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Innovative Technologies for Plant Disease Monitoring and Control: A Survey of Current Methods and Emerging Trends

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ABSTRACT: Food security and agricultural productivity depend on the efficient control of Plant Diseases (PD). New approaches to the Early Detection (ED) and precise PD Prediction (PDP) have been made possible by recent developments in machine learning (ML) and deep learning (DL). This paper presents a hybrid approach combining ML and DL techniques to enhance plant disease prediction. The proposed methodology integrates feature extraction using convolutional neural networks (CNNs) with traditional ML algorithms for classification and prediction. By leveraging the strengths of both paradigms, the model achieves high accuracy in identifying disease patterns from images of plant leaves and other plant parts. A comprehensive dataset of plant images, annotated with disease labels, serves as the basis for training and evaluating the proposed approach. The results demonstrate significant improvements in prediction accuracy and computational efficiency compared to conventional methods. This hybrid model not only facilitates early disease detection but also supports timely intervention, thereby mitigating the impact of plant diseases on crop yields. The integration of DL and ML techniques provides a robust framework for advancing plant disease management and can be extended to various agricultural applications.

Keywords: *Machine Learning (ML), Deep Learning (DL), Plant diseases, Internet of Things (IoT)*

I. INTRODUCTION:

A major challenge to global agriculture, PD have an effect on both economic sustainability and food security. These diseases are primarily caused by pathogens such as fungi, bacteria, viruses, and nematodes, which can severely affect plant growth, yield, and quality [1]. According to the type of pathogen causing the disease, PD are typically divided into two categories: biotic (caused by bacteria, fungus, or viruses) and abiotic (caused by environmental conditions like pollution, drought, or nutritional deficiencies). Figure 1 depicts diseases. The proper identification and control of these diseases are crucial to ensure the optimal growth and productivity of plants [2].

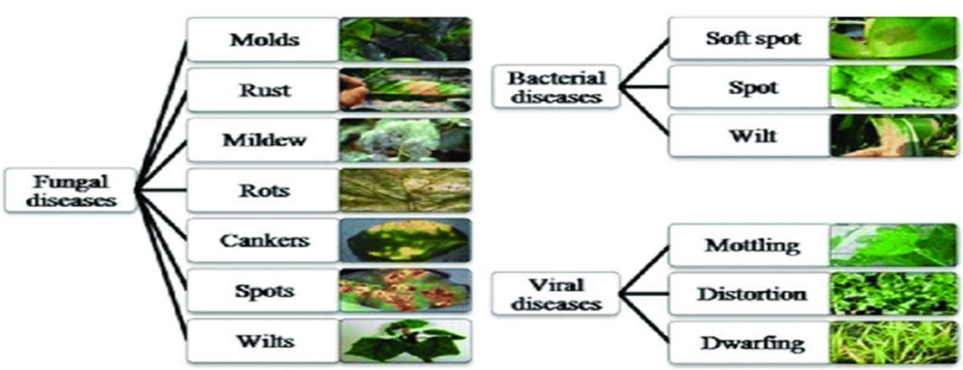

Figure 1. Categories of Plant Diseases

Traditionally, plant diseases have been monitored through visual inspection, molecular diagnostics, and biochemical assays [3]. These methods, while effective, present significant challenges in terms of time consumption, labor intensity, and the need for expert knowledge. In recent years, various innovative technologies have emerged for plant disease monitoring, including remote sensing, drone-based imaging, and hyperspectral cameras [4]. These technologies have improved the ED of PD and reduced the reliance on manual labor. However, conventional methods and current technological advancements still face limitations, including high costs, low scalability, and a lack of comprehensive disease databases for accurate detection and diagnosis.
The problems that conventional PD monitoring systems confront may be solved with the help of ML and DL approaches. Large datasets of plant images are analysed using ML algorithms such as Random Forest (RF), SVM, and CNN in DL. Trends that suggest the presence of diseases are extracted and are shown in Figure 2.

These models can automate the detection and classification of plant diseases by processing leaf images, canopy structures, and hyperspectral data [5]. The key advantage of using ML and DL in plant disease monitoring is their ability to learn from vast amounts of data, continuously improving their accuracy in predicting diseases [6]. However, these technologies also face challenges, such as the need for large annotated datasets, high computational power, and the risk of overfitting in specific environments.

Figure 2. Plant Diseases Prediction Using CNN

In conclusion, there is still significant space for improvement even though the application of ML and DL approaches to PD monitoring has demonstrated great potential. The future of plant disease control lies in developing more sophisticated and cost-effective technologies that can provide real-time, accurate disease diagnosis and prediction [7]. By addressing the current drawbacks, including the need for large datasets and the high cost of technology deployment, researchers and agricultural practitioners can create more robust systems to improve crop health and productivity. This paper aims to survey the current methods of plant disease monitoring, highlight the emerging trends in ML and DL applications, and discuss the future directions for overcoming existing challenges in plant disease control.

II. FUNDAMENTALS OF ML AND DL IN PD MONITORING

Monitoring PD is essential for maintaining high agricultural productivity, reducing the use of hazardous herbicides, and promoting sustainable agriculture. By providing sophisticated, automated, and precise methods for detecting and classifying PD, ML and DL have completely transformed this field of study. An outline of the core ideas of ML and DL, as well as how these techniques are used in PD monitoring, is provided below:

1. INTRODUCTION TO ML

Creating algorithms that enable computers to learn from and make decisions based on data is known as ML. In plant disease monitoring, ML is applied to recognize patterns in plant images, environmental data, and sensor readings, which help predict disease outbreaks or identify infected plants early on.

TYPES OF ML:

Supervised Learning (SL): Labelled data is used to train a model. For plant diseases, this could mean using labeled images of healthy and diseased plants to teach the model how to recognize diseases.

Unsupervised Learning: The model learns from unlabeled data, identifying patterns or clusters. This can be useful for discovering new or rare plant diseases.

Reinforcement Learning (RL): A model learns by interacting with its environment and improving through feedback. This is less common in plant disease monitoring but could be applied in robotics for automated crop monitoring.

ML ALGORITHMS IN PLANT DISEASE MONITORING:

SVM: By determining the most suitable boundary between several classes of plant conditions (such as healthy vs. diseased), SVM are used to classify PD.

Random Forest (RF): A popular method for disease detection, RF uses multiple decision trees to classify plant diseases, offering high accuracy in identifying infected plants.

K-Nearest Neighbors (KNN): By comparing them to existing samples, this method helps identify PD by classifying them according to the majority label of the nearest neighbors.

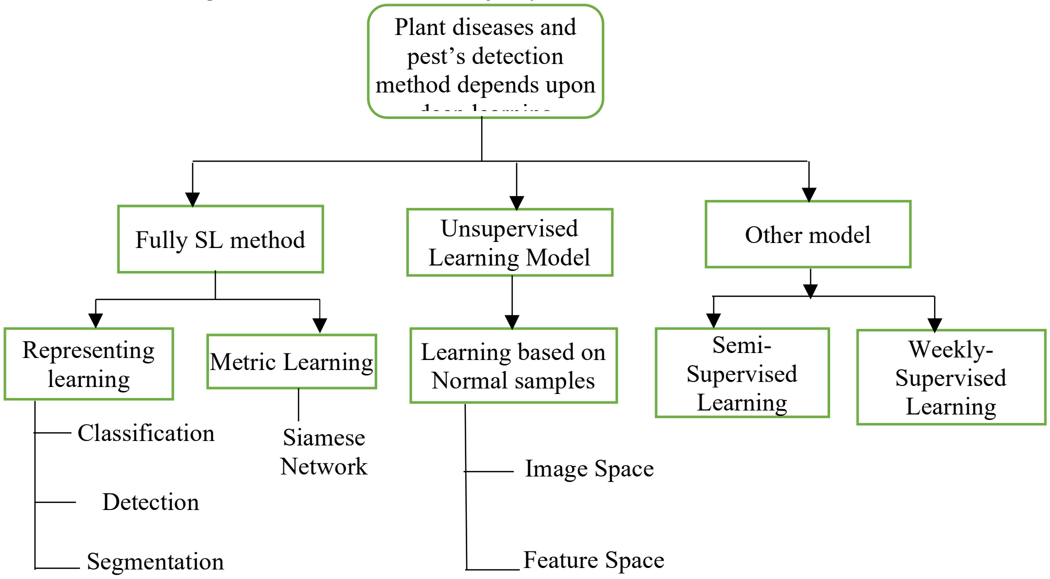

Figure 3. Model of PD and pest's detection approaches depends on DL

2. DL OVERVIEW

A subtype of ML called "DL" models intricate patterns in data by using multi-layered (NN) neural networks, or "deep NN (DNN)".It has become the dominant approach in image recognition (IR) tasks, making it highly suitable for plant disease monitoring is represented in figure 3.

CNN: The most used DL architecture for object Detection and image classification is CNN.In PD monitoring, CNNs can process large sets of plant images, automatically learning to recognize visual symptoms of diseases like leaf spots, rust, and blight. CNNs consist of multiple layers, including:

Convolutional Layers (CL): Extract features (e.g., edges, textures) from images.

Pooling Layers: Keep only the most significant features and reduce the dimensionality of the data.

Fully Connected (FC) Layers: Make the final classification of the input image (e.g., healthy or diseased).

Recurrent NN (RNN): RNNs are useful for Time-Series (TS) data or sequential data, such as monitoring plant health over time using sensor data. They are effective in recognizing patterns in data streams that may indicate the onset of a disease.

Generative Adversarial Networks (GANs): The training dataset can be enhanced by the creation of additional, synthetic data using GAN. This is helpful in cases where there is limited labeled data of plant diseases.

3. DATA COLLECTION AND PROCESSING

The foundation of any ML/DL application is the quality of the data used to train the models. In plant disease monitoring, data typically includes:

- **Images**: Photos of leaves, stems, fruits, or entire plants showing symptoms of disease.
- **Sensor Data**: Temperature, humidity, and soil moisture readings that may indicate conditions conducive to disease development.
- **Historical Data**: Past records of disease outbreaks, treatments, and outcomes.

Data Pre-processing: Raw data needs to be cleaned and pre-processed before feeding it into ML/DL models. This involves:

- **Image Augmentation (IA)**: Methods to provide more varied training data, including cropping, flipping, or rotation.
- **Normalization**: Adjusting the pixel values of images to ensure consistency across the dataset.
- **Feature Extraction**: Identifying key features like color, texture, and shape from plant images that are most indicative of diseases.

4. APPLICATIONS IN PLANT DISEASE MONITORING

- **Disease Classification**: ML and DL models can classify plant diseases based on image data. For instance, CNN models have been effectively used to detect diseases in crops like tomatoes, wheat, and maize with high accuracy.
- **Disease Severity Estimation**: DL models can estimate the severity of a disease by analyzing how much of the plant is affected, helping farmers take timely corrective actions.
- **Real-time (RT)Monitoring**: Integrated with drones and IoT devices, ML/DL models can provide real-time monitoring of large agricultural fields, detecting diseases at early stages and helping in precision agriculture.
- **Automated Diagnostics**: Mobile applications and embedded systems can allow farmers to take pictures of their crops, and the ML/DL model can provide immediate diagnostic results, suggesting treatments or preventive measures.

5. CHALLENGES IN PLANT DISEASE MONITORING WITH ML AND DL

- **Data Scarcity**: Collecting a large, diverse, and well-labeled dataset for training ML/DL models is challenging, particularly for rare plant diseases.
- **Variability in Disease Symptoms**: Symptoms of the same disease can vary based on factors like geography, crop variety, and environmental conditions, making it harder to train a generalized model.
- **Computational Resources**: DL models, especially CNNs, require significant computational power and memory, which may be a limitation for real-time, field-deployed solutions.
- **Model Interpretability**: Despite their superior accuracy, DL models are frequently viewed as "black boxes" with transparent (DM) Decision-Making. In agriculture, where trust is essential, this can be a barrier to adoption.

6. FUTURE DIRECTIONS

- **Transfer Learning (TL)**: Applying pre-trained models from similar domains can help overcome data scarcity, reducing the need for large labeled datasets.
- **Edge Computing (EC)**: Deploying ML/DL models on edge devices like drones or smartphones for real-time, on-field disease detection, without relying on cloud infrastructure.
- **Integration with IoT**: Connecting ML/DL models with IoT devices that continuously monitor environmental conditions can provide early warning systems for disease outbreaks.

ML and DL have immense potential in transforming PD monitoring by offering more accurate, real-time, and automated solutions. From disease detection and classification to predicting outbreaks and optimizing crop management, ML/DL models can help farmers enhance yield and reduce losses. While challenges like data quality, variability, and computational costs remain, advancements in AI, transfer learning, and IoT integration continue to improve the scalability and accessibility of these technologies in agriculture.

III LITERATURE REVIEW

DNN have been suggested by Trivedi et al. [8] to properly identify diseases in their early stages and provide information about it. Such a CNN can effectively describe and classify tomato diseases. Google Colab and a set of 3000 images of tomato leaves with nine different diseases and a healthy leaf are used throughout the entire experiment. The full process is described: Pre-processing of the input images is the initial step in separating the targeted area from the source images. Using various CNN model hyper-parameters (HP), the images are then processed further. CNN also extracts other information from images, such as colours, textures, and borders. The findings demonstrate that 98.49% of the predicted values of the suggested model are accurate.

The DL CNN method put forth by Shewale and Daruwala [9] has been more and more well-liked recently. Due to automated intelligent techniques' precise diagnosis and decreased complexity in terms of time and resources. By integrating patterns of leaf images taken at specific times with image processing (IP), plant leaf diseases can be identified. Current scientific efforts to identify, classify, and diagnose diseases take into account tomato plants. The dataset for our study came from the agricultural fields in Jalgaon city in RT. The suggested approach eliminates feature engineering and threshold segmentation while effectively classifying diseases by automatically extracting features. To implement and expand our network with spatial photos taken under unfavorable situations. Automated disease identification is now feasible due to recent developments in computer vision (CV) through DL. All things considered, DL model training on progressively larger, openly available, real-time image datasets offer an easy approach towards crop disease diagnosis over a huge worldwide extent.

DL methods for the ED and classification of PD have been suggested by Saleem et al. [10]. Several DL architectures that have been built or modified are used in conjunction with various visualization approaches to identify and categorize plant disease symptoms. Furthermore, these architectures/techniques are assessed using a variety of performance criteria. This article offers a thorough description of the several plant diseases that may be seen using DL models. In order to increase transparency in the detection of PD before their symptoms appear, a number of research gaps are also identified.

A CNN technique consisting of five pre-trained models and images of pairs of healthy and sick plants were utilised to create a stepwise (DD) Disease Detection model, which was first presented by Jung et al. [11].

Crop classification, disease detection, and illness classification are the three step classification models that make up the DD model. The "unknown" is incorporated into categories in order to broaden the model's applicability. The DD model recognized crops and disease kinds with excellent accuracy (97.09%) in the validation test. Adding these crops to the training dataset increased the poor accuracy of non-model crops, indicating the model's expendability. By include more diverse crops in the training dataset, our model will become broadly applicable and potentially useful for smart farming of Solanaceae crops.

Degani et al [12] proposed a Bio-Chem Integration Method, is designed to combine biological agents, such as Trichoderma species, with chemical insecticides for agricultural protection. The hybrid approach is to reduce fungicide dependency, while ensuring that bio-protective agents have sufficient stability and early-stage growth support. The treatments both in controlled growing rooms and commercial fields, allowing for direct comparison between bio-based and chemical coating treatments. the effectiveness of this method, the method observed substantial improvements in plant health: root and shoot weights increased by 38% and 45%, respectively, by day 52, and pathogen root infections were significantly reduced by up to 78%, as confirmed by Real-Time PCR data. Interestingly, by day 29, solely biological seed treatments outperformed chemical coatings in shoot weight gains, showing significant results ($p < 0.05$). These results predict that further field applications could confirm the viability of this combined method, ultimately offering a sustainable and environmentally friendly alternative to traditional chemical treatments.

Foysal et al [13] proposed a CNN Disease Detection, is designed to enhance plant disease identification by combining advanced IP techniques, ML, DL, and mobile technology. The rationale behind this approach is to improve real-time, accurate disease detection in crops, addressing challenges posed by common diseases such as blight, mildew, and rust, which affect multiple plant species. CNN are used in the solution to analyse high-resolution images of plant leaves and differentiate between 26 distinct diseases in 14 different plant types. The system demonstrated its robustness in diagnosing a broad spectrum of crop diseases with an impressive accuracy of 98.14%, which was attained by training the model on a diverse dataset.

This model was then integrated into mobile applications, enabling real-time disease detection in the field. The prediction is that this technology will revolutionize agricultural practices by providing farmers with on-the-spot diagnostic tools, significantly reducing the time between detection and intervention, and ultimately leading to better crop health management and yield improvements.

In order to improve PD detection, Hemalatha and Jayachandran [14] presented a PD Localisation and Classification model based on Vision Transformer (PDLC-ViT). In a Multi-Task Learning (MTL) framework, this model combines a Vision Transformer (ViT) with sophisticated attention mechanisms. The limitations of previous models in accurately localizing and classifying plant diseases by introducing co-scale, co-attention, and cross-attention mechanisms. These mechanisms enable the model to capture multi-scale relationships within plant images, thereby improving feature learning and disease localization. The PDLC-ViT model was rigorously trained on the Plant Village dataset, where key hyperparameters—such as learning rate, batch size, and dropout ratio—were optimized using a grid search. An early cutoff strategy based on validation loss was applied to prevent overfitting. The model's performance was notably superior in comparison to earlier approaches, achieving an impressive 99.97% accuracy and high mean average precision across two public datasets. The inclusion of these attention mechanisms in the ViT architecture is what significantly boosted its ability to detect and classify plant diseases more precisely and efficiently.

Chavan et al [15] proposed an InceptionV3 Disease Detection is designed to address inefficiencies in traditional farming practices, particularly in disease management and fertilization. By leveraging the InceptionV3 model, which achieves a high 97.34% accuracy in diagnosing plant illnesses based on real-time field images, the system offers precise disease detection. The rationale for this approach is to enhance both crop health and environmental sustainability by improving the precision of disease detection and fertilizer application. Apart from the diagnostic feature, the system has a special hardware solution that eliminates the need for human intervention in fertiliser formulation by mechanically mixing two liquid fertilisers into a solution with the right proportions. By avoiding direct contact with potentially dangerous materials, this automation improves safety in addition to ensuring precise mixing and optimising fertiliser use. The combination of real-time plant illness detection and automated fertilizer formulation is expected to significantly improve resource efficiency, crop health, and safety in agricultural practices, contributing to more sustainable farming.

In order to detect prevalent leaf diseases in apple, corn and potato crops in a timely manner under a variety of environmental situations, Iftikhar et al. [16] created an Enhanced CNN (E-CNN) for Early DD.

The reason for proposing this approach is to improve early detection of PD, which is crucial for effective disease management and enhancing agricultural productivity. This study undertakes a detailed performance analysis, examining how key HP, such as learning rates and batch sizes, influence the effectiveness of disease identification across these diverse crops. The study compares several ML and pre-trained DL models, fine-tuning parameters for optimal performance. Additionally, Data Augmentation (DA) techniques are employed to further boost detection accuracy. The experimental results demonstrate that the fine-tuned E-CNN model achieved an impressive accuracy of 98.17% in classifying fungal diseases, showcasing its potential in disease control. The integration of these advancements aims to pave the way for more efficient agricultural practices, ensuring increased productivity in the context of global agricultural challenges.

CNN models designed for novel PD detection tasks are automatically constructed using the Meta-Learning Neural Architecture Search (MLNAS) for PD Detection, which was suggested by Verma et al. [17]. The rationale for this approach is to streamline the model development process by utilizing meta-learning to evaluate existing benchmark models on known plant disease datasets and recommend optimal models for unknown tasks. The Neural Architecture Search (NAS) operators are employed to fine-tune and optimize the selected models for specific disease detection challenges. The system demonstrated superior performance, achieving an accuracy of 99.61% on a fruit disease dataset and outperforming the Progressive NAS model with 99.8% accuracy on an 8-class plant disease dataset. These results highlight the efficiency of the MLNAS system in improving plant disease detection, accelerating model development while minimizing computational costs. The automation provided by ML NAS is expected to revolutionize plant disease control, making it more efficient and scalable for diverse agricultural environments.

Ariwa et al [18] introduced a You Only Look Once Version 8 (YOLOv8) algorithm Based Maize Leaf Disease Detection an innovative approach to plant disease identification using the YOLO deep learning model, implemented in Python. The system specifically targets maize leaf diseases and demonstrates significant improvements over traditional algorithms like CNN (84%), KNN (81%), Random Forest (85%), and SVM (82%), achieving an impressive 99.8% accuracy. This high-performance detection system underscores the effectiveness of YOLOv8 for real-time, precise identification. the method is limited by its focus on only three maize leaf diseases and the use of single-leaf images for detection. To enhance its applicability, future research should incorporate environmental factors like temperature and humidity, utilize multi-leaf frames for comprehensive disease identification, and develop systems capable of detecting various stages of disease progression. These enhancements could further improve accuracy and make the system more adaptable to real-world agricultural scenarios.

Punith et al [19] proposed a Mobile-Based Plant Disease Diagnosis Using CNN, is a machine learning-powered mobile application that automates the classification of 38 different plant diseases. The system uses a Convolutional Neural Network (CNN) trained on a comprehensive dataset of 96,206 images of both healthy and diseased plant leaves. Farmers can use the Android-based app to capture images of infected leaves, and the system provides the disease category along with a confidence percentage. This method's justification is to provide farmers with precise, RT disease diagnostics so they may make well-informed decisions about the health of their crops and lessen the overuse of fertilisers that exert stress plants even more. This mobile-based system enhances accessibility to disease diagnostics and supports more sustainable agricultural practices. Finally, the system's performance was validated through rigorous testing, confirming its effectiveness in the field.

Kothawade et al [20] proposed a Residual Network with 152 layers, Version 2 (ResNet152V2) to classify plants as healthy or diseased based on leaf health. By applying these models to two datasets—cotton and Plant Village—the study significantly improved disease detection performance. The results demonstrate that all the models provide effective solutions for diagnosing and managing plant diseases, with ResNet152V2 standing out by achieving 100% accuracy on the cotton dataset and 94.32% accuracy on the Plant Village dataset. This indicates ResNet152V2's superior ability to accurately distinguish between healthy and diseased plants. Furthermore, when diseased leaves are detected, the model supplies detailed information about the specific disease, providing a comprehensive solution for plant disease prediction and management. This framework offers a promising approach to improving crop health and disease management using deep learning.

In response to the growing demand for food in agriculture due to population growth, Goel and Nagpal [21] developed a Feature Extraction with Linear SVM based on Orientated FAST and Rotated BRIEF (ORB) to improve PD classification. Traditional methods often lack precision, particularly for large-scale farming, making automated systems crucial. The reason for proposing this algorithm is its ability to leverage ORB for capturing essential features from plant images, paired with the proven classification strength of Linear SVM, which excels in handling high-dimensional data for disease detection. The solution combines ORB's efficiency in extracting key visual patterns from plant diseases with the precision of SVM to classify these patterns effectively. It is predicted that evaluations of this approach will demonstrate high accuracy, with past studies showing up to 99.98% accuracy when using ORB and Linear SVM together, significantly improving real-time plant disease monitoring and proactive management for farmers. The results are expected to confirm its robustness in distinguishing between various disease types, making it a valuable tool in precision agriculture.

In order to improve accuracy and generalisability across different species, Tosal and Bhalodia [22] introduced CNN designs such as DenseNet121 and VGG16 for PD classification. The reason for selecting these models lies in their proven ability to handle complex image classification tasks, particularly in agriculture, where efficient disease detection is critical for large-scale farming. To achieve this, DenseNet121 and VGG16 are pretrained and fine-tuned on the Plant Village dataset, which includes 15 plant classes and images of both healthy and diseased crops like tomatoes, potatoes, and pepper bell. The models are evaluated based on accuracy, precision, recall, and F1-score to assess their performance, while also considering model complexity and computational efficiency to ensure practicality for real-world applications. Predicted evaluations suggest that both architectures will effectively diagnose plant diseases, with DenseNet121 potentially offering a better balance of high accuracy and lower computational cost, making it more suitable for deployment in real-time agricultural environments.

TABLE 1: COMPARISON OF PLANT DISEASE MONITORING AND CONTROL APPROACHES WITH EXISTING APPROACHES

S.NO	AUTHOR	METHODS	DATASET	MODALITY	ACCURACY	OUTCOMES
1	Trivedi et al [2021]	DNN	Plant Village dataset	Image data (RGB images of tomato leaves)	98.97%	ED and tomato leaf diseases classification, together with early response to improve crop health management.
2	Shewale and Daruwala [2023]	DL Architecture	Public dataset (Plant Village dataset)	Image data (RGB images of plant leaves)	96.12%	Efficient ED and classification of plant leaf diseases, improving the ability to manage and control crop health at an early stage, helping reduce losses in agriculture.
3	Saleem et al	DL	Plant	Image data	99.53%	DL-based

	[2019]		Village dataset			PD detection and classification has potential uses in precision agriculture, allowing for early disease control and lowering crop losses.
4	Jung et al [2023]	DL-based model	Custom dataset of plant images	Image data	90%	creation of an effective DL-based PD detection system that would improve early DD and management techniques in agriculture, increasing crop production and protection.
5	Degani et al [2024]	Bio-Chem Integration Method	Field Study, Remote Sensing	Biological and Chemical, Remote Sensing	78%	Increased cotton yield, improved plant health, and reduced root infection by 78%
6	Foysal et al [2024]	CNN	Multi-crop Dataset	Mobile App, CNN	98.14%	Accurate multi-class disease detection with mobile app integration
7	Hemalatha and Jayachandran [2024]	PDLC-ViT	Plant Village	Vision Transformer	99.97%	Advanced plant disease localization and classification
8	Chavan et al [2024]	InceptionV3	Field Image Dataset	Deep Learning	97.34%	Real-time disease detection with custom fertilizer formulation system
9	Iftikhar et al [2024]	Enhanced CNN (E-CNN)	Apple, Corn, Potato	Deep Learning, Mobile App	98.17%	Early detection of fungal leaf diseases in major crops
10	Verma et al [2024]	Meta-Learning Neural Architecture Search (MLNAS)	Fruit Disease Dataset	Meta-Learning, NAS	99.8%	Automated model generation for efficient plant disease detection

11	Ariwa et al [2024]	YOLOv8	Maize Leaf Dataset	Deep Learning, YOLO	99.8%	Superior disease detection accuracy compared to other algorithms
12	PUNITH et al [2024]	CNN	Tomato Leaf Dataset	Mobile App, CNN	94%	Mobile app-based real-time disease prediction for tomatoes
13	Kothawade et al [2022]	ResNet152V2	Cotton, Plant Village	Deep Learning	100% (Cotton), 94.32% (Plant Village)	Feasible solution for predicting disease with high accuracy
14	Goel and Nagpal [2023]	Oriented FAST and Rotated BRIEF (ORB) based FE using Linear (SVM)	Various Plant Datasets	ML Feature Extraction	99.98%	Examining ML methods for classifying PD
15	Tosal and Bhalodia [2024]	DenseNet121 and VGG16	Plant Village Dataset	CNN	99.47%	Accurate classification of diseases across various species using DenseNet121

The literature review highlights significant progress in applying ML and DL methods for PD detection using various datasets and modalities, primarily image data. Models such as CNN, Vision Transformers, and advanced architectures like ResNet152V2 and Meta-Learning Neural Architecture Search (MLNAS) have achieved high classification accuracy, with some reaching up to 100%. These approaches promote early disease detection and intervention, which are crucial for improving crop management and reducing agricultural losses. While the performance of models is generally high, challenges like the need for large, diverse datasets, the complexity of model training, and real-time deployment remain. Overall, these DL techniques hold promise for revolutionizing crop health monitoring and enhancing agricultural efficiency through precise disease identification.

III ML APPLICATIONS IN PD MANAGEMENT

ML has developed as a transformative tool in the area of PD management, offering innovative solutions that enhance accuracy, efficiency, and scalability in detecting, classifying, and predicting plant diseases [23]. The following is a detailed exploration of various ML applications in this domain:

2.1 DISEASE DETECTION AND CLASSIFICATION

The detection and classification of PD is one of the main uses of ML in PD management [24]. Conventional approaches frequently depend on experts' subjective and prone to error visual assessment. However, ML algorithms can accurately identify disease symptoms by analysing plant images.

Feature Extraction: ML algorithms, such as SVM, RF, and k-NN, are commonly used to extract features from images, such as color, texture, and shape, which are indicative of disease presence. These features are then used to train models that can classify different types of diseases. For instance, color-based features might help in identifying leaf spot diseases, while texture-based features might be used to detect powdery mildew.

Multiclass Classification (MCC): Many ML models are capable of performing multiclass classification, where they can distinguish between several types of diseases or between healthy and multiple diseased conditions. For example, a model might be trained to differentiate between healthy leaves, leaves infected with rust, and leaves showing signs of blight. Techniques such as (DT)decision trees and NN have been employed to achieve this, often achieving high classification accuracy.

Real-Time Diagnosis: By integrating ML models with mobile applications or handheld devices, farmers can perform RT disease diagnosis in the field. The user captures an image of the plant, and the ML model processes the image to identify potential diseases, providing immediate feedback.

2.2 PREDICTIVE MODELLING

ML is also instrumental in developing predictive models that forecast the likelihood of disease outbreaks based on environmental factors and historical data [25].

Environmental Data Analysis: Diseases often correlate with specific environmental conditions, such as temperature, humidity, and rainfall. To evaluate this data and predict the likelihood of disease rate, ML models such as regression analysis, DT, and ensemble approaches (e.g., Gradient Boosting Machines) are employed. These models can help in identifying critical periods when crops are most vulnerable, allowing for timely interventions.

Time Series Forecasting: TS data can be subjected to ML algorithms in order to predict future trends in disease. To predict disease outbreaks, for instance, models such as Long Short-Term Memory (LSTM) networks, a subset of recurrent NN (RNNs), can examine temporal sequences of environmental data.This is particularly useful for managing diseases that have seasonal patterns.

Risk Mapping: ML techniques are used to create risk maps that highlight regions most susceptible to specific diseases. These maps are generated by analyzing historical disease incidence data, along with environmental and geographical data. Risk mapping enables targeted monitoring and resource allocation, improving the efficiency of disease management practices.

2.3 AUTOMATED DIAGNOSIS SYSTEMS

Automated diagnosis systems powered by ML are becoming increasingly popular for monitoring plant health and managing diseases [26].

- **IoT Integration:** ML models are often integrated with IoT devices, such as drones, sensors, and cameras, to automate the collection and analysis of plant health data. Large agricultural fields may be continuously monitored by these devices, which can identify early disease symptoms and alert farmers.
- **Expert Systems:** Expert systems that are based on ML can help farmers by offering suggestions for managing diseases. These systems analyze data from various sources, including sensor data, weather forecasts, and historical disease records, to suggest the best course of action, such as the optimal time for spraying pesticides or implementing preventive measures.
- **Precision Agriculture**: In the context of precision agriculture, ML models are used to optimize disease management practices. For example, by analyzing data from multiple sources, ML algorithms can help determine the precise amount of pesticide needed, reducing waste and minimizing environmental impact.

2.4 DISEASE SEVERITY ESTIMATION

Estimating the severity of plant diseases is crucial for making informed decisions about treatment and resource allocation. This process is progressively being automated with ML models.

Image Analysis for Severity Assessment: To determine the extent of the infection, ML models may examine images of diseased plants. Techniques such as CNN are employed to segment the diseased areas and quantify the extent of the damage. This data supports in assessing the effectiveness of treatment strategies and in deciding whether to escalate intervention measures.

Yield Loss Prediction: By correlating disease severity with historical yield data, ML models can predict potential yield losses, enabling farmers to take proactive steps to mitigate the impact. Regression models and neural networks are commonly used for this purpose, providing valuable insights into the economic implications of disease outbreaks.

2.5 EARLY WARNING SYSTEMS

ML-based early warning systems are designed to detect the onset of plant diseases before they become widespread, allowing for timely interventions.

Anomaly Detection: Anomalies in plant health data, such as sudden changes in colour or texture that could point to the early stages of a disease, can be identified by training ML algorithms. Techniques like unsupervised learning and clustering (e.g., (KMC) k-means clustering) are often used for this purpose, where the model identifies patterns that deviate from the norm.

Proactive Disease Management: By predicting disease outbreaks before they occur, ML models enable proactive disease management. Farmers can implement preventive measures, such as altering irrigation practices or applying protective treatments, to reduce the risk of a full-blown epidemic.

In summary, ML applications in plant disease management offer significant advancements in detecting, classifying, predicting, and mitigating plant diseases. By lowering the need for chemical treatments and minimising their negative effects on the environment, these technologies not only improve the precision and effectiveness of disease management techniques but also promote sustainable agriculture. The management of PD could undergo yet another radical change as ML develops and is combined with other cutting-edge technologies like remote sensing and the IoT.

5. DL APPROACHES FOR PD DETECTION

DL has revolutionized various fields, including plant disease detection, by offering advanced methods for analysing complex data and extracting features that are often challenging to identify using traditional techniques [27]. Here's a detailed exploration of how deep learning approaches are applied to plant disease detection:

5.1 IMAGE-BASED DISEASE IDENTIFICATION

Image-based PD Detection has demonstrated outstanding accuracy with DL, especially with CNNs [28]. In order to identify and classify diseases, this technique analyses images of plant leaves, fruits, or stems.

CNN: Many DL-based PD detection systems depend on CNNs as their core component. In order to automatically and adaptively learn the spatial hierarchies of features from input images, they are composed of several layers, such as CL, pooling layer, and FC layers. CNNs are adept at extracting features such as edges, textures, and patterns that are indicative of PD. Models like AlexNet, VGGNet, and ResNet have been successfully used to classify PD based on leaf images.

TL: Utilising CNN models that have already been trained on sizable datasets and optimising them for particular PD detection tasks is known as TL. Because it enables the utilisation of information acquired from other domains to enhance efficiency, this method is especially helpful when working with small datasets.Popular pre-trained models include VGG16, InceptionV3, and EfficientNet. Transfer learning helps to reduce training time and computational resources while improving accuracy.

DA: DA techniques are used to artificially expand the amount of the training dataset in order to improve the robustness of DL models. To provide a variety of training examples, the photos are subjected to various techniques, including rotation, flipping, cropping, and colour modification. This lessens overfitting and improves the model's ability to generalise to new, untested data.

5.2 ADVANCED NEURAL NETWORK ARCHITECTURES

In addition to traditional CNNs, several advanced neural network architectures have been developed to improve plant disease detection [29].

Residual Networks (ResNets): ResNet solves the vanishing gradient problem (VGP) by including residual connections, which aid in the training of extremely deep networks. These networks are effective in extracting complex features from plant images, making them suitable for detecting subtle disease symptoms.

Dense Convolutional Networks (DenseNets): By connecting every layer in a dense block to every other layer, DenseNets improve feature propagation and utilisation. This connectivity pattern improves the model's ability to learn and retain detailed features, which is beneficial for accurate disease classification.

U-Net for Segmentation: A specialised architecture for image segmentation applications is U-Net. Accurate segmentation of infected areas in plant images is made possible by its encoder-decoder structure with skip connections. U-Net is particularly useful for identifying and quantifying disease severity by segmenting the affected areas from healthy ones.

5.3 MULTI-MODAL AND MULTI-TASK LEARNING (MTL)

Deep learning approaches can also integrate multiple types of data or perform multiple tasks simultaneously to enhance disease detection capabilities [30].

Multi-Modal Learning: Combining image data with other types of information, such as environmental data (e.g., temperature, humidity), can improve disease detection accuracy. Multi-modal models integrate these diverse data sources to provide a more comprehensive understanding of plant health.

MTL: Training a single model to carry out several related tasks, such disease classification and severity assessment, is known as MTL. By transferring data across tasks, this method enables the model to perform better and more efficiently. For example, a multi-task model could simultaneously classify plant diseases and estimate the extent of damage.

5.4 MODEL TRAINING AND OPTIMIZATION

The performance of DL models for PD detection depends on effective training and optimization strategies.

Hyperparameter Tuning: For optimal performance, DL models require optimisation of a variety of HP, including learning rate, batch size, and number of epochs. To determine the ideal collection of HP, methods such as grid search, random search, and Bayesian optimisation are employed.

Regularization Techniques: Regularisation techniques including dropout, weight decay, and Batch Normalisation (BN) are used to enhance generalisation and avoid overfitting. By using these strategies, one can make sure the model works effectively with new, untested data.

Evaluation Metrics: In PD diagnosis, accuracy, precision, recall, F1-score, and area under the curve (AUC) are frequently used evaluation metrics for DL models. In terms of accurately diagnosing illnesses and reducing False Positives (FP) and False Negatives (FN), these metrics help in evaluating the model's performance.

5.5 REAL-WORLD APPLICATIONS AND CHALLENGES

DL approaches is effectively used in many real-world scenarios for plant disease detection.

Mobile and Field Applications: DL models are integrated into mobile applications and field devices, enabling farmers to perform real-time disease diagnosis. These applications often use camera-equipped smartphones or tablets to capture images of plants and provide immediate feedback.

Challenges: DL models have difficulties despite their effectiveness, including the requirement for sizable labelled datasets, processing power, and the interpretability of intricate models. Research and development must continue in order to address these issues and enhance the model's usability, scalability, and efficiency.

In summary, DL approaches have significantly advanced PD detection by leveraging powerful neural network architectures, TL, and multi-modal data integration. These techniques enable accurate, scalable, and real-time detection of PD, contributing to more effective disease management and improved agricultural practices. As technology develops further, DL developments will probably improve PD detection systems' capabilities, resolving existing issues and broadening their range of applications.

6. INFERENCES

Using ML and DL to forecast plant diseases entails applying sophisticated algorithms to evaluate plant images and accurately detect disease symptoms.

ML techniques, such as SVM and RF, provide robust predictions based on FE from images, while DL approaches, particularly CNN, excel at automatically learning complex patterns and features directly from raw image data. By integrating these methods, predictions can be refined and enhanced, leading to more precise early detection and classification of PD. This fusion of ML and DL not only improves diagnostic accuracy but also enables real-time analysis through mobile apps, offering actionable insights and timely interventions for effective plant health management.

V. CONCLUSION:

The integration of ML and DL in PDP and management has revolutionized agriculture by providing accurate, real-time, and scalable solutions for DD, classification, and prediction. These technologies have the potential to significantly reduce crop losses, optimize resource use, and improve overall agricultural efficiency. ML models, including SVM, RF, and DL architectures like CNNs and ResNets, have shown great promise in identifying PD through image analysis, environmental data, and predictive modeling. By automating the detection process and allowing for proactive disease management, these systems enhance decision-making for farmers, reducing the reliance on chemical treatments and fostering sustainable agricultural practices. Despite these advances, challenges such as limited access to high-quality datasets, model complexity, and the need for real-time, large-scale applications still exist. The robustness, accuracy, and efficiency of PD management systems will be enhanced by ongoing research and technical developments that continue to address these challenges.

REFERENCES:

1. Khakimov, A., Salakhutdinov, I., Omolikov, A. and Utaganov, S., 2022, Traditional and current-prospective methods of agricultural plant diseases detection: A review. In *IOP Conference series: earth and environmental science*, vol. 951, no. 1, p. 012002.
2. Balafas, V., Karantoumanis, E., Louta, M. and Ploskas, N., 2023, Machine learning and deep learning for plant disease classification and detection. *IEEE Access*.
3. Hatuwal, B.K., Shakya, A. and Joshi, B., 2020, Plant Leaf Disease Recognition Using Random Forest, KNN, SVM and CNN. *Polibits*, vol.*62*, pp.13-19.
4. Sun, X., Li, G., Qu, P., Xie, X., Pan, X. and Zhang, W., 2022, Research on plant disease identification based on CNN. *Cognitive Robotics*, vol.*2*, pp.155-163.

5. Kumar, V.R., Pradeepan, K., Praveen, S., Rohith, M. and Kumar, V.V., 2021, Identification of plant diseases using image processing and image recognition. In *2021 International Conference on System, Computation, Automation and Networking (ICSCAN)*, pp. 1-4.
6. Shoaib, M., Shah, B., Ei-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., Gechev, T., Hussain, T. and Ali, F., 2023, An advanced deep learning models-based plant disease detection: A review of recent research. *Frontiers in Plant Science*, vol.*14*, p.1158933.
7. Nguyen, C., Sagan, V., Maimaitiyiming, M., Maimaitijiang, M., Bhadra, S. and Kwasniewski, M.T., 2021, Early detection of plant viral disease using hyperspectral imaging and deep learning. *Sensors*, vol.*21*, no.3, p.742.
8. Trivedi, N.K., Gautam, V., Anand, A., Aljahdali, H.M., Villar, S.G., Anand, D., Goyal, N. and Kadry, S., 2021, Early detection and classification of tomato leaf disease using high-performance deep neural network. *Sensors*, vol.*21*, no.23, p.7987.
9. Shewale, M.V. and Daruwala, R.D., 2023, High performance deep learning architecture for early detection and classification of plant leaf disease. *Journal of Agriculture and Food Research*, vol.*14*, p.100675.
10. Saleem, M.H., Potgieter, J. and Arif, K.M., 2019, Plant disease detection and classification by deep learning. *Plants*, vol.*8*, no.11, p.468.
11. Jung, M., Song, J.S., Shin, A.Y., Choi, B., Go, S., Kwon, S.Y., Park, J., Park, S.G. and Kim, Y.M., 2023, Construction of deep learning-based disease detection model in plants. *Scientific reports*, vol.*13*, no.1, p.7331.
12. Degani, O., Chen, A., Dimant, E., Gordani, A., Malul, T. and Rabinovitz, O., 2024, Integrated Management of the Cotton Charcoal Rot Disease Using Biological Agents and Chemical Pesticides. *Journal of Fungi*, vol.*10*, no.4, p.250.
13. Foysal, M.A.H., Ahmed, F. and Haque, M.Z., 2024, Multi-Class Plant Leaf Disease Detection: A CNN-based Approach with Mobile App Integration. *arXiv preprint arXiv:2408.15289*.
14. Hemalatha, S. and Jayachandran, J.J.B., 2024, A Multitask Learning-Based Vision Transformer for Plant Disease Localization and Classification. *International Journal of Computational Intelligence Systems*, vol.*17*, no.1, pp.1-21.
15. Chavan, P., Mahajan, P., Patil, S., Patle, P., Pawar, B. and Pawar, N., 2024, Deep Learning-Driven Plant Disease Detection and Custom Fertilizer Formulation.
16. Iftikhar, M., Kandhro, I.A., Kausar, N., Kehar, A., Uddin, M. and Dandoush, A., 2024, Plant disease management: a fine-tuned enhanced CNN approach with mobile app integration for early detection and classification. *Artificial Intelligence Review*, vol.*57*, no.7, pp.1-29.
17. Verma, S., Kumar, P. and Singh, J.P., 2024, MLNAS: Meta-learning based neural architecture search for automated generation of deep neural networks for plant disease detection tasks. *Network: Computation in Neural Systems*, pp.1-24.
18. R., N., Ariwa., C., Markus., Nora, Godwin, Teneke., Gideon, Adamu, Shallangwa., K., G., Fumlack. 2024, Plant Disease Detection Using Yolo Machine Learning Approach. *British journal of computer, networking and information technology*, vol.7, no.2, 115-129. Available from: 10.52589/bjcnit-ejwgfw6d
19. B, PUNITH., K, T, SIDDESH., K., M., Karthick, Raghunath 2024, Ai and android app-based tomato plant disease prediction system. Indian Scientific Journal of Research in Engineering and Management, vol.08, no.07, pp.1-10. Available from: 10.55041/ijsrem36428
20. Kothawade, P., Varma, S. and Gogate, U., 2022, Plant disease detection and management using deep learning approach.
21. Goel, L. and Nagpal, J., 2023, A systematic review of recent machine learning techniques for plant disease identification and classification. *IETE Technical Review*, vol.*40*, no.3, pp.423-439.
22. C., P.., Tosal, M., Bhalodia. 2024, Detection and Classification on Plant Disease using Deep Learning Techniques. *International journal of scientific research in computer science, engineering and information technology*, vol.10, no.3, 365-375. Available from: 10.32628/cseit2410333
23. Ghosh, D., Chakraborty, S., Kodamana, H. and Chakraborty, S., 2022, Application of machine learning in understanding plant virus pathogenesis: trends and perspectives on emergence, diagnosis, host-virus interplay and management. *Virology Journal*, vol.*19*, no.1, p.42.

24. Ramanjot, Mittal, U., Wadhawan, A., Singla, J., Jhanjhi, N.Z., Ghoniem, R.M., Ray, S.K. and Abdelmaboud, A., 2023, Plant disease detection and classification: A systematic literature review. *Sensors*, vol.*23*, no.10, p.4769.
25. Fedele, G., Brischetto, C., Rossi, V. and Gonzalez-Dominguez, E., 2022, A systematic map of the research on disease modelling for agricultural crops worldwide. *Plants*, vol.*11*, no.6, p.724.
26. Karthickmanoj, R. and Sasilatha, T., 2023, Development of plant disease detection for smart agriculture. *MULTIMEDIA TOOLS AND APPLICATIONS*.
27. Liu, J. and Wang, X., 2021, Plant diseases and pest's detection based on deep learning: a review. *Plant Methods*, vol.*17*, pp.1-18.
28. Khan, R.U., Khan, K., Albattah, W. and Qamar, A.M., 2021, Image-Based Detection of Plant Diseases: From Classical Machine Learning to Deep Learning Journey. *Wireless Communications and Mobile Computing*, vol.*2021*, no.1, p.5541859.
29. Reddy, T.V., 2022, Plant disease detection using advanced convolutional neural networks with region of interest awareness.
30. Zhao, Y., Jiang, C., Wang, D., Liu, X., Song, W. and Hu, J., 2023, Identification of Plant Disease Based on Multi-Task Continual Learning. *Agronomy*, vol.*13*, no.12, p.2863.