay Chi Htun Plant Leaf Disease Detection and Classification using Image Processing, International Journal of Research and Engineering, vol. 5, 2018, pp. 516-523, http://dx.dio.org/10.21276/ijre.2018.5.9.4.

**[17]** Vijai Singh, A. K. Misra, Detection of Plant leaf diseases using image segmentation and soft computing techniques, Information Processing in Agriculture, Volume 4, Issue 1, 2017, Pages 41 - 49, ISSN 2214 – 3173, https://doi.org/10.1016/j.inpa.2016.10.005.

**[18]** Namita M. Butale, Dattatraya V. Kodavade, "Detection of Plant Leaf Diseases using Image Processing and SoftComputing Techniques", International Research Journal of Engineering and Technology (IRJET), Volume: 06, 2019.

**[19]** D. S. Joseph, P. M. Pawar and K. Chakradeo, " Real – Time Plant Disease Dataset Development and Detection of Plant Disease using Deep Learing, " in IEEE Access, vol. 12, pp. 16310-16333, 2024, doi: 10.1109/ACCESS.2024.3358333".

**[20]** H. Amin, A. Darwish, A. E. Hassanien and M. Soliman, "End-to-End Deep Learning Model for Corn Leaf Disease Classification," in IEEE Access, vol. 10, pp. 31103-31115, 2022, doi: 10.1109/ACCESS.2022.3159678. "

**[21]** H. Yu et al., "Corn Leaf Diseases Diagnosis Based on K-Means Clustering and Deep Learning," in IEEE Access, vol. 9, pp. 143824-143835, 2021, doi: 10.1109/ACCESS.2021.3120379"

**[22]** X. Zhang, Y. Qiao, F. Meng, C. Fan and M. Zhang, "Identification of Maize Leaf Diseases Using Improved Deep Convolutional Neural Networks," in IEEE Access, vol. 6, pp. 30370-30377, 2018, doi: 10.1109/ACCESS.2018.2844405."

**[23]** Panigrahi, K.P., Das, H., Sahoo, A.K., Moharana, S.C. (2020). Maize Leaf Disease Detection and Classification Using Machine Learning Algorithms. In: Das, H., Pattnaik, P., Rautaray, S., Li, KC. (eds) Progress in Computing, Analytics and Networking. Advances in Intelligent Systems and Computing, vol 1119. Springer, Singapore. https://doi.org/10.1007/978-981-15-2414-1_66"

[24] Abdul Waheed, Muskan Goyal, Deepak Gupta, Ashish Khanna, Aboul Ella Hassanien, Hari Mohan Pandey, An optimized dense convolutional neural network model for disease recognition and classification in corn leaf, Computers and Electronics in Agriculture, Volume 175, 2020, 105456, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2020.105456.

[25] Ahila Priyadharshini, R., Arivazhagan, S., Arun, M. et al. Maize leaf disease classification using deep convolutional neural networks. Neural Comput & Applic 31, 8887–8895 (2019). https://doi.org/10.1007/s00521-019-04228-3

[26] Shuai-qun PAN, Jing-fen QIAO, Rui WANG, Hui-lin YU, Cheng WANG, Kerry TAYLOR, Hong-yu PAN, Intelligent diagnosis of northern corn leaf blight with deep learning model, Journal of Integrative Agriculture, Volume 21, Issue 4, 2022, Pages 1094-1105, ISSN 2095-3119, https://doi.org/10.1016/S2095-3119(21)63707-3.

[27] P. Ouppaphan, "Corn Disease Identification from Leaf Images Using Convolutional Neural Networks," 2017 21st International Computer Science and Engineering Conference (ICSEC), Bangkok, Thailand, 2017, pp. 1-5, doi: 10.1109/ICSEC.2017.8443919

[28] U. P. Singh, S. S. Chouhan, S. Jain and S. Jain, "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease," in IEEE Access, vol. 7, pp. 43721-43729, 2019, doi: 10.1109/ACCESS.2019.2907383.

[29] T. N. Pham, L. V. Tran and S. V. T. Dao, "Early Disease Classification of Mango Leaves Using Feed-Forward Neural Network and Hybrid Metaheuristic Feature Selection," in IEEE Access, vol. 8, pp. 189960-189973, 2020, doi: 10.1109/ACCESS.2020.3031914. "

[30] Gautam, V., Ranjan, R.K., Dahiya, P. et al. ESDNN: A novel ensembled stack deep neural network for mango leaf disease classification and detection. Multimed Tools Appl 83, 10989–11015 (2024). https://doi.org/10.1007/s11042-023-16012-6

[31] Redwan Ahmed Rizvee, Tasnim Hossain Orpa, Adil Ahnaf, Md Ahsan Kabir, Mohammad Rifat Ahmmad Rashid, Mohammad Manzurul Islam, Maheen Islam, Taskeed Jabid, Md Sawkat Ali, LeafNet: A proficient convolutional neural network for detecting seven prominent mango leaf diseases, Journal of Agriculture and Food Research, Volume 14, 2023, 100787, ISSN 2666-1543, https://doi.org/10.1016/j.jafr.2023.100787.

[32] Venkatesh, N. Y, S. T. S, S. S and S. U. Hegde, "Transfer Learning based Convolutional Neural Network Model for Classification of Mango Leaves Infected by Anthracnose," 2020 IEEE International Conference for Innovation in Technology (INOCON), Bangluru, India, 2020, pp. 1-7, doi: 10.1109/INOCON50539.2020.9298269.

[33] Selvakumar, A., & Balasundaram, A. (2023). Automated Mango Leaf Infection Classification using Weighted and Deep Features with Optimized Recurrent Neural Network Concept. The Imaging Science Journal, 72(3), 285–303. https://doi.org/10.1080/13682199.2023.2204036

[34] E. Elfatimi, R. Eryigit and L. Elfatimi, "Beans Leaf Diseases Classification Using MobileNet Models," in IEEE Access, vol. 10, pp. 9471-9482, 2022, doi: 10.1109/ACCESS.2022.3142817.

[35] Vimal Singh, Anuradha Chug, Amit Prakash Singh, Classification of Beans Leaf Diseases using Fine Tuned CNN Model, Procedia Computer Science, Volume 218, 2023, Pages 348-356, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2023.01.017.

[36] Abed, S.H., Al-Waisy, A.S., Mohammed, H.J. et al. A modern deep learning framework in robot vision for automated bean leaves diseases detection. Int J Intell Robot Appl 5, 235–251 (2021). https://doi.org/10.1007/s41315-021-00174-3

[37] Elfatimi, E., Eryiğit, R. & Shehu, H.A. Impact of datasets on the effectiveness of MobileNet for beans leaf disease detection. Neural Comput & Applic 36, 1773–1789 (2024). https://doi.org/10.1007/s00521-023-09187-4

[38] Girmaw, D.W., Muluneh, T.W. Deep convolutional neural network model for classifying common bean leaf diseases. Discov Artif Intell 4, 96 (2024). https://doi.org/10.1007/s44163-024-00212-6

[39] Kursun, R., Bastas, K.K. & Koklu, M. Segmentation of dry bean (Phaseolus vulgaris L.) leaf disease images with U-Net and classification using deep learning algorithms. Eur Food Res Technol 249, 2543–2558 (2023). https://doi.org/10.1007/s00217-023-04319-5

[40] H. Sabrol and K. Satish, "Tomato plant disease classification in digital images using classification tree," 2016 International Conference on Communication and Signal Processing (ICCSP), Melmaruvathur, India, 2016, pp. 1242-1246, doi: 10.1109/ICCSP.2016.7754351."

[41] D. Jiang, F. Li, Y. Yang and S. Yu, "A Tomato Leaf Diseases Classification Method Based on Deep Learning," 2020 Chinese Control And Decision Conference (CCDC), Hefei, China, 2020, pp. 1446-1450, doi: 10.1109/CCDC49329.2020.9164457."

[42] C. Zhou, S. Zhou, J. Xing and J. Song, "Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network," in IEEE Access, vol. 9, pp. 28822-28831, 2021, doi: 10.1109/ACCESS.2021.3058947."

[43] P. Tm, A. Pranathi, K. SaiAshritha, N. B. Chittaragi and S. G. Koolagudi, "Tomato Leaf Disease Detection Using Convolutional Neural Networks," 2018 Eleventh International Conference on Contemporary Computing (IC3), Noida, India, 2018, pp. 1-5, doi: 10.1109/IC3.2018.8530532."

[44] S. Ashok, G. Kishore, V. Rajesh, S. Suchitra, S. G. G. Sophia and B. Pavithra, "Tomato Leaf Disease Detection Using Deep Learning Techniques," 2020 5th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2020, pp. 979-983, doi: 10.1109/ICCES48766.2020.9137986."

[45] Q. Wu, Y. Chen and J. Meng, "DCGAN-Based Data Augmentation for Tomato Leaf Disease Identification," in IEEE Access, vol. 8, pp. 98716-98728, 2020, doi: 10.1109/ACCESS.2020.2997001."

[46] Nagamani, H S; Sarojadevi, H. Tomato Leaf Disease Detection using Deep Learning Techniques, International Journal of Advanced Computer Science and Applications; West Yorkshire Vol. 13, Iss. 1, (2022). DOI:10.14569/IJACSA.2022.0130138

[47] Mingxuan Li, Guoxiong Zhou, Aibin Chen, Jizheng Yi, Chao Lu, Mingfang He, Yahui Hu, FWDGAN-based data augmentation for tomato leaf disease identification, Computers and Electronics in Agriculture, Volume 194, 2022, 106779, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2022.106779.

[48] Trivedi, Naresh K., Vinay Gautam, Abhineet Anand, Hani Moaiteq Aljahdali, Santos Gracia Villar, Divya Anand, Nitin Goyal, and Seifedine Kadry. 2021. "Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network" Sensors 21, no. 23: 7987. https://doi.org/10.3390/s21237987

[49] Guerrero-Ibañez, Antonio, and Angelica Reyes-Muñoz. 2023. "Monitoring Tomato Leaf Disease through Convolutional Neural Networks" Electronics 12, no. 1: 229. https://doi.org/10.3390/electronics12010229

**[50]** Batool, S. B. Hyder, A. Rahim, N. Waheed, M. A. Asghar and Fawad, "Classification and Identification of Tomato Leaf Disease Using Deep Neural Network," 2020 International Conference on Engineering and Emerging Technologies (ICEET), Lahore, Pakistan, 2020, pp. 1-6, doi: 10.1109/ICEET48479.2020.9048207.

**[51]** Mohit Agarwal, Abhishek Singh, Siddhartha Arjaria, Amit Sinha, Suneet Gupta, ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network, Procedia Computer Science, Volume 167, 2020, Pages 293-301, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2020.03.225.

**[52]** Ahmad, Iftikhar, Hamid, Muhammad, Yousaf, Suhail, Shah, Syed Tanveer, Ahmad, Muhammad Ovais, Optimizing Pretrained Convolutional Neural Networks for Tomato Leaf Disease Detection, Complexity, 2020, 8812019, 6 pages, 2020. https://doi.org/10.1155/2020/8812019

**[53]** T. Anandhakrishnan, S.M. Jaisakthi, Deep Convolutional Neural Networks for image based tomato leaf disease detection, Sustainable Chemistry and Pharmacy, Volume 30, 2022, 100793, ISSN 2352-5541, https://doi.org/10.1016/j.scp.2022.100793.

**[54]** V. K. Vishnoi, K. Kumar, B. Kumar, S. Mohan and A. A. Khan, "Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network," in IEEE Access, vol. 11, pp. 6594-6609, 2023, doi: 10.1109/ACCESS.2022.3232917."

**[55]** L. G. Nachtigall, R. M. Araujo and G. R. Nachtigall, "Classification of Apple Tree Disorders Using Convolutional Neural Networks," 2016 IEEE 28th International Conference on Tools with Artificial Intelligence (ICTAI), San Jose, CA, USA, 2016, pp. 472-476, doi: 10.1109/ICTAI.2016.0078."

**[56]** P. Jiang, Y. Chen, B. Liu, D. He and C. Liang, "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks," in IEEE Access, vol. 7, pp. 59069-59080, 2019, doi: 10.1109/ACCESS.2019.2914929"

**[57]** Liu, Bin, Yun Zhang, DongJian He, and Yuxiang Li. 2018. "Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks" Symmetry 10, no. 1: 11. https://doi.org/10.3390/sym10010011

**[58]** Bansal, Prakhar, Rahul Kumar, and Somesh Kumar. 2021. "Disease Detection in Apple Leaves Using Deep Convolutional Neural Network" Agriculture 11, no. 7: 617. https://doi.org/10.3390/agriculture11070617

**[59]** Chao, Xiaofei, Guoying Sun, Hongke Zhao, Min Li, and Dongjian He. 2020. "Identification of Apple Tree Leaf Diseases Based on Deep Learning Models" Symmetry 12, no. 7: 1065. https://doi.org/10.3390/sym12071065

**[60]** Yan, Qian, Baohua Yang, Wenyan Wang, Bing Wang, Peng Chen, and Jun Zhang. 2020. "Apple Leaf Diseases Recognition Based on An Improved Convolutional Neural Network" Sensors 20, no. 12: 3535. https://doi.org/10.3390/s20123535

**[61]** Pradhan, P., Kumar, B. & Mohan, S. Comparison of various deep convolutional neural network models to discriminate apple leaf diseases using transfer learning. J Plant Dis Prot 129, 1461–1473 (2022). https://doi.org/10.1007/s41348-022-00660-1

**[62]** S. Ghosal and K. Sarkar, "Rice Leaf Diseases Classification Using CNN With Transfer Learning," 2020 IEEE Calcutta Conference (CALCON), Kolkata, India, 2020, pp. 230-236, doi: 10.1109/CALCON49167.2020.9106423."

**[63]** S. M. Taohidul Islam and B. Mazumder, "Wavelet Based Feature Extraction for Rice Plant Disease Detection and Classification," 2019 3rd International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE), Rajshahi, Bangladesh, 2019, pp. 53-56, doi: 10.1109/ICECTE48615.2019.9303567."

**[64]** M. E. Pothen and M. L. Pai, "Detection of Rice Leaf Diseases Using Image Processing," 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2020, pp. 424-430, doi: 10.1109/ICCMC48092.2020.ICCMC-00080."

**[65]** F. T. Pinki, N. Khatun and S. M. M. Islam, "Content based paddy leaf disease recognition and remedy prediction using support vector machine," 2017 20th International Conference of Computer and Information Technology (ICCIT), Dhaka, Bangladesh, 2017, pp. 1-5, doi: 10.1109/ICCITECHN.2017.8281764."

**[66]** Krishnamoorthy N, L.V. Narasimha Prasad, C.S. Pavan Kumar, Bharat Subedi, Haftom Baraki Abraha, Sathishkumar V E, Rice leaf diseases prediction using deep neural networks with transfer learning, Environmental Research, Volume 198, 2021, 111275, ISSN 0013-9351, https://doi.org/10.1016/j.envres.2021.111275.

**[67]** S. Ramesh, D. Vydeki, Recognition and classification of paddy leaf diseases using Optimized Deep Neural network with Jaya algorithm, Information Processing in Agriculture, Volume 7, Issue 2, 2020, Pages 249-260, ISSN 2214-3173, https://doi.org/10.1016/j.inpa.2019.09.002.

**[68]** Md. Ashiqul Islam, Md. Nymur Rahman Shuvo, Muhammad Shamsojjaman, Shazid Hasan, Md. Shahadat Hossain, Tania Khatun, An Automated Convolutional Neural Network Based Approach for Paddy Leaf Disease Detection, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 12, No. 1, 2021, pp- 280-288.

**[69]** Shankarnarayanan Nalini, Nagappan Krishnaraj, Thangaiyan Jayasankar, Kalimuthu Vinothkumar, Antony Sagai Francis Britto, Kamalraj Subramaniam and Chokkalingam Bharatiraja, Paddy Leaf Disease Detection Using an Optimized Deep Neural Network, Computers, Materials & Continua Tech Science Press, 2021, vol.68, no.1, DOI:10.32604/cmc.2021.012431

**[70]** Mainak Deb, Dhal, K.G., Mondal, R. et al. Paddy Disease Classification Study: A Deep Convolutional Neural Network Approach. Opt. Mem. Neural Networks 30, 338–357 (2021). https://doi.org/10.3103/S1060992X2104007X

**[71]** Maheswaran, S., Sathesh, S., Rithika, P., Shafiq, I.M., Nandita, S., Gomathi, R.D. (2022). Detection and Classification of Paddy Leaf Diseases Using Deep Learning (CNN). In: Neuhold, E.J., Fernando, X., Lu, J., Piramuthu, S., Chandrabose, A. (eds) Computer, Communication, and Signal Processing. ICCCSP 2022. IFIP Advances in Information and Communication Technology, vol 651. Springer, Cham. https://doi.org/10.1007/978-3-031-11633-9_6

**[72]** Norhalina Senan, Muhammad Aamir, Rosziati Ibrahim, N. S. A. M Taujuddin, W.H.N Wan Muda, An Efficient Convolutional Neural Network for Paddy Leaf Disease and Pest Classification, International Journal of Advanced Computer Science and Applications, Vol. 11, No. 7, 2020

**[73]** O. K. Pal, "Identification of Paddy Leaf Diseases Using a Supervised Neural Network," 2021 16th International Conference on Emerging Technologies (ICET), Islamabad, Pakistan, 2021, pp. 1-4, doi: 10.1109/ICET54505.2021.9689788.

**[74]** S. Hossain, R. M. Mou, M. M. Hasan, S. Chakraborty and M. A. Razzak, "Recognition and detection of tea leaf's diseases using support vector machine," 2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA), Penang, Malaysia, 2018, pp. 150-154, doi: 10.1109/CSPA.2018.8368703."

**[75]** S. Gayathri, D. C. J. W. Wise, P. B. Shamini and N. Muthukumaran, "Image Analysis and Detection of Tea Leaf Disease using Deep Learning," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 398-403, doi: 10.1109/ICESC48915.2020.9155850."

**[76]** Saikat Datta, Nitin Gupta, A Novel Approach For the Detection of Tea Leaf Disease Using Deep Neural Network, Procedia Computer Science, Volume 218, 2023, Pages 2273-2286, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2023.01.203.

**[77]** Gensheng Hu, Xiaowei Yang, Yan Zhang, Mingzhu Wan, Identification of tea leaf diseases by using an improved deep convolutional neural network, Sustainable Computing: Informatics and Systems, Volume 24, 2019, 100353, ISSN 2210-5379, https://doi.org/10.1016/j.suscom.2019.100353.

**[78]** Chen, Jing, Qi Liu, and Lingwang Gao. 2019. "Visual Tea Leaf Disease Recognition Using a Convolutional Neural Network Model" Symmetry 11, no. 3: 343. https://doi.org/10.3390/sym11030343

**[79]** Rahman, H., Ahmad, I., Jon, P.H. et al. Automated detection of selected tea leaf diseases in Bangladesh with convolutional neural network. Sci Rep 14, 14097 (2024). https://doi.org/10.1038/s41598-024-62058-3

**[80]** Gensheng Hu, Min Fang, Using a multi-convolutional neural network to automatically identify small-sample tea leaf diseases, Sustainable Computing: Informatics and Systems, Volume 35, 2022, 100696, ISSN 2210-5379, https://doi.org/10.1016/j.suscom.2022.100696.

**[81]** S. Bhowmik, A. K. Talukdar and K. Kumar Sarma, "Detection of Disease in Tea Leaves Using Convolution Neural Network," 2020 Advanced Communication Technologies and Signal Processing (ACTS), Silchar, India, 2020, pp. 1-6, doi: 10.1109/ACTS49415.2020.9350413.

**[82]** R. A. Sholihati, I. A. Sulistijono, A. Risnumawan and E. Kusumawati, "Potato Leaf Disease Classification Using Deep Learning Approach," 2020 International Electronics Symposium (IES), Surabaya, Indonesia, 2020, pp. 392-397, doi: 10.1109/IES50839.2020.9231784."

**[83]** M. Islam, Anh Dinh, K. Wahid and P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine," 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, Canada, 2017, pp. 1-4, doi: 10.1109/CCECE.2017.7946594."

**[84]** Sowmiya R, Revathi P, Sasikala A Jayasundar S, Prathep Kumar R and Sauvik Deb, "Potato Leaf Disease Classification Using Deep Learning Approach," 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2024, pp. 1699-1704, doi: 10.1109/ICACCS60874.2024.10716984.

**[85]** Lee, TY., Lin, A., Yu, JY. et al. High Efficiency Disease Detection for Potato Leaf with Convolutional Neural Network. SN COMPUT. SCI. 2, 297 (2021). https://doi.org/10.1007/s42979-021-00691-9

**[86]** Mahum, R., Munir, H., Mughal, Z. U. N., Awais, M., Sher Khan, F., Saqlain, M., … Tlili, I. (2022). A novel framework for potato leaf disease detection using an efficient deep learning model. Human and Ecological Risk Assessment: An International Journal, 29(2), 303–326. https://doi.org/10.1080/10807039.2022.2064814

**[87]** D. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel and S. Bhardwaj, "Potato Leaf Diseases Detection Using Deep Learning," 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2020, pp. 461-466, doi: 10.1109/ICICCS48265.2020.9121067.

**[88]** Kumar, A., Patel, V.K. Classification and identification of disease in potato leaf using hierarchical based deep learning convolutional neural network. Multimed Tools Appl 82, 31101–31127 (2023). https://doi.org/10.1007/s11042-023-14663-z

**[89]** Rashid, Javed, Imran Khan, Ghulam Ali, Sultan H. Almotiri, Mohammed A. AlGhamdi, and Khalid Masood. 2021. "Multi-Level Deep Learning Model for Potato Leaf Disease Recognition" Electronics 10, no. 17: 2064. https://doi.org/10.3390/electronics10172064

**[90]** Khalifa, N.E.M., Taha, M.H.N., Abou El-Maged, L.M., Hassanien, A.E. (2021). Artificial Intelligence in Potato Leaf Disease Classification: A Deep Learning Approach. In: Hassanien, A.E., Darwish, A. (eds) Machine Learning and Big Data Analytics Paradigms: Analysis, Applications and Challenges. Studies in Big Data, vol 77. Springer, Cham. https://doi.org/10.1007/978-3-030-59338-4_4

**[91]** P. B. Padol and A. A. Yadav, "SVM classifier based grape leaf disease detection," 2016 Conference on Advances in Signal Processing (CASP), Pune, India, 2016, pp. 175-179, doi: 10.1109/CASP.2016.7746160."

**[92]** Z. Huang, A. Qin, J. Lu, A. Menon and J. Gao, "Grape Leaf Disease Detection and Classification Using Machine Learning," 2020 International Conferences on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybermatics (Cybermatics), Rhodes, Greece, 2020, pp. 870-877, doi: 10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics50389.2020.00150."

**[93]** B. Liu, C. Tan, S. Li, J. He and H. Wang, "A Data Augmentation Method Based on Generative Adversarial Networks for Grape Leaf Disease Identification," in IEEE Access, vol. 8, pp. 102188-102198, 2020, doi: 10.1109/ACCESS.2020.2998839"

**[94]** Z. Lin et al., "A Unified Matrix-Based Convolutional Neural Network for Fine-Grained Image Classification of Wheat Leaf Diseases," in IEEE Access, vol. 7, pp. 11570-11590, 2019, doi: 10.1109/ACCESS.2019.2891739"

**[95]** Laixiang Xu, Bingxu Cao, Fengjie Zhao, Shiyuan Ning, Peng Xu, Wenbo Zhang, Xiangguan Hou, Wheat leaf disease identification based on deep learning algorithms, Physiological and Molecular Plant Pathology, Volume 123, 2023, 101940, ISSN 0885-5765, https://doi.org/10.1016/j.pmpp.2022.101940.

**[96]** Usha Ruby, A., George Chellin Chandran, J., Chaithanya, B.N. et al. Wheat leaf disease classification using modified ResNet50 convolutional neural network model. Multimed Tools Appl 83, 62875–62893 (2024). https://doi.org/10.1007/s11042-023-18049-z

**[97]** Jiang, Jiale, Haiyan Liu, Chen Zhao, Can He, Jifeng Ma, Tao Cheng, Yan Zhu, Weixing Cao, and Xia Yao. 2022. "Evaluation of Diverse Convolutional Neural Networks and Training Strategies for Wheat Leaf Disease Identification with Field-Acquired Photographs" Remote Sensing 14, no. 14: 3446. https://doi.org/10.3390/rs14143446

**[98]** Zhencun Jiang, Zhengxin Dong, Wenping Jiang, Yuze Yang, Recognition of rice leaf diseases and wheat leaf diseases based on multi-task deep transfer learning, Computers and Electronics in Agriculture, Volume 186, 2021, 106184, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2021.106184.

**[99]** Wen, Xiaojie, Minghao Zeng, Jing Chen, Muzaipaer Maimaiti, and Qi Liu. 2023. "Recognition of Wheat Leaf Diseases Using Lightweight Convolutional Neural Networks against Complex Backgrounds" Life 13, no. 11: 2125. https://doi.org/10.3390/life13112125

**[100]** A. N. I. Masazhar and M. M. Kamal, "Digital image processing technique for palm oil leaf disease detection using multiclass SVM classifier," 2017 IEEE 4th International Conference on Smart Instrumentation, Measurement and Application (ICSIMA), Putrajaya, Malaysia, 2017, pp. 1-6, doi: 10.1109/ICSIMA.2017.8311978."

**[101]** Jia Heng Ong, Pauline Ong, & Woon Kiow Lee. (2022). IMAGE-BASED OIL PALM LEAVES DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK. Journal of Information and Communication Technology, 21(3), 383–410. https://doi.org/10.32890/jict2022.21.3.4

**[102]** Ibrahim, S. , Hasan, N. , Sabri, N. , Abu Samah, K. Airin Fariza and Rahimi Rusland, M. (2022). Palm leaf nutrient deficiency detection using convolutional neural network (CNN). International Journal of Nonlinear Analysis and Applications, 13(1), 1949-1956. doi: 10.22075/ijnaa.2022.5836

**[103]** A.Septiarini, H. Hamdani, E. Junirianto, M. S. S. Thayf, G. Triyono and Henderi, "Oil Palm Leaf Disease Detection on Natural Background Using Convolutional Neural Networks," 2022 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT), Solo, Indonesia, 2022, pp. 388-392, doi: 10.1109/COMNETSAT56033.2022.9994555.

**[104]** Muhammad Ikmal Hafiz Razali; Hairuddin, Muhammad Asraf; Jahidin, Aisyah Hartini; Mohd Hanafi Mat Som; Megat Syahirul Amin Megat Ali. Classification of nutrient deficiency in oil palms from leaf images using convolutional neural network, IAES International Journal of Artificial Intelligence; Yogyakarta Vol. 11, Iss. 4, (Dec 2022): 1314-1322. DOI:10.11591/ijai.v11.i4.pp1314-1322

**[105]** Yufis Azhar, Muhammad Shalahuddin Zulva, DETECTION OF LEAF SPOT DISEASE IN OIL PALM SEEDLINGS USING CONVOLUTIONAL NEURAL NETWORK METHOD, Jurnal Teknologi dan Sistem Informasi, Vol 10, No 2 (2024), DOI: https://doi.org/10.33330/jurteksi.v10i2.2903

**[106]** A. Khattak et al., "Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network Model," in IEEE Access, vol. 9, pp. 112942-112954, 2021, doi: 10.1109/ACCESS.2021.3096895. "

**[107]** Saini, A. K., Bhatnagar, R., & Srivastava, D. K. (2021). AI based automatic detection of citrus fruit and leaves diseases using deep neural network model. Journal of Discrete Mathematical Sciences and Cryptography, 24(8), 2181–2193. https://doi.org/10.1080/09720529.2021.2011095

**[108]** Shastri, R., Chaturvedi, A., Mouleswararao, B. et al. An Automatic Detection of Citrus Fruits and Leaves Diseases Using Enhanced Convolutional Neural Network. Remote Sens Earth Syst Sci 6, 123–134 (2023). https://doi.org/10.1007/s41976-023-00086-9

**[109]** Utpal Barman, Ridip Dev Choudhury, Diganto Sahu, Golap Gunjan Barman, Comparison of convolution neural networks for smartphone image based real time classification of citrus leaf disease, Computers and Electronics in Agriculture, Volume 177, 2020, 105661, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2020.105661.

**[110]** Sathian Dananjayan, Yu Tang, Jiajun Zhuang, Chaojun Hou, Shaoming Luo, Assessment of state-of-the-art deep learning based citrus disease detection techniques using annotated optical leaf images, Computers and Electronics in Agriculture, Volume 193, 2022, 106658, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2021.106658.

**[111]** Q. Chen et al., "Deep Convolutional Network for Citrus Leaf Diseases Recognition," 2019 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom), Xiamen, China, 2019, pp. 1490-1494, doi: 10.1109/ISPA-BDCloud-SustainCom-SocialCom48970.2019.00215.

**[112]** Ahmed R. Luaibi, Tariq M. Salman, Abbas Hussein Miry, Detection of citrus leaf diseases using a deep learning technique, International Journal of Electrical and Computer Engineering (IJECE), Vol. 11, No. 2, April 2021, pp. 1719-1727, ISSN: 2088-8708, DOI: 10.11591/ijece.v11i2.pp1719-1727