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Comprehensive review of early disease detection and classification on plant leaves through deep learning techniques

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ABSTRACT

In modern agriculture, autonomous plant disease detection and prevention are crucial to preserving optimal crop health and raising yields. This survey paper reviews early plant disease detection, highlighting its essential role in maintaining optimal crop yields. The impact of diseases like black measles, black rot, and bacterial spots on plant growth, crop quality, and economic outcomes in agriculture necessitates effective solutions. Models trained using deep learning (DL) have demonstrated exceptional precision in classifying diseases based on spectral features, suggesting that hyperspectral visualization has promise for early disease detection. This paper highlights the urgent need for scalable, early detection methods that can operate efficiently across diverse agricultural settings and reduce the dependency on harmful chemical interventions. By reviewing current methodologies and introducing innovative approaches that leverage DL and computer vision, this survey provides a comprehensive analysis of potential improvements in disease management strategies. Furthermore, it discusses the economic implications of plant diseases and the benefits of adopting technology-driven solutions to enhance crop yield and sustainability in farming practices. Through this study, we aim to bridge the gap between traditional agricultural techniques and modern technological advancements, offering actionable insights for future research and implementation.

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1. INTRODUCTION

Vegetation is crucial for mitigating climate change and bolstering the economy. With the 2019 UN General Assembly addressing climate change, a number of nations, including Pakistan, have committed to planting more trees and other plants to help regulate the planet's temperature. Extensive research has linked industrial plant extinction, which depletes the ozone layer, to an increase in the planet's average temperature. The anticipated pace of future climate change is estimated to be 10 to 100 times more rapid than the current rate of glacial warming in DE. The discipline of plant pathology focuses on the examination of diseases that predominantly impact plants. It involves identifying, understanding, and managing several diseases that can adversely affect the health and productivity of plants. The objective of investigating plant diseases is to enhance plants' resilience to unfavorable climatic conditions and the presence of pathogenic microorganisms that induce sickness. Microorganisms, including bacteria, viruses, nematodes, fungus, and protozoa,

constitute the predominant causes of plant illnesses. Furthermore, a tiny percentage of algae and parasitic plants have the potential to damage plants. By releasing poisons, enzymes, and other chemicals, the organisms harm plants, devour nutrients, and aid in the spread of disease. Plant diseases can have dire repercussions, such as food poisoning that might lead to the extinction of entire plant species, famine, crop failure, and financial losses. Plant infections penetrate plant tissues and cause illness by taking resources from the host cells and using them for their development, proliferation, and spread [1]. The production of growth regulators, poisons, enzymes, and other active chemicals by the infected plant compromises the normal function and structural integrity of its tissues and cells. The development of necrotic lesions on several plant components, including leaves, stems, fruit, and roots, indicates the presence of a pathogen. The abrupt mortality of leaves and young shoots is caused by these lesions, which are frequently referred to as blights. Depending on the particular sort of infection causing them, the symptoms might be anything from minor to completely fatal for the plant. Stressing the value of early illness detection is essential to raising agricultural productivity. Black measles, black rot, and bacterial spot are examples of plant diseases that can have a major impact on crop quality, plant development, and the agricultural industry's overall profitability. To lessen the harmful effects of these illnesses, farmers usually employ pricy methods and pesticides [2]. The industrial site and its surroundings are negatively impacted by the use of chemical procedures. Furthermore, the application of this technology raises production costs, causing agricultural experts to suffer significant financial losses. The effective use of disease management techniques depends on the early detection of developing illnesses. In the field of agriculture, human intervention techniques are frequently used for disease diagnosis. With this technique, plant disease detection and diagnosis are dependent on human expertise [3].

Plant illnesses are caused by the interaction of three primary variables: the pathogen, the host, and the environmental elements that promote the development of the disease. Plant diseases frequently start in the lowest sections of the plant and work their way up, developing symptoms and eventually having an effect. Some plant diseases can spread and multiply across the entire crop after the first infection. Establishing a system of regular crop inspections is essential for effective disease control and containment [4]. After pollination is finished in the later stages of the growth season, plant diseases usually become visible. Plant diseases can cause harm to different plant parts. Plant diseases known as foliar infections manifest as outwardly evident signs on the leaves. Plant pathologists can rapidly diagnose these diseases by looking for particular traits during the examination of the damaged plants. Fungi are responsible for almost half of the losses in agricultural output. The primary area of research at this time is the application of deep learning (DL), machine learning (ML), and computer vision techniques to aid in the diagnosis of diseases. In this sector, using photos of leaves on plants is standard procedure. The integration of several crucial components is necessary for the precise detection of plant diseases. There are several advantages linked to the application of this technology. Early identification of plant diseases is made possible by the system throughout the growing season. Additionally, the technology makes it easier to identify and diagnose a range of illnesses that affect a wide variety of crops. Last but not least, the system may identify several illnesses at once. Determining the ideal pesticide dose, putting into practice workable management strategies, and conducting a thorough assessment of the disease's severity are all necessary for the disease's effective containment [5].

The efficient production of agriculture depends on the early detection of plant diseases. Numerous plant diseases, including bacterial spot, black rot, and black measles, have a major effect on crop growth, quality, and financial results in the agriculture industry. To successfully lessen the effects of these illnesses, farmers frequently employ costly measures like the spraying of insecticides. The use of chemicals has the potential to harm plants as well as the environment. Additionally, this specific strategy's application raises production costs and causes farmers to suffer significant financial losses. Diseases must be identified as soon as symptoms appear to guarantee efficient treatment. It is standard procedure in the agricultural industry to use human professionals to manually identify and diagnose plant illnesses [6]. The ability to automatically diagnose plant diseases from raw pictures has been made possible by developments in artificial intelligence and computer vision. The study looked at plant diseases that impact plant leaves as well as insect infestations. At the moment, image processing techniques (IPT) are widely used in agriculture for several reasons, including plant genomics, fruit grading, weed identification and detection, and the detection and quantification of plant disease infestations. DL methods are becoming more and more popular right now [7]. The phrase "deep learning" refers to sophisticated ML techniques that mimic how the human brain functions by using neural networks. The classification technique used by traditional methods makes use of semantic properties. Figure 1 shows the plant disease classification.

Farmers use the naked eye to detect disease signs on plant leaves and diagnose plants. Diagnosing illnesses may be a difficult and time-consuming procedure that relies significantly on prior expertise. A thorough comprehension of the subject area is required. A disease detection system's goal is to help those who lack experience in the topic, such non-pathologists and botanists. This paper investigates numerous automated techniques established with ML, DL, image processing, and learning by reinforcement. The aforementioned tactics were designed to attain certain objectives. The use of traditional ML algorithms in

agriculture is limited due to their volatility and unsuitability for laboratory conditions. The discipline of DL has achieved substantial advances in the categorization of pictures portraying plant diseases [8], [9].

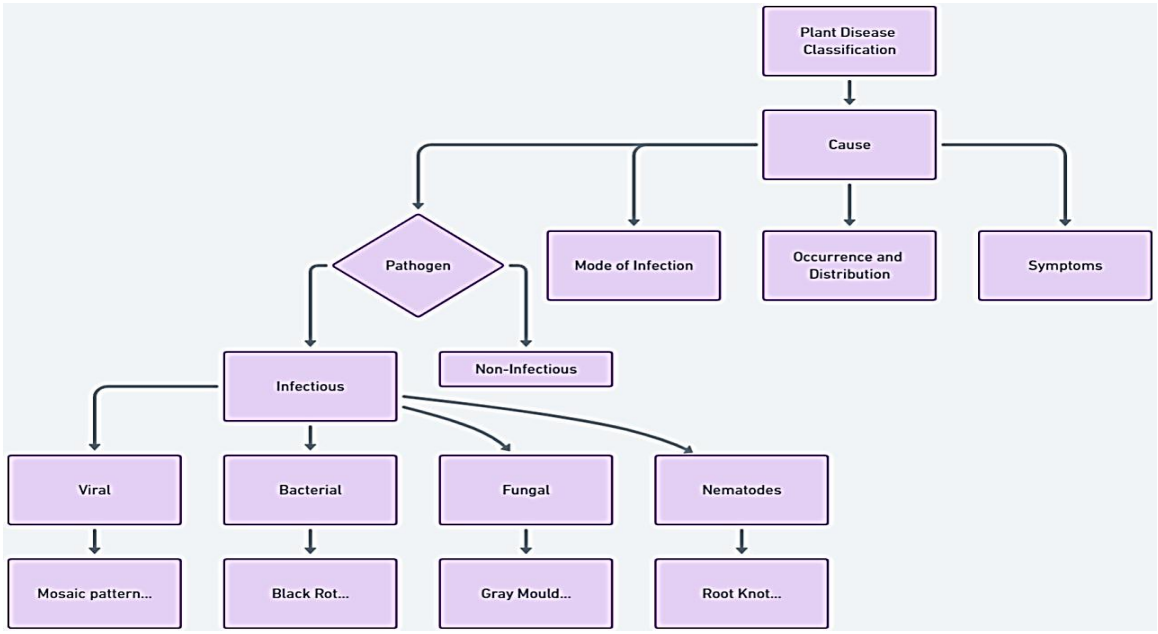


Figure 1. Plant disease classification

Plant diseases are the result of abnormalities in a plant's physiology or behavior. The origin of the phenomenon is illustrated in Figure 1, and it can be attributed to either biotic or abiotic causes [10]. Biotic diseases are caused by infectious agents, while abiotic illnesses are attributed to non-infectious causes. The abiotic sickness is commonly perceived as less hazardous and non-transmissible, thereby making it possible to prevent its occurrence. The primary objective of this study is to investigate biotic illnesses. Classification of plant disease:

a) Bacterial disease: Small green patches on wet plants are commonly thought to be indicative of plant bacterial disease. The enlarging lesions eventually turn into necrotic, desiccated sores or patches. A black stain that has been absorbed with water, a mark that resembles a brown leaf, or a yellow halo of the same size might all be examples of foliage illustrations. If the environment is dry, the defects appear as a splotchy pattern. Bacterial wilt, a phenomenon that causes the entire plant to collapse, is reported to often affect Brindajal crops.
b) Viral disease: Most people agree that studying plant viral infections is the most difficult of all plant diseases. The lack of symptoms and the way it differs from pesticide bruises and nutritional failure suggest the existence of the virus on the plant. The insects, beetles, leafhoppers, aphids, and whiteflies are most frequently seen with green or yellow stripes on their leaves as a result of viral infections such as mosaic virus disease.
c) Fungal disease: Many plant sections, including the leaves, carnal bunt, black point, eyespot (sheath or stem), rust, blight, and ergot (spikes), are susceptible to serious harm by fungi. The gray-green blotch or wet spot on the plant's leaves is the result of the Phytophthora fungus, which causes late blight. Climate change has resulted in alternating rainy and dry seasons, which is why this fungus is present. The late blight illness causes the sores to darken, and as it advances, a white-colored fungus appears on the surface. Early blight is caused by the Alternaria fungus, which appears on dead leaves as a little brown spot with a characteristic bull's-eye pattern made of concentric rings. By providing plant disease monitoring, artificial intelligence systems are used to increase agricultural output. Many review studies are available in the literature. There are several ways available, some focusing on specific medical issues and others on certain methodologies. There isn't yet a thorough summary of plant disease diagnosis, classification, and detection. This study focuses on how researchers combine ML, DL, few-shot learning (FSL), and soft computing methods with image processing for both RGB and hyperspectral images. Furthermore, several molecular methods have been created to lessen and lessen the damage that infections inflict. Figure 2 shows the gray-green blotch on the plants.



Figure 2. Gray-green blotch

The motivation for conducting this survey on plant leaf diseases is anchored in the profound economic and ecological impacts these diseases have on agriculture. Plant diseases not only compromise crop quality and yield but also impose substantial financial burdens on farmers due to the high costs associated with chemical treatments which can also harm the environment. By advancing our understanding of these diseases through your survey, we aim to improve early detection methods which are crucial for managing these diseases more effectively. This could significantly reduce reliance on harmful chemicals, thereby promoting a more sustainable agricultural practice. Additionally, your survey findings could contribute to the development of innovative disease management strategies that leverage the latest advancements in computer vision and ML, offering a faster, more accurate diagnosis of plant diseases. This approach not only supports agricultural professionals by simplifying and speeding up the process of disease identification but also has the potential to enhance global food security by preventing crop failures.

- Advancement in disease detection methods: Our survey provides empirical evidence supporting the integration of advanced image processing and ML technologies in the detection of plant diseases. This contribution is crucial as it enhances the accuracy and efficiency of disease diagnosis, enabling earlier interventions and potentially saving significant agricultural resources.
- Environmental impact reduction: By facilitating early and accurate disease detection, our survey contributes towards reducing the dependence on chemical pesticides and fungicides in agriculture. This aligns with global efforts towards sustainable farming practices, minimizing ecological footprints, and promoting healthier ecosystems.
- Agricultural decision support: The insights derived from this survey enrich the knowledge base available to farmers and agricultural professionals, aiding in strategic decision-making. Enhanced understanding of disease dynamics and management options equips stakeholders with the information needed to optimize disease control, improve crop yields, and ensure economic viability.

2. RELATED WORK

2.1. Machine learning and deep learning techniques adapted to classify plant disease

Plant diseases are the most significant impediment to sustainable processing and maintenance. Scientists have made significant attempts to detect and trace illnesses. ML algorithms for sickness identification have been regularly used for some years. Barbados did a research in 2017 that used many ways to detect and characterize the leaf diagram. The goal of this study is to present a unique way for extracting disease signs from plant leaves. The suggested approach is applicable in a variety of circumstances where Boolean calculations are used to change the color of a sick leaf. The feasibility of the suggested cure was assessed using the plant disease of leaves database [11]. The experimental findings, together with the comparative data, illustrate the practicality of the suggested method. According to Bin *et al.* in 2018, using a Deep Neural Network can help identify apple leaf disease accurately [12]. The diagnosis of apple leaf ailments requires the creation of appropriately diseased photos as well as the development of a unique architecture customized exclusively to the AlexNet neural network. According to the study's findings, using a deep neural network model is a more efficient and accurate way to achieve convergence in apple leaf disease control. The method, created by Chuanlei et al. in 2017, is intended to prioritize picture recognition, pattern analysis, and apple leaf disease analysis. The support vector machine (SVM) group is responsible for identifying these diseases. The suggested technique ensures that the selected subset of attributes is globally optimum.

The use of these methods is common in categorizing both textual information and visual representations. The standard method for identifying machines in plant leaf photographs is preparing the images with various processing images techniques. These approaches frequently include noise reduction, morphological procedures, and picture enhancement. The low-level features of the leaves, such as color, shape, and texture, are retrieved by manually created feature extraction algorithms. Sharif *et al.* developed a technique for diagnosing infections in citrus fruit trees based on textural traits. The feature selection process

used a hybrid method that incorporated feature statistics with principal component analysis. Patil *et al.* described a content-driven image retrieval system capable of recognizing damaged soybean leaves. This method does identification using a variety of properties such as color, shape, and texture. Ebrahimi *et al.* [13] described a strategy for diagnosing grape leaf disease. The study's authors detailed a sophisticated background strategy. Identification performance was evaluated using a variety of characteristics, included the LBP feature, statistical features in RGB planes, and ML approaches such as SVM and random forest (RF). DL architectures have recently demonstrated tremendous potential for applications such as object segmentation, classification, and identification. CNN approaches are widely used in DL, especially for solving complicated issues. Selvaraj *et al.* produced the dataset, which contains banana plants taken from several locations in southern India and Africa. The dataset included 17 samples of infected banana plants and one healthy banana plant from each site. The use of several CNN structures, including ResNet50, InceptionV2, and MobileNetV1, resulted in an accuracy rate of 90%. Zhang *et al.* investigation involved collecting samples of both healthy and sick peach plant leaves. The samples were obtained from the PlantVillage collection by taking pictures. A remarkable accomplishment was achieved by implementing multiple iterations and experiments using the AlexNet architecture, resulting in an amazing accuracy rate of 99%. A further research used photos from the PlantVillage collection to identify disease groups in maize, grape, and soybean leaves [14]. The study discovered that when using photos tagged with three labels for sick classes and one label for healthy classes, accuracy rates varied from 97% to 99%. Fuentes *et al.* used a dataset with nine unique tomato disease classifications. Using the VGG CNN architecture resulted in a 90% accuracy rate. Furthermore, Lu *et al.* performed trials using a dataset that included six categories of defective wheat plants along with a single classification of healthy wheat seeds. An accuracy of 97% was attained. Pantil and Kumar [15] reported detecting tea leaf diseases using a modified DCNN.

Ferentinos' dataset included 25 unique plant specimens. Ferentinos used the VGG architecture to reach 98% accuracy. Sandika *et al.* [16] used image processing methods for pre-processing alongside with CNN model to achieve an astounding 97.62% accuracy rate. Our analysis included current studies on apple leaf diseases. Previous research has used traditional ML algorithms, which have gained extensive expertise in the diagnosis of plant diseases. Nonetheless, these systems are only capable of performing specialized tasks such as picture segmentation, FE, and pattern identification. The core convolutional neural network (CNN) architectures, AlexNet, VGGNet, GoogLeNet, DenseNet, and ResNet, have grown in favor in the field of plant disease categorization. However, these architectures have some drawbacks. The algorithms need a large number of parameters and have low computational performance. DL algorithms have proven remarkable ability in displaying both high-level and low-level characteristics. Nonetheless, there is a lack of uniformity in the description of local spatial features, as noted in reference [17]. To get a perfect picture of plant leaf photographs, it is best to use both manually crafted and deep characteristics.

The effectiveness of DCNN models has been thoroughly documented. However, it is critical to recognize that these models incur a significant computational expense. Fine-tuning and transfer learning approaches allow pre-trained models to be used for a variety of applications. Several well-established models have been created to address issues connected to general-purpose item identification. Plant disease detection can be improved by applying transfer learning techniques to pre-trained models. The challenge of disease detection in various plants was solved by using pre-trained models such as CaffeNet, AlexNet, VGG, and GoogLeNet. Zamani *et al.* [18] investigated a modified VGG-16 model for detecting mildew infections in millet crop photos.

Patil *et al.* [19] investigated rice sickness classification. The study focused especially on three plant diseases: bacteria-driven leaf blight, brown area, and false smuts. The study used a dataset of 400 pictures obtained from diverse sources. The photographs were categorized using a SVM classifier. The categorization technique produced findings showing an accuracy of 94.16%, recall of 91.6%, and precision of 90.9%. The necessity of detecting rice leaf diseases is widely acknowledged as a critical aspect in addressing global rice demand [20]. However, the ability to detect rice disease of the leaves is restricted by the properties of the surrounding image and the image capture parameters. A new approach for identifying disorders in rice leaves has been developed using a CNN [21]. The approach seeks to minimize network parameters while preserving diagnostic accuracy. The training technique made use of a dataset of 4199 photographs of rice leaves. The goal was to train numerous CNN [22] models to correctly recognize five prevalent illnesses affecting rice plants. Kaur *et al.* [23] suggested detecting diseases in images of rice leaves using an InceptionResNetV2 model and a transfer learning approach. The information included three unique disease categories: bacterial blight, brown spot, and leaf blast. The creative procedure entailed using a collection of 5200 images. In their investigation, highlighted the major obstacles farmers confront when visually detecting rice illnesses, which were mostly due to their lack of knowledge in this field [24], [25]. Furthermore, Table 1 summarizes this information.

Table 1. Various methodologies along with its advantage and disadvantage

Reference	Methodology	Advantage	Shortcoming
[11]	Plant leaf disease detection using a proposed method of altering color in unhealthy leaves.	Demonstrated viability using a plant leaf disease database.	Potential limitations in real-world scenarios due to variable lighting and environmental conditions could affect color-based detection accuracy.
[12]	Detection of apple leaf disease using a Deep Neural Network tailored to the AlexNet neural network.	More efficient and accurate management of disease using DL.	High computational cost and potential overfitting to specific features in the training set that may not generalize well to new, unseen conditions.
[13]	Detection of grape leaf disease using IPT, LBP, statistical features, and ML (SVM, RF).	Enhances detection performance with a complex background approach.	The method might struggle with high variability in disease appearance and could be computationally intensive due to the complexity of features and models used.
[14]	Identification of diseases in maize, grape, and soybean leaves using images from the PlantVillage dataset and various CNN architectures.	High accuracy rates (97%-99%) in disease identification.	Dependence on high-quality dataset images; performance might degrade with lower quality or diverse real-world images not represented in the dataset.
[15]	Detection of tea leaf diseases using a modified deep convolutional neural network.	Adapted CNNs provide specialized detection capabilities.	A model may not perform as well when applied to different plant species or diseases outside the training scope, showing limited transferability.
[20]	Challenges in diagnosing rice diseases visually, emphasizing automated systems.	Highlights limitations in traditional methods, advocating for technological solutions.	The transition from manual to automated systems requires significant training and adaptation for end-users, which can be a barrier to adoption.
[21]	CNN-based method to diagnose rice diseases, aiming to reduce network parameters.	Streamlines diagnostic processes, reducing computational demands.	Reduction in network parameters might lead to a loss in accuracy or detail, potentially impacting diagnostic precision.
[22]	Training multiple CNN models on a large dataset of rice leaf diseases.	Specific detection capabilities across common ailments in rice.	Models might overfit to particular features of the training set and not adapt well to variations not present in the training data.
[23]	Used InceptionResNetV2 with transfer learning for rice disease diagnosis.	Advanced neural networks and transfer learning enhance accuracy.	Requires large datasets for effective training; limited data can lead to poor generalization to new or rare diseases.
[24]	Review on visual diagnosis limitations by farmers, suggesting more intuitive tools.	Raises awareness of practical limits in disease identification by farmers.	Methodological shortcomings aren't specified, but general challenges include developing user-friendly interfaces that accommodate varying skill levels.
[25]	Application of general-purpose object identification techniques using pre-trained models.	Enhances disease detection by adapting established models to plant pathology.	Potential mismatch between general object recognition capabilities and the specific needs of plant disease detection, requiring significant customization.

2.2. Deep learning techniques adopted to classify plant diseases

This study found a gap in current research on plant disease detection. The major emphasis has been on recognizing disease symptoms on foliage and fruits, with soil-borne diseases being overlooked. The study [26] investigates the application of IoT, ML, and DL approaches to detect disease indications at various stages, allowing for preemptive actions to prevent large crop losses and the spread of sickness in agricultural areas. To clarify the precise implementation technique of CNN for detecting plant disease severity, 16 relevant high-quality papers were chosen for this study. PlantVillage, plant disease severity, and ImageNet were all used as datasets [27]. The earlier model performance assessment included conventional evaluation metrics such as accuracy, precision, recall, mean average precision (mAP), and the F1 score, which is generated from precision and recall. Mohanty *et al.* created a model capable of detecting 14 crops and 26 diseases, with an overall accuracy of 99.35% on the test set, which did not differ significantly from the validation set. An automated system for plant disease detection using DL [28] with VGG19 begins with the insertion of an input layer, followed by two following layers: the first layer for image resizing and rescaling, and the second layer for image enhancement. The dataset used to construct the model is known as the Plant Village. DenseNet201 has proven the best accuracy across all data types. It had an accuracy of 99.17% on the validation dataset and 98.82% on the test dataset. Incorporating this method into a monitoring system may improve the automation of disease detection.

Data augmentation techniques are used to improve the amount and dimension of the plant leaf disease image collection. This study introduces a unique method for region-based image segmentation that divides a picture into its most important components. Each of the five new crops is represented by five sets of images: grape leaves (healthy, esca, chlorosis, powdery mildew, black rot), wheat leaves (diseases: black chaff, brown rust, powdery mildew, yellow rust), cotton (Verticillium wilt, powdery mildew, nutrient deficiency, Alternaria leaf blight, and healthy), and cucumber. The proposed method outperforms all ML

algorithms on the corn dataset, with sensitivity, specificity, accuracy, precision, F-measure, and MCC values of 0.990, 0.0018, 0.981, 0.988, 0.999, and 0.998, respectively [29]-[31]. This study examines methodologies for evaluating plant disease severity offered by academics in recent years, including IPT, classical ML, and DL. The analysis of these solutions has allowed us to identify their limitations and potential stumbling blocks in assessing plant disease severity. Crop disease diagnosis is inextricably tied with severity assessment. Assessing the severity of infections is critical for efficient plant disease control. Many strategies for assessing crop disease severity have been proposed by researchers, including IPT, ML, and DL [31]-[35]. Figure 3 displays an overview of the datasets used. Figure 4 depicts the popularity of frequently used DL approaches in the articles studied.

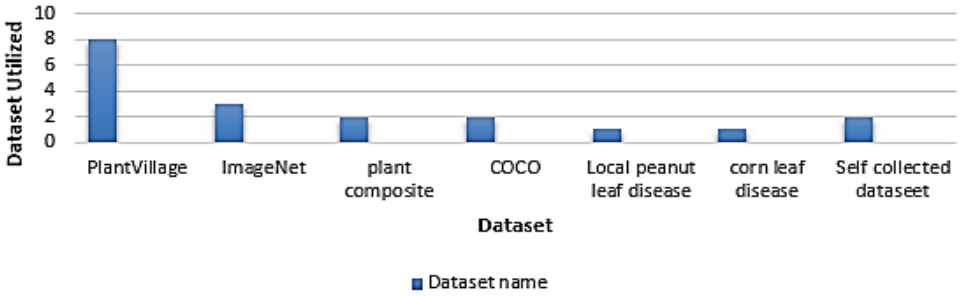


Figure 3. Summary of datasets used

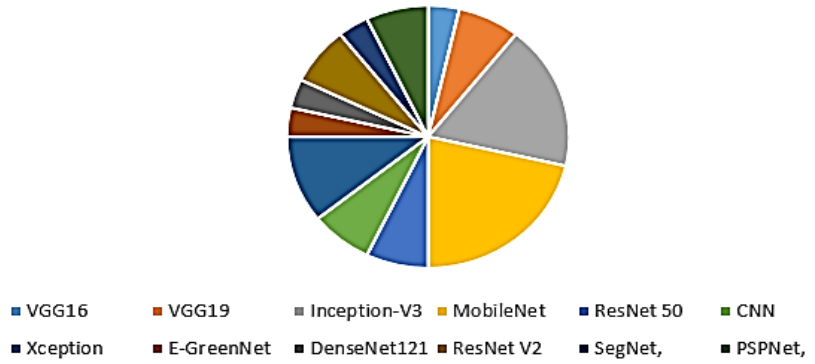


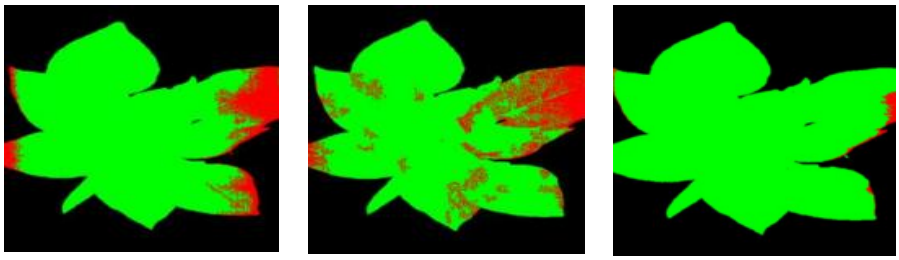
Figure 4. Distribution of widely applied DL algorithms in the reviewed studies

2.3. DL models for hyperspectral imaging

During the development of a plant, it may be affected by several diseases, including the symptoms and manifestations evoked by different pathogens frequently demonstrating significant resemblance. Initial plants infections have indistinguishable symptoms, making identification difficult with visual observation or primitive computer vision approaches. Hyperspectral sensors' electromagnetic spectrum covers mostly from 400 to 1000 nm, covering the visible and near-infrared wavelengths, with occasional addition of shortwave infrared (SWIR, 1000-2500 nm). Several modest spectral bands may provide spectral data suitable for this sensor [36]. These microscopic bands may distinguish between different diseases and are extremely robust to even the most minor changes in plant leaves caused by disease, allowing for early asymptomatic identification. As a result, recent research has focused on hyperspectral imaging to aid in the early diagnosis of plant diseases. Guo *et al.* [37] investigated the feasibility of a hyperspectral imaging approach for detecting two distinct diseases on tomato leaf. The researchers also examined spectral and imaging data. The ELM algorithm was created to identify sick samples. Next, the SPA was used to choose appropriate wavelengths. The SPA-ELM model achieved an accuracy rate for classification of 97.1 percent on the test set. Initial hyperspectral images of cucumber downy mildew in greenhouses, taken in situ, are impacted by ambient light, hindering the extraction of key features. Chen *et al.* [38] proposed a novel method for generating feature bands that improves the integration of the SPA and CARS while using disease variation information. This led to the development of a basic model for recognizing cucumber downy mildew. The detection rate in the test set was 95.8% on the first day of infection, but it increased to 100% during the next

two to twelve days of infection when comparing hyperspectral photos of healthy cucumber leaves to daily hyperspectral photographs taken over the course of the disease. Korra *et al.* [39] used hyper-spectral imaging and the MLP classification technique to divide tomato bacterial spot sickness and bacterial target spot illness into four distinct stages: healthy asymptomatic, early, late, and beyond. Their accuracy percentage was 99%.

A novel hybrid technique (2D-CNNBidLSTM/GRU) for hyperspectral images was later developed, combining a convolutional network with a bidirectional gated recurrent unit. After addressing the overfitting issue, the model attained a 75% F1-score and 73% accuracy in diagnosing wheat disease [40]. The author of [41] created a supervised 3D-CNN model to examine the spatial and spectral properties of hyperspectral images, allowing for the differentiation between samples infected with charcoal rot and those that were not. A saliency map-based visualization approach was used to assess the classification accuracy of hyper-spectral wavelengths. The relevance of the hyper-spectral wavelength may be determined by evaluating the gradient distribution inside the image's saliency map. The infection category received an F1 score of 87%, and the 3D-CNN model achieved a classification accuracy from 95.73% by combining hyperspectral imaging from the inoculation with pictures of simulated infected stems. DL was used to evaluate hyperspectral pictures for the detection of the potato virus, resulting in remarkable accuracy (78%) and recall (88%) [42]-[46]. A novel hyper-spectral analytic proximal sensing approach based on generative adversarial networks (GANs) has resulted in the outlier removal auxiliary classifier generative adversarial nets (ORAC-GAN) for the early detection of tomato plant illness before visible symptoms appear, as documented in [47]-[50]. Figure 5 shows that the categorization accuracy reached 96.25% prior to the appearance of identifiable symptoms on the plant leaf. The model for direct convolutional neural networks. Figure 5(a) shows the AC-GAN model The graphic depicts the comparative results of typical healthy plant segmentation. Figure 5(b) shows the AC-GAN model. Figure 5(c) shows OF-AC-GAN, is the suggested model. A framework for direct convolutional neural networks. The suggested model is the AC-GAN model, and OF-AC-GAN.



(a) (b) (c)

Figure 5. Typical healthy plant segmentation findings compared: (a) the model for direct convolutional neural networks, (b) the AC-GAN model, and (c) OF-AC-GAN, is the suggested model

2.4. Findings

- Enhanced DL architectures: Developing more sophisticated DL architectures tailored specifically for plant disease severity detection. This could involve novel network structures, such as attention mechanisms or graph neural networks, to better capture complex relationships within plant images.
- Multi-modal approaches: Integrating multiple sources of data, such as spectral images, thermal images, and environmental sensor data, to improve disease severity detection accuracy. The fusion of these modalities could provide a more comprehensive understanding of plant health and disease progression.
- Transfer learning and domain adaptation: Further exploring transfer learning and domain adaptation techniques to address challenges related to limited labeled data and domain shift. Pre-training models on larger datasets or similar tasks and fine-tuning them on target plant disease datasets can enhance performance, especially for diseases with sparse data.
- Limited early detection capabilities: Current methods for detecting plant diseases often fail to identify symptoms until they are visibly apparent, which can be too late for effective intervention. There is a need for research into technologies that can detect disease at earlier stages.
- Dependency on chemical interventions: Much of the existing disease management in agriculture still heavily relies on chemical treatments, which are not only costly but also environmentally damaging. Research is needed to develop more sustainable, non-chemical disease management strategies.
- Insufficient integration of advanced technologies: Despite the potential of ML and computer vision, their application in real-world agricultural settings remains underexplored. There is a gap in research regarding the practical implementation of these technologies in diverse farming environments.

- Scalability of solutions: Many of the current solutions for plant disease detection are not scalable or adaptable to different types of crops or varying environmental conditions. Research is needed to create versatile and scalable disease detection methods.
- Economic analysis of disease impact: There is a lack of comprehensive economic analysis regarding the impacts of plant diseases on agricultural productivity and profitability. More detailed studies are necessary to understand the economic stakes involved and to justify investment in new technologies for disease detection and management.

3. CONCLUSION

Recent advances in DL algorithms have greatly improved the automated detection and preventing plant diseases. Researchers used a variety of DL architectures, include RNNs and CNNs, to create robust algorithms capable of diagnosing a variety of plant illnesses. This survey highlights the essential requirement for improving plant disease identification and control with modern ML and image processing technology. The agriculture industry confronts increasing problems from plant diseases; the use of these technologies not only enhances early identification but also markedly diminishes the environmental repercussions of conventional chemical treatments. This study enhances the advancement of sustainable and efficient farming techniques by offering a comprehensive analysis of current methods and proposing novel ways. It underscores the economic advantages of adopting these technologies, accentuating their capacity to enhance agricultural yields and guarantee food security. Subsequent research must concentrate on the pragmatic use of these methodologies in actual environments, guaranteeing their accessibility, scalability, and adaptability across various crops and ecological situations, therefore closing the divide between technology and conventional agriculture. Challenges persist in the domain of automated plant disease identification, notwithstanding recent developments. Robust models need extensive and diverse datasets for training. Furthermore, it is essential to rectify unequal data distributions and provide model resilience across diverse environmental conditions. To further this essential field of study, future attempts should investigate innovative DL architectures, multi-modal data sources, and real-time detection capabilities. DL approaches combined with improved imaging technology have the potential to change automated disease identification and prevention in plants. Researchers and farmers may work together to increase global food safety, promote sustainable agriculture practices, and to enhance farmers' lives worldwide by utilizing DL technology. More investigation and cooperation are needed to harness the benefits of these modern agricultural technology while also addressing existing obstacles.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Laxmi S Shabadi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
Lincy Meera Mathews								✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST

The author declares no conflict of interest.

DATA AVAILABILITY

No dataset is utilized for this research.

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