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REVIEW ARTICLE

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Image-based crop disease detection using machine learning

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Abstract

Crop disease detection is important due to its significant impact on agricultural productivity and global food security. Traditional disease detection methods often rely on labour-intensive field surveys and manual inspection, which are time-consuming and prone to human error. In recent years, the advent of imaging technologies coupled with machine learning (ML) algorithms has offered a promising solution to this problem, enabling rapid and accurate identification of crop diseases. Previous studies have demonstrated the potential of image-based techniques in detecting various crop diseases, showcasing their ability to capture subtle visual cues indicative of pathogen infection or physiological stress. However, the field is rapidly evolving, with advancements in sensor technology, data analytics and artificial intelligence (AI) algorithms continually expanding the capabilities of these systems. This review paper consolidates the existing literature on image-based crop disease detection using ML, providing a comprehensive overview of cutting-edge techniques and methodologies. Synthesizing findings from diverse studies offers insights into the effectiveness of different imaging platforms, contextual data integration and the applicability of ML algorithms across various crop types and environmental conditions. The importance of this review lies in its ability to bridge the gap between research and practice, offering valuable guidance to researchers and agricultural practitioners.

KEYWORDS
algorithms, artificial intelligence, disease detection, imaging, machine leaning

Abbreviations: %MAE, percentage mean absolute error; ADLM, agro deep learning model; AI, artificial intelligence; ANN, artificial neural network; BP, back-propagation; BPNN, back-propagation neural network; CapsNet, capsule neural network; CBAM, convolutional block attention module; CNN, convolutional neural network; DCNN, deep convolutional neural network; DenseNet, densely connected convolutional network; DR-IACNN, deep learning real-time interactive attention-based convolution neural network; DT, decision tree; E-CNN, enhanced convolutional neural network; ELM, extreme learning machine; ESDNN, ensembled stack deep neural network; ExG, excess green; FPS, frames per second; GAN, generative adversarial network; GPDCNN, global pooling dilated convolutional neural network; GPS, global positioning system; G-RecConNN, gated-recurrent convolutional neural network; GRNN, generalized regression neural network; IoU, intersection over union; KNN, K-nearest neighbour; LIME, local interpretable model-agnostic explanation; mAP, mean average precision; MFOBOA, moth flame optimization-butterfly optimization algorithm; ML, machine learning; MLP, multilayer perception; MSAVI, modified soil-adjusted vegetation index; NB, naïve Bayes; NDVI, normalized difference vegetation index; OEDTN, optimal ensemble deep transfer network; RANet, residual attention network; RBF, radial basis function; R-CNN, region-based convolutional neural network; REG, regression; ReLU, rectified linear unit; ResNet, residual network; RF, random forest; RGB, red, green, blue; RNN, recurrent neural network; SCSA-Transformer, spatial convolutional self-attention-based transformer; SGD, stochastic gradient descent; SIDMO, self-improved dwarf mongoose optimization; SIFT, scale-invariant feature transform; SPP, spatial pyramid pooling; SSA, salp swarm algorithm; STA-GAN, spatio-temporal attention-guided generative adversarial network; SVM, support vector machine; SwinT, Swin Transformer; TSRN, two-stream spectral-spatial residual network; UAV, unmanned aerial vehicle; UV-Vis, ultraviolet-visible; VGGNet, visual geometry group network; VI, vegetation index; WOA, whale optimization algorithm; XGB, XGBoost; YOLO, You Only Look Once.

Ting Xiang Neik, Monica F. Danilevicz and Shriprabha R. Upadhyaya contributed equally to the work.

1 | INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) technologies have advanced significantly in recent years, particularly in machine vision. Machine vision involves using cameras and computer algorithms to extract information from images or videos, enabling machines to 'see' and interpret the world around them (Shin et al., 2023). Machine vision technology has the potential to transform agriculture by providing farmers with real-time data that can assist them in making more informed decisions (Tian et al., 2020). For example, machine vision can monitor crops and detect signs of stress (Kacira et al., 2002; Khotimah et al., 2023; Nhamo et al., 2020), disease (Karthik et al., 2020; Sethy et al., 2020) or pests (Sena Jr. et al., 2003). Pathogens and pests significantly impact crop yield, causing annual losses estimated at $220 billion (Ristaino et al., 2021). Climate change further increases the risk of plant disease, endangering global food supply and plant biodiversity. In recent years, imaging platforms such as smartphones, unmanned aerial vehicles (UAVs)/drones and satellites have been increasingly used to detect crop disease, providing farmers with insights into crop health and allowing them to take corrective action.

Farmers can take images of their crops using smartphones and upload them to a cloud-based platform, where ML algorithms analyse the images and provide analysis. For example, Mrisho et al. (2020) developed Nuru, a deep learning model for Android smartphones to diagnose diseases in cassava. The model demonstrated a 65% accuracy, highlighting its potential as a cost-effective and convenient tool that leverages the farmer's existing smartphone for in-field diagnosis. Cameras deployed on UAVs and ground-based platforms can capture high-resolution images of the crops to monitor large areas quickly and efficiently (Hafeez et al., 2022). At a larger scale, satellite sensors can detect pathogen outbreaks in the field and monitor crop health (National Aeronautics and Space Administration [NASA], Science Mission Directorate, 2010; Yang, 2020).

ML approaches are increasingly being used to automatically detect patterns or anomalies indicating the presence of crop disease (Neupane & Baysal-Gurel, 2021). Deep learning networks, including convolutional neural networks (CNNs), recurrent neural networks (RNNs) and autoencoders, can identify these disease patterns in images. For example, Mohanty et al. (2016) used a dataset containing 54,306 images of diseased and healthy plant leaves to train a deep convolutional neural network (DCNN) to identify 14 crop species and 26 diseases. The model achieved 99.35% accuracy on the test set, showcasing the potential of this approach for widespread and efficient crop disease diagnosis.

This review covers various aspects of image-based crop disease detection. We assess the performance of disease detection models reported across multiple studies, highlighting the challenges observed and the role of different sensor technologies in crop disease detection. The review discusses the impact of contextual data (weather, field management) on crop disease detection and considers the evolving landscape under climate change scenarios. We systematically examine various crops and diseases, employing a range of ML/AI strategies for detection. Tailored crop disease detection models for specific regions and species are discussed, followed by an exploration of image detection systems for area surveillance to identify novel pathogens. Real-time monitoring helps in the timely detection of crop diseases and provides insights into autonomous crop disease management. Collaborative mapping is explored as a tool for effective crop disease detection, and we conclude by addressing automated technologies tailored for deployment in developing and low-income countries.

2 | IMAGING PLATFORMS AND SENSORS IN CROP DISEASE DETECTION

Imaging platforms can be deployed at multiple levels (ground, aerial and spatial) to collect images used for plant phenotyping and stress detection (Sawant, 2017). These platforms might be fitted with one or more sensors that can capture spectral variation at different ranges, such as red, green and blue (RGB) optical, infrared thermal, multispectral and hyperspectral sensors, to find spectral profiles associated with disease infection. Optical RGB cameras often capture images within the 400–750 nm wavelength range, being able to record changes in the visible light range, with slight variations in spectral sensitivity observed across smartphone cameras (Tominaga et al., 2021). Optical RGB cameras are the most popular sensors employed for plant phenotyping due to their low entry cost and wide availability of tailored image processing tools (Li et al., 2014). However, in some cases, the disease symptoms are not detected in the visible light range, requiring specialized devices. Infrared thermal devices are usually designed to capture spectral variation at 3–5 μm or 7–14 μm to mean temperature changes and allow for plant stress associated with disease infection, potentially capturing changes in the leaf physiology (Zhu et al., 2018). Multispectral and hyperspectral cameras are even more versatile. They can capture spectral images at more extensive wavelength ranges, including near-infrared and red-edge, often used for health assessments (Scotter, 2005). These wider range sensors can capture disease symptoms invisible to the naked eye, as the narrow wavelength bands allow the separation of specific components in the leaf, such as nutrient accumulation (de Oliveira et al., 2022), pigment changes (Wan et al., 2022) and other stress indicators (Guerrero et al., 2023). The detection accuracy of ML models for disease prediction is intrinsically tied to the sensor and data collection methods employed, which must be selected considering (a) the scientific question, considering if it requires tracking early symptoms invisible to the naked eye or late-stage infection; (b) the target plant and pathogen species, which will guide the pixel resolution and wavelength choice required to detect symptoms; (c) environmental conditions, such as indoors versus field settings that might introduce challenges for camera calibration and increased background complexity; and finally (d) available resources, to design a data collection pipeline with sensors that can effectively depict disease infection at sufficient pixel resolution to enable the model to learn. In a previous study, West et al. (2003) highlighted the potential of using optical sensing and mapping to enhance fungicide applications against fungal diseases.

In addition, a study used a compact, modular optical sensing system to detect early bacterial infection in tomato leaves, achieving effective discrimination between healthy and infected plants 3 days post-inoculation through the application of direct UV–vis spectroscopy, optical fibres and principal component analysis (Reis-Pereira et al., 2021). UAVs equipped with multispectral or hyperspectral sensors can be used to identify the presence of pathogens and to monitor crop health over time (Lowe et al., 2017). Moghadam et al. (2017) used hyperspectral imaging and ML to detect early signs of tomato spotted wilt virus in capsicum plants. Discriminatory features from the entire spectrum, vegetation indices (VIs) and probabilistic models effectively discriminated between healthy and inoculated plants. The results highlight the potential for enhancing precision agriculture by enabling timely responses to plant diseases. In this context, Zhang et al. (2019) aimed to enhance the monitoring and detection of yellow rust in winter wheat. They proposed a novel approach using UAVs equipped with hyperspectral image sensors and introduced a DCNN that used very high spatial resolution hyperspectral images captured by UAVs.

Khotimah et al. (2020) introduced a high-performance two-stream spectral-spatial residual network (TSRN) for hyperspectral image classification and found that the proposed architecture performs well even with small datasets, outperforming state-of-the-art methods in overall accuracy, average accuracy, kappa value and training time.

Thermal sensors can detect differences in temperature between healthy and diseased plants. This can identify plant stress and diagnose diseases, including virusal and fungal infections (Zhu et al., 2018). Thermal sensors can also be used to identify insect infestations, as sensors can detect the heat of insects (Cardim Ferreira Lima et al., 2020). Zhu et al. (2018) explored infrared thermal imaging technology for early detection of tomato mosaic disease and wheat leaf rust. By continuously monitoring temperature changes during the incubation period following inoculation, the study demonstrated that the maximum temperature difference ranged from 0.2° to 1.7°C for tomato mosaic disease and 0.4° to 2°C for wheat leaf rust. The maximum temperature difference increased as the diseases progressed, while the average temperature decreased. They concluded early disease detection was feasible by combining infrared thermal imaging with calculating maximum temperature difference.

One advantage of using UAVs carrying different sensors is the early identification of diseases, preventing infection spread and mitigating crop loss. For example, Kitpo and Inoue (2018) implemented a drone-based system within the internet-of-things (IoT) architecture for early and real-time disease detection in rice. Their system employed image processing techniques for data acquisition and analysis and allowed real-time mapping of the position of infected rice through global positioning system (GPS) sensors. Their paper proposes this system as a preliminary solution to support early and real-time disease detection in rice, emphasizing the potential of IoT-enabled drone technology in agriculture monitoring. Mogili and Deepak (2018) reviewed various types of UAVs and their applications in pesticide spraying. They investigated how UAVs are used for crop monitoring, disease detection and yield optimization.

Similarly, Devi and Priya (2021) concentrated on using UAVs to recognize plant disease through image analysis. They explored various optical techniques, including RGB imaging, multi- and hyperspectral sensors, thermography, chlorophyll fluorescence and 3D scanning, for their potential in automated and objective disease detection systems. The research emphasized the importance of highly sophisticated data analysis methods for accurate disease detection, offering insights into complex plant–pathogen systems.

Implementing decision-support systems with UAVs can enhance decision-making, increase production, improve product quality and reduce labour requirements (Sinha, 2020). However, UAVs have limited flight time and can only cover a small area at a time, limiting the amount of data that can be collected. Adverse wind and weather conditions can also lead to poor-quality images (Abbas et al., 2023).

Satellites can view large areas and collect data over regular intervals. High-resolution satellites provide potential for nonintrusive, extensive, rapid and flexible measurements of plant biophysical and biochemical properties (Blasch et al., 2023). This can be useful for monitoring the spread of crop disease over large regions. However, the spatial resolution of satellite images is not as high as those captured by UAVs, which limits the ability to detect disease at a fine scale (Blasch et al., 2023).

3 | INTRODUCING CONTEXTUAL DATASETS FOR CROP DISEASE DETECTION

Complementary data types, such as weather, soil properties and agronomic practices, can improve the accuracy of crop disease detection by providing additional information on the conditions affecting crop health (Fenu & Malloci, 2021). Multiple studies have linked environmental conditions to pathogen infection risk (Xiao et al., 2019), with a growing literature highlighting the effects of climate change on plant pathogen epidemiology, as detailed by Arslantaş and Yeşilırmak (2020). The strong influence of weather and farming practices in disease development motivates researchers to include this in the ML algorithms. Multimodal ML integrates different data modalities into a global space for training the model. Most commonly, it can be achieved by combining the datasets into a data cube (early fusion) that is used as input data for the model, allowing the model to 'see' the sample data simultaneously (Zamani & Baleghi, 2023). Alternatively, in the late fusion method, the data sources are used separately to train specialized models (i.e., one model per data type) that are combined towards the end to provide a unified prediction (Zamani & Baleghi, 2023). However, it is important to notice that auxiliary data is only relevant in a multi-environment study in which the model has various examples to distinguish how each feature affects disease detection. For example, Kaundal et al. (2006) used six key weather variables to develop and validate models for predicting plant disease by conducting cross-location and cross-year analyses. In cross-year models, the conventional multiple regression (REG) approach achieved an average correlation coefficient (*r*) of 0.50, improving to 0.60 with a back-propagation neural network (BPNN) and 0.70 with a generalized regression neural network (GRNN). The support vector machine (SVM) method demonstrated the highest performance, reaching an *r* of 0.77. Cross-location validation showed similar trends, with SVM outperforming REG, BPNN and GRNN with an *r* of 0.74. The SVM-based approach improved correlation coefficients and reduced percentage mean absolute error (%MAE), highlighting its potential to advance plant disease forecasting. The study further presented a novel SVM-based web server for rice blast prediction.

Soil properties, such as pH, nutrient levels and organic matter content, can also impact crop health and disease susceptibility (Dahikar & Rode, 2014). Kumar et al. (2021) proposed a multilayered perceptron model for predicting fungal diseases in plants, including powdery mildew, anthracnose, rust and root rot/leaf blight, based on real-time data from soil sensors and satellite information on micrometeorological factors. The method involved dataset preprocessing, exploratory data analysis and a detection module. The study emphasized the economic benefits of this cost-effective technique and its feasibility for timely and accurate plant disease detection.

Optimized agronomic practices, such as irrigation, fertilization and pesticide application, can affect crop health and the prevalence of diseases. Remote sensing offers spatial and temporal variability insights in water management, aiding precision in its management. Managing water resources becomes particularly challenging in arid regions, where groundwater is a primary irrigation source (Mauget et al., 2017). Traditional soil assessment methods are expensive and time-consuming, but ML techniques provide a cost-effective solution for analysing heterogeneous data obtained from remote sensing and soil mapping sensors (Benos et al., 2021). ML methods offer a reliable and efficient approach to address issues such as land degradation, soil nutrient imbalance and soil erosion, contributing to improved and sustainable soil management practices.

Overall, contextual data can provide valuable crop disease detection and management information. Integrating ML and image vision technologies can help unlock this potential by enabling more accurate and targeted disease detection and prediction.

4 | IMAGE-BASED CROP DISEASE DETECTION UNDER CLIMATE CHANGE SCENARIOS

Climate change is expected to impact crop health and disease patterns significantly (Burdon & Zhan, 2020), increasing the complexity of crop disease detection. Climate change can impact crop disease detection, particularly through alterations in disease patterns. It can also alter temperature, rainfall patterns and other factors that influence the incidence and severity of crop diseases. This means that models developed using historical data may not accurately predict disease susceptibility under future climate conditions (Yang et al., 2023). In addition, climate change can increase the variability of weather patterns, leading to more unpredictable disease outbreaks. This can make it challenging to develop accurate disease detection models (Rosenzweig et al., 2001).

Moreover, climate change can alter the interactions between crop diseases and pathogens, leading to new disease patterns and complexities in disease detection (Raza & Bebber, 2022). Climate change also induces alterations in crop phenology, impacting the timing of various crop growth stages (Piao et al., 2019). These shifts in phenological patterns can influence disease susceptibility and the timing of disease outbreaks (Jeger, 2022). Consequently, when predicting disease patterns, models need to account for changes in crop phenology to capture the evolving dynamics accurately. The impact of climate change on crop management practices may necessitate adjustments in various aspects, including irrigation, fertilization and pesticide use (González-Domínguez et al., 2020).

Developing sophisticated disease detection models that incorporate various data sources, including historical disease data, weather data, soil data and other contextual data, is important so that ML and image analysis techniques can be used to develop models that account for the complexities of climate change scenarios. However, continued research and development will be needed to ensure these models are effective under future climate conditions.

5 | MACHINE LEARNING AND DEEP LEARNING METHODS

ML, a category of AI, trains algorithms to make predictions based on data. In contrast, deep learning, a subcategory of ML, uses neural networks with multiple layers to learn features and patterns. These algorithms are trained using various learning techniques. Supervised learning trains a model using labelled datasets to learn their relationship, while unsupervised models deal with unlabelled data to uncover hidden patterns (Liu & Wu, 2012). Transfer learning is a common technique in deep learning networks that reuses the knowledge from a pretrained model for related tasks, reducing the need for extensive data and computational resources (Pan & Yang, 2010). Back-propagation, another deep learning architecture training method, involves a forward pass that computes predictions and a backward pass that propagates errors, thereby minimizing errors between predicted and actual outputs through iterative updates (Rumelhart et al., 1986).

Some of the most popular ML methods are random forest (RF), XGBoost (XGB), K-nearest neighbour (KNN) and SVM. RF and XGBoost are ensemble learning algorithms. RF builds a 'forest' of decision trees where each tree is trained independently and then combined, in contrast to XGBoost, which uses a gradient boosting technique where trees are built sequentially, and each tree corrects the error of the previous one (Breiman, 2001). RF can handle larger datasets and is less sensitive to hyperparameters, while XGBoost offers better predictive performance but needs careful tuning and potentially higher computational time. SVM is a supervised algorithm that aims to find the best hyperplane in an N-dimensional plane that can distinctly classify the datapoints (Cortes & Vapnik, 1995). It is usually chosen when the number of features is larger than the number of training instances. KNN is an instance-based learning algorithm that works on the principle that a sample point within a dataset will generally exist near other points with similar properties (Cover & Hart, 1967). One of the main disadvantages of such instance-based classifiers is the large computational time for classification.

The most popular class of deep neural networks are CNNs, known to be inspired by the connectivity patterns in the human brain. It uses a hierarchical pattern of layers to automatically learn and extract features from input images, effectively capturing spatial relationships. Each layer builds on the outputs of previous layers to recognize increasingly complex patterns (O'Shea & Nash, 2015). Various CNN architectures have evolved over the years to handle different tasks. Some of the most common ones are visual geometry group network (VGGNet), residual network (ResNet), AlexNet, densely connected convolutional network (DenseNet) and MobileNet. VGGNet employs 3×3 convolutional filters and is recognized for its straightforward architectures, unlike ResNet, which allows for very deep networks of up to 152 layers to be trained effectively. While VGGNet is effective on smaller datasets, it has high computational and memory demands (Simonyan & Zisserman, 2015). ResNet achieves better performance accuracy but may require more memory resources (He et al., 2016). AlexNet, used for large-scale image classification tasks, uses ReLU activation functions but is shallow compared to ResNet, limiting its performance on complex tasks (Krizhevsky et al., 2017). MobileNet, designed to work on mobile networks, works efficiently with limited computational resources but may have lesser accuracy than VGGNet and ResNet (Howard et al., 2017). DenseNet uses feed-forward architecture connecting each layer to every other layer, enhancing feature propagation and reuse. Yet, it can be challenging to train on extensive datasets due to their computational demands (Huang et al., 2016). These architectures have various strengths and can be used for a specific task considering the computational constraints and dataset.

You only look once (YOLO) is an object detection system that uses a grid-based approach. It processes the entire image in a single pass through the network, making it extremely fast (Redmon et al., 2016).

As postulated in the no-free-lunch theorem, a single algorithm cannot excel in all kinds of problems (Goldblum et al., 2023). As highlighted in the next section, multiple instances are observed where deep learning outperforms ML, as seen in Lu et al. (2017) and Vidhya and Priya (2022). ML methods have also obtained high accuracies (over 90%) on a par with deep learning methods, as observed in Cao et al. (2018), Kaundal et al. (2006) and Narmilan et al. (2022).

6 | MULTICROP DISEASE DETECTION: DIVERSE ML/AI APPROACHES

This section reviews crop disease detection in major crops employing ML/AI algorithms and models summarized in Table 1. In addition, model performance, including a detailed report on model evaluation, hyperparameters used and reported accuracy, are summarized in Table 2.

6.1 | Cereals

Wheat is a major staple crop that faces constant disease threats that can impact crop yield and quality. Goyal et al. (2021) proposed an automatic wheat disease classification method in response to these challenges. The study used deep learning-based image analysis to concentrate on the spike and leaves, the most vulnerable parts of a wheat plant. A novel deep learning model was developed, achieving an accuracy of 97.88%. The comparative analysis demonstrated substantial improvements over popular models such as VGG16 and ResNet50, showcasing advancement in precision, recall and *F*-score metrics. The findings highlight the potential of this approach for effective wheat disease classification, contributing to enhanced crop quality assessment and pricing strategies. In another study, Picon et al. (2019) aimed to enhance fungal infection identification, which minimizes yield losses and optimizes fungicide treatments. The researchers developed an adapted deep residual neural network-based algorithm using over 8178 images for detecting septoria, tan spot and rust in real acquisition conditions. Their findings underscore the algorithm's efficacy for early identification of wheat diseases in real-world conditions.

Rice is essential for global food security. Rahman et al. (2020) developed disease and pest detection approaches in rice plant images. The study applied a two-stage CNN architecture suitable for mobile devices and compared its performance with memory-efficient CNN architectures such as MobileNet, NasNet Mobile and SqueezeNet. Results showed the architecture's ability to achieve an accuracy of 93.3% with a significantly reduced model size, approximately 99% smaller than VGG16.

Lu et al. (2017) developed a method for rice disease identification using a dataset of 500 images of diseased and healthy rice leaves and stems. The CNNs were trained to identify 10 common rice diseases. Employing a 10-fold cross-validation strategy, the CNN-based model demonstrated an accuracy of 95.48%, surpassing the performance of conventional ML models.

A network architecture called Mobile-DANet was developed by Chen et al. (2020) to identify maize crop diseases. Based on DenseNet, this architecture incorporated depth-wise separable convolution in dense blocks and an embedded attention module to assess interchannel relationships and spatial points in input features. The model used transfer learning to enhance accuracy while conserving computational power compared to deep CNNs. Mobile-DANet achieved an average accuracy of 98.50% on an open maize

TABLE 1 Studies that have used artificial intelligence/machine learning to identify disease from images.

Crop	Diseases and pests	Method/model of detection	References
Pine	Little leaf disease	Genetic algorithm, random forest (RF) support vector machine (SVM), K-nearest neighbour (KNN), MobileNet, VGG16, RestNet18, ResNet50, ResNet152, InceptionV3, optimal ensemble deep transfer network, AlexNet, agro deep learning model (ADLM), BananaSqueezeNet, EfficientNetB0, recurrent neural network (RNN)-convolutional neural network (CNN), gated-recurrent convolutional neural network (G-RecConNN)	Bharathi Raja and Selvi Rajendran (2023); Bhuiyan et al. (2023); Elfatimi et al. (2023); Karthickmanoj and Sasilatha (2024); Nandhini et al. (2022); Ramachandran et al. (2023); Sanga et al. (2020); Singh and Misra (2017); Vidhya and Priya (2022)
Rose	Bacterial disease		
Beans	Bacterial disease, fungal disease, rust, angular leaf spot		
Lemon	Sun burns disease		
Banana	Banana leafspot, yellow sigatoka, black sigatoka, Panama wilt disease, Fusarium wilt, banana bacterial wilt, Cordana leaf spot, Pestalotiopsis leaf blight, banana fruit scarring beetle, bacterial soft rot, pseudostem weevil, banana aphids, Xanthomonas wilt, bunchy top disease		
Apple	Scab, black rot, cedar apple rust, leaf black disease	SVM, logistic regression model, multilayer perceptron model, CNN, Inception-v3, ResNet 152, MobileNet, InceptionNet, Stacking Ensemble Learning-Based Model, R-CNN detection algorithm, a deep-learning-based faster DR-IACNN, faster region-based (R)-CNN and residual network block, CapsNet, attention mechanism, DenseNet201, multichannel capsule network ensemble, GoogleNet Spatial pyramid pooling structure, UNet, Refinement Filter Bank, Mask R-CNN model	AlArfaj et al. (2023); Chen et al. (2021); Dai et al. (2023); Fuentes et al. (2018); Haque et al. (2022); Jung et al. (2023); Karthik et al. (2020); Karthickmanoj and Sasilatha (2024); Mahum et al. (2023); Panchal et al. (2023); Peker (2021); Pradhan et al. (2022); Sapna et al. (2023); Stewart et al. (2019); Xie et al. (2020)
Cherry	Powdery mildew		
Maize	Cercospora leaf spot, grey leaf spot, common rust, northern leaf blight, southern leaf blight, banded leaf and sheath blight, rust		
Grapes	Black rot, esca, grape leaf blight, black measles		
Bell pepper	Bacterial spots, early blight, pepper scab, powdery mildew, anthracnose, white spot disease, blight, *Botrytis cinerea*		
Potato	Early blight, late blight		
Tomato	Target spot, yellow leaf curl virus, early blight, late blight, leaf mould, Septoria leaf spot, spider mites, tomato bacterial spot, tomato mosaic virus		
Wheat	Karnal bunt, black chaff, crown and root rot, Fusarium head blight, powdery mildew, tan spot, wheat loose smut, wheat streak mosaic, stripe rust, leaf blotch, Septoria leaf spot, yellow rust, brown rust	CNN, VGG16 model, multiple instance learning (weakly supervised learning methodology), generic algorithm, deep convolutional neural network-based approach, Vision Transformer	Borhani et al. (2022); Goyal et al. (2021); Johannes et al. (2017); Lu et al. (2017), Picon et al. (2019); Zhang et al. (2019)
Rice	Rice blast, rice false smut, rice brown spot, rice bakanae disease, rice sheath blight, rice sheath rot, rice bacterial leaf blight, rice bacterial sheath rot, rice seeding blight, rice bacterial wilt, neck blast, sheath blight, brown spot, rice stack burn, leaf smut, leaf scald, rice stem rot, rice white tip, rice stripe blight, bacterial leaf streak	CNNs, MobileNet-V2 with attention mechanism	Lu et al. (2017); Rahman et al. (2020)
Pomegranate	*Alternaria alternata*, anthracnose, bacterial blight, Cercospora leaf spot	ResNet 152, MobileNet, InceptionNet, Stacking Ensemble Learning-Based Model	Karthickmanoj and Sasilatha (2024); Nirmal et al. (2023)

TABLE 1 (Continued)

Crop	Diseases and pests	Method/model of detection	References
Cucumber	Anthracnose, downy mildew, powdery mildew, target leaf spots, bacterial angular, *Corynespora cassiicola*, scab, grey mould, black spot, spider, leaf miner	Deep CNN: SVM, K-means-based segmentation followed by neural-network-based classification, texture feature-based classification and plant leaf image-based classification, U-net, Swin Transformer (SwinT), SwinT-based and spatio-temporal attention-guided generative adversarial network (STA-GAN), squeeze-and-excitation-module-based ADDLight model, global pooling dilated convolutional neural network (GPDCNN), improved YOLO V5 with BottleneckCSP and convolutional block attention module (CBAM)	Lin et al. (2019); Liu et al. (2022); Ma et al. (2018); Omer et al. (2023); Wang et al. (2022); Zhang et al. (2017); Zhang et al. (2019)
Cassava	Brown leaf spot, red/green mite damage, brown streak disease, cassava mosaic disease	CNN	Ramcharan et al. (2017)
Pearl millet	Blast, rust	Automatic and intelligent data collector and classifier	Kundu et al. (2021)
Soybean	Soybean brown leaf spot, frog eye leaf spot, Phyllosticta leaf spot, soybean rust	Residual attention network, ConvNeXt with CBAM attention module	Wu et al. (2023)
Sunflower	Rust (*Puccinia helianthi*), leaf downy mildew, grey mould, flower downy mildew	Transfer learning approach, CNN: Xception, ResNet50, EfficientNetB4, MobileNet-V2	Ghosh et al. (2023); Shahoveisi et al. (2023)
Dry bean	Rust (*Uromyces appendiculatus*)		
Field pea	Rust (*Uromyces viciae-fabae*)		
Citrus	Citrus black spot, citrus bacterial canker, citrus blight, scab, greening (huanglongbing), melanose, anthracnose, sand paper rust, sunscald	CNN, MobileNetv2, DenseNet201, Whale Optimization Algorithm (WOA), CBAM-MobileNetV2, ResNet50, InceptionV3, YOLO-V4, EfficientNet, two-stage deep CNN based on Faster R-CNN, Enhanced CNN (E-CNN)	Çetiner (2022); Dou et al. (2023); Liu et al. (2021); Shastri et al. (2023); Syed-Ab-Rahman et al. (2022); Yadav et al. (2022), Zhang et al. (2022)
Coffee	Leaf rust, phoma, miner, *Cercospora*	SVM, Ensemble-based	Novtahaning et al. (2022); Soares et al. (2022)
Cotton	Root rot, cotton leaf curl, cotton sooty mould	Semi-Supervised Classifier Based on k-means and SVM, radial basis function (RBF) SVM algorithm, YOLOX, Spatial Pyramid Pooling	Noon et al. (2022); Wang et al. (2020)
Eucalyptus	Various leaf diseases	VARI-green algorithm	Megat Mohamed Nazir et al. (2021)
Kiwifruit	Kiwifruit decline, brown spots, bacterial cankers, mosaic, anthracnose	Unsupervised algorithms, K-means and a hierarchical method, YOLOX, DeepLabv3+, Kiwi-ConvNet	Liu et al. (2020); Savian et al. (2020); Yao, Wang, et al. (2022)
Oilseed rape	*Sclerotinia sclerotiorum*	SVM, RF, KNN and naïve Bayes, ResNet50	Cao et al. (2018); Liang et al. (2023)
Tea	Anthracnose, brown blight, red leaf spot, leaf blight, *Apolygus lucorum*, Exobasidium blight, tea red scab, tea red rust, tea algae leaf spot, tea coal disease, black rot, rust	Faster RCNN, RGReLU, Res4net-CBAM, TSBA-YOLO, shuffle attention mechanism, TeaDiseaseNet with multiscale self-attention mechanism, SVM, LSTM, ResNet18, VGG16, AlexNet, deep hashing with integrated autoencoders, LC3Net	Bhuyan et al. (2023); Jayapal and Poruran (2023); Jiang et al. (2023); Lin et al. (2023); Sun et al. (2023); Xu, Mao, et al. (2023); Zhao et al. (2022)
Sugarcane	White leaf phytoplasma, sugarcane smut, mosaic, red rot, rust, yellow leaf disease	XGBoost, RF, decision tree (DT), KNN, dual self-attention block, VGG19, ResNet50, XceptionNet, MobileNetV2, EfficientNet-B7	Bao et al. (2021); Daphal and Koli (2023); Narmilan et al. (2022)
Onion	Anthracnose-twister, downy mildew, purple blotch	SVM, CNN, InceptionV3	Alberto et al. (2020); Kim et al. (2020)
Okra	Cercospora leaf spot	t-SNE, Class Activated Mapping	Rangarajan et al. (2022)
Radish	Fusarium wilt	CNN model (RadRGB)	Dang et al. (2020)

(Continues)

TABLE 1 (Continued)

Crop	Diseases and pests	Method/model of detection	References
Peanut	Bacterial wilt, scab, grey spot, web blotch, anthracnose, scorch, leaf spot, rust	Multilayer perception (MLP) back-propagation (BP) neural network, X-ception network, attention-augmented branches, stack ensemble	Qi et al. (2021); Xu, Cao, et al. (2023)
Watermelon	Downy mildew	MLP, DT	Abdulridha et al. (2022)
Olive tree	Peacock spot	CNN models, ResNet50, MobileNet	Ksibi et al. (2022)
Mango	Powdery mildew, anthracnose, dieback, Phoma blight, bacterial canker, red rust, sooty mould	Ensembled stack deep neural network (ESDNN)	Gautam et al. (2023)
Cauliflower	Bacterial spot rot, black rot, downy mildew	Densenet201	Kanna et al. (2023)
Strawberry	Grey mould, *Gnomonia fructicola* fall, blight, Pestalotiopsis leaf spot, common leaf spot, anthracnose	Spatial convolutional self-attention-based transformer (SCSA-Transformer)	Li et al. (2023)
Pear	Foliar diseases, *Septoria piricola*, *Alternaria alternata*, *Gymnosporangium haracannum*, powdery mildew, dry rot, fire blight, leaf spot, leaf curl, slug	CBAM attention mechanism in combination with CNNs, ResNet50, ResNet101, DL CNN, faster R-CNN, ensemble CNN	Alirezazadeh et al. (2023); Fenu and Malloci (2023); Kang et al. (2020); Linker and Dafny-Yalin (2024); Yang et al. (2021)
Dry bean (*Phaseolus vulgaris*)	Angular leaf spot, bean rust, white mould	U-Net, VGG16, AlexNet, MobileNet-V2, DenseNet201, GoogLeNet, extreme learning machine (ELM), salp swarm algorithm (SSA), SVM, RF, artificial neural network (ANN)	Kursun et al. (2023); Shahoveisi et al. (2022)
Mung bean (*Vigna radiata*)	Cercospora leaf spot, yellow mosaic, white fly, bruchid, stem fly, aphid, halo blight, charcoal rot	MobileNet-V2, lightweight Android smartphone-based deep learning model	Mallick et al. (2023)
Black gram (*Vigna mungo*)	Yellow mosaic disease, anthracnose, leaf crinkle, powdery mildew	CNN VirLeafNet, self-improved dwarf mongoose optimization method (SIDMO), deep ensemble	Hajare and Rajawat (2023); Joshi et al. (2021)
Peach	Brown rot, anthracnose, scab, bacterial shot hole disease, gummosis, powdery mildew, bacterial spots, bacterial shot hole, leaf curl	Xception Network ensemble with L2M Loss, AlexNet, VGGNet, YOLO-V3, LWNet model based on VGG19, Focal Loss Mask R-CNN and Mask Scoring R-CNN, EfficientNet	Akbar et al. (2022); Farman et al. (2022); Yadav et al. (2021); Yao et al. (2021); Yao, Ni, et al. (2022)

dataset and 95.86% on a local dataset under complex conditions, highlighting its effectiveness and feasibility in identifying maize crop diseases.

Haque et al. (2022) used 5939 images captured from experimental fields, focusing on three diseases: southern corn leaf blight, northern corn leaf blight, and banded leaf and sheath blight. The image dataset consisted of the three mentioned disease classes and one healthy class. Additional images were generated through rotation and brightness enhancement methods to address the class imbalance. Three different architectures based on the Inception-v3 network framework were trained using a baseline training approach. The best-performing model achieved an overall classification accuracy of 95.99% with an average recall of 95.96% on a separate test dataset. Comparative analysis with pretrained state-of-the-art models revealed the superiority of the proposed model.

A multimodal deep learning model integrating multispectral images and vegetation indices collected by a UAV early in the growing cycle accurately predicted maize performance, enabling breeders to identify high-yielding varieties sooner and accelerate crop breeding (Danilevicz et al., 2021).

6.2 | Legumes

Beans, as nutritious and versatile legumes, constitute an important component of diets worldwide. Elfatimi et al. (2023) investigated rust and angular leaf spot diseases affecting bean crops by employing the MobileNet architecture. The study evaluated three distinct bean leaf image datasets with varying difficulty levels. MobileNet was chosen for its high performance with reduced parameters and faster execution time, achieving over 92% accuracy on all three datasets. The comparative analysis of the datasets and the application of the GradCAM technique to model predictions contributed insights into model behaviour.

A rapid identification method for soybean brown leaf spot, soybean frog eye leaf spot and soybean Phyllosticta leaf spot was developed based on a residual attention network (RANet) model (Yu et al., 2022). Otsu's algorithm was employed to remove the

TABLE 2 Hyperparameter tuning and reported accuracy based on Table 1.

Crop	Model	Aim	Learning rate	Batch size	Optimization method	Epoch	Precision (%)	Recall (%)	F_1 score (%)	References
Cereals	New deep learning method	Learn from huge training data with moderate usage of resources	–	–	Adaptive moment estimation (Adam)	1000	96–98	97–98	96–98	Goyal et al. (2021)
	Adapted deep residual neural network-based algorithm	Detect multiple plant diseases in actual field conditions at early disease stage using artificial background-based augmentation	10^{-4}	–	Stochastic gradient descent (SGD)	100	96–98	–	–	Picon et al. (2019)
	ViT based model, combining attention blocks with convolutional neural network (CNN) blocks	Solve classification tasks on a small and large dataset, faster prediction speed on multiple plants and multiple diseases	10^{-3}	–	Adam W, lightweight	100	93	91.7	92	Borhani et al. (2022)
	Simple CNN with two-stage training	Small number of parameters used effective for mobile application	10^{-4}	64	Adam	100	94.33	–	–	Rahman et al. (2020)
Legumes	ConvNeXt	Develop an enhanced deep learning network model to more accurately recognize soybean leaf diseases	10^{-6}	64	Cross-entropy loss function and Adam optimizer	–	85.42	67.52–88.44	66.57–88.37	Wu et al. (2023)
	Artificial neural network (ANN), logistic regression, classification, regression, Cohen's kappa	Evaluate five machine learning models for predicting disease establishment caused by *Sclerotinia sclerotiorum* in dry bean under different air temperatures and leaf wetness duration conditions	0.7	–	–	–	82–90	82–93	82–91	Shahoveisi et al. (2022)
	Xception, Residual networks (ResNet)50, EfficientNetB4, MobileNet	To evaluate the effectiveness of various convolutional neural network models for detecting rust disease on three commercially important field crops	10^{-3}	1080	Adam	100	82.16–96.86	–	79.98–96	Shahoveisi et al. (2023)
	Improved X-ception, Inception-V4, ResNet 34, MobileNet-V3	To create a precise deep learning model for identifying peanut leaf diseases, enhancing detection reliability across various crops	10^{-3} to 2×10^{-3}	16–64	Adam	2400	98.49–99.72	–	98.05–99.29	Xu, Cao, et al. (2023)
	Pretrained VGG16, AlexNet, MobileNet-v2, DenseNet201	To investigate the performance of the U-Net architecture, which has been successful in medical image segmentation, in the segmentation of agricultural images	–	–	–	100	88.89–100	–	0.9107–0.9459	Kursun et al. (2023)
	VirLeafNet1-3	To develop automatic viral infection detection methods for monitoring crops analysing symptoms at different parts of plants	0.001	32	SGD	1000	65.45–100	–	77.01–100	Joshi et al. (2021)

(Continues)

TABLE 2 (Continued)

Crop	Model	Aim	Learning rate	Batch size	Optimization method	Epoch	Precision (%)	Recall (%)	F_1 score (%)	References
Oilseeds	ANN model	Modelling impact of environmental factors on plant disease outcomes as a disease prevention strategy	0.5–0.7	–	–	–	Up to 91	Up to 93	Up to 91	Shahoveisi et al. (2022)
	VGG19 + CNN	Minimize training time complexity through transfer learning	–	–	Local interpretable model-agnostic explanations (LIME)	8	93	93	93	Ghosh et al. (2023)
Fruits	ResNet, InceptionV3	Develop mobile apps with lower computational cost that can achieve real-time early detection of banana fungal diseases	10^{-3}	4	SGD	1500	95.5	–	–	Sanga et al. (2020)
	Optimal ensemble deep transfer network (OEDTN)	Optimize OEDTN weights, increasing the robustness of the ensemble learning	–	–	Hybrid moth flame optimization-butterfly optimization algorithm (MFOBOA)	–	Up to 94	Up to 94	Up to 94	Bharathi Raja and Selvi Rajendran (2023)
	Proposed CNN	Low processing load for hardware for mobile app development using adapted MobileNetV2 and ResNet50	10^{-4}	20	Adam	36	Up to 98	Up to 97	Up to 97	Çetiner (2022)
	Proposed deep learning scheme	Use geometric augmentation to enhance image quality and a combination of MobileNetv2 and DenseNet201 for optimized feature set	10^{-2}	64	Whale optimization algorithm	–	95.7	–	95.4	Zia Ur Rehman et al. (2022)
	Convolutional block attention module (CBAM-MobileNetV2)	Smaller number of trainable parameters in lightweight models suitable for use in resource-limited devices	10^{-3}	32	Adam	100	98.75	–	–	Dou et al. (2023)
	Proposed deep learning algorithm	Automated identification of citrus diseases against complicated background by combining and tuning a detection network YOLO-V4 and a classification network EfficientNet	10^{-5}	24	Adam	70	95.7	95.2	95.3	Zhang et al. (2022)

TABLE 2 (Continued)

Crop	Model	Aim	Learning rate	Batch size	Optimization method	Epoch	Precision (%)	Recall (%)	F_1 score (%)	References
Vegetables	InceptionV3 transfer learning model	To address the problem of plant disease identification by leveraging advanced image processing techniques	–	–	Optimized CNN	–	99.97	99.99	99.398	AlArfaj et al. (2023)
	CNN	To develop a semantic segmentation model based CNN to segment the powdery mildew on cucumber leaf images	10^{-4}	2	Adam	32	56.90–85.88	86.48–99.77	79.14–96.58	Lin et al. (2019)
	A pretrained Efficient DenseNet	To classify potato leaf diseases efficiently	10^{-3}	32	–	100	96.05–99.4	98.4–100	98.4–99.3	Mahum et al. (2023)
	Deep neural network models	To present an image-based field monitoring system for automatic crop monitoring	0.005	–	–	7 ± 2 to 49 ± 3	–	–	–	Kim et al. (2020)
	CNN	To compare two distinct approaches in detecting radish wilt using red/green/blue images and near-infrared images taken by unmanned aerial vehicles	0.001	32	Adam	30	Over 95	Over 96	–	Dang et al. (2020)
	Ten deep transfer learning model	To enhance understanding regarding the significance of cauliflower disease identification and detection in rural agriculture using advanced deep transfer learning techniques	10^{-4}	256	–	30	61.81–99.9	63.61–99.9	63.39–99.9	Kanna et al. (2023)
Other crops	Transfer learning models (VGG19, ResNet-50, XceptionNet, MobileNetV2, EfficientNet B7	To suggest a transfer learning method that will be the most suitable for a real-time system for diagnosing sugarcane disease	–	32	–	20 and 50	0–100	0–100	0–100	Daphal and Koli (2023)
	YOLOX models	To propose a modified spatial pyramid pooling (SPP) layer to effectively extract relevant features at various scales from the training data	0.01	32	α-IoU regression loss function	30	99	–	–	Noon et al. (2022)
	CNNs, Res4net-CBAM	To propose Res4net-CBAM, a deep CNN specifically designed for tea leaf disease diagnosis, aiming to reduce the model's complexity and improve disease identification accuracy	0.01–0.001	–	Adam, SGD, Adagrad optimizer	50	94.41–98.35	–	94.27–98.37	Bhuyan et al. (2023)

background from the original images, and the dataset was expanded using image enhancement. The resulting RANet model achieved an average recognition accuracy of 98.49%, an F_1 score of 98.52% and a recognition time of 0.0514 s. This demonstrated the model's effectiveness, providing an accurate, fast and efficient method for recognizing soybean leaf disease.

The limited application of deep learning models in identifying soybean leaf disease was addressed by an enhanced deep learning network model developed by Wu et al. (2023). They applied data augmentation techniques, including random masking and generating feature maps at different depths, focusing on discriminative features and reducing background noise. The enhanced network model achieved an average recognition accuracy of 85.42% for diagnosing soybean leaf diseases, surpassing that of six other deep learning comparison models (ConvNeXt: 66.41%, ResNet50: 72.22%, Swin Transformer: 77.00%, MobileNetV3: 67.27%, ShuffleNetV2: 59.89% and SqueezeNet: 72.92%).

6.3 | Oilseeds

Shahoveisi et al. (2023) evaluated four convolutional neural network models (Xception, ResNet50, EfficientNetB4 and MobileNet) for detecting rust disease on three important field crops, sunflower, dry bean and field pea. The dataset included 857 positive and 907 negative samples from field and greenhouse environments. Training and testing were conducted using 70% and 30% of the data, respectively, with different optimizers and learning rates. The results revealed that the EfficientNetB4 model achieved the highest accuracy (average 94.29%), followed by ResNet50 (average 93.52%), offering the potential of precision spraying of rust disease in these crops.

Ghosh et al. (2023) studied sunflower disease recognition using a hybrid deep learning approach. Using a small dataset, their model combined transfer learning and a simple CNN. Among the eight models tested with four different disease classes (downy mildew, grey mould, leaf scars and fresh leaf), the VGG19+CNN hybrid model demonstrated superior performance in various metrics, including precision, recall, F_1 score, accuracy, Hamming loss, Matthews's coefficient, Jaccard score and Cohen's kappa.

To detect *Sclerotinia sclerotiorum* on oilseed rape, Cao et al. (2018) established an indoor UAV low-altitude remote sensing simulation platform. Thermal, multispectral and RGB images were captured before and after inoculation with *S. sclerotiorum*. The study introduced new image registration and fusion methods based on the scale-invariant feature transform (SIFT) to produce a fused database from multimodel images. Analysing thermal images revealed temperature distribution changes, with the maximum temperature difference reaching 1.7°C on a single leaf 24 h after infection. Four ML models (SVM, RF, KNN and naïve Bayes [NB]) were developed using thermal and fused images. Image fusion improved classification accuracy by 11.3%, and the SVM model achieved a classification accuracy of 90.0% in disease severity classification. The results suggested that the UAV low-altitude remote sensing simulation platform, equipped with multisensors, holds promise for early detection of *S. sclerotiorum* in oilseed rape.

6.4 | Fruits

The major apple leaf diseases, apple scab and apple rust, were investigated by Sapna et al. (2023) using deep learning, specifically the capsule neural network (CapsNet) architecture, to perform image classification without requiring intricate feature engineering. A total of 3642 RGB images consisting of 1200 images of apple scab, 1399 images of cedar apple rust, 187 images showing complex disease symptoms and 865 images of healthy leaves were used. The model was trained on a dataset reflecting real-world growing conditions, with images enhanced to improve the learning ability of the model. The researchers achieved a recognition accuracy of 91.37% on the test set and demonstrated a 3.67% improvement in accuracy compared to existing literature that used the same Kaggle Plant Pathology 2020—FGVC7 dataset.

In a study focusing on leafspot and sigatoka diseases in bananas, Vidhya and Priya (2022) developed three models using ML (KNN and SVM) and deep learning (AlexNet) approaches. RGB colour images were employed to train the models with and without background. After augmentation, a total of 4353 healthy images, 4154 leafspot images and 4037 sigatoka images were used to train the model. Preprocessed images after data augmentation enhanced model training and accuracies were reported as 76.49%, 84.86% and 96.73% for KNN, SVM and AlexNet, respectively. These findings demonstrate the effectiveness of the deep learning approach (AlexNet) in achieving high accuracy in banana leaf disease detection and classification.

Sangeetha et al. (2023) studied Panama wilt disease in bananas. The approach introduced an improved method using an agro deep learning algorithm. The proposed method not only assisted in early detection but also served as a valuable tool for monitoring the effectiveness of treatments. The algorithm predicted the severity of the disease by analysing colour and shape changes in banana leaves and achieved an accuracy of 91.56%, precision of 91.61%, recall of 88.56% and an F_1 score of 81.56%.

Grapes hold immense importance as a fruit, yet diseases pose significant threats. A real-time detector for common grape leaf diseases, including black rot, black measles, leaf blight and mites, was developed based on improved deep CNNs (Xie et al., 2020). The authors began by expanding the dataset of grape leaf disease images through digital image processing technology, generating the Grape Leaf Disease Dataset. Using this dataset and the faster region-based convolutional neural network (R-CNN) detection algorithm, the researchers introduced a deep-learning-based faster DR-IACNN (deep learning real-time interactive attention-based convolution neural network) model. This model incorporated higher feature extraction capabilities by integrating the

Inception-v1 module, Inception-ResNet-v2 module and SE-blocks. The results demonstrated that the model achieved 81.1% mean average precision (mAP). Additionally, the detection speed reached 15.01 frames per second (FPS). The findings of this research suggest that the detector offers a real-time solution for diagnosing grape leaf diseases.

Citrus fruits face a significant threat from diseases such as citrus greening (huanglongbing). Dou et al. (2023) developed a classification model, convolutional block attention module (CBAM)-MobileNetV2, leveraging MobileNetV2 with a convolutional block attention module and transfer learning to enhance citrus huanglongbing disease recognition. The dataset comprised 751 images, initially 3648 × 2736 in size, categorized into early, middle and late leaf images. These images were enhanced to a total of 6008 images, uniformly adjusted to 512 × 512 size, with 80% of these images used for training. The model demonstrated a high performance with a recognition accuracy of 98.75%, outperforming other network models. The model achieved notable accuracy improvements on the test set through parameter fine-tuning in transfer learning. The findings suggested that CBAM-MobileNetV2 provides an effective solution for high-accuracy huanglongbing image recognition, offering applications in disease diagnosis for citrus cultivation.

In a study by Shastri et al. (2023), an enhanced convolutional neural network (E-CNN) was developed for citrus disease detection. The model demonstrated a significant improvement over previous models with an average F_1 score of 92.06%, precision of 95.14%, recall of 96.67%, recognition accuracy of 98% and classification accuracy of 99%. These outcomes, surpassing previous approaches by more than 6%, suggest the potential of this approach to enhance disease management practices in the citrus industry.

6.5 | Vegetables

Deep learning methods are considered the most advanced in image recognition (Bayer & Edwards, 2021; Kamilaris & Prenafeta-Boldú, 2018). Recognizing and classifying potato leaf diseases on time is important to mitigate losses. Mahum et al. (2023) proposed an improved deep learning algorithm for the detection and classification of potato leaves into five classes: late blight, early blight, potato leaf roll, Verticillium wilt and healthy. The model was trained on the Plant Village dataset and employed a pretrained Efficient DenseNet model with an extra transition layer in DenseNet-201. Manual data collection was performed for additional classes. The algorithm, using a reweighted cross-entropy loss function and dense connections with regularization, successfully detected and classified these diseases with an accuracy of 97.2%.

Omer et al. (2023) collected and established a new cucumber leaf pest and disease dataset of 3057 images and developed an improved cucumber leaf disease and pest detection model based on the YOLOv5l model. The model's mAP was 80.10%, with precision and recall values of 73.8% and 73.9%, respectively. Notably, the improved model's weight occupied only 13.6 MB of memory, showcasing superior performance compared to the original model.

The use of deep learning methods, specifically focusing on the Swin Transformer (SwinT), for dataset augmentation and recognition of plant leaf diseases, particularly in practical cucumber leaf disease scenarios, was explored by Wang et al. (2022). Transformer-based models such as SwinT have shown competitive or superior performance compared to CNN models. Their approach involved a SwinT-based backbone network for feature extraction in patch partitions, achieved through stepwise small patch embeddings. They showed that SwinT-based and attention-guided GAN outperform LeafGAN in generating high-quality images, even with fewer training images. When using STA-GAN, disease recognition accuracies reached high levels, surpassing those achieved with LeafGAN. Specifically, recognition accuracies were 98.97%, 96.81%, 94.85% and 90.01% when employing the improved SwinT, original SwinT, EfficientNet-B5 and ResNet-101 as recognition model backbones, respectively.

6.6 | Other crops

Deep learning techniques were used by Daphal and Koli (2023) for disease classification in sugarcane. They introduce a database of sugarcane leaf diseases comprising 2569 images across five categories. Among the transfer learning methods applied, MobileNet-V2 was the best performer, with an accuracy of 84% and minimal parameters. Their ensemble model achieved a higher accuracy of 86.53% with fewer epochs, demonstrating promising results for sugarcane disease classification.

Sugarcane white leaf phytoplasma was studied by Narmilan et al. (2022), who introduced an approach to detect sugarcane white leaf disease using high-resolution multispectral sensors mounted on small UAVs combined with supervised ML classifiers. The pipeline was validated, and pixel-wise segmented samples such as ground, shadow, healthy plant and early and severe symptoms were classified. Employing XGBoost, RF, decision tree (DT) and KNN algorithms, along with various Python libraries, VIs and spectral bands, the study achieved an accuracy of 94% in detecting white leaf disease in the field. Key VIs for distinguishing healthy and infected sugarcane crops included modified soil-adjusted vegetation index (MSAVI), normalized difference vegetation index (NDVI) and excess green (ExG). The technology demonstrated its reliability, cost-effectiveness and efficiency in providing a method for white leaf disease detection.

A study by Noon et al. (2022) introduced an enhanced YOLOX model with a modified spatial pyramid pooling layer for effective feature extraction at various scales. Using skip connections and an αIoU-based regression loss function, the model addresses challenges associated with multidisease occurrences and similar symptoms. Tested on a dataset of 1112 cotton plant images, the improved YOLOX-s model achieved a mean average precision of 73.13%, outperforming the original YOLOX by 3.27%.

The use of UAVs for high-resolution remote sensing in cotton root rot-infested fields was studied by Wang et al. (2020). Supervised, unsupervised and combined classification methods and two new automated methods leveraging UAV remote sensing images were evaluated for distinguishing cotton root rot from healthy cotton zones. The automated methods outperformed conventional ones by up to 8.89% in overall accuracy. Combining *k*-means segmentation and morphological opening and closing achieved the best results, boasting an overall accuracy of 88.5% and the lowest errors of omission (11.44%) and commission (16.13%) among all methods considered.

In summary, the variants of deep learning tools are designed to address different types of problems, and the strength of these tools can be consolidated and built upon each module's capabilities. Beyond disease detection using images, ML approaches have now begun to integrate with genomic selection and genome-wide association studies to enhance disease resistance prediction, as shown in cereal crops, wheat and rice (Liu et al., 2024), making plant disease management more wholesome. When applied to phenomics-scale datasets, ML methods allow researchers to efficiently derive meaningful insights for disease segmentation and classification (Rahaman et al., 2019).

7 | MONITORING TO DETECT NEW CROP DISEASES AND PATHOGENS

Disease detection models can be tailored for disease and crop species, often using a dataset collected in targeted regions, as differences in environmental conditions can affect the observed disease symptoms, incidence and severity. Climate change brings further challenges to the development of tailored models for disease detection, as there is an increased risk of new pathogens being introduced to regions where they were not previously present (Chaloner et al., 2021). This means that disease detection models must be designed to be adaptable to new pathogens and changing disease patterns. Multiple studies have improved disease detection model flexibility by training large datasets with varied crop disease images and metadata from different regions to develop more robust models (Shoaib et al., 2023; Yang et al., 2021). These algorithms can identify patterns and anomalies that may indicate the presence of a new pathogen (Neupane & Baysal-Gurel, 2021). Unsupervised deep learning models, such as clustering and anomaly detection, have been used to identify patterns in the data that do not conform to known disease patterns and identify areas that may be experiencing an outbreak of a previously unseen disease, allowing for intervention to prevent further spread (Liu & Wang, 2021; Pardede et al., 2018). The detection system's accuracy will depend on the data quality and the ML algorithm's ability to distinguish between normal and abnormal patterns (Shoaib et al., 2023). This can be challenging for novel pathogens, as sufficient data may not be available to train the algorithm.

Incorporating updated data on new pathogens and emerging disease patterns into disease detection models is important, as ML architectures allow continuous fine-tuning to accompany changes in the real world. Updating a trained deep learning model to be responsive to disease pattern changes can be achieved by regularly monitoring disease outbreaks and pathogen distribution and incorporating data from other sources, such as weather and soil conditions, that can impact the spread of new pathogens (Buja et al., 2021). Although most image-based ML models do not currently incorporate climate conditions or disease patterns into disease identification, these aspects of disease prediction will become more prominent in the coming years as the changing weather patterns change disease distribution and severity.

8 | AUTONOMOUS CROP DISEASE MANAGEMENT

Once a disease is detected, autonomous crop disease management systems can manage the disease by targeted application of pesticides (Shaikh et al., 2016) or other treatments (Abioye et al., 2022). These actions can be carried out automatically by robotic systems, such as autonomous tractors or crop sprayers programmed to respond to the data collected by sensors and imaging technologies. One of the benefits of autonomous crop disease management is that it can help to reduce the environmental impact of agriculture by minimizing the use of pesticides (Mesías-Ruiz et al., 2023). This can reduce the risk of run-off into waterways. It also helps in reducing plant yield loss and economic impact. Despite the benefits, challenges associated with the cost and complexity of autonomous systems exist (Bhat & Huang, 2021). Developing, deploying and integrating these technologies into existing agricultural systems can be challenging and expensive (Gackstetter et al., 2023). In addition, there may be concerns about the ethical implications of autonomous systems, mainly if they are designed to make decisions without human oversight (Bhat & Huang, 2021). Overall, autonomous crop disease management has the potential to revolutionize the way we approach agricultural management and improve the sustainability and efficiency of our food systems. However, ongoing research and development will require overcoming technical and ethical challenges and ensuring these technologies are used responsibly and effectively.

9 | COLLABORATIVE MAPPING FOR CROP DISEASE DETECTION

Collaborative mapping for crop disease detection involves sharing information on crop diseases in a particular region. This approach allows stakeholders to track the spread of diseases and develop strategies for disease management and control (Hulbert et al., 2023). One of the benefits of collaborative mapping is that it can improve the accuracy and timeliness of disease detection, resulting in identification of patterns and trends that may not be immediately apparent to individual growers (Brown et al., 2017). This supports disease management and control strategies, preventing disease from spreading to other regions. Collaborative mapping also has the potential to improve the resilience of agricultural systems by building networks for information sharing and collaboration (Sherman et al., 2019). By connecting stakeholders in a particular region, generating a shared knowledge base and developing communication channels for responding to disease outbreaks and other challenges is possible. However, challenges related to data quality and privacy may arise. Ensuring that the data collected by different stakeholders is consistent and accurate can be challenging. Concerns about the security and privacy of sensitive information, such as crop yield or disease incidence, may exist. In general, collaborative mapping for crop disease detection is a promising approach that can help improve the resilience and of sustainability agricultural systems. By fostering collaboration, information sharing and leveraging the power of technology, it is possible to develop more effective disease management and control strategies.

10 | AUTOMATED CROP DISEASE DETECTION TECHNOLOGIES IN DEVELOPING AND LOW-INCOME COUNTRIES

Automated crop disease detection technologies have the potential to revolutionize agriculture in developing and low-income countries, where smallholder farmers are particularly vulnerable to crop losses due to disease. These technologies can help to improve the accuracy and speed of disease detection, allowing farmers to respond quickly and effectively to disease outbreaks (Ashwinkumar et al., 2022). However, several challenges are associated with implementing these technologies in developing and low-income countries. One of the main challenges is the availability and affordability of the necessary infrastructure (i.e., imaging platform, sensors and computer resources) and data processing pipelines (Klauser, 2018). Automated crop disease detection typically requires specialized sensors, cameras and software, which can be expensive and difficult to access in developing countries. Another challenge is the lack of technical expertise to support these technologies (Quinn et al., 2011). The cost of developing the software applications is estimated to be a significant part of the expenses associated with implementing automated plant phenotyping. However, this cost can be reduced to 10%–20% if the project partially reuses previously developed tools (Reynolds et al., 2019). An increase in open-source software has been released to address these challenges, decreasing the entry barrier in technical expertise and economic resources to implement effective plant phenotyping pipelines. For example, Pheno-box, released in 2018, is an automated phenotyping device and RGB image analysis pipeline that is fully open-source, providing detailed construction plans, software source code and documentation to rebuild the system (Czedik-Eysenberg et al., 2018). Other studies have released software pipelines for hyperspectral imaging processing for trait extraction, allowing the processing of 10 GB of images in under 73 min in an ordinary personal computer (ElManawy et al., 2022). A system for biomass-related traits was developed, including a graphical interface for easy usage (Klukas et al., 2014) and even an open-source, scalable management system for image data collection and associated environmental metadata (Wass et al., 2019). Plant image datasets and pretrained deep learning models have also been released to reduce the need for extensive data collection when training a model from scratch (Hu et al., 2024). Recently, a study in Ghana demonstrated an end-to-end pipeline using open-source tools for field-based disease detection in peanuts. The drone was the only expensive item purchased (Kassim et al., 2022). Nonetheless, there is still a need for innovative approaches to technology development and deployment tailored to researchers and smallholder farmers in low-income countries. This may involve the use of low-cost hardware, as well as training and support programmes to help use these technologies. Significant investment is also needed to produce robust and effective crop disease detection technologies that can be adapted to specific pathogens commonly encountered in developing countries. Hence, the pipeline addresses their specific needs and conditions. This may involve collaboration between researchers, industry and government agencies to develop and test new technologies and to build the necessary infrastructure and support systems to ensure their success.

11 | CONCLUSION

Automated crop disease detection holds significant potential for improving agriculture with implications for food security and economic sustainability. Technologies such as ML and image detection systems offer new and innovative ways to detect and manage crop diseases. These technologies have many benefits, including increased accuracy and speed of disease detection and the ability to monitor crop health in real-time. However, there are also significant challenges to their deployment, particularly in developing and low-income countries. These challenges include the availability and affordability of necessary hardware and software, as well as the lack of technical expertise and infrastructure to support these technologies.

The performance of these technologies can be affected by factors such as the image distance from the target, occlusion and plant density. Additionally, contextual data, such as weather data, soil properties and agronomic practices, can improve the accuracy of crop disease detection. It is also important to note that the performance of these technologies can be affected by changes in climate conditions, which can introduce new pathogens and affect the accuracy of existing models. Therefore, it is important to tailor crop disease detection models to the target region and crop species and be aware of new pathogens that can be introduced due to changes in climate conditions. In addition, automated crop disease detection technologies offer new opportunities for area surveillance to identify novel pathogens, real-time monitoring to detect crop diseases and new pathogens, autonomous crop disease management and collaborative mapping for crop disease detection. Overall, the development and deployment of automated crop disease detection technologies offer a powerful tool for managing crop diseases and mitigating the impact of climate change on global food production. Further investment in research and development and innovative approaches to technology development and deployment tailored to the needs and constraints of smallholder farmers in developing countries is essential to ensure their success.

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable as no new data was generated.

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