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Crop Disease Detection Systems: Techniques, Challenges and Trends

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***Abstract*— Early and accurate detection and diagnosis of diseases in crops is critical to ensuring global food supply, reducing agricultural losses and increasing agricultural productivity. Traditional methods, such as manual by visual professionals, are time-consuming, subjective and very easily made wrong. Due to the developments in recent technologies such as ML, DL, IoT and image processing, there has been a significant change in the crop disease detection domain. Considering that early and correct diagnosis of the diseases of a plant from multi-modal data sources, including leaf images, environmental factors, and remote-sensing images, is crucial, such approaches are designed to assist to provide timely and accurate prediction. In this paper, give a complete review on the state-of-the-art in detecting crop disease using images, sensors and both of them. It also includes a commentary on the relative effectiveness of the approaches, examining their specific outcomes, constraints and suggestions. Meanwhile the paper also shares some lessons-learned and bottlenecks when deploying state-of-the-art algorithms in practice based on the practical application with limited datasets and generalizability of models. The paper concludes by proposing some potential ways forward to achieve scalable, generalizable, farmer led implementation of such solutions.**

***Keywords*— Crop Disease Detection, Deep Learning, Image Processing, Smart Agriculture, Internet of Things (IoT), Precision Farming.**

I. INTRODUCTION

Agriculture forms a sine qua non of many economies, which in turn underlies the income base for billions of people while facilitating cross country flow of food. One of the primary risk factors faced by agriculture is crop disease, which can lead to significant loss in yield and quality as well as reduce market access for food. Plant diseases cause 40% crop losses annually and are responsible for the world wide economic loss and shortage of food [1]. therefore, timely and precise diagnosis of these diseases is essential to prevent such loss.

Conventional techniques to diagnose crop diseases are through visual examination by a farmer or agricultural extension officer. Although people with specific knowledge are usually able to diagnose diseases fairly accurately, such expertise is not always available and may be quite limited in the more remote and less developed areas. Additionally, visual symptoms are not always symptomatic and may occur only in late stage of the disease, which hampers the timely application of intervention strategies [2].

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A. Evolution of Technological Approaches

In response to limitations of empirical methods, solutions not empirically driven are sought for by researchers and developers. The rise of artificial intelligence (AI), machine learning (ML), computer vision and wireless sensor networks has greatly facilitatated the field of automated crop disease detection. These technological solutions and several others offer numerous advantages:

- High accuracy and consistency
- Capability of real-time monitoring
- Automation and scalability
- Lowering labour and workmanship expenses

This is where machine learning models can be trained on large datasets of plant images to detect these subtle patterns and signs that are difficult, or in some cases impossible to see with the human eye. In particular, powerful deep learning networks such as Convolutional Neural Networks (CNN) can learn discriminative image features automatically and have achieved superior performance for disease classification over various plant species [3].

In addition to these image-based approaches, sensor systems based on the Internet of things (IoT) which sense environmental parameters such as humidity, temperature and soil moisture are used for mapping plant health and predicting disease before visible symptoms degrade quality 114-4].

B. Data for Detection Types

Contemporary crop disease detection methodologies make use of one or more of the following data types:

- Image Data Types: Visual leaf, stem or whole plant images; Multispectral.
- Sensor Information: It is acquired from IoT devices that monitor the environmental conditions.
- Spectral Information: Obtained through satellite or drone remote sensing.
- Source Data: Field logs, expert annotations, historical records.

Different takes on each type of data. For visible symptoms, image-based data work very well and sensor or spectral data can provide early warnings etc [5].

C. Deep Learning and Image-Based Methods

Of all the technologies, deep learning (DL) has paved the way in this domain. For instance, CNNs automatically learn hierarchical features from raw image data and have been used to diagnose diseases with crops such as tomatoes, potatoes, and wheat including early blight, late blight, powdery mildew, and leaf rust [6,7].

Popular architectures include:

- AlexNet
- VGGNet
- ResNet
- DenseNet
- MobileNet (for lightweight, mobile deployment)

These models can make accurate predictions from signals, in some cases over 98% with controlled settings. Nevertheless, issues like the generalization under real-world conditions and class imbalance remain [8].

D. IoT and Sensor-Based Detection

Disease detection systems based on IoT include a mesh of sensors that are interconnected, to gather data like soil moisture, leaf wetness, temperature and humidity of air together. When they find conditions conducive to disease development these systems alert farmers in real time. For instance, certain temperatures along with high humidity may initiate a risk warning for blister diseases [9].

Such proactive systems can:

- Prevent disease outbreaks
- Optimize pesticide application
- Reduce costs and environmental impact

Some representative applications are installations in vineyards for the monitoring of downy mildew, or greenhouses for tomato disease surveillance [10].

E. Remote Sensing and UAV-Based Systems

Satellites or Unmanned Aerial Vehicles (UAVs/drones) carrying multispectral or hyperspectral cameras are used in remote sensing. Reflectance is measured at several bands by these instruments making early stress detection in plants possible. Methods such as Normalized Difference Vegetation Index (NDVI) are routinely employed in this context [11].

UAV-based detection offers:

- High spatial resolution
- Large area coverage
- Frequent data acquisition

The systems have been proved efficacious in monitoring of wheat rust, rice blast and Maize Streak Virus over different regions [12, 13].

F. Hybrid and Multimodal Systems

Most recent works are devoted to utilizing image data, sensor data and weather data in the same framework. The trust of combined data and the availability will be enhanced in those hybrid systems. Multi-modal deep learning networks that take multiple inputs (images+sensors) have outperformed standard models under adversity [14].

Cloud-based solutions or mobile applications are also under development to make such technologies available in the hands of farmers where disease classification is combined, for example with weather alerts and best practices advises [15].

G. Existing Challenges

B/ Challenges Despite the exciting progress, there are two main challenges for real-world deploy:

Small and homogeneous datasets : Most public available datasets (e.g. PlantVillage) are captured under controlled facilities. There is not good representation of real-field variabilities [16].

Domain Adaptivity: Work done using a model on one crop, disease or geography will not generalize.

Computation and Infrastructure Requirement: Advanced DL models are computationally-intensive, which hinders their application in resource-limited regions.

User Acceptance and Training: Uptake is hinged on the extent to which farmers find the technology user-friendly, cost-effective and trustworthy.

H. Research Motivation and Survey Objectives

In light of the above scenario, this survey seeks:

- Brief the reader on major developments in crop disease diagnosis.
- Classify the technologies based on approach (image/sensors/remote).
- Compare current models with respect to accuracy, computational efficiency and usability.
- Discuss open research issues and future agenda.

II. LITERATURE REVIEW

Crop disease is an emerging hot topic in the field of computer vision, artificial intelligence, remote sensing and agricultural science. This part evaluates in more detail the major contributions in this field divided into four categories: image-based sensor-based approaches, remote sensing approaches and hybrid models reported in Fig. 1 tree chart.

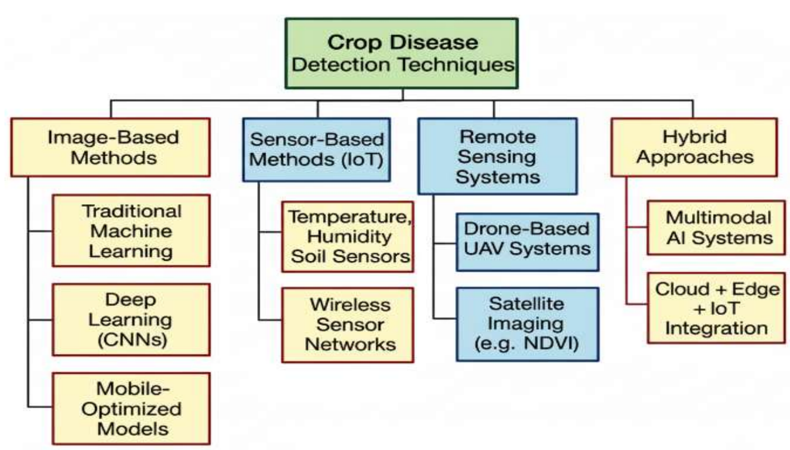

Figure 1. Crop disease detection Tree Diagram.

A. Image-based Disease Detection

Traditional Machine Learning Approaches
Results: Patil and Kumar [1]; and Arivazhagan et al. [2] proved that using handcrafted features (color, texture, shape) and classifiers such as SVM and KNN would result in the accuracies between 80-92% for some diseases in considered environment. Such techniques were relatively efficient computation-wise and did not demand large data.
Limitations: Performance depends greatly on the quality of feature engineering, a laborious and expert-mediated process. These models suffered from considerable generalization loss in lighting, leaf orientation and background clutter and were unable to recognize novel disease strains. They lacked robustness and generalizability.
Solutions: To address these challenges, researchers have started using more sophisticated feature extraction methods such as Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) to gain better invariance. But the inherent bottleneck of manual feature engineering paved the way for deep learning.

Deep Learning Models
Results: Mohanty et al. [3] was a constitutive milestone, since the CNN could be designed to reach almost perfect classification accuracy (> 99%) over large sanitized datasets as PlantVillage. The architectures such as VGGNet, ResNet, and DenseNet [4, 5] successfully learned discriminative features directly from pixels that were not possible to extract into human-made patterns. More recently developed models such as Vision Transformers (ViTs) [6, 30] have achieved better performance in capturing global context of images.
Cons: The main problem is how "brittle" these models are. They perform poorly when tested in real-field environment, and a major factor is that their performance degrades because of domain gap: gap between the background, lighting variability, occlusion residual and camera quality between training images. They are data hungry and need thousands of labeled images per class, as well as being computationally expensive to train.
Solutions: To overcome these difficulties, several approaches have been used:
Data Augmentation: Methods of on-the-fly data augmentation such as namely rotation, flipping, scaling and color jittering to artificially increase dataset diversity and enhance model invariance are adopted [21].
Transfer Learning: By initializing the model from a pre-trained network (for example, trained on ImageNet), large agricultural datasets and training time are no longer essential [5].
Attention Mechanisms: Including attention blocks [28] which enable models to concentrate more on the relevant parts of the leaf (diseased spots) increases accuracy and ease of explanation.
Generative Adversarial Networks (GANs): It apply GANs for synthetic data generation [21] in order to design additional samples from rare disease populations that assist with balancing datasets and ultimately, minimizing model bias.

Mobile and Lightweight Models
Results Architectures such as MobileNetV2, ShuffleNet [7] and EfficientNet have been successfully deployed on mobile devices achieving a good tradeoff between classification accuracy (usually in the range of 90-95%) and processing time. Commercial applications, e.g., Plantix are also examples for the application feasibility of real-time field diagnostic tools with these architectures.
Cons: The models inherent trade-off; having fewer parameters leads to limited representation capacity, when compared with very deep network (e.g., ResNet152). This limitation may cause a significant decrease of performance given complex multi-class disease classification problems.
Solutions: What is being researched to address is architecture search (NAS) for lightweight structures. Moreover, model compression methods such as pruning and quantization are used to make existing models more efficient. These approaches try to adapt architectures according to the limitation of mobile devices and maintain classification accuracy as much as possible.

B. Sensor-based Disease Detection

IoT (Internet of Things)--based sensor networks have been used in crop health observation and prediction of disease outbreaks.

Environmental and Soil Sensors
Findings: The studies of Patel et al. [8] and Chen et al. [9] showed that DHT11 (temperature and humidity sensor) and soil moisture sensors in IoT frameworks can effectively describe microclimatic scenarios which makes it favorable for diseases like powdery mildew and rice blast. These systems showed ability to predict disease-favorable conditions with accuracies between 85% and 93%.

Disadvantages: The major flaw of these systems lies in the manner that they are indirect risk markers, and not direct pathogen finders. They cannot indicate a particular disease-causing agent, but only serve as warnings of conditions favourable to its occurrence. This sensitivity results in heightened risk for false positive alerts. Moreover, such systems rely on an inviolable infrastructure of sensors and communication network data that is also reliable and it is relatively expensive to configure the system in the first place and maintain this infrastructure (with subsequent potential hardware failures).
Solutions: Sensor-based data is typically not utilized in isolation. Best performance is achieved when this modality is combined with others (Hybrid Approaches). For such challenge, the redundancy in sensor networks and low-power, long range (LoRa) communication protocol would help improve reliability and deployment feasibility.

Multisensor Fusion
It is further good in that reliability of detection is improved and false alarm rate minimized. Ghosal et al. [10], who developed a fuzzy logic model by combining temperature, humidity and soil moisture information into a decision-support system (the SAPIRS) for predicting the probability of occurrence of disease. These models enhance prediction accuracy of the disease and lower misuse of pesticides.

C. Remote Sensing and UAV-Based Techniques

R.S.R.Samsul Arefin and M. Hannan Remote sensing gives a flier view of crop health by using satellite or drone or airplane images analyzed with vegetation indices, and spectral profiles.

Satellite Imaging
Results: Satellites such as Landsat-8 and Sentinel-2 have been successfully applied for detecting disease-induced stress at large scale using vegetation indices (e.g., NDVI or SAVI) [11]. Sankaran et al. [11] could reach 85% accuracy to detect wheat rust in a regional level.
Cons: Major limitations are poor spatial resolution (that does not allow early detection of small symptoms) and sensitivity to cloud cover, which can block the image for long periods. The revisit time can also be too long for applications where a fast developing disease is being monitored.
Solutions: Constellations of smallsats (e.g., Planet Labs) with daily revisit times and improved resolution are starting to resolve this issue. Cloud-piercing radar information (SAR) is also under investigation.

UAV and Drone Imaging
Results: Drones equipped with multispectral and hyperspectral cameras were very effective. Athanasiadis et al. [12] and Xie et al. [13] achieved above 90% accuracies for disease detection in olives and in rice. They represent an ideal trade-off between high spatial resolution and large-area coverage.
Cons: It's an expensive operation, you have to buy drones/sensors and hire certified pilots. The data processing itself is complex, and legal restrictions for flight permissions are hurdles. In particular, the analysis of hyperspectral data is highly skilled work.
Solutions: Computer-aided flight paths and automated data processing pipelines are scaling costs down and complexity. The evolution of more user-friendly software that translates imagery into health maps that speak for themselves will be critical for farmer uptake.

D. Hybrid and Multimodal Approaches

Results: This seems to be the most promising way. Khan et al. [14] demonstrated that combining the image data (CNN outputs) with temporal sensor-level representations (LSTM output) outperformed unimodal models and obtained an F1 of 0.93. Cloud based systems [15, 20] use drone imagery, soil data and weather prediction for a comprehensive view.
Cons: The main con is system overhead. It also adds complexity to system design, applica- tion and maintenance due to complicated fusion algorithms in intergraded heterogeneous sources. So the price tag is higher, too.
Solutions: The investigation of simpler and more effective data fusion (e.g., early, late, attention-based) techniques is ongoing. The trend toward modular software architectures makes it easier to integrate diverse data streams.

E. Public Datasets and Benchmarking

There is an urgent need to develop private-public benchmarks. The most popular dataset is PlantVillage [3], which includes more than 50,000 labeled images of diseased and healthy leaves from various crops.

Other datasets include

- AI Challenger 2018 Plant Disease Data [17]
- Rice Leaf Disease Dataset (RLDD) [18]
- PlantDoc (real-field images) [19]

However, such datasets are limited in diversity of lighting conditions, angle and background and cannot generalize well to real world situations.

F. Performance Metrics Used

The following metrics are commonly used for assessing the performance of disease detection systems:

- Accuracy
- Precision, Recall, F1-score
- Area Under Curve (AUC)
- Inference time (for mobile apps)
- Confusion matrix

In real-world applications, precision and recall are typically more important than accuracy alone because of an imbalance between classes (healthy or diseased).

G. Summary of Literature Trends

Table 1 provides a consolidated overview of contemporary literature trends in modern AI solutions, illustrating a clear progression from conventional, low-cost machine learning techniques to advanced hybrid multimodal frameworks that deliver superior accuracy. While deep learning and remote sensing methodologies significantly enhance detection performance, they also introduce challenges related to extensive data requirements, increased computational overhead, and elevated operational costs.

TABLE I. LITERATURE TRENDS AT A CRITICAL GLANCE

Method	Usual Accuracy	Main Results	Limitations	Perspectives on Ambiguity & Unsettled Issues in Emotion-State Measurement
Conventional ML	80–90%	Works well in controlled environments with hand-crafted features; low computational cost.	Poor generalization; expert-dependent manual feature engineering.	Automated feature extraction; use of improved pre-processing pipelines for comparison.
CNN-Fusion Models	90–99% (Lab)	Automatically learns features; provides state-of-the-art performance on curated datasets; captures complex patterns.	Data-hungry; computationally expensive; weak generalization in real-world field conditions (domain shift).	Transfer Learning, Data Augmentation, GAN-based synthesis, Explainable AI (XAI).
Mobile Deep Learning Models	90–95%	Enables real-time on-field diagnosis via smartphone; good speed-accuracy trade-off.	Slight accuracy drop vs larger models; limited complexity due to device constraints.	Neural Architecture Search (NAS), Model Pruning, Quantization, and Edge-optimized designs.
IoT Sensor Systems	85–93%	Continuous monitoring using soil, temperature, humidity and environmental sensors; good for early alerts.	Infrastructure cost; hardware failures; low reliability due to battery constraints.	Improve sensor durability, energy-harvesting systems, hybrid multisensor fusion.
Remote Sensing (Drone)	85–92%	Excellent coverage; early stress detection; suitable for precision agriculture.	High cost; requires trained pilots; limited flight time.	Mini-UAV swarms, autonomous navigation, low-cost multispectral sensors.
Remote Sensing (Satellite)	80–90%	Wide-area coverage; suitable for large-scale crop surveillance; free public data availability.	Coarse spatial resolution; cloud/weather interference.	Higher-resolution satellites, weather-corrected vegetation indices, temporal fusion.
Hybrid Multimodal AI Systems	95–99%	Combines CNN, IoT, weather, and multispectral information; context-aware and noise-robust.	High system complexity; costly deployment; integration challenges.	Advanced multimodal fusion, digital twin agriculture, scalable cloud-edge workflows.

Traditional Machine Learning
These methodologies (SVM and Random Forests) belong to the first computational approaches in disease detection based exclusively on manually extracted features (color, shape, texture). They are easy to calculate and generally have limited ability to scale computationally with complex or multiple corrupting input data.

Deep Learning Approaches
CNN can learn to extract hierarchical features automatically and has been proven effective in image-based disease classification. ResNet, DenseNet, etc. have already raised the bar of classification accuracy close to > 99%, at least for controlled datasets. Their main limitation is heavy training data and GPU requirement.

Mobile-Optimized Models
Models which are light on parameters such as the MobileNet and EfficientNet strike a good balance between performance and speed. They are ideal for use as on-site systems through mobile phones, particularly in remote parts of the world where many farmers live. Although they may be less accurate than larger CNNs, their compactness makes them an excellent choice regarding field use.

IoT-Based Systems
These are designed to incorporate the environmental context and predict exposure to disease in favourable conditions. Fungi, for example, grow in a specific temperature range and humidity level. The advantages are that they control disease actively, but have to be installed and operated properly.

UAV and Satellite Based Remote Sensing
These methods are used to monitor crop health at the macro level. Drones offer better spatial resolution than satellites, and fine details can be detected using DR; however, operational costs are higher. On the other hand, satellite or aerial images, often available in the public domain and at no cost, are useful for wide scale macro surveillance but typically do not carry sufficient resolution to detect early/ subtle signs of stress and disease symptoms in plant.

Hybrid and Multimodal Systems
Such systems integrate a variety of complementary data streams such as images, sensor data or meteorological measurements to provide an omni-sensor detection and prediction capability. This combination increases the strength of these sensors and better accuracy under all conditions. However, the technical challenges for combining such heterogeneous sources and the consequent costs are formidable barriers to broad-based multi-scale implementation.

III. CONCLUSION

The application of advanced computational and sensing technologies has greatly improved the current status of crop disease detection in agriculture. The area from crude image processing methods to advanced multi-modal analytical tools has developed with substantial gains on its accuracy and functional potential. Deep learning has become the underlying approach for image-based diagnosis, while IoT networks is providing the necessary environmental context needed for predictive modeling. However, the present review makes clear that a scaling from high laboratory accuracy to field-deployable robustness still constitutes a major challenge. Among the challenges are over-reliance on curated datasets, computational cost and complexity of integrated cyber-physical systems. Hence more literature attention should be placed on a these other lead factors : 1) marginal increments of accuracy in standard benchmarks begin to converge after which justifying continued model architecture development is difficult, and 2) the typical user must care that code will run in production environment without crashing due to instability.

FUTURE SCOPE

Some of the future work should focus on the following directions: (1) Mining and cleaning various disease-related concepts for each patients from HHP, (2) Considering external knowledge that can help a system detect rare diseases mentioned in documents, and also mine diseases automatically compatible with NGD.

- Federated Learning [22]: The next approach is to train the model in federated style at multiple farms where no sensitive data will be centralized, an essential step for harvesting representative and diverse dataset.
- Explainable AI (XAI) [24]: From black-box models that produce opaque diagnosis and actionable advice, to systems which can be interpreted at least on a high-level in order to obtain the user trust.

- Low-Power Edge AI Devices [23]: More sophisticated hardware/software solutions performing inference at in-field, real-time for overcoming latency and connectivity constrained scenarios.
- Advanced Data Synthesis: Using GANs [21] and digital twins to create high-quality synthetic data of rare diseases and atypical patient's conditions.
- Public Benchmarking: Creating standardized public benchmarks for evaluating the performance of models under realistic field variations such as varied background, lighting and weather conditions.
- Farmer-centered Solutions: Developing user-friendly, multilingual interfaces and setting up diagnostic applications that are integrated into practical advisory services on pest management.

These progresses will be critical for transitioning crop disease diagnostics from a promising technical concept to an openly distributed tool contributing to global food security.

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