SATSA Mukhapatra - Annual Technical Issue **30** : 2026 ISSN 0971-975X **Invited Paper**

Hyperspectral Imaging for Early Detection of Plant Diseases : Principles, Spectral Signatures, and Applications in Precision Agriculture

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(Received : December 29, 2025; Revised : January 20, 2026; Accepted : January 30, 2026)

ABSTRACT

Minimizing crop losses under constraints of land, water, and environmental sustainability is the prime need to meet the anticipated 50–60% rise in the world's food demand by 2050. Plant diseases continue to be a significant barrier to production, frequently resulting in lower yields, lower quality, and higher chemical inputs. Laboratory diagnostics and visual scouting based on symptomatology are the mainstays of conventional disease detection techniques. However, these methods are limited by subjectivity, destructiveness, unable to identify infections in their latent or early phases and time consuming. Hyperspectral imaging (HSI) has emerged as a powerful, non-destructive technology capable of bridging the gap between physiological disruption and the onset of visible symptoms. By capturing hundreds of continuous narrow spectral bands across the visible, near-infrared, and shortwave infrared regions, HSI enable pixel-level characterization of plant physiological status. This review highlights the recent advancement in HSI based sensing for early detection of plant diseases, with emphasis on detection mechanisms, key spectral regions and vegetation indices, and applications across viral, fungal, bacterial and complex etiological patho-systems. We further discuss about the development of deep-learning frameworks, machine learning integration, and remote sensing platforms like UAVs. Lastly, the main obstacles and potential paths for converting HSI from experimental research to functional disease surveillance systems are described.

Keywords : Hyperspectral imaging, Early disease detection, Plant pathology, Remote sensing, Precision agriculture, Machine learning

Introduction

Global food security assurance under accelerating population growth, dietary transitions, and climate variability represents one of the most pressing challenges of the 21st century. Global food demand has been projected to rise by 50–60% between 2019 and 2050, with the most severe pressure anticipated in developing country like India, where the

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demographic expansion, urbanization, and rising incomes are reshaping consumption patterns (Falcon *et al.*, 2021). This incremental demand for food, in the perspective of shrinking arable land and freshwater resources, is necessitating the substantial gains in productivity per unit input. Plant diseases constitute a major threat to achieving these goals. Globally, pathogens and pests account for significant yield losses in major food crops, reduce market quality, and increase reliance on chemical control measures, thereby exacerbating environmental risks and resistance development (Savary *et al.*, 2019). Climate change, increasing monoculture, landscape simplification, and pesticide selection pressure further augment the occurrence and severity of disease outbreaks (Ristaino *et al.*, 2021; Singh *et al.*, 2023). Mixed and synergistic infections further complicate diagnosis and management, often accelerating disease progression and increasing crop losses (Moreno, 2020).

Early detection is widely considered as the most efficient way to restrict disease spread, enable focused remedies, and reduce pesticide load. However, the conventional diagnostics rely mainly on observable symptom expression or laboratory-based methods such as microscopy, cultural, serological and molecular approaches, which are time-consuming, destructive, and impractical for continuous large-scale monitoring. These limitations have driven the interest in non-invasive sensing technologies capable of identifying early pre-symptomatic physiological stress. Among emerging approaches, the hyperspectral imaging has exceptional potential to bridge the gap between invasion of pathogen and visible symptom development. By capturing detailed spatial and spectral information, the HSI enables early detection of disease-induced biochemical and structural changes on leaves and canopies in field scales. This review critically evaluates the principles, spectral foundations, and applications of hyperspectral imaging for early and premature detection of plant diseases, highlighting achievements, limitations, and future prospects.

Limitations of Conventional Plant Disease Detection

Traditional plant disease diagnosis is primarily based on visual symptom assessment, expert knowledge, and laboratory confirmation. While these approaches remain indispensable for definitive pathogen identification, they exhibit significant limitations when applied to early detection and large-scale surveillance. Visual scouting depends on observable symptoms such as chlorosis, necrosis, wilting, and lesion formation (Agrios, 2005). However, the visible symptoms typically appear only after substantial progress of pathogen colonization followed by physiological disruption. Many viral, bacterial, and fungal pathogens exhibit prolonged latent periods during which infection progresses without external manifestation of symptoms (Pethybridge and Nelson, 2015). Consequently, the symptom-based detection fails to identify latent or mixed infections and often underestimates disease prevalence. Observer subjectivity and inconsistent disease rating scales further reduce reproducibility and comparability across studies and environments (Bock *et al.*, 2010). Laboratory-based diagnostics such as microscopy, culture-based methods, serological and molecular based diagnostics provide high specificity and sensitivity. These methods not only require the destructive sampling, skilled personnel, extra time and labour, costly infrastructure but also delay in taking decision on disease management (Martinelli *et al.*, 2015), offer chances of examining limited and selected samples and propose no scope for large scale field monitoring. In laboratory-based system, the detection of biotic/abiotic problem and its expert advisories take time which leads to the adoption of no or late disease management (Liu *et al.*, 2023; Mishra *et al.*, 2020). These constraints limit their applicability for continuous monitoring and early warning systems at the field scale. Collectively, these limitations underscore the need for advanced, non-destructive sensing technologies capable of detecting early physiological stress at high spatial and spectral resolution.

Optical sensing technique which quantifies the spectral response of crop canopy to pathogen infection using traditional RGB photography, multispectral imaging, hyperspectral imaging and thermal imaging offers opportunity for non-destructive method for early detection of plant diseases. These imaging systems can be used as hand-held device (proximal sensing) or mounted on different airborne and spaceborne platforms to facilitate regular disease monitoring. The present article focuses on scope of hyperspectral sensing as quick and non-destructive disease monitoring tool for plant disease monitoring.

Fundamentals of Hyperspectral Imaging

Imaging vs Non-imaging Sensors

Spectral observation is generally carried out using two fundamental types of sensors – imaging and non-imaging sensors. The imaging sensors capture detailed spatial data to form pictures (like in cameras) constituting of array of pixels representing the spatial arrangement of features in the object plane showing their shapes, size and typical spectral contract with respect to the neighboring features, while non-imaging sensors provide single-point measurements (like IR thermometer or portable spectroradiometer) representing the whole object plane, without pixel-level detail. The concept of imaging and non-imaging sensors is explained in Figure 1. The output of non-imaging sensors is simple but less spatially rich. The non-imaging spectroradiometer sensors are typically used for getting spectral signature of surfaces of different objects. On the other hand, the imaging sensors mounted on UAV, Aircraft or satellite platforms to get the imageries of areas in the 'Footprint' or 'Swath'.

Multi-spectral vs Hyperspectral Sensors

Spectral resolution is one of the important characteristics of optical sensing which deals with the visible and near infrared (VNIR) range of radiation. There are three basic categories of optical imaging namely, panchromatic, multispectral and hyperspectral. The panchromatic sensor combines the visible spectrum with non-visible wavelengths, such as ultraviolet or infrared to produce single band gray scale images like black and white photographs. As this system integrates the reflected

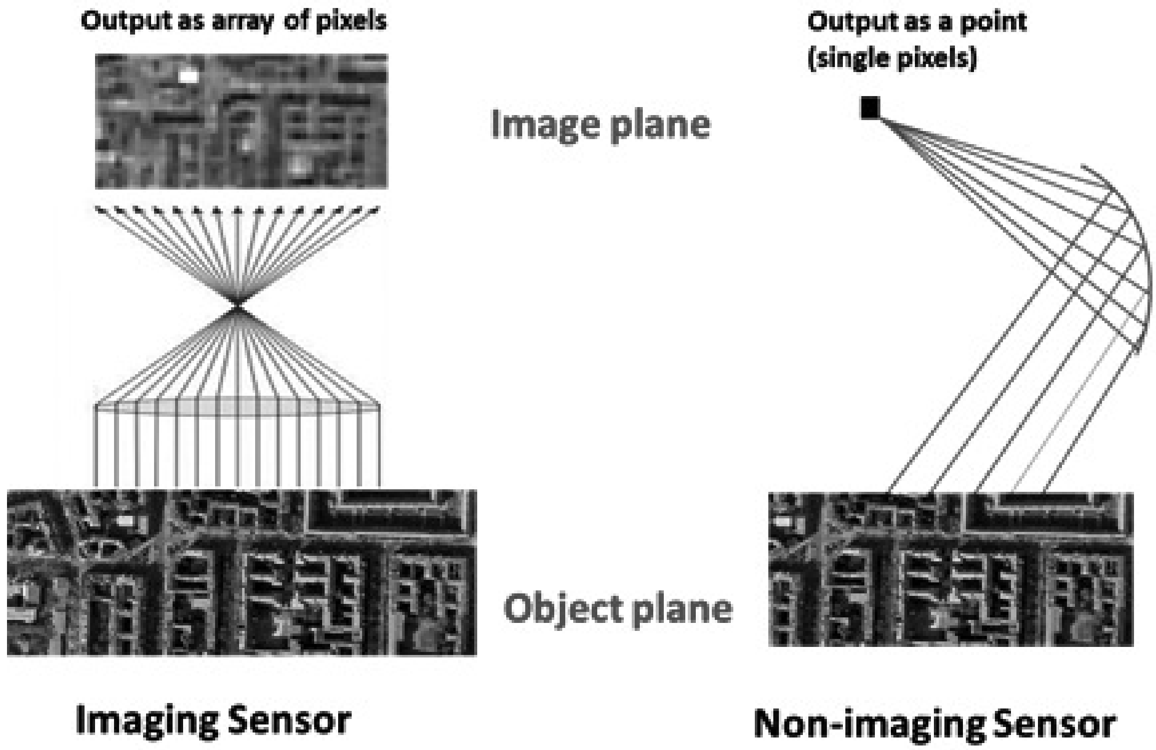

Figure 1. Schematic diagram demonstrating output from imaging and non-imaging sensors (Drawn after Wintson *et al.*, 2018)

energy in all spectral bands in the range it can produces image of higher spatial resolution. The multispectral imaging (MSI) sensors segregate the reflected power into different spectral bands (typically 3 to 10 bands) in the visible and near infrared region. On the other hand, hyperspectral imaging (HIS) sensors capture data in hundreds of extremely narrow spectral bands to form the image of higher spectral details.

Both the systems have their own advantages and limitations. As the HSI sensors capture the energy in small spectral bands the energy gain for each band is comparatively low, hence these images are typically of low spatial resolution as compared to MSI images (Feng *et al.*, 2020). Furthermore, hyperspectral remote sensing involves large data volume and hence, the data processing is complex and resource-intensive whereas the multispectral data processing is easier and faster.

Hyperspectral Imaging for Plant Disease Monitoring

Spectral Response to Plant Diseases

Plant tissues exhibit characteristic interactions with electromagnetic radiation across different spectral regions. In the visible range, reflectance is dominated by photosynthetic pigments such as chlorophylls and carotenoids. The near-infrared region is primarily influenced by internal leaf structure and mesophyll

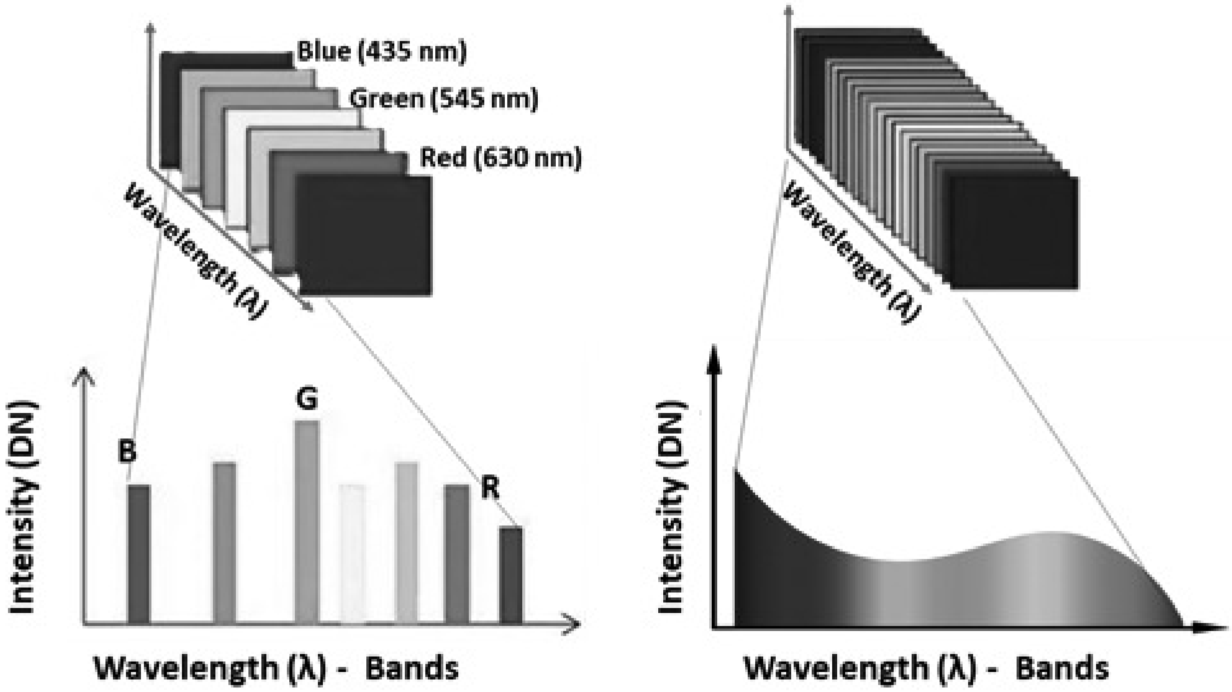

Figure 2. Schematic diagram of multispectral and hyperspectral sensing systems

scattering, while the shortwave infrared region is sensitive to water content, proteins, and structural carbohydrates (Curran, 1989; Jacquemoud and Ustin, 2019).

Pathogenic infection causes detectable changes in plant canopy as a result of metabolic disorder leading to the change in plant water relation, canopy temperature, biochemical characteristics as well as pigment composition. While symptom-based detection fails to identify latent or mixed infections and often underestimates disease prevalence, the subtle changes in crop canopy during early stages of disease development is often detectable in its spectral characteristics. Disease-induced alterations in these components produce measurable spectral changes that can be exploited for early diagnosis. The typical spectral characteristics expressed by plotting the spectral reflectance (and emittance) at different wavelengths is termed as 'spectral signature'. The spectral signature of potato late blight (PLB) at different stages of disease development in shown in Figure 3.

Critical Wavelength Regions

A healthy vegetation is often characterized by high reflectance in the middle of visible spectrum (i.e., green band) and again a very high reflectance in the Near Infrared (NIR) range. Extensive research has identified key spectral regions associated with disease-induced physiological changes. In the visible spectrum, the bands around 550–560 nm and 660–680 nm are sensitive to

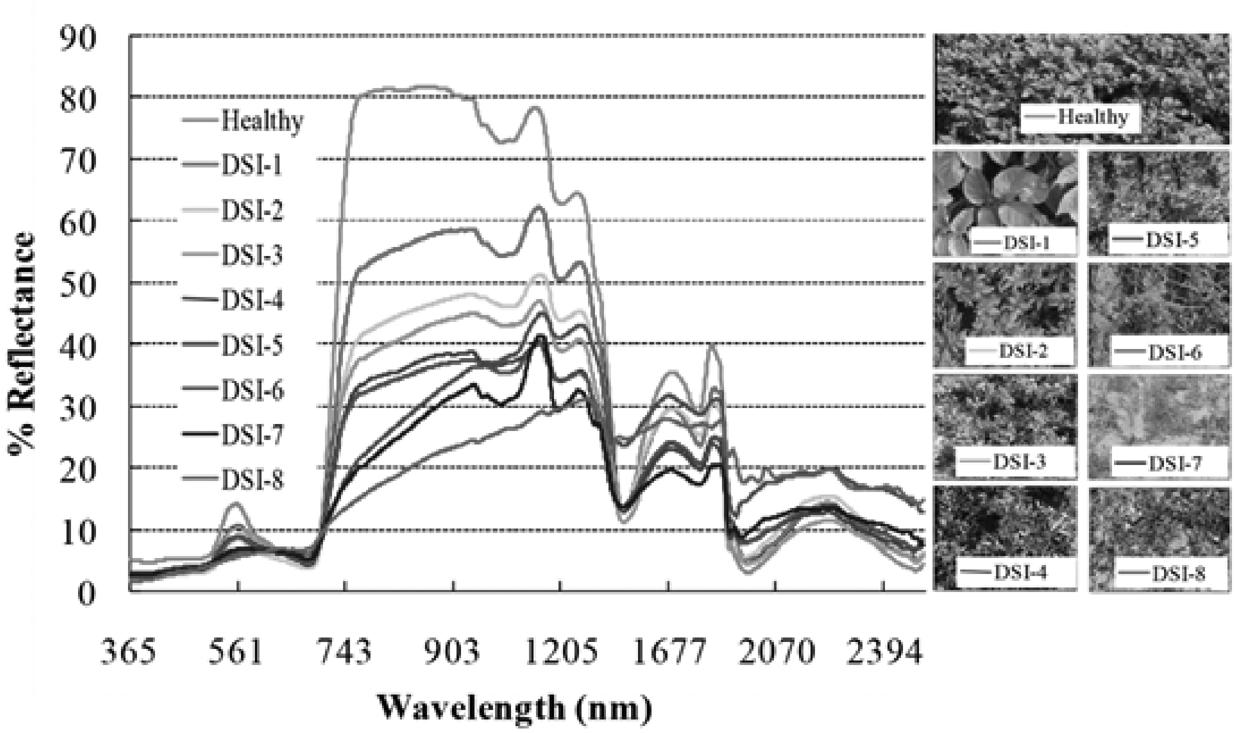

Figure 3. Spectral signature of PLB at different stages of disease development (Kundu *et al.*, 2021)

chlorophyll degradation and chlorosis (Mahlein *et al.*, 2012). The red-edge region (700–750 nm) is particularly responsive to early stress, often exhibiting a “blue shift” under disease conditions. Near-infrared wavelengths (750–1000 nm) reflect internal leaf structure and are sensitive to tissue degradation and water imbalance. In the shortwave infrared region, strong water absorption features around 1400 nm and 1900 nm provide reliable indicators of dehydration and cellular damage. These spectral regions form the foundation for disease detection across diverse crops and pathogens. The spectral regions at which significant differences in bio-optical response of PLB was observed between healthy and diseased canopy include, 680-730 nm (47.84%), 750-900 nm (76.14%) and 860-1040 nm (68.60%) (Kundu *et al.*, 2021).

However, optical sensing using RGB and multispectral cameras that include RGB, NIR and middle IR bands remain constrained by limited spectral resolution. The RGB sensors capture only three broad bands, while multispectral sensors typically acquire fewer than ten bands, insufficient to detect subtle biochemical changes preceding visible symptoms (Mahlein, 2016; Calderón *et al.*, 2015). Hyperspectral imaging integrates spectroscopy and imaging to acquire reflectance or radiance data across hundreds of contiguous narrow spectral bands, typically spanning the visible (400–700 nm), near-infrared (700–1000 nm), and shortwave infrared (1000– 2500 nm) regions (Govender *et al.*, 2009). Unlike multispectral systems, which sample discrete broad bands, HSI provides continuous spectral information with high fidelity, enabling detailed characterization of plant biochemical and structural properties. The resulting hyperspectral data are organized into a three-dimensional "hypercube" consisting of two spatial dimensions (X, Y) and one spectral dimension (ë). This structure allows extraction of complete spectral signatures at individual pixels, spatial mapping at specific wavelengths, or combined spatial spectral analysis. Such integration is critical for detecting localized disease hotspots and understanding spatial heterogeneity within plant canopies.

Mechanisms of Asymptomatic Disease Detection

The key advantage of hyperspectral imaging lies in its ability to detect physiological stress before visible symptoms emerge. During early infection stages, host plants activate defense responses, alter metabolism, and experience subtle structural damage that precedes external manifestation of symptoms. One major pathway involved in the activation of defence response the accumulation of secondary metabolites such as phenolics and flavonoids, which are synthesized rapidly in response to pathogen invasion. These compounds influence the reflectance in specific spectral regions, particularly near the red edge and ultraviolet-visible bands. Shifting of red-edge position around 705–740 nm has been consistently reported as early indicators of stress.

Pathogen colonization also disrupts cellular integrity, leading to reduced leaf water content and altered mesophyll structure. These changes are reflected in decreased near-infrared scattering and increased reflectance in water absorption bands around 1400 nm and 1900 nm in the SWIR region (Gold *et al.*, 2020). By capturing these subtle spectral responses, HSI enables discrimination between healthy and infected tissues days before symptoms appear.

Studies on late and early blight in potato demonstrated that the hyperspectral signatures associated with water content and internal structure enabled detection two to four days prior to symptom expression, achieving classification accuracies exceeding 90% (Bauriegel and Herppich, 2014). Recent studies at BCKV demonstrated the use of hyperspectral tools for measuring disease severity index (DSI) of potato late blight (Kundu *et al.*, 2021). Such findings illustrate HSI's capability to monitor disease progression mechanistically rather than symptomatically.

Spectral Signatures and Vegetation Indices

Disease-centric Vegetation Indices

Vegetation indices (VIs) condense spectral information into quantitative metrics linked to physiological traits. While conventional indices such as NDVI (Normalized difference vegetative index) are sensitive to general greenness, disease-specific applications benefit from integrating multiple indices sensitive to pigments, water content, and senescence. Indices such as NDWI (Normalized difference water index), PSRI (Plant senescence reflectance index), MCARI (Modified chlorophyll absorption ratio index), and PRI (Photochemical reflectance index) have shown strong associations with disease stress. Studies consistently demonstrate that combining multiple indices within machine-learning frameworks significantly improves diagnostic accuracy compared to single-index approaches. Disease-specific indices, such as the *Fusarium* disease index developed for wheat, further enhance sensitivity and specificity by targeting pathogen-relevant spectral features. Among the various spectral indices, the Red-edge normalized difference vegetation index and disease water stress index could be able to predict PLB infestation with reliable accuracy level (Kundu *et al.*, 2021).

Applications Across Pathosystems

Viral Diseases

Viral infections induce systemic physiological stress, making them particularly amenable to early detection using HSI. Changes in stomatal conductance, pigment composition, and water status alter spectral signatures even in asymptomatic tissues. Hyperspectral imaging has successfully detected grapevine viruses, tobacco mosaic virus, tomato spotted wilt virus, and cereal viruses prior to visible symptom development. Importantly, the hyperspectral sensing does not detect the virus directly but serves as an effective early-warning system by capturing host stress responses. Field and greenhouse studies consistently report reliable discrimination between infected and healthy plants using VIS–NIR (Visible near infrared) hyperspectral data coupled with machine learning.

Fungal Diseases

Fungal pathogens have been extensively studied using hyperspectral imaging across cereals, vegetables, fruits, and industrial crops. Fungal pathogens induce localized and progressive structural damage, pigment degradation, and water loss, all of which produce distinct hyperspectral signatures. Early detection of rusts, blights, powdery mildew, and *Fusarium* infections has been achieved at leaf, canopy, and grain levels. HSI has been successfully applied to detect fungal diseases such as *Fusarium* head blight in wheat, orange rust in sugarcane, and powdery mildew in grapevine, often days before visible symptoms appear. More recently, Mukhopadhyay *et al.* (2025) reported spectral insights into symptom development and biochemical changes during the advancement of cucumber downy mildew disease. Studies demonstrate that reflectance changes in the visible, red-edge, and near-infrared regions correlate strongly with fungal colonization and mycotoxin accumulation, enabling early intervention and improved food safety. HSI has also been applied to detect toxigenic fungi in stored grains, demonstrating near-perfect classification accuracy under controlled conditions.

Bacterial Diseases

Bacterial diseases often progress rapidly and are difficult to manage once symptoms appear. HSI has shown strong potential for early detection of bacterial leaf blight in rice and bacterial leaf spot in tomato seedlings by identifying disease-induced biochemical and structural changes. When combined with advanced learning frameworks such as convolutional neural networks (CNN) and data augmentation techniques, the hyperspectral analysis achieves robust classification even with limited training data.

Complex Disease Detection

In real-world conditions, crops frequently experience multiple stresses simultaneously. HSI excels in disentangling such complex disease syndromes by leveraging high-dimensional spectral information. It has been used to differentiate overlapping diseases and abiotic stresses, such as distinguishing Huanglongbing from drought stress in citrus and separating mixed fungal–viral infections in grapevine and sugar beet systems. This capability positions HSI as a critical and reliable tool for holistic plant health monitoring.

Table 1. Application of hyperspectral imaging system for detection of few important crop diseases

Crops	Diseases & causal organisms	HSI sensor / spectral range	Key findings	References
Grapevine	Grapevine vein-clearing virus (GVCV)	SPECIM IQ (400–1000 nm)	Detected spectral deviations before visible symptoms	Nguyen *et al.*, 2021a
Grapevine	Leaf roll & Red blotch viruses (GLRaVs)	VIS–NIR hyperspectral sensors	Early vineyard-scale discrimination of virus stress	Sudarshana *et al.*, 2015
Tobacco	Tomato spotted wilt virus (TSWV)	VIS–NIR hyperspectral imaging	Virus detected as early as 14 days post-inoculation	Krezhova *et al.*, 2014
Wheat	Soil borne wheat mosaic virus	Visible (VIS), 400–700 nm, NIR, 700–2500 nm, spectral regions.	Scientists used one machine-learning process to build a categorization model that automatically sorts pixels into symptomatic, non-symptomatic, and healthy groups.	Haagsma, *et al.*, 2023
Soybean	Soybean yellow mottle mosaic virus	Most effective information gained in a range from 653 nm to 682 nm.	Random forest and k-nearest neighbour, these two models were used to classify the infected and healthy plants ery accurate.	Ghimire, *et al.*, 2025
Wheat	*Fusarium* head blight (*Fusarium* spp.)	VIS–NIR HSI + PLS	Early detection via DON-related spectral features	Polder *et al.*, 2005
Wheat kernels	*Aspergillus, Penicillium, A. niger*	NIR HSI (1000 –1600 nm)	Up to 100% accuracy for infected vs. healthy kernels	Dowell *et al.*, 1999
Bok choy	*Fusarium commune, Rhizoctonia solani*	VNIR HSI (445–728 nm)	99% accuracy within 1–2 days post-infection	Nguyen *et al.*, 2021b

Crops	**Diseases & causal organisms**	**HSI sensor / spectral range**	**Key findings**	**References**
Jujube	Black spot caused by *Alternaria alternata*	Visible and near-infrared (Vis-NIR, 400–1000 nm) and short-wave infrared (SWIR, 1000–2000 nm) spectral regions	During postharvest storage, both Vis–NIR and NIR hyperspectral imaging techniques showed a good ability to detect black spot infection in winter jujubes. Additionally, the spectrum data from VIS–NIR HSI made it possible to clearly visualize the disease's evolution in space, making it possible to discriminate between the fruit's infected areas at each stage of the pathogen's development.	Jiang, *et al.*, 2023.
Peach	Gray mold (*Botrytis cinerea*) Soft rot (R*hizopus stolonifer*) Anthracnose (*Colletotrichum acutatum*)	VIS-NIR region (400-1000) nm	Application of PCA (Principal component analysis) decreased the large dimensionality of the hyperspectral imaging.	Sun, *et al.*, 2018.
Apple	*Botrytis cinereaRhizopus stolonifer*	VIS-NIR region (400-1000) nm	CNN and PRS were used to skillfully obtain the best determinants of the degree of the infection.	Zhu, *et al.*, 2023
Citrus	Anthracnose (*Colletotrichum gleosporioides*)	VIS-NIR region	Machine learning algorithms were practically used to assess the disease detection performance.	Tang, *et al.*, 2023.
Tomato seedlings	Bacterial leaf spot	VIS–NIR HSI + ML	Early greenhouse detection before field transfer	Zhang *et al.*, 2024
Citrus	Huanglongbing (CLas) vs drought	UAV HSI + thermal	Red-edge signatures separated biotic and abiotic stress	Zarco-Tejada *et al.*, 2021

RGB-to-Hyperspectral Spectral Reconstruction for Plant Disease Applications

Recent advances in RGB-to-hyperspectral (RGB to HSI) spectral reconstruction provide a cost-effective alternative to direct hyperspectral sensing, addressing the limited availability and high cost of HSI hardware in agricultural applications. Spectral reconstruction, also known as spectral super-resolution, aims to recover dense hyperspectral signatures from standard RGB images by learning spatial–spectral correlations from hyperspectral datasets. State-of-the-art deep learning approaches, including transformer-based architectures such as MST++ (Cai *et al.*, 2022) and SPECAT (Yao *et al.*, 2024), as well as label-efficient pixel-level reconstruction frameworks (Leng *et al.*, 2025), have demonstrated strong performance in reconstructing high-fidelity hyperspectral data from RGB inputs. While these methods have primarily been evaluated on general-purpose benchmark datasets, their relevance to plant disease detection is increasingly evident, as disease-induced physiological changes such as chlorophyll degradation, water stress, and red-edge shifts exhibit structured spectral patterns that can be partially inferred from RGB observations. Integrating RGB to HSI reconstruction into plant disease monitoring pipelines enables broader deployment of spectral analysis using consumer-grade imaging devices, while retaining much of the diagnostic value associated with hyperspectral data for early disease detection.

Remote Sensing Platforms and Future Integration

Initially, hyperspectral imaging applications in Plant Pathology were largely confined to proximal sensing under controlled laboratory or greenhouse conditions, where they provided critical insights into plant–pathogen interactions and disease physiology (Mahlein *et al.*, 2012). However, advances in sensor miniaturization and improved portability have transformed HSI from a research-oriented technique into a field-deployable remote sensing technology. Hyperspectral sensors can now be mounted on ground-based platforms, unmanned aerial vehicles (UAVs), and satellite systems, enabling scalable disease monitoring under realistic agricultural conditions (Govender *et al.*, 2009; Zarco-Tejada *et al.*, 2019). Rapidly developed remote sensing technology offers strong technical support for the non-destructive disease detection and monitoring of crop diseases in large scale (Dhingra *et al.*, 2018; Zhu *et al.*, 2018). Remote sensors provide a synoptic view of the crop condition in a periodic manner over extensive areas simultaneously and capture the subtle canopy reflectance variabilities caused due to changes in the bio-optical response of vegetation canopy as a result of biotic and/or abiotic stress (Xue and Su, 2017).

Among available platforms, UAV-based hyperspectral systems currently dominate operational research and precision agriculture applications. UAVs offer an optimal compromise between spatial resolution and coverage, bridging the gap between ground observations and satellite remote sensing. Their ability to acquire high-resolution and repeatable imagery allows early detection of disease hotspots and accurate mapping of disease severity. UAV-based HSI has been successfully applied to detect fungal, bacterial, and viral diseases in crops such as wheat, potato, grapevine, citrus, and olive, often several days to weeks before visible symptoms appear (Gold *et al.*, 2020; Zhang *et al.*, 2024). For example, hyperspectral UAV observations enabled pre-symptomatic detection of late blight and early blight in potato by capturing disease-specific changes in leaf water content and internal structure (Gold *et al.*, 2020).

Traditionally, the HSI systems were large, complex and expensive. NASA's EO-1 Hyperion (2000 to 2017), pioneered Hyperion hyperspectral imager, which collected 220 detailed spectral bands for precise mapping of land, water, and atmosphere at 30 m resolution (https://cmr.earthdata.nasa.gov/search/concepts/C1220567951-USGS_LTA.html). Recently, there has been significant development in sensor design and small satellite technology (CubeSats) which led to the development of and cost-effective, miniaturized HSI payloads. The recently launched Pixxel's Firefly in August, 2025 (https://www.pixxel.space/firefly) is capable to capture about 135 spectral bands at a 5-meter resolution across a 40-kilometre swath. The Copernicus Hyperspectral Imaging Mission for the Environment (CHIME), the future mission of European Space Agency (ESA) will capture earth image in over 200 spectral bands, with a 30-meter resolution to support of environmental and resource monitoring.

Despite these advantages, challenges remain related to data volume, sensor sensitivity under variable illumination, and integration across sensing platforms. Differences in spatial resolution, spectral configuration, and data formats complicate data fusion between proximal, UAV, and satellite systems. Furthermore, hyperspectral datasets require advanced analytical frameworks to address redundancy, noise, and limited labeled samples. Recent studies demonstrate that coupling HSI with machine learning and deep learning significantly improves robustness and classification accuracy in field environments (Rumpf *et al.*, 2011; Wan *et al.*, 2022).

Looking ahead, the future of hyperspectral remote sensing for plant disease detection lies in system integration and increasing autonomy. Climate change and globalized trade are accelerating the spread of plant pathogens, heightening the demand for rapid, non-invasive, and scalable surveillance tools. Hyperspectral sensing stands out among remote sensing technologies due to its ability to discriminate disease types, map affected areas, and quantify severity using continuous spectral information. Integration of HSI with complementary sensors such as thermal imaging and LiDAR is expected to enhance diagnostic reliability by combining physiological, thermal, and structural indicators (Zarco-Tejada *et al.*, 2021). Moreover, emerging satellite-based hyperspectral missions hold promise for regional-scale disease surveillance, complementing high-resolution UAV observations. Together, these advances position hyperspectral remote sensing as a cornerstone technology for next-generation precision agriculture and proactive plant health management.

To extend plant disease monitoring from field- and plot-level analysis to regional and national scales, recent research increasingly focuses on satellite-only and satellite–ground fusion frameworks that emphasize both scalability and interpretability. Multispectral satellite imagery from sensors such as Sentinel-2 (ESA, Copernicus Mission), Landsat-8/9 (Roy *et al.,* 2014), PlanetScope and MODIS (Justice *et al.*, 2002) enables continuous, large-area observation of crop conditions when coupled with robust pre-processing pipelines, including atmospheric correction, cloud and shadow masking, and cross-sensor spectral harmonization. Disease-relevant signals can be enhanced through the integration of interpretable vegetation indices related to chlorophyll content, canopy structure, red-edge dynamics and photosynthetic stress, optionally augmented with climatic and soil moisture data to disentangle biotic stress from environmental variability. Attention-based classifiers, such as transformer or U-Net variants, allow spatial context to be incorporated into per-pixel health classification, while emerging vision–language model (VLM) frameworks enable the generation of natural-language explanations grounded in spectral and index evidence. To mitigate the inherent spatial-resolution limitations of satellite imagery, dual-encoder contrastive learning approaches can be proposed that align satellite representations with fine-grained ground-level observations, allowing satellite models to inherit plant-level disease cues during training while remaining satellite-only at inference. Together, these strategies offer a promising pathway for scalable, explainable crop disease surveillance that bridges local diagnostics and large-scale agricultural decision-making.

Data Analysis Advances and Challenges

Modern hyperspectral systems capture dozens to hundreds of narrow spectral bands, enabling detailed characterization of plant physiological and biochemical properties. While this richness enhances diagnostic potential, it also introduces substantial computational and analytical challenges, particularly for platforms with limited onboard processing capacity such as satellites. Consequently, hyperspectral data analysis has evolved into a dynamic research field focused on transforming high-dimensional observations into actionable agricultural insights. One of the principal challenges in hyperspectral image classification is the Hughes phenomenon, where increasing spectral dimensionality combined with limited labeled samples leads to reduced model performance. Feature engineering and active learning strategies have emerged as effective solutions to this problem. By selectively identifying the most informative samples for annotation, active learning reduces labeling requirements while improving classifier generalization under data-scarce conditions. This targeted approach is especially valuable for agricultural applications, where ground truth data collection is labour-intensive and costly.

In parallel, there has been a notable shift from traditional machine-learning methods toward deep learning architectures capable of jointly exploiting spatial and spectral information. Although originally developed for natural image analysis, deep learning models are increasingly adapted to hyperspectral data by addressing challenges related to massive data volumes, spectral redundancy, and spatial–spectral resolution trade-offs. These developments have substantially improved classification, accuracy and robustness. More recently, integrated analytical frameworks have been proposed to enhance early plant disease diagnosis. These systems combine spatial segmentation techniques to isolate highly informative, early symptomatic regions with advanced preprocessing methods to improve data quality. Final disease classification is achieved using deep networks that integrate chlorophyll-related indices with spectral–spatial features. Collectively, these innovations represent a significant step toward fast, accurate, and scalable hyperspectral-based disease detection systems for precision agriculture.

The high dimensionality of hyperspectral data introduces challenges including redundancy, noise, and limited labeled datasets. Feature selection, dimensionality reduction, and active learning strategies are essential to mitigate the Hughes phenomenon. Recent shifts toward deep learning architectures have improved spatial–spectral feature extraction and classification accuracy. Integrated frameworks combining segmentation, preprocessing, and advanced neural networks demonstrate superior performance for early disease detection. However, challenges related to data standardization, computational demands, and generalizability remain significant.

In addition to improving predictive performance, interpretability and explainability have become important analytical considerations in hyperspectral-based plant disease detection. Deep spatial–spectral models often learn complex representations that are difficult to relate directly to underlying plant physiological processes, limiting transparency and user trust. Recent approaches, therefore, emphasize linking predictions to meaningful spectral bands, vegetation indices, or spatial regions through attention visualization, saliency mapping, and spectral attribution. Emerging vision–language model (VLM) integrations further extend interpretability by translating spectral–spatial evidence into concise natural-language explanations, enabling models to communicate diagnostic reasoning in human-readable form. Despite these advances, ensuring reliable and consistent explanations across crops, sensors, and environmental conditions remains an open challenge.

Conclusion

Hyperspectral imaging has established itself as a powerful, non-destructive tool for early plant disease detection, capable of identifying asymptomatic infections across diverse pathosystems. Its ability to capture mechanistic physiological changes provides a decisive advantage over conventional diagnostics. Despite its potential, HSI faces hurdles including: i. Data complexity: Large volumes of data and the “curse of dimensionality” (Hughes phenomenon) require advanced dimensionality reduction like PCA or band selection. ii. Environmental sensitivity:

Fluctuations in illumination and background noise necessitate rigorous calibration. iii. Cost: While HSI matches the speed of some laboratory tests, it remains less cost-effective than standard RGB or thermal imaging.

To achieve large-scale operational adoption, future research must prioritize sensor affordability, protocol standardization, robust data pipelines, and integration with decision-support systems. Addressing data bottlenecks through transfer learning and synthetic data generation will be critical. Future research focusing on cost reduction and the development of robust, field-deployable machine learning models will be essential for the widespread adoption of HSI in global disease surveillance. Ultimately, the convergence of hyperspectral sensing, machine intelligence, and autonomous platforms holds transformative potential for precision phytopathology and sustainable agriculture.

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