Plant Disease Detection Using Computational Approaches: A Systematic Literature Review

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Rapid improvements in ML and DL techniques have made it possible to detect and recognize objects from images. Computational approaches using ML and DL have been recently applied to agriculture or farming applications and are proving successful in increasing per-yield production. Automatic identification of plant diseases can help farmers manage their crops more effectively, resulting in higher yields. Detecting plant disease in crops using images is an intrinsically difficult task. In addition to their detection, individual species identification is necessary for applying tailored control methods. A survey of research initiatives that use DL and ML approaches to address various plant DD concerns was undertaken in the current publication. In this work, we have reviewed 35 of the most recent DL and ML-based articles on detecting various plant leaf diseases over the last five years. In addition, we identified and summarized several problems and solutions corresponding to the ML and DL used in plant leaf DD. Moreover, DCNN trained on image data was the most effective method for detecting early DD. We expressed the benefits and drawbacks of utilizing CNN in agriculture, and we discussed the direction of future developments in plant DD.

Machine Learning	ML
Deep Learning	DL
Deep Convolutional Neural Networks	DCNN
Convolutional Neural Network	CNN
Image Processing	IP
Systematic Literature Review	SLR
Research Questions	RQs
Exclusion Criteria	EC
Inclusion Criteria	IC
Disease Detection	DD

Keywords: ML, DD, DL, IP

Introduction:

In agriculture, ensuring plant health is vital to sustaining crop vitality amid a growing global population. The fields of CNN, ML, and IP form a unique trio of technological advancements poised to transform plant DD.

CNN is a type of DL algorithm specifically designed to process and analyze visual data by training on thousands of images, these networks can identify the subtle signs of disease in plants, often invisible to the human eye [1]. ML complements this by adapting and improving each new data set, refining the system's accuracy [2]. IP acts as the preparatory stage, enhancing the quality of images so that the CNN can perform their analysis more effectively [3]. Together these technologies offer a powerful solution for rapid and accurate plant DD [4]. They enable continuous monitoring and real-time analysis, providing farmers with the tools to take immediate action [5]. This not only helps in reducing crop losses but also contributes to sustainable agricultural practices and food security worldwide [5].

This SLR sets the stage for a deeper dive into how CNN, ML & IP are revolutionizing the way we detect and manage plant diseases, offering hope for a future of healthier crops and a more secure food supply [6]. In this work, we have reviewed 35 articles in which the images of leaves have been processed using IP, ML, and DL techniques. This review contributes significantly to the body of knowledge of agriculture studies as it not only worked out to determine which of the given techniques is mostly applied in the literature for the detection of plant diseases but also provided valuable suggestions that farmers may follow to increase pre-yield production of their crop.

Novelty:

The novelty of this research lies in its comprehensive focus on the intersection of computational methods and plant DD, particularly with an emphasis on practical agricultural implementation. Key points of uniqueness may include:

1. **Critical Analysis of Techniques**: Consolidately evaluate and compare advanced methods like ResNet, Random Forests, and image preprocessing e.g., histogram equalization.
2. **Implementation-Oriented Insights**: The emphasis on translating findings into real-world agricultural practices adds value, addressing practical challenges such as scalability, cost-effectiveness, and ease of deployment.
3. **Trend and Gap Identification**: Highlighting emerging trends and research gaps for future innovation in plant DD.
4. **Application Focus**: Specifically addressing deployment challenges and outcomes for large-scale agricultural operations.
5. **Related Work:**

Recent studies emphasize the utilization of CNN, ML & IP for effective plant DD. Various ANNs have demonstrated success in accurately classifying plant health issues. These approaches showcase the significance of advanced computational methods, providing valuable insights for further innovations in plant pathology through the integration of IP & ML techniques.

The Role of CNNs:

CNNs are a type of DL algorithm specifically designed to process and analyze visual data [7] [8]. CNNs excel at recognizing complex patterns and features in images, making them ideal for diagnosing a wide range of plant diseases from visual symptoms.

Enhancing Accuracy with ML:

ML complements CNNs by continuously adapting and improving each new data set. As more data is collected, ML algorithms refine their predictions, enhancing the system's overall accuracy [9][10]. This adaptive learning process is crucial for maintaining high detection accuracy in diverse and changing agricultural environments. ML algorithms can also integrate other data sources, such as environmental conditions and soil health metrics, providing a more comprehensive analysis of plant health [11].

IP as the Foundation:

IP acts as the preparatory stage, enhancing the quality of images so that CNNs can perform their analysis more effectively [12]. This step is crucial for noise reduction and feature enhancement, ensuring that the images fed into CNNs are of the highest quality [13][14]. IP techniques such as filtering, contrast adjustment, and segmentation help in highlighting the critical features of plant diseases, making it easier for CNNs to detect them accurately.

D. Synergy for Sustainable Agriculture:

These technologies offer a powerful solution for rapid and accurate plant DD. They enable continuous monitoring and real-time analysis, providing farmers with the tools to take immediate action [15].

ResNet for Plant Leaf Disease Detection:

A novel approach integrated ResNet with Leaky ReLU for plant leaf DD using the Plant Village dataset. The study achieved high accuracy 94.56% and showed significant improvements in precision and recall metrics, highlighting the potential of ResNet in addressing vanishing gradient issues and ensuring superior feature extraction for diverse plant disease patterns [16].

Random Forest for Disease Identification:

Random Forest was employed in studies as an ensemble learning method for identifying plant diseases. By leveraging its ability to handle complex and high-dimensional datasets, researchers demonstrated its utility in accurately classifying multiple diseases in heterogeneous plant datasets [17].

Histogram Equalization in Pre-Processing:

Histogram equalization improved image contrast in preprocessing pipelines, enhancing the visibility of disease symptoms. This technique synergized with ML and DL models, ensuring better input quality for effective feature extraction and DD [18].

Research Methodology:

This study employs a SLR methodology, systematic searching, categorizing, and synthesizing literature based on predefined objectives. The process comprises defining study objectives, formulating research questions, developing a search strategy, establishing inclusion/exclusion and quality grading criteria, shortlisting studies, ranking them based on quality, and classifying and synthesizing findings. Figure 1 illustrates the nine steps of this research technique, providing a roadmap for future investigations in the specific domain. The results are subsequently discussed and analyzed, offering valuable insights for further research directions.

Research Objectives:

The primary objective of this research is to comprehensively investigate the evolution of CNN architectures in the context of Plant DD. This entails a thorough examination of the historical development, advancements, and adaptations of CNN models specifically tailored for the identification and diagnosis of plant disease.

RO1. To evaluate the evolution of CNN architectures in plant DD.

RO2. To assess the impact of ML integration on the accuracy and efficiency of the Plant DD system.

RO3. To examine the influence of different ML and DL approaches on model design for plant disease identification.

RO4. To identify challenges and limitations in current research on plant DD.

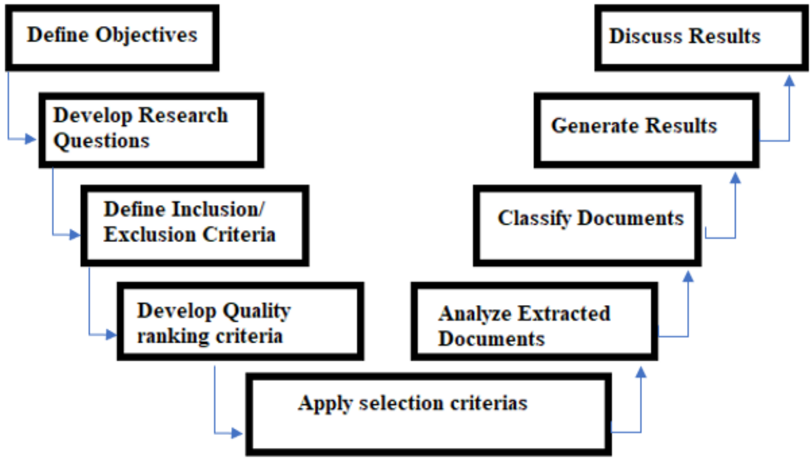

Figure 1: Proposed Methodology

Research Questions:

Table 1 outlines the selected research areas for exploring the underlying domain, along with their respective reasons.

Table 1: Research Questions

RQ#	Statement
RQ1	What are the bibliometric key facts of ML, Dl, and IP-based plant DD publications?
RQ2	How effective are DL, ML, and IP algorithms in improving the accuracy and efficiency of plant DD?
RQ3	What is the type of plant and other key aspects of ML, DL, and IP considered in the classified publications?
RQ4	What limitations exist in current research on plant DD using CNN, ML, and IP?

Search Scheme:

The SLR search scheme employs thoughtfully selected keywords meticulously chosen to encapsulate the intricacies of the research domain. The subsequent Table 2 presents these keywords, offering a transparent glimpse into the search strategy. This ensures precision, relevance, and a comprehensive approach to retrieving studies, contributing to a nuanced understanding of the subject.

Inclusion Exclusion Criteria:

To narrow down the pertinent literature from the articles identified through the application of the search query in digital repositories, specific IC and EC were meticulously established.

The following criteria were devised to encompass the selected studies.

IC1. Articles are based on plant DD using ML.

IC2. Different types of DL used for plant DD

IC3. Articles that applied IP and feature selection

EC1. Research is based on theoretical assessment.

EC2. The study is published before 2013.

EC3. Research articles are not in the English language.

Figure 2 Presents the Article Filtration Process.

Table 2: Keywords

Primary Keywords	Secondary Keywords	Tertiary Keywords
IP	Visualization	Feature Maps
ML	Expert Systems	Crop Analysis

DL	Disease Identification	Explainable AI in agriculture
Disease Classification	ConvNet	Autonomous Greenhouses
Training Dataset	Feature Selection	Disease Analysis
CNN	Precision Farming	
Computer Aided Agriculture	Object Detection	
Leaf Image Analysis	Image Classification	

Table 3 details the search query employed for targeted exploration across distinct digital repositories. We have mainly focused on WoS and Scopus-indexed articles.

Table 3: Search String

Repository	Search Keys	Query	No. of articles
IEEE Xplore	Plant Detection Plant Disease Neural Network IP ConvNet ANN	"All Metadata": Plant Detection AND "All Metadata": Plant Disease AND "All Metadata": Neural Network AND "All Metadata": IP OR "All Metadata": ConvNet OR "All Metadata": ANN OR "All Metadata": Crop Yield	**7972**
ACM Digital Library	Plant Detection Illness ML ConvNet Image ANN	[All: plant detection] AND [All: illness] AND [All: ML] AND [All: conv net] AND [All: image] AND [All: ann]	**384**
Science Direct	Plant identification Pests Picture Processing ML	Custom input type fields	**400**

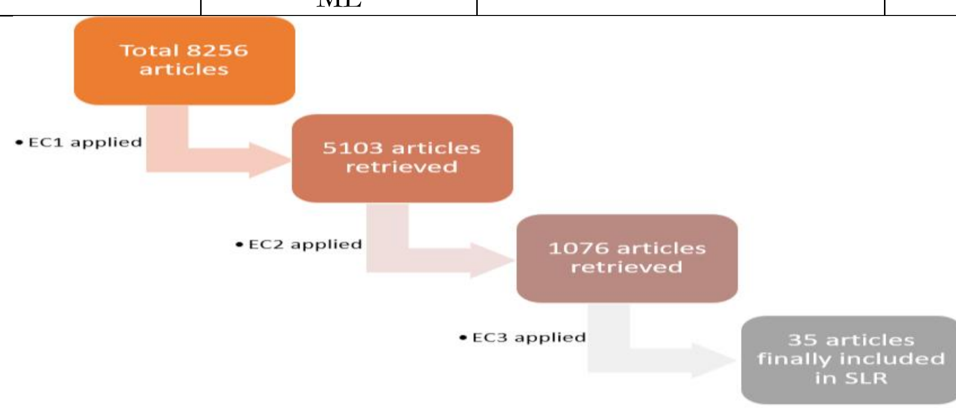

Figure 2: Study selection

Shortlisting Procedure:

Implementing the search terms in the digital databases yielded a substantial amount of data necessitating a systematic multi-stage shortlisting process. The process initiated with the initial search assessment of articles from databases. Subsequently, duplicate records were eliminated. The selected papers underwent further scrutiny through title and abstract reviews. Additional exclusions occurred after reading the introductions and conclusions. Throughout this process, specific inclusion/EC played a key role in screening candidates at different stages.

Quality Scoring Criteria:

Assessing the quality is a vital step in SLRs to gauge the excellence of the included research. The quality of the selected studies was appraised based on the criteria outlined in Table 4.

Table 4: Scoring criteria

Criteria	Description	Rank	Score
Internal Scoring			
a	Did the abstract mention technologies?	Yes Partially No	1 0.5 0
b	Did the study show how to record data?	Yes Partially No	1 0.5 0
c	Was methodology clearly defined?	Yes Partially No	1 0.5 0
d	Was the conclusion according to the results?	Yes Partially No	1 0.5 0
External Scoring			
e	What is the ranking of publication sources?	Yes Partially No	1 0.5 0

Results:

The classification table has been populated using data extracted using the RQs specified in section III. Classification is presented in Table 5.

RQ1: What are the bibliometric key facts of ML, Dl, and IP-based plant DD publications?

The bibliometric analysis of publications related to ML, DL, and IP in plant DD reveals several key facts. There has been a significant increase in the number of publications over recent years, reflecting the growing interest and advancements in these technologies for agricultural applications. The rise is particularly pronounced in the last decade, coinciding with advancements in computational power and algorithmic development. Year-wise publications included in this study are presented in Figure 3.

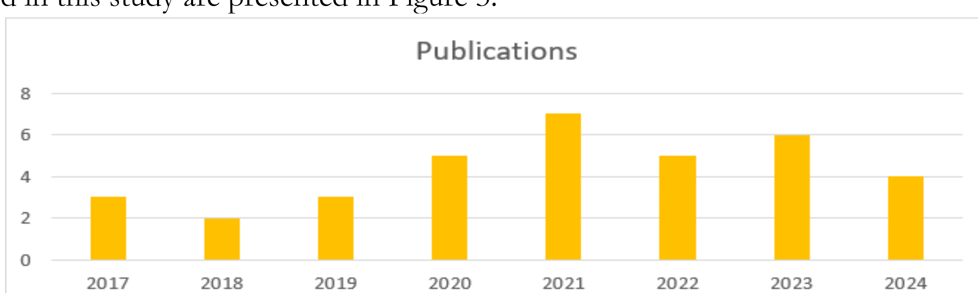

Figure 3: Per year distribution of the articles included for review

RQ2: How effective are DL, ML, and IP algorithms in the detection of plant DD

43% of the selected articles have applied Dl algorithms for the detection of plant diseases while 27% of the selected studies have applied ML methods. Many researchers have also practiced other computational methods based on AI and IoT.

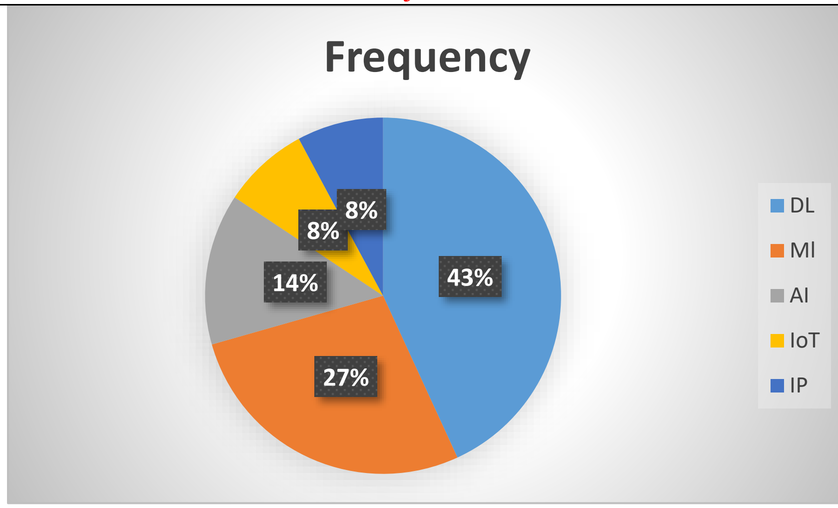

Figure 4: Technique-wise frequency of articles

RQ3: What is the type of plant and other key aspects of ML, DL, and IP considered in the classified publications?

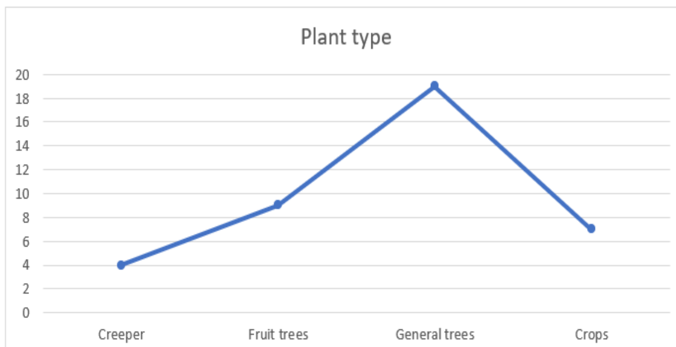

Figure 5: Plant Type Analysis

Most of the research conducted in the last ten years has mainly focused on general DD. There are very few studies that have worked to detect diseases affecting fruit trees as presented in Figure 4.

Table 5. Classification Table

Discussion:

The CNN models exhibited exceptional accuracy surpassing 95% in identifying plant diseases highlighting their effectiveness in automated detection. Hybrid models combining CNNs with ML algorithms showcased improved accuracy and reduced overfitting, signifying a promising approach for precise disease classification Comparison is provided in Table 6. Image preprocessing methods such as augmentation significantly bolstered model performance by expanding datasets and isolating diseased areas enhancing detection accuracy. These findings offer practical implications by enabling early disease intervention in agriculture potentially curbing crop losses and fostering sustainable practices.

Ref No	Publication	Classification			Internal Scoring				External Scoring	Total Score
	Year	Technology	Tools	Plant Type	1	2	3	4	JCR	
[1]	2021	AI, DL	EfficientNetV2, CNN	Cardamom	1	0	1	1	3	6
[2]	2022	DL	RFCN	Kiwi, apple, pear, avocado, grapevine	0.5	0	1	1	3	5.5
[19]	2023	ML	2D CNN	Tomatoes, cotton	1	0	1	0.5	1	3.5
[3]	2021	IoT, DL	Transfer Learning, MobileNet	General plants	0.5	0	0.5	0.5	2	3.5
[4]	2021	DL, IoT	AlexNet, VggNet, ResNet	General plants	1	0.5	0.5	0.5	2	4.5
[5]	2022	DL	MobileNet-V2	Citrus fruit	1	0	1	0.5	3	5.5
[5]	2022	DL	MobileNet-V2 CNN	Citrus Plants	1	0	0.5	0.5	4	6
[6]	2019	DL	INAR-SSD	Apple	0.5	0	0	0.5	2	3
[7]	2020	AI	LFC-Net	Tomato	0.5	0	0	0.5	2	3
[8]	2023	IoT, AI	CNN	Rice	0.5	1	0.5	0.5	3	5.5
[9]	2022	DL	CNN	Blight	1	0	1	1	3	6
[10]	2020	ML	RF, NN	Wheat	0.5	0	1	1	3	5.5
[11]	2021	ML, DL	RL	General	1	0	1	0.5	3	5.5
[12]	2020	DL	NN, CNN	General	0.5	0	0.5	0.5	3	4.5
[13]	2021	IP, ML	IP	Sugar Beet	1	0.5	0.5	0.5	4	6.5
[14]	2021	DL	RNN	Areca Nut	1	0	1	0.5	2	4.5
[15]	2023	DL	CNN	General	1	0	0.5	0.5	2	4
[20]	2020	IoT, AI	Net	Wheat	0.5	0	0	0.5	3	4
[21]	2023	DL	DS	General	0.5	0	0	0.5	3	4
[22]	2023	ML, DL	IP	General	0.5	1	0.5	0.5	2	4.5
[4]	2023	DL	CNN	General	1	0	1	1	4	7
[23]	2021	DL, ML	CNN	Mango	0.5	0	1	1	3	5.5
[24]	2019	ML	CNN, NN	General	1	0	1	0.5	3	5.5
[25]	2018	ML, DL	NO	Paddy Leaf	0.5	0	0.5	0.5	1	2.5
[26]	2019	ML, IP	CNN	General	1	0.5	0.5	0.5	2	4.5
[27]	2018	AI, ML	NO	General	1	0	1	0.5	2	4.5
[28]	2017	IP, AI	Seg	General	1	0	0.5	0.5	3	5
[29]	2017	IP, AI, DL	Seg	Rice	0.5	0	0	0.5	4	5
[30]	2017	DL	LNet	General Plants	0.5	0	0	0.5	2	3
[31]	2022	DL, ML	CNN	Seasonal Plants	0.5	1	0.5	0.5	2	4.5
[32]	2020	DL	CNN	General	1	0	1	0.5	3	5.5
[33]	2024	ML	RF, NN	Rice	1	0	1	1	4	7
[34]	2024	DL	LSTM	General	0.5	0	1	1	3	5.5
[35]	2024	ML	DT, NN	General	1	0	1	0.5	3	5.5
[36]	2024	DL	CNN	Tomato	0.5	0	0.5	0.5	1	2.5

Table 6: Comparison with other studies

Aspect	SLR 1: [36]	SLR 2:[37]	SLR 3: [38]
Focus	ML & DL models, especially CNNs for plant disease detection	Use of hybrid models combining IoT with ML for disease prediction	Role of hyperspectral imaging integrated with AI techniques in agriculture
Key Models Discussed	ResNet, MobileNet, SVM	Random Forest, LSTM, CNNs integrated with IoT	Multi-layer perceptrons (MLPs), hyperspectral DL models
Applications Highlighted	Early disease detection, reduced pesticide use	Automated disease monitoring via IoT sensors	Crop yield improvement, disease monitoring with minimal human intervention
Challenges Identified	Environmental conditions affecting model robustness	Scalability of IoT networks and real-time processing	High computational cost of hyperspectral imaging models
Future Research Directions	Expand datasets, improve resilience to environmental variations	Enhance interoperability and real-time analysis	Reduce cost and improve accessibility of hyperspectral technologies

Limitations of This Research:

Despite significant advancements in the use of CNNs, ML, and IP for plant DD, several limitations remain persistent, including data-related issues, environmental factors, computational demands, model interpretability, practical integration, and generalizability:

1. High-quality annotated datasets are essential for training accurate models. However, such datasets are often limited, especially for less common diseases or specific plant varieties. This scarcity can lead to overfitting and poor model generalization.
2. Datasets collected from different sources or under varying conditions can introduce inconsistencies. For example, images captured in controlled environments may differ significantly from those taken in natural, variable lighting conditions, impacting model performance.
3. Changes in lighting, weather, and other environmental factors can significantly affect image quality and, consequently, the accuracy of DD. Models trained under specific conditions may struggle to adapt to different field conditions.
4. Plants go through various growth stages, each with distinct visual characteristics. A model trained on images from a particular growth stage may not perform well across all stages.
5. DL models, particularly those with deep architectures like CNNs, require substantial computational power and memory. This can be a barrier to implementation in resource-constrained environments such as small farms or developing regions.
6. The training and deployment of DL models can be energy-intensive, raising concerns about the sustainability and environmental impact of these technologies.

Advice for Practitioners:

Familiarize yourself with the basic concepts of ML, DL, and IP. Understand how these technologies can help in detecting plant diseases early and accurately.

Keep up-to-date with the latest advancements and applications in agricultural technology. Attend workshops, webinars, or local training sessions to enhance your knowledge.

Choose tools and applications that are easy to use and understand. Look for those that offer clear instructions and have a user-friendly interface.

Before investing in any technology, read reviews and get recommendations from other farmers or agricultural experts.

Implemented In Real-World Agricultural Scenarios:

The SLR emphasizes the practical application of computational methods for plant DD in agriculture. Scoring criteria were tailored to include:

- **Scalability:** Methods that can be applied across large agricultural fields.
- **Cost-Effectiveness:** Affordable technologies suitable for resource-constrained farmers.
- **Ease of Deployment:** Approaches using accessible tools, such as smartphone-based systems.

High scores were assigned to studies demonstrating:

- **Real-Time Applications:** Systems offering disease predictions or management support.
- **Integration Potential:** Use of drones, IoT devices, or cloud-based platforms.
- **Robustness in Variable Conditions:** Methods addressing environmental and data constraints.

This approach ensures the findings are relevant for practical deployment in enhancing crop health management.

Conclusion:

The integration of CNNs, ML, and IP marks a transformative era in the field of agriculture, particularly in plant DD and management. These advanced technologies collectively provide a robust framework for identifying plant diseases with unprecedented accuracy and speed. The synergy of CNNs, ML, and IP enables real-time monitoring and analysis, empowering farmers to make immediate and informed decisions. This proactive approach not only mitigates crop losses but also promotes sustainable farming practices by reducing the need for chemical interventions. Moreover, it supports global food security by ensuring healthier crops and higher yields. Future research directions include exploring more sophisticated DL methods and adapting models for diverse environmental conditions and plant species, highlighting the transformative potential of these technologies in revolutionizing plant DD for global crop health preservation.

Moving forward, the continued evolution and adoption of these technologies promise to further revolutionize agriculture. The potential for these tools to integrate with other innovations, such as Internet of Things IoT devices and precision farming techniques, highlights an exciting future for agriculture. Embracing these advancements will be crucial in addressing the challenges of a growing global population and the need for sustainable food production. In conclusion, the convergence of CNNs, ML, and IP in plant DD offers a powerful and promising solution for the agricultural industry. This technological revolution not only safeguards the health of crops but also paves the way for a more secure and sustainable food supply, ensuring that the agricultural sector can meet the demands of the future. Future research focusing on advanced DL techniques and adapting models to diverse conditions and plant species remains critical underscoring the potential of these technologies in transforming global crop health monitoring.

Author's Contribution: Arslan AkramAA led this research work and statistically analyzed the whole article. This manuscript presents the network architecture, taxonomies, and model that are designed to measure plant disease effectively. Rabia Tehseen RT has supported the problem statement refinement with a state-of-the-art literature review. Shahan Yamin Siddiqui SYS and Muhammad Farrukh Khan MFK have contributed to the selection of frequently used open-source software in the field of diabetes. The manuscript draft was proofread and revised three times before submitting to your prestigious journal by Nusratullah Tauheed NT and Nosheen Qamar NQ. SYS and MKF have made a contribution to designing the methodology and proofreading of the manuscript. In the end, all authors read and finalize the manuscript.

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