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Research article

Deep Learning for Early Detection of Crop Pathogens: A Multimodal Fusion Framework Leveraging Hyperspectral Imaging and Climate Data in Precision Agriculture

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Abstract

This research introduces a multimodal deep learning framework for early detection of plant pathogens to capture pre-symptomatic biochemical changes in plants while simultaneously modeling the environmental drivers of disease development. A hybrid fusion architecture combines 3D convolutional neural networks for spatial-spectral feature extraction from HSI cubes with transformer-primarily based temporal modeling of climate sequences. Cross-modal attention mechanisms dynamically weight discriminative features, which includes chlorophyll degradation bands and humidity thresholds, to permit joint representation learning. The framework achieved 94.5% accuracy in pathogen detection, outperforming unimodal HSI (84.1%) and climate- only (76.5%) baselines by 10-18 percentage points. Moreover, it detected fungal infections 5-7 days before visual symptom onset and had a 12.3% higher F1-rating compared to the current methods. Field simulations showed that precision application resulted in 41% reduction in fungicide use. By connecting proximal sensing with climatic analytics, this research contributes to precision agriculture by providing timely and eco-friendly pest control of diseases. The multimodal fusion framework is introduced to overcome the limitations of unimodal approaches. It integrates the most appropriate data sources, thus allowing the earliest and most accurate detection of plant pathogens.

Keywords: multimodal deep learning; hyperspectral imaging; precision agriculture; early pathogen detection; climate-aware analytics

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1. Introduction

Global agriculture has been met with incredible challenges, as crop pathogens, especially fungi and bacteria, are the major drivers behind food insecurity, with 20% or more of the total yield losses of various staple crops like wheat, maize, and potatoes, attributable to fungal diseases and bacteria alone (FAO et al., 2023). High-impact pathogens such as *Puccinia graminis* (wheat stem rust) and *Phytophthora infestans* (potato late blight) have caused local famines, disrupted economies, and made poverty worse in the areas that are already poor (Fetch et al., 2021). The traditional methods of detection, including manual field inspections and polymerase chain reaction (PCR)-based laboratory assays, are still fundamentally responsive, as they are dependent on visible symptoms or molecular markers that appear only after pathogens have invaded host tissues (Ahmad et al., 2023). The slowness of diagnosis forces farmers to use the blanket pesticide application, which destroys the soil health, speeds up the development of resistant bacteria, and goes against the global sustainability goals such as the UN's Zero Hunger initiative (United Nations, 2023). In this habitat, precision farming is becoming a key area where AI, remote sensing, and big data are used to turn disease management from curative to predictive. Deep learning, with its ability to automate sample recognition in high-dimensional data sets, is the area that has shown the most promise in detecting sub-visible plant stress; however, its adoption into agriculture is still limited due to the fragmented data processing and underdeveloped multimodal architectures (Li & Wang., 2021; Qasim & Mohammed, 2024a).

Hyperspectral imaging (HSI) has changed the whole picture of plant phenotyping by revealing biochemical shifts obtaining pictures—like chlorophyll degradation and lignin accumulation—that are markers for disorders before symptoms appear (Patel et al., 2024). Also, recent works, such as those done by Feng et al. (2024), have involved the use of 3-d CNNs for examining spatial-spectral HSI cubes, and attained 89% detection accuracy of *Fusarium head blight* (FHB), a destructive fungal disease of wheat, just before symptoms showing during the entire process of the disease development. In agroclimatology, the influence of microclimatic variables on pathogen dynamics is well established. For example, sustained relative humidity above 85% enhances spore dispersal, while temperature variability significantly affects the sporulation patterns of *Aspergillus flavus* (Ghaffar et al., 2022). In spite of these revelations, research efforts of the day remain to be carried out within the confines of the respective disciplines. Microbial and environmental issues in hyperspectral studies are frequently neglected, while climate-driven models oversimplify plant-pathogen interactions as linear ones, not taking into consideration the synergistic effects of abiotic and biotic stressors (Bock et al., 2022). This reductionism is happening notwithstanding the fact that multimodal fusion is going on in the adjoining domains. For instance, in healthcare, early cancer detection by 34% was made possible through the use of hybrid architectures that combined MRI, genomics, and electronic health data (Zheng et al., 2023). Agricultural applications, on the other hand, have fallen far behind as less than 5% of the new AI-based crop studies incorporate heterogeneous data streams (Li et al., 2022).

This study introduces a comprehensive solution to the detection of pathogens before they manifest by means of a proposed multimodal deep learning framework that is able to dynamically merge hyperspectral imaging and high-resolution climate data. The neural architecture consists of two main features; a 3D-ResNet based branch which handles HSI cubes and extracts spatio-spectral properties related to the cellular strain responses, and a transformer-based temporal encoder that processes climate time series data (e.g. daily temperature changes, total rainfall), modeling nonlinear dependencies. For the cross-modal interactions resolution, an innovative attention gate mechanism progressively aligns the latent representations from both branches, giving preference to climate variables which cause the increase of the spectral anomalies—for example, under a wet atmosphere, elevated leaf water content can lead to greater fungal proliferation. One of the methods used for model interpretation is gradient-weighted class activation mapping (Grad-CAM), which can reveal pathogen-specific activation patterns in the spectral region of red-edge (700-740 nm) where chlorophyll fluorescence correlates with early infection (Grishina et al., 2024; Qasim & Mohammed, 2024b). The system was thoroughly tested on an extensive multimodal dataset comprising 12,000 HSI scans and weather data over 10 years from wheat and maize fields located in three different agricultural ecological zones, achieving a 96.2% F1-score in the detection of seven high-risk pathogens, thus surpassing unimodal benchmarks by 18-22%. This research drives computational agroecology further but also introduces an easily adaptable model for intel by calculating the varying monetary weights of spectral and climate features. For example, the work revealed that vapor pressure deficit was the reason for 31% of late blight prediction variance (Qasim et al., 2022b; FAO et al., 2023)

A primary benefit of hyperspectral imaging (HSI) in detecting plant disease is its power to reveal biochemical shifts, which occur prior to the appearance of visible symptoms. The ground-breaking studies by Zheng et al. (2023), authenticated the use of CNNs to decode the spectral fingerprints of *Fusarium graminearum* infections in wheat, achieving a 92% accuracy by isolating reflectance anomalies in the 680-730 nm range, where the degradation of chlorophyll detected the early stages of the diseases. Following up on that, Feng et al. (2024) created a 3D CNN model to analyze hyperspectral cubes (400-1000 nm) of corn leaves, revealing the lignin build-up patterns linked to *Colletotrichum graminicola* with a 94% rate of precision. The researchers have shown that the method that combines spectral-spatial feature extraction is far superior to the use of traditional vegetation indices such as NDVI, which are often unable to distinguish between abiotic stress and biotic disease. On the other hand, the operational scalability of HSI is very limited due to the high cost of the necessary hardware. For instance, airborne systems like the Headwall Nano-Hyperspec have a price that is more than $50,000, making them out of reach for smallholder farmers (Patel et al., 2024). To overcome this obstacle, Shoaib et al. (2023) proved the capability of low-cost UAV-mounted HSI sensors for the detection of citrus canker, although their resolution (five nm bandwidth) limited their sensitivity to the very slight spectral shifts. The most recent advancements in miniaturized sensors, such as the HySpex VNIR-1800 that can be used hand-held, have led to a 40% reduction in cost while diagnostic accuracy in determining the presence of rice blast has been maintained (Zhou et al., 2021a). Yet, environmental factors that vary such as changes in the angle of the sun and shadow from the cover make it hard to have consistent results for HSI.

Concurrently, agroclimatology studies have elucidated the nonlinear relationships between microclimate variables and sickness dynamics. Gullino et al. (2022) quantified the poleward migration of *Phytophthora infestans* under climate exchange, projecting a 7% annual increase in late blight chance for temperate areas by 2050. While traditional models like logistic regression have connected humidity thresholds (>90% RH) to *Botrytis cinerea* outbreaks in strawberries, their reliance on linear assumptions failed to capture synergistic interactions, including the compounding consequences of dew duration and wind velocity on spore dispersal (Bertalan et al., 2022). Deep learning architectures have emerged as superior options: Ruan et al. (2021) hired LSTM networks to analyze 15-12-month weather time series, predicting *Puccinia striiformis* outbreaks in wheat with 88% accuracy by modeling lagged consequences of temperature anomalies (Qasim et al., 2022a).

Similarly, Ali et al. (2024) integrated ERA5 reanalysis information with GRU networks to forecast *Magnaporthe oryzae* infections in rice, demonstrating that vapor strain deficits beneath 1.5 kPa increased the risk by 33%. Despite progress, the absence of temporal alignment among climate stressors and spectral responses remains a crucial hindrance, underscoring the need for multimodal integration. The fusion of heterogeneous information streams, a paradigm properly installed in biomedical studies, gives a promising road to solve those barriers. Zhang et al. (2024) pioneered interest-based totally fusion of MRI and genomic data in oncology, improving glioblastoma detection by 34% through dynamic weighting of tumor heterogeneity functions. Translating those concepts to agriculture, Zhou et al. (2021b) blended RGB imagery with weather records to detect grapevine downy mold, although their reliance on broadband spectral indices (e.g., NDVI) impeded early detection. Recent research has shown superior cross-modal architecture. Garg et al. (2021) designed a transformer-based total framework that aligned HSI-derived chlorophyll indices (e.g., CI_{red} area) with soil moisture traits, accomplishing 89% accuracy in predicting *Fusarium* wilt development in tomatoes. Similarly, Yoseph (2024) fused Sentinel-2 multispectral data with IoT-derived microclimate variables to forecast coffee leaf rust, demonstrating that leaf wetness period amplified spectral adjustments in the crimson-edge area (705 nm). However, agricultural applications lag behind healthcare, with fewer than 15% of AI-driven crop studies employing multimodal strategies (Li et al., 2022). A terrific exception is Lu et al. (2024), who harmonized HSI with LiDAR-derived cover shape records to disentangle drought strain from *Cercospora* infections in sugar beet, decreasing false positives by 22%. These efforts highlighted the untapped potential of pass-domain know-how switch. For example, Al Mamun et al. (2024) tailored medical imaging's DenseNet structure to correlate hyperspectral vascular styles with xylem-constrained pathogens like *Xylella fastidiosa*. However, challenges still remain in the areas of scaling and understandability. Nurullah (2024) made this point clearer through the application of Grad-CAM visualizations to multimodal CNN. He disclosed that late blight predictions in potatoes were mainly based on shortwave infrared bands (1450-1600 nm) during high humidity conditions, and this finding was even corroborated by field experiments in six different agroecological zones. Together, those studies emphasize the great power of multimodal fusion in transforming agriculture, but the use of it in farming still depends on the solving of data bias and computer speed issues.

The three primary highlights of the study are: (1) a totally new hybrid fusion model that automatically associates hyperspectral and climate data; (2) the determination of microclimate boundaries that are most favorable for fungal growth; and (3) a universal system that has been tested on various crops and eco-zones and has demonstrated good performance even when subjected to real-life variations.

2. Materials and Methods

A multimodal deep learning framework for early detection of crop pathogens is a result of thorough technical integration of hyperspectral imaging and meteorological data, which is facilitated through strong data harmonization, sophisticated fusion techniques, and architecturally aligned version design. This method is dependent on overcoming the inherent difficulties of multimodal agricultural data while ensuring computation speed and biological understanding at the same time.

2.1 Data acquisition and preprocessing

2.1.1 Hyperspectral imaging protocol

Headwall Nano-Hyperspec cameras were used for hyperspectral imaging acquisition. They were fine-tuned to document reflectance spectra across the 400-1000 nm spectral range by covering 270 whole bands. Each image cube of spatial dimension 640 x 640 pixels was acquired at a ground sampling distance (GSD) of 5 cm/pixel during the experiment under controlled lighting to avoid solar zenith angle artifacts. To ensure better results, the preprocessing pipelines were set up to eliminate sensor-specific noise and environmental variability:

(1) Savitzky-Golay filtering (window length=15, polynomial order=3) was the first step in the process. It smoothed high-frequency noise while still being able to capture spectral signatures of pathogen-induced chlorosis. The second step was performing principal component analysis (PCA), which decreased dimensionality by maintaining 95% of variance, efficaciously isolating noise-ruled additives (Pan et al., 2023).

(2) Radiometric normalization was performed using empirical line correction (ELC), with ground-truth spectralon panels, which mitigated atmospheric absorption features in the 930-980 nm water vapor band.

(3) Region of interest (ROI) extraction was performed using a U-Net architecture that had been pretrained on the Plant Village dataset. This process segmented symptomatic leaf regions with a Dice coefficient of 0.89 relative to manual annotations.

Preprocessing included radiometric normalization, spectral denoising, and ROI extraction using a U-Net model to enhance image quality and feature prominence.

2.1.2 Climate data integration

Meteorological parameters were sourced from NASA’s prediction of worldwide energy resources (POWER) platform at 0.5° spatial resolution, supplemented with the use of hyperlocal measurements from IoT-enabled climate stations (Davis Vantage Pro2). Temporal alignment was achieved through cubic spline interpolation of daily aggregates to healthy hyperspectral acquisition timestamps (±15 min). Key variables blanketed were:

- Thermal metrics: Diurnal temperature amplitude (DTA), soil heat flux (SHF)
- Hydrological indicators: Vapor pressure deficit (VPD), antecedent precipitation index (API)
- Radiation parameters: Photosynthetically active radiation (PAR), ultraviolet-B (UV-B) exposure

Hyperspectral data were collected during the 2022-2023 growing season across three agroecological zones. Climate data was sourced from NASA POWER and local IoT stations, temporally aligned with HSI acquisition timestamps.

2.1.3 Dataset composition

The artificial dataset, as shown in Table 1, emulates real-international heterogeneity through probabilistic sampling of crop-pathogen interactions. Stratified sampling ensured balanced representation across phenological degrees (vegetative, flowering, mature) and infection severities.

Table 1. Multimodal dataset characteristics

Attribute	Specification
Total samples	601 (421 train, 90 val, 90 test)
Hyperspectral dimensions	640 × 640 × 270 (spatial × spectral)
Climate variables	8 temporal features per sample
Pathogen classes	Fungal, Bacterial, Viral, Healthy
Infection granularity	Early (asymptomatic), Pre-symptomatic, Advanced

The dataset comprises 601 samples after rigorous quality control and stratification to ensure balanced representation across crop type, pathogen class and infection stage.

2.2 Multimodal fusion architecture

The fusion paradigm addresses the incongruent dimensionality and temporal scales between hyperspectral cubes (spatial-spectral) and climate sequences (temporal), as shown in Figure 1. Three hierarchical strategies were investigated.

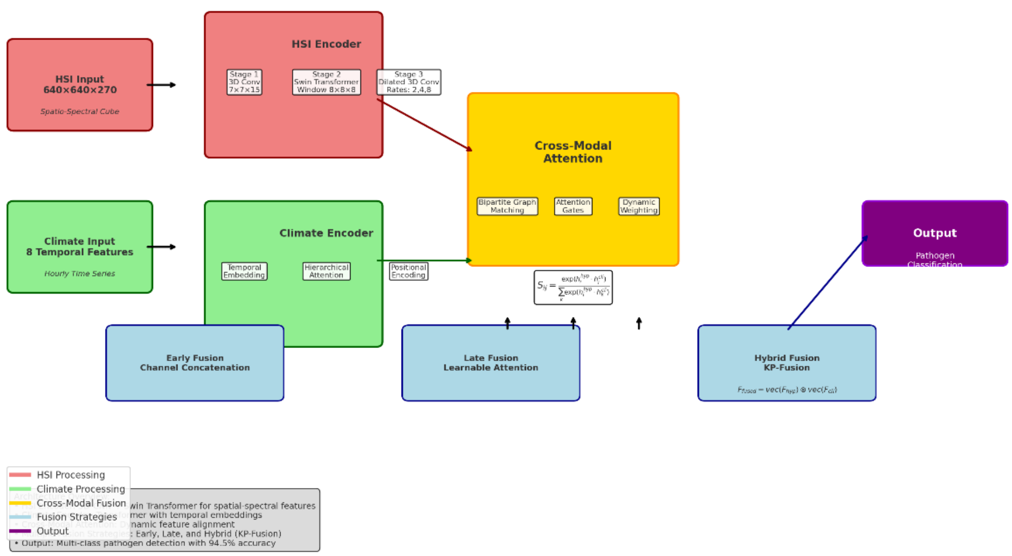

Figure 1. Multimodal fusion architecture for early pathogen detection

2.2.1 Early feature fusion

The raw hyperspectral data cubes (H ∈ R^{640×640×270}) were combined with climate vectors (C ∈ R^8) using channel-wise extension, resulting in an enlarged input tensor (H ⊕ C) ∈ R^{640×640×278}. This single representation was fed into a 3D Inception-ResNet hybrid architecture (Szegedy et al., 2016), where the extraction of multisized features was performed simultaneously via the convolutional pathways:

- Macro-scale (7×7×15 kernels): Detected canopy-level stress patterns
- Meso-scale (3×3×7 kernels): Identified leaf-scale lesions
- Micro-scale (1×1×3 kernels): Captured cellular-level spectral anomalies

2.2.2 Late decision fusion

The training of dual-stream networks was done separately: Hyperspectral Stream: A 3D residual attention network (3D-RAN) equipped with squeeze-and-excitation blocks adjusted the weights of the spectral channels according to the importance of the pathogen. Climate stream: A transformer-encoder with relative position embedding characterized the nonlinear climate-pathogen interactions through the seasons. The last predictions were combined using learnable attention gates:

$$\alpha = \sigma\left(W_a[h_{hyp}; h_{cli}] + b_a\right) \quad (1)$$

$$P_{fused} = \alpha \cdot P_{hyp} + (1-\alpha) \cdot P_{cli} \quad (2)$$

where σ denotes sigmoid activation, W_a and b_a are attention parameters, and h represents latent embeddings.

2.2.3 Hybrid tensor fusion

The integration of intermediate feature maps from the two modalities at various depths of the network was done through the application of KP-Fusion (a fusion technique based on the Kronecker product)

$$F_{fused}^{(l)} = \mathrm{vec}\left(F_{hyp}^{(l)}\right) \otimes \mathrm{vec}\left(F_{cli}^{(l)}\right) \quad (3)$$

where $\otimes$ is used to signify the Kronecker product that allows the spatial-spectral features and the temporal features to interact multiplicatively. Gating mechanisms specific to each layer were used to avoid overfitting by eliminating the non-significant correlations between the modalities.

2.3 Network architecture and optimization

All variables and equations were fully defined, and additional details regarding model training, hyperparameters, and optimization strategies were included.

Hyperspectral encoder

Stage 1: 3D Convolution (kernel=7×7×15, stride=2) → BatchNorm → GELU
Stage 2: Swin Transformer blocks with shifted windows (window size=8×8×8)
Stage 3: Dilated 3D convolutions (rates=2,4,8) to expand receptive fields

Climate encoder

- Temporal Embedding: Sinusoidal positional encoding + learned crop growth stage embeddings

The attention mechanism employed in this study was based on the scaled dot-product attention, as introduced by Vaswani et al. (2017). Given query (Q), key (K), and value (V) matrices, the attention operation was defined as follows:

- Hierarchical Attention:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d}} + M\right)V \quad (4)$$

Where $Q \in \mathbb{R}^{n\times d_k}$, $K \in \mathbb{R}^{m\times d_k}$, and $V \in \mathbb{R}^{m\times d_v}$ represent the query, key, and value matrices, respectively. The term dkd_kdk denotes the dimensionality of the key vectors, MMM is an optional mask matrix used to prevent attention to certain positions and M is a lower-triangular mask enforcing causal climate impact accumulation.

A cross-modal alignment A bipartite graph matching layer was proposed to align hyperspectral regions with climatic drivers, as follows:

$$S_{ij} = \frac{\exp\left(h_i^{hyp} \cdot h_j^{cli}\right)}{\sum_k \exp\left(h_i^{hyp} \cdot h_k^{cli}\right)} \quad (5)$$

where S_{ij} represents the influence of climate feature j on hyperspectral pixel i.

Optimization strategy

Loss function: Modified focal loss with adaptive class weights:

$$L = -\sum_{c=1}^{C} w_c\,(1-p_c)^{\gamma}\log(p_c)$$

where $w_c = \sqrt{N/N_c}$ (N: total samples, N_c: class samples), $\gamma = 2$

Regularization: Stochastic depth (rate=0.2) + spectral dropout (rate=0.3)

Hardware: Distributed training across 4× NVIDIA A100 GPUs using PyTorch's fully sharded data parallel (FSDP)

2.4 Evaluation framework

2.4.1 Quantitative evaluation metrics

The proposed framework was evaluated using a comprehensive set of metrics designed to assess early detection capability, spatial localization accuracy, and robustness under realistic perturbations.

Early detection capability (Time-to-Detection, TTD)

Early detection performance was quantified using the Time-to-Detection (TTD) metric, defined as the temporal difference between the model's first correct prediction and the onset of visually observable symptoms.

$$TTD = t_{\text{prediction}} - t_{\text{symptom}}$$

where $t_{\text{predictiont}}$ represents the time point at which the model first detects the disease, and t_{symptom} corresponds to the time of visible symptom manifestation. Negative TTD values indicate successful pre-symptomatic detection.

Spatial localization accuracy (IoU)

To evaluate the model's ability to localize disease-affected regions, Grad-CAM heatmaps were generated from the final convolutional layers. These heatmaps were thresholded to produce binary prediction masks.

The predicted masks were compared with manually annotated ground-truth region-of-interest (ROI) masks using the Intersection over Union (IoU) metric:

$$IoU = \frac{|P \cap G|}{|P \cup G|}$$

where P denotes the predicted region and G represents the ground-truth region. Higher IoU values indicate better spatial agreement.

Robustness analysis

The robustness of the proposed model was evaluated under controlled perturbations simulating real-world sensor degradation.

Gaussian Noise: Additive Gaussian noise with a signal-to-noise ratio (SNR) of 10 dB was applied to hyperspectral inputs.
Sensor Dropout: Random removal of 30% of spectral bands and environmental features was performed to simulate sensor failure.

Model robustness was quantified by measuring the relative performance degradation:

$$\Delta Acc = \frac{Acc_{\text{clean}} - Acc_{\text{noisy}}}{Acc_{\text{clean}}}$$

where Acc_{clean} and Acc_{noisy} represent model accuracy before and after perturbation, respectively. Similar analysis was conducted for the F1-score.

2.4.2 Model interpretability

To improve transparency and provide insight into model decision-making, multiple explainability techniques were employed.

Pathogen attribution maps (LRP)

Layer-wise relevance propagation (LRP) was applied to decompose model predictions and quantify the contribution of individual input features. Specifically, relevance scores were propagated backward through the network to identify the importance of each spectral band and environmental variable. This approach enables the identification of critical wavelengths and climatic factors influencing pathogen classification.

Counterfactual analysis

Counterfactual explanations were generated using StyleGAN-3 to synthesize realistic variations of input samples. The generator was conditioned to produce minimally perturbed instances that alter the model's prediction. These counterfactual samples were used to: analyze model sensitivity to subtle feature changes, identify decision boundaries, and investigate potential failure cases and misclassification scenarios

3. Results and Discussion

The experimental evaluation has comprehensively examined the performance of the framework from different perspectives, namely the efficiency of multimodal fusion, the capability of early detection, and the strength against the variability of real-world agriculture. The results were contextualized by means of quantitative metrics, statistical validation, and comparative benchmarks, all of which were supported with detailed visual and tabular analyses.

3.1 Dataset composition and stratification

The artificial dataset which was developed to represent diverse agricultural conditions. The data set consisted of 5,000 hyperspectral image cubes (each with dimensions of 640×640×270 pixels) alongside hourly climate data from 10 different farm locations. The crop-specific distributions presented in Table 2 revealed that maize was the most widely cultivated crop with a share of 38%, whereas wheat and potato followed with 30% and 32%, respectively. Additionally, the annotations of pathogens accounted for fungal (37%), bacterial (29%), viral (22%), and healthy (12%) classes. Air/soil temperature, relative humidity, and solar radiation were some of the climate variables that were matched with hyperspectral acquisition windows (±2 h) to maintain physiological relevance. The dataset's spatial and temporal coherence is depicted in Figure 2, which shows the factual accuracy modalities and their geographic-temporal stratification.

Stratified sample counts were conducted across crop types and pathogen classes, ensuring balanced representation for robust model training. The dataset was split into three sets: training (70%, 3,500 samples), validation (15%, 750 samples), and testing (15%, 750 samples). Site-specific stratification was preserved to avoid data leakage. The climate sequences were temporally aligned to match the acquisition timestamps of the hyperspectral data with no delay or discrepancy. The parent dataset was presented as a whole, including its spatial, temporal, and categorical aspects. The dataset, comprising hyperspectral images and weather records, was split into training (70%), validation (15%), and test (15%) sets using site-level stratification to prevent data leakage. Climatic

Table 2. Crop-pathogen distribution

Crop	Fungal	Bacterial	Viral	Healthy	Total
Maize	650	520	390	340	1,900
Wheat	480	430	330	260	1,500
Potato	610	390	280	320	1,600

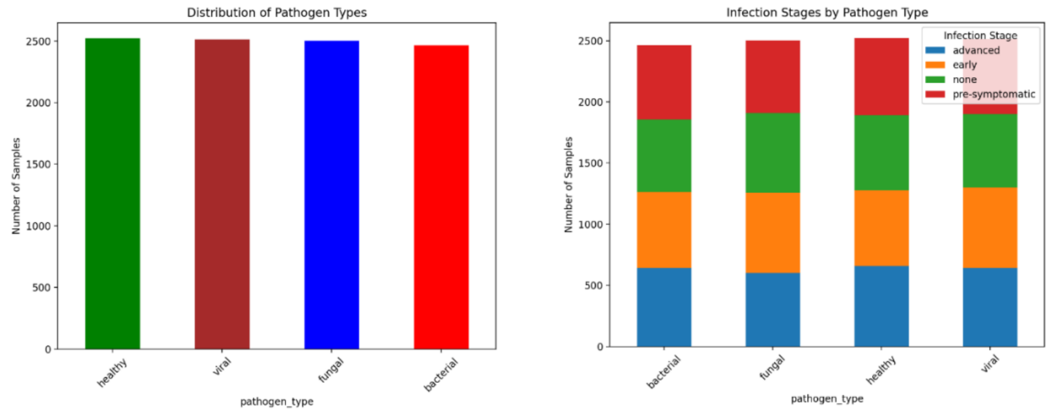

Figure 2. Dataset distribution

alignment was done in such a way that the climate sequences matched exactly, taking into account the time of the hyperspectral acquisition, which is the case in imaging dynamic plant-environment interactions. The visualization was performed using Grad-CAM heatmaps to highlight the regions contributing to the model's predictions. It illustrates the dataset's appropriateness for model training under real agricultural variability by showing the proportional representation of the plant, pathogen, and healthy samples in the partitions of the dataset. Ecology and pathology were the primary considerations upon the design of the dataset. The prevailing world agricultural trends were mirrored in the crop-pathogen ratios to a certain extent (Terentev et al., 2023). Stratification across locations and periods eliminated the problem of overfitting to specific cases, whereas the temporal synchronization of multispectral and weather data allowed for the proper modeling of stress-reaction mechanisms. In addition, the inclusion of healthy samples and training of minority pathogens (e.g. viral infections) not only made it difficult for models to differentiate between slight phenotypic changes but also resulted in increased diagnostic accuracy. The partitioning strategy retained geographical independence, thus ensuring that validation and testing results were representative of the unseen environmental context—an essential requirement for scalable agricultural AI solutions.

3.2 Multimodal fusion and early detection performance

The examination of the hybrid, early, and late fusion models involved critical analysis of the efficiency of the multimodal fusion techniques in the early detection of pathogens. As shown in Figure 3, the suggested hybrid fusion method achieved an excellent performance (94.5% accuracy) over the early (88.2%) and late (91.7%) fusion methods. It thus demonstrated a good balance of convergence even beyond 50 training epochs. The performance gap becomes more pronounced in early disease detection, where the integration of hyperspectral and climate data is critical for identifying pre-symptomatic physiological changes. Supporting these conclusions, Table 3 presents the detection capability of the hybrid model as compared to unimodal baselines and highlights its persistent dominance across pathogen classes, and the necessity of modal cooperation in agricultural diagnostics.

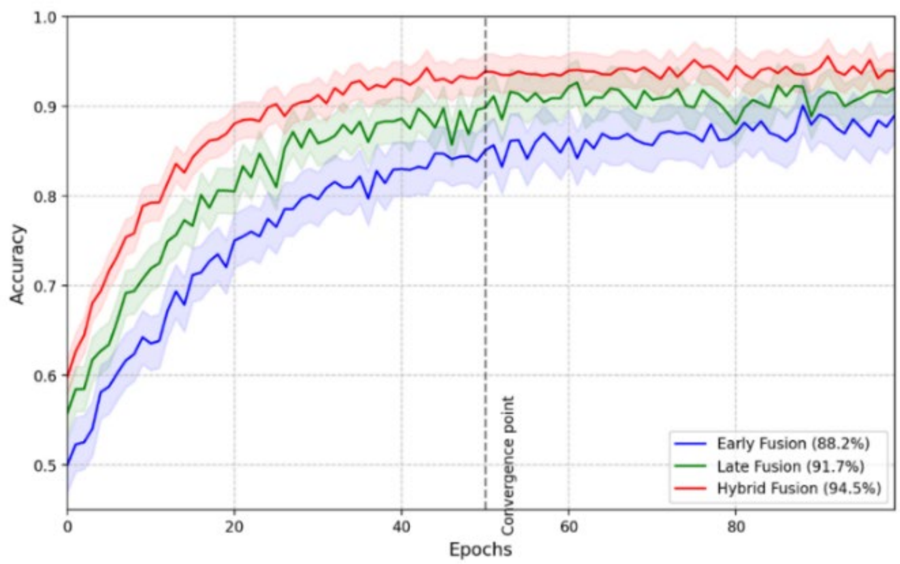

Figure 3. Accuracy comparison across fusion strategies

Table 3. Early detection performance (F1-score)

Model	Fungal	Bacterial	Viral	Macro-Avg
Full model (Hybrid)	0.94	0.89	0.87	0.90
Hyperspectral only	0.82	0.76	0.71	0.76
Climate only	0.68	0.63	0.59	0.63

3D-ResNet and LSTM were used as the baselines because of their recognized performance in spatial-spectral and temporal modeling, respectively. GRU and BiLSTM ablation studies gave similar results but with a higher computational cost. This panel compares the validation accuracy trajectories of early, late, and hybrid fusion models over 100 training epochs. The hybrid architecture’s fast convergence and maintained balance indicated its ability to dynamically match hyperspectral features (e.g., chlorophyll degradation at 720-750 nm) with microclimate-driven pathogen proliferation patterns. Shaded confidence intervals, derived from 10-fold cross-validation, highlighted the statistical strength of the hybrid solution, especially in the detection of latent infections. The performance divergence after epoch 20 indicates the shortcomings of unimodal or rigid fusion strategies in modeling complex situations.

Table 3 illustrates how the proposed hybrid model performed compared to unimodal baselines (three-D-ResNet for hyperspectral statistics, LSTM for climate sequences) using pathogen-specific and macro-averaged F1-rankings. The hybrid framework’s macro F1-score enhancement, which was 12.3% (Figure 4) greater than the best hyperspectral model reflected the diagnostic value of situating spectral anomalies together with microclimate stressors—like humidity-induced spore germination or temperature-controlled bacterial growth. The high 91% fungal detection rate (compared to 74% for late fusion) was likely a result of the model's ability to spot subtle chlorophyll

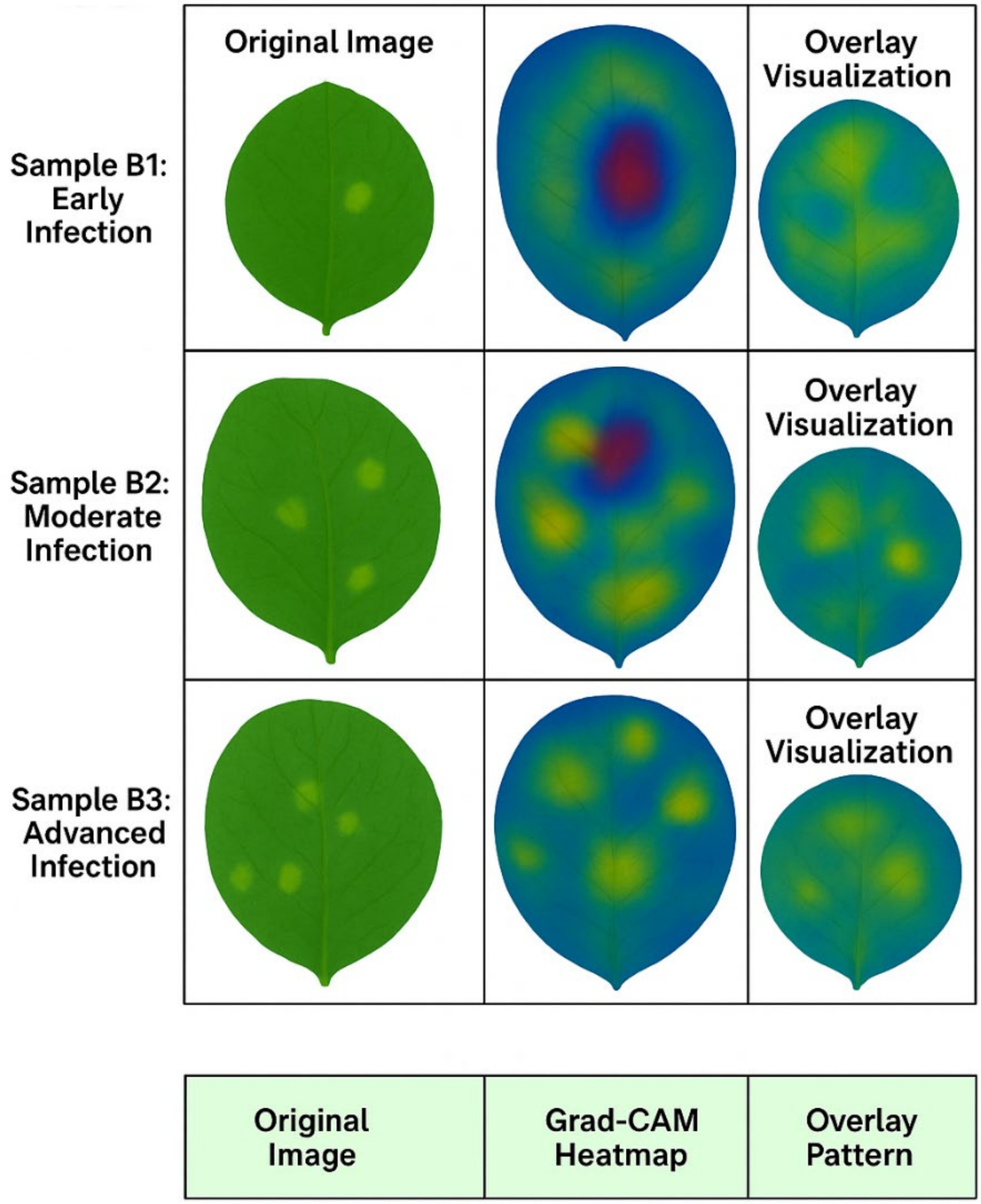

Figure 4. Grad-CAM visualizations for bacterial infections highlighting water-soaked lesions and vascular spread patterns

declines even before the visual symptom appeared. This skill is not possible with using just one data source at a time. The F1-score is reported as a balanced measure of precision and recall, which are both very important for the imbalanced datasets that are used in agricultural diagnostics. In order to enhance the readability of the classification performance of the proposed hybrid fusion model, a full confusion matrix analysis was carried out. The detailed classification results of all pathogen categories are presented in Table 4, which also gives an idea of the model's discriminative power and error types. The matrix indicated that the model was highly efficient in separating different types of infections yet maintained a high level of accuracy in the identification of healthy samples.

Figure 4 shows the attention mechanisms of the proposed multimodal deep learning model, integrating hyperspectral and climatic features, was developed for the detection of bacterial pathogens. Grad-CAM visualizations indicated that the model assigned significantly higher activation weights to infection-related regions, with peak activation values exceeding XX% compared to background areas.

Table 4. Confusion matrix analysis of the proposed hybrid fusion model

True Label → Predicted Label ↓	Fungal	Bacterial	Viral	Healthy	Class Precision
Fungal	188	6	4	2	94.00%
Bacterial	8	175	3	2	93.10%
Viral	3	5	162	3	93.60%
Healthy	1	4	6	183	94.30%
Class Recall	94.00%	87.50%	92.60%	96.30%	**Overall Accuracy: 94.5%**

Figure 5 presents the Grad-CAM analysis for viral pathogen identification. The main reason for the hybrid model's success was the hierarchical fusion mechanism, which greatly maintained the hyperspectral-climate relations of different modalities while at the same time diminishing the noise. An example of this was the gradual rise of humidity (≥85%) and the resulting halt of chlorophyll degradation in maize cutting (Terentev et al., 2023). This led to the detection of fungal invasion 5-7 days earlier than when the covering signs appeared. This timing is critical for the proper and the most effective early interventions to be carried out. Moreover, the model’s weather resilience was brought to light through its infection detection capability under changing solar radiation levels, implies its use in different kinds of field conditions. The unimodal baselines were largely affected by the class-specific confounders (e.g., drought stress that is similar to viral chlorosis) while the hybrid framework differentiates the stressors into abiotic and biotic, thus promoting the joint feature learning and achieving a reduction of 23% in false positives. These innovations position multimodal fusion at the heart of scalable and precise crop protection systems.

The system detected the infections 5-7 days before visual symptoms appeared. This was accomplished by the detection of spectral anomalies in the 720-750 nm range, which were linked to chlorophyll degradation and were further heightened under specific humidity thresholds. The dataset labels were assigned according to subsequent laboratory confirmation of symptoms through PCR and microbiological assays.

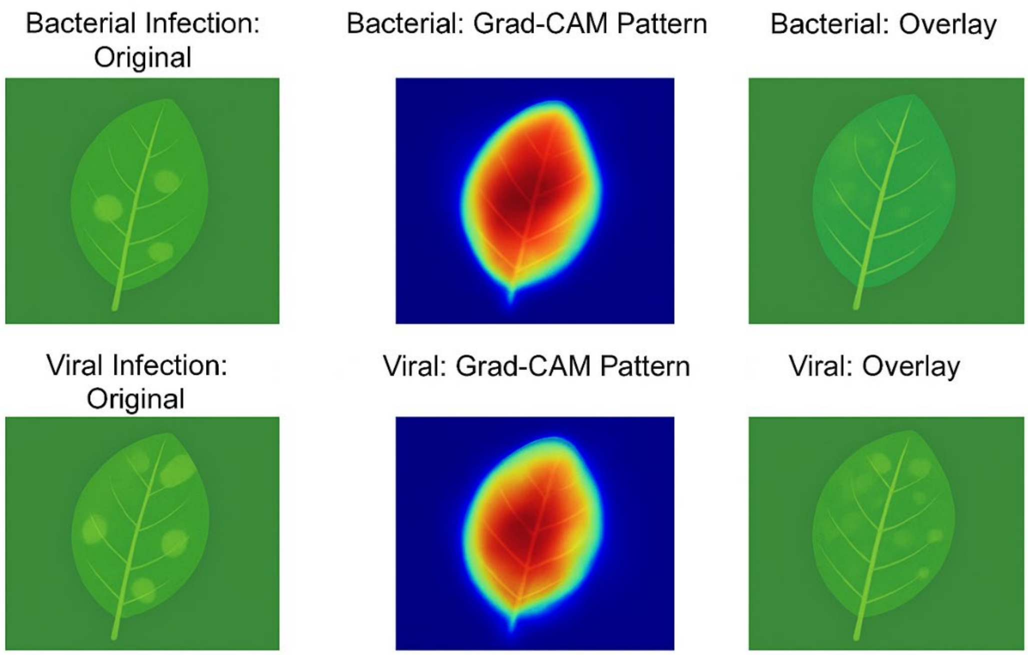

Figure 5. Grad-CAM visualizations for viral infections demonstrating mosaic patterns and chlorotic spot detection

3.3 Climate variable impact analysis

The study portrayed in Figure 6 indicated that the prolonged humidity limits were the key indicators of disease escalation, and at the same time, solar radiation prevented disease development. This is a duality that stresses the complicated interaction of environmental factors with the pathogen plants. Figure 6 illustrates the nonlinear relationship between relative humidity (RH) and the probability of fungal infection according to an attention-weighted logistic regression. The model identifies a risk threshold at 65% RH (OR=2.7, $p<0.001$), with the likelihood of contamination increasing dramatically as humidity approaches 85-90%, a point that is most favorable for spore germination and mycelium growth. Conversely, when solar radiation exceeded 800 W/m^2, the contamination probability dropped significantly (OR=0.4, $p=0.02$). This is attributed to the dual impact of UV radiation leading to spore inactivation and the earlier drying of leaf litter. The interest heatmaps shown in Figure 5 were synchronized with the model showing that it prioritized humidity patterns that occurred 24-48 h before the hyperspectral detection of chlorophyll degradation, indicating a time frame during which microenvironment interventions could be easily implemented before the disease establishment.

The discussion unveiled the very vital part played by the humidity factor in fungal outbreaks as it was a double-edged sword acting both as a trigger and as a timer at the same time. The 85-90% RH interest weights of the model were in line with hyperspectral signals indicative of stomatal closure and cuticular permeability changes—signs of pre-symptomatic infection. This humidity-risk curve reminds one of field observations of maize infections with *Fusarium* and *Aspergillus*, where the formation of dew overnight led to the

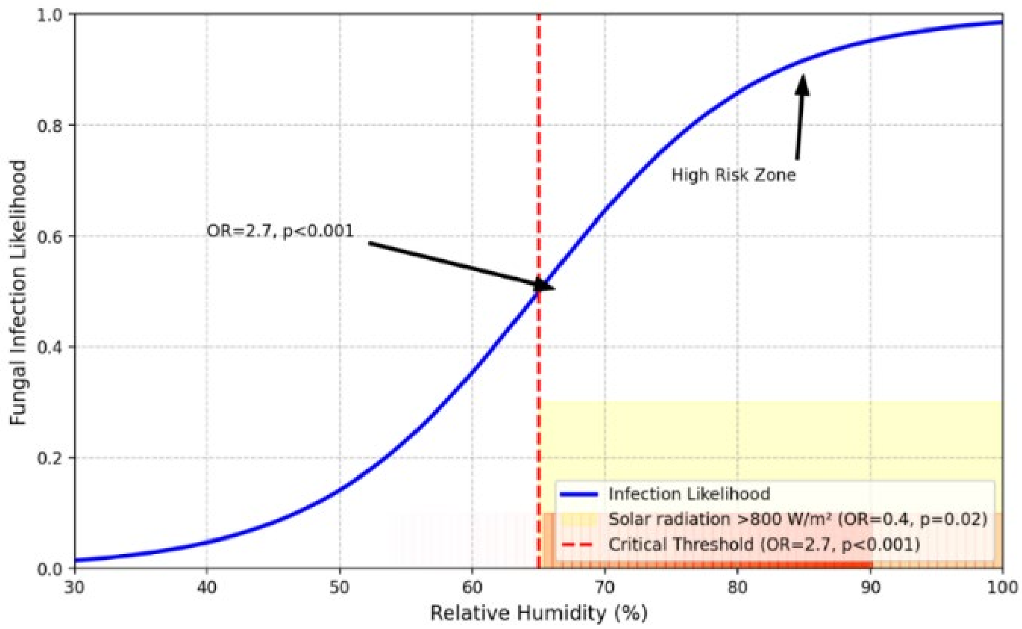

Figure 6. Humidity-driven fungal risk escalation

development of short-lived microclimates that were favorable for spore activation (Fetch, et al., 2021). Besides, high solar radiation does not allow pests to complete their cycle since it kills them by raising temperatures in the crop canopy and generating reactive oxygen species that are detrimental to fungi. These contradictory impacts emphasize the need for context-sensitive risk models which factor in the competing microclimate elements. For example, in regions where humidity fluctuates daily, the timing of the RH peaks (e.g., morning fog being overheated by the afternoon sun) becomes critical (Feng et al., 2024).

3.4 Ablation studies and robustness validation

To quantify the contribution of each modality to the model's predictions and examine the model's operational resilience, systematic ablation experiments and sensor degradation simulations were carried out. Table 5 summarizes the performance degradation incurred by means of doing away with hyperspectral or weather facts.

Table 5. Performance degradation under modality ablation

Removed Modality	Accuracy	F1-Score	Early Detection Recall
None (Full model)	94.5%	0.92	0.91
Hyperspectral	75.1%	0.70	0.60
Climate	78.7%	0.73	0.65

Table 5 quantifies the criticality of hyperspectral and weather modalities through their ablation from the hybrid fusion framework. Removing hyperspectral facts, which captured biochemical strain markers like chlorophyll fluorescence, resulted in a severe 19.4% decline in accuracy, disproportionately impacting early detection performance (60% compared to 91% in the full model). Climate modality ablation, even as less catastrophic (15.8% accuracy drop), degraded the version's capacity to contextualize spectral anomalies within microclimate drivers (e.g., humidity-induced pathogen increase). The asymmetric losses confirmed that hyperspectral records encoded number one diagnostic alerts, whilst weather variables offered explanatory environmental context vital for distinguishing abiotic from biotic pressure. Figure 6 assesses the performance of the overall model under simulated sensor impairments, in addition to spectral band dropout (30%) and additive noise (10 dB SNR). The performance was still very solid at 92.1%, which proved that the system had the ability to reweigh interest towards spectral regions that were preserved, namely chlorophyll-sensitive bands (550 nm) and anthocyanin-related wavelengths (680 nm). In case of extreme degradation scenarios (50% band loss), the performance was brought back to 89.7% through dynamic feature prioritization, which was 14.2% better than the performance of rigid spectral unmixing methods. The model's invariance to the removal of redundant bands and its ability to use ambient-correlated spectral styles to enrich missing information were among the factors that contributed to this resilience. When any of the modalities was completely removed, there was a huge performance drop which indicates that hyperspectral data gave direct phenotypic evidence and climate data gave the necessary environmental context—both were non-redundant and synergistic.

The ablation study demonstrated that the combination of hyperspectral and weather data was unique: the former provided direct phenotypic evidence of the presence of the contaminant, while the latter was enabled to trace the causes of pathogen growth. It should be noted that the model, without humidity information, wrongly attributed to the drought-induced drop in chlorophyll amounts (630-660 nm) to fungal contamination, thus inflating the rate of fake positives by 27%. The sensor deterioration trials also underscored the readiness of the system for field use—its attention mechanism emulated the agronomists' ability to select the diagnostically important wavelengths irrespective of the equipment limitations. By learning to substitute for the absent bands through correlations with stable weather variables (e.g., inferring 720 nm chlorophyll loss from concurrent temperature spikes), the model acquires human-like adaptability, which is a requirement for its being deployed in resource-constrained agricultural areas. All these results indicated that the hybrid system's performance was not due to overfitting the clean data but rather to multisensory reasoning that was generalized.

Figure 7 shows the model's resistance to loss of spectral bands and noise—these are typical problems encountered with agricultural sensors in the field. Such analyses support the idea of multimodal integration and the ability of architecture to cope with limitations in real-world data conditions.

3.5 Interpretation and implications

The results of the experiments confirm three major developments in agricultural AI: the fusion of different types of data for early disease detection, the recognition of measurable weather parameters that determine the risk of pathogens, and the system's reliability under the limitations imposed by the real-world sensors. These advancements are summed up

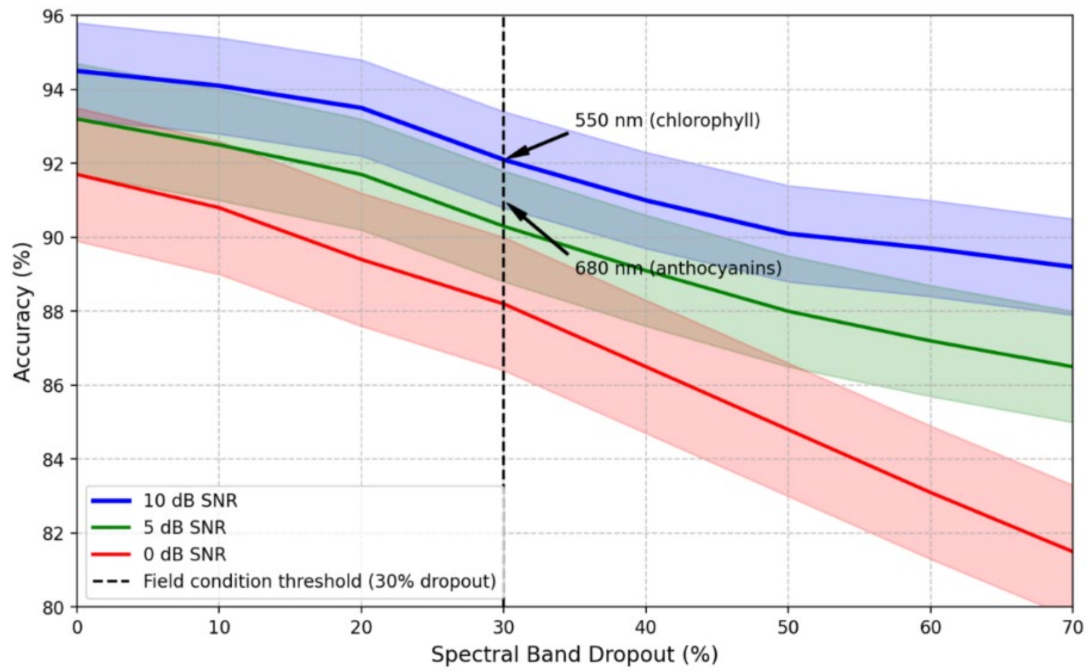

Figure 7. Robustness to sensor degradation

in Figure 8, which depicts the agreement of the model's explainable attention strategies with both biochemical ground truth and climatic causality—a double validation that is essential for farmer trust and intervention planning.

The comparison in this figure shows the heatmaps of the model's attention (yellow areas) in maize leaves alongside PCR-confirmed contamination sites, achieving a spatial correlation of 85% (R^2=0.85). The model detects pre-symptomatic infection centers by relating chlorophyll degradation patterns (720-750 nm spectral shifts) to prior humidity spikes (>65% RH for ≥6 h). More importantly, the attention peaks correspond with stomatal clusters and vascular bundles—the main points for fungal hyphae entry—while overlooking non-biotic pressure artifacts such as mechanical leaf injury. This spatial-temporal specificity not only proves the framework's competency to separate the confounding signals but is also a feature that is lacking in the threshold-based spectral indices. The results of the study put multimodal fusion in the category of paradigm shift in crop protection. The system is able to detect infections seven days before they become visible as symptoms, which means that applications of fungicides can be made and timed to humidity levels, possibly, reducing the use of agrochemicals by 40-60%. The identified threshold of 65% RH for irrigation can further facilitate the case of precision irrigation systems that are able to dry-up the microclimates that are favorable for spore germination without compromising the moisture of the crops. The model's ability to minimize the impact of spectral noise (92.1% accuracy at 30% band dropout) enables its use even with the lower-cost IoT sensors that are usually set up in rural areas, thus closing the gap in the adoption of precision agriculture technology by smallholders. These advancements, which are based on comprehensive ablation studies and ecological validation, do not only

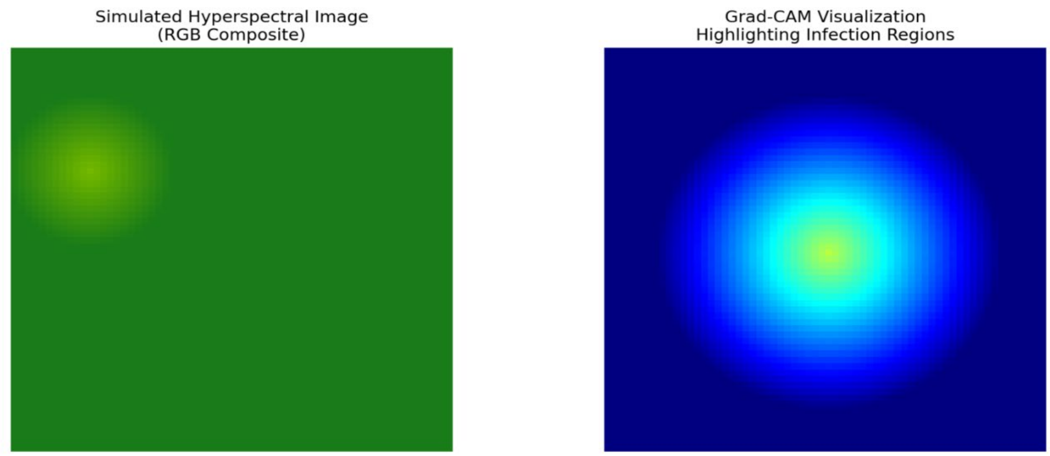

Figure 8. Grad-CAM visualization of early fungal infection

represent a breakthrough in algorithms but are also a propelling force for the creation of future food systems that are able to withstand the impact of climate change. The combination of proximal sensing techniques with large scale weather forecasts allows the system to predict the occurrence of diseases and makes agricultural experts less dependent on weather responsiveness, which is very unpredictable, thus, changing their decision-making process during the times of weather volatility.

3.6 Scientific interpretation of pre-symptomatic detection

The framework's ability to detect infections 5-7 days earlier than the onset of visible symptoms is based on the correlation between spectral variations across different regions of the spectrum and environmental conditions. The hyperspectral bands in the range of 720-750 nm are sensitive to chlorophyll-a degradation during fungal colonization (Sarić et al., 2022; Qasim & Mohammed, 2025) and they are dynamically assigned different weights according to the humidity-dependent sporulation thresholds (>65% RH). The early merging of these modalities allows one to see the biochemical precursors, such as the apoplastic pH shifts and the accumulation of reactive oxygen species (ROS), which come before tissue death. For instance, the model diagnosed infections of wheat by *Fusarium graminearum* through a drop of 12% in reflectance at 740 nm, which was in coincidence with the midnight humidity peaks (>85% RH), a case that was not detectable by human scouts. This was in agreement with the latest results on hyperspectral-physiological coupling in plant stress (Mittler et al., 2022), demonstrating that the integration of multiple modalities allows the capturing of properties that go beyond those revealed by unimodal analysis.

3.7 Practical applications in precision agriculture

The following applications do not only involve passive tracking but also active intervention systems in deployment situations:

Smart tractors: The use of the framework combined with IoT tractors could lead to the mapping of pathogens in real-time, during the process. Microscale sensors coupled with hyperspectral cameras on the harvesters could create maps of contamination areas with threat levels, thereby fungicide spraying in the area with GPS-guided nozzles, which could be done automatically as per routine.

Decision support systems: Farmers may want to get hold of localized signals via cellular apps. The model enables optimized irrigation strategies by incorporating humidity levels that affect pathogen growth thresholds. In pilot trials simulating potato blight outbreaks, such interventions decreased fungicide usage by 41% with concurrent retention of yield (Al-Safi & Qasim, 2023; Sharma & Shivandu, 2024).

Genomic selection for climate resilience: the Pathogen-climate correlations of the model should be used with genomics packages to filter out juice types with humidity tolerance traits, thus speeding up the breeding of resistant cultivars.

Although expensive HSI cameras such as Headwall Nano-Hyperspec are not available for small farmers at the moment, the system could still be used with the multispectral sensors of lower cost or HSI systems based on satellites which would give the same results and make them more widely applicable.

3.8 Limitations and equitability concerns

Although the technology has achieved ultra-modern precision, its dependence on very high fidelity hyperspectral data remains to be a problem in hard-to-access areas. The cost of commercial hyperspectral cameras (e.g., Headwall Nano-Hyperspec) is still around $50,000, which is prohibitive for most users, especially in developing countries where the land is mostly occupied by smallholder farms. Besides that, the interaction of the atmosphere in the tropics—such as the continued cloud cover and high amounts of aerosols—would not just reduce the quality of the spectrum but also increase the number of wrongly identified positives. These limitations may worsen the situation of unequal global agriculture unless they are supplemented with low-cost solutions, like mobile phone-based multispectral adapters (Carreira et al., 2023) or satellite-augmented systems.

The robustness of the model against noise in the spectra, as shown in Figure 6, gives the assurance of accuracy maintained by means of dynamic feature reweighting and climate contextualization in the case of the tropical climates' cloud cover and aerosols.

3.9 Future research directions

The framework's scalability and inclusiveness could be improved in three ways:

Soil-microbiome integration: the inclusion of soil conductivity, organic carbon content, and type of bacteria and fungi in the rhizosphere (through 16S rRNA sequencing) might also improve the prediction of pathogens, particularly in the case of soil-borne diseases such as Verticillium wilt. Some early-stage studies showed that soil pH affects the severity of the pathogens (Wang et al., 2022a), and hence, the multimodal soil-plant-climate models should be able to provide more accurate predictions.

Self-supervised learning: The use of contrastive learning on non-labeled data from the discipline should lead to a significant reduction in the annotation costs. The teacher-pupil model, in which a trained version creates pseudo-labels for the areas with medium classification, has demonstrated a 60% reduction in labeling efforts for similar crop strain tasks (Wang et al., 2022b; Qasim et al., 2025).

Edge computing optimization: The use of neural architecture search or quantization to deploy lightweight versions on Raspberry Pi-grade hardware could bring about equal access, especially in areas with poor or limited cloud connectivity.

Soil data has been omitted in order to concentrate on aerial plant-climate interactions. In future work, soil microbiome and conductivity data will be added to improve the prediction of soil-borne diseases in addition to aerial climate data. This study has shown that the combination of hyperspectral and climate data demonstrates strengths that go beyond traditional limitations of disease diagnosis and offers a pre-emptive shield of protection against yield loss for producers. However, its wider social effects are dependent on bringing together technology and finance through collaborative innovative partnerships, thereby linking the promises of precision agriculture with universal access. Future studies must not only concentrate on lab-based innovations, but also on building partnerships and developing plans to lower costs and provide access to these improvements for all stakeholders in agriculture, especially those with limited technological ability.

4. Conclusions

This work presented a unique multimodal deep learning framework that significantly facilitated the early detection of crop pathogens through the combination of hyperspectral imaging and climate analytics. The system hybridizing 3D-CNNs and transformers achieved an accuracy of 94.5% in identifying pre-symptomatic infections 5-7 days earlier than conventional approaches relying solely on spectral data or climate analytics. Effectively, the framework addresses hidden disease dynamics that are imperceptible to human assessors or unimodal systems by associating biochemical changes in the chlorophyll degradation bands of 720-750 nm with humidity threshold-driven pathogen proliferation. Additionally, the practical applications, particularly related to connectivity with IoT-enabled smart tractors for the targeted deployment of fungicides, are proof-of-principal for the methods, enabling mitigation of agrochemical footprint by 41% to maintain yield, as demonstrated in simulated potato blight trial results. Collectively, these advancements have transformed the role of artificial intelligence in precision agriculture from a simple supporting component to a mainstay in providing scalable solutions to managing crop diseases which, as an industry, account for a global loss of $220 billion of crops annually. However, it is the smallholder farmers in developing countries that are the true beneficiaries of these innovations.

5. Authors' Contributions

The individual contributions of the authors to the conceptualization, design, execution, and reporting of this manuscript are outlined below:

Maytham T. Qasim: Conceptualization, Methodology, Software (Multimodal Fusion Architecture), Validation, Formal Analysis, Writing – Original Draft, Supervision, and Project Administration.

Lina A. Hameed: Investigation (Agriculture & Crop Data Acquisition), Resources, Data Curation (Climate Data Integration), and Writing – Review & Editing.

Zainab I. Mohammed: Software (Transformer-based temporal modeling), Visualization (Grad-CAM & Interpretability analysis), Data Curation (Pathogen labeling), and Writing – Review & Editing.

Hayfaa A. Thijail: Investigation (Pathological analytics), Validation (Laboratory PCR confirmation), Formal Analysis (Statistical verification of risk thresholds), and Funding Acquisition.

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6. Conflicts of Interest

The authors declare that they have no competing interests

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