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Artificial Intelligence for Crop Health Monitoring: A Comprehensive Review of Deep Learning

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ABSTRACT:

Crop health monitoring must be precise, scalable, and timely due to the increased demand for sustainable food production worldwide. Conventional manual scouting techniques frequently result in delayed treatments and yield losses because they are labor-intensive, subjective, and have limited spatial and temporal coverage. Agricultural monitoring has been transformed by recent developments in deep learning (DL) and artificial intelligence (AI), which allow for automated analysis of massive image and sensor information. Crop diseases, pests, and abiotic stresses can be detected with high accuracy using convolutional neural networks (CNNs), transformer-based architectures, object detection models, generative adversarial networks (GANs), and multispectral/hyperspectral imaging. Even with these achievements, there are still issues with equitable deployment, multisensor data fusion, early-stage detection, and generalization across crops and geographical areas. The state-of-the-art DL techniques for crop disease and stress detection are discussed, their workflows and performance are compared, research gaps are identified, and future directions—such as foundation models, self-supervised learning, explainable AI, drone-satellite data fusion, and low-cost edge AI for farmers—are outlined. The information offered is intended to help researchers and practitioners create reliable, comprehensible, and globally scalable AI-driven crop monitoring systems.

Keywords: Crop disease detection, Deep learning, Hyperspectral imaging, Object detection, Precision agriculture, Vision Transformers.

1. Introduction

1.1 Importance of Crop Health in Global Food Security

Global food production, nutritional security, and agricultural sustainability are all directly impacted by crop health. Global food systems are under tremendous strain due to challenges to crop yields that have increased in recent decades, primarily due to climate instability, rapid disease evolution, and growing abiotic stresses, including drought and soil degradation. According to estimates from the Food and Agriculture Organization (FAO), pests and diseases cause up to 40% of the world's crop yields to be lost each year, seriously disrupting food supply chains and resulting in billions of dollars' worth of financial losses [1]. Therefore, early and precise crop health monitoring is essential to reducing production losses, enabling farmers and policymakers to act before stressful conditions cause permanent harm.

Abiotic stressors linked to climate change, such as temperature swings, harsh weather, and water scarcity, worsen agricultural performance in addition to biotic stressors, including fungal diseases, insect infestations, and viral outbreaks [2]. Farmers can adopt precision inputs, minimize resource waste, and maximize yield outcomes by promptly identifying such stress signals. While effective for small-scale farms, traditional field-based methods are becoming more and more inadequate for big farmlands, varied topography, and geographically distributed agricultural systems [3].

An additional degree of urgency is created by the growing global population. Food production must rise by over 70% to fulfill demand as the world's population is expected to reach 9.7 billion by 2050 [4]. In order to support global food security plans, dependable and scalable crop monitoring frameworks are essential. Understanding crop phenology, identifying stressors, and making data-driven agronomic decisions all depend on continuous, multi-temporal observation of crop conditions, according to recent breakthroughs in digital agriculture [5]. As a result, crop health monitoring is now essential to modern agriculture in order to create resilient, sustainable, and climate-smart food production systems.

1.2 Limitations of Manual Crop Health Detection

Despite being widely used, manual crop scouting has limitations due to its subjective, labor-intensive, and time-consuming nature. In the past, farmers visually monitored fields to spot indicators like wilting, blemishes, discolored leaves, or the presence of pests. However, this strategy is limited by the inability to reliably monitor vast agricultural areas, human error, and variations in farmer expertise [6]. Because subtle physiological changes frequently precede obvious signs, studies show that visual scouting can miss early infection stages, leading to delayed management and considerable yield losses [7].

The temporal and spatial coverage of manual detection is another drawback. There is a greater chance of stress hotspots being unnoticed since human observers are unable to constantly examine large or fragmented fields at high frequencies. Furthermore, pests and diseases move quickly, and even a few days between inspections can increase crop damage throughout entire fields [8]. In situations where eye examination is impracticable, such as inadequate field accessibility, severe weather, or thickly planted crops, manual approaches also fall short.

Subjective bias is introduced by human-dependent assessments, and environmental factors like bad illumination or plant growth density, as well as experience levels and exhaustion, frequently affect the accuracy of diagnoses. The absence of consistency in manual procedures was highlighted by comparative research that showed human inspection accuracy for disease detection to differ by up to 30% between specialists and non-experts [9].

Furthermore, manual techniques are incompatible with the scale of modern agriculture, especially in countries with millions of hectares under cultivation. As farming systems become increasingly mechanized and data-driven, reliance on manual scouting hinders timely decision-making and prevents large-scale adoption of precision agriculture practices [10]. This inefficiency highlights the urgent need for automated, objective, and scalable crop health monitoring solutions.

1.3 Role of Remote Sensing and AI in Scalable, Early Crop Stress Detection

Artificial intelligence (AI) and remote sensing technologies have become revolutionary tools for agricultural surveillance, allowing for quick, extensive, and ongoing evaluation of crop conditions. Sentinel-2, Landsat-8/9, and high-resolution commercial systems are examples of satellite platforms that enable the regular capture of multispectral and hyperspectral data over large agricultural landscapes. Through indices like NDVI, EVI, and red-edge reflectance, these datasets support early stress detection by capturing minute physiological changes in plants that are frequently imperceptible to the human eye [11].

The prediction ability and interpretability of remote sensing data are improved by AI, especially deep learning. By automatically extracting hierarchical spatial-spectral information from satellite data, Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and hybrid deep architectures may accurately classify diseases, pests, nutrient deficits, and water stress [12]. According to recent research, AI-based remote sensing models provide more accuracy and generalization across various crops and meteorological circumstances, outperforming conventional statistical and machine learning techniques [13]. Additionally, remote sensing offers reliable temporal coverage, recording past and current trends that aid in stress progression forecasts. By combining AI with multi-temporal images, early-stage detection—often before visual symptoms manifest—is made possible, minimizing production losses and maximizing the use of resources like pesticides, fertilizers, and irrigation [14].

Another significant benefit is scalability. For national-scale crop monitoring programs and climate-smart agricultural initiatives, remote sensing technologies are perfect since they can evaluate thousands of hectares at once [15]. AI-driven remote sensing systems provide complete decision-support frameworks for precision agriculture when combined with weather data and ground-based IoT sensors. All things considered, the combination of AI and remote sensing is a paradigm change that offers previously unheard-of chances for sustainability, early intervention, and agronomic intelligence at regional and global levels.

2. AI in Agriculture : Overview

Over the past thirty years, artificial intelligence (AI) has revolutionized agricultural systems, progressing from basic rule-driven decision systems to extremely sophisticated deep learning and multi-modal frameworks. Rule-based expert systems, which combined manually created thresholds, logical rules, and symptom descriptions to offer suggestions on pest control, irrigation, and fertilization, were the mainstay of the first computerized agricultural systems in the 1990s [16]. Despite being innovative at the time, these systems were not scalable and were unable to manage complex crop stress patterns or environmental variability. Traditional machine learning models, such as Support Vector Machines (SVM), Random Forests (RF), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN), gained popularity between 2000 and 2010. By utilizing manually created features taken from the textures, colors, and forms of leaves, these models made it possible to classify basic disease signs, identify plant species, and estimate yield [17]. However, while working with large-scale, diversified agricultural datasets, their performance deteriorated due to their reliance on manually created features, which hampered robustness.

The use of deep learning in agriculture after 2014 signified a fundamental paradigm change. Because Convolutional Neural Networks (CNNs) can automatically learn hierarchical features from high-dimensional imagery, they have been widely used for plant disease classification, pest detection, and nutrient disorder diagnosis [8], [18]. More potent designs like ResNet, EfficientNet, DenseNet, and, more recently, Vision Transformers were created as a result of subsequent developments, and they have shown state-of-the-art accuracy in crop stress detection across a variety of crops and climates [19].

Four main categories can be used to broadly classify AI applications in agriculture today:

A. Systems Based on Images (RGB & Drone Imagery)

Real-time evaluation of pests, illnesses, and anomalies in the canopy is made possible by high-resolution drone and ground-based imaging. Early identification of localized diseases and fine-scale crop variability is made possible by drones with RGB or multispectral sensors, which provide centimeter-level spatial resolution [20].

B. Systems Based on Satellites (NDVI, Multispectral, Hyperspectral)

Satellite platforms with medium and high resolution, like Landsat-8 and Sentinel-2, offer continuous spectral data that is crucial for monitoring vegetation. AI algorithms identify stress patterns over thousands of hectares using indices such as NDVI, EVI, NDWI, and red-edge bands, allowing for national agricultural monitoring and macro-scale decision-making [11], [21].

C. Sensor-Based IoT Systems

Precision agriculture is supported by IoT technology that incorporate soil moisture probes, leaf wetness sensors, climate stations, and nutrient sensors. To forecast irrigation requirements, anticipate disease outbreaks, and maximize fertilizer use, artificial intelligence models examine real-time sensor data [22].

D. Multimodal and Hybrid Systems

In order to create reliable multi-modal AI systems, recent research focuses on integrating imaging, IoT sensors, meteorological data, and temporal satellite observations. These designs are fundamental to climate-smart agriculture programs and greatly enhance generality [23].

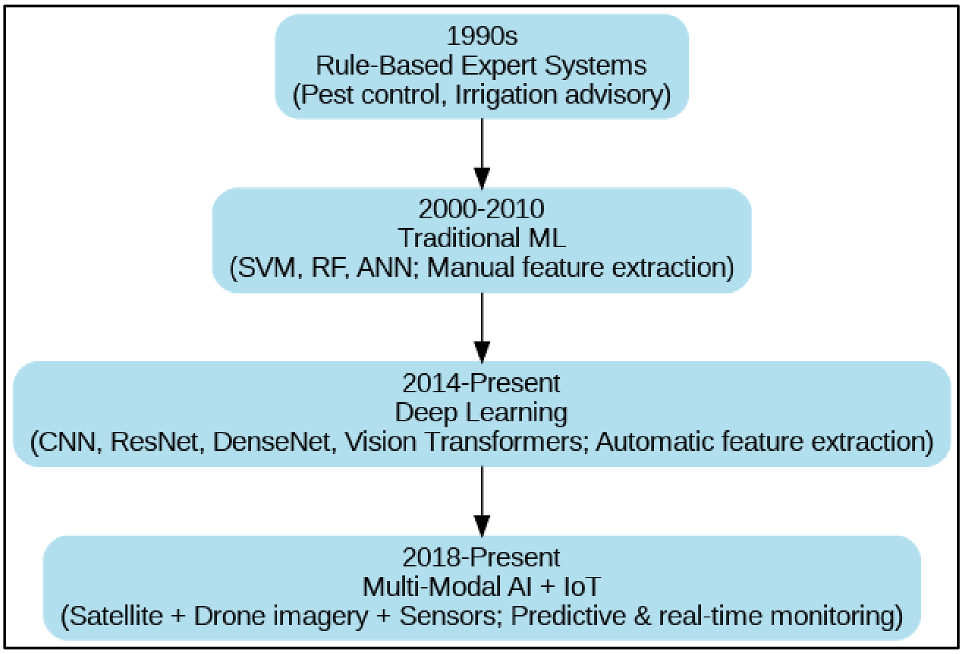

Fig 2.1 Timeline of AI adoption in agriculture

3. Deep Learning for Crop Disease and Stress Detection

By making it possible to automatically extract hierarchical spatial and spectral information from photos, deep learning has significantly improved crop disease and stress detection. For this, Convolutional Neural Networks (CNNs) are frequently used. Preprocessing procedures, including scaling, normalization, and data augmentation, come next in the standard pipeline, which starts with image gathering from RGB leaf photos, drone photography, or field cameras. After extracting features from the images using several convolutional and pooling layers, fully connected layers produce classification results. ResNet and DenseNet designs performed well when this method was used to classify rice leaf diseases. The efficacy of CNNs for single-crop disease identification was demonstrated using an ensemble model that combined DenseNet121, Inception-V3, and ResNet152V, achieving 98% accuracy [24]. While comparable CNN techniques attained over 95% accuracy on tomato and potato leaf datasets [26], DenseNet-201 also showed strong multi-class performance for a variety of rice disease categories [25]. When lesions or stress indicators are visually distinguishable, the CNN workflow's capacity to extract local features works especially well, but when global context or overlapping leaves are involved, performance may suffer.

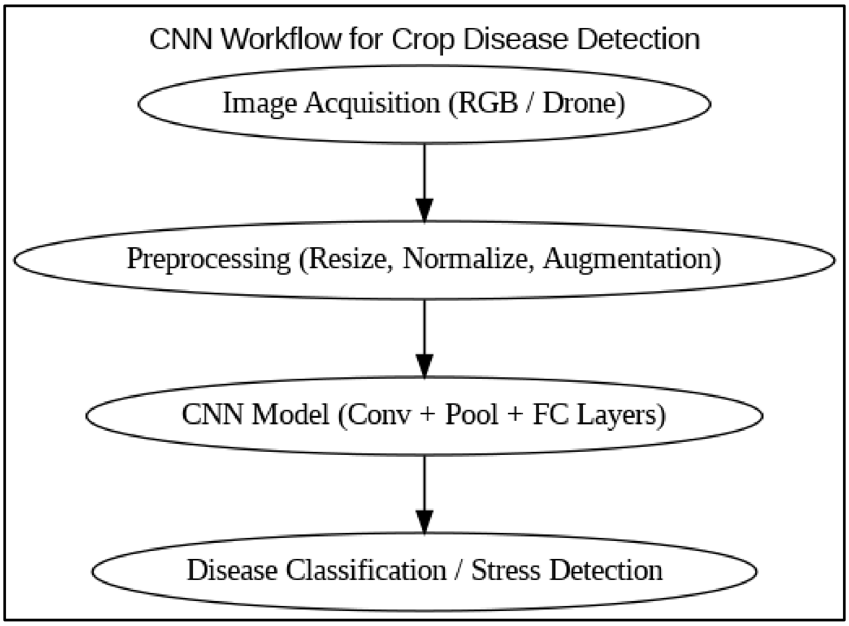

Fig 3.1 CNN Workflow

By collecting global dependencies over the whole image, transformer-based models like Vision Transformers (ViTs) and Swin Transformers build upon CNNs. Patch embedding of input images is the first step in their workflow, which is followed by positional encoding and processing using transformer encoder layers made up of feedforward networks and multi-head self-attention. Lastly, the disease label is predicted by a classification head. Transformers are able to identify intricate and overlapping disease patterns thanks to this global feature extraction. For example, a pretrained DeiT model outperformed DenseNet121 and EfficientNet models in the classification of mango leaf disease, with 99.75% accuracy [27].In rice disease detection tasks, hybrid methods that combine ViTs with lightweight CNN backbones, such as ResNet-18, have also enhanced generalization [28]. MangoLeafCMDF-FAMNet substantially improves multi-class illness classification robustness by combining transformer and ConvNeXt features [29]. Transformers are very useful for identifying complicated diseases because they can examine global relationships, even though they need more computer power and larger datasets than CNNs.

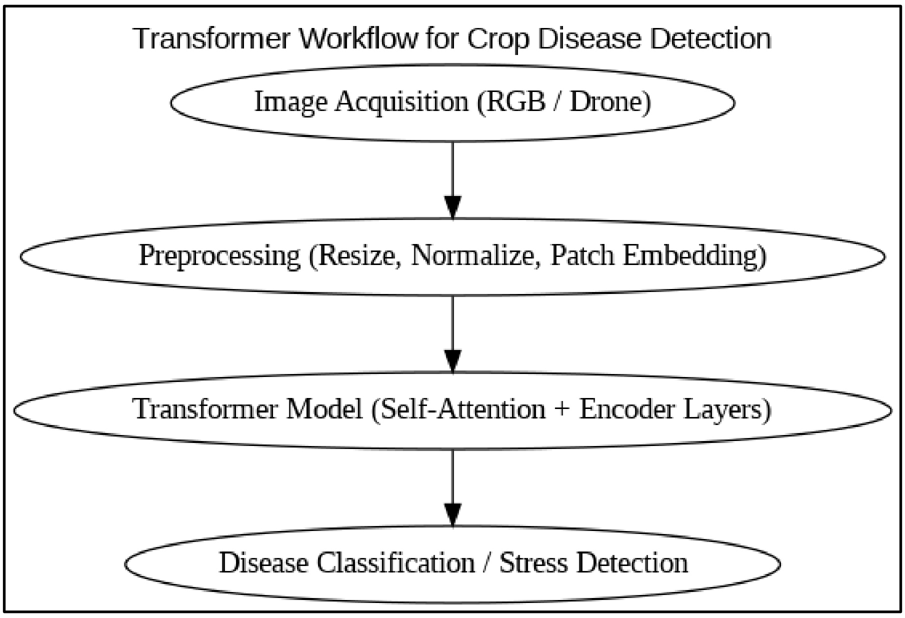

Fig 3.2 Transformer Workflow

Object detection models, such as SSD, YOLOv5/v8, and Faster R-CNN, concentrate on both the location and classification of sick regions. Bounding box regression with class predictions, region proposals, or anchor boxes, and feature extraction utilizing a CNN backbone comprise their approach. This enables spatially aware decision-making and focused therapy actions.For instance, YOLOv5 successfully localized many disease spots in tomato leaf pictures with a mean average precision (mAP) of 93.2% [30]. This method works especially well for drone or UAV-based imagery that covers wide areas. In contrast to conventional classification models, object detection necessitates well-annotated bounding-box datasets, which increases the effort required for data preparation.

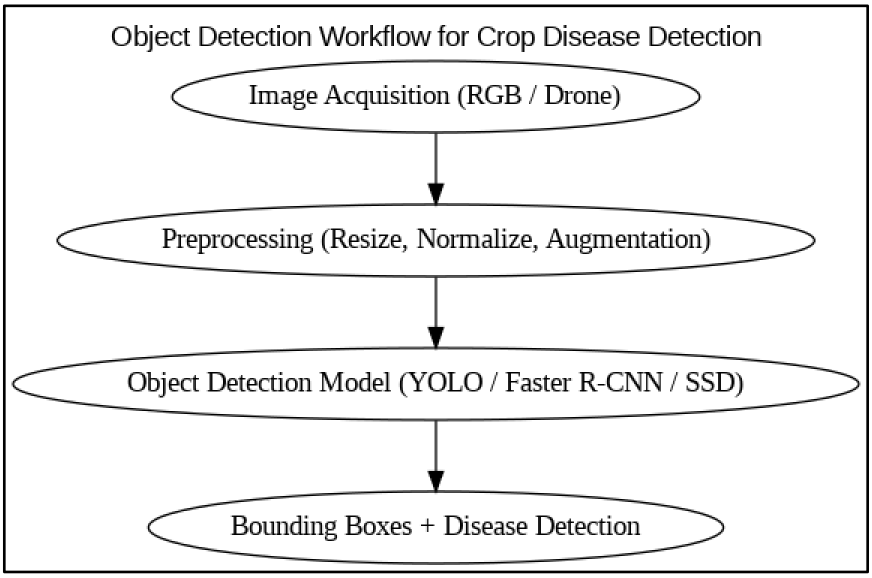

Fig 3.3 Object Detection Workflow

Datasets with underrepresented illness classes are supplemented using Generative Adversarial Networks (GANs). In order to improve both networks iteratively, a generator creates synthetic images and a discriminator assesses how realistic they are. In order to improve robustness and generalization, CNNs or transformer models are trained using artificial data. It has been demonstrated that CycleGAN-based augmentation enhances the categorization of rice leaf diseases, allowing models to get more accuracy on uncommon classes [31]. Although GANs are effective in reducing class disparity, they must be carefully trained to prevent the introduction of artificial artifacts.

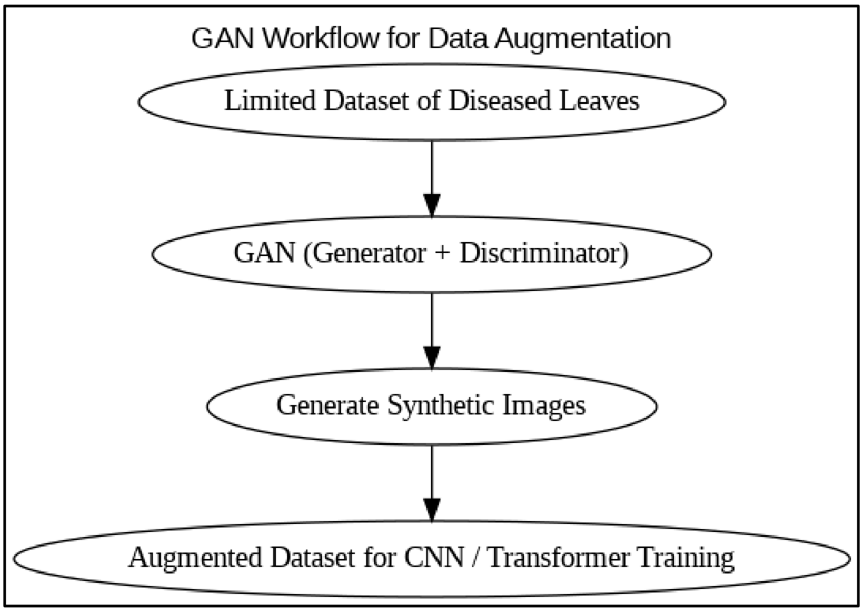

Fig 3.4 GAN Workflow

By recording spectral bands beyond visible RGB images, multispectral and hyperspectral deep learning algorithms offer early-stage stress detection. In order to extract spatial-spectral information, the method entails preprocessing the spectral cube to eliminate noise, choosing pertinent bands, and running the data through 3D convolutional layers or band-fusion networks. Additionally, temporal sequences can be used to track the development of stress. For example, using hyperspectral soybean stem pictures, a 3D-CNN was able to identify between healthy and charcoal-rot-infected samples with 95.73% accuracy; the most important features were found at NIR wavelengths [32]. Similar methods for wheat and maize enable proactive interventions by detecting nutrient deficits and water stress early on [33]. Although hyperspectral imaging provides physiologically interpretable predictions, it needs specialized sensors and a lot of processing power.

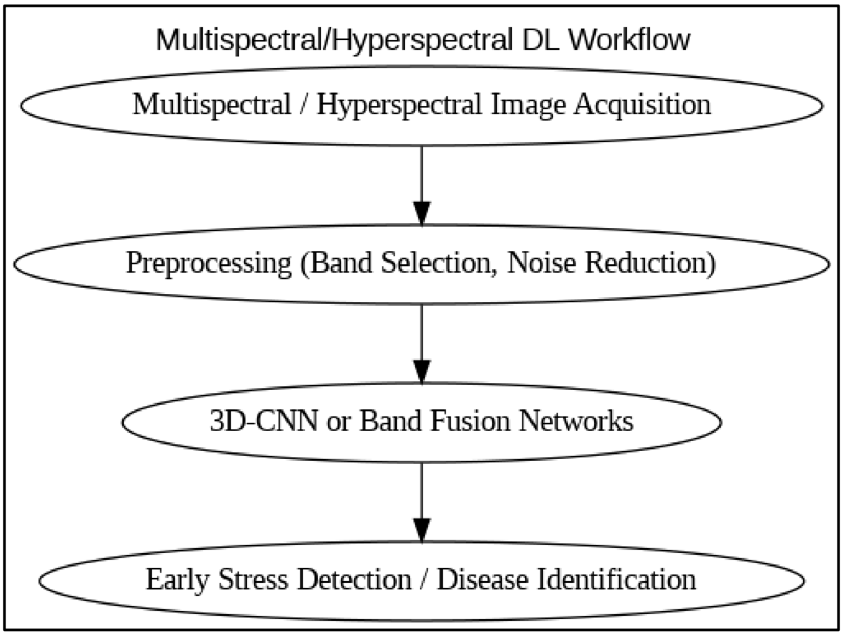

Fig 3.5 Multispectral/Hyperspectral Workflow

In conclusion, based on the needs of a crop monitoring scenario, each deep learning method offers distinct benefits. GANs address class imbalance and dataset scarcity, CNNs are very good at extracting local features from datasets with obvious visual symptoms, transformers capture global patterns in complex or overlapping structures, object detection models enable precise localization for targeted interventions, and multispectral/hyperspectral models enable early stress detection with physiologically meaningful insights. The quantity of the dataset, spatial resolution, processing power, and whether early vs extensive monitoring is required all influence the best strategy. Researchers can obtain high accuracy and useful insights for precision agriculture by combining these models with multi-modal data and high-resolution photography.

Table 3.1 Comparison / Decision Parameters of Models

Model Type	**Dataset Requirement**	**Spatial Context**	**Computational Load**	**Early Detection**	**Localization**	**Scalability**
CNN	High	Local	Low–Medium	Moderate	No	Moderate
Transformer	Medium	Global	High	Moderate–High	No	Moderate
Object Detection	High (with bounding boxes)	Local + Spatial	Medium–High	Moderate	Yes	High (drone imagery)
GAN	Low (for augmentation)	N/A	Medium	Indirect	N/A	High (synthetic data)
Multispectral / Hyperspectral	Medium–High	Local + Spectral	High	High	Partial	High (drone/satellite)

Table 3.2 Summary of Deep Learning Models for Crop Disease Detection

Deep Learning Model	Input Type	Crop Disease	Key Contribution / Result	Reference
DenseNet121 / ResNet152V	RGB leaf images	Rice leaf diseases	The ensemble model achieved 98% classification accuracy across multiple disease classes	[24]
DenseNet-201	RGB leaf images	Rice leaf diseases	Robust multi-class disease classification	[25]
DeiT (Vision Transformer)	RGB leaf images	Mango leaf diseases	Achieved 99.75% accuracy; outperformed DenseNet121 and EfficientNet	[26]
Hybrid ViT + ResNet18	RGB leaf images	Rice leaf diseases	Better generalization across diverse datasets; improved classification accuracy	[27]
MangoLeafCMDF-FAMNet (ConvNeXt + ViT)	RGB leaf images	Mango leaf diseases	Enhanced robustness in multi-class classification; adaptive feature fusion	[28]
Faster R-CNN / YOLO / SSD	RGB / Drone images	Localized leaf/canopy diseases	Precise disease localization enables targeted intervention	[29]
CycleGAN + CNN	RGB leaf images	Rice leaf diseases	Data augmentation; improved model generalization and accuracy	[30]
3D-CNN	Hyperspectral stem images	Soybean (Charcoal rot)	Achieved 95.73% accuracy; NIR wavelengths most informative	[31]

4. Discussion and Research Gaps

Despite substantial advances in AI-driven agricultural health monitoring, numerous major research gaps persist, restricting the technology's mainstream application and scalability. The absence of a single, worldwide dataset covering various crops, temperatures, and geographical areas is a significant drawback. The majority of research uses tiny, localized datasets that are frequently limited to a single crop variety or geographic area [34], [35]. This restricts the models' capacity to properly generalize, especially when used to novel crop kinds or climatic conditions. Global adoption would be facilitated by the creation of a large-scale, consistent dataset that combines RGB, multispectral, hyperspectral, and temporal observations. This would enable more reliable model training and benchmarking.

Early diagnosis of agricultural diseases and abiotic stress is another urgent concern. Subtle physiological changes frequently go unnoticed until later stages, despite the fact that deep learning models like CNNs, Transformers, and multispectral/hyperspectral architectures have shown great accuracy in identifying apparent symptoms [36], [37]. This is particularly problematic in scenarios with rapidly progressing pathogens, where even a short delay in detection can result in substantial yield losses. Explainable AI methods, multisensor data fusion, and temporal analysis could improve early stress detection and allow for prompt intervention.

One major worry is yet generalization between crops and locations. Due to differences in soil types, climatic conditions, and plant phenotypes, models trained on one crop or region sometimes perform poorly when applied elsewhere [38]. These restrictions might be addressed by transfer learning, domain adaptation, and hybrid multi-modal techniques, but further research is needed to evaluate their scalability and dependability in practical settings. The integration of multisensor and multimodal data raises significant research gaps. Although there are few standardized pathways for such multi-source fusion, combining drone footage, satellite observations, IoT sensor data, and meteorological information can increase accuracy and robustness [39]. Research is required to create interpretable, lightweight models that can manage a variety of inputs without requiring a lot of processing power, particularly for use in rural areas with limited resources.

Lastly, adoption-related, socioeconomic, and ethical issues cannot be disregarded. AI-driven monitoring technologies have the potential to worsen the digital gap by marginalizing smallholder farmers while disproportionately benefiting large-scale farms with access to cutting-edge technology [40]. Concerns about data privacy, the transparency of AI models, and the socioeconomic effects of automated crop management are important challenges that need to be addressed in order to guarantee ethical and equitable implementation. In order to develop inclusive and socially acceptable AI solutions for agriculture, future research should include participatory methods engaging farmers, agronomists, and legislators.

5. Future Directions

The future of AI-driven crop health monitoring lies in using new modeling paradigms, multisensor integration, and cost-effective deployment tactics to make precision agriculture more accurate, scalable, and accessible. Applying foundation models for agriculture, such as large-scale vision-language models or pre-trained deep learning frameworks tailored to crop imagery, is one possible approach. These models can generalize across crops, diseases, and environmental conditions, reducing the need for large task-specific datasets and enabling rapid adaptation to new regions or crop types [41]. Techniques for self-supervised learning are another new area. Self-supervised techniques can overcome the restrictions of dataset scarcity, a prevalent problem in agricultural surveillance, by allowing models to learn meaningful feature representations from unlabeled or weakly labeled data. For instance, multispectral and hyperspectral pictures have been subjected to contrastive learning and masked autoencoder approaches, which have improved early disease identification and stress prediction without requiring considerable manual annotation [42].In the agricultural setting, explainable AI (XAI) is becoming more and more crucial since farmers and agronomists must comprehend and have faith in model predictions in order to make wise decisions. Actionable and transparent recommendations are made possible by integrating saliency maps, attention mechanisms, or feature attribution techniques with deep learning models to provide interpretable insights into which spectral bands or spatial regions influence disease or stress classification [43]. The combination of satellite and drone data has enormous promise as well. While satellites offer extensive temporal and spatial coverage, high-resolution drone imaging allows for the fine-scale diagnosis of localized stress or disease. Deep learning-based hybrid pipelines can monitor crop health on a broad scale, improve early detection, and produce continuous forecasts for precise interventions [44].

Finally, for smallholder farmers to profit from AI-powered monitoring, affordable edge AI solutions are essential. Crop disease detection and irrigation recommendation systems can be deployed on smartphones, microcontrollers, or edge devices with limited computational resources thanks to lightweight CNNs, model pruning, and quantization approaches. These solutions can help close the digital divide in agriculture by offering near-real-time feedback and useful insights without depending on cloud infrastructure [45].

6. Conclusion

This review emphasizes how AI and deep learning can revolutionize crop health monitoring for contemporary agriculture. Traditional manual scouting methods are increasingly unsuitable due to their labor-intensive, subjective, and spatially limited character. Crop diseases and abiotic stressors can now be accurately, scalably, and early detected because to advances in AI, especially convolutional neural networks, transformer-based architectures, object identification models, GAN-based augmentation, and multispectral/hyperspectral imaging. Each method has unique benefits: GANs reduce dataset scarcity, CNNs are excellent at extracting local features, transformers capture global dependencies, object detection models enable accurate intervention, and spectral imaging enables physiologically interpretable predictions and early stress identification.

Despite these developments, there are still significant research gaps, such as the requirement for unified global datasets, advancements in early-stage detection, generalization across crops and regions, multisensor fusion, and consideration of socioeconomic and ethical aspects. Filling in these gaps is essential to creating dependable solutions that work everywhere. Foundation models, self-supervised learning, explainable AI, drone-satellite fusion, and low-cost edge AI systems all offer better scalability, interpretability, and accessibility for a variety of farming situations in the future of AI-driven agriculture.

In summary, crop health monitoring enabled by AI signifies a paradigm change in agriculture toward precision, sustainability, and climate resilience. These technologies will effectively contribute to global food security, efficient resource use, and fair agricultural practices through strategic research, cooperative development, and inclusive deployment.

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