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A Review of Hyperspectral Imaging Analysis Techniques for Onset Crop Disease Detection, Identification and Classification

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Abstract

Recently, intensive research has been conducted to develop innovative methods for diagnosing plant diseases based on hyperspectral technologies. Hyperspectral analysis is a new subject that combines optical spectroscopy and image analysis methods, which makes it possible to simultaneously evaluate both physiological and morphological parameters. Among the physiological and morphological parameters are classifying healthy and diseased plants, assessing the severity of the disease, differentiating the types of pathogens, and identifying the symptoms of biotic stresses at early stages, including during the incubation period, when the symptoms are not visible to the human eye. Plant diseases cause significant economic losses in agriculture around the world as the symptoms of diseases usually appear when the plants are infected severely. Early detection, quantification, and identification of plant diseases are crucial for the targeted application of plant protection measures in crop production. Hence, this can be done by possible applications of hyperspectral sensors and platforms on different scales for disease diagnosis. Further, the main areas of application of hyperspectral sensors in the diagnosis of plant diseases are considered, such as detection, differentiation, and identification of diseases, estimation of disease severity, and phenotyping of disease resistance of genotypes. This review provides a deeper understanding, of basic principles and implementation of hyperspectral sensors that can measure pathogen-induced changes in plant physiology. Hence, it brings together critically assessed reports and evaluations of researchers who have adopted the use of this application. This review concluded with an overview that hyperspectral sensors, as a non-invasive system of measurement can be adopted in early detection, identification, and possible solutions to farmers as it would empower prior intervention to help moderate against decrease in yield and/or total crop loss.

Key Words: hyperspectral technologies, hyperspectral image analysis, plant disease, early diagnosis of stress, plant protection

Introduction

Food security has become a global issue affecting the agricultural revenue of many countries while the rising costs of overcoming challenges have driven up the price of staple foods (Misman et al. 2022). Agriculture provides endless wealth and nutrition to tropical people such as cash crops (such as cocoa, coconut, and rubber), fruit trees (such as mango, orange, papaya, and garcinia cola), and root crops (such as potato, yam, and cassava). These crops have re-

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cently gained popularity in tropical regions and are now one of the primary sources of agricultural income, though were initially planted for domestic consumption. However, regardless of this contribution to human livelihood, these plant crops are faced with a lot of constraints that threaten it future existence (Misman et al. 2022). One of these constraints includes the high rates of destructive plant disease pathogens. Pests and diseases are important biotic factors that cause a loss of over 20% to 40% of agricultural productivity, affecting the global economy (Misman et al. 2022). Crop plant diseases are a naturally occurring phenomenon limiting crop plant growth, development, and reproduction (Agrios 2005). Crop plant diseases are typically caused by microbes including viral, bacterial, and fungal-like organisms that hinder the normal growth of plants and cause variations in their vital functions (Shurtleff et al. 2021). The diseases and pathogens causing them are a direct threat to the global economy and food security (Sibiya and Sumbwanyambe 2019). A recent assessment documents how these disease pathogens collectively affect all of the components of crop production from overall production to physical availability, distribution, economic access, stability of production, quality, and nutritive value (Savary et al. 2012). According to Altieri (2018) disease management and control procedures must be carried out effectively to reduce output losses and ensure agricultural sustainability, underlining the importance of continual crop monitoring paired with prompt and accurate disease detection. Therefore, to solve these relevant problems, the timely monitoring of crop diseases and pests is necessary. Early detection, quantification, and identification of these plant diseases are crucial for the targeted application of plant protection measures. This must be combined with the preservation of natural ecosystems through the use of environmentally friendly farming methods. Food must keep a high nutritious value while still being secure worldwide (Carvalho 2006). This can be accomplished by using new scientific methodologies for disease diagnosis and crop management, as well as applying these new technologies to large-scale ecosystem monitoring. Thus, hyperspectral imaging can be used to solve a wider class of problems for the accurate and timely determination of the physiological status of crops. Hyperspectral imaging is a technology useful to detect damages in crops over a large area in less time (Avinash et al. 2022). Due to biotic stress, plants showed various symptoms like wilting, curling or stunned growth, chlorosis, necrosis, etc. (Prabhakar et al. 2011). Biotic stress impacts in crop plants can be identified, detected, and estimated through hyperspectral remote sensing and their spectral signatures (Fitzgerald et al. 2004). Therefore, this study aimed to provide an overview of the integrated views presented on the biotic stress factors, the phases of stress, and respective crop plant responses, hyperspectral imaging technologies, and the different approaches for detecting crop stress in agriculture and lastly representative results of a systematic literature analysis are highlighted by identifying the different approaches that were adopted in stress detection and monitoring. Nonetheless, to enhance agricultural productivity the detection of diseases in plants at an early stage is quite significant.

Crop Plant Disease Pathogens

Effects of disease pathogens

For years, the damage caused by these stress factors has been controlled by the use of chemicals. But nowadays, interest in the use of chemicals against biotic stress is decreasing as a result of its various limitations such as there is need for more than one chemical application, an investment that is not affordable by most small-scale farmers (Brading et al. 2002). Besides, the application of chemicals may have adverse effects on human health and the environment, including beneficial organisms (Miedaner et al. 2013).

Among several diseases that affect plants are those that have the potential to cause devastating economic, social, and ecological losses for instance *Podosphaera leucotricha, Rastrococcus invadens, Xylella fastidiosa, Ralstonia solanacearum, Erwinia carotovora* etc.

Crop reaction to disease incidence

Crop plants' reactions to and manifestations of the incidence of pests and diseases are heterogeneous in the field Lowe et al. (2017), usually starting in a small region of foliage and spreading out to the whole field. The ability to spot the disease at an early stage would provide an opportunity for early intervention to prevent and control the spread of infection before the whole crop is infected or damaged.

Concerning the above, it can be seen that there is a need to put in place appropriate measures towards plant protection in crop production. There are current challenges in agriculture faced by plant breeders in plant stress, disease identification, and detection because visible indicators depending on the crop size and type are manually observed. Hence this manual detection makes monitoring of plant health both time-consuming and demanding. This manual detection is not reliable as disease-infecting plants are usually manifested in the middle up to the later stage which usually starts from a small region on the foliage. It is of paramount importance that the infection should be detected at an early stage as this will provide the avenue for early intervention in controlling and preventing the spread of infection before the whole crop stands are completely infected or damaged. Such precision approaches would result in the reduction of pesticide and herbicide usage, with subsequent beneficial impacts on the environment, ecosystem services, grower finances, and the end consumer. In other words, the plant production and protection sector should be of keen interest in replacing this manual technique with a more sophisticated, automated, and objective approach (Table 1).

In plant production, disease severity, and incidence usually hurt crop yield quantity and quality. It is important within this context, that a timely and accurate assessment of crop disease occurrence and spread should be enabled to target plant protection activities. Conventionally, the detection of crop plant diseases monitoring is usually carried out by visual monitoring alongside molecular, microscopic, microbiological, and serological methods (Bock et al. 2010; Martinelli et al. 2015). However, there is the availability of a non-invasive optical sensor that enables the assessment of the reflectance of plants in different areas of the electromagnetic spectrum. This non-invasive sensor supports plant disease identification and detection (Mutka and Bart 2015; Mahlein 2016) thereby facilitating plant phenotyping for resistance breeding development.

Hyperspectral Sensor Imaging

There are several non-invasive optical sensors available, including RGB, hyperspectral, thermography, chlorophyll fluorescence, and multispectral sensors; however, hyperspectral sensors are the most in demand. A sophisticated imaging method that gathers in-depth spectral data about an object or scene is called hyperspectral imaging (HSI). The technology captures reflected or emitted light in multiple contiguous spectral bands, usually from the visible to the near-infrared regions of the electromagnetic spectrum, using a hyperspectral sensor or camera (Rastogi et al. 2022). A sophisticated imaging technique used to obtain and analyze the spectral details of a scene or object is called hyperspectral imaging (HSI). Materials and objects that are difficult to distinguish with the unaided eye or conventional imaging systems can now be identified and described thanks to HSI technology (Jaiswal et al. 2023). The improved spectral data enables more effective object detection,

Table 1. Stress identification of some diseases pathogens infections

S/N	Plant/ pathogen name	Alternative names	Host plants	Process of infection	References
1	*Cercospora fragariae*	Cercosporal leaf spot	Sugar beets, beetroot	Spore germination and then causes cell necrosis and leaf spots	Tan et al. 2023
2	*Podosphaera leucotricha*	Apple powdery mildew	Apples, cucumber, radish	Infected bud breaks in springs primary infections begin when the fungus which infected the plant in the previous year breaks its dormancy and resumes its growth	David et al. 2021
3	*Rastrococcus invadens*	Fruit tree mealybug	Mango, citrus, shea butter	Females and nymphs feed on plant leaves and fruits and produce honeydew that causes sooty mold, leading to yield reduction	Azrag et al. 2023
4	*Puccinia striiformis*	Yellow rust	Wheat barley	Formation of masses of spores between the grain and the glumes	Chen et al. 2014
5	*Xanthomonas axonopodis*	Canker lesions	Citrus	The bacteria that cause citrus canker enter leaves through stomata, or wounds caused by weather damage or insects	Shahbaz et al. 2022

and classification, and enhanced target identification. However, it has several advantages and a significant potential in plant disease monitoring and host-pathogen interactions (Thomas et al. 2017). Other optical sensors are not as effective as hyperspectral sensors in that they can only detect plant stress without specification of the causal agent but the hyperspectral sensor can go beyond by identifying the pathogen/disease responsible for the infection (Bravo et al. 2003; Mahlein et al. 2010; Hillnhütter et al. 2012).

Basic principle of hyperspectral sensors

Hyperspectral imaging (HSI) is a spectroscopic technique that can combine conventional spectroscopy with digital imaging. It collects images as a function of length and provides an individualized reflectance spectrum for each pixel in an image. Furthermore, hyperspectral sensors have various applications on different scales ranging from laboratory plant tissue investigation, and screening in greenhouses up to open field application in the detection and identification of disease infection (Thomas et al. 2017). The most important advantage of the application of hyperspectral sensor imaging is that it is non-invasive and non-destructive hence this enables both the breeder and researchers to conduct their experiment on a series of plant sample measurements Berdugo et al. (2014) and thus reduction in samples required. Moreover, HSI finds versatile applications across various fields, including agriculture, environmental monitoring, food quality control, geology, and more.

Benefits of hyperspectral sensors for plant pathology, phenotyping and precision farming

However, in laboratories, plant samples are analyzed through metabolic processes with photometrical applications after specific extraction and isolation procedures (Carocho and Ferreira 2013). This technique is destructive in that it prevents further investigation of plant samples making time series measurement impossible. Hyperspectral imaging sensors in a similar way also utilize this principle i.e. the absorption features and optical properties of biochemical compounds in assessing the different parameters in plants but in a non-invasive way (Berdugo et al. 2013, 2014). Hyperspectral reflectance interpretation can be best achieved during plant–pathogen interactions because at this point this interaction influences the plant's physiology, water content, structure, etc. state of the plants. Take for instance; Cercospora leaf spot, rust, and powdery mildew on sugar beet through a combination of different spectral vegetation indices identified by Mahlein et al. (2010) and infections with an accuracy of over 90% was detected.

In a nutshell, this indicates that hyperspectral imaging can detect metabolic changes in plants during a pathogenic attack (Arens et al. 2016). Therefore, the identification and detection of disease outbreaks are possible through hyperspectral imaging on different scales (Thomas et al. 2017) (Fig. 1).

As a result of this, timely detection of specific diseases and an early application of disease-specific countermeasures in precision farming are enabled. Apart from the usage of hyperspectral sensors in the identification and detection of

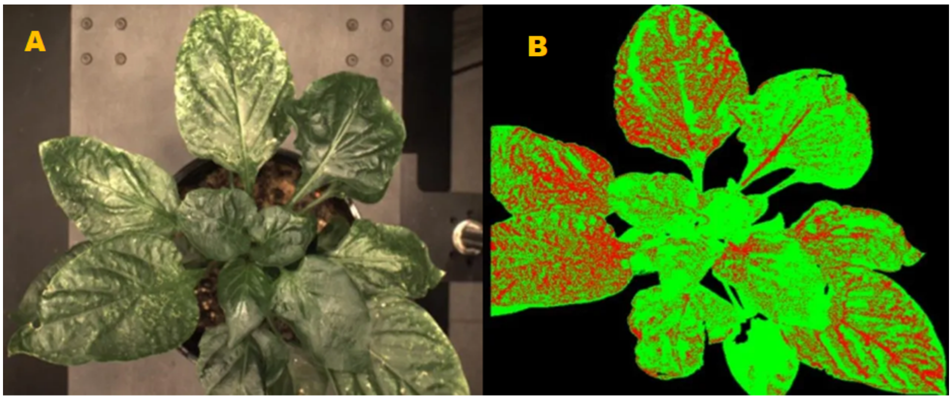

Fig. 1. Illustration of plant disease detection and identification by hyperspectral imaging (A). The image is of a normal color camera (B). Hyperspectral Imaging colored green is classified as normal and those colored red are classified as diseased using a hyperspectral camera (Moghadam et al. 2017).

plant diseases, it is also used in assessing biotic, abiotic, and soil properties. Vigneau et al. (2011), thereby allowing farmers to adjust nutrients and water distribution during growing seasons. Gerhards et al. (2019) made use of hyperspectral remote sensing imaging techniques to detect drought and were able to summarize the importance and response of plants to water stress. As a result, the response of plants to water stress is complex and numerous, then their physiological interactions affect the electromagnetic signal in different spectral domains. It can also be used in gathering other information for example the differences in soil quality to create soil maps (Hbirkou et al. 2012). These maps can be used to plan an ideal nutrient composition based on the determined soil parameters in different parts of the field (Thomas et al. 2017).

De Silva et al. (2023) results highlight the potential of hyperspectral imaging for monitoring crop nutrient levels, which could assist growers in maximizing orchard productivity through timely fertilizer management. The rapid assessment of crop nutrition may also help to minimize fertilizer costs and reduce nutrient runoff to the downstream environment. For instance, Ding and Ma (2020) used a hyperspectral imaging system to obtain hyperspectral images of *Aronia melanocarpa* leaves under a saline-alkali stress state to improve yield and quality.

Identification of relevant literature reviewed for plant disease detection

Several authors have investigated using hyperspectral image analysis in the identification and detection of crop plant disease pathogens. In the present study, we aim to provide a comparative analysis of the recent research papers that have utilized hyperspectral image analysis highlighting their contributions to the field and identifying areas for future research. For instance; Bravo et al. (2003) made use of this spectral image to detect early yellow rust in wheat in an open field while Nansen et al. (2009) were able to detect insect-induced stress in wheat plants. Also, Polder et al. (2014) combined different optical sensors for the detection of tulip-breaking viruses. Furthermore, Qin et al. (2009) and Balasundaram et al. (2009) were able to make use of a hyperspectral imaging approach in detecting canker lesions on citrus fruits. The use of non-invasive sensors in observing plants during their growth period provides new insight into the interaction of plants with biotic stresses.

Before hyperspectral imaging is said to be utilized, the decision has to be made first on which measurement scale it should be based. Usually, the scale of measurements is plant leaf, tissue single plant, and/or canopy are in the focus. These measurement scales are processed for metabolic changes that occur during the plant–pathogen interaction (tissue and leaf scale), disease detection (leaf, single plant, and canopy scale), disease distribution and distribution patterns (canopy scale) meanwhile, in the laboratory, leaf and tissue scale experiment are performed while leaf, single plant and canopy measurement scale are required for more applications that are practical. The tissue scale allows fungi spores observation during early interaction and infection. Examination of individual plant–pathogen interaction on a tissue scale estimation utilizing hyperspectral imaging empowers the characterization of subcellular forms (Simko et al. 2017). This sub-cell procedure can be utilized to set up later on a connection between phenotyping and physiological investigations of plant diseases (Groβkinsky et al. 2015; Mahlein 2016) a basic reason for plant resistance breeding.

This arrangement permits small-scale image investigation and has been utilized for plant disease detection and explicit resistance characterization (Kuska et al. 2015; Leucker et al. 2016). This can be confirmed by a study conducted by Kuska et al. (2015) which reveals that microscopic hyperspectral studies show an early change in powdery mildew disease before side effects become noticeable for the natural eye.

Leucker et al. (2016) performed point-by-point examinations of the pathogenesis of Cercospora leaf spot on sugar beet through hyperspectral microscopy. The consequences of these estimations could be utilized to assess the sporulation density of the parasite on various host genotypes. These discoveries show tissue-scale estimations as an important instrument to watch and gauge the spread of pathogenic contagious species over different ages relying upon their communication with the host plants.

Leaf scale measurements such as leaves, stems ears, and roots require high-resolution assessment to observe specific changes in spectral characteristics of plants during pathogenesis (Thomas et al. 2017). The experiments conducted in the lab are usually done under stable environmental conditions without any risk of change in environmental factors such as the direction of light intensity that might influence the results. On leaf scale estimation, reflection and transmission estimations on leaf scale are conceivable in estimating various leaves with laboratory-based hyperspectral sensor arrangement (Bergsträsser et al. 2015; Kim et al. 2015; Thomas et al. 2016). This arrangement is sufficiently adequate to identify changes in the plant's digestion and structure before they are obvious to the natural eye. The discovery of Bauriegel et al. (2011) proposes that hyperspectral imaging can likewise be utilized to recognize infections on plant parts other than leaves. In their examination, they discovered that wheat ears, which were inoculated with Fusarium head scourge and were explored through hyperspectral imaging and fluorescence estimation in a time series test were able to determine infected ears within 7 days after inoculation through hyperspectral imaging.

Benhural et al. (2013) adopted hyperspectral imaging to measure the various colors of *Parinari curatellifolia* fruits from a different location. The color of the fruits from different sites ranged from green to yellowish to brown with shades of grey. Hence the quantitative measurement of the color of the fruit was successfully achieved by using the hyperspectral package.

Wahabzada et al. (2015) utilized advanced information investigation strategies on hyperspectral time-series pictures of datasets of barley plants, which were inoculated with powdery mildew, brown rust, and net blotch. After the inoculation, it was conceivable to separate the features of the three pathogens and to make the course of events based on maps for a representation of the three pathogens during the pathogenesis on barley plants. These discoveries could be associated with pathogen-explicit biological procedures during disease infection. Along these lines, it is conceivable to get a diagram of the specific infection changes in the plant's metabolism at a given time during the pathogenesis.

However, a large-scale application is required in the field, and greenhouse investigation combines controlled hyperspectral experiments. Using current hyperspectral sensors high-throughput in nurseries and fields has been demonstrated to be a promising instrument for considering plant–pathogen associations (Thomas et al. 2017). The spatial resolution is adequate to identify biotic and abiotic stresses on single plants at an early stage (Vigneau et al. 2011). Consequently, nursery and field-based methodologies permit a quick evaluation of different plants on a leaf or canopy scale, which cannot be coordinated in research laboratories. Moshou et al. (2005) applied a hyperspectral sensor to distinguish yellow rust infection in winter wheat under field conditions with surrounding light and it was conceivable to recognize areas with high disease pressure in the field. In utilizing this sensor, it was possible to distinguish and evaluate both pathogens by checking the connection between assessed disease severity and pathogen pervasion. In addition, hyperspectral imaging can recognize different variables influencing the plant's well-being.

For instance, Rumpf et al. (2010) in these studies were able to detect and differentiate plant diseases at an early stage before they were visible to the human eye. Furthermore, Mahlein et al. (2012) were also able to detect and identify Cercospora leaf spot, sugar beet rust, and powdery mildew on sugar beet. These scientists were able to achieve this through spatial resolution and throughput. In a nutshell, it is very important for hyperspectral investigations, to select a sufficient spatial resolution.

Limitations

However, HSI has particular challenges as a result of the demands on data processing and storage. The significant amount of data produced by HSI presents challenges for processing and storage, which makes using it in certain situations a laborious undertaking (Ghamisi et al. 2017). Moreover, HSI equipment's relatively high cost may restrict its accessibility and limit its availability to particular users. The quality and dependability of the recorded data can also be impacted by external variables that are sensitive to HSI, such as atmospheric conditions, changes in lighting, and the distance between the imaging system and the object (Geladi et al. 2004). These elements may cause HSI data distortions or inaccuracies, which may affect how reliable the outcomes appear. However, various technologies and approaches can be used to address these issues. Furthermore, with more study and development, this method has the potential to significantly improve the interpretation and analysis of hyperspectral data (Jaiswal et al. 2023).

Conclusion

In the management of crop plants, disease detection is a major pursuit both in horticulture and agriculture. Specifically, distinguishing an early stage of disease and stress would be valuable to farmers as it would empower prior intervention to help moderate against decrease in yield and/or total crop loss. There has been an outstanding increment in scientific writings in recent times concentrating on the detection of plant stress by utilizing hyperspectral imaging analysis. Hyperspectral imaging is a non-invasive procedure where the plants are checked to gather high-resolution information. There are different strategies accessible to investigate the information to recognize biotic and abiotic stress in plants, instances of which have been discussed above, with an attention on the classification of diseased and healthy plants, early detection, and the gravity of the stress symptoms.

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