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HYPERSPECTRAL IMAGING IN PLANT VIRUS DETECTION: PRINCIPLES, APPLICATIONS, AND FIELD PROSPECTS

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ABSTRACT

Plant viral diseases cause substantial crop losses worldwide and are often detected only after visible symptoms appear. Hyperspectral imaging (HSI) is a non-destructive sensing technology that captures reflected light across hundreds of narrow spectral bands (400–2500 nm), enabling early detection of biochemical changes in infected plants before symptom expression. Integrated with artificial intelligence (AI) and high-throughput phenotyping (HTP), HSI supports large-scale, automated virus detection. This article reviews HSI principles, spectral signatures, sensing platforms, computational analysis, and field challenges, highlighting its potential to advance precision agriculture, disease management, and sustainable food security.

KEYWORDS: Artificial intelligence, high-throughput phenotyping, hyperspectral imaging, plant virus detection, precision agriculture

INTRODUCTION

Plant viral diseases are among the most economically damaging threats in modern agriculture. Infections by Tobacco Mosaic Virus (TMV), Potato Virus Y (PVY), Barley Yellow Dwarf Virus (BYDV), and others reduce photosynthetic capacity and render harvests unmarketable (Bravo et al., 2003). Plant diseases and pests collectively account for 20–40% of global food losses, costing the world economy approximately USD 220 billion annually (John et al., 2023).

Traditional diagnosis relies on visual inspection, enzyme-linked immunosorbent assay (ELISA), or polymerase chain reaction (PCR) methods, which are time-consuming, labour-intensive, and often inaccurate (Behmann et al., 2015). HSI bridges this gap by recording reflectance across 100–500 continuous spectral channels, identifying subtle biochemical changes in plant tissue before visible symptoms manifest (Lowe et al., 2017; Patil et al., 2023). Research has shown that HSI can detect viral infections 5–14 days before visual symptoms emerge, providing a critical early intervention (Kuska et al., 2019).

Principles of Hyperspectral Imaging

A hyperspectral sensor produces a three-dimensional data cube with two spatial dimensions (x, y) and one spectral dimension (λ). At each pixel, a full reflectance spectrum is recorded rather than a single intensity value, encoding surface chemistry, cellular structure, and molecular composition that broad-band systems cannot resolve (Lowe et al., 2017). Three spectral regions carry distinct plant physiological information: (i) the Visible range (VIS; 400–700 nm) governs chlorophyll and carotenoid pigments; (ii) the Near-Infrared (NIR; 700–1000 nm) reflects cell-wall structure and water content, including the diagnostically critical red-edge inflection point at 680–740 nm; and (iii) the Short-Wave Infrared (SWIR; 1000–2500 nm) tracks leaf water status through absorption bands at 970, 1450, and 1940 nm and detects protein and starch disruptions from systemic viruses (Behmann et al., 2015; John et al., 2023). Vegetation indices (VIs) derived from these regions, including Normalised Difference Vegetation Index (NDVI), Green Normalised Difference Vegetation Index (GNDVI), Chlorophyll Index green (CIgreen), and Chlorophyll Index red-edge (CIred-edge), quantitatively assess key parameters such as biomass, chlorophyll content, and canopy structure (Ali et al., 2025).

SPECTRAL SIGNATURES OF VIRUS-INFECTED PLANTS

Viral infection disrupts chloroplast integrity and triggers defensive metabolite accumulation before visible symptoms appear (Kuska et al., 2019). Consistent pre-symptomatic spectral indicators include: (i) reduction in chlorophyll absorption depth at 680 nm (Mahlein, 2016); (ii) blue-shift of the red-edge inflection point from ~725 nm toward 710–715 nm (Yuan et al., 2014); (iii) increased reflectance at 550 nm from carotenoid accumulation and anthocyanin synthesis (Bravo et al., 2003); and (iv) changes in water-band depth at 970 nm and 1450 nm from osmotic imbalance (Lowe et al., 2017) (Fig 1).

Different viruses produce distinguishable spectral profiles. TMV preferentially degrades chlorophyll and creates spatially heterogeneous reflectance maps (Zhao et al., 2022), BYDV triggers systemic yellowing detectable across 500–600 nm (Yuan et al., 2014), and Cucumber Mosaic Virus (CMV) alters canopy-scale backscatter in the SWIR through leaf curl and reduced leaf area (Lowe et al., 2017). Detection accuracy across five major viruses and sensing platforms is summarized in Table 1.

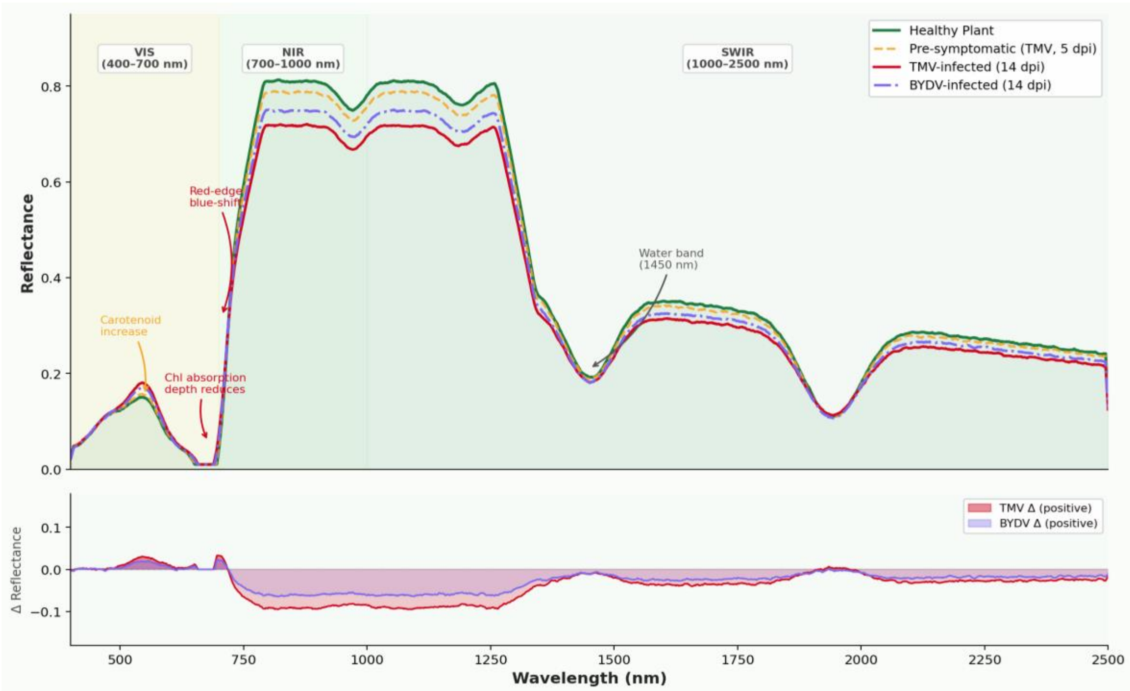

Figure 1: Hyperspectral reflectance spectra of healthy, pre-symptomatic, and virus-infected plants (TMV and BYDV) across 400–2500 nm. Lower panel: difference spectrum (infected − healthy).

Table 1: HSI-based virus detection accuracy across spectral regions

Virus / Disease	Host Crop	Spectral Region	Accuracy (%)
Tobacco Mosaic Virus (TMV)	Tomato, Pepper	400–700 nm (VIS)	91–96
Cucumber Mosaic Virus (CMV)	Cucumber, Squash	700–1000 nm (NIR)	88–93
Barley Yellow Dwarf Virus (BYDV)	Wheat, Barley	1000–2500 nm (SWIR)	87–95
Potato Virus Y (PVY)	Potato	VIS + NIR combined	89–94
Citrus Tristeza Virus (CTV)	Citrus	SWIR + Thermal	85–91

Source: Compiled from Zhao et al. (2022); Yuan et al. (2014); Behmann et al. (2015); Kuska et al. (2019)

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COMPUTATIONAL PROCESSING PIPELINE

Raw hyperspectral data requires radiometric calibration, atmospheric correction, and spectral smile correction before analysis (Mahlein, 2016). Dimensionality reduction via Principal Component Analysis (PCA), wavelet transforms, Minimum Noise Fraction (MNF) transformation, or Partial Least Squares (PLS) regression condenses 200–400 spectral bands into manageable components (Patil et al., 2023; Behmann et al., 2015). Machine learning classifiers including support vector machines (SVM) and convolutional neural networks (CNN) then map spectral features to infection status. Integrating automated deep learning CNN algorithms with phytopathology expertise has shown strong promise for accurate disease classification (John et al., 2023; Zhao et al., 2022). (Fig 2) Vegetation indices such as NDVI, Soil Adjusted Vegetation Index (SAVI), and CIred-edge can be computed in real time on embedded hardware for rapid field screening (Ali et al., 2025).

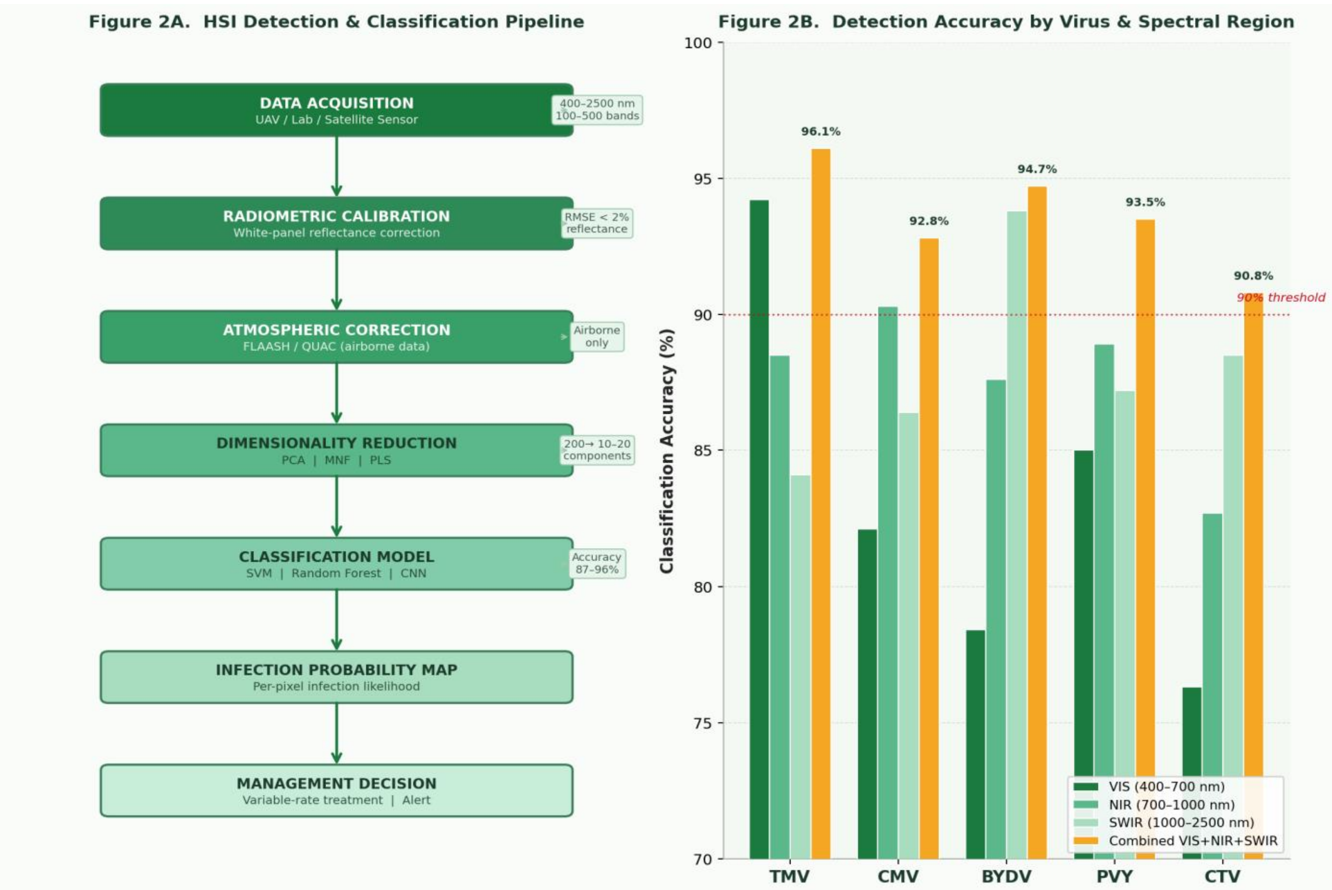

Figure 2: (A) Complete HSI detection and classification pipeline from data acquisition to management decision. (B) Classification accuracy (%) by virus species across VIS, NIR, SWIR, and combined spectral regions; dashed red line = 90% threshold.

SENSING PLATFORMS

HTP platforms employ unmanned aerial vehicles (UAVs) equipped with hyperspectral, multispectral, thermal, and Light Detection and Ranging (LiDAR) sensors (Ali et al., 2025). Laboratory pushbroom line-scan cameras generate labeled datasets for model training (Kuska et al., 2019). UAVs flying at 20–50 m altitude survey several hectares per flight at ground sampling distances of 5–10 cm. Autonomous drones with HSI and AI algorithms efficiently cover large agricultural areas (Patil et al., 2023). Spaceborne sensors such as DESIS (Deutsches Zentrum für Luft- und Raumfahrt Earth Sensing Imaging Spectrometer), PRISMA, and Environmental Mapping and Analysis Program (EnMAP) provide global coverage at 30 m resolution, enabling field-level disease pattern tracking (John et al., 2023).

CHALLENGES AND LIMITATIONS

Viral infection spectral signatures overlap significantly with those from nutrient deficiency, drought, fungal infection, and insect damage, making unique spectral identification of diseases uncertain (John et al., 2023; Behmann et al., 2015). A single hyperspectral flight generates 50–200 GB of raw data, and building well-annotated ground-truth datasets is expensive and labor-intensive (Patil et al., 2023). Model performance degrades when deployed across different growth stages, illumination conditions, or geographic regions (Bravo et al., 2003). High sensor cost and the need for strong digital infrastructure further hinder adoption by smallholder farmers (John et al., 2023).

INTEGRATION WITH PRECISION AGRICULTURE

HSI-derived infection probability maps can trigger variable-rate pesticide applications, flag infected zones for removal, or prompt confirmatory PCR testing within integrated pest management (IPM) frameworks (John et al., 2023; Behmann et al., 2015). The synergy of HTP with VIs accelerates crop improvement by providing precise, high-resolution phenotypic data, supporting the development of resilient, resource-efficient cultivars (Ali et al., 2025). Real-time monitoring systems incorporating HSI sensors provide continuous crop health surveillance (Patil et al., 2023), while standardised data formats such as cloud-optimised GeoTIFF enable interoperability with farm management information systems (FFMIS) (Lowe et al., 2017).

CONCLUSION

HSI has matured from a laboratory tool into a credible field-deployable technology for plant virus detection, capable of identifying infections days before visual symptoms appear (Mahlein, 2016; Kuska et al., 2019). The combination of HSI with AI represents a game-changer for plant disease diagnosis, making detection more rapid, accurate, and affordable (Patil et al., 2023). Integrating HTP platforms with VIs promises to enhance yield prediction, resource management, and sustainable farming practices, ultimately ensuring food security in the face of climate change and global population growth (Ali et al., 2025; John et al., 2023). Addressing remaining challenges in data labelling, model generalizability, and platform cost will require sustained interdisciplinary collaboration across plant pathology, remote sensing, and machine learning.

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