Applications of Drone for Crop Disease Detection and Monitoring: A Review

Abstract

Crop diseases are one of the major threats to global food production. The different crop diseases result in significant yield losses, where their effective monitoring and accurate early identification techniques are considered crucial to ensure stable and reliable crop productivity and food security. Efficient monitoringand detection of plant pathogens are necessary in restricting and effectively managing the spreadof the disease and reducing the cost of pesticides. Traditional methods like molecular and serological methodsthat are widely used for plant disease detection are often ineffective if not applied during the initialstages of pathogenesis. On the contrary, remote sensingtechniques utilizing drones are very effective for the rapid identification of plant diseases intheir early stages.Remote sensing technology is vital for precision agriculture, aiding in early disease detection, resource management, and environmentally friendly practices. Recent advances in remote sensing technology and data processing have propelled unmanned aerial vehicles (UAVs) into valuable tools for obtaining detailed data on plant diseases with high spatial, temporal, and spectral resolution. Presently, drones play a pivotal role in the monitoring of plant pathogen spread,detection and diagnosis to ensure crops' health status. The advantages of drone technology includehigh spatial resolution, high efficiency, usage flexibility,andmore significantly, quick detection of plant diseases across a large area with low cost, reliabilityand provision of high-resolution data. Drone technology works by employing an automated procedure thatbegins with gathering images of diseased plants using various sensors and cameras.After extracting features, image processing approaches use the appropriate traditional machine learning or deeplearning algorithms. Features are extracted from images of leaves using edge detection and histogramequalization methods. Drones have many potential uses in agriculture, including reducing manuallabor and increasing productivity. Recent advances in drones and deep learning-based computer vision algorithms to identify crop diseases,providing early warning thereby allowing farmers to prevent costly crop failuresand improve food production.

Keywords: crop disease detection,unmanned aerial vehicle,deep learning, precision agriculture, image analysis, smart agriculture, digital technologies

1. Introduction

One of the biggest risks to the world's food supply is plant disease, which has an effect on ecosystems, agriculture, economies, and human health. This leads to massive yield losses, poor crop quality, and even total crop failures, which can cause supply chain disruptions, raise food prices and possibly cause shortages, and have a detrimental effect on food security and the standard of living for those involved in agriculture and related industries(Ristaino *et al.*, 2021; Chaloner *et al.*, 2021). Therefore, precise detection and reliable diagnostic method for identifying the etiological agents of disease are essential for conserving time and money by preventing or limiting crop damages (Singh *et al.*, 2018). In the past, diseases were identified using conventional techniques, which were frequently arbitrary, solely reliant on the observer, labor-intensive, and prone to errors(Qin *et al.*, 2021).Hence, a technologically driven agricultural revolution is important to permanently solve the problems mentioned earlier at a reasonable cost with little environmental impact.

The ongoing adoption of new, cutting-edge technologies, including sensors, intelligent algorithms, Internet of Things (IoT) devices, and contemporary machinery, has altered agriculture. Robots and intelligent agricultural machinery are replacing human labor in the execution of technology. There are now intelligent agricultural robots and machines that can both identify plant diseases early and track their spread over great distances(Cui *et al.*, 2018). High-resolutionimagery collectedfrom satellites, airplanes, on-the-ground machines and drones are used to identify agriculturaldiseases. Satellites and airplanes can cover vast areas in a short amount of time. However, satellites and airplanes have poor spatial and temporal image resolutions compared to drones and are highly susceptible to weather conditions that can affect overflight (Martinelli*et al.*, 2015).

Therefore, aerial remote sensing using drones (Unmanned Aerial Vehicles (UAV)or Unmanned Aerial Systems (UAS)) with intelligent visual systems is an efficient andinexpensive way for farmers to detect crop and plant diseases in agriculturalfields (Herrmann*et al.*, 2020).In recent years, unmanned aerial vehicles (UAVs), or drones, have been increasinglyused in precision agriculture giving an opportunity to bridge the existinggap between satellite remote sensing data and field monitoring (Barbedo, 2019). UAVs cover large areas quickly and efficiently and collects high-resolution images in real-time(Neupane*et al.*, 2021). They can be regularly deployed to monitor crops and fly at particular altitudes and angles, producing reliable and accurate image data. Additionally, UAVs offer a digital record of crop health over time, which can be helpful for research, analysis, and even insurance claims in the event that diseases or severe weather conditions cause crop losses (e.g. G. flood, frost, drought, etc.)

In plant disease management, they are revolutionizingtraditional methods of disease monitoring and treatment as they help in quantifying theextent of disease outbreaks and in detecting and identifying disease symptoms when humanassessment is unsuitable or unavailable (Barbedo, 2018).UAVs allow farmers to make timely decisions regarding disease management strategies because they can be deployed on a regular basis and provide frequent updates on the spatial distribution of diseases. Additionally, UAVs can reach places that are hard to reach with conventional tools, like big fields, dense vegetation, or hilly terrain, allowing for thorough disease monitoring throughout the agricultural landscape. UAV-based imagery offers vital information that can be utilized to enhance crop yields, time efficiency, and management techniques, all of which contribute to more lucrative and sustainable farming operations. (Panday, 2020).

Digital (red, blue, and green or RBG), multispectral, hyper-spectral, fluorescent, andthermal infrared-based imaging sensors coupled with effective algorithms mounted ondrones can efficiently detect, differentiate and quantify the severity of the symptoms induced by various pathogens under field conditions (Bauriegel*et al.*, 2014).With their digital, multispectral, hyperspectral, thermal, and fluorescence sensors, drones can detect plant diseases with greater precision and help detect them earlier than satellite systems can(Zhang*et al.*, 2018). Data acquired bydrones can be simultaneously sampled by their autonomous systems at various heightsin the atmosphere. Further, these data can then be rapidly elaborated to provide forecasting modelsacross fields, regions and even whole continents (Abdulridha*et al.*, 2020). Finally, information can bedelivered to farmers, allowing them to make appropriate decisions regarding timely managementof disease. Hence, precision agriculture (Smart Agriculture) may benefit greatlyfrom using drone remote sensing technology because of its cheap cost and high-flyingflexibility (Yamamoto*et al.*, 2023). There are a large number of studies on using drone platforms with different sensors for plant disease sensing. For example, drones were equipped with ahyperspectral image sensor to obtain an image of winter wheat yellow rust and realizeitseffective detection (Zhang *et al.*, 2019).

Drone-collected images must be analyzed using efficient algorithms. Because they rely on manual feature extraction techniques, which are particularly inefficient in complex environments, traditional machine learning approaches have drawbacks. A promising new substitute for improving computer vision-based systems for autonomous crop disease monitoring is deep learning algorithms. They are capable of autonomous feature extraction without human help, giving farmers information that can raise crop yields and save treatment expenses(Abbas *et al.*, 2023). A prominent area of study atpresent isthe use of computer vision methods, deep learning algorithms, and drone-basedplatforms for the early and accurate diagnosis of a wide variety of plant diseases (Tallapragada*et al.*, 2011).Even though drones are very effective, inexpensive, flexible, precise, and fast at the field level, their short flight times make them unsuitable for gathering data over wide areas, and they can't carry heavy sensors. Therefore, selecting the right drone and choosing the sensors, software, algorithms, and drone settings are essential to getting the best results. (Christiansen*et al.*, 2017).

Acknowledging the importance of drones incrop disease detection and monitoring, a review is presented discussing the methods for crop disease detection, novel approaches in crop disease detection and applications of drone for crop disease detection and monitoring using deep learning algorithms.

2. Methods

Themethods for disease detection have been categorized into direct and indirect methods (Mahlein, 2016). Direct methods, known as "Old Generation'' methods, include traditional(symptomology, microscopy, and incubation) methods, molecular diagnostic methods (e.g.,polymerase chain reaction (PCR), rapid fragment length polymorphisms (RFLP), real-timePCR, loop-mediated isothermal amplification (LAMP), recombinase polymerase amplification(RPA), and point-of-care diagnostic methods), and serological methods (Mahlein, 2016). These techniques' slowness and low capacity make them unsuitable for field use, delaying early disease outbreak detection and response. It is necessary to develop a rapid and highly accurate method for the early detection of plant diseases in order to successfully prevent and control future outbreaks. Conventional approaches typically evaluate the pathogens' outward manifestations and distinctive disease symptoms. Temporal fluctuations may have an impact on the assessment of disease symptoms, which is carried out by qualified professionals. Furthermore, conventional approaches rely entirely on personal experience, and they only become accurate and trustworthy when the standards and procedures for evaluation are appropriately adhered to. Observation of the pathogen inoculum is necessary for microscopic identification (e.g. G. fruiting bodies, spores, and mycelia). Specific dichotomous keys and identification manuals are available for microscopic methods; however, this method is too time-consuming because the pathogens must be cultivated on artificial selective media before identification can take place(Chen*et al.*, 2018).

Molecular and serological methods are commonly utilized in quarantines departmentsand research institutes for detecting and identifying phytopathogens, which can be applieddirectly in the greenhouse or the field. For example, to assess the presence of the potatoviruses*Phytophthora infestans*, *Ralstoniasalanacarum*, *Erviniaamylovora*, *Papillus mosaic virus*,and *Tomato Mosaic Virus*, a lateral flow-through version of ELISA is often used (Franceschini*et al.*, 2017). The time commitment and need for skilled operators are two disadvantages of molecular and serological methods. Despite their high sensitivity, accuracy, and efficacy, these techniques are sadly unreliable when plant pathogens are asymptomatic and when tracking cryptic pathogens that have infiltrated plants before manifesting symptoms(Torres-Sánchez*et al.*, 2013).

Indirect methods, known as "New Generation", essentially exploit biomarker-basedtechniques such as metabolite profiling from plant–pathogen interactions as well as stress-baseddetection techniques such as imaging and spectroscopy using drones (Qin *et al.*, 2021). In contrast to molecular, serological, and microbiological diagnostic techniques, a number of indirect methods have recently been introduced, especially in drones, that can estimate disease more accurately. Drones have been equipped with sensors to measure fluorescence, temperature, and reflectance. Numerous sensor types—including RGB, multispectral, hyperspectral, thermal, and fluorescence—have been developed and are emerging instruments for the identification, detection, and measurement of plant diseases(Kuska*et al.*, 2015; Bleecker*et al.*, 2000). Sensors are the essential parts of any drone because they enable it to navigate, identify, and locate possible crop diseases based on visual data. They also provide a map of the crop condition that farmers or other machines working with the drones can use to perform a variety of tasks on their own with little to no human assistance. Multispectral and hyperspectral images significantly increase the precision and application of disease diagnosis. Nevertheless, there are many obstacles to overcome when putting a hyperspectral data acquisition protocol into practice. Spectral reflectance may be influenced by a number of factors, including technical attributes (brightness, resolution, etc.). conditions of sample preparation (field or laboratory), and sample properties (size, texture, humidity, etc.). Throughout crop development and infection, more research on reflectance using crop vegetation indices is required. Alongside RGB and hyperspectral imaging, thermal sensors are especially useful for detecting plant diseases. The main driving force is the fact that leaf temperature serves as a valuable gauge of plant health.

Identification of plant diseases and other aspects of agricultural monitoring at the plot level have been made much easier by drones. It is possible to deploy a drone with numerous cameras. Machine learning algorithms are applied to the taken images in order to rapidly and precisely classify crop health. Drones are therefore becoming more popular since they can provide useful information on soil and the upper part of plants across a wide spectrum through spectral imaging. Based on camera sensors mounted on drone platforms, remote sensing systems can be divided into two basic categories: drone type and camera sensor type. One of the most important and useful forms of data that can improve the agricultural sector is drone-based aerial imagery. When choosing drone platforms and sensor types, the intended application's objective and the type of crop are usually taken into account(Bauriegel*et al.*, 2014). The detection of any change in the optical characteristics of plants is the foundation of these remote sensing techniques. In essence, they identify any alteration in plant physiology brought on by biotic or abiotic stressors, transpiration rates, plant density, morphology, and variations in solar radiation among plants. Remote sensing platforms are crucial to the implementation of precision agriculture because of their many benefits, including high spatial resolution in contrast to satellite remote sensing, high efficiency, low cost, and versatility. Through the use of site-specific fungicide applications, this technique improves the efficacy of disease management by enabling the timely and accurate detection of plant diseases and disorders at the field level(Barbedo, 2018).

The movement of plant pathogens or their products can be traced from tens to hundreds of meters above cropfields and numerous plant disease images can be captured directly and in real-time, allowing application of algorithms to monitor the occurrence of specific plant diseases (Zhang *et al.*, 2018). Sensor-equipped drones can measure morphological and spectral data, including canopy surface profiling and plant height. Even though super-resolution techniques have recently been developed that can create a high-resolution image from one or more low-resolution images, the captured images at higher altitudes typically have low spatial resolution, making it challenging to detect features of disease lesions at the level of plant organs(Barbedo, 2018).

Plant morphological information is acquired through twomainmethods i.e., LiDAR (LightDetection and Ranging) and Structure-from-Motion (SfM) photogrammetry (Christiansen*et al.*, 2018). To determine an object's position, LiDAR measures the distance between the sensor and the ground. Through the crop canopy, its beams can transmit data about the ground surface, plant density, and crop structure. As drones fly over the fields, SfM photogrammetry gathers pictures from various angles. With the use of high-resolution digital cameras, phenotypic traits of the plant population, including individual height, lodging, developmental stages, and yield, can be measured from the images. An essential metric for identifying soil characteristics, plant diseases, and plant vigor is spectral reflectance or radiance (Bendig*et al.*, 2014; Geipel*et al.*, 2014). Multispectral(usually from 3 to 6 spectral bands, from 0.4 to 1.0m) and thermal cameras (commonly in the7-14 mrange) aboard drones can detect diseases in the fields, monitor crop vigour, estimate biomass and yield, and detect symptoms of both abiotic and biotic stresses. Digital cameras candetect one or a few broad near-infrared (NIR) bands (Yang*et al.*, 2014), while hyperspectral cameras (tens tohundreds of spectral bands) measure narrow bands; despite having been reduced for droneutilization, the latter require extra space and payload capacity (Shi*et al.*, 2016; Rango*et al.*, 2006; Laliberte*et al.*, 2011)

3. Novel approach to detect crop diseases - Drones

Plants can be affected simultaneously by several plant pathogens, such as nematodes, fungi, viruses, viroids, bacteria, and phytoplasmas. There are several novel approaches which have been used that can rapidly, easily, and reliably detect plant pathogens at pre-symptomatic to early stages of plant diseases. This method includes Lateral flow microarrays (Carter *et al.*, 2007), Analysis of Volatile Organic Compounds (VOCs) as biomarkers (Baldwin*et al.*, 2006), remote sensing (RS) drone usages (De Jong*et al.*, 2004), electrochemistry (Goulart*et al.*, 2010), Phage display (Ellington *et al.*, 1990), and biophotonics(Ahmed *et al.*, 2008).

Lateral flow microarrays (LFM) are a hybridization-based nucleic acid detection method that uses an easily visualized calorimetric signal to detect plant pathogens rapidly. However, this method depends on the availability of strong and reliable host and pathogen biomarkers discovered through transcriptomics and metabolomics approaches (Degefu*et al.*, 2016).Volatile Organic Compounds (VOCs) are a class of intriguing plant metabolites that are ideal for assessing the health of plants as biomarkers. For a variety of biological and ecological reasons, plants are known to release volatile organic compounds (VOCs) into the immediate environment.

Growth, defense, survival, and communication with other nearby and/or related organisms are all attributed to these substances (Bleecker *et al.*, 2000).

Phage display, biophotonics, and electrochemistry are additional methods. Using phage display technology, ligands that attach to particular biological molecules can be found. To identify plant diseases, the ligands can be employed as immunogens or antigens. The ligands could be fragments of antibodies or peptides. Signal transduction and biorecognition are the foundations of the electrochemistry and biophotonics techniques. The foundation of optical biosensors is the way that chemical or biological processes cause light to be absorbed or emitted. On the other hand, biochemical reactions that result in electron transfer in plant sap or any other solution are the foundation of electrochemical biosensors. The fundamental idea behind these plant disease detection techniques is that a particular antibody recognizes a particular antigen to create a stable complex(Luppa*et al.*, 2001).These biophotonics-based sensors can be used to rapidly detect plant disease at theasymptomatic stage in the orchards and field conditions.

Remote sensing (RS) is based on measuring electromagneticradiations reflected/backscattered or emitted from the surface target object. The informationis obtained without any physical contact with the targeted object. Therefore,RS measurements are known as non-contact measurements (De Jong*et al.*, 2004). Since RS is a noncontacttechnique, portable tools and various platforms such as droneswhich sense the plants health and retrieve information are being used. To sense informationabout plants' health, passive sensors are being widely used. Active sensorsmeasure the reflected radiations from diseased plants, while passive sensors measurethe reflected solar radiation in the electromagnetic spectrum's visible, near-infrared,and shortwave regions. RS is used to monitor the changes in plant health, since plant leaves not only reflect radiations, transmit or absorb but release energyby fluorescence (Apostol*et al.*, 2003) or thermal emission (Cohen *et al.*, 2005).Plants contain a variety of pigments that absorb light in particular electromagnetic spectrum regions. Chlorophyll pigments in plants, for instance, absorb light in the visible spectrum between 400 and 700 nm. Consequently, the amount of radiation absorbed by plant pigments and the amount of radiation reflected by plants are inversely correlated. Variables like the leaf area index (LAI), chlorophyll content, or surface temperature alter when a plant is infected by a pathogen or experiences abiotic stress. These alterations, which differ from those of healthy and unstressed plants, are referred to as spectral signatures(Meroni*et al.*, 2010; Witten*et al.*, 2002). Some disadvantages of RS include the high cost of drones and the need for specialized professionals to collect and analyze data on plant diseases. Despite the existence of protocols, they focus on a limited number of valuable crop diseases. With recent advancements in satellite sensor spatial resolution and plant disease data acquisition costs, RS is a promising tool for combining with conventional plant disease techniques. Drones are now equipped with tiny, low-cost, high-resolution spatial and spectral sensors to monitor crop diseases at the farm level(Martinelli*et al.*, 2015; Khanal*et al.*, 2017). Drone imaging offers interestingadvantages over RS. Acquiring images using drones has become a common practicebecause installing onboard digital cameras is very easy(Al-Saddik*et al.*, 2019).

4. Drone and deep learning algorithms - tools to detect and monitor crop diseases

With the aim to overcome the constraints of conventional machine learning, deep learning models have been constructed and used for the problem of plant disease identification in drone images. In the past decade, agriculture has seen promising results from applying computer vision techniques based on deep learning (Zhang*et al.*, 2021; Su*et al.*, 2020).Crops that are diseased may lose fruit, develop twisted leaves or patches, or change color. Deep learning algorithms may therefore be the best choice for identifying these illnesses. The three primary computer vision-based tasks that can enhance crop disease identification from drone imagery and be applied to plant disease identification are image classification, object detection, and image segmentation. Image classification is the process of classifying an image by determining whether the desired disease is present throughout the entire input image. Typically, the classification task is used to detect diseases at the leaf level. On the other hand, object detection seeks to identify the class and exact location of the targeted disease within an input image by constructing a bounding box around each disease that is detected. The deep learning algorithm process for disease detection and classification using drone images is as follows:

1. Collection of data on the target plant disease by selecting a suitable flight altitude for the drone;
2. Data labeling, augmentation, cleaning, splitting, and vegetative index generation;
3. Use of models such as VGG or Res Net for image classification, Faster-R-CNN or YOLO for object detection and U-Net or Seg-Net for image segmentation; and
4. Model training/validation and model evaluation(Zhang*et al.*, 2021; Su*et al.*, 2020).

The use of deep learning algorithms applied to the analysis of images collected bydrones has recently attracted a great deal of attention due to its potential to identify plant diseases. Recent research on crop disease identification using drone photography has relied heavily on deep learning models to circumvent the shortcomings of more conventionalmethods, particularly Convolutional Neural Network (CNN) algorithms. Majority of thisresearch aims to improve the yield of staple crops such as wheat, maize, potato andtomato. For example, Zhang *et al.*, (2021),developed many computer vision models based on deep learning to identify yellow rust illness and lessen its devastating effects. Usingmultispectral data gathered through a UAV platform, they suggested a new semanticsegmentation approach derived from the U-Net model to detect wheat crop patches affectedwith yellow rust disease. There are three modules, namely, the Irregular Encoder Module(IEM), Irregular Decoder Module (IDM) and Content-aware Channel Re-weight Module(CCRM), embedded into the basic U-Net architecture as enhancements. The authors lookedat how the format of the input data affected the accuracy with which the deep learningmodel identified wheat plants infected with yellow rust. According to their findings, theproposed Ir-Unet model outperformed the results of Su *et al.*, (2020), who only obtained anF1-score of 92% when using all five bands of information obtained from the Red Edgemultispectral camera.Combined with all the raw bands and their varied measurements of Selected Vegetation Indices (SVIs), they were able to improve the accuracy to 96.97%.

Liu *et al.*, (2020), suggested a BPNN model to track Fusarium Head Blight usinghyperspectral aerial images, and found that it outperformed both SVM and RF, with anoverall accuracy of 98%. Using RGB pictures captured by UAVs, Huang *et al.*, (2019), focusedon a different wheat disease, *HelminthosporiumLeaf Blotch Disease*. It was suggested that aLeNet-based CNN model can be used to categorize HLBD according to illness stage. Comparedto a collection of methods plus the SVM model, the accuracy of the adopted CNN modelwas higher (91.43%). By merging the visible and infrared bands from drone-collectedphotos, Kerkeche*et al.*, (2020), developed a deep learning-based semantic segmentation systemto automatically diagnose mildew disease in vineyards using RGB photographs, infraredimages, and multispectral data. The SegNet model was used to determine whether a givenpixel in a picture represents a sick leaf or grapevine. Similarly, Northern Leaf Blight (NLB)has been the focus of ongoing research, as it represents a significant threat to the maizecrop. Stewart *et al.*, (2019), used a DJI Matrice 600 to capture low-altitude RGB aerial imagesand then used an instance segmentation approach (Mask R-CNN) to identify NLB diseasefrom these images. On average, the suggested method achieved an accuracy of 96% whendetecting and segmenting individual lesions.

To segment UAV-based RGB images into regions affected or unaffected by NLB disease,Wiesner-Hanks *et al.*, (2018), combined crowdsourced ResNet-based CNN and ConditionalRandom Field (CRF) techniques, using the crowdsourced CNN to generate heatmaps andthe CRF to classify each pixel as lesion or non-lesion. Using this method, they could detectNLB disease in maize crops within a millimeter, outperforming the method used byWu*et al.*, (2021), by more than 2%. To automate detection of mildew disease in vineyards, adeep learning-based semantic segmentation system was designed to process RGB photos, infrared images and multispectral data obtained from a UAV integrating the visible andinfrared bands. The SegNet model was used to determine whether a given pixel in animage represented a sick leaf or grapevine. Using visible, infrared, fusion AND, and fusionOR data, the suggested technique obtained accuracies of 85.13%, 78.72%, 82.20%, and90.23% at the leaf level and 94.41%, 89.16%, 88.14%, and 95.02% at the grapevine level,respectively (Wu *et al.*, 2021).

For enhancing the identification of unhealthy Pinus trees using RGB UAVdata, Hu *et al.*, (2022),integrated a Deep Convolutional Neural Network (DCNN), a DeepConvolutional Generative Adversarial Network (DCGAN), and an AdaBoost classifier.The suggested method outperformed classic machine learning techniques, achieving anF1-score of 86.3% and a recall of 95.7%, as opposed to recall rates of 78.3% and 65.2%,respectively, for SVM and AdaBoost classifiers. Deep learning models have certain drawbacks such as, training takes a long time, perhaps weeks, depending on the size ofthe dataset, the complexity of the model, and the computer's processing power.

When itcomes to early disease detection in plants, datasets are either insufficient or not accessiblein sufficient quantities. The first step is to learn about the area's crop, disease, and pestpatterns. Researchers typically choose to either inoculate the fungus causing the diseasein an experimental greenhouse (Zhang*et al.*, 2021;Kerkech et al., 2020). To obtain a hyperspectral picture, one must usesophisticated high-priced equipment and consult with trained professionals throughoutthe data collection process (Zhang*et al.*, 2021). In addition, when creating a new dataset, annotation is required. Since the annotation of various diseases is beyond the capabilities of ordinaryvolunteers, this task requires the assistance of agriculture experts. To minimize overfitting, researchers often resort to data augmentation techniques for tiny datasets, although thesetechniques are not always effective. After the data have been collected, they may be skewed, either because healthy plant samples are more valuable than diseased plant samples orbecause of seasonal and regional difficulties with different types of crop diseases(Zhang*et al.*, 2021; Su*et al.*, 2020).

5. Conclusion

To improve crop production and attain food security, it is crucial to monitor and identify crop diseases early on in large agricultural fields in a timely, accurate, and reliable manner. Numerous deep learning algorithms and remote sensing technologies have been developed in recent decades with promising results for the early detection of crop diseases. Deep learning-based algorithms for semantic segmentation, object detection, and image classification are efficient means of preventing various diseases that destroy agricultural crop fields and lower food productivity early on. In this paper, we discussed the latest developments in UAV technologies, such as deep learning-based computer vision algorithms and remote sensing platforms, to detect crop diseases early and stop their widespread spread. Precision agriculture can benefit from effective monitoring and detection capabilities provided by the use of drones in crop disease assessment. Timely disease detection is made possible by drones' enhanced accessibility, better coverage, and quick data collection. We can use drones to collect useful data on plant health indicators thanks to sophisticated sensors and imaging techniques. To find patterns in the disease and gauge its severity, these data can be processed using analytics and deep learning algorithms. Drone integration into plant disease assessment systems enables targeted intervention, early detection, and real-time monitoring. Drones can support precision agriculture techniques, minimize yield losses, minimize the need for chemical treatments, and promote sustainable farming methods.

6. References

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