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DETECTION OF PLANT DISEASES AND PESTS USING DEEP LEARNING MODELS: A RECENT RESEARCH

Dr. M. Lakshmi Naga Nandini*

*Assistant Professor, Department of Plant Pathology, Agricultural & Horticultural Sciences, School of Agriculture & Food Technology, Vignan's Foundation for Science, Technology & Research (Deemed to be University), Vadlamudi-522 213, Andhra Pradesh, India.

Email: nandinichowdarymuppalla@gmail.com Phone Number: 9154636448

***Corresponding Author:** Dr. M. Lakshmi Naga Nandini

*Assistant Professor, Department of Plant Pathology, Agricultural & Horticultural Sciences, School of Agriculture & Food Technology, Vignan's Foundation for Science, Technology & Research (Deemed to be University), Vadlamudi-522 213, Andhra Pradesh, India.

Email: nandinichowdarymuppalla@gmail.com Phone Number: 9154636448

Abstract:

Crop yield and quality are significantly impacted by plant diseases and pests. Many plant diseases and pests can be identified with the help of digital photographs of the affected plants. In the field of digital image processing, deep learning has recently set a new, exceptionally high standard. Researchers have shown considerable enthusiasm for the prospect of using deep learning methods in the study of plant diseases and the detection of pests. Through a definition of the problem and a comparison to more conventional approaches, this study defines the topic of plant disease and pest detection. In this research, we will analyse previous deep learning-based studies on plant pest identification and detail the benefits and drawbacks of various network architectures utilised for classification, observation, and segmentation. Everyone has access to the same resources, and studies are compared. The goal of this research is to identify potential challenges associated with using deep learning to detect plant diseases and pests in the field. Solutions and areas for further research are recommended. In conclusion, this research provides a thoughtful analysis based on existing information, as well as future directions for plant disease and pest identification.

Keywords: Convolutional neural network, Deep learning, Classification, Plant diseases and pests, Object detection, Segmentation.

BACKGROUND:

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It is crucial that researchers look into the use of machine vision to detect plant illnesses and pests. A method that analyses plant pictures for signs of potentially damaging insects or other creatures [1]. The use of human eyes has been mostly superseded by machine vision-based plant pest detection technology. Traditional machine vision algorithms use both standardised image processing techniques and human aid in feature generation and classification for plant disease and pest identification [2]. Taking advantage of the unique properties of plant diseases and pests, this strategy can be used to design an imaging system that consistently illuminates images by selecting the right light sources and camera angles. However, there is a price to be paid for the ease with which sophisticated imaging methods might simplify the development of new algorithms. Unfortunately, in practise, it is not always possible for classical algorithms to completely minimise the impact of scene changes on identification outcomes [3]. Small differences between the lesion area and the background, low contrast, large variations in the scale of the lesion area, and differences in the scale of the lesion area between different species, and a large amount of noise in the lesion image all hinder the detection of plant diseases and pests in truly complex natural environments. Photographs of plant diseases and pests taken in natural light are also subject to interference. It is difficult to achieve better detection results using conventional approaches. Convolutional neural networks (CNNs) are a type of deep learning model that has seen widespread adoption in recent years for use in computer vision (CV) applications due to their demonstrated efficacy in domains as varied as traffic detection [4], medical image recognition [5], text recognition [6], expression recognition [7], face recognition [8], etc. There are several applications for deep learning in agriculture, including the detection of diseases and pests. Businesses in Japan and abroad have developed methods like the WeChat plant pest detection applet, which uses Deep Learning, and the photo recognition APP. This means that there is a lot of space for innovation in the application of deep learning to the problem of identifying plant diseases and pests, both in the academic and commercial sectors. This study summarises and searches the relevant literatures from 2014 to 2022 in order to help researchers quickly and systematically understand the relevant methods and technologies in the field of deep learning-based methods for detecting plant diseases and pests. This research is organised as follows: Having defined the plant disease and pest detection problem in Chapter 1 ("Definition of Plant Diseases and Pests Detection Problem"), we move on to Chapter 2 ("Image Recognition Technology Based on Deep Learning"), where we introduce this exciting new field. Three distinct approaches to this problem are compared and contrasted in Section 3 (entitled "Plant Diseases and Pests Detection Methods Based on Deep Learning"); and Plant diseases and pests are the subject of Chapter 4. Some of the difficulties experienced while using deep learning to detect plant diseases and pests are discussed in the "Challenges" section. We conclude by discussing some potential avenues for future study and advancement in the section titled "Conclusions and Future Directions."

1. DEFINITION OF PLANT DISEASES AND PESTS DETECTION PROBLEM

Natural catastrophes, such as plant diseases and pests, can cause harm to and even kill plants at any stage of development, including seed germination, early seedling development, and later stages of plant growth. Rather than relying on a strict mathematical definition, machine vision applications often rely on intuitive human understanding when it comes to plant diseases and pests.

1.1. Definition of plant diseases and pests detection

While computer vision classification, detection, and segmentation operations tend to be highly specialised, the needs for identifying plant diseases and pests are more broad [9]. In reality, its needs are comprised of three parts: what, where, and how [10]. The "what" in this context refers to the categorization task in computer vision. We may call it classification for the time being because all it does is output the image's class information. In computer vision, the "positioning" job is similar to the "where" inquiry in step two, though placement is a purely perceptual task. This technique allows for the identification and naming of each of the numerous pests and diseases depicted in the image. In computer vision, this "how" could be viewed as the segmentation problem. When compared to object classification, the approach taken by object recognition is to provide a local description, or to determine which object can be observed in a particular part of an image. With the help of a feature expression and a classification function, we may detect whether or not an image has a given object class. As a result, studies on object classification tend to focus on feature expression, while studies on object perception tend to centre on structure learning. There are three steps in the process of diagnosing plant diseases and pests, and each has its own set of objectives and functional needs. For instance, the "what" of the first step may determine the "how" of the third step, which in turn may determine the "where" of the second step. This first step's "what" can inform the "why" and "how" of the subsequent two. Plant disease and pest detection will be used throughout this effort until a more precise network architecture and set of functions can be developed.

1.2. Comparison with traditional plant diseases and pests detection methods

Existing references [11-15] are used to evaluate and contrast deep learning-based plant disease and pest detection approaches with conventional methods from four angles (nature, method, required circumstances, and presented and applicable scenarios). The findings of this comprehensive comparison are displayed in Table 1.

Table 1 Contrast between traditional image processing methods and deep learning methods

Technology	Traditional image processing methods	Deep learning methods
Essence	Manual design features+ classifiers (or rules)	Automatic learning of features from large amounts of data
Method	Image segmentation method: Threshold segmentation; Roberts, Prewitt, Sobel, Laplace and Kirsh edge detection; region segmentation Feature extraction method: SIFT, HOG, LBP,	CNN

	shape, colour and texture feature extraction method Classification method: SVM, BP, Bayesian	
Required conditions	Relatively harsh imaging environment requirements, high contrast between lesion and non-lesion areas, less noise	Adequate learning data and high-performance computing units
Applicable scenarios	It is often necessary to change the threshold or redesign the algorithm when imaging environment or plant diseases and pests class changes, which has poor recognition effect in real complex natural environment	It has ability to cope with certain real and complex natural environment changes

2. IMAGE RECOGNITION TECHNOLOGY BASED ON DEEP LEARNING

To gain the global and contextual components of images with great robustness and superior recognition, deep learning-based technology does not rely on the extraction of unique features but rather on repeated learning to discover acceptable characteristics.

2.1. Deep learning theory:

The term "deep learning" (DL) was coined in a paper by Hinton *et al.* [16] published in Science in 2006. Deep learning is predicated on the process of teaching a neural network to analyse data and learn new features. Feeding input features into a hierarchy of hidden layers, each of which may be thought of as a perceptron, can considerably minimise the local minimum problem by extracting low-level functions and merging them to form abstract high-level functions. Because deep learning can function without the contrived data that traditional algorithms rely on, it is attracting the attention of researchers looking for a solution. Some examples of its application include natural language processing, recommendation systems, recursive recommendation engines, pattern recognition, voice recognition, and computer vision [17]. The extraction of rich and complex picture feature information has historically proven challenging for image classification and human-designed feature detection systems [18]. To avoid this issue, we can employ deep learning techniques. It may directly execute unsupervised learning on the raw image to collect features at different levels of abstraction, from the most basic to the most meaningful. The hand-drawn image identification used by most conventional algorithms for plant disease and pest detection is laborious, inconsistent, and wholly at the mercy of the artist's skill and luck. Deep learning, on the other hand, can automatically discover patterns in huge datasets. This multi-layered model exhibits exceptionally high levels of both autonomous learning and feature expressivity, allowing it to automatically extract features from images for use in classification and recognition. This is why using deep learning to analyse plant pictures for signs of disease or pests makes perfect sense. In recent years, deep learning approaches have been used to construct models of deep neural networks as the Deep Boltzmann Machine (DBM), Stack DE noising Auto encoder (SDAE), and Deep Convolutional Neural Network (DCNN) [19]. Using these deep neural network models to automatically extract features from a high-dimensional feature space has various advantages over more traditional methods of feature extraction, which require human input, in the field of image identification. An increase in training samples and processing power have boosted deep neural networks' already exceptional efficacy. There has been a significant uptick in the use of deep neural networks in both industry and academics as a result of their superiority to more conventional models. The deep convolutional neural network has quickly surpassed all other deep learning architectures in recent years.

2.2. Convolutional neural network

Convolutional neural networks (CNNs) are able to conduct convolutional operations because of the complex network structure they employ. A convolutional neural network model has the following layers: input, convolutional, pooling, fully connected, and output. Full connection is not necessary if the neurons in the convolution layer are related to the neurons in the convergence layer, as seen in one model where the roles of these layers are repeatedly swapped. In deep learning, CNN is among the most widely used models. Due to its fundamental structural properties, which provide immense modelling power and complex information, CNN is able to achieve its benefits in picture identification. Furthermore, CNN's achievements in several computer vision tasks have contributed to the widespread acceptance of deep learning. The convolution kernel is initially set in the convolution layer. A convolutional neural network's main benefit is the local receptive field it generates thanks to its convolutional kernel. The data is processed by sliding the convolutional kernel across the feature map to extract features. Following feature elimination training in the convolution layer, neurons are passed on to the sum layer, where feature elimination is performed once more. Computing the mean, maximum, and random values of the local receptive field is standard to the currently employed binning methods [20, 21]. Data from lower layers is not received by neurons in a full connection layer until after they have travelled through several convolutional and connection layers. After the inputs from the connection layer are processed, the SoftMax algorithm is used to label them, and the resulting values are passed on to the output layer.

2.3. Open source tools for deep learning

Some of the most well-known open-source deep learning systems were created by firms outside of the Google family, and they include Tensor Flow [22], Torch/PyTorch [23], Cafe [24], and Teano [25]. Table 2 provides a comparison of the available open source applications and their respective features. The four most popular deep learning third-party open source tools support all major platforms, including Linux, Windows, iOS, Android, etc. Torch/PyTorch and Tensor Flow are the preferred tools for training huge CNNs on GPU because to their better scalability, wide variety of third-party libraries, and interoperability with deep network frameworks.

3. PLANT DISEASES AND PESTS DETECTION METHODS BASED ON DEEP LEARNING

We'll talk about the state of the art in using deep learning to spot plant diseases and pests. Plant disease and pest identification using deep learning techniques can be seen as an application of these classical networks in agriculture because the goal is in perfect alignment with the computer vision challenge. Analysis of the network's topology allows for the extraction of subsets of the network, such as classification networks, perception networks, and segmentation networks.

Table 2 Comparison of open source tools for deep learning

Tools	Publisher	Supporting hardware	Applicable interface	Usability
Tensor Flow	Google	CPU, GPU, Mobile	C, Python	Flexible development, portability, powerful performance, support for distributed applications
Torch/PyTorch	Facebook	CPU, GPU, FPGA	C, Python, Lua	Easy to debug and develop, support dynamic neural network, easy to expand, modularization and low learning cost
Cafe	BAIR	CPU, GPU	Python, Matlab	High readability, easy to expand, fast speed, large number of users and wide community
Theano	MILA	CPU, GPU	Python	Flexible and high performance

3.1. Classification network

It is difficult to detect plant diseases and pests in their natural habitats because to the wide variety in size, shape, texture, colour, backdrop, positioning, and illumination. CNN has quickly become the standard architecture for diagnosing plant diseases and pests due to its superior feature extraction. Following the input's recovery via the cascaded convolutional layers of a pooling layer, a CNN will typically use a fully connected layer (or average pooling layer) of SoftMax structure to assign classes to the input. Classification networks for plant pests already exist, such as AlexNet [26], GoogleLeNet [27], VGGNet [28], ResNet [29], Inception V4 [30], DenseNets [31], MobileNet [32], SqueezeNet [32,33] and other forthcoming networks. Several researches [34-37] also created network topologies based on real-world situations. Images are categorised according to their content using a classification network. Classification network techniques can be broken down into three broad classes: feature extraction, direct classification, and lesion location.

3.2. Using network as feature extractor

Many of the initial investigations of deep learning-based classification approaches for plant diseases and pests [38] used CNNs' strong feature extraction capabilities in conjunction with classical classifiers. A conventional machine learning classifier (such a support vector machine) is fed data from a convolutional neural network (CNN) that has been trained on the input image. *Yalcin et al.* [39] work with his SVM classifier employing various kernels and feature descriptors, such as LBP and GIST, influenced his architecture for convolutional neural networks to extract visual information. The experimental outcomes verify the efficacy of this method. To determine whether a plant is healthy or not, Fuentes *et al.* [40] proposed using a CNN-based meta-architecture with many feature extractors. Hasan *et al.* [41] used a support vector machine trained on data from a deep convolutional neural network model to correctly identify and classify nine distinct rice-borne illnesses.

3.3. Using network for classification directly

The first and most used CNN method for detecting plant diseases and pests is to directly use categorization networks to categorise lesions. Original image classification, ROI localization classification, and multi-category classification are all sub-categories that can be broken down further depending on the aforementioned body of literature.

3.3.1. Original image classification. This digital photograph of plant pathogens is then uploaded to the internet for research and education purposes. To improve upon an already-trained model, Tenmozhi *et al.* [42] suggested a deep CNN model that makes use of transfer learning. The accuracy rates for three publicly available bug datasets were 96.75%, 97.47%, and 95.97%, respectively. Fang *et al.* [43] trained ResNet50 to identify plant-harming microbes. Adam optimisation, using a focal loss function in place of the traditional cross-entropy loss function, achieved a 95.61 percent success rate in predicting the severity of leaf disease.

3.3.2. Classification after locating ROI. The presence or absence of a lesion in a specific region requires a thorough analysis of the entire image. It is common practise to pre-collect a ROI and feed it into the network in order to identify the type of problem at hand. Soybean stalk rot samples were correctly labelled as either healthy or diseased 95.73% of the time using Nagasubramanian *et al.* [44] state-of-the-art three-dimensional deep convolutional neural network (DCNN) and saliency map visualisation approach.

3.3.3. Multi-category classification. The original picture classification approach is equivalent to the conventional plant pest classification network for classifying plant pests into more than two categories. The total number of Class 1 plant pests is what the network's output node represents. In a network employing a multi-category classification algorithm, some of the feature extraction utilised to classify the lesion is also used to categorise the normal. This approach is analogous to establishing weight parameters for training a multi-objective plant pest classification network in the future, except that instead of using normal and plant pest samples for binary training, we use them for unsupervised learning. Using a CNN architecture, Picon *et al.* [45] were able to train a single model on contextual metadata for disease detection across five different crop types. The following objectives can be advanced with the use of this format: (a) Put together a set of colours with more depth and variety than you'd get from a single harvest. b) Cross-symptomatic illnesses can't spread between different types of crops. illness classifications that (c) easily account for cultural context; With an average balanced accuracy of 0.98 and 71% of the classifier error eliminated, experimental results show that the suggested model outperforms previous methods and alleviates the data imbalance problem.

3.4. Using network for lesions location

Classification networks can usually only get as precise as labelling images. Multiple approaches combined allow for accurate lesion localization and even pixel-wise categorization. Subtypes can be determined by the specific techniques used, such as the sliding window, heat map, and multi-task learning network.

3.4.1. Sliding window. This is the simplest and fastest way to get a feel for where the lesion is. The requirement to manually overlap and rotate the original photos is eliminated when images taken within the sliding window are fed into a classification network trained to distinguish plant diseases and pests. The final step in lesion localisation involves merging all sliding panes. Chen *et al.* [46] used a convolutional neural network with a sliding window to produce automatic feature learning, feature fusion, detection, and location regression calculation for plant disease and pest species. Across 38 frequent symptoms, field detection rates varied from 50% to 90%.

3.4.2. Heat map. Every detail of this piece of art was carefully made. Darker colours signify more serious concerns. In a heat map, a darker colour indicates a higher risk of plant disease. In 2017, Dechant *et al.* [47] trained a convolutional neural network (CNN) to categorise each image as an infected leaf by using heat maps representing the risk of infection for each region in a maize disease image. The wealthy and the poor are now separated by a wall. He obtains a heat map of the image after two minutes and 1.6 GB of RAM, and classifying a set of three heat maps takes less than a second. On the test set, 96.7 percent of the experiments passed with flying colours. To determine precise maize disease contour areas in 2019, Wiesner-Hanks *et al.* [48] employed a heat map technique. The model's 99.79% accuracy establishes a new standard for diagnosing air plant illnesses, and its use of UAV-collected pictures to accurately display lesions as small as millimetres is revolutionary.

3.4.3. Multi-task learning network. Without additional features, an image classification task is beyond the scope of a purely classified network. Due to this, it is often required to include additional nodes in the proposed network, with the two nodes exchanging feature extraction results. Therefore, the network's extensive plant pathogen and pest segmentation results coalesced into a multi-task learning network. We account for the fact that every network is different. Each pixel in the input image can be used as a training sample for a segmented network. Accordingly, the multi-task learning network's segmentation offshoot produces a unique lesion segmentation result, and the classification offshoot's sample requirement is greatly diminished. Ren *et al.* [49] developed a model called Deconvolution-Guided VGNet (DGVGNet) for disease detection on plant leaves, which are easily obscured by shadows or washed out by strong lighting. Deconvolution was used to direct the CNN classifier to the correct lesion location. The results demonstrate the model's robustness under occlusion, poor lighting, and other conditions; sickness class classification was achieved at an accuracy of 99.19%, and lesion segmentation at an accuracy of 94.66%. It has been shown that classification network-based approaches are useful in the real world by their application to the problem of classifying plant diseases and pests [50-53]. Table 3 lays forth the benefits and drawbacks of a few supplementary approaches.

3.5. Detection network

In computer vision, object positioning is ground zero. This is also the most comparable work to traditional methods of detecting plant diseases and pests. The collected information will be utilised to pinpoint the position of the object and label it appropriately. Object detection methods based on deep learning are currently abundant. One such two-stage network for plant disease and pest identification using deep learning is Faster R-CNN [54]. Single-hop network designs like SSD [55] and YOLO [56-58]. The primary distinction between the single-stage network and the two-stage network is that the latter must first create candidate boxes (proposals) that can contain the lesion before proceeding on to the object recognition procedure. However, single-stage networks rely on their own feature extraction to make predictions about the locations and types of lesions.

Table 3 Comparison of advantages and disadvantages of each sub-method of classification network

Method	Advantages	Disadvantages
Using network as feature extractor	Obtaining effective lesion features	Relying on other classifiers for final classification results
Original image classification	Classic in structure, it is also the basis of other classification network sub-methods and can refer to many existing networks	Lesions need to account for a certain proportion in the image, otherwise their characteristics are easily pooled out, and generally

		only one class of lesion is allowed in an image
Classification after locating ROI	Obtaining ROI information of the lesions	Additional methods are needed to obtain ROI
Multi-category classification	Solving sample imbalance to some extent	Secondary training is needed
Sliding window	Get rough localization of lesions in images	Sliding window size requires accurate selection, and can only get rough position, slow speed of traversal and sliding
Heat map	Generate more accurate lesion areas	Accurate lesions location depends on network classification performance
Multi-task learning network	Combining other networks to obtain exact location and category of lesions simultaneously, and reducing the number of training samples required	The network structure is relatively complex, and a pixel by-pixel label is required when adding segmentation branches

3.6. Plant diseases and pests detection based on two stages network

To get the recommendations, faster R-CNN first gets the feature map of the input picture from the backbone network, and then uses RPN to compute the confidence of the anchor boxes. After combining the regions of interest, the feature map for the proposed region is fed into the network, the quality of the initial detection results is improved, and the final results, the location and classification of the lesion, are obtained. In light of the nuances involved in plant disease and pest identification, the most popular methods tend to improve the backbone structure or its feature map, anchoring rate, ROI pooling, and loss function. Faster R-CNN was initially used for direct disease and pest diagnosis in tomatoes by Fuentes *et al.* [59] in 2017. His mAP score on a dataset of 5,000 tomato diseases and pests categorised into 9 groups using deep feature extraction technologies like VGG-Net and ResNet was 85.98%. In 2019, Ozguven *et al.* [60] optimised a CNN model's parameters to create a faster R-CNN architecture for automatically identifying beetroot spot disease. 155 images were used for both training and evaluation. According to the statistics, this method is successful 95.48 percent of the time. Zhou *et al.* [61] demonstrated the efficacy of FCM-KM coupled with Faster R-CNN for the rapid diagnosis of rice diseases. Using 3010 images, we discover that we have a 96.71% detection accuracy for rice blight, a 97.53% detection accuracy for bacterial blight, and a 0.82 second detection time for sheath blight. Using an enhanced version of the R-CNN detection algorithm, Xie *et al*. [62] proposed a faster DR-IACNN model for the grape leaf disease dataset (GLDD). We introduce SE and its associated modules (Inception-v1 and Inception-ResNetv2). The mAP accuracy of the suggested model is 81.1%, and it speeds up feature extraction by 15.01FPS. The system's effectiveness and responsiveness in real time are both enhanced by the two-stage detection network, which is tailored for fast detection. When compared to simpler, single-stage detection networks, however, their accuracy falls short and their inference times are too long.

3.7. Plant diseases and pests detection based on one stage network

The single-stage object detection approach dramatically improved inference speed by adding detection heads directly to the backbone network for classification and regression, skipping the region proposal phase in the process. Single-stage detection networks come in two flavours: SSD and YOLO. For both types of networks, the full image serves as input, while the output layer reveals both the image's bounding box's location and the class to which it belongs.

Instead of using a traditional convolutional neural network to extract features from different layers and provide predictions, SSD chooses VGG16 as the core network and augments it with a trademark pyramid network. Singh *et al.* [63] created the PlantDoc dataset to aid in the identification of plant diseases. Since the programme needs to make predictions in real time on the mobile processor, an app based on Mobile Networks and SSD was designed to facilitate the identification of model parameters. An improved method for SSD-based maize blight diagnosis employing multiscale feature fusion case detection using convolutional neural networks was developed by Sun *et al.* [64]. The proposed method incorporated data processing, feature combination, feature segmentation, and disease diagnosis into a single step. By a large margin (71.80% to 91.83%), the new model's map is superior to the SSD model's original map.

The updated model's improved frame rate (from 24.0 to 28.4) facilitates in-the-moment detection of happenings. YOLO models the detection task as a regression issue and makes use of global knowledge to anticipate the endpoint's bounding box and class. YOLO can be optimised on a global scale, resulting in quicker and more precise detection. Prakruti *et al*. [65] established a method for identifying pests and diseases in tea gardens using uncontrolled images. YOLOv3 has aided in the detection of insects and diseases. In the production environment, we were able to get mAP of about 86% with 50% IOU. The work of Zhang *et al*. The method combines spatial pyramid matching with advanced YOLOv3 to effectively detect small-scale crop pest samples in an image by up sampling and a convolution operation. The relative difficulty is reduced as a result of this. The detection of crop pests is complicated by their enormous variety. When assessing 20 samples across pest classes collected in the wild, the average detection accuracy can hit 88.07%. Detection network-based disease and pest identification has also been the focus of numerous scholarly studies [47, 67-73]. The development of the computer vision target detection network is anticipated to lead to the increased usage of detection models for the diagnosis of plant diseases and pests. In conclusion, it can be mentioned that two-stage models are currently used more frequently in the field of plant disease and pest detection, which places a premium on detection accuracy.

Can a detection network replace a classification network?

The observation network is geared towards addressing the local problem of plant diseases and pests. The goal of the network is to make an educated guess as to what kind of plant pest or disease is being dealt with. Both the visible class information provided by the observation network and the previously described information on plant diseases and pests are required for a proper site evaluation. It would appear from this vantage point that the components of the classification network are already present in the observation network; in other words, the observation network can answer the question "where are the plant diseases and pests?" It's widely believed that "which plant diseases and pests" are preset, even though what's stamped in the training may not be the true consequence. In the case of high model separation, i.e. if the network can offer correct findings, an observation network can help answer the issue of "which plant diseases and pests are present in which location?" Despite its complexity and significance, the categorization network sometimes fails to adequately capture the inherent differences between groups of plant diseases and pests. As a result, all it can do is tell you is "which plant diseases and pests can be found in which location." This necessitates the usage of a classification network in conjunction with an expression network.

3.8. Segmentation network

A semantic and smooth segmentation of damaged and uninjured areas is carried out using a segmentation network in order to detect plant diseases and pests. The damage's location, size, shape, and other geometrical qualities (such as its centre, diameter, and perimeter) are all determined by this factor. A recurrent neural network (R-CNN) or fully convolutional network (FCN) [74] are common examples. [75].

3.8.1. FCN

Full Convolution Neural Networks are used for semantic image segmentation. Currently, FCN is the backbone of virtually all semantic segmentation models. Convolution is used to extract and encode features from the input image in FCN, while deconvolution or up sampling is used to progressively restore the feature image to the size of the original image. In the case of plant disease and pest segmentation, the conventional FCN, U-net, and SegNet [76, 77] methods can be roughly classed according to their FCN network designs.

3.8.2. Conventional FCN. Wang *et al.* [78] proposed a new full convolutional neural network-based segmentation solution for maize blight, and the segmentation accuracy reached 96.26, overcoming the problem that traditional computer vision is sensitive to variable illumination and complicated backgrounds. Wang *et al*. [79] suggested using FCNs as a means of more precisely classifying plant diseases and pests. Multilayer feature information was collected from the input image of maize leaf damage using a convolutional layer, and then the image was de-convolved to restore its original size and resolution. Overall accuracy was 95.87%, a substantial improvement over the traditional FCN method, and the lesion's integrity was preserved while also giving special attention to the segmentation of the tiny lesion area.

3.8.3. U-net. A U network is a frequent structure in both encoder-decoders and FCNs. The segmentation data is recovered via layer-hop connection, which links the feature map constructed during encoding to the map retrieved during decoding. Lin *et al.* [80] used a convolutional neural network trained on a U network to categorise 50 leaves from wild cucumbers. A group normalisation layer was added after each convolutional layer in the modified neural network to increase the network's sensitivity to weight initialization over the baseline U network. Using a convolutional neural network based on the U network, we are able to segregate cucumber leaves infected with powdery mildew with an average pixel accuracy of 96.08%, beating the state-of-the-art K-means, Random Forest, and GBDT methods. Segmenting the lesion region against a complex background is no match for the U-net method, even when working with fewer data points.

3.8.4. SegNet. A conventional encoding and decoding architecture. The decoder is distinguished by the fact that the greatest aggregate function serves as an index for the up sampling function. Kerkech *et al.* [81] suggested a method for segmenting images captured by unmanned aerial vehicles. SegNet was used to categorise photos taken with both visible and infrared light sources (480 samples from each site) into four groups: shadows, soil, healthy vines, and symptomatic vines. The proposed method achieved a 92% detection rate on vines, and an 87% detection rate on leaves.

3.8.5. Mask R-CNN. Mask R-CNN is currently one of the most widely used methods for segmenting images. This could be viewed as a network-based multi-task learning technique for recognition and segmentation. Segmenting the samples can separate individual lesions when many lesions of the same type have adhesions or overlaps, significantly reducing the number of lesions. On the other hand, semantic segmentation typically addresses clusters of homogenous lesions as a single entity. The Mask R-CNN model was trained by Stewart *et al.* [82] to segment maize northern leaf blight (NLB) lesions in a UAV picture. One lesion can be detected and correctly segmented by a trained model. When the IOU threshold was set to 0.50, the average accuracy was 0.96, with a divergence of 0.73 between the actual baseline IOU value and the predicted harm. Some studies on the subject of plant disease and pest identification have made use of object detection networks and the Mask R-CNN architecture. Wang *et al.* [83] used two models: faster R-CNN for detecting disease categories and mask R-CNN for detecting and segmenting diseases based on their location and shape. The results show that the proposed model can accurately categorise 11 distinct tomato illnesses and rapidly split their geographic areas and geometric features. We were able to identify 99.64% of disease conditions affecting tomatoes using Mask R-CNN. The segmentation method has various benefits over the classification and detection network methods when it comes to acquiring data on damage. However, resources are typically exhausted because to the detection network's incessant demand for large amounts of annotation data, much of which is of a pixel-by-pixel nature.

3.9. Dataset and performance comparison

The current state of the art in deep learning-based plant disease detection models is compared and analysed after a brief introduction to key background reading on plant pathogens, pests, and the evaluation index for the deep learning model.

3.9.1. Datasets for plant diseases and pests detection

The detection of plant diseases and pests relies on records, which serve as the backbone of scientific study. ImageNet, PASCALVOC2007/2012, and COCO are all examples of large-scale datasets used for computer vision research, however there is currently no equivalent for plant disease and pest identification. Information on plant diseases and pests is available through self-gathering, internet collection, and public resources. A variety of tools, including unmanned aerial vehicles, ground cameras, hyperspectral imagers, near-infrared spectrometers, drone aerial cameras, and more, are used to gather the necessary visual data. It is normal practise to obtain public datasets from Plant Village, an established public standard library. The practical relevance of personal observations of plant pests and diseases in their natural habitat is higher. While there has been an uptick in the dissemination of images taken in the field, it remains difficult to make valid comparisons between observation sites and scenarios based on distinct sickness types. Here you'll find research-backed methods for recognising plant diseases and blights. The outcomes are shown in Table 4.

Table 4 Common datasets for plant diseases and pests detection

Species	Collection environment
Plant Village-Dataset: 50,000 images of classified plant diseases of 14 crop varieties and 26 diseases [84]	Detached leaves on a plain background
Rice Leaf Diseases Data Set: three classes of diseases: Bacterial leaf blight, Brown spot, and Leaf smut, each having 40 images [85, 86]	Captured with a white background in direct sunlight
Image Database for Plant Disease Symptoms (PDDB): 2326 images of 171 diseases and other disorders affecting 21 plant species [87]	Field
New Plant Diseases Dataset (Augmented): 87 K rgb images of healthy and diseased crop leaves which is categorized into 38 different classes	Detached leaves on a plain background

38 disease classes from Plant Village dataset and 1 background class from Stanford's open dataset of background images—DAGS [88]	Network
18,222 images annotated with 105,705 northern leaf blight (NLB) lesions [89]	Field
40 classes of insects from rice, maize, soybean, sugarcane and cotton crops	Field
17,624 high quality JPG image data of rice, wheat and maize of 200 GB	Field
Plant Doc dataset: 2598 data points in total across 13 plant species and up to 17 classes of diseases [63]	Field
Northern Leaf Blight (NLB) dataset for Maize	Field
3651 images of apple leaf disease [90]	Field
IP102: Insect Pest Recognition Database: 75,000 images belonging to 102 categories [91]	Field
A database of eight common tomato pest images [92]	Network

3.9.2. Performance comparison of existing algorithms

Right now, deep learning-based research into plant diseases and pests is useful for a wide variety of food crops. Basic operations like classification, detection, and segmentation are performed alongside more complex ones like computing an infection rate. This makes it challenging for researchers to create and test novel deep-learning-based detection methods, as many datasets are not publicly available and there is still no one publicly available and complete dataset that allows for a consistent comparison of plant diseases and pests. The mean average precision (mAP), F1 score, and frame rate (FPS) of numerous common method implementations have all increased as deep learning has developed. Even though there have been tremendous advances in this area of study, there is still a wide gap between still-photos of pests and mobile-based, real-time disease and pest identification in the field. This is due primarily to the inherent difficulty of infectious diseases and the state of the relevant literature. More research is needed to discover methods that work with larger, more complex, and more realistic datasets.

4. CHALLENGES

4.1. Small dataset size problem

The use of deep learning techniques in agriculture for the identification of plant diseases and pests is still relatively new, despite the fact that these methods are increasingly being used to a wide range of computer vision tasks. The number of available disease and pest samples is inadequate. In comparison to open standard libraries, the breadth of self-collected datasets is much narrower, and substantial manual data tagging is required. In contrast to the over 14 million sample data in the ImageNet collection, sample scarcity is the biggest problem with plant disease and pest detection. Due to low disease prevalence and high image collection costs, however, the widespread use of deep learning techniques in plant disease and pest diagnosis remains limited. In fact, three methods exist today to address the problem of small sample sizes.

4.2. Data amplification, synthesis and generation

Validating data is essential for training deep learning models. With the right data augmentation strategy, plant diseases and pests may be more accurately identified. Gathering extra samples via editing (using techniques like mirroring, rotation, translation, warping, filtering, contrast correction, etc.) on existing photos is a common way for enlarging photographs of plant diseases and pests. In addition, VAEs [95,96] and generative adversarial networks (GANs) [93,94] can supply a more diverse set of samples to fill in gaps in sparse datasets.

4.3. Transfer learning and fine-tuning classical network model

Through the process of transfer learning (TL), knowledge gained from broad, massive data sets can be transferred to narrower, more specialised domains. Using transfer learning, newly collected unlabelled samples can be modelled after being pre-trained on a known dataset with similar features. After having its settings or components altered, it can be used to detect local plant diseases and pests, reducing the cost of model training and allowing the convolutional neural network to accommodate small sample data. Oppenheim *et al.* [95] used a VGG network trained specifically for this task to identify infected potatoes of varied sizes, colours, and shapes that had been left out in the open. The results confirmed the usefulness of transfer learning for training new networks. Bring *et al.* [96] fine-tuned and compared several conventional networks. Experiments showed that Dense Networks' accuracy improved over time. Chen *et al.* [97] showed that transfer learning surpasses training from scratch by using it to distinguish images of rice diseases against complex backdrops, with an average accuracy of 92.00%.

4.4. Reasonable network structure design

A well-planned network architecture can greatly reduce the requirement for sampling. Zhang *et al.* [98] created a convolutional neural network model with three channels, each representing one of the three colours, to detect diseases in plant leaves. Each of the three RGB leaf diseases composes the TCCNN component of each individual channel. In [99], Liu *et al.* described an improved CNN method for diagnosing viticulture problems. By using depth-separated convolution instead of standard convolution, the model reduced the possibility of overfitting and simplified the number of parameters. The unique framework was incorporated into the model to improve multivariate feature extraction performance for a range of grape leaf lesion sizes. Our model outperforms the ResNet and Google Net baselines in both speed and accuracy during training. The detection accuracy of this approach was 97.22%.

4.5. Fine-grained identification of small-size lesions in early identification

4.5.1. Small-size lesions in early identification

Correct early detection of plant diseases is essential for optimising crop yields [36]. Downward sampling approaches in the deep object extraction network frequently overlook small-scale targets in the actual early detection of plant diseases and pests due to the tiny size of the damage object itself. Due to the problem of background noise in the collected images, the large-scale complex background may also lead to more false detections, especially for low-resolution shots. Due to the scarcity of existing algorithms, we trace the development of one designed to find tiny objects and propose several improvements, such as an attention mechanism, to increase its detection efficiency.

The alert system allows for more efficient resource allocation. The attention process allows us to pay attention only to what is most crucial and ignore everything else. When applied to plant disease and pest photos, the weight sum method can first learn the features, then apply that information to extract the features with a weighted coefficient while concurrently minimising noise. An edited feature image can be combined with the original feature image using the Softmax function to produce new composite components for denoising, and the attention mechanism module can retrieve the visible picture to separate the item from the background. In the future, alerting methods can be utilised in early detection research for plant diseases and pests, allowing for more precise information selection and resource allocation. Karthik *et al.* [100] emphasis on the mechanism's residual network allowed for experiments to be done on the plant village dataset with an accuracy of 98%.

4.5.2. Fine-grained identification

To begin, plant symptoms and pests can vary widely, even among members of the same group. The reason for this is that similar photos of diseases and pests might appear very differently due to environmental conditions such as uneven lighting, dense resistance, unclear equipment vibration, and other interruptions. Detection tasks at the fine-grained level are notoriously difficult [101], and this includes jobs like identifying plant diseases and pests in complex environments. An example of a finer level of "intra class differentiation" is the fact that the same diseases and pests might appear to be characterised differently at different stages due to variances in their rates of growth. Second, some attributes are shared by objects that otherwise belong to different classes. It is challenging to appropriately identify "interclass similarity" due to similarities in biological morphologies and lifestyles among subclasses, which results from the proliferation of taxonomic classifications of biological subspecies and subclasses of various pests and diseases. Symptoms that are so similar that not even plant pathologists can tell them apart was a possibility that Barbedo proposed [102]. Third, in the real world, background disturbance makes it less probable that plant diseases and pests will emerge against an extremely clean background. It is difficult to identify plant diseases and pests when the background is too cluttered to provide good views of the objects of interest. Since the pictures are taken in a controlled environment, this issue is rarely considered in the literature [103]. Technical challenges, such as low identification accuracy and generalisation strength, arise when existing deep learning algorithms are applied to the aforementioned real-world agricultural settings, limiting the efficiency of disease and pest decision management. The "intelligent agricultural Internet" [104] is made easier by Tings' service. Current research is only applicable to the granular detection of a rarer category of illnesses and pests, making it impossible to instantly disseminate its results. This means that the challenge of precise and efficient large-scale detection of diseases and pests remains unsolved.

4.6. Detection performance under the influence of illumination and occlusion

4.6.1. Lighting problems

Previous research often relied on indoor light boxes to photograph plant pests and diseases [105]. It's not the same as taking a picture in broad daylight, but it could help eliminate the effects of artificial lighting and streamline post-production. It is easy to inadvertently distort colours when photographing in dynamic light circumstances, such as daylight, by going beyond or below the camera's dynamic range. Because the visible properties of plant diseases and pests vary dramatically with viewing angle and distance, the visual detection algorithm has a tough time completing its job.

4.6.2. Occlusion problem

Scientists today rarely make an effort to identify plant pests and diseases in complex ecological contexts. They are narrowing their focus to one period of history. However, occlusion is rarely considered while extracting the region of interest from the collected images. That's why occlusion detection isn't very reliable and only good for so much. Natural settings frequently feature blade occlusion due to differences in blade position, branch occlusion due to variations in branch orientation, light occlusion due to variations in ambient light, and mixed occlusion due to the presence of many occlusion types. Plant disease and pest identification is complicated by a lack of features produced by occlusion and noise overlap. Depending on the nature of the occlusion, the detection algorithm may be tricked into missing an object or may fail to identify it at all. In recent years, a number of academics have tackled the challenge of real-world plant disease and pest detection by developing deep learning algorithms [106, 107]. These researchers have made substantial progress that lays a solid foundation for practical plant disease and pest detection. However, occlusion is difficult to predict and often involves multiple steps. The difficulty in training the core framework, as well as the framework's continued reliance on hardware performance, means that the framework's own innovation and optimization. It including the design of lightweight network architecture that needs to be strengthened. To ensure precise identification and lessen the load of model training, improvements in GAN research and other areas are required. Although GANs have significant advantages over traditional methods when it comes to adapting to position changes and chaotic backgrounds, their design is still in its infancy, making it easy for them to crash while learning and produce unpredictable issues during model training.

4.6.3. Detection speed problem

Deep learning algorithms are more computationally costly than traditional methods, yet they yield better results. Real-time requirements can't be met with a guarantee of high identification accuracy because of the time and effort required to train the model on all of the image attributes. Reduced computational effort is a common strategy for reducing detection times. However, this results in insufficient training, which in turn leads to either poor performance or missed opportunities. Therefore, developing a powerful algorithm for rapid and precise detection is essential. Data annotation, model training, and model inference are the three main links between deep learning-based detection systems for plant diseases and pests in agricultural applications.

Agricultural applications that operate in real-time lend additional weight to model reasoning. Most modern techniques for diagnosing plant ailments focus on improving diagnostic precision. Model inference is rarely evaluated on its efficiency. In reference [108], a model for detecting plant leaf ailments based on a deeply separable convolutional structure was provided with the intention of enhancing the model's computational process to meet actual agricultural needs. Several different models were created and tested. Reduced Mobile Network classification parameters were 29 times lower than VGG parameters and 6 times smaller than mobile network parameters, while maintaining a 98.34% accuracy rate. This provides a fair delay-accuracy trade-off suitable for low-power mobile device plant disease diagnosis in real time".

CONCLUSIONS AND FUTURE DIRECTIONS

Traditional image processing approaches to plant disease and pest detection deal with these tasks in stages and links, but deep learning-based approaches combine them for comprehensive feature extraction, opening up vast new avenues of development and potential. Rapid progress is being made in the field of plant and pest identification, allowing its use in new settings such as agriculture; however, there is still a long way to go before the technology is ready for general deployment in the natural world.

i. Plant diseases and pests detection dataset

Thanks to deep learning technologies, we have made great strides in the detection of plant diseases and pests. Numerous image recognition algorithms have been developed and expanded to give a theoretical foundation for discriminating between various diseases and pests. Images have been used in the past to study the effects of illness, locate insects, and assess leaf damage. Most research has been done in controlled laboratory settings, and the results are generally only relevant to specific instances of plant pests and diseases. The primary reason for this is the recurrent, non-stop, seasonal, and geographical patterns of plant development. Similarly, a single disease or pest may manifest itself in a variety of ways during a crop's life cycle. How distinct plant species are graphically represented differs from region to region. Thus, it is not possible to generalise most studies' findings. Despite a test's high recognition rate, data collected at different periods cannot be guaranteed to be consistent.

A more complete picture can be obtained by combining data collected using several wavelengths of light, such as visible light, near infrared, and multi-spectrum data. Although visible-range images have been the backbone of most past research, there is a wealth of data contained in the electromagnetic wave that cannot be seen. collect data on plant diseases and pests and save it in a database. Early identification of plant diseases and pests by multi-information fusion is an exciting field of research. Moreover, image databases of plant diseases and pests in natural environments are still in their infancy. As a means of identifying extensive parcels of farmland and compensating for the absence of chance. A data collection platform, which includes portable automatic field spore collection device, unmanned aerial photography system, online monitoring equipment of agricultural objects, to its maximum potential in order to expand upon the findings of prior studies, particularly those involving the acquisition of picture samples. The algorithm's usefulness is broadened, and the dataset's accuracy and consistency are ensured.

ii. Early recognition of plant diseases and pests

Detecting plant diseases and pests early can be difficult through visual inspection or computer analysis because the signs are sometimes subtle. However, from a scientific perspective, early diagnosis is more crucial since it allows for the prevention and management of plant diseases and pests, preventing them from spreading and becoming more severe. Cloudy weather makes taking images more challenging and reduces the detection power compared to shooting in direct sunlight. Even high-resolution images of plant diseases and pests in their early stages can be difficult to analyse. Integrating meteorological and plant protection data, such as temperature and humidity, is necessary for the detection and forecast of diseases and pests. In today's scientific literature, early diagnosis of plant diseases and pests remains mostly unexplored.

iii. Network training and learning

Using manual visual detection, it is difficult to collect samples for all plant diseases and pests, and only healthy data (positive samples) are often available. As supervised learning based on a large number of disease and pest samples is time-consuming to gather, it is crucial to explore unsupervised learning as an alternative to current deep-learning-based detection methodologies for plant diseases and pests. Because it needs so many tagged training instances, deep learning is complicated and challenging to grasp. What is currently understood about brain-inspired computing and the human visual cognitive model can also be applied to online training and learning. However, deep models are not practical for application on mobile devices due to their large memory and testing needs. Finding methods to reduce complexity in models without compromising runtime, functionality, or precision is essential. Finally, selecting appropriate hyper parameters like learning rate, filter size, and number of iterations has always been a major hurdle in adjusting a deep learning model to diverse applications. Cooperation across academic fields until empirical data is more tightly integrated with theories like agronomic plant protection, field diagnostic models will not be able to better match crop growth rules or increase the efficiency and accuracy of plant disease and pest detection.

The future of plant health research depends on a shift from simple experimental conditions to practical applied research that takes into complete consideration the law of growing crops, environmental. variables, etc. To do so, we must move beyond simple image recognition to determine the underlying causes of the spread of disease and pests. The focus of machine vision-based plant disease and pest detection research has evolved from classic image processing and ML approaches to more advanced DL approaches that can tackle more difficult problems, as a result of the rapid development of AI technology in recent years. There is still a long way to go before this technology is mass-produced and employed, but the prospects for development and utility are enormous. If we are to fully exploit the potential of this technology, experts from the relevant fields will need to collaborate to appropriately incorporate information from agriculture and plant protection into deep learning algorithms and models for deep learning-based detection of plant diseases and pests. Implementing the research findings into agricultural machinery equipment is essential for putting theory into practise.

CONFLICT OF INTEREST:

Author declare no conflict of interest.

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