Conventional and Computer Aided Methods for Citrus Disease Detection using Image Processing and AI: A review

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Abstract: Agriculture was influential since ages in the development of human civilization. It is the basis of our economic structure and depends much on horticulture. Many illnesses can affect the plants grown by farmers in a timely way, therefore improving output. Controlling and eradicating plant diseases will help to avoid their spread and so enable best yields and earnings. Many academics are developing image processing-based approaches to automatically detect diseases. By means of attribute analysis from the leaf or fruit image, images acquired from cameras help to identify and differentiate the type of disease. Lesion features define the several disease categories and enable the system to identify either illness presence or absence. This work presents an analysis for the state of the art techniques in citrus disease detection. This work evaluates several machine-learning models for greening disease and chooses a best solution for system design.

Keywords: Citrus Diseases; Image Processing; Machine learning; Feature vector optimization; Disease detection

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Introduction

Agriculture serve as backbone for boosting economies of the nation worldwide. Especially citrus fruits due to their properties hold the benefits of immunity builder and helps to fight many infections. These citrus fruits affected due to numerous types of diseases thereby resulting in financial losses to the farmers.The early and accurate identification of citrus diseases is essential for effective disease control, minimising financial losses, and ensuring sustainable citrus production. Traditional disease detection methods rely heavily upon laboratory setups for testing and expert knowledge for manual analysis, which can be laborious, time-consuming, and susceptible to human error. Conventional disease detection methods mostly rely on manual assessment by agricultural experts, which is arduous, time-intensive, and frequently prone to human error [1]. The delayed detection and intervention may result in wide spreading of disease and resulting in huge financial losses. There is a need to develop automation-based methods that can firstly detect the disease at early onset, secondly, classify the type of disease and then suggest the preventive measures.

Recent developments in the field of Artificial Intelligence especially machine learning (ML) have made it possible to identify diseases effectively and automatically[2]. The integration of Imaging methods and machine learning methods can detect the disease with high level of accuracy. These models trained effectively are capable of disease prediction based on the unknown input image provided. The models effectively measures and captures the statistical behaviors through image feature extraction and selection mechanism, which makes them capable to predict the category and severity of disease, present in the fruit [3].

The accuracy of machine learning based methods primarily depends upon

- The availability of appropriate dataset,
- high quality images,
- optimized training features.

Feature optimization is crucial for improving the performance of machine learning models by selecting the most relevant variables from image datasets.

By use of feature selection and extraction techniques, one can keep high classification accuracy while improving computing economy. More dependable and interpretable disease detection systems can be developed by means of the integration of machine learning algorithms with better feature selection techniques [4]. This effort intends to provide a machine learning framework combining feature optimization techniques with diagnosis of citrus illnesses. By means of identification of the most discriminative features from citrus leaf images, the suggested method seeks to improve model accuracy and efficiency [5]. To build a consistent sickness detection system, this work investigates several machine learning classifiers, feature selection techniques, and performance evaluation criteria. The findings of the study should improve precision agriculture by offering an automated, scalable, effective method of citrus disease surveillance.

In recent years, machine learning (ML) techniques have surfaced as a potent option for automating and improving citrus disease identification. Machine learning algorithms can precisely detect disease signs in citrus leaves, fruits, and stems utilizing sophisticated image processing, feature extraction, and classification techniques [6]. The incorporation of feature optimization approaches enhances model performance by identifying the most pertinent characteristics, diminishing computing complexity, and improving classification accuracy. This study investigates the utilization of machine learning and feature optimization for the detection of citrus illnesses, with the objective of delivering an effective, scalable, and cost-efficient solution for practical agricultural implementation [7].

Traditional vs. Technology driven methods:

Conventional approaches for detecting citrus diseases predominantly rely on visual examination by farmers and agricultural specialists [8]. Various aspects of detection methods are shown inn figure 1. Listed below are the several limitations associated with traditional diagnosis methods:

- Availability and knowledge of domain expert: Manual detection's accuracy relies on the evaluator’s expertise. Unsuited treatments result from inexperienced staff mistakenly identifying diseases.
- Time-Consuming and Labor-Intensive: Field visits take a lot of time and effort, hence thorough monitoring is difficult.
- Timely Diagnosis: The manual methods are not effective to detect the disease at early onset; the disease may have already spread, reducing treatment effectiveness.
- Laboratory Testing Constraints: Conventional laboratory-based pathogen detection techniques, such polymerase chain reaction (PCR) and enzyme-linked immunosorbent assay (ELISA), are accurate but expensive, labor-intensive, and necessitate specific equipment and expertise.

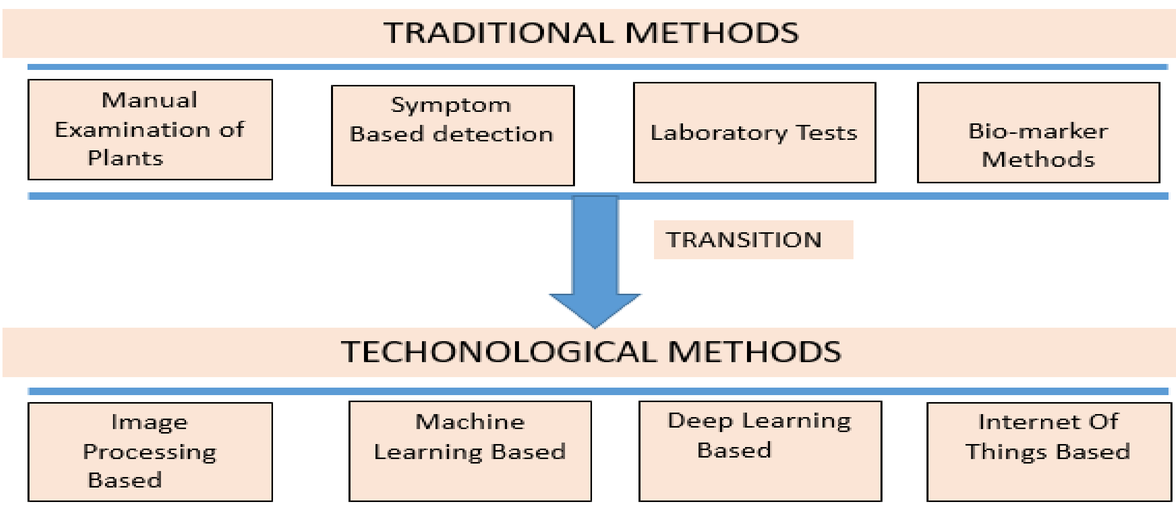

Figure 1.Evolution from traditional to technological methods for Plant disease detection.

On the other hand, machine learning-based approaches have a number of benefits:

- Automated and Scalable Detection: ML models can process large datasets and provide rapid disease identification without human intervention.
- Increased Accuracy and Consistency: By minimizing human subjectivity-related errors, deep learning and feature selection increase classification accuracy.
- Early Diagnosis: ML models can detect diseases in early stages using subtle visual cues, enabling timely intervention [9].
- Cost-Effective and Accessible: Once trained, ML models can run on mobile or edge devices, making them accessible to farmers with minimal technical knowledge.

Table 1 presents parametric based comparison for different methods.

Table 1. Comparison of Traditional and AI based methods

Feature	**Traditional Methods**	**Machine Learning/Deep Learning Methods**
Detection Approach	Visual inspection and lab testing	Automated image analysis and ML models
Expert Dependency	High	Low
Time Consumption	Time-consuming and labor-intensive	Fast and efficient

Scalability	Limited to small-scale monitoring	Scalable for large farms
Diagnosis Timing	Late-stage detection	Early-stage detection
Accuracy	Depends on expertise, prone to errors	High accuracy with optimized features
Cost	Expensive (manual labor, lab tests)	Cost-effective after initial setup
Automation	Not automated	Fully automated and real-time capable
Intervention Speed	Slow due to delays in diagnosis	Rapid due to real-time processing
Adaptability	Limited to predefined symptoms	Can learn and adapt to new diseases

Key Contribution and Motivation of this study

Citrus diseases represent a substantial risk to worldwide citrus industry, impacting both yield and fruit quality. The economic consequences of undiscovered or misidentified diseases can be catastrophic for farmers, resulting in diminished income, heightened production expenses, and interruptions in the supply chain. Conventional disease detection techniques including laboratory testing and hand-searching are inadequate for thorough surveillance and resource-intensive. Moreover, if visible signs show up, the disease might have already spread and will complicate quick management.

Recent advances in image processing, machine learning, and feature optimization provide a promising path to produce exact, scalable systems for citrus disease detection. Using computer vision techniques and deep learning models lets one quite effectively identify diseases early on. Optimizing features reduces noise and improves classification efficiency, hence improving detection performance. Legislators, researchers, and farmers can significantly lower disease outbreaks, boost crop output, and ensure citrus growing's sustainability by applying such a technologically driven method.

This paper studies the existing methods for plant disease detection. Previous section presents a comparison with traditional diagnosis and detection methodologies.

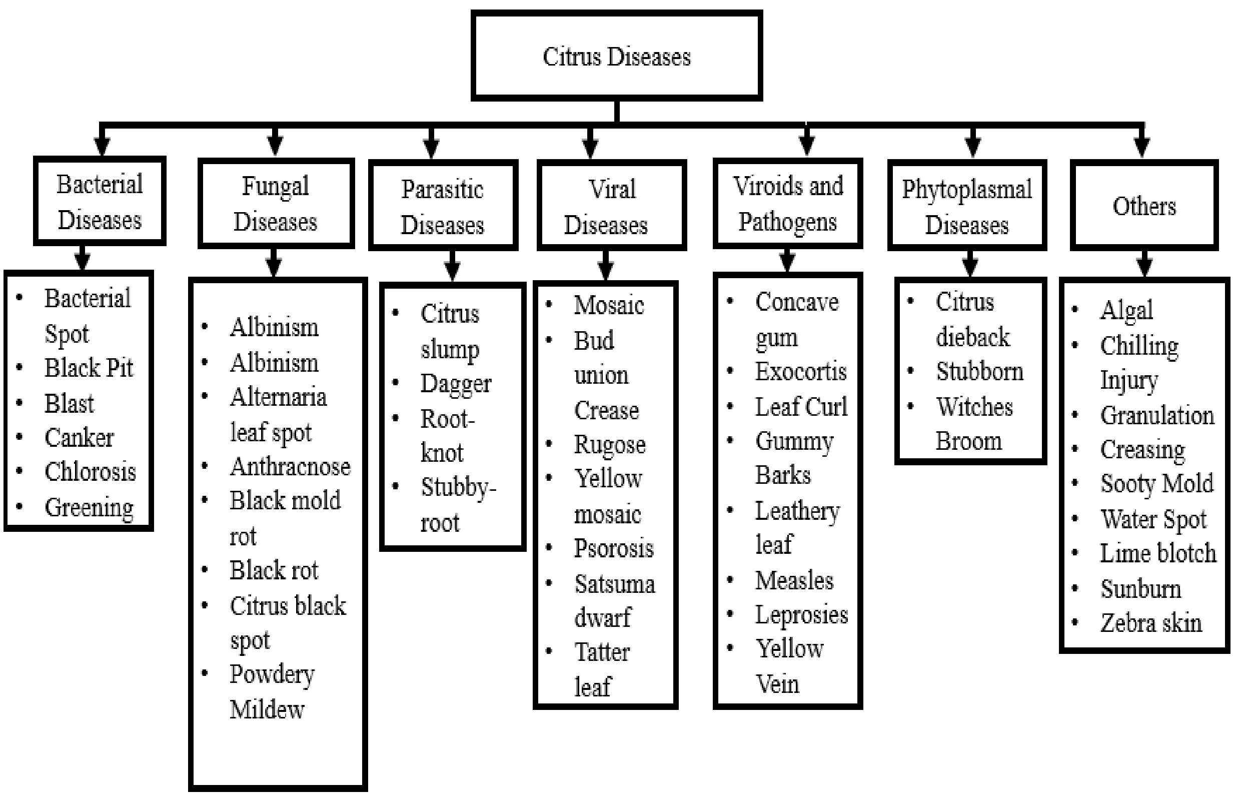

Figure 2.Categorization of Citrus diseases

Method, Study of categories of Citrus Diseases

Citrus diseases are caused by a variety of pathogens, environmental conditions, and pest infestations [10-13]. Understanding their causes, types, and symptoms is essential for effective disease management and mitigation. Figure 2 depicts the detailed categorization of citrus diseases.

Causes of Citrus Diseases

Bacterial Infections: Caused by bacteria such as Xanthomonas spp., leading to cankers and gummosis.

Viral Infections: Spread by insect vectors like aphids, resulting in diseases such as citrus tristeza virus (CTV).

Fungal Pathogens: Includes diseases like citrus black spot and greasy spot, affecting fruit and leaf quality.

Nutrient Deficiencies: Imbalanced soil nutrition can weaken plant immunity and induce symptoms resembling disease.

Environmental Factors: High humidity, poor drainage, and temperature fluctuations create favorable conditions for pathogen proliferation.

Pest Infestations: Insects such as aphids and psyllids transmit diseases and cause direct damage to the plant.

Table 2. Disease types and sample images from dataset

Disease Name	Symptoms	Sample Image [14]
Citrus Canker	Yellow halos as outside borders and inside corky, rough and brownish.	
Greening (HLB)	Yellow lesions bounded by green ribs and veins	
Anthracnose	Brownish spots with diameter greater than or equal to 1.5 mm	
Greasy Spot	Yellow-brown blisters on leaves, premature defoliation.	
Scab Disease	Corky outgrowths on fruit and leaves.	

Research questions for Citrus Diseases detection:

RQ1: What are the prevalent deep learning and machine learning models employed for the classification, detection, and segmentation of citrus diseases?

RQ2: What are the performance differences among various AI models in the classification, detection, and segmentation of citrus diseases, and what evaluation criteria are employed to assess their efficacy?

RQ3: What are the prevalent image processing techniques incorporated into deep learning models for the identification of citrus diseases?

RQ4: What datasets are frequently utilized for training and assessing AI models in citrus disease detection?
RQ5: Which citrus plant problems, such as greening, canker, and black spot, are most commonly examined in the chosen research?
RQ6: What problems or opportunities for enhancement are present in the research on AI-driven categorization, detection, and segmentation of citrus diseases?

The inclusin and exclusion criteria to conduct the research is presented through table 2.

Table 2. Inclusion and exclusion criteria

	Inclusion Criteria	**Exclusion Criteria**
Population	Studies focusing on citrus plants, including common varieties such as oranges, lemons, limes, and grapefruits, targeting diseases like greening disease, black spot, canker, anthracnose)affecting citrus leaves, fruits, or overall plant health.	Studies not focused on citrus plants or those targeting unrelated crops and the studies on citrus diseases that do not impact leaves or fruits (e.g., root-only diseases). Also the studies focusing on biotic and abiotic factors to be excluded.
Intervention	Studies focusing on image-based detection and Artificial Intelligence techniques	Studies focusing solely on hardware solutions and human intervention without computational methods
Comparison	Studies comparing machine learning/deep learning models with traditional image analysis methods or manual disease identification methods.	
Outcomes	Studies reporting accuracy, precision, recall, F1-score, ROC-AUC, or other relevant metrics for evaluating the effectiveness of machine/deep learning models.	Studies not reporting sufficient quantitative results
Study	Original research articles, case studies, and experimental studies and published in peer-reviewed journals or reputable conferences (2020-2025)	Studies not published in English, unpublished theses, Conference abstracts. Studies with less samples(<50).

Detailed Analysis of the state of the art methods:

Many researchers have focused on image-based illness detection by use of convolutional neural networks (CNNs), for feature extraction and classification. Using AlexNet, VGG16, and ResNet among other deep learning models, researchers have accurately classified citrus leaf diseases. Particularly for small datasets, conventional machine learning techniques have been under study. Manual defined attributes from citrus leaf images have been extracted using Random Forest classifiers, k-Nearest Neighbors (k-NN), and Support Vector Machines (SVM). Still, these approaches sometimes call for hand feature engineering, therefore limiting scalability. Table 3 describes the detailed analysis of state of the art methods for Plant disease detection.

Table 3. Comparative analysis of the State of the art methods

Year/ Author	**Method**	**Dataset**	**Key Contributions**	**Performance Metric**
2025/Butt et al. [15]	Fusion of Alexnet and Densenet followed by optimized feature selection	7500 images of both leaf and fruit part with 7 classes of disease	Optimal feature selection using meta heuristic followed by serial fusion	Accuracy=99.9%

2025/ Syed et al. [16]	Employing non-destructive X-ray techniques to assess mandarin orange quality	X-ray of 280 citrus fruits	Hierarchical fruit classification was performed by embedding CNN blocks with transfer learning models	Accuracy=98.07%
2024/ Islam et al. [17]	Employed two deep learning models, InceptionV3 and VGG16, to classify images of citrus leaves affected by diseases such as black spot, greening, canker, and melanoses	Citrus disease image dataset with 4 different diseases	Demonstrated that the InceptionV3 model outperforms VGG16 in detecting citrus leaf diseases	Accuracy= 99%
2024/Yadav et al. [18]	Employed convolutional neural network (CNN) generated features from hyperspectral images, combined with machine learning classifiers such as SoftMax and support vector machines (SVM)	Hyperspectral images of citrus fruits and leaves affected by diseases such as citrus black spot and canker	Demonstrated the effectiveness of combining CNN-based feature extraction with machine learning classifiers for accurate disease classification in citrus fruits and leaves	Accuracy=95.0%
2024/Saini et al. [19]	Self-Attention Dilated Convolutional Neural Network (SADCNN) for disease segmentation; Restricted Boltzmann Machine (RBM) optimized by Self-Adaptive Coati Optimization (SACO) algorithm for classification	Conghua Citrus Leaf 2020 (CCL'20) dataset, containing images of healthy and diseased citrus leaves	Introduced a hybrid model combining SADCNN for segmentation and SACO-optimized RBM for classification, effectively categorizing diseases into anthracnose, melanose, and brown spot	Accuracy= 99.7%

2024/Zhang et al. [20]	Proposed a hybrid attention network combining spatial and channel attention mechanisms to enhance feature representation	A citrus disease dataset in orchard background with 5 different disease	Introduced a novel hybrid attention network that improves the model's ability to focus on relevant features for disease identification	Accuracy= 98.83 %
2024/Zhu et al. [21]	Multi-Models Fusion Network (MMFN) combining transfer learning with model fusion	Integrated dataset with more than 3000 images	Introduced a hybrid model integrating transfer learning and ensemble algorithms for enhanced disease classification accuracy	Accuracy=99.72%
2023/ Barman et al. [22]	Support Vector Machine (SVM) with various kernels (Linear, Gaussian, Polynomial)	Public dataset(Citrus ID) with 6 different diseases	Proposed an SVM-based classification method for categorizing citrus diseases using image processing techniques	Accuracy=79.7%
2023/Neves et al. [23]	Combined fluorescence imaging spectroscopy (FIS) with a convolutional neural network (AlexNet) for feature extraction and classification	Fluorescence imaging spectroscopy data of citrus leaves affected by diseases such as citrus canker and Huanglongbing	Demonstrated that combining FIS with a CNN can effectively identify and differentiate between various citrus diseases, offering a rapid and cost-effective alternative to traditional methods	Accuracy=95.0%

2023/ Challagundla et al. [24]	Image embedding performed using pre-trained CNN models; classification using machine learning models including Random Forest, KNN, Gradient Boosting, SGD, and Neural Network with 5-fold cross-validation	Citrus disease image dataset with 4 different diseases with 759 images	Proposed a hybrid approach combining deep learning-based image embedding with traditional machine learning classifiers for effective citrus disease detection	Accuracy= 96.6%
2022/Aljahdali et al. [25]	Minimum Redundancy Maximum Relevance (MRMR) feature selection combined with machine learning classifiers	2 different datasets	Proposed a hybrid feature development approach integrating MRMR for feature selection to enhance disease detection accuracy	Accuracy= 99.4%
2021/Negi et al. [26]	Convolutional Neural Networks (CNNs)	Dataset with 5 different diseases	Proposed a two-stage CNN-based approach for classifying citrus diseases, focusing on diseases such as Canker, Black spot, Greening, Scab, and Melanose	Accuracy= 91.2%

Conclusion

Using machine learning to identify citrus diseases has become a feasible approach to increase agricultural output and minimize financial losses. Emphasizing numerous machine learning techniques—classical classifiers, deep learning architectures, hybrid strategies—used for the exact identification of citrus diseases—this review has focused on Data scarcity, class imbalance, and real-time implementation remain major obstacles even if feature extraction, image processing, and model optimization have made great advances possible.

Future studies should focus on developing more generalizable and durable models able to operate efficiently under many environmental conditions. Citrus disease detection systems' dependability and scalability could be enhanced by including advanced deep learning architectures, explainable artificial intelligence techniques, and real-time monitoring systems. Moreover, training models competent in handling real-world complexity will depend on the development of large, diverse, and annotated datasets. Considering the study presented, citrus disease detection driven by computer-aided diagnosis presents great potential for precision agriculture. Still, continuous multidisciplinary study combining computer vision, agronomy, and artificial intelligence is crucial to improve these technologies and ensure their efficient application in practical agricultural environments.

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