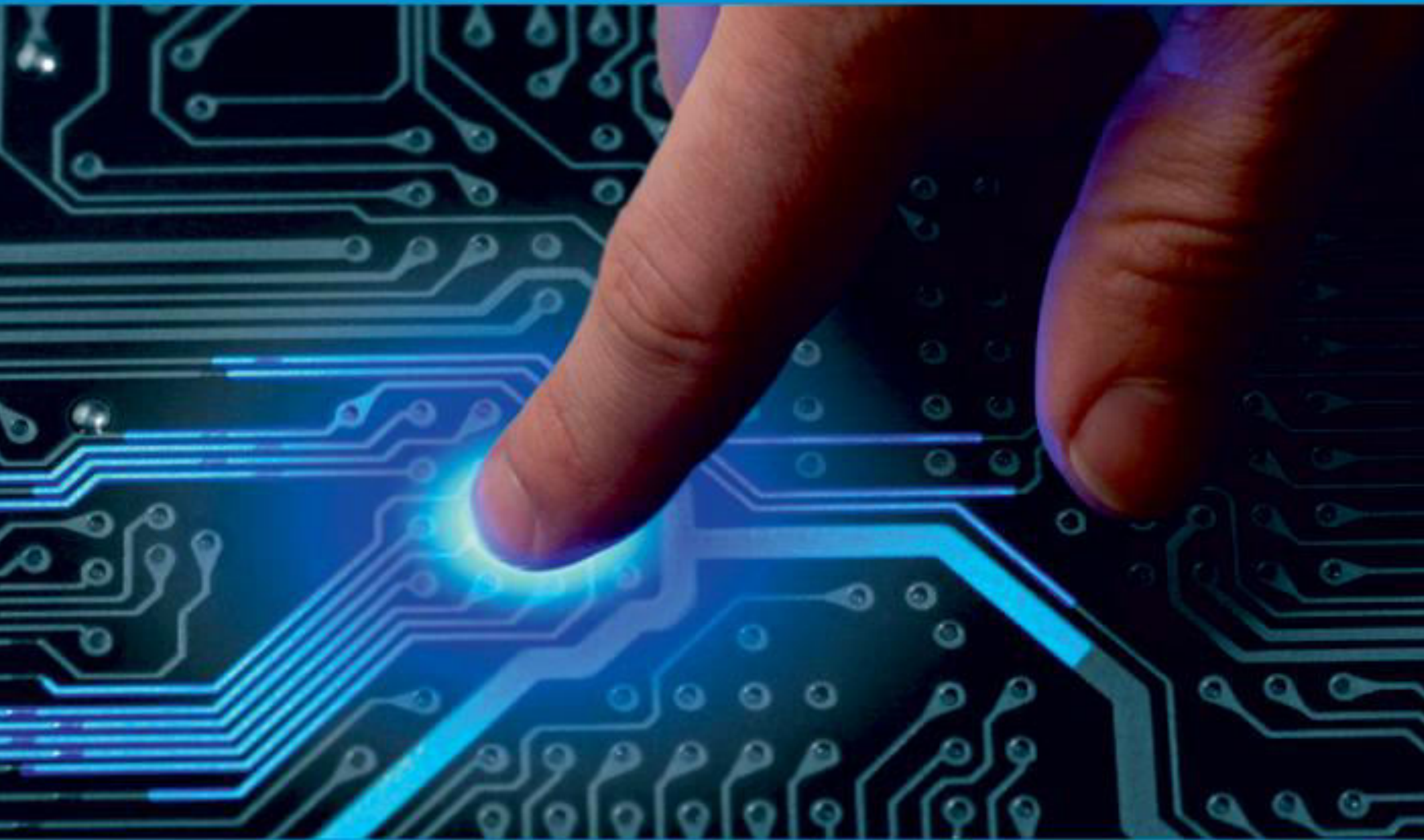
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 4, April 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 4, April 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1204024 |

A Review on Deep Learning Based Tomato Leaf Disease Detection for Smart Farming

Arshad[1], Kantharaja S K[1], Karthik M [1], Subhash[1], Dr. Kiran S N[2]

8th Semester Students of ECE, Vidyavardhaka College of Engineering, Mysuru, India [1]

Professor, Department of ECE, Vidyavardhaka College of Engineering, Mysuru, India[2]

ABSTRACT: The leaf diseases have come a serious concern for the agrarian assiduity, yet timely opinion and recognition are challenging in multitudinous regions of the globe owing to a deficit of automated crop complaint identification methods. However, food instability will rise, affecting the country's income, if factory conditions aren't honored in a prompt way. Factory complaint identification is critical for successful crop forestallment and control of conditions, as well as ranch product operation and decision- timber. Factory complaint discovery technologies aid in finding infected shops in their early phases and also help the stoner in cost-effectively expanding factory complaint identification system to a variety of shops. This paper's major donation is a piled ensemble fashion grounded on Machine literacy and Deep literacy ways. This exploration composition also elaborates on how factory complaint discovery frame will be realized using new segmentation and point birth strategies for rooting significant features for classification. Once the features are uprooted, they're transmitted to the pall platform to apply web enabled automated covering system. The proposed piled ensemble literacy is estimated by comparing different machine literacy and Deep literacy ways models exercising perfection, recall. When compared to traditional machine literacy and deep literacy ways approaches, the findings show that the proposed fashion achieves about 99% delicacy.

KEYWORDS: Deep Learning, Neural Network, Farming, Leaf disease detection, Image recognition.

I. INTRODUCTION

The agriculture sector plays a pivotal role in global food security, and technological advancements have become essential to address the challenges faced by modern farming. Plant diseases, if not detected and managed in a timely manner, can lead to significant crop losses. Traditional methods of disease identification often rely on manual inspection, which is time-consuming and may not be accurate. In this context, the integration of deep learning techniques offers a promising solution for automating the detection of plant diseases. Deep learning models, particularly CNNs, have demonstrated exceptional capabilities in image recognition tasks. The use of these models for leaf disease detection allows for rapid and accurate identification, aiding farmers in implementing timely interventions. Transfer learning, a technique where a model trained on one task is adapted for a related task, enhances the performance of the disease detection model, especially when labeled datasets are limited. This research contributes to the ongoing efforts to develop smart farming solutions by introducing a deep learning-based leaf disease detection system. By combining the power of deep learning with user-friendly interfaces, this system aims to empower farmers with a tool that can revolutionize crop management practices.

II. METHODOLOGY

Capturing high-quality plant images is the initial step in a plant disease detection system, employing devices like digital cameras, scanners, drones, or utilizing web sources. Platforms such as Kaggle provide access to diverse datasets containing both healthy and diseased leaf samples. After image acquisition, preprocessing techniques are applied to enhance image quality and eliminate undesired noise, including contrast adjustment and color correction.

1. Data collection: A large dataset of images of tomato leaves with and without disease is collected. This dataset is essential for training the deep learning model.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |
|| Volume 12, Issue 4, April 2024 ||
| DOI: 10.15680/IJIRCCE.2024.1204024 |

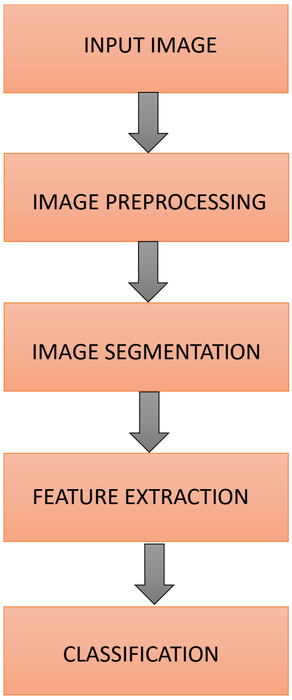


Figure 1: Flowchart for Leaf Disease Recognition

2. Data preprocessing: The images in the dataset are then preprocessed. This may involve resizing the images, normalizing the pixel values, and applying other techniques to improve the quality of the data.

3. Model training: A deep learning model, typically a convolutional neural network (CNN), is then trained on the preprocessed dataset. The CNN learns to identify the features of tomato leaf diseases in the images.

4. Model testing: Once the model is trained, it is tested on a separate dataset of images. This helps to evaluate the accuracy of the model.

5. Deployment: If the model performs well on the test dataset, it can then be deployed in a smart farming application. The application can be used to capture images of tomato leaves in the field and then use the model to classify the leaves as healthy or diseased.

III. LITERATURE REVIEW

Shankarnarayanan Nalini [1] In this paper focuses on using advanced technology like IoT and networking for Precision Agriculture. Specifically, it tackles the problem of plant diseases affecting crop quantity and quality. The researchers developed a smart system using a deep neural network (DNN) with a unique optimization method called crow search algorithm (CSA). This system analyzes images of paddy leaves to identify diseases, achieving high accuracy (96.96%) compared to traditional methods. The goal is to help farmers detect and diagnose plant diseases in real-time using images from the field, providing timely support for better crop management.

Mr. Sachin B. Jagtap [2] In this paper explores the use of expert systems, computer programs that provide solutions like human experts, in the field of agriculture. The aim is to improve diagnosis of plant disorders, especially leaf batches, by integrating image processing with a diagnostic problem solver. By automatically detecting abnormalities in plant images, the system reduces the risk of human error and enhances accuracy. The focus is on identifying disorders through image analysis, and the proposed system involves four key phases: image enhancement, segmentation, feature extraction, and classification. The potential future developments include extending the system to detect abnormalities in other plant parts and exploring robotic systems for direct treatment operations.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 4, April 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1204024 |

Rudresh Dwivedi [3] In this paper addresses the timely detection of diseases in plants to ensure healthy growth and agricultural productivity. It introduces a method called L1-ELM, which is an efficient one-class classifier, for classifying leaves as healthy or diseased. The approach involves preprocessing with Kuan filtering and evaluating multiple features for accurate diagnosis. L1-ELM reduces computational complexity and achieves high generalization, resulting in a recognition rate of 98.5% for peach and 97.7% for strawberry datasets. This novel mechanism aims to enhance disease detection in plants with minimal learning time and improved efficiency.

L. Sherly Puspha Annabel [4] In this paper reviewed the significant issue of plant diseases impacting crop production and economic value. It emphasizes the importance of timely leaf disease detection in agriculture. To overcome challenges like manpower and processing time, machine learning techniques are applied. The paper reviews various classification techniques in machine learning, focusing on morphological features and properties like color and intensity of plant leaves. It also explores methods for detecting bacterial, fungal, and viral diseases. The future work involves identifying mulberry plant leaf diseases using Convolutional Neural Networks (CNN) and enhancing recognition rates and classification accuracy through hybrid algorithms. The goal is to automate disease detection in plant leaves for improved agricultural management.

Ashutosh Kumar Singh [5] In this paper focuses on leveraging artificial intelligence, specifically convolutional neural networks (CNNs), for the automatic detection of plant diseases. The aim is to address the significant impact of diseases, pests, and harmful substances on agricultural production. The paper discusses the limitations of traditional methods and introduces the use of AI, particularly machine learning and deep learning, for more accurate and efficient disease diagnosis. Various CNN architectures like AlexNet, GoogLeNet, and others are compared for their effectiveness in classifying diseases in different crops. The study concludes that CNNs, particularly MobileNet, achieved a high accuracy of 96.1% in detecting leaf diseases across various plant species. The findings suggest the potential of CNNs in providing smart solutions for farmers and improving disease detection in agricultural settings.

Rupali Patil [6] In this paper explores various classification techniques for identifying plant leaf diseases based on morphological features. Methods like k-means clustering and Support Vector Machine are discussed, emphasizing the challenge of selecting the most suitable technique for diverse input data. The significance of plant disease detection in agriculture, particularly in India, is highlighted. The paper emphasizes the shift from unscientific methods to reliable, technologically advanced approaches that enable early disease detection with minimal turnaround time. The detection process involves segmentation and classification, with a focus on addressing the open problem of proper segmentation based on plant family types. Overall, the research aims to contribute to improving agriculture productivity by effectively identifying and managing plant diseases.

Hu Gensheng [7] In this paper presents an improved deep convolutional neural network (CNN) for identifying tea leaf diseases efficiently. By enhancing a CIFAR10-quick model with a multiscale feature extraction module and using depth wise separable convolution, the model achieves a high average identification accuracy of 92.5%. This outperforms traditional machine learning and classical deep learning methods like VGG16 and AlexNet, while also having fewer parameters and faster identification speed. The approach automates feature extraction for different tea leaf diseases, offering advantages in accuracy and efficiency over manual methods and other existing models.

Md. JanibulAlam Soeb [8] In this paper introduces an artificial intelligence solution using YOLOv7 for detecting and identifying tea leaf diseases in Bangladesh's tea gardens. The model achieved high accuracy (97.3%) in distinguishing between healthy and diseased leaves, outperforming other existing models. The system aims to reduce workload for entomologists, enhance disease identification, and minimize economic losses in tea production. The YOLOv7 model proves effective in automating the detection of five types of tea leaf diseases. Future improvements could involve faster training using batch normalization and expanding the dataset with diverse samples. The model's compatibility with IoT devices suggests real-world applications, and potential extensions include adapting it for other crops and implementing it in a mobile app for farmers. The study emphasizes the importance of early disease detection and proposes future research on multi-data fusion for creating an early warning system for tea leaf diseases.

Minah Jung [9] In this paper aimed to create a smart farming tool for early detection of crop diseases using a deep learning model. The model, based on image pairs of healthy and diseased plants, consists of three steps: identifying the crop, detecting disease occurrence, and classifying the disease type. They used pre-trained CNN models and achieved high accuracy (97.09%) in classifying crops and diseases. To improve the model, they included "unknown" crops and suggested expanding the dataset for broader application in smart farming, particularly for Solanaceae crops. The study emphasizes the potential for detecting various crop diseases by adding diverse data in future research.

Ümit Atila [10] In this paper focuses on the crucial role of timely plant disease diagnosis in agriculture, highlighting challenges faced by traditional methods. It reviews various machine learning approaches, including SVM, CNN, and deep learning, applied to plant disease detection. The research proposes using Efficient Net for classification, comparing its performance with established CNN architectures like AlexNet and ResNet50. The study emphasizes the increasing use of deep learning in plant disease diagnosis and underscores the need for efficient

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 4, April 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1204024 |

models. The remainder of the paper covers the dataset, experimental details, results, and concludes with a summary of findings.

Iftikhar Ahmad [11] In this paper underscores the crucial role of plants, particularly tomatoes, in daily diets and the challenges posed by diseases. It emphasizes the need for rapid and accurate disease detection to sustain agro-ecosystems, especially with a rising reliance on chemicals negatively affecting agriculture. The paper advocates for technology-driven approaches, combining image processing and deep learning, to identify tomato plant leaf diseases. Evaluating various CNN models on both real field and controlled laboratory datasets, the study introduces robust metrics such as accuracy, recall, precision, and F1-score. The methodology addresses limitations of controlled datasets, providing a more representative evaluation for real-world scenarios.

Yong Zhong [12] In this paper, China leads globally in apple cultivation, a crucial economic crop. However, apple leaf diseases result in significant production and economic losses. Traditional machine learning methods, including SVM, have shown promise in disease recognition. Recent advancements involve feature fusion and deep learning techniques like AlexNet and GoogLeNet, achieving high accuracy. The paper introduces DenseNet-121 to address imbalances in plant disease datasets, proposing regression, multi-label classification, and focus loss functions. A dataset with various apple leaf diseases is created for evaluation. The study compares these novel methods with traditional cross-entropy loss-based classification in deep learning, aiming to enhance recognition accuracy in unbalanced datasets.

Muhammad Hammad Saleem [13] In this paper explores the elaboration of Deep Learning [DL] in two phases, emphasizing improvements and operations from 2012 onward. Notable infrastructures like AlexNet converted image recognition, extending into husbandry for splint bracket, crop/ weed demarcation, and factory complaint discovery. colorful DL models and criteria, similar as bracket delicacy, perfection, and F1 score, are examined in agrarian surrounds. The paper addresses gaps in being reviews, emphasizing recent developments and visualization ways in DL for factory complaint identification. The inflow illustration illustrates the DL perpetration process from dataset collection to visualization mapping. The review concludes with perceptivity and recommendations for unborn advancements in factory complaint discovery.

Wenxia Bao [14] In this paper introduces layoff-RetinaNet, a bettered RetinaNet for accurate tea splint complaint discovery in natural scene images. Addressing challenges like complex backgrounds and thick leaves, layoff-RetinaNet incorporates an enhanced multiscale point emulsion module(X-module) and a channel attention module. The X-module enriches semantic information through multi-scale point mixtures, while the attention module optimizes channel weights, reducing hindrance. relative trials show layoff- RetinaNet outperforming being networks, achieving a mean Average Precision(chart) of 93.83 and an F1- score of 0.954. The proposed model significantly improves discovery delicacy, recall, and identification delicacy compared to original networks, addressing pivotal issues in tea husbandry.

Melike Sardogan [15] In this paper focuses on agrarian complaint discovery, specifically concerning tomato shops. It introduces a methodology using a Convolutional Neural Network (CNN) combined with the Learning Vector Quantization (LVQ) algorithm for the discovery and bracket of four distinct tomato splint conditions bacterial spot, late scar, Septoria splint spot, and unheroic twisted splint. The approach utilizes a dataset comprising 500 images of tomato leaves flaunting these conditions. RGB factors are employed to conduct complications across three channels. The CNN is designed to prize features from these images. These uprooted features are also employed by the LVQ algorithm for training and testing purposes, enabling the successful recognition and bracket of the mentioned conditions. The study concludes that the proposed system effectively identifies the four types of tomato splint conditions. also, it suggests implicit advancements for enriching the bracket process, including exploring different pollutants or varying complication sizes to potentially ameliorate the delicacy of complaint recognition.

Konstantinos P. Ferentinos [16] In this paper introduces specialized deep learning models, primarily Convolutional Neural Networks (CNNs), designed for plant disease detection and diagnosis using leaf images of both healthy and diseased plants. The models were trained on a vast dataset comprising 87,848 images, encompassing 25 different plant species across 58 distinct combinations of plant and disease types. Despite the promising results, the study acknowledges limitations, including the need for a more extensive and diverse dataset comprising a wider variety of plant species and diseases. The authors emphasize the challenges in obtaining such data, especially from various geographic areas, cultivation conditions, and image sources. They note that while the model exhibited high accuracy within the training dataset, its performance dropped substantially when tested on data from different sources, highlighting the necessity for broader and more diverse training data to enhance the system's robustness and applicability in real cultivation conditions.

Halil Durmuú [17] In this paper focuses on leveraging deep learning to detect diseases affecting tomato plants in fields or greenhouses. The goal is to enable real-time disease detection by implementing the deep learning algorithm on a robot. This allows the robot to identify plant diseases while moving manually or autonomously within the field or

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 4, April 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1204024 |

greenhouse, and sensors within fabricated greenhouses can also capture close-up photographs for disease detection. The diseases under examination manifest physical changes in tomato plant leaves, which can be captured using RGB cameras. Unlike prior studies that used standard feature extraction methods, this research employs deep learning techniques for disease detection. The selection of deep learning architectures becomes crucial; thus, two different architectures, AlexNet and SqueezeNet, were tested. Training and validation were conducted on the Nvidia Jetson TX1 using tomato leaf images from the Plant Village dataset, encompassing ten different classes, including healthy images. The trained networks were tested on internet images for evaluation. The study demonstrates that SqueezeNet proves to be a promising choice for mobile deep learning classification due to its lightweight nature and low computational requirements. Additionally, using a smaller network offers advantages in terms of model updates. Updating the mobile application via mobile communication incurs lower data costs and enables faster updating speeds.

Sammy V. Militante [18] In this paper capitalizes on recent advancements in computer vision, employing deep learning techniques for the detection and diagnosis of various plant diseases. The study focuses on detecting diseases in several plant varieties, specifically targeting apple, corn, grapes, potato, sugarcane, and tomato plants. By utilizing a dataset comprising 35,000 images featuring healthy leaves and those infected with diseases deep learning models were trained to detect and recognize these diseases and differentiate healthy plants. The trained model demonstrated an impressive accuracy rate of 96.5%, achieving up to 100% accuracy in identifying both the plant variety and the specific diseases afflicting them. This high accuracy signifies the potential for real-world applications in agriculture, aiding in early disease recognition critical for the agricultural industry. The study underscores the significance of the agricultural sector and its reliance on healthy crops for sustaining global food needs. It successfully utilized convolutional neural networks (CNNs) to identify 32 different plant varieties and their associated diseases. The trained model's capabilities extend to real-time detection and recognition of plant diseases. Future research directions include expanding the dataset to include additional plant varieties and different types of plant diseases to enhance the model's accuracy and versatility. Additionally, experimenting with various CNN architectures, learning rates, and optimizers aims to further refine the model's performance. With its 96.5% accuracy rate, the proposed model stands as a valuable tool to assist farmers in promptly detecting and recognizing plant diseases, potentially aiding in preserving crop health and improving agricultural yield.

Belal A. M. Ashqar [19] In this paper highlights the threat crop diseases pose to food security, especially in regions lacking necessary infrastructure for rapid disease identification. Leveraging the widespread availability of smartphones and recent advancements in computer vision enabled by deep learning, the study focuses on smartphone-assisted disease identification. Using a publicly available dataset of 9,000 images depicting both infected and healthy tomato leaves under controlled conditions, a deep convolutional neural network was trained to detect five specific diseases. Remarkably, the trained model achieved an outstanding accuracy of 99.84% on a separate test set, demonstrating the effectiveness of this approach. The conclusion emphasizes the achievement of the best model (Full-Color) with its impressive 99.84% accuracy on the held-out test set. Additionally, the second-best model (Gray-Scale) attained an accuracy of 95.54%. Figures depicting the models' accuracy progression over epochs showcase their robust performance. Overall, the study underscores the potential of training deep learning models on large, publicly available image datasets. This approach presents a promising pathway toward smartphone-assisted crop disease diagnosis on a global scale, offering immense potential for enhancing agricultural productivity and food security.

Federico Martinelli [20] In this paper reviewed Plant diseases cause significant economic losses in agriculture globally. Detecting these diseases early is crucial for effective management. Traditional methods involve visually scouting for symptoms or using DNA and serological methods, but they have limitations, especially in asymptomatic stages. This study explores modern methods like nucleic acid and protein analysis. Innovative approaches include sensors analyzing host responses, biosensors using phage display and bio photonics, and remote sensing coupled with spectroscopy. These tools provide rapid and spatialized results, complementing traditional methods. While serological and PCR-based methods are reliable, new sensors offer instantaneous results, aiding in identifying infections at asymptomatic stages.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 4, April 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1204024 |

IV. COMPARISON ANALYSIS

Researcher	Technology Used	Key Method	Accuracy	Focus	Future Directions
Shankarnarayan Nalini [1]	IoT, Networking, DNN, CSA	Image analysis for disease identification	96.96%	Real-time detection, crop management support	Further improvement, broader application
Rudresh Dwivedi [3]	L1-ELM, Kuan filtering	Efficient one-class classifier for leaf classification	98.5%(peach), 97.7%(strawberry)	Timely disease detection, minimal learning time	Improved efficiency, further applications
Ashutosh Kumar Singh [5]	Artificial Intelligence, CNNs	CNNs for automatic detection of plant diseases	96.1% (MobileNet)	Accurate and efficient disease diagnosis	Smart solutions for farmers, improvement in disease detection
Hu Gensheng [7]	Improved CNN with Multiscale Features	Deep CNN for efficient tea leaf disease identification	92.5%	Efficient feature extraction, faster identification	Automation of feature extraction, advantages over manual methods
Md. JanibulAlam Soeb [8]	YOLOv7, IoT	YOLOv7 for tea leaf disease detection	97.3%	Reduction in workload for entomologists	Faster training, extension to other crops, mobile app implementation
Minah Jung [9]	Deep Learning, CNNs	Deep learning model for early detection of crop diseases	97.09%	Identification of crop and disease type	Expansion of dataset for broader smart farming application
Ümit Atila [10]	Machine Learning, EfficientNet	EfficientNet for plant disease classification	Not specified	Increased use of deep learning in disease diagnosis	Efficient models for plant disease detection
Wenxia Bao [14]	Improved RetinaNet, Image Processing	Improved RetinaNet for tea leaf disease discovery	93.83%(MAP), 0.954 (F1-score)	Enhanced multiscale point emulsion module	Optimization for complex backgrounds, improved delicacy

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 4, April 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1204024 |

Melike Sardogan [15]	CNN, Learning Vector Quantization	CNN with LVQ algorithm for tomato plant disease detection	Not specified	Recognition and bracketing of distinct tomato splint conditions	Implicit advancements for improving bracket process
Sammy V. Militante [18]	Deep Learning, CNNs	CNNs for detection and diagnosis of various plant diseases	96.5%	Disease detection in multiple plant varieties	Expanding dataset, experimenting with CNN architectures

Table I. Comparative Overview of Innovative Approaches for Plant Disease Detection in Agriculture

Summary:

This table provides a comprehensive overview of diverse projects utilizing advanced technologies for plant disease detection. The comparison includes key technologies, focus areas, reported accuracy, and future directions for each project, highlighting the richness and variety of approaches in modern agriculture.

V. CONCLUSION

In the present paper, we reviewed the diverse range of advanced technologies, including deep learning and expert systems, to address the critical issue of Leaf diseases in agriculture. These innovative solutions, ranging from CNN-based disease detection to unique optimization algorithms, demonstrate high accuracy rates. It explores the integration of expert systems, image processing solutions for Leaf disease detection. Specialized convolutional neural networks tailored to specific crops, like a tomato, tea, rice leaves and apple trees, demonstrate the customization of models for heightened accuracy. As technology continues to advance, the synergy between deep learning and agriculture holds immense potential for transforming traditional farming methods into smart and data-driven approaches.

REFERENCES

[1] Shankarnarayanan Nalini, Nagappan Krishnaraj, Thangaiyan J Jayasankar, Kalimuthu Vinothkumar, Antony Sagai Francis Britto, Kamalraj Subramaniam and Chokkalingam Bharatiraja, “Paddy Leaf Disease Detection Using an Optimized Deep Neural Network” Published 2021 http://dx.doi.org/10.32604/cmc.2021.012431

[2] Mr. Sachin B. Jagtap, Mr. Shailesh M. Hambarde, “Agricultural Plant Leaf Disease Detection and Diagnosis Using Image Processing Based on Morphological Feature Extraction” Volume 4, Issue 5, http://www.iosrjournals.org/

[3] Rudresh Dwivedi, Tanima Dutta, Senior Member, IEEE, and Yu-Chen Hu, Senior Member, IEEE, “A Leaf Disease Detection Mechanism Based on L1-Norm Minimization Extreme Learning Machine” published 2022, https://doi.org/10.1109/LGRS.2021.3110287

[4] L. Sherly Puspha Annabel, Member, IEEE, T. Annapoorani and P. Deepalakshmi, “Machine Learning for Plant Leaf Disease Detection and Classification” Published April 4-6, 2019, 978-1-5386-7595-3/19/$31.00 ©2019 IEEE

[5] Ashutosh Kumar Singh, SVN Sreenivasu, U.S.B. K. Mahalaxmi, Himanshu Sharma, Dinesh D. Patil and Evans Asenso, “Hybrid Feature-Based Disease Detection in Plant Leaf Using Convolutional Neural Network, Bayesian Optimized SVM, and Random Forest Classifier” Volume 2022, Article ID 2845320, 16 pages https://doi.org/10.1155/2022/2845320

[6] Rupali Patil1, Sayali Udgave2, Supriya More3, Dhanashri Nemishte4Monika Kasture, “Grape Leaf Disease Detection Using K-means Clustering Algorithm”, Published Volume: 03 Issue: 04 | Apr-2016 http://www.irjet.net/

[7] Hu Gensheng, Yang Xiaowei, Zhang Yan, Wan Mingzhu, “Identification of Tea Leaf Diseases by Using an Improved Deep Convolutional Neural Network” Published 5 October 2019 https://doi.org/10.1016/j.suscom.2019.100353

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 4, April 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1204024 |

[8] Md. JanibulAlam Soeb, Md. Fahad Jubayer, Tahmina AkanjeeTarin Muhammad Rashed Mamun, Fahim Mahafuz Ruhad, Aney Parven, Nabisab Mujawar Mubarak, Soni Lanka Karri & Islam Md. Meftaul, "Tea leaf disease detection and identifcation based onYOLOv7 (YOLO T)" Published 2023 https://doi.org/10.1038/s41598-023-33270-4

[9] Minah Jung, Jong Seob Song, Ah Young Shin, Beomjo Choi, SangjinGo, Suk Yoon Kwon, Juhan Park, SungGoo Park & Yong Min Kim, "Construction of deep learning based disease detection model in plants" Published 2023 https://doi.org/10.1038/s41598-023-34549-2

[10] Ümit Atila, Murat Uçar, Kemal Akyol, Emine Uçar, "Plant leaf disease classification using EfficientNet deep learning model", Published 2 October 2020 https://doi.org/10.1016/j.ecoinf.2020.101182

[11] Iftikhar Ahmad, Muhammad Hamid, Suhail Yousaf, Syed Tanveer Shah, and Muhammad Ovais Ahmad, "Optimizing Pretrained Convolutional Neural Networks for Tomato Leaf Disease Detection" Published 2020 https://doi.org/10.1155/2020/8812019

[12] Yong Zhong, Ming Zhao, "Research on deep learning in apple leaf disease recognition" Published 12 December 2019 https://doi.org/10.1016/j.compag.2019.105146

[13] Muhammad Hammad Saleem, Johan Potgieter and Khalid Mahmood Arif, "Plant Disease Detection and Classification by Deep Learning" Published on 2019 http://dx.doi.org/10.3390/plants8110468

[14] Wenxia Bao, Tao Fan, Gensheng Hu, Dong Liang & Haidong Li, "Detection and identifcation of tea leaf diseases based on AX RetinaNet" Published 2022 https://doi.org/10.1038/s41598-022-06181-z

[15] Melike Sardogan, Adem Tuncer, Yunus Ozen "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm" 978-1-5386-7893-0/18/$31.00 ©2018 IEEE, (UBMK'18) 3rd International Conference on Computer Science and Engineering

[16] Konstantinos P. Ferentinos "Deep learning models for plant disease detection and diagnosis" Published 12 January 2018, https://doi.org/10.1016/j.compag.2018.01.009

[17] Halil Durmuú, Ece Olcay Güneú, Mürvet KÕrcÕ, "Disease Detection on the Leaves of the Tomato Plants by Using Deep Learning" published by T.R. Ministry of Food, Agriculture, and Livestock I.T.U. TARBIL Environmental Agriculture Informatics Applied Research Center

[18] Sammy V. Militante, Bobby D. Gerardoij, Nanette V. Dionisio "Plant Leaf Detection and Disease Recognition using Deep Learning" Published on 2019 IEEE Eurasia Conference on IOT, Communication and Engineering, ISBN: 978-1-7281-2501-5

[19] Belal A. M. Ashqar, Samy S. Abu-Naser, "Image-Based Tomato Leaves Diseases Detection Using Deep'' Vol. 2 Issue 12, December – 2018, Pages: 10-16 http://www.ijeais.org/ijaer

[20] Federico Martinelli, Riccardo Scalenghe, Salvatore Davino, Stefano Panno, Giuseppe Scuderi, Paolo Ruisi, Paolo Villa, Daniela Stroppiana, Mirco Boschetti, Luiz R. Goulart, Cristina E. Davis, Abhaya M. Dandekar "Advanced methods of plant disease detection. "Published 2015 https://doi.org/10.1007/s13593-014-0246-1