UAV-Based Applications for Plant Disease Detection and Monitoring

Subjects: Agronomy

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Remote sensing technology is vital for precision agriculture, aiding in early issue 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. Given the growing body of scholarly research centered on UAV-based disease detection, a comprehensive review and analysis becomes imperative to provide a panoramic view of evolving methodologies in plant disease monitoring and to strategically evaluate the potential and limitations of such strategies.

unmanned aerial vehicle | plant disease | disease monitoring | image processing | machine learning

1. Introduction

Plant diseases have multifaceted and far-reaching consequences, impacting agriculture, ecosystems, economies, and human well-being. They can lead to reduced crop yields, lower crop quality, and even complete crop failures, which can disrupt the supply chain, result in increased food prices and potential food shortages, and negatively impact food security and the livelihood of stakeholders engaged in agricultural sectors [1][2]. Globally, the economic impact of crop yield loss due to plant diseases is estimated to be around US$220 billion each year [3]. Annual yield losses due to plant diseases and pests in the top food staple rice, maize, and wheat range from 24.6% to 40.9% for rice, from 19.5% to 41.1% for maize, and from 10.1% to 28.1% for wheat worldwide [4]. Plant diseases can also alter ecosystems by affecting the abundance and distribution of plant species and disrupting the food web and ecosystem dynamics [5][6]. Some plant diseases may cause health issues in humans and livestock. For example, mycotoxins produced by certain fungi can contaminate crops, leading to the ingestion of toxins through food consumption [7]. It is, therefore, essential to adopt good management practices to reduce disease risk and potential epidemic outbreaks in order to minimize their impact and ensure good crop production [8][9].

There have been multiple review articles dealing with the use of UAV for monitoring and assessing biotic plant stresses, including plant diseases (e.g., [10][11][12][13][14][15]). For example, Barbedo [10] discussed UAV imagery-based monitoring of different plant stresses caused by drought, nutrition disorders, and diseases and the detection of pests and weeds using UAVs.

In all the reviews listed above, an overview of the types of plants and diseases investigated using UAV imagery, the trends of sensor and camera types, along with the related data analysis methods has yet to be provided. Furthermore, as UAV-based plant stress detection is still a subject of ongoing research, a comprehensive overview and interpretation of current research on UAV-based applications for plant disease detection and monitoring is of particular interest. For farmers willing to adopt such approaches, such a comprehensive review can serve as a repository of knowledge, elucidating the evolving landscape of technological advancements and methodologies pertinent to disease management. It also offers a strategic perspective on the potential and limitations of these approaches. For agribusinesses, comprehensive reviews can facilitate informed decision-making regarding investment, implementation, and integration of UAV systems within farm activities. For researchers, in addition to providing potential research avenues, the findings of the review can help create and/or foster collaboration and information exchange, encouraging innovation and cross-sectoral synergy.

2. UAV-Based Applications for Plant Disease Detection and Monitoring

Plants of Interest Found in Articles

The systematic quantitative literature review indicated that current research has dealt with disease symptoms on 35 different plants (**Figure 1**). Not surprisingly, diseases in cereal crops were most often investigated in the articles, with wheat and maize being the cereal crops that were most investigated (**Figure 1**). Other plant species most often studied included potato and sugar beet (**Figure 1**). When breaking down the number of research articles by plant species investigated for the top countries of studies China, USA, Brazil, Malaysia, Germany, and Italy, the analysis showed that in China or the USA, diseases in 10 different plant species were investigated. Diseases on wheat, pine tree, and banana were the most studied in China, whereas in the USA, it was research on maize diseases that dominated (**Figure 1**a). In this latter country, the number of research articles reporting on UAV-based approaches for disease monitoring was the same for apple, citrus, cotton, tomato, and watermelon (**Figure 1**a). In Brazil, diseases on five plant species were investigated, with coffee and soybean dominating. For Malaysia, research on UAV-based monitoring of diseases affecting oil palm ranked first among the three plant species of study (rice and eucalyptus were the two other plant species). A distinct trait was found for Germany, where most studies (four out of five) concerned sugar beet (**Figure 1**a).

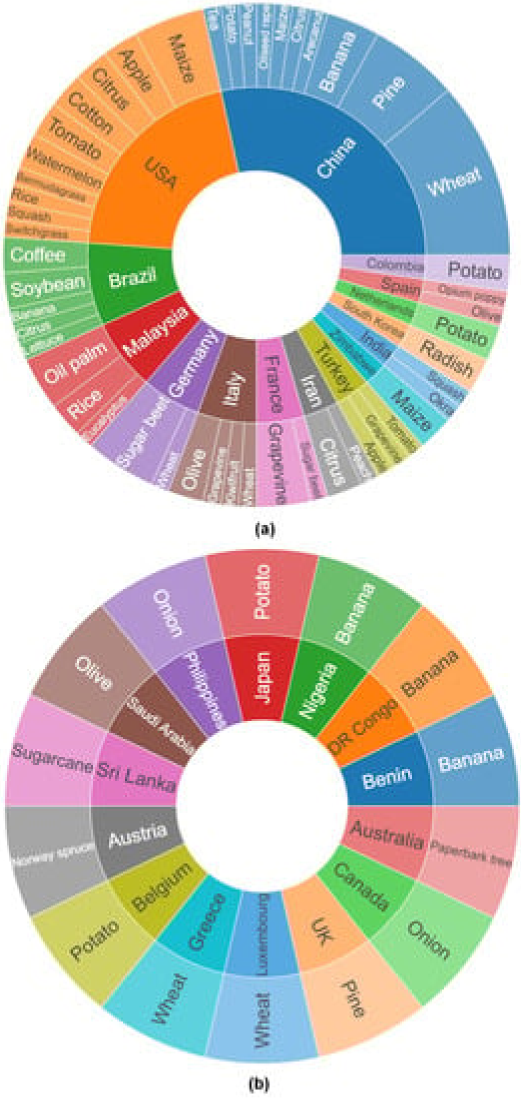

Figure 1. The proportion of plant species whose diseases were investigated in the research articles. (**a**) Countries with more than one study plant; (**b**) countries with one study plant.

Diseases and Groups of Pathogens Investigated

The list of plant diseases whose symptoms and/or severity were assessed using UAV-based imagery is presented in **Table 1**. Overall, the symptoms and/or severity of more than 80 plant diseases have been monitored using UAV-based approaches. Depending on the plant and the disease, the studies involved disease symptoms visible on either leaf, stem, or fruit, with most of the studies focusing on leaf diseases. In wheat, six main diseases were investigated, including leaf rust (caused by *Puccinia triticina*) [16], yellow rust (caused by *P. striiformis* f. sp. *tritici*) [16][17][18][19][20][21][22][23][24][25], powdery mildew (caused by *Blumeria graminim* f. sp. *tritici*) [26], tan spot (caused by *Pyrenophora tritici-repentis*) [27], Septoria leaf blotch (caused by *Zymoseptoria tritici*) [27], and Fusarium head blight (caused by a complex of *Fusarium graminearum* Schwabe and *F. culmorum*) [28][29] (**Table 1**). The first four diseases typically attack wheat leaves, whereas yellow rust can cause damage to the leaves and stems, whereas symptoms of Fusarium head blight are visible on infected spikelets. For potatoes, symptoms of five diseases have been investigated using UAV-based approaches (**Table 1**). These diseases include potato early blight (caused by

Alternaria solani Sorauer) [30], late blight (caused by *Phytophthora infestans* (Mont.) De Bary) [31][32][33][34], the Y virus (caused by the potato virus Y) [35], soft rot (caused by *Erwinia bacteria*) [30], and vascular wilt (caused by *Pseudomonas solanacearum*) [36].

Table 1. List of plant diseases whose symptoms and/or severity were investigated.

Plant	Disease	Related Reviewed Study
Apple tree	Cedar rust	[37][38]
	Scab	[37]
	Fire blight	[39]
Areca palm	Yellow leaf disease	[40]
Banana	Yellow sigatoka	[41]
	Xanthomonas wilt of banana	[42]
	Banana bunchy top virus	[42][43]
	Fusarium wilt	[44][45][46]
Bermudagrass	Spring dead spot	[47]
Citrus	Citrus canker	[48]
	Citrus huanglongbing disease	[49][50][51][52]
	Phytophthora foot rot	[52]
	Citrus gummosis disease	[53]
Coffee	Coffee leaf rust	[54][55]
Cotton	Cotton root rot	[56][57]
Eucalyptus	Various leaf diseases	[58]
Grapevine	Grapevine leaf stripe	[59][60][61][62]
	Flavescence dorée phytoplasma	[63]
	Black rot	[38][62]
	Isariopsis leaf spot	[61][62]
Kiwifruit	Kiwifruit decline	[64]
Lettuce	Soft rot	[65]

Plant	Disease	Related Reviewed Study
Maize	Northern leaf blight	[66][67][68]
	Southern leaf blight	[69]
	Maize streak virus disease	[70][71]
	Tar spot	[72]
Norway spruce	Needle bladder rust	[73]
Oil palm	Basal stem rot	[74][75][76]
Oilseed rape	Sclerotinia	[77]
Okra	Cercospora leaf spot	[78]
Olive tree	Verticillium wilt	[79]
	Xylella fastidiosa	[80][81]
	Peacock spot	[82]
Onion	Anthracnose-twister	[83]
	Stemphylium leaf blight	[84]
Opium poppy	Downy mildew	[85]
Paperbark tree	Myrtle rust	[86]
Peach tree	Fire blight	[87]
Peanut	Bacterial wilt	[88]
Pine tree	Pine wilt disease	[89][90][91][92][93]
	Red band needle blight	[94]
Potato	Potato late blight	[31][32][33][34]
	Potato early blight	[30]
	Potato Y virus	[35]
	Vascular wilt	[36]
	Soft rot	[35]
Radish	Fusarium wilt	[95][96]

Plant	Disease	Related Reviewed Study
Rice	Sheath blight	[97]
	Bacterial leaf blight	[98]
	Bacterial panicle blight	[98]
Soybean	Target spot	[99][100]
	Powdery mildew	[99][100]
Squash	Powdery mildew	[101]
Sugar beet	Cercospora leaf spot	[102][103][104][105][106][107]
	Anthracnose	[103][104]
	Alternaria leaf spot	[103][104]
	Beet cyst nematode	[108]
Sugarcane	White leaf phytoplasma	[109]
Switchgrass	Rust disease	[110]
Tea	Anthracnose	[111]
Tomato	Bacterial spot	[112][113][114]
	Early blight	[112]
	Late blight	[112]
	Septoria leaf spot	[112]
	Tomato mosaic virus	[112]
	Leaf mold	[112]
	Target leaf spot	[112][113][114]
	Tomato yellow leaf curl virus	[112][114]
Watermelon	Gummy stem blight	[115]
	Anthracnose	[115]
	Fusarium wilt	[115]
	Phytophthora fruit rot	[115]

Plant	Disease	Related Reviewed Study
	Alternaria leaf spot	[115]
	Cucurbit leaf crumple	[115]
	Downy mildew	[116]
Wheat	Yellow rust	[16][17][18][19][20][21][22][23][24][25]
	Leaf rust	[16]
	Septoria leaf spot	[27]
	Powdery mildew	[26]
	Tan spot	[27]
	Fusarium head blight	[28][29]

Sensors Used for the Detection and Monitoring of Plant Diseases

Various types of sensors mounted on UAVs have been used to collect high spatial and spectral resolution data for plant disease detection and monitoring (**Figure 2**). The most used sensors were multispectral, RGB, hyperspectral, and digital cameras. Wheat was the plant whose diseases were investigated using different sensor types (individually or in combination) (**Figure 2**). Thus, symptoms of yellow rust on wheat leaves have been investigated using data from multispectral sensors [17][19][25], RGB cameras [16][22][24], hyperspectral sensors [18][20][21], and RGB + multispectral sensors [23]. Symptoms of Fusarium head blight were identified using data captured by hyperspectral sensors [29] and thermal infrared + RGB sensors [28], whereas symptoms of Septoria leaf blotch and tan spot were detected using RGB + multispectral sensors [27] (**Figure 2**). Images acquired using multispectral and RGB sensors were more often used to derive vegetation indices (VIs), which allowed for the detection of changes in vegetation health indicative of disease (e.g., discoloration, wilting, spots). Owing to their capability to capture images in different narrow spectral bands, hyperspectral sensors were used to detect more subtle changes in vegetation health that may not be visible with other sensors. Such data were used to create spectral signatures characteristic of a given disease.

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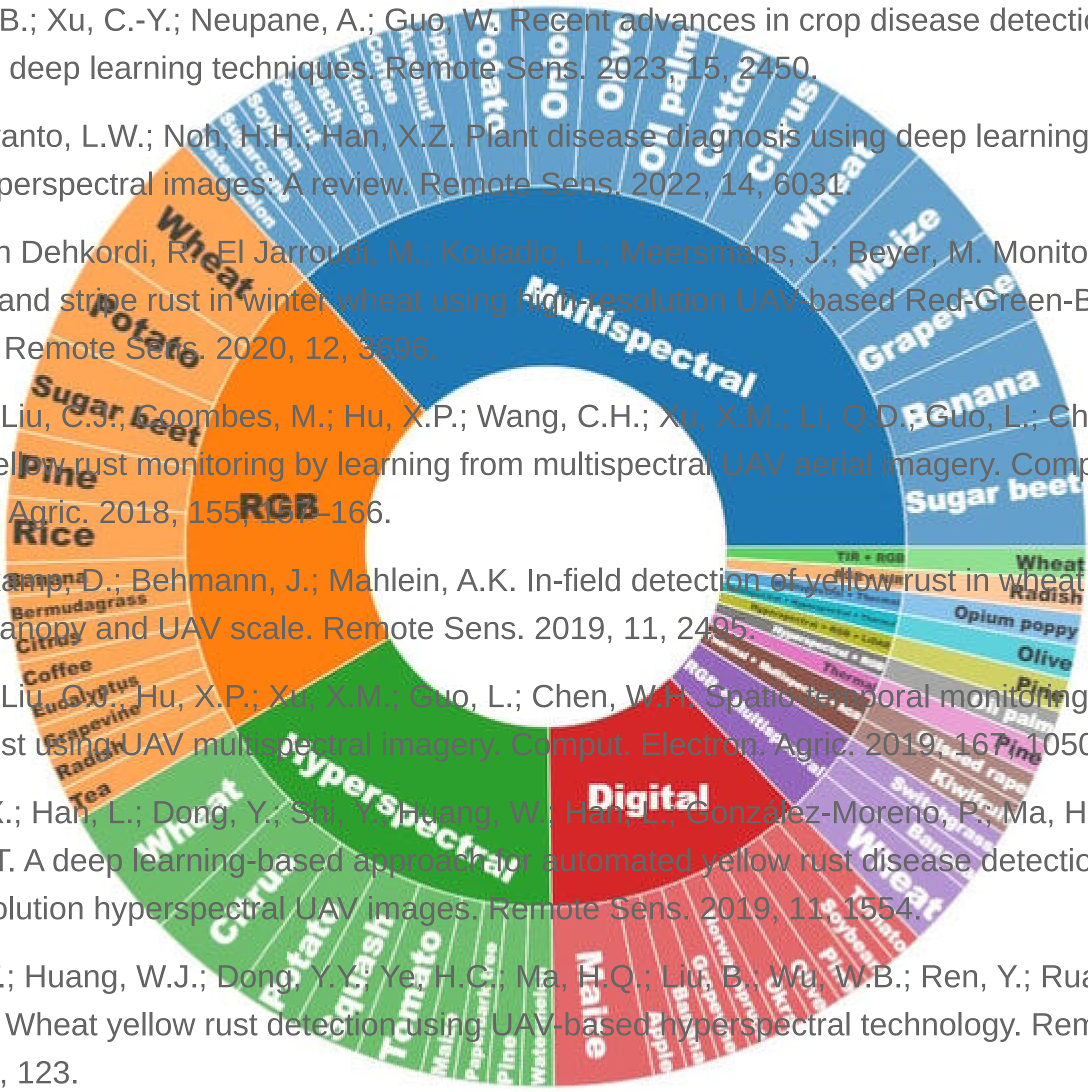

Figure 2. The distribution of sensor types and plants whose diseases were investigated. The segments in each ring are proportionate to the number of related research articles reviewed in the systematic quantitative literature review. RGB, NIR, and LiDAR stand for red-green-blue, near-infrared, and light detection and ranging, respectively.

Methods Used for Image Processing and Data Analysis

By capturing high spatial and spectral resolution images, sensors and cameras mounted on UAVs provide valuable data that can be leveraged to analyze and detect plant disease symptoms. Results of the SQLR showed that various techniques, including visual analysis, computer vision, and ML-based analysis, have been used to process and analyze UAV-based imagery data for plant disease detection. Among these techniques, computer vision was the most used technique. In computer vision, the algorithms used for image classification and object recognition were machine learning (ML) algorithms that enabled the extraction of meaningful information from the images by automatically identifying and classifying visual patterns associated with disease symptoms. Generally, after image pre-processing, feature extraction techniques were employed to identify the relevant visual characteristics associated with disease symptoms. Then, the extracted features were classified into different categories (e.g., healthy, diseased, etc.). Next, ML algorithms were trained on labeled datasets where regions of interest have been annotated manually as healthy or diseased by human experts. Through the training process, the algorithms learn to recognize and distinguish between healthy and diseased plant organs. Depending on the extracted features, the classification analysis was either color, texture, shape, or spectral-based. Color-based analysis examines variations in coloration of the plant organ of interest (i.e., leaf) that may indicate the presence of disease.

3. Promising Means for Improving Plant Disease Management

Eleven years on from the work of Mahlein et al. [117], which critically reviewed the use of non-invasive sensors for the detection, identification, and quantification of plant diseases, there has been noticeable progress in the field of plant disease detection and monitoring using remote sensing-derived information. In recent years, UAV-based imagery has become the new norm for plot and field-level studies. UAV-based approaches for plant disease detection and identification have several advantages over traditional methods as sensors mounted on UAVs provide high-resolution and spectral images that can be used to identify small-scale changes in crop health. UAVs also provide a fast and effective solution for capturing images over larger farmland areas, which can be challenging when using ground-based methods, though the use of UAVs in larger areas can be limited by the payload capacity and battery resources [10]. Other advantages of UAV-based approaches for plant disease monitoring include the reduced reliance on manual inspection and scouting, thereby saving time and resources. While the initial investments in UAV technology might be significant, they can lead to long-term cost savings. As such, UAVs offer a promising approach for improved plant disease management.

While UAV-based approaches for plant disease monitoring offer several advantages, it is important to acknowledge their limitations [10][11][12]. Challenges related to background interference, weather conditions, sensor constraints, resource limitations (e.g., peripherals, sensors) and disparities between ML-based model training and validation stages, variations in disease symptoms over time and in space have been addressed in [10][11][12]. These challenges will not be discussed extensively here. Adverse weather, such as strong winds, rain, or low light conditions during UAV flights, can hinder image acquisition and potentially impact the accuracy of disease detection. Another limitation is related to the image annotation consistency. Because the accuracy of disease detection relies on the expertise and experience of the human annotators who label the training datasets, variations in annotations among different operators can introduce inconsistencies and affect the generalization capabilities of the classification models. To overcome limitations associated with weather conditions, careful consideration and planning are required to avoid unfavorable weather conditions as much as possible and ensure a representative sampling of the field. Another potential solution would be to develop autonomous UAV systems that can operate in complex environments (e.g., under reduced light conditions) and adapt to changing conditions to improve flight operations. To address annotation consistency, regular training and calibration sessions are possible solutions to help overcome such a challenge.

4. The Way Forward

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Research on using UAV-based approaches to detect and monitor plant stress caused by diseases is still underway, and there are ample opportunities to develop innovative solutions and improve the effectiveness and efficiency of these approaches. Current image analysis techniques for plant disease detection can be time-consuming, labor-intensive, and computationally demanding, particularly when it comes to using sophisticated CNN-based approaches, that require graphical processing units to train models. Balancing the trade-offs between resource requirements, model complexity, performance, and interpretability, and transfer learning opportunities has guided the choice of the most suitable ML technique for analyzing UAV imagery data. Future research can focus on improving the efficiency of ML-based approaches through the development of more advanced ML algorithms that can analyze images quickly and accurately. This will allow for the development of methods for real-time data analysis and decision-making tools that can be integrated with UAV systems. In this line, future research can investigate the use of reinforcement learning algorithms for plant disease management, which will involve training the models to learn from past actions and make decisions that optimize long-term plant health and minimize disease outbreaks.

There have been encouraging outcomes in integrating multiple sensors to provide more detailed and accurate data for plant disease detection, as highlighted by the number of related research articles, though this remains limited to a few numbers of plant species and diseases (**Table 1**). Future research can explore extending such approaches to economically important plant diseases of major food crops, such as rice, wheat, maize, cassava, plantains, potatoes, sorghum, soybeans, sweet potatoes, and yams, around the world. Research can also focus on integrating UAV data from multiple sensors or with satellite imagery (i.e., data fusion) for plant disease detection, as it has been explored for crop yield forecasting [118] and crop monitoring [119]. Such UAV and satellite data fusion will allow for a better understanding of crop health patterns and trends over large areas [120].

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