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

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Review Article

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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. Restricting and managing the disease's spread and lowering the cost of pesticides require effective plant pathogen monitoring and detection. If not used in the early stages of pathogenesis, traditional

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techniques such as molecular and serological methods—which are frequently employed for plant disease detection—are frequently ineffective. Conversely, drone-based remote sensing methods are highly successful in quickly detecting plant diseases in their early stages. 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. Drones have many potential uses in agriculture, including reducing manual labor 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 failures and improve food production.

Keywords: Crop disease detection; unmanned aerial vehicle; deep learning; precision agriculture; image analysis.

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). "To detect agricultural diseases, high-resolution imagery gathered from satellites, aircraft, ground-based equipment, and drones is utilized. Both satellites and aircraft have the ability to quickly cover large areas. Nevertheless, drones have better spatial and temporal image resolutions than satellites and airplanes, and overflight can be affected by weather conditions" (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 and inexpensive way for farmers to detect crop and plant diseases in agricultural fields" (Herrmann et al., 2020). In recent years, unmanned aerial vehicles (UAVs), or drones, have been increasingly used in precision agriculture giving an opportunity to bridge the existing gap between satellite remote sensing data and field monitoring (Barbedo et al., 2019). "UAVs cover large areas quickly and efficiently and collects high-resolution images in real-time" (Neupane and Baysal-Gurel, 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.).

"Because they can quantify the extent of disease outbreaks and detect and identify disease symptoms when human assessment is inappropriate or unavailable, they are revolutionizing traditional methods of disease monitoring and treatment in the field of plant disease management" (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 et al., 2020).

"Digital (red, blue, and green or RBG), multispectral, hyper-spectral, fluorescent, and thermal infrared-based imaging sensors coupled with effective algorithms mounted on drones can efficiently detect, differentiate and quantify the severity of the symptoms induced by various pathogens under field conditions" (Bauriegel and Herppich, 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). "Drones' autonomous systems have the ability to sample data at different atmospheric heights at the same time. Furthermore, forecasting models across fields, regions, and even entire continents can be quickly developed using these data" (Abdulridha et al., 2020). "Lastly, farmers can receive the information they need to make informed decisions about the prompt management of disease. Drone remote sensing technology may therefore be very advantageous for precision agriculture (Smart Agriculture) due to its low cost and high flying flexibility" (Yamamoto et al., 2023). "The use of drone platforms equipped with various sensors for the detection of plant diseases has been the subject of numerous studies. In order to effectively detect winter wheat yellow rust, for instance, drones were fitted with a hyperspectral image sensor" (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). Currently, a lot of research is focused on using deep learning algorithms, computer vision techniques, and drone-based platforms to accurately and early diagnose a wide range 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 in crop 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

The methods for crop disease detection are categorized into direct and indirect methods (Mahlein, 2019). Known as "Old Generation" techniques, direct methods comprise conventional techniques such as incubation, microscopy, and symptomology, as well as molecular diagnostic techniques (e.g. serological techniques, loop-mediated isothermal amplification (LAMP), recombinase polymerase amplification (RPA), polymerase chain reaction (PCR), rapid fragment length polymorphisms (RFLP), real-time PCR, and point-of-care diagnostic techniques (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).

"In order to detect and identify phytopathogens that can be used directly in the greenhouse or the field, quarantine departments and research institutes frequently employ molecular and serological methods. For instance, a lateral flow-through version of ELISA is frequently used to evaluate the presence of the potato viruses *Phytophthora infestans, Ralstonia salanacarum, Ervinia amylovora*, *Papillus* mosaic virus, and tomato mosaic virus" (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, 2013).

The "New Generation" or indirect methods basically takes advantage of stress-based detection methods like drone spectroscopy and imaging, as well as biomarker-based methods like metabolite profiling from plant–pathogen interactions" (Qin et al., 2013). "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 and Kende, 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" (Bleecker and Kende, 2000).

"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 and Herppich, 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).

"Numerous plant disease images can be taken directly and in real-time, enabling the use of algorithms to track the occurrence of particular plant diseases. It is also possible to trace the movement of plant pathogens or their products from tens to hundreds of meters above crop fields" (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" (Panday et al., 2020).

"Plant morphological information is acquired through two main methods i.e., LiDAR (Light Detection and Ranging) and Structure-from-Motion (SfM) photogrammetry" (Christiansen et al., 2017). "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). Drones equipped with multispectral (typically from 3 to 6 spectral bands, from 0.4 to 1.0m) and thermal (typically in the 7-14 m range) cameras can monitor crop health, identify symptoms of biotic and abiotic stressors, estimate biomass and yield, and detect diseases in the fields. One or a few broad near-infrared (NIR) bands can be detected by digital cameras (Yang et al., 2014). Hyperspectral cameras, which measure narrow bands with tens to hundreds of spectral bands, require additional space and payload capacity even though they have been reduced for drone use (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 and Cary, 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 and Szostak, 1990) and biophotonics (Ahmed et al., 2008).

"Plant pathogens can be quickly identified using lateral flow microarrays (LFM), a hybridization-based nucleic acid detection technique that employs an easily observable calorimetric signal. Nevertheless, this approach relies on the presence of robust and trustworthy pathogen and host biomarkers identified by transcriptomics and metabolomics techniques" (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 and Kende, 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 the asymptomatic stage in the orchards and field conditions.

"The foundation of remote sensing (RS) is the measurement of electromagnetic radiations that are emitted, reflected, or backscattered from the target object on the surface. The targeted object is not physically touched in order to obtain the information. RS measurements are therefore referred to as non-contact measurements" (Jong, 2004). "Since RS is a noncontact method, it is used with portable instruments and a variety of platforms, including drones, that sense the health of the plants and gather data. Passive sensors are widely used to sense information about the health of plants. While passive sensors measure the reflected solar radiation in the visible, near-infrared, and shortwave portions of the electromagnetic spectrum, active sensors measure the reflected radiation from diseased plants. Since plant leaves release energy through fluorescence in addition to reflecting, transmitting, and absorbing radiation, RS is used to track changes in plant health" (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 and Frank, 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, 2015, Khanal et al., 2017). Drone imaging offers interesting advantages over RS. Acquiring images using drones has become a common practice because 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

"Deep learning models have been developed and applied to the problem of plant disease identification in drone images in an effort to get around the limitations of traditional machine learning. Deep learning-based computer vision techniques have shown encouraging results in agriculture over the last ten years" (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: Gathering information about the specific ailment affecting the target plant by determining an appropriate drone height for flight; Data preprocessing tasks like labeling, enhancement, tidying up, segmentation, and vegetative index formation; Employment of models such as VGG or Res Net for picture categorization, Faster-R-CNN or YOLO for object recognition, and U-Net or Seg-Net for picture segmentation; and Model training/validation and assessment" (Zhang et al., 2021, Su et al., 2020).

The potential for identifying plant diseases has recently drawn a lot of attention to the application of deep learning algorithms to the analysis of drone-collected images. In order to overcome the drawbacks of more traditional techniques, specifically Convolutional Neural Network (CNN) algorithms, recent research on crop disease identification using drone photography has mainly relied on deep learning models. Enhancing the yield of staple crops like wheat, maize, potatoes, and tomatoes is the main goal of this research. For example, Zhang et al., 2021, created numerous deep learning-based computer vision models to detect yellow rust disease and mitigate its destructive impacts. They proposed a novel semantic segmentation method based on the U-Net model to identify wheat crop patches afflicted with yellow rust disease using multispectral data collected via a UAV platform. Three modules—the Content-aware Channel Re-weight Module (CCRM), the Irregular Decoder Module (IDM), and the Irregular Encoder Module (IEM)—are incorporated as improvements into the fundamental U-Net architecture. The authors examined the impact of input data format on the deep learning model's ability to accurately identify wheat plants infected with yellow rust. The proposed Ir-Unet model outperformed the results of Su et al., 2020, who, using data from the Red Edge multispectral camera's five bands, only managed to achieve an F1-score of 92%. They were able to increase the accuracy to 96–97 percent by combining various measurements of Selected Vegetation Indices (SVIs) with all the raw bands.

Liu et al., 2020 found that a BPNN model outperformed both SVM and RF, with an overall accuracy of 98 percent, when used to track Fusarium Head Blight using hyperspectral aerial images. Using RGB pictures captured by UAVs, Huang et al., 2019, concentrated on Helminthosporium Leaf Blotch Disease, a distinct wheat disease. The idea was put forth that HLBD could be categorized by stage of illness using a CNN model based on LeNet. In contrast to a set of techniques plus the SVM model, the adopted CNN model's accuracy was higher (91.43%) By merging the visible and infrared bands from drone-collected photos, Kerkech et al., 2020 created a semantic segmentation system based on deep learning to automatically identify mildew disease in vineyards using multispectral data, RGB photos, and infrared images. Whether a particular pixel in an image depicts a sick leaf or a grapevine was ascertained using the SegNet model. In a similar vein, research on Northern Leaf Blight (NLB), which poses a serious risk to the maize crop, has been ongoing. Stewart et al., 2019 employed a DJI Matrice 600 to take RGB aerial photos at low altitudes, and then identified NLB disease from the photos using an instance segmentation technique (Mask R-CNN). The proposed method segmented and detected individual lesions with an average accuracy of 96%.

to divide RGB images taken by UAVs into areas that are impacted by NLB disease and those that are not, Wiesner-Hanks et al., 2021, mixed Conditional Random Field (CRF) and crowdsourced ResNet-based CNN methods, with the CRF classifying each pixel as lesion or non-lesion and the crowdsourced CNN creating heatmaps. They outperformed Wu et al., 2021 method by using this technique to detect NLB disease in maize crops within a millimeter by over 2%. RGB photos, infrared images, and multispectral data from a UAV integrating the visible and infrared bands were processed by a deep learning-based semantic segmentation system in order to automate the detection of mildew disease in vineyards. The SegNet model was used to identify if a particular pixel in an image was a grapevine or a sick leaf. With the use of visible, infrared, fusion AND, and fusion OR data, the proposed method achieved 94.41 percent, 89.16 percent, 88.14 percent, and 95.02 percent at the grapevine level and 85.13 percent, 78.72 percent, 82.20 percent, and 90.23 percent at the leaf level. (Wu et al., 2021).

For enhancing the identification of unhealthy Pinus trees using RGB UAV data, Hu et al., 2022, combined an AdaBoost classifier with a Deep Convolutional Neural Network (DCNN) and a Deep Convolutional Generative Adversarial Network (DCGAN). With an F1-score of 86.3 percent and a recall of 95.7 percent, the proposed approach outperformed traditional machine learning techniques. In contrast, the SVM and AdaBoost classifiers had recall rates of 78.3 percent and 65.2 percent, respectively. One of the disadvantages of deep learning models is that, depending on the size of the dataset, the model's complexity, and the processing power of the computer, training can take weeks.

There are either not enough datasets or they are not available in large enough quantities for early disease detection in plants. Finding out about the crop, disease, and pest patterns in the area is the first step. Usually, scientists decide to either inoculate an experimental greenhouse with the fungus that causes the disease (Zhang et al., 2021, Kerkech et al., 2020). One needs to use expensive, specialized equipment and seek advice from qualified experts at every stage of the data collection process in order to get a hyperspectral image (Zhang et al., 2021). Furthermore, annotation is necessary when generating a new dataset. The annotation of different diseases is a task that requires the help of agriculture experts because it is beyond the capabilities of regular volunteers. Although they are not always successful, researchers frequently use data augmentation techniques for small datasets in an effort to reduce overfitting. Data may be skewed after collection due to seasonal and regional challenges with various crop diseases or because healthy plant samples are more valuable than diseased plant samples (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.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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