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Review Article

Role of Artificial Intelligence in Plant Disease Detection: A Review

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Abstract: Agriculture is the backbone of human civilization, playing a vital role in sustaining national economies. Enhancing food production is crucial for mitigating hunger and ensuring global food security. However, plant diseases caused by fungi, bacteria, viruses, and nematodes pose a significant threat to agricultural productivity, resulting in substantial economic losses worldwide. Effective crop protection and improvement of crop quality and quantity are inextricably linked to plant disease management. Accurate identification and detection of plant diseases are essential for devising strategic control measures. Traditional disease detection methods have proven inadequate, with delayed diagnosis and inaccurate results hindering effective disease control. Recent advances in Artificial Intelligence (AI) have revolutionized plant disease detection, enabling rapid and accurate identification of diseases across vast areas. This review aims to investigate the efficacy of automated plant disease detection using Machine Learning (ML), Deep Learning (DL), and Hyperspectral Imaging. By leveraging these cutting-edge technologies, we can develop more accurate and reliable disease detection systems, ultimately contributing to enhanced crop yields and global food security.

Keywords: Hyperspectral Imaging, Artificial Intelligence, Deep and Machine Learning Models

Introduction

Agriculture biodiversity is one of the essential components of human civilization. It helps the economy, providing humans with food (Radoglou *et al.,* 2020). The disease can be spread through fungi, bacteria, viruses and nematodes as well as with abiotic factors such as climate changes, environmental degradation and resource sustainability. It is estimated that diseases, insect and weed cause annual losses of between 31% and 43% of all crops produced worldwide. Food waste is less in rich countries and more in poor countries that need food. On average 36% food is lost with 14.3% of that is due to diseases which amount to $210 billion each year (Chen *et al.,* 2021). Plant Disease infection significantly impact both quality and quantity of crop (Zafar *et al.,* 2024). Growing more food is essential for agriculture farm production because farmland is shrinking, and natural resources are running out. Early prediction and recognition of these infections, loss in quantity and quality of crop are vital to prevent crop damage and enhance crop yield (Chen at al., 2021). Detecting diseases

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and pests early is crucial to preventing the disease and crop losses. However, this is challenging because many diseases can affect crop and wild plants (Agrios 2005). High control costs not only increase the economic burden on agricultural producers but also limit the sustainability of agriculture production. Traditional monitoring methods rely on manual observation and sampling which are limited inaccuracy. Furthermore, monitoring and disease identification performed manually which is inaccurate, time consuming and expensive. (Zafar *et al.,* 2024). This literature review examines the evidence on the benefits and risks of AI plant Disease detection.

Research has shown that to improve crop yield the current era characterized by significant technological advancement such as AI (Artificial intelligence), IOT (Internet of things). In a systematic review utilizing AI techniques in agriculture can reduce crop quality. Moreover, the rapid development of data acquisition modalities such as UAVs high technology remote sensors, ML algorithms and DL techniques have opened new perspectives monitoring and disease identification. Especially UAV swarms offer better protection of brassica plants, sustainability and optimize profitability. UAVs are not only economically beneficial but also environmentally friendly as they produce negligible or no pollution (Karpyshev *et al.,* 2021) Furthermore for analyzing image accurately ML algorithms are employed. Additionally, IOT devices capture climate conditions such as cloud cover rain, sunshine temperature and humidity. DL techniques can work on such real time datasets captured by IOT devices (Delalieux *et al.,* 2007).

While there are potential benefits of AI, there are also concerns about the risk associated with this AI plant disease detection. AI plant disease detection faces three main limitations such as technology issues, data problems, Social and economic challenges (Adam et al., 2017). Furthermore, human expertise and training are crucial for successfully using AI in agriculture disease detection. (Liu *et al.,* 2018) While AI automates some tasks, humans are still needed to interpret results, validate AI outputs, make informed decisions (Howard et al., 2017).

Artificial intelligence presents a highly effective strategy for detecting plant diseases, offering numerous benefits that can enhance crop yield, quality, and quantity. Notably, AI's precision and efficiency enable accurate monitoring, identification, and control of pests and diseases, thereby improving agricultural production efficiency and quality. Moreover, AI's sustainable and environmentally friendly nature reduces the reliance on chemical pesticides, minimizes pesticide residues, and helps protect the ecological environment, ultimately promoting sustainable agriculture development.

Phytopathology

Phytopathology is the scientific study of plant pathogens, encompassing the causes, mechanisms, and control methods of diseases affecting plants. Derived from Greek roots, phytopathology literally means "plant disease knowledge" (Phyto-plant, Patho-disease, and Logo-knowledge). This field aims to investigate the etiology, development, and interaction between hosts and pathogens, as well as methods for controlling, eradicating, and managing diseases. Phytopathology has made significant contributions to agricultural science, drawing from various disciplines, including microbiology, mycology, bacteriology, virology, nematology, and molecular biology, to advance our understanding of plant diseases and develop effective management strategies.

Plant Disease

The changes in behavior or physiology of plant due to any abnormality either caused by biotic or abiotic factor referred to as plant disease. Abiotic diseases are non-infectious and cannot be spread from one host to another and these diseases are non-hazardous while in contrast biotic diseases are infectious in nature and can be spread from infectious host to noninfectious host and these are hazardous in nature.

Bacterial Disease

The diseases which can be caused and spread by pathogenic bacteria are referred to as bacterial diseases. The common symptoms shown in the result of bacterial diseases are spot and wilting of plant.

Viral Disease

The Diseases which are spread through viruses. The symptoms are not clearly shown on the plant these are similar as nutrients failure. The viral diseases are commonly transferred or spread by insects such as beetles, leaf hopper, white flies, aphid etc. which indicates some symptoms such as mosaic abdication and leaf curl etc.

Fungal Diseases

Plant fungal disease effects a large component of plant and approximately cause huge no of disease. The common symptoms are wilting, rust, mildew, root rot, smut, ergot and Carnal bunt etc. The above-mentioned diseases symptoms may rise due to infectious and non-infectious disease. Accurate disease detection is difficult for the identification of pathogen using specific symptoms.

Plant disease detection Symptoms

Artificial intelligence can be an effective plant disease detection strategy for the accurate disease identification. It enhances agriculture production by minimize plant diseases. Further research studies have been completed for the identification and detection of plant disease by using artificial intelligence. Various review research focus on approaches while other focuses on specific disease. Review focuses on certain research using certain techniques such as Machine learning (ML), deep learning (DL), Hyperspectral imaging and certain molecular techniques used to prevent and mitigate pathogens.

Machine learning

The identification of disease by using machine learning with image processing by using sequential steps Image Acquisition, Image Pre-Processing, Image Segmentation, Feature Extraction and Selection, and Classification (Bahargava *et.al.,* 2021). Foremost the plant roots stems branches and leaves are captured. Then image preprocessing after that segmentation for the detection of infected region. This segmentation is used in the feature of classification.

Image Acquisition

This is the initial step of any machine learning system. This process taking pictures or by using existing images from collection. The cameras setting and conditions affect the accuracy of disease detection. It used specialized cameras for better image identification such as hyperspectral, thermal, fluorescent. Poor quality images effect the image quality performance. Using right camera technique helps improve image quality which improve system performance (Arnal *et al.,* 2019).

Image Pre-Processing

Image Pre-Processing is very important step in machine learning. It improves image quality which is effect by any distortion. Most data in preprocessing is collected is used to enhance the image quality and to reduce Processing time. Some common processing includes image quality, cropping, background removal and rotation. Image Pre-Processing and augmentation create more imaging from existing data which help model to enhance database (Kaur *et al.,* 2018).

Image segmentation

Image segmentation separate the affected part of an image from the rest. It identifies the affected and unaffected areas of image. It is essential process in machine learning, but it faces some challenges such as incorrect boundaries, shadows lightning issues. There are two main methods of segmentation are conventional method and computational methods commonly work better than Conventional method. Accurate segmentation is essential for extracting features from Imaging (Karadag *et al.,* 2020).

Image classification and Feature extraction

Feature extraction is the main step in machine learning system. It helps to differentiate the one part of object from another and identity object. Commonly used feature includes color shape, texture etc. Feature extraction technique is important for Image identification and classification. It is necessary to recognize object and reduce computational cost.

The final and most important step in machine learning is classification. Machine learning allows computer to learn from experience. Various techniques of classification have been used in research such as labeled data, unlabeled data and semi supervised data (Baharguava *et al.,* 2024).

Deep learning

Deep learning was first proposed in 1943. There are three phases for the development of DL. Phase 1, during 1943-1969 was a linear model of neural network for classification. Phase 2, during 1986-1988 was a non-linear mapping of multi-layer perceptron for the BP (Backpropagation) algorithm. Phase 3, from 2006 to the Present, has a ReLu activation function, ImageNet recognition, and deep learning model-AlexNet.

Deep learning has emerged as the most effective tool for maximizing accuracy in plant disease detection, offering easy and accurate evaluation of obtained data. This technology relies on two primary components: layers and neurons within a deep network, which work together to extract valuable insights. Deep learning has also driven significant advancements in various fields, including automatic medical diagnosis, automatic financial management, and autonomous vehicles. Furthermore, a range of deep learning models, such as Generative Adversarial Networks (GAN), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Multilayer Perceptron (MLP), are commonly utilized to achieve remarkable results in plant disease detection and beyond.

The implementation of DL requires basic steps

Image Acquisition

It is the first step in deep learning. High quality images are crucial for accurate detection of plant disease. The data must be accurate to obtain perfect model. It consists of training validation and test. Sharp focuses are essential for obtaining accurate models. The model is learned by the training set, hyper parameters are adjusted during validation and the performance evaluation is done by the test set. In literature DL techniques are used to identify the classification of disease.

Image Augmentation

Image Augmentation is the technique used to artificially increase the size of data base by using transformation of existing image. The plant leaf labelling, collection and detection techniques are cover under the image augmentation. The recognition rate will be increasing therefore the identification of dataset is essential for the detection of disease. The original image color will not be changed by the image enlargement. There are two ways for data augmentation conventional augmentation and generating adversarial network.

Image classification

Certain research established a great full application of Deep Learning in image classification of plant disease detection. The main objective of image classification is that plant must have the disease, symptoms and as well as achieve high accuracy.

Hyperspectral Imaging

Plant diseases can often be identified through visible symptoms, either by the naked eye or through computer vision analysis, which can detect pathogens present on the plant's surface. To detect and identify plant diseases, hyperspectral imaging sensors are primarily employed. These sensors operate within the electromagnetic spectrum, capturing a wide range of information that enables the early detection of diseases.

RGB Imaging

RGB (Red Green Blue) is the easy source of digital images for identification and detection of disease. There is certain parameter such as photo sensor for light sensitivity, optical focus and spatial resolution has a great significant role in Disease detection (Baharguava *et al.,* 2024).

Multi and hyperspectral sensor

It accesses the various spectral sensor information in certain wave band. It has ability to provide RGB and near infrared wave band. Hyperspectral sensor gives spatial and spectral information from the data. It depends upon the object and the sensor (Wang *et al.,* 2022).

Thermal sensor

It referred to as the identification of plant temperature and is correlated with plant water and microclimate in plant state. It can be used in plant science at various spatial and Temporal scale from small scale application (Mahlein *et al.,* 2016).

Related work

Machine learning especially Convolutional Neural Networks (CNNs) has been widely used for agriculture for several years. One of its important applications is to detect crop disease by analyzing symptoms. Since a while back researchers have exploded various techniques and strategies to create accurate models. This field has been heavily studied resulting in many different methods such as subset of Artificial intelligence enable computers to learn patterns and make predictions from data. Usually, research related to plants village datasheet as a source of image detection. More than 50,000 images of healthy leaves and ill leaves with disease symptoms are used for the detection strategy. This dataset was used, for example, to identify three diseases in bananas with an accuracy of 97.6% using s LeNet LeCun et al.,1989. Szegedy et al., 2015 develop architecture to detect black rot of apple they used transfer learning and VGG-16 architecture with an accuracy of 90.5%. Fuentes at al., 2017 develop architecture used to detect tomato disease they used Faster R-CNN and V-GG 16, which obtained accuracy 84% by using image magnification technique.

Tahir et al., 2018 built a machine learning solution capable of detecting fungi with 94.8% accuracy using a exclusive dataset with 40,700 labelled images. Another study by Sarangdhar and Pawar's 2017 revealed that comprehensive system for cotton leaf disease detection and soil quality assessment, offering mobile-based disease identification, treatment advice, and soil analytics, were quite significant AI models. Similar studies by Howard at al., 2017 emphasizes that MobileNetv1 as AI tool was not reliable for instant classification due to high error rate and frequent misclassification. Its performance was hindered by a significant no. of misclassification making unfit for real time classification, respectively. It is pertinent to mention that that although the existing research demonstrates promising results, its effectiveness is hindered by limitations. Specifically, utilizing the Plant village dataset for training yields models with suboptimal performance on real-world image inference. Whereas the use of AI in plant disease detection has shown promising results, but on the other hand there are several areas that still require further research and exploration followed by diverse development.
Some potential future research directions include.

Future Research directions

Investigating DL models for plant disease detection in diverse plant regions

This involves exploring the effectiveness of DL models in detecting diseases in various plant species and regions.

Developing automated parameter search techniques for weather data augmentation
This involves creating automated methods for searching and optimizing parameters for weather data augmentation, which can improve the accuracy of disease detection.

Examining data augmentation and large dataset strategies for enhanced accuracy
This involves investigating various data augmentation techniques and large dataset strategies to improve the accuracy of disease detection.

Contributing to sustainable agriculture through innovative techniques
This involves exploring innovative techniques and technologies that can contribute to sustainable agriculture practices.

Optimizing datasets through preprocessing techniques
This involves developing preprocessing techniques to optimize datasets and improve the accuracy of disease detection.

Designing real-time DL-based disease detection systems
This involves creating real-time systems that can detect diseases using DL techniques.

Developing Android apps for plant disease detection using DL models
This involves creating Android apps that can detect plant diseases using DL models.

Integrating DL and ML techniques for plant leaf detection and classification
This involves combining DL and Machine Learning (ML) techniques to improve the accuracy of plant leaf detection and classification.

Conclusion

Accurate detection and classification of plant diseases are critical for sustainable crop cultivation, yet are complicated by the need for substantial resources, expert knowledge, and consideration of agricultural operations and disease characteristics. The conclusion drawn from this study contributes meaningfully efficacy of Artificial intelligence in the accuracy of plant disease detection. Our finding suggest that AI can improve disease detection by combining multiple data sources. Consequently, when sufficient data is available for training, DL techniques can detect and classifying plant leaf diseases with high accuracy. Future research directions for plant disease detection and classification include Investigating DL models for plant disease detection in diverse plant regions. Developing automated parameter search techniques for weather data augmentation. Examining data augmentation and large dataset strategies for enhanced accuracy. Contributing to sustainable agriculture through innovative techniques. Optimizing datasets through preprocessing techniques. Designing real-time DL-based disease detection systems. Developing Android apps for plant disease detection using DL models. Integrating DL and ML techniques for plant leaf detection and classification.

Conflict of Interest: No potential conflict of interest is declared regarding this review.

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