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DEEP LEARNING MODELS FOR DISEASE AND PEST DETECTION IN CROPS USING MULTISPECTRAL AND HYPERSPECTRAL IMAGING

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Abstract
Deep learning models combined with multispectral imaging (MSI) and hyperspectral imaging (HSI) offer a transformative, non-destructive approach for early detection of crop diseases and pests, addressing the 40% global yield losses caused by biotic stressors. Traditional manual scouting and laboratory methods are slow, subjective, and often too late for effective intervention, whereas spectral imaging captures subtle biochemical and structural changes (e.g., chlorophyll degradation, water content shifts, red-edge shifts) before visible symptoms appear. CNNs (including 1D, 2D, and 3D variants), Vision Transformers, and hybrid architectures (MSCVT) achieve high accuracies (often >95–99%) by extracting spatial-spectral features from hypercubes or selected bands. Key techniques include spectral preprocessing (Savitzky-Golay smoothing, MSC/SNV), dimensionality reduction (PCA, EGPO), and advanced training strategies (transfer learning, few-shot learning, GAN-based augmentation). Applications span fungal/bacterial/viral pathogen detection and pest infestation monitoring across cereals, vegetables, and other crops. Explainable AI (XAI) methods like Grad-CAM and SHAP enhance model transparency for agronomic decision-making, while model compression enables edge deployment on UAVs and IoT devices. Despite challenges such as the Hughes phenomenon, data scarcity, and model generalization, GeoAI-driven spectral analysis supports precision agriculture, reduces pesticide overuse, and advances sustainable crop protection.

1. INTRODUCTION

The global agricultural landscape is currently undergoing a paradigm shift, driven by the urgent need to sustain a population projected to reach 9.1 billion by the year 2050 (Ondrasek & Zhang, 2023). To meet the caloric requirements of this expanding population, total agricultural output must increase by approximately 70% (Hemathilake & Gunathilake, 2022). However, this imperative for increased productivity is fundamentally threatened by plant pests and diseases, which collectively account for an

estimated 40% loss in global crop production annually (Gai & Wang, 2024). These losses translate into significant economic instability, undermining food security, rural livelihoods, and international agricultural trade. Fungal pathogens alone are responsible for approximately 85% of plant diseases, while bacteria, viruses, and worms contribute to the remainder of the pathological burden (Fones et al., 2020). The economic impact of specific diseases, such as wheat rust comprising stem rust (Puccinia\ graminis), stripe rust (P.\ striiformis), and leaf rust (P.\ triticina) is catastrophic, with stripe rust alone capable of causing total crop failure under favorable environmental conditions and global costs estimated at US 5 billion annually (Chen, 2020).

Traditional methods for identifying these threats rely heavily on manual visual inspection by trained agronomists or laboratory-based molecular assays (Dhavale et al., 2025). Manual scouting is inherently subjective, time-consuming, and labor-intensive, often leading to diagnosis only after visible symptoms have manifested, by which time the window for effective intervention has frequently closed (Rovira-Más et al., 2021). While molecular techniques such as Polymerase Chain Reaction (PCR) and DNA sequencing offer high specificity, they are destructive, costly, and lack the throughput necessary for real-time, large-scale field monitoring (Kadri, 2019). Consequently, there is a profound need for non-destructive, rapid, and automated diagnostic tools (Abdollahi-Mamoudan et al., 2025). The convergence of multispectral imaging (MSI), hyperspectral imaging (HSI), and deep learning (DL) architectures has emerged as a transformative solution, enabling the detection of physiological and biochemical alterations in crops long before they are perceptible to the human eye (Khonina et al., 2024).

2. Photobiological Fundamentals and Spectral Fingerprinting

The efficacy of spectral imaging in agricultural diagnostics is predicated on the complex physical interactions between incident electromagnetic radiation and plant tissues (Khaled et al., 2018). When light strikes a leaf, it is reflected, absorbed, or transmitted depending on the wavelength and the chemical and structural properties of the target (Ustin & Jacquemoud, 2020). A healthy plant possesses a unique "spectral signature" characterized by low reflectance in the visible (VIS) range due to high absorption by photosynthetic pigments, a sharp increase in the red-edge region, and high reflectance in the near-infrared (NIR) region due to internal leaf structure scattering (Falcioni et al., 2023).

2.1 Spectral Regions and Diagnostic Indicators

Agricultural spectral analysis typically utilizes the range from 250 nm to 2500 nm, encompassing the ultraviolet (UV), visible (VIS), near-infrared (NIR), and short-wave infrared (SWIR) regions. Each of these segments provides distinct insights into the health status of the crop (Vaudour et al., 2018).

Table 1. Spectral Regions and Their Biological Correlates for Crop Health Assessment

Spectral Region	Wavelength Range (nm)	Primary Biological Correlate	Response to Pathogen/Pest Stress
Ultraviolet (UV)	250 – 400	Phenolic compounds and protective waxes	Alterations in secondary metabolites and defense signaling (Beyer, 2025).
Visible (VIS)	400 – 700	Chlorophyll a/b, Carotenoids, Anthocyanins	Reductions in chlorophyll lead to higher blue/red reflectance (yellowing) (Beyer, 2025).
Near-Infrared (NIR)	700 – 1300	Mesophyll cell structure and leaf thickness	Structural degradation reduces light scattering, decreasing NIR reflectance (Beyer, 2025; Semyalo et al., 2025).
Short-Wave Infrared (SWIR)	1300 – 2500	Water content, proteins, lignin, cellulose	Dehydration and chemical breakdown alter absorption peaks (Semyalo et al., 2025).

Biotic stress, whether induced by a fungal pathogen or an insect pest, systematically alters these biological correlates. For instance, pathogen-induced stress can significantly impair chloroplast function, reduce photosynthetic efficiency and alter the concentration of pigments such as chlorophyll (Saed-Moucheshi et al., 2024). These changes manifest spectrally as a "blue shift" of the red-edge the boundary between the red and NIR regions where the point of maximum slope moves toward shorter wavelengths (Roberts et al., 2018). Furthermore, sucking pests such as aphids or thrips interfere with the plant's vascular system, leading to measurable changes in water content that are most evident in the SWIR region (Steenbergen et al., 2018).

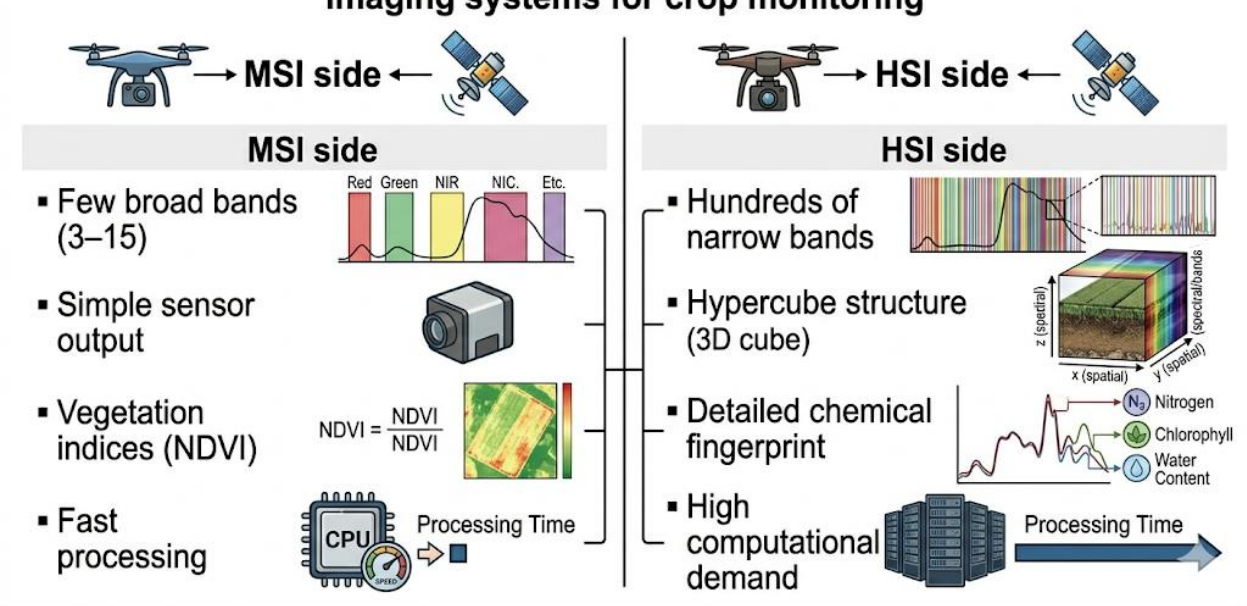
2.2 Multispectral vs. Hyperspectral Modalities

While both technologies transcend the limitations of standard Red-Green-Blue (RGB) imaging, they differ significantly in spectral resolution and operational trade-offs (West et al., 2018).

- **Multispectral Imaging (MSI):** MSI systems typically capture data in 3 to 15 discrete, broad wavelength bands (Mukhtar et al., 2025). These bands are often pre-selected to target known vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) or the Photochemical Reflectance Index (PRI). MSI is characterized by lower hardware costs, faster data acquisition speeds, and streamlined processing, making it ideal for large-scale field monitoring via satellite or high-altitude UAV platforms (Ali, 2022).
- **Hyperspectral Imaging (HSI):** HSI, or imaging spectroscopy, captures hundreds of narrow (2–10 nm), contiguous bands, providing a nearly continuous spectral profile for every pixel (Hong et al., 2026). This "hypercube" data allows for the detection of subtle biochemical shifts at pre-symptomatic stages sometimes detectable up to 14 days before visible lesions appear (Wan et al., 2025). HSI is uniquely capable of differentiating between pathogens with similar visual phenotypes and assessing disease severity with high precision (Bonah et al., 2019).

The choice between MSI and HSI often involves a trade-off between the depth of physiological insight and the breadth of spatial coverage (Ortega et al., 2020). While HSI provides the "chemical fingerprint" necessary for specific pathogen identification, its high data dimensionality requires more sophisticated deep learning architectures to extract meaningful patterns without succumbing to the "curse of dimensionality" (Vatansever et al., 2021). While both MSI and HSI provide non-invasive crop monitoring capabilities, they differ significantly in spectral resolution and computational complexity. Figure 3 highlights their key operational differences.

Figure 1: Conceptual comparison between multispectral and hyperspectral imaging systems for crop monitoring



3. Deep Learning Paradigms for Spectral Data Analysis

Deep learning has revolutionized the field of computer vision and, by extension, agricultural remote sensing (Akbar et al., 2024). Unlike traditional machine learning methods that require manual feature engineering, DL models autonomously learn hierarchical representations of the data (Eldeeb & Elshawi, 2024). This is particularly advantageous for multispectral and hyperspectral datasets, where the relationship between spectral bands and spatial features is non-linear and complex (Coliban et al., 2020).

3.1 Convolutional Neural Network (CNN) Architectures

CNNs remain the dominant architecture for image-based disease and pest detection. Depending on the input data format, several CNN variants are utilized (Ngugi et al., 2024).

1. **1D-CNN:** These models treat the spectral profile of a pixel as a one-dimensional vector (Shafaey et al., 2022). They are highly efficient for spectral-only classification tasks where spatial context is less critical (Ma et al., 2020).
2. **2D-CNN:** The most common architecture for MSI and RGB data, 2D-CNNs extract spatial features like texture, shape, and color patterns from individual bands or a combination of channels (Ivanda et al., 2025).
3. **3D-CNN:** These models employ three-dimensional kernels that convolve across both the two spatial dimensions and the spectral dimension simultaneously (Jurado et al., 2020). 3D-CNNs are the gold standard for hyperspectral "hypercubes" because they capture "spatial-spectral" features integrating the physical shape of a lesion with its chemical signature (Bothara et al., 2026).

3.2 Vision Transformers and Hybrid Architectures

A major trend in the 2023–2025 research period is the adoption of Vision Transformers (ViTs) (Wang, 2025). While CNNs are excellent at modeling local relationships, they struggle to capture long-range dependencies due to their limited receptive field. ViTs address this by utilizing self-attention modules to process image patches globally (Khan et al., 2023).

Table 2. Performance Comparison of Deep Learning Architectures in Crop Disease Detection

Model Type	Primary Strength	Accuracy/Performance Metric
Traditional CNN	Local feature extraction	Upwards of 95% in controlled environments (Beyer, 2025; Sindhushree et al., 2025).
Vision Transformer (ViT)	Global context modeling	Achieved 99.3% accuracy in some plant disease detection tasks (Beyer, 2025).
Hybrid (MSCVT)	Combined local and global feature fusion	Recognition accuracy of 99.86% on the PlantVillage dataset (Ullah et al., 2025).
Capsule Networks (CSSNet)	Preservation of spatial hierarchies	High stability in intercropping disease detection (Rahman et al., 2025).

Hybrid models like the Multi-Scale Convolutional Vision Transformer (MSCVT) combine the local information gathering of CNNs with the global receptive fields of ViTs (Xia et al., 2024). In intercropping systems (e.g., maize-soybean), where leaf overlap and visual complexity are high, architectures like the Swin Transformer utilize "shifted windows" to maintain hierarchical features, achieving recall rates near 99.9% (Pradhan et al., 2024).

3.3 Advanced Training Strategies

To handle the unique challenges of agricultural data, such as seasonality and lack of labeled samples, several advanced training methodologies are employed (Cravero et al., 2022).

- **Transfer Learning (TL):** Models pre-trained on large datasets (like ImageNet) are fine-tuned on smaller, crop-specific datasets, significantly reducing training time and data requirements (Luca, 2025).
- **Few-Shot Learning (FSL):** Designed for scenarios where only a handful of labeled images are available for a new disease. Models like AgriFewNet have achieved 97.1% accuracy using only 10 training samples per class (Albahli, 2025).
- **Generative Adversarial Networks (GANs):** Used to synthesize realistic images of diseased plants to balance datasets where certain classes (e.g., rare pests) are under-represented (Nazki et al., 2020).

4. Data Engineering and the Challenge of Dimensionality

Hyperspectral data is intrinsically complex due to its high dimensionality and the presence of redundant information across adjacent spectral bands (Morales et al., 2021). This leads to the "Hughes Phenomenon," where the classification accuracy of a model decreases beyond a certain point as the number of bands increases, unless the volume of training data grows proportionally (Richards, 2022).

4.1 Preprocessing and Dimensionality Reduction

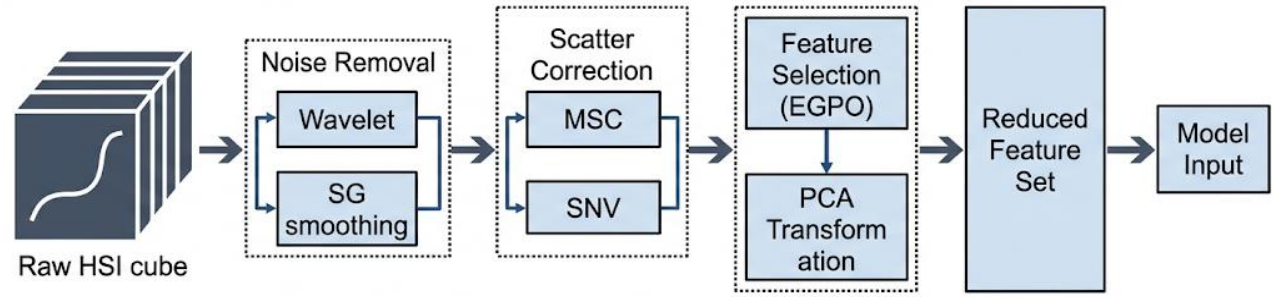
To mitigate these issues, raw spectral data must undergo rigorous preprocessing and dimensionality reduction (Xu et al., 2019).

Table 3. Common *Spectral Data Preprocessing and Dimensionality Reduction Techniques*

Technique Category	Specific Method	Purpose/Mechanism
Spectral Smoothing	Savitzky-Golay (SG)	Noise reduction while preserving peak features of the spectrum (Beyer, 2025).
Scatter Correction	MSC / SNV	Removing the effects of light scattering due to leaf surface texture (Beyer, 2025).
Noise Filtering	Wavelet Transform	Enhancing spectral contrast and eliminating baseline drift (Beyer, 2025).
Dimension Reduction	PCA	Transforming bands into a smaller set of uncorrelated components (Beyer, 2025).
Feature Selection	EGPO	Identifying and retaining only the most discriminative wavelengths (Rahman et al., 2025).

Dimensionality reduction is a critical step in streamlining models for real-world deployment (Chhikara et al., 2022). Wrapper-based strategies, such as Enhanced Greedy Political Optimization (EGPO), select a compact subset of bands that minimize redundancy while maximizing diagnostic accuracy (Got et al., 2022). For instance, in peanut stem rot detection, specific informative bands at 501–505 nm, 690–694 nm, 763 nm, and 884 nm were identified as sufficient for accurate classification (Wei, 2021). Due to the high dimensionality of hyperspectral data, preprocessing is essential to improve model stability and accuracy. Figure 2 summarizes the key preprocessing and feature reduction steps.

Figure 2: Workflow of hyperspectral data preprocessing and dimensionality reduction techniques



4.2 Spectral Unmixing and Mixed Pixels

A significant challenge in remote sensing is the presence of "mixed pixels," where a single pixel's spectral signature is a composite of different ground covers (Feng Fan, 2020). Spectral unmixing techniques decompose these mixed signals into their constituent "endmember" spectra and their corresponding fractional abundances

(Yin et al., 2026). Methods like Multivariate Curve Resolution-Alternating Least Squares (MCR-ALS) have been successfully used to detect pesticide residues on perilla leaves, achieving an explained variance of 99% for targeted chemicals (Semyalo et al., 2025).

5. Detection of Pathogens vs. Pests: Spectral Distinctions

Deep learning models must be tailored to the specific biophysical impacts of the stressor (Muhammad et al., 2025).

5.1 Pathogen Detection (Fungi, Bacteria, and Viruses)

Pathogens typically induce biochemical changes at the cellular level, altering chlorophyll concentration, water status, and cell structure (Cheaib & Killiny, 2025).

- **Early Fungal Detection:** HSI has achieved over 90% accuracy in detecting wheat foliar diseases in greenhouses. In potato crops, HSI can detect late blight (Phytophthora\ infestans) and early blight (Alternaria\ solani) before visible symptoms appear (Appeltans et al., 2022).
- **Bacterial Identification:** Tomato bacterial leaf spot (Xanthomonas\ perforans) shows distinct spectral responses in the pre-symptomatic stage, particularly around 750 nm (defense hormones) and 1400 nm (water content changes) (Skolik, 2020).
- **Viral Stress:** Grapevine vein-clearing virus and cassava mosaic virus have been successfully identified using HSI/MSI, with accuracy ranging from 60% to 93% depending on field conditions (Nkwocha & Chandel, 2025).

5.2 Pest Detection and Infestation Monitoring

Pests cause stress through direct feeding damage, defoliation, and the transmission of diseases (Navarro-Cerrillo et al., 2022).

- **Direct Detection of Pests:** HSI can identify insects based on their chitin structure and body color (Lacotte et al., 2023). Research classified 12 different wheat pest species with high accuracy by analyzing their unique spectral fingerprints between 400 and 2500 nm (Basati et al., 2018).
- **Indirect Damage Monitoring:** Sucking pests like aphids and thrips cause systemic changes in host physiology. Research on cotton aphid infestation utilized Sentinel-2 multispectral data to effectively identify infestation grades (Ribeiro et al., 2024).
- **Weed Management:** Site-specific management of weeds, particularly in wheat fields, has been enhanced through the integration of spectral indices that identify broad-leaf and grassy weeds, which can cause yield reductions of over 50% (Su et al., 2022).

6. Explainable AI (XAI) in Agricultural Decision Support

Farmers and agronomists require diagnostic tools that provide transparency (Jakku et al., 2019). Explainable AI (XAI) techniques provide this by highlighting specific spatial and spectral features influencing the model's decision (Abdollahi & Pradhan, 2021).

6.1 Principal XAI Methodologies

The integration of XAI into spectral analysis typically involves visualizing the model's attention (Bhati et al., 2024).

- **Grad-CAM (Gradient-weighted Class Activation Mapping):** This method identifies the spatial regions of an image that contribute most to a specific classification (Huang et al., 2018).
- **SHAP (SHapley Additive exPlanations):** Based on cooperative game theory, SHAP provides a quantitative attribution of each feature (e.g., each spectral band) to the final prediction (Li et al., 2024).
- **LIME (Local Interpretable Model-agnostic Explanations):** LIME approximates the complex model locally to explain individual predictions (Henninger & Strobl, 2025).

In HSI intercropping studies, activation maps generated by Grad-CAM showed a high region consistency (Dice score: 0.999) with expert-marked disease regions, affirming the model's diagnostic accuracy (Ebrahimi & Kumar, 2025).

7. Deployment at the Edge: Lightweight Models and Hardware

For spectral imaging to be practically useful, it must transition to real-time inference on edge devices (Cui et al., 2025).

7.1 Model Compression and Optimization

Lightweight architectures are essential for deployment on resource-constrained platforms (Albanese et al., 2022).

Table 4. Model Optimization Techniques for Resource-Constrained Agricultural Edge Deployment

Optimization Technique	Description	Impact on Deployment
Pruning	Removing redundant neural connections (Babu et al., 2025).	Reduces model size and speeds up inference (Babu et al., 2025).
Quantization	Reducing weight precision (e.g., 32-bit to 8-bit) (Babu et al., 2025).	Significantly lowers memory footprint and power (Babu et al., 2025).
Distillation	Training a small "student" model from a "teacher" (Wu et al., 2025).	Retains teacher accuracy while fitting into edge hardware (Wu et al., 2025).

A notable success is the **Simple Efficient CNN**, which utilizes depthwise separable convolutions to reduce parameters to 0.231 million approximately 92 times smaller than ResNet-34 while achieving 98.5% accuracy in rice seed classification (Gao et al., 2021).

8. Dataset Engineering and Global Benchmarks

The success of deep learning is fundamentally dependent on the availability of large-scale, diverse, and well-annotated datasets (Tsuneki, 2025).

8.1 Prominent Agricultural Benchmarks

Over the last decade, several key datasets have facilitated model development (Gettelman et al., 2022).

Table 5. Prominent Agricultural Benchmark Datasets for Deep Learning Model Training

Dataset Name	Focus/Scale	Target Modality	Key Feature
PlantVillage	54,305 images	RGB	Baseline for classification in controlled settings (Beyer, 2025).
OpenPlant	635,176 images	RGB	Large-scale classification across 1167 species (Zhu et al., 2024).
DLCPD-25	221,943 images	RGB/Field	Realistic complexity and long-tail distribution (Beyer, 2025).

Despite these advancements, a significant gap remains in the availability of public hyperspectral datasets specifically for disease detection. Most existing HSI datasets focus on crop type mapping or land cover rather than subtle signatures of infection (Bourriz et al., 2025).

Conclusion

Deep learning models integrated with multispectral and hyperspectral imaging have established a new frontier in precision agriculture, enabling rapid, non-destructive, and pre-symptomatic detection of diseases and pests that traditional methods cannot match in scale or timeliness. By leveraging the rich spectral signatures of plant stress chlorophyll loss, water content changes, structural degradation, and secondary metabolite shifts these systems achieve high diagnostic accuracy while supporting early intervention and reduced chemical inputs. Architectures ranging from CNNs and 3D-CNNs to Vision Transformers and hybrid models,

enhanced by preprocessing, dimensionality reduction, transfer learning, and XAI techniques, provide both performance and interpretability for practical farm-level use. Edge-optimized lightweight models further facilitate real-time deployment on UAVs and IoT platforms. While challenges remain in dataset diversity, model generalization across crops and environments, and computational demands, continued advancements in hybrid physics-informed networks, few-shot learning, and multi-sensor fusion will drive greater robustness and accessibility. Ultimately, the widespread adoption of these GeoAI technologies will be pivotal in minimizing global crop losses, optimizing resource use, enhancing food security, and promoting environmentally sustainable agriculture in the face of climate change and increasing biotic pressures.

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