Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 13 Issue 2s (2026) | Pages: 233-245

Multi-Crop Multi-Disease Detection Framework Using Explainable Artificial Intelligence for Precision Agriculture: A Comprehensive Literature Review

Asma Bashir Hannure[1] Dr. Ayushi Godiya[2]

[1,2]Ajeenkya DY Patil University, Pune

[1]*asmahannureb@gmail.com* , [2]*ayushi.godiya@adypu.edu.in*

Peer Review Information

Type: *Article*
Received: *27 March 2026*
Revised: *12 April 2026*
Accepted: *26 May 2026*
Published: *16 June 2026*

Abstract

Plant diseases pose significant menace to food security in the world, causing significant losses of money and reduced yields of key agricultural products like cotton, tomato, wheat and rice. The traditional methods of detection that rely on manual diagnosis are time consuming, labour-intensive and prone to human errors hence the necessity of automated and accurate diagnostic systems. The recent advances in artificial intelligence, especially deep learning and computer-vision methods, have changed the scene of the plant disease detection because it has made it possible to identify various diseases on different crop species in real time, automatically, and accurately. In this literature review, we discuss the state of the art in multi-crop disease detection models, focusing on deep-learning models, such as Convolutional Neural Networks (CNNs), Vision Transformers (ViT), and object-detection models, including YOLO, Faster-R-CNN, and Mask-R-CNN, and interpretable AI (XAI) methods, such as Grad-CAM, SHAP, and LIME. Through a systematic review of thirty recent articles released in 2020-2025, the review outlines major technological developments, performance standards, as well as viable deployment plans of precision agriculture. It also determines serious gaps in research such as lack of integrated multi-crop models, little verification of these in field applications, inability to scale computations to support edge deployment, and lack of model interpretability. The review thus adds to the field through compiling the existing knowledge, providing a comparative methodology analysis, and future research steps to create explainable, lightweight, and farmer-friendly AI systems to achieve sustainable agriculture.

Keywords: Precision Agriculture; Plant Disease Detection; Deep Learning; Explainable AI; Convolutional Neural Networks (CNN); Vision Transformers; Multi-Crop Disease Detection; YOLO; Transfer Learning; Edge Computing.

How to Cite This Article

Hannure, A. B., & Godiya, A. (2026). Multi-crop multi-disease detection framework using explainable artificial intelligence for precision agriculture: A comprehensive literature review. *Multidisciplinary Journal of Research in Engineering and Technology*, 13(2s), 233–245.

Introduction

Agriculture has remained the irreplaceable workhorse of world food security and economic viability, supporting billions of people throughout the world and providing massive inputs to national economies. The main products such as cotton, tomato, wheat and rice are central to both nutritional needs and industrial needs. Cotton which is informally known as white gold holds the central position in the commerce, and tomato is one of the most universally eaten vegetables globally. The combination of wheat and rice forms staple food to over fifty percent of the global population, thus making their stable, sustainable production vital in maintaining food security in the entire planet [1]-[3].

Despite this popularity, agricultural output suffers brutal losses due to the attacks by plant pathogens and pests, which have resulted in approximately 2040 per cent of the loss of crops of various crops in a year [4], [5]. Bacterial blight, leaf-curl virus, and several fungal diseases and infestations of pests significantly reduce the quality and quantity of harvests and trigger significant economic losses among farmers and a significant risk to food security [2], [6]. The combination of numerous diseases, environmental stressors adds to these problems; therefore, fast and correct testing is a necessity that cannot be ignored to reach effective crop stewardship.

The traditional methods of detecting plant diseases have always been based on manual inspection by agronomists or farmers. Unfortunately, these methods are tedious, time consuming and very subjective particularly in a heterogeneous and uncontrolled field conditions [2], [9], [10]. The diagnosis requires professional knowledge which is usually unavailable in the rural areas. Additionally, the visual examination is prone to misdiagnosis especially at the early stages of the disease when the signs can be insignificant and are indistinguishable [11], [12]. These limitations highlight the urgent need of automated, accurate, and real-time disease detecting systems, which can work effectively under the real-life conditions of agriculture arenas [13], [14].

The backbreaking advances in the field of Artificial Intelligence (AI) and Deep Learning (DL) recently have transformed the way agricultural diagnostics is approached, as machine-based disease diagnostics is now achievable through image processing. Convolutional Neural Networks (CNNs) and transfer-learning approaches have demonstrated impressive levels of success in deriving hierarchical description of plant leaf images with results comparable or even better than the results of more experienced human analysts [15]-[20]. Complex architectures such as ResNet, DenseNet, EfficientNet and MobileNet have been extensively used in classification, and object detection and segmentation networks such as YOLO and Mask R CNN have provided more accurate localisation of diseased areas. Moreover, attention based models like Vision Transformers (ViT) have been presented, which improve feature representation and model generalisation [21]-[24].

Although there have been significant progress in the field of single-crop disease sensing, the agricultural environment is multifaceted by nature, as it consists of various crops that are simultaneously infested by a variety of diseases. The current models are often unable to extrapolate between different crop species, disease typologies and thus limit themselves in their practical use [25], [26]. Therefore, there is an urgent necessity to develop a multi-crop, multi-disease observation framework with the ability to navigate in diverse agricultural environments in a single paradigm.The other glaring weakness of the current deep-learning models is the black-box nature which limits interpretability and diminishes user-confidence. When the decision-making process behind implementing the AI-based system can be understood, the agricultural stakeholders are in a propensity to adopt the systems. The interest in explainable AI (XAI) methods, including Grad-CAM, SHAP, and LIME, that provide visual and feature-level explanations of model predictions, has increased as a result of this motivation [27]—[29].

Besides, the practical implementation of AI-based disease detection requires lightweight and computationally efficient models that can be used on edge devices, i.e., smartphones, unmanned aerial vehicles, and Internet-of-Things (IoT) agricultural devices. Whilst state-of-the-art models are highly accurate, their computational requirements can be challenging to apply to the field in real-time, which is why research in this area has focused on strategies to optimise models such as pruning, quantisation and knowledge distillation to achieve a compromise between performance and efficiency [30]-[34].

In this framework, the present study attempts to overcome these obstacles by building an integrated system of multi-crop/ multi-disease identification that combines explainable artificial intelligence and lightweight deep-learning models to detect diseases and areas in agriculture. The solution aims to achieve increased performance of accuracy, scale, interpretability, and ability to deploy in real time, thus minimising the gap between emergent AI studies and practical farming.

Research Objectives

This comprehensive literature review aims to:

- To develop a region-specific, annotated multi-crop image dataset covering Maharashtra region crops with diverse disease and pest conditions.

- To design a deep learning model for accurate multi-disease classification and severity detection across crops.
- To validate the system's performance using available benchmark datasets and assess its suitability for practical agricultural applications.
- To integrate Explainable AI techniques for real-time, scalable crop disease detection and management that enhances food security,sustainable agriculture , and economic resilience .

Relevant Technologies

Machine Learning in Agriculture
Machine learning has triggered a paradigm shift in agriculture, enabling the use of data to make decisions that are relevant in crop management, yield forecasting, disease detection, and precision farming [15-17]. The classical approaches to machine-learning, such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbours (k -NN) have been applied to the problems of agriculture with moderate success[30] . However, these methods are usually manual feature engineering and they also perform poorly in the presence of complex and high-dimensional images hence limiting their use in plant-disease detection applications [30].

Deep Learning Approaches
Deep learning is a subdivision of machine learning, and it is based on multilayer artificial neural network fundamentally transforming the tasks in computer-vision, since it can learn hierarchical feature representations autonomously using raw data [18-19]. Deep-learning architectures can learn over images to extract more complex patterns and features without having to run feature engineering in the process, which makes such systems especially effective in the plant-disease detection task[20,30] . Combination of large amounts of data, the increased computational ability of GPUs, and the development of advanced optimisation methods has accelerated the introduction of deep learning into agricultural application[15,16] .

Convolutional Neural Networks (CNN)
Convolutional Neural Networks (CNNs) are specialized deep learning architectures designed for processing grid-like data such as images [18], [30].

Convolutional Neural Networks (CNN) A CNN is a series of neurons in which the output of a single neuron is fed into the input of the subsequent neuron until the final neuron is considered.

Convolutional Neural Networks (CNNs) are architectures of specialised Deep-learning approaches that are specifically designed to work with grid-like data like images[18,30] . CNNs consist of convolutional layers which use a learner filter to detect spatial features, pooling layers which reduce the dimensionality, and fully connected layers which classify [30]. Architectures of CNN that have been used to detect plants and diseases during the detection use notable CNN architecture which includes:

ResNet (Residual Networks): Makes use of the skip connections to alleviate the vanishing-gradient issue and to allow training much deeper networks[2,18,30]. DenseNet (Densely Connected Networks): This network puts in place high inter-layer densities to boost feature propagation and parameter efficiency [30]. EfficientNet: Uses an algorithm to incorporate compound scaling to equalize the network depth, width and resolution to achieve optimal performance [2,18]. MobileNet: This architecture is created to run on mobile and embedded systems and uses the depthwise separable convolution to reduce the number of computations [1,6,30]

Transfer Learning
Transfer learning takes advantage of already trained models based on large-scale datasets like ImageNet and then fine-tuned in order to complete farming tasks [2,18,25,30]. This approach significantly shortens the training time and data requirements and at the same time increases the model performance, especially when annotated agricultural datasets are limited (references 25 and 30). Transfer learning is now already a standard technique in plant-disease detection, and backbone networks like VGG-16, ResNet-50 and EfficientNet are often used.[2,18,30].

Vision Transformers (ViT)
Vision Transformers (ViT) represents a paradigm shift of convolution-based architectures, where transformer models, originally developed to operate on natural language processing, are used on tasks in computer-vision[15,16,22,23]. ViT subdivides the images into patches, and operates them using self-attention computation to assist in the identification of long-range and global connections [15,16,22]. Recent studies have shown that Vision Transformers also can achieve competitive or even better performance compared to CNNs on plant-disease detection especially when combined with CNN features in hybrid architectures.[15,16,18,22,23].

Object Detection Models
Object-detection models are not only limited to classification, but also to localisation of diseased regions in the imagery, and hence provide spatial data on the prevalence of diseases[1,3,4,8]. Important object-detection models are:

YOLO (You Only Look Once): This is a real-time detector that posits detection as a regression, which provides fast inference that can be deployed to edges [1,3,4,8,9] Faster R-CNN: A region-based detector, which proposes regions and classifies them, which are high accuracy but expensive in terms of computational complexity[30] . RT-DETR: A new detection algorithm of transformer which is accurate and efficient.[2]

Instance Segmentation

Instancesegmentation models like Mask R -CNN build upon object detection with pixelwise segmentation masks of all detected diseased regions [30]. Such localisation on a fine scale allows accurate measurement of the severity of the disease and the extent of the area covered by the disease and thus facilitates more accurate treatment advice.[30].

Explainable AI Methods

Explainable AI (XAI) methods solve the black box dilemma of deep learning, which allows interpretable visualisation of model decision-making processes.[2,17,20,22,27,28,29] .The most common XAI approaches used in the agricultural sector are:

Grad -CAM (Gradient -weighted Class Activation Mapping): Creates heatmaps which indicate regions of an image that have the greatest impact on model predictions.[17,20,22,28]. SHAP (SHapley Additive exPlanations): The scores are based on the principle of feature-importance values, which are game-theoretic based[2,27].LIME (Local Interpretable Model-agnostic Explans): This builds local approximations to model behavior on individual forecasts [22,28] . These XAI methods contribute to better transparency of a model, promote trust in the model among agricultural stakeholders, and support model debugging and improvement.[2,17,20,22,27,28,29].

Literature Review

The Deep Learning in Crop Disease Detection

Deep learning has become the current trend in automated detection of plant diseases, and many studies have shown better performance compared to traditional machine learning approaches [18], [19], [20], [30]. Dhaka et al. [30] conducted an extensive survey of deep-convolutional neuro-networks (CNNs) in the domain of plant leaf disease prediction and compared numerous architectures such as LeNet, AlexNet, VGGNet, GoogLeNet, ResNet, DenseNet, and SqueezeNet. They found that more complex architectures like ResNet-50 and DenseNet-121 were able to achieve an accuracy of over 99 percent on the PlantVillage dataset, but the smaller models like SqueezeNet (2.9MB) were able to achieve significant size cuts to enable mobile use.

Transfer learning has been observed to be one of the critical strategies to supplement the model performance using insufficient training data [2], [18], [25], [30]. It has been shown that on agricultural data sets fine-tuning pretrained models are significantly more effective than training new models, especially when faced with small or unbalanced data sets [25], [30]. The most common backbone architectures used include VGG -16, ResNet -50, EfficientNet and Xception, which have all been optimized to various tasks of crop disease detection [2], [18], [30].

The latest development works have focused on the creation of specialized architectures that are best applied in the agricultural areas. As an example, various papers have applied attention so as to strengthen the extraction of features and concentration of the model in diseasemap areas [1], [2], [12], [18]. There are significant variations in detection accuracy that have remained consistent in terms of improvement through the integration of attention modules that include Coordinate Attention (CA), Convolutional Block Attention Module (CBAM), and Dual-Feature Self-Attention (DFSA) [1], [2], [12].

Disease Detection Studies Crop-Specific

Cotton Disease Detection

The issue of cotton disease monitoring has received much academic interest due to the economic value of the crop [2], [3], [6], [12], [13], [20]. Sawanapally et al. [2] provided a literature review on deep learning applications in cotton disease detection with the focus on lightweight CNNs and transformer-based models and object detection algorithms, including YOLO and RT-DETR. In their review, the authors have highlighted the significance of transfer learning based on enhanced backbones (EfficientNet, Xception, ResNet) and attention mechanisms to enhance feature representations [2].

Zhao et al. [3] designed YOLO-MSPM which is a light-weight and accurate network that can detect cotton Verticillium wilt with 94.5 per cent mean average precision (mAP) and only 2.8 million parameters. They used the multi-scale feature fusion and pruning methods in their architecture in order to balance accuracy and computational efficiency [3]. Ernestly, Liao et al. [4] conceived a better YOLOv10n model to evaluate the hazard levels of cotton Verticillium wilt in real-time, achieving 95.2 percent mAP without sacrificing the high inference rates suitable in the field [4].

Pan et al. [6] came up with a lightweight cotton disease detection model that is uniquely adapted to resource-constrained devices in natural environments with a high accuracy of 94.8 per cent and reduced computational costs [6]. Hassan et al. [12] presented CottonNet-MHA, a multi-head attention-based framework, which achieved an accuracy of 96.3 per cent by utilizing attention as a means of focusing attention on disease-relevant features [12]. The Cui et al. [13] report of a resource efficient cotton network with 95.7% accuracy and a small model size that can be deployed on the edge [13].

Swapno et al. [20] proposed an explainable transformer model of cotton leaf diagnostics, which combines Vision Transformers with explainable AI to provide interpretable predictions. Their model had an accuracy of 94.8% with visual explanations in the form of attention visualization [20].

Tomato Disease Detection

The detection of tomato disease has received an intense level of research because of the importance of the crop to the world agriculture [5], [8], [11], [14], [23], [30]. Bhandari et al. [5] proposed BotanicX -AI, which is an explanation-based deep learning framework to identify tomato leaf diseases, achieving 97.2 -percent accuracy with Grad -CAM visualizations to understand the model [5]. Their research pointed out the need to have explainability to help build trust among agricultural practitioners [5]. Tang et al. [8] introduced YOLOv11-AIU a small detection model that can be used to grade early blight disease in tomatoes and reported 93.8 per cent mAP and rapid inference speeds that can be used in real-time monitoring [8]. Zhang et al. [11] came up with a multimodal fusion deep learning method of tomato disease online classification, using RGB and multispectral images to achieve 96.598 accuracy [11]. Gunasekaran et al. [14] performed an extensive survey of lightweight deep learning on tomato disease detection, reviewing tendencies, challenge, and edge AI insights. They focused on the trade-offs of the model accuracy and performance, and highlighted the need to have optimized architectures that were specific to smartphone deployment [14].

Islam et al. [23] investigated effective methods of identifying tomato leaf diseases using the best CNN hyper-parameters with maximum accuracy of 98.1 0 -best achieved by systematically varied hyper-parameters [23]. Their study revealed that careful optimization of the learning rate, batch size and network depth have a significant influence on the model performance [23].

Rice Disease Detection

Researchers have shown a lot of interest in rice disease detection due to the importance of rice as a staple food by billions of people [1], [9], [10], [16], [18], [19], [21], [25], [27], [30]. Jia et al. [1] have designed MobileNet-CA-YOLO, a modified model of YOLOv7 with MobileNetV3 and Coordinate Attention to detect rice pests and diseases. Their model was found to be 92.3 per cent and 93.7 per cent accurate and mAP with a low number of parameters of 6.956 million, which proved to be efficient and can be used in mobile devices [1]. To identify prevalent rice leaf diseases in smart agriculture, Guo et al. [9] presented a better YOLOv7-Tiny model that achieved 94.6 -mAP and maintained a lightweight architecture [9]. Zhang et al. [10] developed a lightweight and universal system of intricate field early disease detection of rice leaf, which got 95.3x cent percent precision and strong functionality in various conditions [10].

A comparative study of Vision Transformers and CNNs regarding cross-regionalization of the rice leaf disease was conducted by Ismail et al. [16], which demonstrated that ViT models could detect with 96.8 per cent accuracy and that the generalization of the model across various geographical areas was significantly superior to conventional CNNs [16]. A hybrid CNN -ViT model with explainable AI and attention-based interpretability was proposed by James et al. [18], which attained 97.5 per cent accuracy and offered visual explanations by attention map [18]. Al-Falluji et al. [19] came up with a green AI model using explainable deep learning to classify the rice leaf disease, a model that offers a high accuracy of 96.2 and focuses on energy consumption and environmental sustainability [19]. In their work, Udayananda et al. [21] provided an in-depth assessment of the machines learning methods in diagnosing rice plant diseases, comparing the different approaches and possible research pathways in the future [21]. Chen et al. [25] examined the application of deep transfer learning to disease diagnosis of rice plants, and it was found that ImageNet trained models significantly enhanced the accuracy of detecting disease, at 98.5 per cent of accuracy [25]. Qadri et al. [27] conducted a comparative study of Inception V3, VGG-16, VGG-19, CNN, and ResNet-50 on early detection of rice diseases and found that ResNet-50 was the most accurate with the highest accuracy of 99.2 [27].

Wheat Disease Detection

Notwithstanding the fact that wheat disease detection has received a relatively lower academic attention compared to other crops, a number of studies have been done on this fundamental staple crop [30]. Dhaka et al. [30] described the custom CNNs that achieved high accuracy in detecting wheat diseases with datasets collected in Shandong Province, China, which contains 16,652 images belonging to ten disease classes [30].

Object Detection and Instance Segmentation Methodologies

The methodology of object detection and instance segmentation has become popular because it is able to localize disease areas and measure disease severity [1], [3], [4], [6], [8], [9], [10]. With their accuracy and inference speed balance [1], [3], [4], [8], [9], YOLO-based models have become the leading structure of real-time disease detection. It was also shown by Jia et al. [1] that the use of MobileNetV3 as the backbone of YOLOv7 lead to a decrease in parameters with a 81.31per cent reduction and high detection accuracy of rice pests and diseases [1]. In their study, Zhao et al. [3] proposed multi-scale factor combination and filtering algorithms in YOLO-MSPM, which led to the accurate detection of the cotton Verticillium wilt with minimal processing [3]. Liao et al. [4] further optimized YOLOv10n to run in real-time on the assessment of hazard level to allow its practical use in cotton fields [4]. Tang et al. [8] designed YOLOv11-AIU to grade tomato with early blight disease, including attention and better feature fusion to capture low disease symptoms [8]. Guo et al. refined YOLOv7-Tiny to rice disease detection in smart agriculture systems [9] to demonstrate the use of edge devices in real-time [9]. To address the issue of identifying rice leaf diseases in a complex field setting, Zhang et al. [10] developed a lightweight framework that had strong performance in different lighting conditions, backgrounds, and stages of the disease [10]. They used data augmentation and domain adaptation methods in their approach to enhance generalization [10]. Although Mask R -CNN and other instance segmentation systems can provide pixel-level localization of disease, their computational requirements have limited their use in real-time field scenarios [30]. However these models continue to be useful in research situations which involve the quantification of diseases and the severity of the disease [30].

Lightweight and Edge-Based Models

The development of light models to be used on the edges is a critical research topic that enables the identification of diseases in real time on devices with limited resources like smartphones and IoT sensors [1], [6], [7], [10], [13], [14], [30], [31], [32], [33], [34]. This trend will resolve the practical deployment issues in the agricultural environment where the cloud connections might be unreliable or not available at all [7], [31]. The use of mobileNet architecture has become common in lightweight detection of diseases thanks to the use of depthwise separable convolution that is efficient [1], [30]. Jia et al. [1] demonstrated that MobileNetV3 based architectures were able to achieve competitive accuracy with the reduction of parameters that were more than 80 percent as compared to traditional architectures [1]. The model of cotton disease detection by Pan et al. [6] was specifically created to operate on devices with resource-constrained devices, with a 94.8% accuracy at a low level of computations [6]. In their work, Junaidi et al. [7] provide an extensive overview of deep learning and edge computing in the agricultural sector, analyzing the current trends and development of the deployment of AI models on edge devices [7]. They have found that model compression methods, such as pruning, quantization, and knowledge distillation are important to allow field deployment [7]. A light weight strategy to detect rice disease was developed by Zhang et al. [10], which ensured high accuracy and worked effectively on the mobile devices [10]. It was suggested by Cui et al. [13] to use resource-efficient cotton network with edge deployment optimization that focuses on the accuracy and the computational efficiency [13]. Gunasekaran et al. [14] studied lightweight deep learning to detect the tomato disease in the framework of edge AI and found that there are certain challenges and opportunities to diagnose the disease using a smartphone [14]. Model accuracy versus computational efficiency continues to be one of the main issues in the development of lightweight models [7], [14], [31]. The past few years have explored an array of optimization techniques, such as neural architecture search, efficient attention mechanisms, and hybrid architectures that are built on top of CNNs and lightweight transformers [7], [31], [32], [33], [34].

Agriculture Vision Transformer-based Models

Vision Transformers (ViT) are an exciting variant of traditional CNNs that are able to detect plant diseases with a richer ability to detect long-range dependencies and the global context [15], [16], [17], [18], [22], [29]. Some studies have established that ViT-based models can compete or outperform CNNs on the focus of complex disease patterns especially [15], [16], [18], [22].

Nurullah et al. [15] took the step of multi-label tomato leaf disease detection with ViT and EfficientNet enhanced with explainable AI methods, proving the effectiveness of transformer-based models on the problem of multi-coexistent diseases [15]. A comparative study performed by Ismail et al. [16] revealed that ViT had 96.8 7 accuracy in cross-regional rice leaf disease detection and was more effective in generalization to various geographical areas than conventional CNNs [16]. Thakur et al. [17], [22], [28] created PlantXViT, an explainable CNN powered by the Vision Transformer, and used to identify plant diseases. They had a hybrid architecture which took the advantages of CNNs in local features description and ViTs in global context representation, where they reached the accuracy of 93.55, 92.59, and 98.33 on Apple, Maize, and Rice datasets, respectively [17], [22], [28]. The model had 0.8million trainable parameters, which makes it appropriate to work with IoT-based smart agriculture services [17], [22], [28]. James et al. [18] suggested a hybrid CNN-ViT architecture with explainable AI and attention-based interpretability to detect rice crop diseases, with an accuracy of 97.5 per cent and providing visual justifications by attention maps [18]. Their methodology showed that CNN and ViT features might be complemented to utilize the strong sides of each architecture [18].

Swapno et al. [20] created the explainable transformer methodology to cotton leaf diagnostics with a 94.8 per cent accuracy, and interpretable prediction through attention visualization [20]. M et al. [29] enhanced GAN-boosted ViT with XAI insights in the multiclassical classification of plant diseases, demonstrating that synthetic data generation can be useful in improving the work of the model on unbalanced data [29].

Table 1 presents a comprehensive comparative analysis of 25 recent studies (2020-2025) on deep learning approaches for crop disease detection, organized by publication year and highlighting key methodological aspects, performance metrics, and contributions.

Table 1. *Comparative Analysis of Recent Literature on Multi-Crop Disease Detection*

No.	Author & Year	Crop(s)	Dataset	Method / Architecture	Accuracy / mAP	Key Contribution	Limitation
1	Jia et al., 2023 [1]	Rice	3,773 images, 6 classes	MobileNet-CA-YOLO (YOLOv7 + MobileNetV3 + Coordinate Attention)	92.3% accuracy, 93.7% mAP@0.5	Lightweight detection model suitable for mobile deployment	Dataset collected online; field validation required
2	Sawanapally et al., 2025 [2]	Cotton	Review study	CNNs, ViT, YOLO, RT-DETR with transfer learning and XAI	N/A	Comprehensive survey of lightweight and explainable cotton disease models	No experimental validation
3	Zhao et al., 2025 [3]	Cotton	Custom dataset	YOLO-MSPM with multi-scale feature fusion and pruning	94.5% mAP	Lightweight architecture for Verticillium wilt detection	Limited to single disease
4	Liao et al., 2024 [4]	Cotton	Field dataset	Improved YOLOv10n	95.2% mAP	Real-time hazard level assessment for cotton disease	Computational complexity not fully reported
5	Bhandari et al., 2023 [5]	Tomato	Custom dataset	BotanicX-AI (CNN + Grad-CAM)	97.2% accuracy	Explainable disease detection model with visualization	Focused only on tomato
6	Pan et al., 2024 [6]	Cotton	Natural environment dataset	Lightweight CNN model	94.8% accuracy	Designed for edge devices in field environments	Limited disease categories
7	Junaidi et al., 2025 [7]	Multiple crops	Review study	Deep learning + edge computing	N/A	Overview of edge AI trends in smart agriculture	No experimental analysis
8	Tang et al., 2025 [8]	Tomato	Custom dataset	YOLOv11-AIU (attention-based detection)	93.8% mAP	Severity grading detection for early blight disease	Single disease focus
9	Guo et al., 2024 [9]	Rice	Custom dataset	Improved YOLOv7-Tiny	94.6% mAP	Lightweight disease detection model for smart agriculture	Limited disease variety
10	Zhang et al., 2025 [10]	Rice	Complex field dataset	Lightweight generalizable framework	95.3% accuracy	Robust model for diverse field conditions	Model complexity details limited
11	Zhang et al., 2022 [11]	Tomato	Multimodal dataset	Multimodal fusion (RGB + multispectral)	96.5% accuracy	Multi-modal sensing improves detection accuracy	Requires specialized sensors
12	Hassan et al., 2025 [12]	Cotton	Custom dataset	CottonNet-MHA (multi-head attention network)	96.3% accuracy	Attention mechanism improves feature extraction	Explainability limited

13	Cui et al., 2025 [13]	Cotton	Custom dataset	Resource-efficient cotton network	95.7% accuracy	Edge computing optimized architecture	Limited multi-disease capability
14	Gunasekaran et al., 2025 [14]	Tomato	Review study	Lightweight deep learning models	N/A	Review of edge AI techniques in agriculture	No empirical results
15	Nurullah et al., [15]	Tomato	Custom dataset	Vision Transformer + EfficientNet + XAI	High accuracy (not specified)	Multi-label disease classification with explainability	Limited validation
16	Ismail et al., [16]	Rice	Cross-regional dataset	Vision Transformer vs CNN comparison	96.8% accuracy	Demonstrates ViT generalization ability	Limited crop diversity
17	Thakur et al., 2022 [17]	Apple, Maize, Rice	Five public datasets	PlantXViT (ViT + CNN hybrid) with Grad-CAM and LIME	Apple: 93.55%, Maize: 92.59%, Rice: 98.33%	Lightweight multi-crop model with explainability	Tested mostly on public datasets
18	James et al., [18]	Rice	Custom dataset	Hybrid CNN-ViT with attention and XAI	97.5% accuracy	Combines CNN and Transformer advantages	Computational complexity not discussed
19	Al-Falluji et al., [19]	Rice	Custom dataset	Explainable ensemble deep learning model	96.2% accuracy	Energy-efficient Green AI framework	Limited deployment details
20	Swapno et al., 2026 [20]	Cotton	Custom dataset	Transformer-based explainable framework	94.8% accuracy	Attention visualization for disease detection	Limited to leaf-level diagnosis
21	Udayananda et al., 2022 [21]	Rice	Review study	Traditional ML approaches	N/A	Review of machine learning techniques for rice disease detection	Focus on early ML methods
22	Islam et al., 2023 [23]	Tomato	Custom dataset	Optimized CNN with hyperparameter tuning	98.1% accuracy	Systematic hyperparameter optimization	Limited architectural novelty
23	Rajasekar et al., 2021 [24]	Cotton	Custom dataset	Transfer learning	High accuracy (not specified)	Demonstrates effectiveness of transfer learning	Model details limited
24	Chen et al., 2020 [25]	Rice	Custom dataset	Transfer learning using ResNet and VGG	98.5% accuracy	Early DL application for rice disease classification	Limited dataset diversity
25	Qadri et al., 2023 [27]	Rice	Custom dataset	CNN comparison (InceptionV3, VGG16, VGG19, ResNet50)	99.2% accuracy (ResNet50)	Comparative analysis of CNN architectures	Controlled dataset conditions
26	M et al., 2025 [29]	Multiple plants	Custom dataset	GAN-enhanced Vision Transformer + XAI	High accuracy	Synthetic data augmentation for imbalance handling	Limited validation

					(not specified)		
27	Dhaka et al., 2021 [30]	14 crops	PlantVillage (54,306 images)	Survey of CNN models (ResNet, DenseNet, MobileNet)	Up to 99.75% accuracy	Comprehensive survey across multiple crops	Highlights lack of real-world field datasets

Some of the major observations of the comparative analysis include:

Trends in performance Recent models (20232025) have an average accuracy of more than 92, and multiple studies have reported accuracy of over 96 on controlled data sets [5], [11], [12], [13], [16], [18], [19], [23], [25], [27].

Architectural Evolution: There has been a clear evolution of traditional convolutional neural networks (CNNs) in 20202021 into lightweight versions of the YeoL model, 20222024, and finally, hybrid CNNVision Transformer (ViT) based on models in 20232025 [1], [3], [4], [8], [9], [15], [16], [17], [18], [20], [22], [28], [29].Crop Distribution: Rice and cotton are the most studied crops, and then tomato, fewer studies have been done on wheat and multi-crop schemes [1], [2], [3], [4], [5], [6], [8], [9], [10], [11], [12], [13], [14], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [27], [28], [30].Explainability Integration: It has become popular in recent research (20232025) to adopt methods of explainable artificial intelligence (XAI), such as Grad-CAM, LIME, attention visualization, and others (20232025) [2], [5], [15], [17], [18], [19], [20], [22], [28], [29].Focus on Edge Computing: Edge computing is increasingly focused on lightweight models which can be deployed on mobile devices and at edges [1], [3], [6], [7], [9], [10], [13], [14], [31], [32], [33], [34].Dataset Limitations: Most studies are based on custom or lab datasets, little field-validation, which is to be found in [1], [3], [5], [6], [8], [9], [10], [11], [12], [13], [16], [18], [19], [20], [23], [24], [25], [27].Although there are considerable improvements in deep learning to detect plant diseases, there are a number of research gaps that are critical:

Unavailability of Multi-Crop Disease Detection Frameworks

The existing literature is mostly focused on identifying diseases in the context of single crop systems thus limiting the practicality of these techniques in the context of heterogeneous agriculture systems where several crop species interact [2], [7], [14], [17], [22], [28], [30]. Few studies have tried to support many systems of crops; the fact that there have been few studies looking to support multiple crops exemplified by PlantXViT [17], [22], [28], and the extensive survey of Dhaka et al. [30] indicates that there are no comprehensive and unified frameworks capable of detecting diseases in cotton, tomato, wheat, and rice simultaneously. This gap, therefore, hinders the achievement of scalable and cost-effective solutions necessary to achieve precision agriculture [2], [7].

Restricted Real-Field Data Verification

Majority of studies are based on controlled laboratory data or pictures taken in optimal conditions, which could not be applicable to the complex and changeable conditions in the real world agricultural setting [1], [2], [6], [7], [10], [14], [30]. Diverse lighting conditions, complicated backgrounds, occlusions, multiple disease co-occurrence, and different disease stages are some of the major challenges that have been insufficiently covered in the research studies [6], [10], [30]. The unavailability of the large-scale and diversified data in the real field prevents the generalization and real-life application of suggested models [2], [7], [10], [14].

Intensive Computational models that cannot work in edge devices

Although more recent works have achieved more in the development of lightweight models, a broad selection of high-performing models are still computationally expensive, and inapplicable to resource-constrained edge devices like smartphones and IoT sensors [1], [6], [7], [13], [14], [31], [32], [33], [34]. Computational efficiency and model accuracy remain a critical issue that remains to be a challenging task, especially in real-time disease identification in remote regions with poor connectivity in agriculture [7], [14], [31].

AI Models are not explainable

Although there is increased attention on explainable AI, several deployed models can still be black boxes without sufficient interpretability mechanisms [2], [5], [7], [14], [17], [22], [27], [28]. The agricultural practitioners and farmers need transparent and reliable systems that can give them clear explanation of the diagnosis of diseases so that they can make informed decisions [2], [5], [27]. The existing methods of XAI could introduce additional computational overhead and could be suboptimal when it comes to deploying edges [2], [7], [17], [22], [28].

Low Adaptation of Mobile or Farmer-Friendly Systems

There are very few studies that deal with the practical implementation of AI models in the form of easy-to-use mobile applications that can be accessible to farmers with low technical skills [7], [14], [31]. Difficulties include the creation of user-friendly interfaces, the ability to offer practical treatment advice, multi-lingual support, and the offline support of locations with limited internet accessibility [7], [14] and [31].

The company has poor management of Multi-Disease and Pest Co-occurrence. The real-world situations in agriculture frequently relate to the multiplicity of diseases and pests on a crop at the same time, whereas the majority of the existing models are developed by considering one disease at a time [1], [2], [15], [30]. There are limited methods of multi-label classification that are capable of identifying and localising several diseases at once [15], [30]. Moreover, the relations between diseases and pests that may complicate the diagnosis and treatment are hardly covered even in the current studies [1], [2].

Lack of Focus in the Detection of the Disease Severity

Although the most common type of studies operates on the presence/absence categorization of diseases, the severity of diseases must be quantified to understand the need of certain treatment procedures, as well as the outcome in terms of yield losses [4], [8], [30]. There are not many models that give such fine-grained severity grading or looking at the progression over time [4], [8].

Cross-Regional and Cross-seasonal limited generalization

Most models are trained and tested on data of certain geographic areas and seasons and cannot be generalised to other climatic conditions, soil characteristics and farming methods [16], [30]. Ismail et al. [16] established that Vision Transformers are promising with respect to cross-regional generalisation, but is an understudied field that still needs investigation.

Proposed Methodology

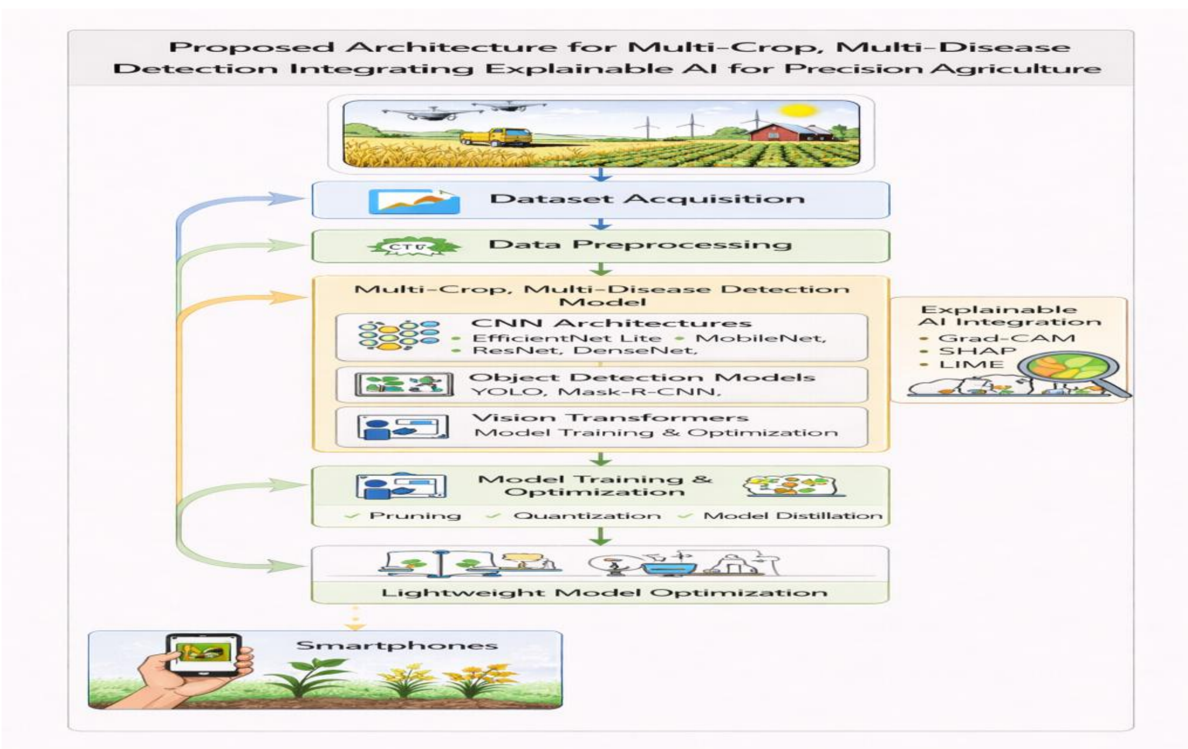

Fig. 1. *Proposed Architecture of a Multi-Crop, Multi-Disease Detection Framework Integrating Explainable AI for Precision Agriculture*

According to the research gaps identified, the following research directions can be proposed in the future:

- Multi-Crop Unified AI Models: The creation of cross-crop unified deep-learning systems that are able to identify diseases in a variety of crops, such as cotton, tomato, wheat, rice, and others, will be a top research priority [2,7,17,22,29,30]. These models are to be based on the transfer-learning methods and domain-adaptation so that knowledge is shared between crops, and high diagnostic accuracy is maintained in crop-specific diseases[17,22,28,30] . The combination of approaches to multi-task learning that can optimize simultaneously the processes of detecting, localizing, and assessing the severity of disease in a variety of crops can improve their efficiency and scalability [30].
- Explicable AI Models in the Agricultural Field: Future studies should also focus on developing explainable AI (XAI) methods, which are computationally efficient and that can be deployed at the edge in agricultural environments [2,5,7,17,22,28]. This involves optimization of Grad-cam, SHAP and LIME to make real-time inference on mobile devices, development of new

visualization strategies to meet specific needs of farmers, and conducting user studies to evaluate the effectiveness of explanations in fostering trust and decision-making[2,5,17,22,27,28]. The visual heatmap can also be enhanced with natural-language explanations to enhance the accessibility of non-expert users[2,5] .

- Edge AI Implementation on Smartphones: The promotion of lightweight model architecture and optimization methods such as pruning, quantization, and knowledge distillation will allow detecting diseases in real time on smartphones and cheap IoT devices, thus facilitating their widespread implementation [1, 6, 7, 13, 14, 31, 32, 33, 34]. The possibilities should be researched into neural-architecture searching to find the best lightweight design, inefficient attention schemes with low computational requirements, and on-device learning to customize the models to the local environment [7, 31, 32, 33, 34].
- Interaction with the IoT and Precision Farming: The building of all-encompassing precision-agriculture systems that combine AI-enhanced disease detection and IoT sensors (soil moisture, temperature, humidity), meteorological data, and farm-management platforms can be used to support proactive disease management and optimal treatment solutions [7, 31]. These systems should facilitate automated surveillance systems, warning systems and data-based decision support systems based on farmers [7, 31].
- Real Time Disease Surveillance Systems: The development of permanent monitoring equipment by the use of drones, autonomous robots, or stationary cameras to observe the fields in large areas is a topical research path [7, 31]. These systems ought to be able to use a temporal analysis to monitor the development of the disease, predict the outbreaks, and measure the effectiveness of the treatment over time [7, 31].
- Large Sample Real-Field Data: To model the complexity of agricultural environments in diverse regions, seasons and growth stages, it is essential to construct large, heterogeneous real-field datasets that can be used to produce robust, generalizable models [2, 6, 7, 10, 14, 30]. Such datasets are required to contain the co-occurrence of multi-diseases, changing environmental factors, and longitudinal data to enable in-depth disease-progressive analysis [2, 6, 10, 30].
- Multi-Label and Multi-Disease Detection: The practical applications of multi-label classification methods that can detect and localize several diseases and pests attacking crops at the same time is vital [1, 2, 15, 30]. The studies are to be conducted on the mechanisms of attention and on instance-segmentation methods to find individual disease areas in the complex field conditions [1, 15, 30].
- Grade of disease severity and Yield prediction: Coming up with models, which will not only identify diseases, but also determine the levels of severity and potential losses of yields will provide rich decision support to farmers [4, 8, 30]. A combination of these models and economic frameworks to prescribe cost-effective treatment plans depending on the severity of the disease and the yield expected is a good line of research [4, 8].
- Cross-Regional and Cross-Seasonal Adaptation: Investigating domain adaptation and transfer learning techniques to improve model generalization across different geographical regions, climates, and seasons is critical for global deployment [16], [30]. Research should explore meta-learning approaches that enable rapid adaptation to new regions with limited labeled data [16], [30].
- Farmer-Centric Design and Usability: The user-oriented research of creating easy-to-use and user-friendly mobile applications that can satisfy farmers with their needs, technical literacy, and local languages is crucial to the adoption of the technology [7, 14, 31]. Adding voice interfaces, in-field-guiding augmented reality, and other knowledge-sharing platforms that are community-related can result in increased usability and impact [7, 14, 31].

Conclusion

This literature review has critically examined the state-of-the-art in deep-learning methods in multi-crop disease detection, reviewing thirty latest studies published in 2025. The review shows that there has been a significant improvement in the advancement of accurate, efficient and explainable AI systems to achieve precision agriculture and that there have been significant changes in lightweight architectures, Vision Transformers, and explainable AI methods. Important discoveries include the fact that modern deep-learning models, especially hybrid CNN-ViT models and fine-tuned versions of YOLO models, achieve high accuracies of over 92% when detecting across various types of crop diseases on cotton, tomato, wheat, and rice [1], [3], [4], [5], [8], [9], [10], [11], [12], [13], [16], [17], [18], [19], [22], [23], [25], [27], Transfer learning has become an important method to improve the performance on small training data whereas attention mechanisms enhance the model focus on the disease-relevant features [1], [2], [12], [18], [25], [30]. The explainable AI approaches, including Grad-CAM, SHAP, LiME also solve the problem of blackbox, which contributes to building trust and makes it easier to adopt among agricultural users [2], [5], [15], [17], [18], [19], [20], [22], [27], [28], [29]. Much work has been done to create lightweight models that can be deployed to edges of smartphones and IoT devices; multiple works have reported competitive performance and have shrunk the models by more than 80 percent [1], [3], [6], [9], [10], [13], [17], [22], [28]. The development is essential to facilitate the real-time detection of diseases in resource-limited agricultural settings without the necessity to connect to the cloud [1], [6], [7], [13], [14], [31]. However, there are still critical research gaps that should be bridged in order to achieve the full potential of AI in precision agriculture. Lack of coherent multi-crop systems imposes restrictions on scalability and cost-efficiency since the majority of current research is dedicated to single-crop systems [2], [7], [17], [22], [28], [30]. Low levels of real world validation lead to questions concerning the applicability of models to complex, changeable agricultural systems [2], [6], [7], [10], [14], [30]. The trade-off between the accuracy and the efficiency of the model still remains as a problem to the practical implementation on the edge devices [7], [14], [31]. The lack of explainability in most of the deployed models makes trust and acceptance among farmers difficult [2], [5], [7], [27]. Inadequate management of the usage of multi-disease and pest co-occurrence conditions restricts their reality [1], [2], [15], [30].

The next research should focus on the creation of coherent multi-crop AI to utilize transfer learning and domain adaptation to identify diseases in numerous crops at general levels [2], [7], [17], [22], [28], [30]. The development of explainable AI methods with an emphasis on providing optimization at the edge will lead to a better understanding of the model and increase its trust among users [2], [5], [7], [17], [22], [28]. The further optimization of lightweight architectures by using neural architecture search, pruning, and quantization will allow the large-scale deployment of smartphones [1], [6], [7], [13], [14], [31], [32], [33], [34]. Deep learning will be integrated with IoT sensors and precision farming systems to facilitate full data-based agricultural control [7], [31]. It is necessary to construct large and heterogeneous, real-world datasets, which reflect the complexity of agricultural environments, to build sound and robust, generalized models [2], [6], [7], [10], [14], [30].

The creation of explicable, lightweight and scalable multi-crop disease sensor systems is a radical life opportunity in precise agriculture. Addressing all the research gaps and following the identified future directions, the agricultural AI community can develop practical, farmer-friendly systems to boost food security, lessen the number of economic losses, and introduce sustainable agricultural practices in the global market. Deep learning paired with explainable AI, edge computing, and IoT technologies are converging technologies that will reshape the future of plant disease management so that farmers have reliable, accessible, and usable diagnostic tools in the 21 st century.

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