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A Comprehensive Review on Plant Disease Detection Systems

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ABSTRACT:

Effective prediction of plant diseases throughout their life cycle is crucial for sustainable agriculture and helps minimize productivity and economic losses. This review paper examines various plant disease detection systems, highlighting their method-ologies, technologies, and effectiveness in diagnosing diseases at different growth stages. The review categorizes these systems into traditional and modern approaches, with a focus on image-based techniques leveraging machine learning and computer vision. This paper reviews traditional and modern methods of plant disease detection, focusing on how technology is enhancing our ability to monitor and manage crop health. It covers key advancements in deep learning algorithms, such as Convolutional Neural Networks (CNNs), and discusses their applications in real-time disease detection using mobile and remote sensing technologies. Additionally, we analyze the strengths and limitations of different systems, including data acquisition methods, accuracy, and user accessibility. By synthesizing the current state of research and technological innovation, this paper aims to provide insights into the potential for enhancing disease management in agriculture, ultimately contributing to sustainable farming practices and improved crop yields. The findings underscore the need for continued development in this field to address existing challenges and promote the adoption of effective plant disease detection systems.

Keywords: Plant disease detection, Sustainable agriculture, Machine learning, Deep learning algorithms, CNNs,Image-based techniques, Real-time detection Remote sensing, Crop health monitoring, Technological innovation

1. Introduction

Agriculture is a vital part of life for millions of people around the world, providing not only food but also a primary source of income for many communities. It plays a key role in global economies and is essential for food security. However, farmers face constant challenges, and one of the most significant is plant diseases[1]. These diseases can harm crops at any stage of their growth, affecting their quality and yield. They spread quickly, often leading to devastating economic losses and threatening farmers' livelihoods.

1.1 Effects of Plant Diseases

- Lower Crop Yields:Plant diseases can drastically reduce the amount of crops farmers harvest. Whether it's stunted growth, damaged leaves, or plants dying altogether, these losses take a direct toll on production and farmers' livelihoods[1].
- Poor Quality Crops: Diseases don't just affect the quantity of crops they also reduce their quality. Infected crops may become discolored, deformed, or contami-nated, making them harder to sell and less appealing to consumers[1].
- Financial Losses: For farmers, plant diseases mean more than just damaged crops they mean lost income. The cost of managing outbreaks, replanting, and dealing with lower market prices can be devastating, especially for small-scale farm-ers[2].
- Rapid Spread of Diseases:Many plant diseases can spread quickly, wiping out entire fields or even crossing into neighboring farms and regions. This creates large-scale agricultural challenges that are hard to control.
- Food Shortages and Price Hikes:When plant diseases reduce crop availability, food supplies shrink, and prices go up. This can lead to food insecurity, particularly in areas where agriculture is the main source of food[2].
- Environmental Damage:In the rush to control diseases, farmers often rely on ex-cessive pesticide use, which can harm the environment. Soil, water, and ecosystems suffer from the overuse of chemicals.

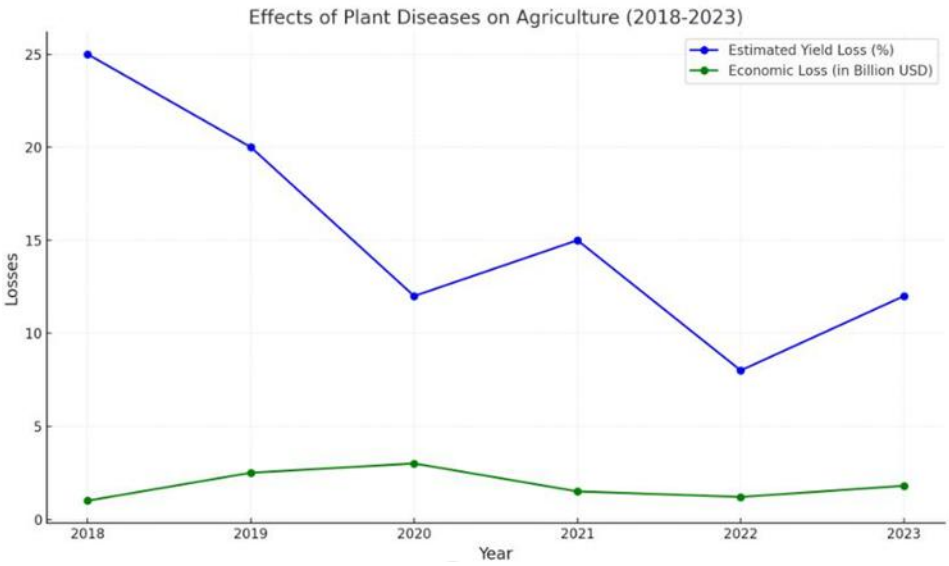

Figure 1: Effects of Plant Diseases on Agriculture (2018-2023)

Figure 1 is a Line chart illustrating the impact of plant diseases on agriculture from 2018 to 2023, focusing on two key metrics: estimated yield loss percentage and economic losses in billions of USD. Yield losses, represented by the blue line, show significant fluctuations, peaking at 25% in 2018 and tapering to a lower but steady range between 8-15% in subsequent years. Economic losses, represented by the green line, follow a similar trend, with a notable spike in 2019 (2.5 billion dollars) and 2020 (3 billion dollars) due to widespread outbreaks and global impacts on key crops. The chart highlights the persistent challenges posed by plant diseases and underscores the need for effective detection and management systems to mitigate both productivity and financial losses in agriculture.

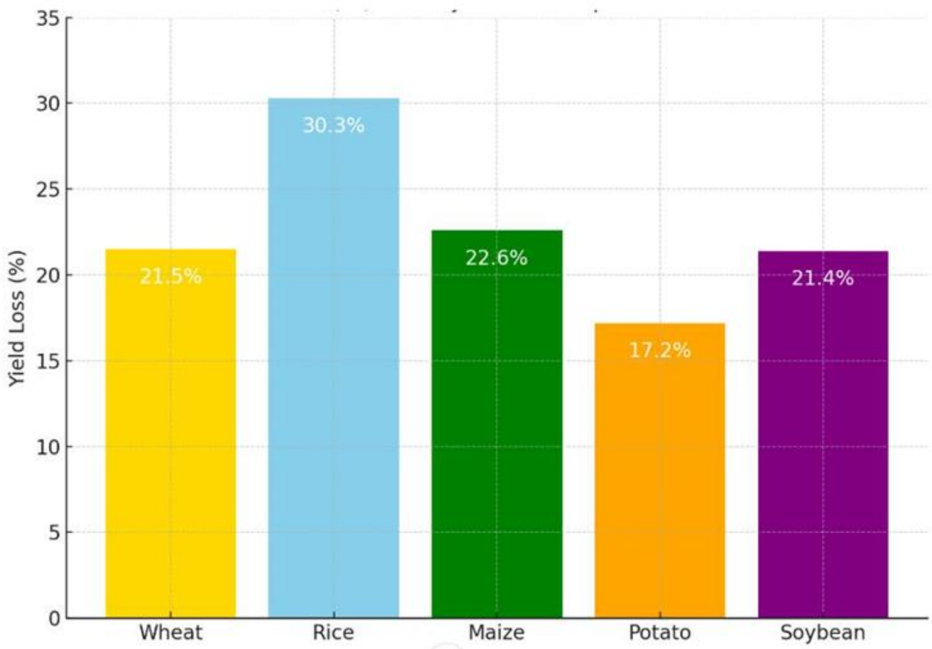

Figure 2: Yield Losses for Food Crops Due to Plant Diseases

Figure 2 is the bar chart illustrating the mean yield losses (%) for major food crops due to plant diseases. Each bar represents the percentage of yield loss for a specific crop, showcasing the impact of plant diseases on different agricultural sectors. Global crop yield losses due to pests and diseases are estimated to range from 20% to 40% annu-ally, with plant diseases alone costing the global economy around $220 billion each year. While advancements in detection and management have been made, significant challenges persist, including climate change, emerging pathogens, and invasive species introduced through global trade.Major food crops face substantial yield losses due to diseases: wheat (21.5%), rice (30.3%), maize (22.6%), potato (17.2%), and soybean (21.4%). These losses emphasize the critical impact on food security and the economy, underlining the need for continued innovation in disease management practices.

For farmers, detecting plant diseases early and accurately is crucial to prevent these losses. Yet, traditional methods—like visually inspecting crops or relying on outdated tools aren't always enough. These methods can be time consuming, exhausting, and prone to errors. Factors like varying weather conditions, differences in plant types, and simple human mistakes often make it hard to catch diseases in time. Delayed diagnoses not only hurt crop health but also lead to higher treatment costs and lower profits for farmers.

Thankfully, modern technology is stepping in to offer better solutions. Advances in image processing and machine learning (ML) have made it possible to build systems that automatically detect and classify plant diseases[2]. These technologies use sophisticated tools like support vector machines (SVM), k-nearest neighbors (KNN), and convolutional neural networks (CNN) to analyze crop images and identify problems with incredible precision.

With these tools, farmers can monitor their crops throughout the growing cycle, catch-ing diseases early and applying targeted treatments. This not only helps stop diseases from spreading but also reduces costs and boosts productivity. These systems are effi-cient, scalable, and adaptable, making them a game-changer for farmers everywhere[3].

By blending technology with traditional farming practices, we're finding new ways to tackle old problems. These advancements don't just improve how we fight plant diseases they're helping to secure the future of farming, ensuring better harvests, stronger rural economies, and more resilient communities.

2. Evolution of Plant Disease Detection Approaches

The evolution of plant disease detection has moved from simple manual methods to cutting-edge technologies, reshaping the way diseases are identified and managed. Tra-ditional approaches, such as manual inspection, rely on human expertise to spot visible signs of disease like discoloration or spots on leaves. While this method is affordable and straightforward, it is prone to human error, subjective judgment, and inefficiencies when applied to large-scale farming. Microscopy-based analysis adds scientific precision by identifying pathogens at the microscopic level, providing critical insights into the dis-ease's nature. However, these methods are time-consuming, require skilled professionals, and are better suited for research or small-scale operations rather than large agricultural systems.

Modern detection systems have introduced Machine Learning (ML) and Deep Learn-ing (DL), enabling more efficient and scalable solutions. Techniques like Support Vector Machines (SVM) and CNNs are evaluated for their ability to classify plant diseases with remarkable accuracy. These technologies are assessed using metrics such as accuracy, precision, and recall, ensuring they are effective across diverse conditions. CNNs, for example, can detect early disease symptoms by analyzing minute patterns in images that are often undetectable to the human eye. The scalability and adaptability of these sys-tems are crucial, as they are deployed across different crops, environments, and disease stages, making them an indispensable part of modern agriculture[3].

Advanced technologies, such as Internet of Things(IoT)-based monitoring systems, spectral imaging, and hybrid models, are further enhancing plant disease detection. IoT systems are evaluated based on their ability to provide real-time insights by collecting environmental and crop health data through interconnected sensors. Spectral imaging, using non-visible wavelengths, helps detect stress or disease in plants even before symp-toms are visible to humans[3]. Drone and satellite imaging are assessed for their ability to cover vast agricultural areas and pinpoint disease hotspots with precision. These sys-tems are judged not only on their technical performance but also on their ease of use and cost-effectiveness, ensuring they meet the needs of farmers and large-scale agricul-tural operations. The evaluation process for modern approaches emphasizes adaptability, efficiency, and the potential to revolutionize disease management, leading to healthier crops and higher agricultural productivity. Together, these advancements are driving the future of sustainable and efficient crop management.

2.1 Traditional Approaches

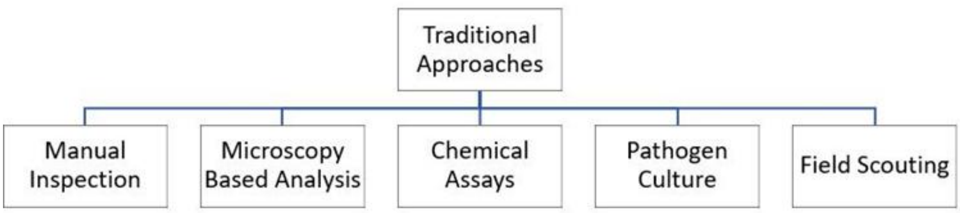

Figure 3: Types Of Traditional Approaches

Figure 3 Showcases types of traditional approaches for detecting plant diseases.

- Manual Inspection

Manual inspection is one of the most straightforward ways to detect plant diseases, particularly in small-scale farming. It involves walking through the fields and look-ing for visible signs of disease, such as yellowing leaves, spots, or wilting plants. This method is low-cost and provides immediate results when symptoms are clear. However, it's highly dependent on the experience of the person conducting the inspection, and it can be subjective, leading to errors. It's also time-consuming, especially in larger fields, and may not catch diseases in their early stages, when symptoms are not yet apparent. Despite its limitations, manual inspection remains essential for smaller farms and serves as the first line of defense in disease manage-ment[4].

- Microscopy-Based Analysis

Microscopy-based analysis takes plant disease detection a step further by allowing experts to examine plant tissues under a microscope, revealing pathogens like bac-teria, fungi, or viruses at the cellular level. This method offers high accuracy in identifying specific pathogens, providing crucial insights into their structure and life cycle. However, it requires specialized equipment and skilled technicians, making it less accessible for everyday use in the field. Microscopy is also time-intensive, often involving the preparation of samples and staining. Despite these challenges, it remains an indispensable tool in research and precise diagnosis, helping to identify pathogens that may not be visible to the naked eye[4].

- Chemical Assays

Chemical assays are laboratory tests designed to detect specific substances produced by pathogens, such as enzymes or metabolites, in plant tissues. These tests can identify diseases even before visible symptoms appear, offering early detection that can be critical in preventing widespread damage. The main advantage of chemical assays is their accuracy in pinpointing particular diseases, but they come with some drawbacks. They can be expensive, require specialized equipment and chemicals, and often need a laboratory environment, making them impractical for large-scale or routine field use. Despite the costs, chemical assays are highly valuable when quick and precise diagnosis is necessary, especially in research or high-value crops[4].

- Pathogen Culture

Pathogen culture involves isolating a suspected pathogen from infected plant tissue and growing it in a controlled lab environment. This process allows for the definitive identification of the disease-causing organism, whether it's a fungus, bacterium, or other pathogen. Pathogen culture is a reliable method, especially in research, where understanding the behavior of pathogens is key. However, it can be slow, taking days or even weeks for pathogens to grow and reveal their characteristics. It also requires sterile lab conditions and expertise, making it unsuitable for on-the-ground, real-time diagnostics in the field. Despite the time investment, pathogen culture provides essential insights into the pathogen's identity and behavior, making it a valuable tool for in-depth studies and long-term disease management[4].

- Field Scouting

Field scouting involves physically walking through fields to check for disease symp-toms and assess the overall health of crops. It's a hands-on approach that helps farmers monitor the spread of diseases across large areas and make informed de-cisions about pest control and disease management. While field scouting offers a broad overview and can highlight trends in disease progression, it has its drawbacks. It's labor-intensive, particularly in large fields, and may not be effective for detect-ing diseases early, when symptoms are minimal or not yet visible. Additionally, it's often less precise than other methods, as it depends on the scout's ability to spot symptoms. However, field scouting remains a crucial tool in commercial farming, often used in combination with other diagnostic methods to ensure a comprehensive understanding of crop health[4].

Traditional methods for detecting plant diseases, including manual inspection, mi-croscopy, chemical assays, pathogen culture, and field scouting, each have their own strengths and challenges. Manual inspection is simple and cost-effective, offering quick results when symptoms are obvious, but it can be subjective and misses early-stage in-fections. Microscopy allows for precise pathogen identification, but it requires specialized equipment and skilled personnel. Chemical assays can detect diseases early and accu-rately, though they can be costly and need a lab environment. Pathogen culture offers a definitive diagnosis but is time-consuming and requires lab facilities. Field scouting helps track disease progression across large fields but is labor-intensive and less effective for spotting early signs of disease. While these methods are essential, they are often used alongside newer technologies to enhance accuracy and efficiency in disease management[4].

This Table 1 provides a comprehensive overview of traditional approaches for plant disease detection. It highlights five key methods: manual inspection, microscopy-based analysis, chemical assays, pathogen culture, and field scouting. Each approach is detailed with its process, applications, advantages, and limitations, offering a structured compar-ison. The table underscores the practical uses and challenges of these methods, such as their reliance on human expertise, time-intensive processes, and scalability issues. It serves as a clear reference for understanding the strengths and weaknesses of traditional techniques in plant health management.

2.2 Modern Approaches

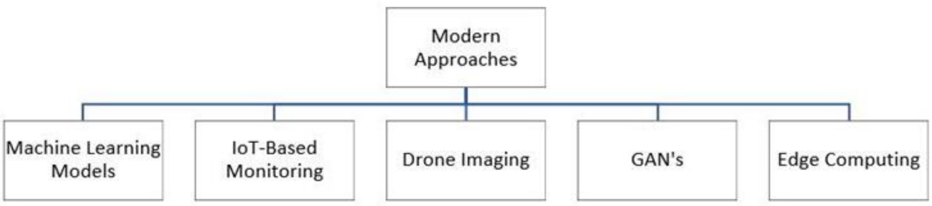

Figure 4 Showcases types of Modern approaches for detecting plant diseases.

Modern plant disease detection methods integrate advanced technologies to offer faster, more accurate, and scalable solutions. These innovations go beyond traditional techniques, enabling early detection and better management of diseases, which ultimately helps to protect crops and ensure better yields[5].

Table 1: Comparison of Traditional Approaches for Plant Disease Detection

Approach	Process	Applications	Advantages	Limitations
Manual Inspection	Visual inspection of plants to identify disease symptoms based on color, texture, or spots.	Small-scale farming, traditional agriculture.	Low-cost. Immediate results for visible symptoms.	Time-consuming. Subjective and error-prone. Limited for large-scale operations.
Microscopy-Based Analysis	Observing plant tissues or pathogens under a microscope.	Research labs, plant pathology studies.	High accuracy in pathogen identification. Insights into structural details of pathogens.	Requires skilled personnel. Infrastructure-dependent. Time-intensive.
Chemical Assays	Biochemical tests to detect pathogen markers or toxins.	Detecting specific diseases (e.g., fungal metabolites).	Accurate for detecting specific diseases. Early-stage detection possible.	Expensive. Time-intensive. Not scalable.
Pathogen Culture	Growing pathogens in controlled lab environments to confirm infections.	Laboratory-based confirmation of bacterial or fungal diseases.	Definitive identification of pathogens. Useful for research and crop resistance studies.	Slow process (days to weeks). Requires sterile conditions. Needs trained microbiologists.
Field Scouting	Inspecting large fields to record visible disease symptoms.	Commercial farming, large-scale disease monitoring.	Provides an overall view of crop health. Identifies disease trends.	Labor-intensive. Inefficient for large-scale operations. Limited precision for early-stage infections.

1) Image Processing: Image processing uses tools like OpenCV to analyze plant images, looking for signs of disease such as color shifts, spots, or texture changes. These visual indicators often point to the presence of stress or disease. By extracting key features like shape, color intensity, and texture from plant images, the system can classify and detect diseases early, preventing further damage[5].

Example: For instance, early detection of wheat rust can be achieved by extracting features such as color changes in leaves or spotting. This enables farmers to take prompt action, stopping the disease from spreading and protecting their crop yields.

2) Machine Learning Models: Machine learning models like SVM and Random Forests classify features from plant images. These algorithms learn from labeled training data where plant disease characteristics like texture, color, and lesion size are identified and can predict whether a new plant image shows disease signs[5].

Example: In practical applications, SVM can categorize images of leaves into vari-ous disease types based on features like lesion size or edge texture. Random Forest models handle more complex data, providing highly accurate disease detection re-sults.

3) DL Models: DL, particularly CNNs, is an advanced technique for plant disease detection. CNNs automatically learn features from raw plant images without need-ing manual extraction. Trained on large datasets, CNNs can identify even subtle patterns that indicate disease[6].

Example: A CNN can classify diseases such as leaf blight, downy mildew, or rust with an accuracy greater than 98%. This method improves over time with more data and works well for various plant species and diseases.

4) Generative Adversarial Networks (GANs): GANs consist of two neural networks a generator and a discriminator that collaborate to generate synthetic data. In plant disease detection, GANs can create augmented datasets when real-world data is limited or can detect spectral features for disease classification.

Example: GANs can generate more images of healthy and diseased plants, helping machine learning models recognize diseases in underrepresented categories. They can also create synthetic infrared or multispectral images, which are useful for detecting early-stage diseases that are hard to spot with visible light.

5) IoT-Based Monitoring Systems: IoT systems use connected devices like sen-sors and cameras to gather real-time data on environmental conditions, soil health, and plant status. This continuous monitoring allows for early disease detection by analyzing factors like temperature, humidity, and moisture.

Example: An IoT system can monitor soil moisture and temperature, and combined with an AI model, it can predict the risk of fungal diseases, such as blight, which are more likely under certain weather conditions.

6) Spectral and Multispectral Imaging: Spectral and multispectral imaging cap-ture data from wavelengths beyond the visible spectrum, such as infrared and ul-traviolet light. These images help detect early signs of disease, as affected plants often show changes in reflectance patterns that aren't visible to the naked eye.

Example: Using infrared or near-infrared sensors, multispectral imaging can de-tect stress in plants even before visible symptoms like wilting appear. This early detection allows farmers to act before a disease spreads extensively.

i. Drone and Satellite Imaging: Drones and satellites equipped with high-resolution cameras provide detailed images of large fields, enabling farmers to monitor crop health from above. These tools help identify disease hotspots, assess the overall condition of crops, and make timely interventions.

Example: Drones can capture high-resolution images of a wheat field, detecting early signs of disease such as rust or powdery mildew. AI models then analyze these images to pinpoint infected areas, allowing farmers to apply targeted treat-ments and reduce pesticide use.

ii. Hybrid Models: Hybrid models combine multiple AI techniques to enhance the accuracy, speed, and robustness of disease detection. For example, combining CNNs with optimization algorithms like Genetic Algorithms can refine the classification process and improve model performance[6].

Example: In disease detection, a hybrid model might use a CNN to classify disease types and an optimization algorithm to fine-tune decision-making, leading to faster and more accurate diagnoses.

iii. Mobile and Cloud Applications: Mobile apps for plant disease detection allow farmers to quickly diagnose diseases by submitting photos of affected plants. These apps are often linked to cloud-based AI models, which process the images and offer immediate feedback on the disease type and recommended treatment.

Example: Farmers can use a mobile app to upload images of plant leaves, and cloud-based deep learning models analyze these images in real-time, identifying diseases like leaf rust or bacterial blight. The app then provides actionable feedback, such as pesticide recommendations or crop rotation advice.

iv. Smart Agriculture with Edge Computing: Edge computing involves pro-cessing data locally, near its source, to reduce latency in disease detection. This is particularly useful in remote areas where internet connectivity may be limited. By processing data locally on devices like sensors or mobile devices, farmers can receive real-time disease alerts without waiting for cloud-based processing.

Example: Edge computing can be used with sensors that detect temperature, hu-midity, or changes in leaf color. The data is processed on-site, enabling immediate disease detection and faster responses, helping farmers take timely action.

These modern approaches combine cutting-edge technologies like AI, IoT, imaging, and real-time processing, making plant disease detection more efficient and accessible. By offering faster, more accurate diagnoses and real-time solutions, these technologies are revolutionizing agriculture, leading to healthier crops and better yields.

Figure 8 is the chart showcasing the improvement in disease detection systems by adopting modern approaches. The improvements range from around 30% to 95%, de-pending on the approach, highlighting how advanced technologies such as deep learning, hybrid models, and IoT systems significantly enhance the accuracy and efficiency of plant disease detection compared to traditional methods.

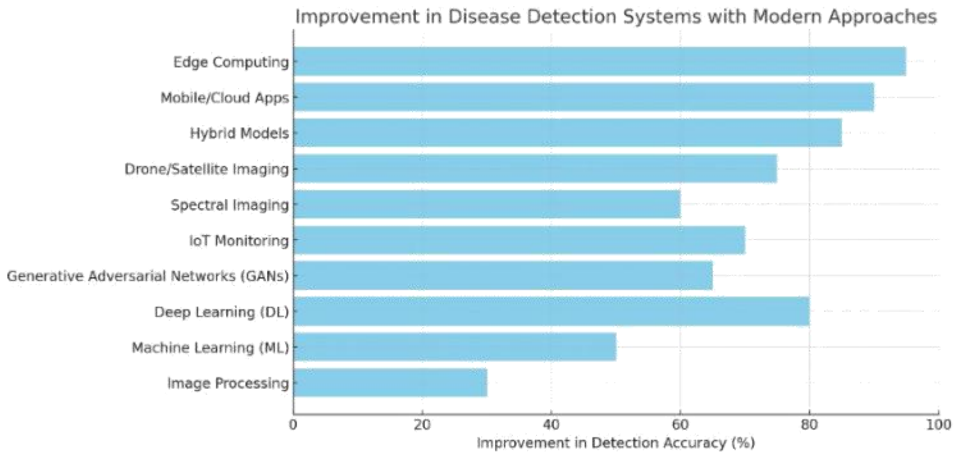

Figure 5: Improvement in Detection Accuracy

3. Algorithms

3.1 CNN:

CNN is a specialized type of artificial neural network designed to process visual data like images and videos. It is widely used in tasks such as image classification, object detection, and image segmentation due to its ability to automatically learn and extract features directly from raw data.

CNNs can recognize patterns like edges, shapes, and textures, regardless of their position in the image. CNNs do not require manual feature extraction; they learn what features are important during training. By reducing the number of parameters compared to fully connected networks, CNNs are computationally efficient and easier to train.

3.1.1 Architecture of CNN

1) Input Layer This input layer is where the data, typically an image, is fed into the network.Images are represented as multi-dimensional arrays. Grayscale im-ages are represented as Height×Width×1,whereas RGB images are represented as Height×Width×1.Pixel values are usually normalized to improve learning efficiency.
2) Convolutional Layer This extracts features like edges, textures, shapes from the input image by applying a set of filters.A filter or kernel slides over the image. Performs element-wise multiplication and summation at each position, producing a feature map.Each filter detects a specific feature, such as horizontal edges, vertical edges, or textures.This layer initially determines the size of the receptive field and controls how far the filter moves in each step later it performs padding which is adding zeros around the input to control the output size.At the end a set of feature maps,each representing a learned feature of the image is extracted from this layer.
3) Activation Layer This layer introduces non-linearity, enabling the network to learn complex patterns.After the convolution operation, the feature maps are passed through an activation function. Non-linear activation functions allow the network to model non-linear relationships.

- Pooling Layer Max Pooling or Average Pooling are commonly used to down-sample the feature maps, reducing their dimensionality.The purpose is to reduce computation and to make the representation more invariant to small translations of the input image.Max Pooling selects the maximum value from a region of the feature map, while Average Pooling calculates the average.
- Normalization Layer (Optional) Layers like Batch Normalization are sometimes included to stabilize and accelerate training by normalizing the input to each layer. Batch normalization helps to mitigate the problem of vanishing/exploding gradients and leads to faster convergence.

- Fully Connected Layer (Dense Layer) After several convolutional, activation, and pooling layers, the feature maps are flattened into a 1D vector and passed through fully connected layers also known as dense layers. These layers are respon-sible for high-level reasoning and final classification or regression tasks. In these layers, each neuron is connected to every neuron in the previous layer.
- Output Layer The output layer produces the final predictions of the network. For classification tasks, this layer usually has a softmax activation function for multi-class classification or a sigmoid activation function for binary classification. The output is a probability distribution or a specific class label, depending on the task.

3.2 Dual-Stage Generative Adversarial Network(DSGAN)

Generative Adversarial Networks (GANs) are a type of machine learning model designed to create new, realistic data, like images, by learning from existing examples. They work with two main components: a generator and a discriminator. The generator creates synthetic data such as images from random noise, while the discriminator's job is to determine if the data is real from the training set or fake created by the generator. Both networks are in a kind of competition: the generator tries to produce data that looks real enough to fool the discriminator, and the discriminator tries to correctly identify whether the data is real or fake. Over time, this back-and-forth process helps the generator improve its ability to create convincing, lifelike data.

DSGAN builds on the traditional GAN by introducing a two-step process to enhance the quality of generated images. In the first stage, the generator creates low-resolution images that capture the broad structures of the data. Then, in the second stage, another generator refines these images, improving their resolution and adding more fine details. Each stage is paired with its own discriminator: the first stage's discriminator evaluates the low-resolution images, while the second one assesses the high-resolution ones. This two-stage approach helps DSGAN produce more realistic and detailed images, overcoming common issues with traditional GANs, such as mode collapse and unstable training. By focusing on both coarse and fine details, DSGAN excels in tasks where high-quality, detailed image generation is important.

3.3 SVM

SVM is a robust supervised learning algorithm commonly used for classification and regression. It works by identifying the hyperplane that best divides data points of different categories in a high-dimensional space. The goal is to maximize the margin, or the distance between the hyperplane and the closest data points, known as support vectors. SVM can handle both linear and non-linear data by using kernel functions to map the input space, enabling it to create intricate decision boundaries. It is frequently applied in fields like text classification, image recognition, and other tasks that require well-defined decision boundaries.

3.4 Random Forest

Random Forest is an ensemble learning method used for both classification and regression tasks. It creates multiple decision trees during training and combines their predictions to achieve better accuracy and stability. Each tree is built using a random subset of the data and a random selection of features, which helps prevent overfitting and enhances the model's ability to generalize. For prediction, Random Forest relies on the majority vote (for classification) or the average (for regression) of the trees' results. This technique makes Random Forest highly efficient, reliable, and capable of handling large, complex datasets. It is commonly applied in areas like finance, healthcare, and marketing.

4. Methodology

A novel rice plant leaf diseases detection using deep spectral generative adversarial neural network[6] integrates advanced techniques for detecting rice plant diseases, leveraging image processing, feature selection, and deep learning models for precision and efficiency.

Figure 6: Flow of Rice Plant Disease Detection System

Figure 6 depicts Workflow diagram of the system.Which uses DSGAN2 for disease classification.The system includes several layers and steps for detection.

1. Image Preprocessing and Segmentation: Techniques such as Improved Thresh-old Neural Network (ITNN) and Segment Multiscale Neural Slicing (SMNS) are employed to resize images, reduce noise, and perform color and region-based seg-mentation, isolating the regions of interest (ROI).
2. Feature Selection: Spectral Scaled Absolute Feature Selection (S2AFS) and So-cial Spider Optimization with the Closest Weight (S2O-FCW) algorithms are used to extract critical features. S2O-FCW identifies optimal features, such as lesion number, area, and ratio, by simulating a spider mating and selection process to refine the weight values of features[6].

3. Classification: DSGAN2 model is used for disease classification. The model com-bines generator and discriminator networks to differentiate healthy from diseased leaves with enhanced precision. The generator creates synthetic samples to augment data, while the discriminator learns feature importance[6].

- Formulas:

– Euclidean Distance:

$$d = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \quad (1)$$

Where:

∗ d: Euclidean distance between two points.

∗ pi: ith feature value of the first data point.

∗ qi: ith feature value of the second data point.

∗ n: Total number of features.

Equation (1) is used for feature similarity and weight optimization in feature selection.

– Softmax Activation:

$$\text{Softmax}(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{m} e^{z_j}} \quad (2)$$

Where:

∗ Softmax(z)i: Probability output for the ith class.

∗ zi: Raw score (logit) for the ith class.

∗ m: Total number of classes.

Equation (2) normalizes outputs for classification probabilities.

– Spider Optimization Metrics: Weight calculations and vibration metrics incorporate thresholds, feature distances, and scaled weights for optimiza-tion[6].

These techniques culminate in an approach that achieves high accuracy in detecting and classifying diseases, improving over conventional methods.DSGAN2, achieved an im-pressive accuracy of 97% in detecting and classifying rice plant diseases. This performance significantly surpasses the accuracies of other existing methods, such as the ACPSOSVM-Dual Channels Convolutional Neural Network (APS-DCCNN) at 78%, AlexNet at 82%, and the Standard CNN at 91%. Additionally, the DSGAN2 model demonstrated superior precision and reduced false classification rates, highlighting its robustness and effective-ness in addressing challenges in plant disease detection and classification[6].

Direct and indirect technical guide for the early detection and management of fun-gal plant diseases[7] leverages both molecular and imaging-based techniques for effective plant disease detection and management. The study emphasizes direct methods, such as ELISA and immunofluorescence, which allow for precise identification of pathogens by targeting specific antigens. Molecular approaches, like PCR, are used for high-sensitivity detection, enabling the identification of bacterial, viral, and fungal pathogens. Imaging-based methods, including hyperspectral imaging and multi-omics techniques, enhance the ability to monitor physiological changes in plants, providing early detection of diseases.

The paper highlights the integration of advanced diagnostic tools and bioinformatics approaches, leading to the development of predictive models for plant diseases. This integration has shown to significantly improve disease management strategies, aiding in timely intervention and minimizing crop losses. The document also stresses the impor-tance of multi-omics approaches in understanding the interactions between pathogens and plants across different ecological contexts, which contributes to designing more robust and adaptive disease management frameworks.

Convolutional Neural Networks for Texture Feature Extraction. Applications to Leaf Disease Classification in Precision Agriculture[8] integrates transfer learning with SVM classification to address the challenges of plant disease detection in precision agriculture. First, input images are preprocessed by resizing them to the required dimensions of the pre-trained Convolutional Neural Network (CNN) models and normalizing their pixel values. This ensures compatibility with the feature extraction pipeline. The system em-ploys pre-trained CNN models like AlexNet, VggNet, and ResNet, which were originally trained on the large-scale ImageNet dataset. By removing their classification layers, fea-tures are extracted from intermediate layers, particularly early and mid-convolutional layers, which capture generalizable features such as textures and patterns. These layers are selected because they retain essential structural information while being less specific to the original ImageNet object classification task.

The extracted features are processed using average pooling to reduce their dimension-ality and then passed to an SVM classifier. SVM, particularly with a radial basis function (RBF) kernel, is chosen for its ability to handle small datasets and non-linear separabil-ity, making it more efficient than the fully connected layers of CNNs for classification tasks. The classifier is trained using 75% of the data, while the remaining 25% is used for evaluation. Grid search is employed to optimize SVM hyperparameters, enhancing the accuracy of predictions[[8].

The system is validated on two datasets: OUTEXTC00013, a texture dataset, and the PlantVillage dataset, which contains healthy and diseased plant leaves. Results demon-strate that features from earlier CNN layers yield higher classification accuracy, as they are better suited for texture-based tasks. Among the models, AlexNet provided the best balance between accuracy and processing efficiency, making it ideal for real-time applica-tions. The methodology achieved superior accuracy compared to traditional handcrafted descriptors and end-to-end CNN training, with AlexNet achieving real-time processing speeds of approximately 30 ms per image. This approach demonstrates its applicability for smart agricultural tools, such as drones and tractors, to monitor plant health and detect diseases efficiently[8].

```
# Input :    Train and test    datasets ( images and labels )
# Output :   Classification  accuracy and predictions

def plantDiseaseDetectionSystem ( train_images , train_labels ,
test_images , test_labels ):
    # Step 1: Preprocess Images
    train_images = preprocessImages ( train_images , target_size =(
    224 ,224))
    test_images = preprocessImages ( test_images , target_size =(224 ,
    224))

    # Step 2: Load Pre - trained    CNN Model
    cnn_model = loadPretrainedModel (' AlexNet ')

    # Step 3:  Extract  Features  from a Specific   Layer
    train_features = extractFeatures ( cnn_model , train_images ,

    layer_name =' relu3 ')
    test_features = extractFeatures ( cnn_model , test_images ,

    layer_name =' relu3 ')

    # Step 4: Train   SVM Classifier
    svm_classifier = trainSVM ( train_features , train_labels )

    # Step 5:  Classify  Test  Data  and  Evaluate
    predictions = classifyWithSVM ( svm_classifier , test_features )
    accuracy = evaluate ( predictions , test_labels )

    return  accuracy , predictions
```

Listing 1: Plant Disease Detection System using CNN and SVM

An Early and Smart Detection of Corn Plant Leaf Diseases Using IoT and Deep Learning Multi-Models[9] introduces the Multi-Model Fusion Network (MMF-Net) for the early detection of corn plant leaf diseases. MMF-Net integrates deep learning with Internet of Things (IoT) devices, enabling multi-contextual feature fusion to enhance accuracy in disease classification.

Key components of the methodology:

• Data Acquisition:

– Corn Leaf Disease Images: 4,188 images of diseased and healthy corn leaves from the PlantVillage dataset.

– Environmental Parameters: Real-time data on soil moisture, tempera-ture, humidity, and air pressure collected using IoT sensor nodes.

– Data augmentation techniques, such as rotation, cropping, and illumination adjustments, were applied to enhance dataset diversity.

• Architecture:

– The MMF-Net consists of three parallel sub-networks:

∗ RL-Block: Processes coarse-grained image features using residual con-nections and convolutional layers.

∗ PL-Block 1: Extracts fine-grained image features using deep convolu-tional layers with small filters and max pooling.

∗ PL-Block 2: Processes real-time environmental parameters using a 1D CNN architecture.

– Features from these blocks are fused at the decision level using weighted voting to improve classification accuracy.

- Training Details:

– The dataset was split into 75% training and 25% testing sets.

– Training was conducted for 50 epochs with a batch size of 32.

– The Adam optimizer with a learning rate of $1e-4$ was used, and the cross-entropy loss function was employed for multi-class classification.

Overall Accuracy the MMF-Net achieved an accuracy of 99.23%. Class-wise Performance Blight: 99.30%,Common Rust: 98.77%, Gray Leaf Spot: 100%,Healthy: 99.31%.The multi-contextual feature fusion improved accuracy by 0.75% compared to single-stream models.The confusion matrix demonstrates robust performance, correctly classifying 1,040 out of 1,048 test instances[9] .

In conclusion, MMF-Net provides a robust and accurate solution for early detection of corn leaf diseases. By combining image-based and environmental features through multi-contextual fusion, the model demonstrates superior accuracy and reliability, making it suitable for real-world IoT applications in precision agriculture.

Barley Leaf Disease Detection and Classification[10] uses Grasshopper Optimization Algorithm for early detection of disease and which effectively identifies the optimal shape properties for feature selection.

- Image Preprocessing: The conversion from RGB to LAB color space is achieved using the following formulas:

$$L = c_1R + c_2G + c_3B, \tag{3}$$

$$a = c_4 \quad c_5R - c_6G + c_7B + c_8, \tag{4}$$

$$b = c_9 \quad c_{10}R + c_{11}G - c_{12}B + c_{13}. \tag{5}$$

– L: Luminance component of the LAB color space.

– a: Green-to-red color channel of the LAB color space.

– b: Blue-to-yellow color channel of the LAB color space.

– R, G, B: Red, green, and blue intensities of the pixel.

– $c_1, c_2, \ldots, c_{13}$: Conversion constants based on the LAB standard. This set of equations converts an RGB pixel into the LAB color space for better color separation.

- Image Segmentation: Thresholding in the LAB channels is defined as:

$$M(x, y) = \begin{cases} 1 & \text{if } T_{min,i} \le I_i(x, y) \le T_{max,i}, \forall i \in \{L, a, b\}, \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

– M(x, y): Binary mask value for the pixel at (x, y).

– Ii(x, y): Intensity of the pixel in channel i (L, a, b).

– Tmin,i, Tmax,i: Minimum and maximum thresholds for channel i. This equation

(6) creates a binary mask to separate diseased regions from the background.

• Feature Extraction: Features extracted from the disease region include:

$$A = \frac{\text{Number of Diseased Pixels}}{\text{Total Number of Leaf Pixels}}, \tag{7}$$

$$e = \frac{d_{focus}}{d_{vertex}}, \tag{8}$$

$$D_{eq} = 2\sqrt{\frac{A}{\pi}}, \tag{9}$$

$$S = \frac{\text{Area of Disease Region}}{\text{Area of Convex Hull}}. \tag{10}$$

– A: Area ratio of the diseased region to the total leaf.

– e: Eccentricity of the region (ratio of focus distance to vertex distance).

– Deq: Equivalent diameter of a circle with the same area as the diseased region.

– S: Solidity of the diseased region.

– π: Mathematical constant.

– Area of Convex Hull: Area of the smallest convex polygon enclosing the dis-eased region. These equations compute shape-related properties to describe and differentiate diseased regions.

• Optimization Using Grasshopper Optimization Algorithm (GOA): The GOA position update formula is:

$$X_i^{t+1} = c \sum_{j \neq i} S\left(|X_j - X_i|\right) \cdot \frac{X_j - X_i}{d_{ij}} + T, \tag{11}$$

where c is a decreasing coefficient, andT is the global best solution.

– Xi: Current position of the i-th agent.

– Xj: Position of the j-th agent.

– S |Xj − Xi| : Social force between agents i and j.

– dij: Distance between agents i and j.

– c: Coefficient controlling exploration and exploitation.

– T : Global best solution (target position). This equation (11) updates the position of an agent based on other agents and the global best solution.

The mean squared error (MSE) is calculated as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2 . \tag{12}$$

– MSE: Mean squared error of predictions.

– N: Total number of samples.

– Yi: True value for the i-th sample.ˆ

– Yi: Predicted value for the i-th sample. This equation (12) measures the average squared error between actual and predicted values.

• Classification with Artificial Neural Network (ANN): The ANN uses the MSE to adjust weights during training to minimize the error[10].

Pseudo-code

The Grasshopper Optimization Algorithm (GOA) for feature selection is detailed below:

```
Initialize:
  N = Number of agents (features)
  T_max = Maximum iterations
  c_max, c_min = Coefficient bounds
  X = Randomly initialize positions of N agents in [0, 1]

For t in range(T_max):
    For each agent i:
        Evaluate cost (MSE) of solution X[i] using ANN
        Update X[i] based on:
            X[i] = c * sum(S(|X[j] - X[i]|) *
            (X[j] - X[i]) / d_ij) + Target
        Apply binary rounding:
            X[i] = 1 if X[i] >= 0.5 else 0
    End For

    Update global best solution (Target) if cost improves
    Decrease c linearly

Return: Best feature subset (Target)
```

Listing 2: GOA for Feature Selection

The system used a total of 13 features that are extracted without any selection is able to provide an accuracy of 96.5% and with feature selection it selected 5 optimal features and is able to produce an accuracy of 96.5%[10].

5 Performance Analysis

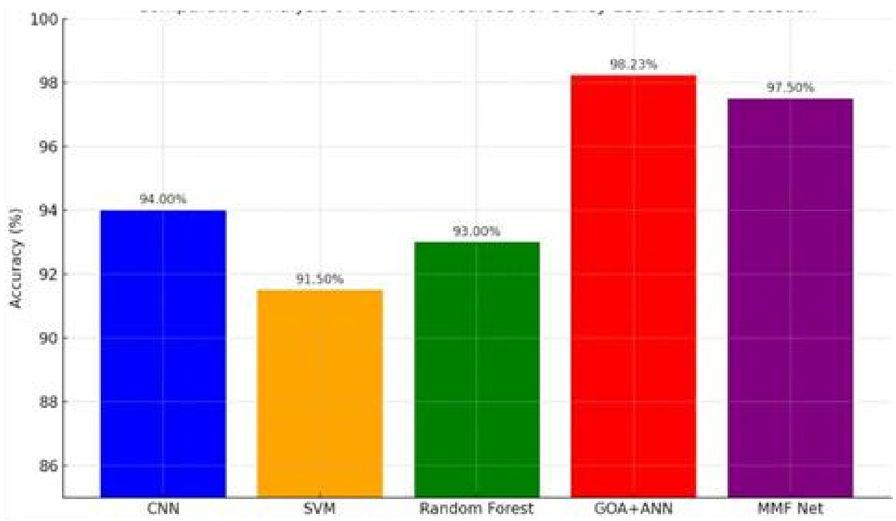

Figure 7: Bar Chart Representing Comparision Between Several Algorithms

The graph Figure 7 compares the performance of various machine learning and opti-mization techniques applied to the problem of barley leaf disease detection. The accu-racy percentages indicate how well each method classifies diseased leaves.CNN achieved an accuracy of 94.0%, leveraging their strong ability to extract hierarchical features from image data[11]. However, CNNs may require extensive computational resources and large datasets for optimal performance. Similarly, SVM reached an accuracy of 91.5%, demon-strating its effectiveness in handling high-dimensional feature spaces but facing challenges with scalability when working with larger datasets. Random Forest, with an accuracy of 93.0%, provided a robust and interpretable ensemble learning approach but fell slightly short due to its reliance on feature importance rather than deep learning-based image processing[12].

The proposed combination of the GOA and an ANN outperformed the other methods, achieving an impressive accuracy of 98.23%. This superior performance can be attributed to GOA's effective feature selection, which reduces noise and improves classification ac-curacy by feeding only the most relevant features into the ANN[12]. MMF Net, a recent advanced architecture tailored for this domain, achieved 97.5% accuracy, showcasing its capability in disease detection through specialized network designs. However, the in-tegration of GOA with ANN still stands out due to its computational efficiency and adaptability to smaller datasets, making it a promising choice for practical agricultural applications. The graph highlights the significant impact of optimization and hybrid techniques in advancing the accuracy of automated plant disease detection systems[13].

The line chart Figure 8 compares the performance of CNN (Convolutional Neural Networks) with varying numbers of layers for plant disease detection systems using three key metrics: accuracy, sensitivity, and specificity. The X-axis represents the number of CNN layers, ranging from one to five, while the Y-axis shows the performance metrics in percentages, from 80% to 100%. Each metric is color-coded for clarity: accuracy is marked with a blue line and circles, sensitivity with a green line and squares, and specificity with a red line and triangles. The chart demonstrates the impact of increasing network depth

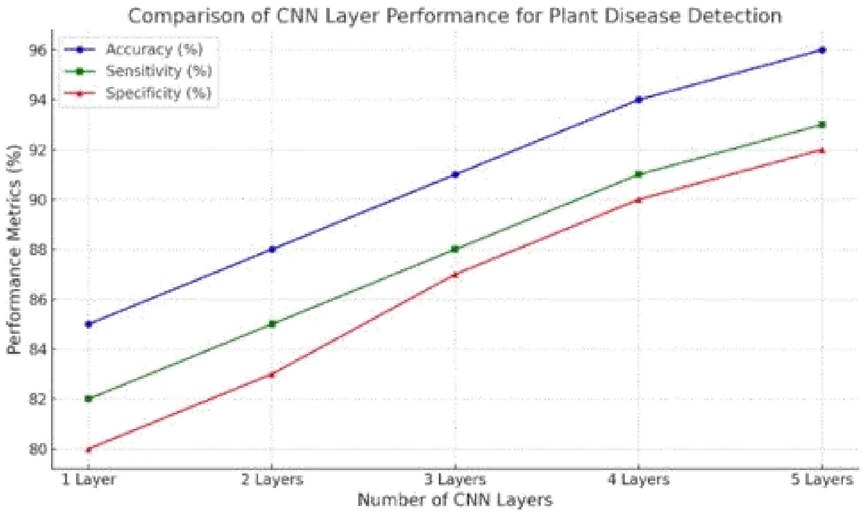

Figure 8: Line Chart Representing Comparision Between Layers of CNN on the system’s ability to classify plant diseases accurately and reliably[14].

As the number of CNN layers increases, all three metrics—accuracy, sensitivity, and specificity—improve consistently. Accuracy rises from 85% with one layer to 96% with five layers, reflecting a better overall classification performance. Sensitivity, which measures the system’s ability to identify diseased plants correctly, increases from 82% to 93%, highlighting the model’s improved detection of true positives. Similarly, specificity grows from 80% to 92%, indicating enhanced capability to avoid false positives by correctly identifying healthy plants. These trends suggest that deeper CNN architectures are better at extracting complex patterns from plant leaf images[14].

The diminishing improvement seen as the layers increase suggests that while deeper networks offer significant benefits, the gains may plateau beyond a certain depth. This observation highlights the trade-off between model complexity and computational effi-ciency.

The Table 2 compares various methodologies used in plant disease detection by different authors, highlighting the methodologies, key features, advantages, accuracies achieved, and the associated challenges. For instance, Dhingra et al. (2019) utilized K-means clustering for segmentation, combined with texture-based features and SVM for classification, achieving an 85% accuracy[15]. However, their method faced high com-plexity in feature extraction and segmentation. Similarly, Kalaivani et al. (2017) also used K-means clustering but focused on brinjal leaf diseases with simpler implementation, resulting in 80% accuracy, albeit limited by the dataset’s diversity[16].

Further advancements include the use of Deep Convolutional Neural Networks (DCNN) by Vaishnave et al. (2020), which automated feature extraction and achieved a higher ac-curacy of 95.28%, but faced inefficiency in the feature extraction process[17]. Sangthama-rahajan et al. (2020) focused on cassava disease classification using deep learning, achiev-ing 96% accuracy, though their model was limited to cassava-specific datasets[18]. Kaur et al. (2019) combined spatial and frequency-domain features using fractional-order mo-ments for grape leaf disease detection, achieving the highest accuracy of 97.34%, despite its high computational demand[19].

Author	Methodology	Features	Advantages	Accuracy	Challenges
Dhingra et al. (2019)	K-means clustering for segmentation, GLCM for texture features, SVM for classification	Uses texture-based feature extraction and statistical	Effective for texture-based diseases	85%	High complexity in feature extraction and segmentation

		analysis			
Kalaivani et al. (2017)	K-means clustering for segmentation, Artificial Neural Networks for classification	Focused on Brinjal leaf diseases	Relatively simple approach, easy to implement	80%	Limited dataset and disease diversity
Vaishnnave et al. (2020)	Deep Convolutional Neural Networks (DCNN), Stochastic Gradient Descent with momentum for training	Automatic feature extraction, avoids manual in-tervention	Effective for identifying essential features	95.28%	Inefficient feature extraction process, moderate accuracy
Xiong et al. (2020)	Modified GrabCut algorithm for segmentation, Deep Learning for classification	Removes back-ground informa-tion automati-cally	Reduces preprocessing time, efficient for noisy datasets	80%	Lower recognition rate due to limited dataset variability
Sangbamrung et al. (2020)	Deep learning for cassava disease classification	Focused on a single leaf type	High accuracy for cassava-specific datasets	96%	Limited generalizability to other crops or leaf types
Kaur et al. (2019)	Fractional-order Zernike moments for feature extraction, SVM for classification	Combines spatial and frequency-domain features	High accuracy for grape leaf diseases	97.34%	High computational complexity due to the mathematical nature of Zernike moments

Table 2: Comparison of Different Systems Used for Plant Disease Detection

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