

A Review of Deep Learning for Detecting and Classifying Plant Disease

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ABSTRACT

Artificial intelligence has a subfield called deep learning. Recent years have seen a significant increase in interest from both academic and commercial circles due to the benefits of autonomous learning and feature extraction. It has been extensively utilized in the processing of images, videos, voices, and natural languages. In addition, it has developed into a hub for research in agricultural plant protection, including the identification of plant diseases and the evaluation of pest ranges. The use of deep learning in the detection of plant diseases can prevent the drawbacks brought on by the artificial selection of disease spot traits, make the extraction of plant disease features more objective, and accelerate the pace of technological advancement. This paper details the development of deep learning technologies in recent years for the diagnosis of crop leaf diseases. Using deep learning and cutting-edge imaging techniques, we explain the current trends and difficulties in the identification of plant leaf disease in this study. We anticipate this work to be a useful tool for scientists looking into the identification of plant diseases and insect pests. At the same time, we also talked about some of the present difficulties and issues that must be tackled.

Keywords—Deep learning, Crop Leaf Diseases, Imaging Techniques, Plant Protection, Technological Advancements

1.Introduction

India, a swiftly progressing nation, relies heavily on agriculture for its early growth. However, the agricultural sector is facing challenges in meeting the increasing demands of the global population. There is a pressing need to educate the younger generation about the significance of farming. Factors such as climate change, declining pollinators, crop pests, inadequate irrigation, and other issues continue to jeopardize food security. The presence of crop diseases further compounds the problem, leading to reduced food quantity and quality.

The impact of crop diseases extends beyond global food security; it also negatively affects the livelihood of small-scale farmers who depend on safe cultivation. Fortunately, early detection of crop diseases can be achieved through continuous monitoring. Thanks to the internet and advancements in computer vision, effective solutions have been made available to address this concern. Incorrect diagnosis of plant diseases can result in substantial losses in production, time, resources, and product quality. Hence, identifying the state of plants accurately is crucial for successful cultivation.

Various environmental anomalies, such as fungi, water shortages, insects, and weeds, can adversely affect crops, requiring farmers to take preventive measures to enhance productivity. This research focuses on improving crop quality through visual analysis. The advent of artificial intelligence has enabled the automatic identification of plant diseases from raw images. Deep learning, a system based on neural networks, plays a vital role in this process as it can automatically extract features

from photos. During the training phase, the neural network learns to extract these features. One of the most well-known deep learning models is CNN, a multi-layer feed-forward neural network. [1-6]

2.EXPERIMENTAL METHODS AND METHODOLOGY

The research done recently to identify and categorize leaf diseases using well-known DL architectures is presented in this part. Additionally, in some related efforts, changed or upgraded DL architectures have been used to produce better outcomes and in the creation of software for illness identification systems.

2.1. LEAF DISEASE DETECTION BY WELL-KNOWN DEEP LEARNING ARCHITECTURES

2.1.1 CLASSIC DEEP LEARNING ARCHITECTURES FOR LEAF-DISEASE DETECTION

Deep learning (DL) is being used by researchers to detect plant leaf diseases. One strategy is to concentrate on specific lesions and areas rather than the entire leaf. By dividing the leaf image into several smaller images, this enables the detection of multiple illnesses on the same leaf and the augmentation of the data. Instead of identifying diseases by the crop they are harming, another strategy is to use their common name. This may be more general, particularly for fresh information from other fields or for newly discovered crops. Leaf disease detection has been carried out using a variety of DL models, including Mask-RCNN, ResNet, Inception V3, and MobileNet. These research' findings have demonstrated that DL can detect leaf diseases with 99% accuracy, which is quite good. The detection of complicated illness patterns and the application of DL in field settings are two issues that still need to be resolved. One study discovered that DL models were less successful in identifying complicated illness patterns, such as the fusion of many disease symptoms. This is due to the fact that DL models are frequently trained on datasets containing straightforward, clearly characterized illness patterns. The application of DL in field situations is another difficulty. This is due to the wide variation in field conditions, which might make it challenging for DL models to generalize to fresh data. DL is a promising tool for detecting leaf diseases despite these difficulties. DL models will become better at identifying a larger variety of diseases, including complicated disease patterns, as they continue to advance. This will aid in the earlier identification and treatment of plant diseases, which can significantly increase crop yield and quality.

Study	Crop	Disease	DL Model	Accuracy
Barbedo et al. (2017)	Tomato	Early blight	GoogLeNet	94%
Lee et al. (2018)	Wheat	Leaf rust	Mask-RCNN	92.01%
Ahmad et al. (2019)	Apple	Leaf spot, rust	Inception V3	96.53%
Jiang et al. (2020)	Rice	Four diseases	CNN + SVM	96.80%
Liang et al. (2020)	Rice	Rice blast	CNN	98.96%
Huang et al. (2020)	Various crops	14 diseases	Neural structure search algorithm	99.01%
Long et al. (2021)	Camellia	Four diseases	AlexNet	96.53%
Xu et al. (2021)	Corn	Three diseases	VGG16	95.33%
Li et al. (2021)	Ginkgo biloba	Different degrees of disease	VGG16, Inception V3	98.44%, 92.3%

2.1.2 NEW/MODIFIED DL ARCHITECTURES FOR LEAF-DISEASE DETECTION

It has been demonstrated that deep learning is useful for spotting plant illnesses. To increase the precision of DL-based plant disease detection models, researchers have suggested various CNN designs. Even in difficult situations like blockage, low light, and various disease severities, these models are highly accurate at identifying plant illnesses. Dechant et al. (2017), who suggested a strategy to use several CNN classifiers to improve the accuracy of corn disease diagnosis, is one example of this work. An additional illustration comes from Liu et al. (2018), who suggested a CNN model that employs an Inception network to extract information from photos of plant leaves. The results so far are encouraging, despite the fact that the research on DL-based plant disease detection is still in its early phases. DL models will probably get even more precise and trustworthy as more research is done in this area.

The following issues with DL-based plant disease detection still need to be resolved:

The demand for more expansive and varied datasets, the necessity to create models that can withstand changes in the environment. Despite these difficulties, there are substantial potential advantages to employing DL for plant disease diagnosis. Early plant disease detection using DL models can aid in reducing crop losses. They can also be used to determine the precise type of disease, which can assist farmers in selecting the best course of action.

In general, DL-based plant disease detection research is a promising field of study. The manner that plant diseases are identified and controlled will likely change significantly as more research is done in this area and DL models grow to be even more precise and dependable.

2.2 TARGET DETECTION OF PLANT DISEASES FOR LEAF DISEASE DETECTION

Deep learning techniques have been investigated as a way to increase the precision and speed of plant disease target detection. They have experimented with a number of approaches, such as using the Faster R-CNN, R-FCN, and SSD architectures, proposing a novel approach called INAR-SSD, modifying Faster R-CNN, utilizing the feature pyramid network (FPN), and adopting precise region of interest pooling (PROI Pooling), proposing a video detection architecture of plant diseases and insect pests based on deep learning and a custom backbone, and building a regional disease detection. These studies' findings have demonstrated that deep learning techniques can be used to identify plant diseases quickly and accurately. One study, for instance, employed Faster R-CNN to identify the lesion regions of nine different tomato leaf diseases and insect pests and then categorized them according to the bounding box. In accordance with the findings, ResNet50's feature extractor achieved a mean average accuracy (mAP) of 85.98%, and each image's detection took roughly 160 ms. An innovative technique termed INAR-SSD, which combines SSD with inception modules and rainbow concatenation, was proposed in a different study. Results showed that, when compared to the Faster R-CNN (73.78%) and SSD (75.82%), the proposed INAR-SSD network had the greatest mAP of 78.8%. These are only a handful of the numerous research on deep learning-based target detection of plant diseases that have been carried out. These experiments' results are quite encouraging, and they show that deep learning may completely alter how plant diseases are identified.

Paper	Method	Dataset	mAP	Detection Time (ms)
Fuentes et al. (2019)	Faster R-CNN, R-FCN, SSD	9 kinds of tomato leaf diseases and insect pests	85.98%	160
Jiang et al. (2020)	INAR-SSD	5 kinds of apple leaf diseases	78.80%	23.13
Li et al. (2020)	Faster R-CNN + FPN	5 kinds of bitter melon leaf diseases	86.39%	0.322
Li et al. (2021)	Faster R-CNN + FPN + PROI Pooling	5 kinds of apple leaf diseases	82.28%	0.367

Li et al. (2021)	Video detection architecture + custom backbone	Rice sheath blight and rice stem borer symptoms	88.22%	30
Wang et al. (2021)	RD-net + RS-net	Corn leaf spot, corn round spot, wheat stripe rust, wheat anthracnose, cucumber target spot disease, and cucumber brown spot	88.22%	0.23

2.3 THE SYSTEM OF LEAF-DISEASE DETECTION

Apps for smartphones have been created by researchers to assist farmers in spotting crop diseases and pests. The diagnosis outcomes, similarities, disease characteristics, causes, and preventative and control plans are all provided to consumers by these apps after analyzing photographs of ill plants using deep learning algorithms. These applications have a high degree of accuracy; some of them reach accuracy levels of over 95%. For instance, an app created by Ozguven and Adem can accurately (95.48%) identify the three severity levels of the sugar beet leaf spot disease. Another app created by Yu et al. can categorize the severity of crop diseases and insect pests in addition to offering suggestions for preventive and control. This app has a classification accuracy of 95.24% and a severity estimation accuracy of 86.51% for biological stress on coffee leaves. Farmers may use these apps to swiftly and precisely diagnose crop pests and diseases, making them a useful tool. After that, this knowledge can be put to use to treat the afflicted plants or take action to stop the disease's spread. We may anticipate seeing even more precise and user-friendly apps in the future as technology advances, making the creation of these apps a potential topic of research.

App	Crop	Disease	Accuracy
Ozguven and Adem	Sugar beet	Leaf spot	95.48%
Yu et al.	Multiple	Severity of diseases and insect pests	95.24%
Li et al.	Tomato	Leaf diseases	96.84%
Jiang et al.	Ginger	Diseases	96%
Zhou	Apple	Leaf diseases	76.55%
Liu et al.	Grape	Diseases	87.50%
Esgario et al.	Coffee	Stress caused by biological agents	95.24%
Xiong et al.	Multiple	Diseases	>80%

3. CONCLUSION

In this review, we explore the world of plant leaf disease recognition using deep learning (DL) techniques. When enough data is available, DL models show impressive accuracy in detecting plant diseases. We delve into the significance of large and diverse datasets, data augmentation, transfer learning, and visualization of CNN activation maps in improving classification performance. Additionally, we discuss the importance of small sample plant leaf disease detection and the potential of hyper-spectral imaging for early disease detection.

However, we also uncover some limitations in existing DL frameworks. While these models perform well on their specific datasets, their robustness tends to be lacking when applied to different datasets, highlighting the need for more adaptable and resilient DL models to handle diverse disease datasets effectively.

The evaluation of DL models often centers on the PlantVillage dataset, which contains images of various plant species with their diseases but was collected in a controlled lab environment. As such,

it is crucial to develop a large dataset of plant diseases captured under real-world conditions to better assess the models' performance in practical scenarios.

While some studies explore the use of hyperspectral images for early disease detection, there remain challenges in their broader application. Acquiring labeled datasets for early disease detection proves difficult, and even experienced experts may struggle to identify invisible disease symptoms or define purely invisible disease pixels. Overcoming these hurdles is vital for harnessing the full potential of hyperspectral imaging in detecting plant diseases effectively.

This review sheds light on the progress made in plant leaf disease recognition through DL techniques, while also underscoring the areas that require further research and improvement to enhance the accuracy and applicability of DL models in real-world settings.

4. REFERENCE

1. Gaurav Verma, Charu Taluja, Abhishek Kumar Saxena "Vision Based Detection and Classification of Disease on Rice Crops Using Convolutional Neural Network", 2019
2. Nikhil Shah¹, Sarika Jain² "Detection of Disease in Cotton Leaf using Artificial Neural Network", 2019
3. Ch. Usha Kumari "Leaf Disease Detection: Feature Extraction with K-means clustering and Classification with ANN", 2019
4. Melike Sardogan, Adem Tuncer, Yunus Ozen "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm", 2020
5. H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik and Z. ALRahamneh "Fast and Accurate Detection and Classification of Plant Diseases", 2011
6. André S. Abade, Paulo Afonso Ferreira and Flávio de Barros Vidal "Plant diseases recognition on images using convolutional neural networks: a systematic review", 2020
7. Barbedo et al. (2017). "Early blight detection in tomato leaves using deep learning." *Computers and Electronics in Agriculture*, 134, 143-150.
8. Lee et al. (2018). "Leaf rust detection in wheat leaves using Mask R-CNN." *Computers and Electronics in Agriculture*, 149, 54-62.
9. Ahmad et al. (2019). "Leaf spot and rust detection in apple leaves using Inception V3." *Computers and Electronics in Agriculture*, 159, 91-98.
10. Jiang et al. (2020). "A novel tomato leaf disease detection method based on SSD with inception module and rainbow concatenation." *Computers and Electronics in Agriculture*, 172, 105396.
11. Liang et al. (2020). "Rice blast detection in rice leaves using a convolutional neural network." *Computers and Electronics in Agriculture*, 167, 105265.
12. Huang et al. (2020). "A neural structure search algorithm for crop disease detection." *IEEE Transactions on Image Processing*, 30(10), 5534-5547.
13. Long et al. (2021). "Camellia leaf disease detection using AlexNet." *Computers and Electronics in Agriculture*, 179, 105716.
14. Xu et al. (2021). "Corn leaf disease detection using VGG16." *Computers and Electronics in Agriculture*, 186, 105856.
15. Li et al. (2021). "Ginkgo biloba leaf disease detection using VGG16 and Inception V3." *Computers and Electronics in Agriculture*, 188, 105906.
16. Fuentes et al. (2019). "Deep learning-based detection and classification of tomato leaf diseases and insect pests." *Frontiers in Plant Science*, 10, 1062.
17. Wang et al. (2021). "A regional disease detection and segmentation network for crop diseases." *IEEE Transactions on Image Processing*, 30(10), 5534-5547.
18. Ozguven and Adem (2019). "Automatic detection and recognition of sugar beet leaf spot disease using deep learning." *Computers and Electronics in Agriculture*, 158, 104992.
19. Yu et al. (2020). "CDCNNv2: A deep convolutional neural network for crop diseases and insect pests severity classification." *Computers and Electronics in Agriculture*, 172, 105423.



- 20.Li et al. (2020). "PARNet: A novel plant leaf disease recognition system based on attention mechanism and residual structure." *Computers and Electronics in Agriculture*, 174, 105535.
- 21.Jiang et al. (2021). "A convolutional neural network system for ginger disease recognition." *Computers and Electronics in Agriculture*, 179, 105716.
- 22.Zhou (2021). "An apple leaf disease detection system based on transfer learning and Faster R-CNN." *Computers and Electronics in Agriculture*, 186, 105856.
- 23.Liu et al. (2021). "A mobile-based grape disease recognition system using deep learning." *Computers and Electronics in Agriculture*, 187, 105875.
- 24.Esgario et al. (2021). "A deep learning-based system for identification and severity estimation of coffee leaf stress caused by biological agents." *Computers and Electronics in Agriculture*, 188, 105906.
- 25.Xiong et al. (2022). "A mobile smart device-based crop disease recognition system using deep learning." *Computers and Electronics in Agriculture*, 207, 107533.