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Original

A comparative study of the deep learning-based image segmentation techniques for crop disease detection: Understanding of image segmentation techniques for crop disease detection

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Abstract: Productivity in agriculture is a major driver of economic expansion. The fact that plant diseases are so frequent is one of the reasons why plant disease detection is so important in the agricultural industry. Plants suffer severe effects if proper care is not given in this area, which might affect the amount, quality, or productivity of the relevant products. For instance, both living and non-living organisms can cause various diseases in stone fruits and other crops. Early disease patterns and clusters can be identified using computer vision technologies. This work focuses on deep learning-based crop image segmentation research. Firstly, the fundamental concepts and features of deep learning-based crop leaf image segmentation are presented. The future development path is enlarged by outlining the state of the research and providing a summary of crop image segmentation techniques together with an analysis of their own drawbacks. Crop image segmentation based on deep learning has still faced challenges in research, despite recent remarkable advances in crop image segmentation. For instance, there are not many crop images in the datasets, the resolution is modest, and the segmentation accuracy is not very great. The real-field criteria cannot be satisfied by the imprecise segmentation findings. With an eye towards the aforementioned issues, a thorough examination of the state-of-the-art deep learning-based crop image segmentation techniques is offered to assist researchers in resolving present issues.

Keywords: CNN, crop image, image segmentation, leaf disease, segmentation techniques,stone fruits.

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1. Introduction

India's economy is based primarily on agriculture. Since plants are the primary source of food for humans, it is imperative that they be cared for. Around the world, stone fruits are grown on 5.07 million hectares of land, yielding 35.24 million tons of fruit annually. Apricots, peaches, nectarines, plums, and cherries are grown on over 43,000 hectares in India, where they yield about 0.25 million tons of fruit annually (Bagga & Goyal, 2024). If fruit wines are made from the increased fruit production, orchardists will benefit financially from greater employment prospects and higher returns (Joshi et al., 2017). However, identifying healthy and diseased plants is a crucial step in the development of successful agriculture. To keep uninfected plants safe from diseased ones, it's critical to identify the afflicted plants (Haq, 2020). Since most disease symptoms are evident on the leaves, plant leaves are the primary source for leaf infection detection (Abd Algani et al., 2023). The best method for identifying plant infections is to look for leaf disease (Sai Reddy & Neeraja, 2022). This is because various infections have distinct symptoms. Numerous illnesses affecting stone fruits are brought on by both known viruses and unknown graft-transmissible pathogens (Khan et al., 2021). Mangos, like other stone fruits, are susceptible to several diseases throughout their lives. One such disease is bacterial canker disease, which manifests as elevated, yellow-to-brown patches that are encircled by a continuous white halo. Pale yellow dots on leaves are the initial sign of powdery mildew disease. They spread rapidly to form massive blotches that can completely cover the surfaces of the petiole, stem, and leaves. Twisted and puckered leaves with black, round scabby patches on the underside are signs of scab disease. As the illness worsens, leaves drop and become yellow (Rao et al., 2021). Production of olive oil accounts for about 80% of olive farming, with table olives making up the remaining 20% (Alshammari et al., 2022). Harvests of olives can be impacted by a variety of diseases and deficiencies, including olive Aculus olearius, olive fly/bug, leaf mold, prays oleae, olive bark beetles and olive borers. These include olive wilt, angular leaf spot, Verticillium wilt of olive, olive knot, peacock spot, and bacterial leaf blight. Aculus olearius, leaf mould and leaf spot can all be observed on the leaves of the host olive (Lachgar et al., 2022). Peaches are a significant stone fruit, and their production can be impacted by a variety of diseases such as cankers/fruit rot, anthracnose, scab, bacterial spot, cytospora canker, powdery mildew, peach leaf curl, and others (Yao et al., 2021). The production rate of stone fruits is impacted by four primary illnesses. Such disorders have never been easy to detect. Prior to now, the sole method for diagnosing plant diseases was visual analysis, or observation with the unaided eye. For accurate disease assessment by specialists in the field, this technique necessitates ongoing crop field surveillance. For vast plant areas, the visual analysis procedure can be exceedingly expensive, labor-intensive, and time-consuming because it necessitates continuous human observations. The population's exponential growth is quickly altering the availability and demand for food. A situation like this compels society as a whole to consider the application of cutting-edge technology in order to accurately and early diagnose diseases and apply corrective measures when needed (Bedi & Gole, 2021). Image segmentation algorithms have been shown to be one of the most cost-effective and precise methods for evaluating the characteristics associated with different plant diseases. Among the various methods, deep learning (DL) methods that use "convolutional neural networks (CNN)" and are based on artificial intelligence (AI) performed well in image recognition tests. According to (Liu et al., 2022), convolutional neural network (CNN) is a useful method for automatically identifying and categorizing pests, illnesses, and lesions. On the other hand, automatic detection and image categorization in the field face difficulties. Concerns regarding the type of diseased images include the background's complexity, which complements the lesion's subject, lighting variations, the photography hardware and the angle at which the pictures were captured (Saradhambal et al., 2018). The importance of identifying lesions rather than merely categorizing them has been emphasized by Barbedo (2019). The category by itself will not yield adequate results until it is combined with the disease's position. Using radial basis function neural networks, an automated technique is presented for the separation of the fungal pathogen from the mango plant's leaves. In comparison to the k-means algorithm, which produce an average specificity of 0.8178 and an average sensitivity of 0.8091, the suggested approach achieves greater performance with an average specificity of 0.9115 and an average sensitivity of 0.9086 (Chouhan et al., 2020). Using marker-controlled watershed segmentation (hue and gradient information), the affected areas of mango leaves are automatically identified. It was discovered that the suggested disease identification achieved approximately 90% and 80% accuracy when the affected regions were chosen automatically and manually, respectively (Zeng et al., 2009). The test dataset was made up of images that were sourced from the internet. The precision of a quantitative evaluation of crop disease severity and the recognition of crop illnesses are directly impacted by the segmentation of disease lesions in the images of leaves. Research is focused on finding the most effective and high-quality ways to remove damaged leaves from crops. Lesions have been extracted and recognized during the past 20 years using conventional techniques of image processing such as edge detection, color space transformation, feature space transformation, and others. It has proven difficult to develop an automated system for detecting leaf disease in stone fruits. Many diseases might have outwardly similar symptoms, making it challenging to distinguish between them using more nuanced indicators. For example, mango anthracnose and scab share similar visual signs. This study looks at several stone fruit leaf diseases that have been identified and categorized early on using deep learning technologies. In addition, Table 1 presents a comparison of strong deep learning tools, which greatly aids the researcher in selecting one based on their problem description. The literature has been reviewed, and then the topic of segmentation and categorization has been discussed. The segmentation portion receives less attention. Additionally, a more universal plant segmentation technique that works in both controlled and uncontrolled settings needs to be created and put into practice. Since the primary goal of image segmentation is to separate the symptom information from the backdrop, the most important task in a complex environment is how to segment the images while localizing and detecting damaged plant leaves (Nanehkaran et al., 2020). Using previously trained DL models, numerous authors have investigated the categorization of both single- and multi-biotic leaf diseases. Once the dataset was pre-processed as part of the initial phase of image processing, the authors used classification algorithms to identify the disease's spots. The classification model does not yet provide adequate boundary identification for the lesion. Consequently, it is especially crucial to instantly identify these illnesses on the leaves of stone fruits. To identify illnesses on plant leaves, several excellent image-based segmentation techniques have been developed (Singh & Misra, 2017). Lee et al. (2024) presented a multimodal deep learning architecture to detect disease as well as disease severity, this architecture is a combination of CNN and LSTM (Long short-term memory) which used crop image and environmental data like humidity and temperature to diagnose the actual disease on leaves.

We searched Google Scholar using the keywords "deep learning-based image segmentation techniques for crop disease detection" or " crop disease detection using image segmentation methods" to find the most recent research to better summarize the DL based Image Segmentation Techniques. The following is the article's structure: Section 2 investigates the concept of crop image segmentation. We covered the definition of deep learning and its applications in Section 3. The primary body of the examined literature is contained in Sections 4 and 5. Based on deep learning crop (Leaf) image segmentation, Section 4 presents the five network structures: Mask R-CNN, U-Net, SegNet, Mask Scoring R-CNN, and DeepLabv3+. The segmentation techniques employed recently on solely stone fruits are introduced in Section 5. Sharing evaluation metrics and data sets that come from the well-known crop image analysis tasks takes place in Section 6. Section 7 contains the article's outlook and summation.

Table 1. A comparison of popular open-source deep learning tools.

Tools	Suitable user Interface	Practicality
TensorFlow	Python	Support for distributed applications, high performance, portability, and flexible development
Keras	Python	Adaptable and makes building neural networks easier
Caffe	MatLab, Python	High readability, scalability, speed, quantity of users, and community reach
Pytorch	Python, Lua, C	Modularization, support for dynamic neural networks, ease of development and debugging, minimal learning costs
Theno	Python	Adaptable and very effective
Deeplearning4j	Python, Scala, Java	Scalable and useful for many uses, including voice, picture, and natural language processing. It can also be used to train models on huge datasets.

2. Crop image segmentation

2.1. Problem statement

Using computer image processing technologies to analyze and process images to attain segmentation, extraction, and three-dimensional rearrangement is known as image segmentation based on crop leaves imaging. To distinguish the affected region from the entire area of the leaf, some studies have employed segmentation algorithms to split an image into two or more useful parts. The accuracy and dependability of crop disease identification can be significantly increased by using the fundamental DL-based architectures to analyze lesions and other regions of interest qualitatively or even quantitatively. The basic workflow diagram for crop disease detection using image segmentation is shown in Figure 1, it basically starts from taking images as an input then augmentation of data takes place to avoid model overfitting, followed by segmentation of image so that feature extraction works well to predict leaf disease with more accuracy. Image processing is also used to estimate the severity of crop leaf disease in addition to evaluating the quality of fruit (Patil & Shekhawat, 2022). The primary variety of crops used as objects now are their leaves, stems and fruit surfaces.

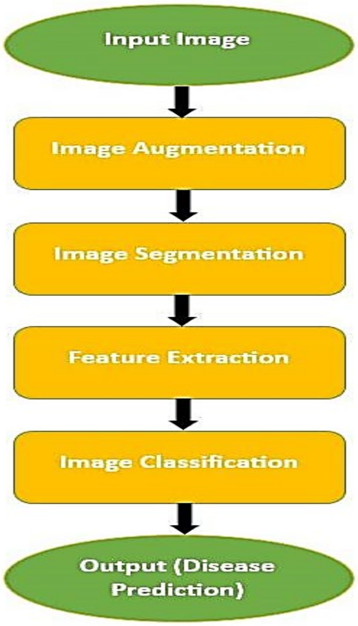

Figure 1. Basic workflow for crop disease detection.

The following steps comprise the image segmentation technique for crop disease detection:

- Acquire a data set of images of crops, usually consisting of training, validation, and test sets. A common practice in deep learning image processing is to partition the data set into three sections. These are: the test set is used to confirm the model's outcome; the verification set is used to modify the model's tunable parameters; and the training set is used to train the network model.
- To increase the size of the data set, preprocess and enlarge the image, usually by standardizing the original image and applying random rotation and scaling.
- To segment the leaf image of a crop, apply the appropriate image segmentation method. Next, export the segmented photos. This essentially entails identifying the infected leaf and stem, measuring the affected area, figuring out the infected area's shape, and figuring out its color.
- To validate the efficacy of crop image segmentation, it is necessary to establish effective performance indicators for verification. This is a crucial step in the procedure, which is called estimating performance evaluation.

2.2. Image segmentation

In the domain of image understanding, segmentation of images has emerged as a prominent subject and an enduring issue in the field of machine vision. The term "image segmentation" describes the process of dividing a picture into multiple disconnected regions based on characteristics including color, grayscale, spatial texture, and geometric structures. In the same location, these qualities demonstrate consistency or similarity, but there is a noticeable variance when compared to various areas. Segmentation of images can be classified as semantic, instance, or panoramic based on the varying coarse and fine granularities of the segmentation process and eventually segmentation process makes lot of improvements in every field whether it is agriculture, medical, robotics, mechanical or wind forecasting (Halidah et al., 2023; Srivastava et al., 2023; Ranjan et al., 2023; Huerta-Soto et al., 2023). Figures 1 and 2 demonstrate the segmentation of tomato and peach leaf.

Conventional image segmentation techniques such as threshold-based segmentation, region-based segmentation, and edge detection-based segmentation should be feasible for the segmentation. These techniques segment the image using mathematical and digital image processing knowledge. Although the segmentation process is quick and the calculation straightforward, the segmentation's detail accuracy cannot be assured. Although deep learning-based segmentation techniques are now incomparable to traditional picture segmentation techniques, the concepts are still valuable to understand. Deep learning-based techniques have currently made significant progress in image segmentation. Their accuracy in segmentation has outperformed that of conventional segmentation techniques. The first deep learning system to effectively use image semantics with instance segmentation was the fully CNN (convolutional neural network). This was the first study to segment images using convolutional neural networks. The notion of complete convolutional networks was put up by the writers. Exceptional segmentation networks with a strong advantage in processing fine edges are U-Net (Ronneberger et al., 2015; Zhang & Zhang, 2023), Mask R-CNN (Yao et al., 2022), Mask Scoring R-CNN (Huang et al., 2019), SegNet (Badrinarayanan et al., 2017), and DeepLabv3+ (Wang et al., 2021).

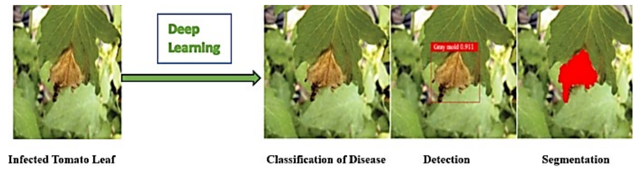

Figure 2. Extraction of infected portion from tomato leaf through segmentation.

2.3. Disease recognition techniques for plants

The accuracy of a legitimate inspection has been greatly increased by automated plant disease identification systems, especially CNNs, using images and machine learning. CNNs, a branch of artificial intelligence, have gained popularity as a flexible technique for ingesting copious volumes of diverse data and producing accurate forecasts of difficult-to-predict occurrences (Liu et al., 2022).

3. Deep neural network architectures for image segmentation

Instead of being a single strategy, a class of algorithms and architectures called deep learning can be used to a variety of problems like augmented reality, video surveillance, driverless cars, medical image analysis, crop disease detection and even processes videos in real time to keep an eye on drivers' actions while they're driving (Álvarez et al., 2024; Gutiérrez et al., 2023; Kathirvelan, 2024; Kokate et al., 2023; L. K et al., 2023; Sait & Panwar et al., 2022). An overview of supervised and unsupervised deep neural network architectures, including encoder-decoder and autoencoder models, generative adversarial networks, convolutional neural networks, recurrent neural networks, and long short-term memory, is given in this section. These networks are primarily used for image segmentation. Convolutions are a powerful tool for creating semantic activation maps with constituents that naturally comprise different semantic segments. These internal activations have been used in a variety of ways to segment the images. Table 2 provides an overview of the main deep learning-based segmentation methods and a succinct explanation of their main contributions.

3.1. Convolutional neural networks

An animal's visual brain served as the biological model for the multilayer neural network known as CNN. The architecture is especially helpful for applications that process images. Yann LeCun invented the first CNN, with an architecture that was centered on handwritten character identification, including interpretations of postal code. Deep CNN consists of several layers, such as fully connected, pooling, and convolutional layers. Starting layers of a deep structured network identify features like edges, while later layers merge these elements to create higher-level input qualities. The basic architecture of CNN is shown in Figure 3. Among the most popular CNN architectures used for crop disease detection are GoogleNet (Zhang K. et al., 2019), AlexNet (Rao et al., 2021), ResNet (Rajbongshi et al., 2021), VGGNet (Uğuz & Uysal, 2021).

Figure 3. Leaf area segmentation in peach image of infected leaf area.

Table 2. Brief description of segmentation algorithms.

Year	Segmentation Model	Segmentation Type	Description
2022	Mask RCNN	Instance segmentation with ResNet50 and ResNetx101 as the backbone architecture	Segmenting using masked lesion area to improve accuracy
2022	Mask Scoring RCNN	Instance segmentation with ResNet50 and ResNetx101 as the backbone architecture	Segmenting using masked lesion area to improve accuracy
2021	UNet	Attention mechanism used with semantic segmentation	Multi-scale extraction integration
2020	SegNet	Semantic segmentation	A fully convolutional neural network approach is used
2019	Faster RCNN	Instance segmentation with region proposal network	Deep convolutional neural networks with object detection models are used
2019	SegNet	Semantic segmentation with encoder-decoder architecture	SqueezeNet encoder with depth-wise separable convolution
2018	DeepLab	Semantic segmentation	Pyramid of spatial pooling, atrous convolution, and DenseCRF
2017	WNet	Semantic segmentation with encoder-decoder architecture	Segmentation in unsupervised learning with normalized cut loss
2017	Attention based Segmentation	Instance segmentation with recurrent Neural Network architecture	Focus modules for the segmentation of images
2017	PspNet	Semantic segmentation	Multiple scale pooling to achieve scale-invariant segmentation
2017	Mask-RCNN	Semantic segmentation	Segmenting using region proposal network
2015	DeepMask	Class specific segmentation	Segmentation and classification through concurrent learning
2015	FCN	Semantic segmentation	Full convolutional layers

3.2. Recurrent neural networks

This is one of the major types of ANN i.e. Recurrent neural networks (RNNs) are a subclass of neural networks in which the connections among the nodes in a layer create a directed graph along a temporal order of variables. It is usually possible to model the relationship between a variable's current state and its past states thanks to recurrent connections. Because the RNN-based method can handle sequential data to create predictions, like in motion recognition, it has drawn a lot of interest (Rumelhart et al., 1986). Newer RNN models that overcome issues like vanishing gradients allow training on longer sequences, such as gated recurrent units (GRU) or long short-term memory networks (LSTMs). A few recent studies have demonstrated the efficacy of RNN techniques for processing fixed size variable length data in a sequential manner, like an image. It has been demonstrated, for instance, that an RNN architecture based on GRU can effectively describe dependencies across various plant observation photos (Lee et al., 2018) or that discriminating regions of images may be captured using LSTM for fine-grained categorization (Zhao et al., 2017).

3.3. Generative adversarial networks

For the model to be able to create new occurrences using the initial dataset, the process of generative modelling involves automatically recognizing and picking up patterns in the incoming data. The generative adversarial network could produce images that could be falsified to accomplish a significant dataset enlargement with a minimal loss of image attributes. GANs consist of two parts: a generator that is taught to create new datasets; for instance, in computer vision, it creates new images from real-world images already in existence; and a discriminator that compares those images with some real-world instances to distinguish between real and false images. To detect positive plant diseases, authors employ an enhanced method that combines generative adversarial networks with CNN (Pujari et al., 2013). Authors presented a deep learning-based technique for identifying tomato leaf diseases that creates artificial images of tomato plant leaves using a conditional generative adversarial network (Abbas et al., 2021).

4. Literature review of DL-based image segmentation models used for crop disease detection: Assessing current review articles and determining a justification for the current review

The effects of biotic and abiotic diseases on plants' health have been the subject of extensive research in recent years. Even if there aren't many review publications that address the significance of image segmentation for crop disease diagnosis, some have tried to provide an overview of the procedure and offer insights into this intricate and ever-changing issue. These review studies' approaches, levels of quality, and findings, however, differed widely. Aside from that, a few review publications have concentrated on fields like compression of images, robotic perception, and medical image analysis. While some review articles have employed qualitative techniques like thematic analysis to examine the effects of image segmentation algorithms like U-Net, SegNet, Mask-RCNN, etc. for crop disease detection, others have used quantitative techniques like meta-analysis or systematic review to summarize the findings of primary studies. Review articles have described segmentation techniques based on advanced CNN architecture, which allow semantic segmentation techniques to be transformed to adapt to different data patterns and characteristics of agricultural images. Others have discussed the challenges of gathering samples of infected leaves because deep neural networks require large amounts of data to train. Still others have discussed the advantages and disadvantages of various cutting-edge deep learning-based image segmentation algorithms. Consequently, a thorough and critical evaluation of review articles is required to paint a clear and coherent picture of the state of knowledge as well as the gaps and difficulties that currently exist in this subject. The most fundamental ideas that support the effectiveness of deep learning-based picture segmentation algorithms are made clear to the reader by the straightforward explanations. This research examines potential obstacles in real-world plant disease detection applications employing deep learning-based image segmentation. Furthermore, we have addressed the implications and suggestions for further research and practice in this subject, as well as provided a full explanation of the field's discoveries and their limitations.

It is challenging to identify plant diseases in their natural environments due to the significant variations in their shape, size, texture, color, backdrop, arrangement, and imaging illumination. Because CNN has a powerful feature extraction capacity and have good feature expression potentialities when it comes to picture segmentation. Consequently, in recent years, CNN has been utilized to segment crop leaf images. In the field of detection of diseases, it has had remarkable results. Figure 4 presents a chronology of some of the best-performing models for DL image segmentation since 2015. Several learning-based segmentation techniques are surveyed in this part as shown in Table 3.

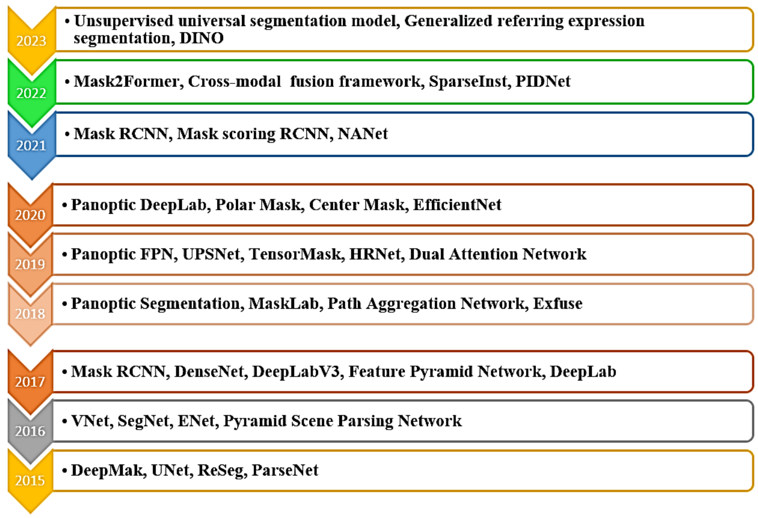

Figure 4. Progression of image segmentation methods based on deep learning.

Table 3. Examining and contrasting several segmentation methods for the diagnosis of plant diseases.

Ref	Year	Objective	Techniques Applied	Result
(Gulhane & Gurjar, 2011)	2011	Utilized to separate individual cotton leaf pixels in a picture to recognize and classify cotton diseases.	Color-image segmentation method	Accuracy 90.5
(Al Bashish et al., 2011)	2011	plant leaf disease detection and categorization using leaf texture characteristics calculations.	k-means clustering technique	Precision 93%
(Revathi & Hemalatha, 2014)	2014	demonstrated varying classifier accuracies for cotton leaf disease identification by using color and texture data to identify the edge.	Particle swarm optimization feature Selection method	Accuracy 94%
(Ali et al., 2017)	2017	Citrus disease classification based on textural characteristics and color histogram	ΔE color difference algorithm	Accuracy 99.9% and sensitivity with 0.99 area under the curve
(Naranjo-Torres et al., 2020)	2019	This technique extracted the region of interest from the Softmax layer and measured the maturity of the fruits.	Convolutional autoencoder (CAE) + Backpropagation neural network (BPNN)	Accuracy 100%
(Pujari et al., 2013)	2013	identified diseases in mango, grape, and pomegranate using an ANN classifier by employing the Runlength Matrix approach to extract textural information from ROI.	watershed techniques, K-means clustering, Thresholding and region growing	The respective classification accuracies for the affected and normal fruit varieties are 76.6% and 84.65%.
(Khan et al., 2022)	2022	Using deep learning, a framework can identify the type of disease and determine how much of a particular tomato leaf is afflicted.	Semantic segmentation based deep convolutional neural network (DCNN)	accuracy 97.6%
(Sodjinou et al., 2022)	2021	To separate weeds and crops using agronomic color pictures	U-Net	Accuracy 99.19%
(Chen et al., 2021)	2021	A novel method was developed to increase the accuracy of lesion segmentation in rice leaves by utilizing an attention mechanism and multi-scale extraction integration.	U-Net	Accuracy 94%

Ref	Year	Objective	Techniques Applied	Result
(Zabawa et al., 2020)	2020	This framework counts the number of grapevine berries in a picture by identifying individual berries in the image using a convolutional neural network.	Semantic segmentation	Accuracy 94.0%
(Shao et al., 2021)	2021	This technique integrated the watershed algorithm for dense rice image recognition with the Transfer learning-based localization-based counting fully convolutional neural network model.	FCN + watershed algorithm	Accuracy 89.88%
(Bai et al., 2017)	2017	Image segmentation using fuzzy clustering based on neighborhood grayscale data to identify cucumber leaf spot disease	fuzzy C-means	Average positive error: 0.04%, Average negative error: 0.10%, Average segmentation error: 0.12%,
(Yadav et al., 2021)	2021	CNN models that are used for automatic disease identification in peach crops are segmented using grey level slicing on pre-processed leaf pictures.	Gray level slicing imaging method	Accuracy 98.75%
(Joshi et al., 2021)	2019	Utilizing black gram leaf picture segmentation and enhancement, a fully automated, non-invasive technique is suggested to promptly identify the illnesses.	Otsu thresholding + mask VGG 16 CNN	accuracy 98.2% Otsu thresholding + mask VGG 16 CNN.
(Rani & Amsini, 2017)	2017	Fuzzy set operation for Otsu-based color image segmentation is used to identify the diseased area in litchi fruits and leaves to extract the existence of diseased areas from the images.	Otsu-based color image segmentation	Not mentioned
(Singh & Misra, 2017)	2017	Provided a method for image segmentation that is used to automatically detect and categorize plant leaf diseases in pine trees.	Genetic algorithm	Accuracy 97.6%
(Chouhan et al., 2020)	2020	A scale-invariant feature transform technique is used to provide an automated method to separate the fungal diseases from the mango leaves.	Radial basis function Neural Network	Average Specificity = 0.9115 and Sensitivity = 0.9086
(Sinha, & Shekhawat, 2020)	2019	A dependable technique for recognizing certain leaf spot-type illnesses that affect olive trees is found.	Histogram thresholding + k-means segmentation	Not mentioned
(Mohapatra et al., 2022)	2022	suggested using convolutional neural networks (CNNs) as a metaheuristic to identify and diagnose diseases in mango leaves.	Fuzzy c-means	Accuracy 91.2%

Ref	Year	Objective	Techniques Applied	Result
(Saleem et al., 2021)	2021	The suggested leaf vein-seg method uses a cubic support vector machine to segment the leaf's vein pattern to quickly diagnose the disease in mango leaves.	Novel leaf vein-seg approach	Accuracy 95.5%
(Yao et al., 2022)	2022	ResNet50 and ResNetx101 are utilized as the backbone architecture for classification, and instance segmentation is employed to obtain detailed information about peach leaves, such as peach disease, masked lesion regions and the severity level of a disease.	Mask R-CNN and Mask Scoring R-CNN	Focal Loss function improved rate of recognition and segmentation accuracy
(Lin et al., 2019)	2019	The degree of leaf infection on a cucumber plant was determined by the CNN model, which has a higher computational complexity.	U-net	average pixel accuracy = 96.08%, Dice accuracy = 83.45% and intersection over union = 72.11%
(Kaur et al., 2022)	2022	The deep segmentation CNN model was trained using the labelled, enriched and augmented data. This semantic segmented data was identified and classified for both single and multiple tomato leaf illnesses.	Unet + Segnet	Accuracy 98.2%
(Wang, & Zhang, 2018)	2018	Suggested a full convolution neural network-based approach to give a crop leaf disease monitoring system a theoretical foundation.	FCN	Segmentation accuracy 96.26%
(Kerkech et al., 2020)	2020	The objective is to map out unhealthy regions of the vineyard so that they may be precisely and quickly treated. This will ensure that the vines remain in a healthy state, which is crucial for managing yield.	Segnet	Not mentioned
(Stewart et al., 2019)	2019	shown how deep learning-based instance segmentation techniques combined with UAV technology can be used to give precise, high-throughput quantitative measurements of maize plant disease.	R-CNN	Not mentioned
(Wang Q., et al., 2019)	2019	A tomato disease detection system is presented that is based on object detection models and deep convolutional neural networks.	Faster R-CNN and Mask R-CNN	Lowest mean time (0.123)

4.1. Fully convolutional models

Full convolution neural network (FCN) is used for picture segmentation based on semantics. These days, FCN serves as the foundation for nearly all semantic segmentation models. Using convolution, FCN initially extracts and codes the features from the input image. The feature image is then gradually resized using either up sampling or deconvolution to match the original image's size. Plant diseases and pest segmentation techniques can be categorized into three groups based on variations in FCN network topology: conventional FCN, U-net (Sodjinou et al., 2022; Chen et al., 2021), and SegNet (Goodfellow et al., 2016). The network structure of FCN is shown in Figure 5.

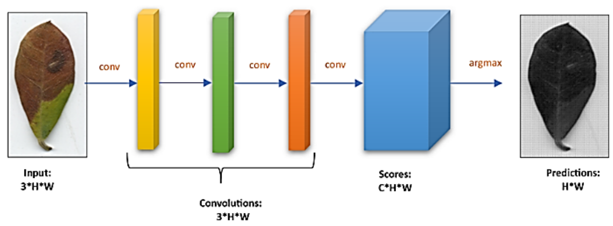

Figure 5. The Structure of full convolution neural network for olive leaf scorch.

Conventional FCN: A unique approach to segmenting leaf diseases of maize crop is based on complete convolution neural networks was presented by Wang and Zhang (2018) in response to the difficulty that typical computer/machine vision is sensitive to changing lighting and complicated backgrounds. This novel method's accuracy of segmentation technique was 96.26%. Authors suggested a method for classifying pests and plant diseases relying on enhanced fully convolutional model (FCN) (Wang F., et al., 2019). After a convolution layer had collected feature information from multiple layers from the leaf lesion image of maize crop, this approach performed a deconvolution operation to restore the dimension and clarity of the original image. The accuracy rate was 95.87%, the small affected area's segmentation was highlighted, and the lesion's integrity was ensured in comparison to the first FCN technique.

U-Net: U-net is a conventional FCN structure in addition to an encoder-decoder structure. To facilitate the recovery of segmentation information, it is characterized by the introduction of a layer-hopping connection that links the feature map from the coding step with that from the decoding stage. Fifty cucumber powdery mildew leaves that were collected in a natural setting were separated using a U-net-based convolutional neural network by authors in Lin et al. (2019). To safeguard the neural network against weight initialization, a batch normalization layer has been added to each convolution layer, in contrast to the original U-net. The investigation demonstrates that the convolutional neural network based on U-net is superior to the RF i.e. random forest, K-means, and GBDT techniques currently in use for effectively segmenting powdery mildew on cucumber leaves at the pixel level, with an average pixel accuracy of 96.08%. With fewer samples, the U-net technique can segment the lesion site in a complicated backdrop rapidly and precisely. The network structure of U-Net is shown in Figure 6.

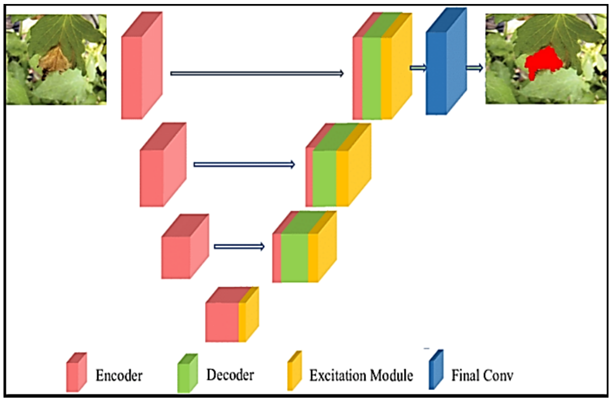

Figure 6. The structure of the UNet.

SegNet: A traditional encoder-decoder architecture is also included. One of its features is that the decoder's up sampling operation uses the index of the encoder's largest pooling operation. An algorithm for segmenting images for unmanned aerial vehicles was proposed by the authors in Kerkech et al. (2020). SegNet was used to segment 480 samples of visible and infrared pictures into four categories: healthy, symptomatic, shadows, and ground. On grapevines leaves, the recommended method's detection rates were 92% and 87%, respectively. The network structure of SegNet is shown in Figure 7.

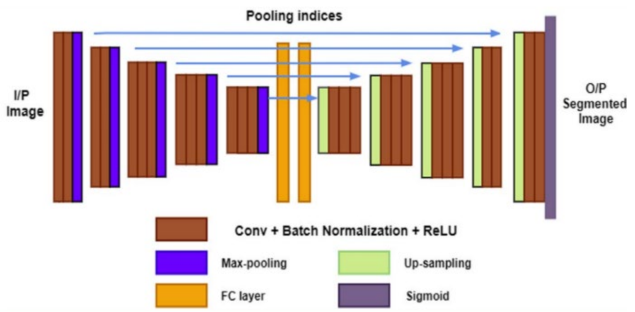

Figure 7. The structure of the SegNet.

4.2. Mask R-CNN

One of the most popular image instance segmentation techniques available now is mask R-CNN. It can be conceptualized as a detection- and segmentation-based network-based multitask learning technique. To identify individual lesions and count the number of lesions, for example, instance segmentation can be applied when numerous lesions of the same sort exhibit adhesion or overlap. semantic segmentation, however, frequently addresses numerous lesions of the same kind collectively. Using an image from an unmanned aerial vehicle, authors trained a Mask R-CNN model to segment lesions of maize affected by northern leaf blight (NLB) (Stewart et al., 2019). One lesion may be correctly identified and segmented by the trained model. The IOU between the projected lesion and the baseline real value was 0.73, with an average accuracy of 0.96, at the IOU threshold of 0.50. In addition, several research use object detection networks in conjunction with the Mask R-CNN architecture to identify plant diseases and pests. Ask R-CNN and Faster R-CNN are the two models that authors utilized in Wang Q. et al. (2019). Mask R-CNN was used to detect and segment the position and form of the infected area, whereas Faster R-CNN was utilized to determine the class of tomato infections. The mask R-CNN network construction for a plant leaf is shown in Figure 8.

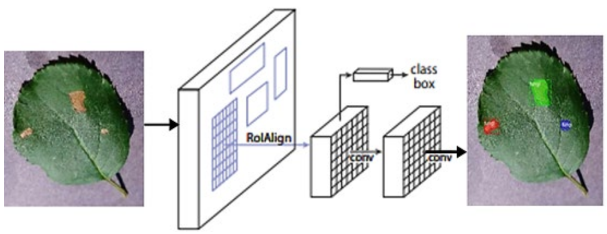

Figure 8. The network structure of mask R-CNN.

The findings demonstrated that the suggested method is capable of precisely and swiftly identifying 11 tomato classes of infections by dividing the position and form of damaged patches. Mask R-CNN achieved a good identification rate of 99.64% for all tomato disease classes. The segmentation strategy outperforms the categorization and identification network approaches in terms of obtaining lesion information. However, it requires a large amount of labelled data and obtaining that data pixel by pixel can be costly and time-consuming, much like the detection network.

5. Measures for image segmentation models

Depending on the study's aim, evaluation indices may differ. But up until now, most studies have concentrated on metrics that measure model correctness. The most widely used metrics are precision, pixel accuracy, mean average precision (mAP), F1 score, recall and IoU:

Definitions of precision and recall are:

$$Precision = \frac{(TP)}{(TP)+(FP)} * 100\% \quad (1)$$

$$Recall = \frac{(TP)}{(TP)+(FN)} * 100\% \quad (2)$$

In Formulas (1) and (2) TP is true positive, FP is false positive, and FN is false negative, it is expected to be 1 and is actually 1, indicating the quantity of lesions on plant leaves that the algorithm correctly identified. The number of lesions that the algorithm misidentified—with a predicted value of 1 and an actual value of 0—is known as false-positive, or FP (False Positive). The number of lesions that have not yet been identified is indicated by false-negative data, or FN (false negative). When it should be zero, it is actually one.

mAP is most frequently used to assess detection accuracy. The average accuracy for each class in the dataset must first be determined:

$$P_{average} = \sum_{x=1}^{N(class)} precision(x).Recall(x).100\%$$

The precision and recall of class x are represented by precision (x) and recall (x), respectively, in the formula above, which also indicates the number of categories as N(class).

For every category, average accuracy is defined as mAP:

$$mAP = \frac{P_{average}}{N(class)}$$

The F1 score is also introduced to evaluate the correctness of the model. The F1 score is also influenced by the recall and accuracy of the model. The formula is as follows:

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} * 100$$

Pixel accuracy is defined as the percentage of accurately identified pixels to total pixels. A pixel that is successfully detected as not belonging to the specified class is called a true negative, whereas a pixel that is correctly predicted to belong to the supplied class is called a true positive.

$$Accuracy = \frac{(TP)+(TN)}{(TP)+(TN)+(FP)+(FN)}$$

Mean pixel accuracy (MPA), which calculates the percentage of correct pixels for each class and averages it across all classes, is an extension of PA.

The Jaccard Index/IoU, also known as the Intersection over Union (IoU) metric, is a statistical measure that computes the ratio of the total number of pixels included in both the target and prediction masks to the number of pixels that are common between them.

$$IoU\ or\ Jaccard\ Index = \frac{target \cap prediction}{target \cup prediction}$$

Mean-IoU is the IoU average across all classes.

6. Findings

6.1. To expand the size of the dataset to produce more precise outcomes

Techniques of deep learning is currently used in computer/machine vision applications at broader level, which are generally regarded to have specific applications in the agricultural sector, such as diagnosing plant diseases. Plant disease samples for agriculture are not easily accessible. Compared to public repositories, self-gathered data sets are smaller and need more burdensome data labelling. Approximately 80% of research publications mention the limitation of smaller datasets as a significant issue that ultimately calls for the usage of data augmentation (Arivazhagan & Ligi, 2018; Mia et al., 2020; Salamai, 2023; Trang et al., 2019). Techniques of deep learning have not been broadly applied in the domain of plant disease diagnostics since many plant diseases are uncommon yet expensive associated with collecting disease pictures. This leads to the acquisition of merely a few data for training the model.

6.2. Intricate background images results in poor accuracy

Large-scale intricate backgrounds may result in more false detections due to the background noise issue on the gathered photos, particularly on low quality images. Due to the lack of available algorithms, the direction of various object identification algorithms' improvement is examined, and several techniques, including attention mechanisms, regional CNNs, and encoder-decoder-based architectures are suggested to enhance the performance of images with complicated backgrounds. (Kao et al., 2019). The rational allocation of resources is improved by the employment of such techniques. Such systems' primary function is to identify an area of interest fast and dismiss irrelevant information.

6.3. Model architectures

Despite the optimistic results that DL-based models have shown on challenging benchmarks, there are still unresolved issues with these models. What precisely are deep models learning, for instance? What meaning should we provide to the traits that these models learn? For a given dataset, what is the minimum neural network architecture that can attain a particular segmentation accuracy? While there are methods for visualizing the learned convolutional kernels of these architectures, a thorough analysis of their underlying behavior is yet missing. ResNet-10 (Yao et al., 2021), for instance, has the best detection rate but requires the most time to train and detect. Therefore, a deeper comprehension of these models' theoretical underpinnings can help in the development of improved models suited to various segmentation situations.

6.4. Lesion overlapping

The fuzziness, complexity, and overlap of the many sections in the infected leaf image makes segmentation of images inherently problematic challenge. Most disease leaf segmentation algorithms use gray-level variations between background, spot, and regular pixels as well as a predefined threshold or criterion to identify leaf image spots. However, in reality, as Figure 9 illustrates, the areas of these pixels in a disease leaf image are typically hazy and unclear, the normal and spot regions' colors are likewise uneven and ambiguous, and the disease leaf image's grey histogram is constantly overlapping. Therefore, in overlapping cases, the accuracy of illness diagnosis decreases since the image segmentation approaches are unable to recognize and classify these minute lesions. For increased accuracy, alternative morphological traits and dataset sizes can be utilized.

Figure 9. Segmentation of plant leaf images original plant leaf and converted grayscale leaf (Zhang S. et al., 2019)

6.5. Limited to single disease only

The literature review conducted by the authors concentrated on one disease, one class, and two or more illnesses on numerous crops. Furthermore, no study is conducted on a specific group of crops, such as pome fruits, cereals, grains, millets, and stone fruits, which are one of the primary energy sources that humans consume.

7. Conclusion and future directions

Drawing from the research conducted to automate the identification and categorization of plant leaves using deep-learning-based image segmentation approaches, the following research points could contribute to the advancement of state-of-the-art methods.

7.1. Plant diseases datasets

Numerous databases containing various plant diseases found in authentic natural settings are still in the first stages of development. Very few photos from real-time fields have been used in studies on a single disease, single crop, and several diseases of a single crop; instead, plant leaves with lesions are generated in laboratories or data augmentation procedures are used (Fazari et al., 2021). To identify farmland over a large area and coverage and to compensate for the prior research' use of image samples that lacked randomization, future research should fully utilize data information acquisition platforms such as IoT monitoring models based on agriculture, unmanned aerial vehicle aerial photography systems, and portable field spore auto-capture instruments. Additionally, it can guarantee the quality and comprehensiveness of the dataset and enhance the algorithm's generality.

7.2. Pros and cons of plant disease detection systems

The authors concentrated on the single disease, single class, and multi-class datasets when conducting a literature review. Less research has been done on the dataset of multiple diseases affecting numerous crops, though. Separation and categorization were other topics of discussion. Attention is focused on the entire leaf region, not just the affected area. The development and application of a crop separation technique that works in both controlled and uncontrolled conditions is required. To increase accuracy, database expansion was also necessary.

7.3. Drawbacks of recent techniques for disease detection system

Over the past ten years, every study utilizing image processing, machine learning, and deep learning has focused on identifying and detecting leaf diseases, up to five or six different types of illnesses affecting several crops, or numerous leaf diseases affecting a single crop. Though these are the primary sources of energy for humans, there isn't much research to our knowledge on any specific category of crops for many diseases on leaves, such pome fruits, cereals, grains, millets, and stone fruits. Additionally, other crop parts like the panicle and stem have not yet been subjected to disease detection. The CNN method immediately addresses problems with memory requirements and computational complexity. Even with the adoption of new imaging technology and learning methodologies, they are meaningless if the general population cannot use them in an intuitive manner. Thus, designing a completely automated system while maintaining mobile and online availability specifications is one potential answer to this. From the above survey most popular image segmentation models like UNet, SegNet, Mask RCNN etc. can be used effectively in combination with pre-trained CNN models to detect leaf diseases more accurately.

7.4. Detection speed problem

Although AI is on peak in every field whether it is something about security (Sumathi et al., 2023) or object detection but speed is a major concern of AI. Deep learning techniques yield greater outcomes than standard methods, but at the cost of increased computer complexity. To ensure detection accuracy, the model needs to increase its processing load and comprehend all of the information in the image. This will unavoidably result in a slow detection speed and an inability to satisfy real-time demands. Reducing the quantity of calculations is frequently required to assure the detection speed. On the other hand, this will lead to inadequate training and missed or false detection. As a result, creating an effective algorithm that possesses both speed and accuracy of detection is crucial.

Nomenclature

DL	Deep Learning
CNN	Convolutional neural network
RCNN	Region-based CNN
DCNN	Deep CNN
GAN	Generative adversarial network
GRU	Gated recurrent units
LSTM	Long short-term memory network
FCN	Full convolution neural network
VGG	Visual geometry group
ResNet	Residual network
NLB	Northern leaf blight

Conflict of interest

The authors have no conflict of interest to declare.

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