

Review

Intelligent Agriculture for Plant Disease Management: A Critical Review of Operational Value, Field Reliability, Adoption Barriers, and Research Priorities

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Abstract: Plant disease management increasingly integrates artificial intelligence (AI), Internet of Things (IoT) sensing, remote and proximal sensing, disease forecasting, robotics, cloud-edge computing, and decision-support systems (DSS). This critical narrative review evaluated their operational value, reliability under production conditions, barriers to adoption, and priorities for improving field performance. An initial 99-record bibliography was screened, yielding 45 eligible sources; targeted searches of DOI/indexing services and publisher databases from 2010 to July 2026, while retaining earlier foundational studies, identified 35 additional DOI-verified sources, producing an 80-reference corpus. Evidence was appraised across five deployment-oriented domains: field representativeness, diagnostic ground truth, comparator quality, uncertainty and failure reporting, and operational outcomes. Intelligent tools provide three main benefits: earlier or more scalable detection, continuous and spatially explicit risk assessment, and targeted intervention. Field evidence is strongest for established disease-warning systems and selected precision-spraying applications, whereas image classifiers, foundation models, and autonomous robots remain more commonly validated in curated or crop-specific settings. Distribution shift is a major reliability concern, with commercial-field studies showing substantial performance losses under open-set conditions. Wider adoption is constrained by interoperability, cost, maintenance, connectivity, data governance, trust, liability, and unequal access. The most credible near-term pathway is supervised, context-sensitive autonomy. Future progress requires multi-farm and multi-season validation, explicit uncertainty reporting, FAIR (Findable, Accessible, Interoperable, and Reusable) data architectures, economic evaluation, climate-adaptive hybrid models, and end-to-end comparisons with best conventional practice. Intelligent agriculture should therefore be developed as accountable plant-health infrastructure that keeps plant pathologists, advisers, and farmers in the decision loop.

Keywords: Intelligent Agriculture; Plant Disease Management; Artificial Intelligence; Disease Forecasting; Remote Sensing; Precision Crop Protection

1. Introduction

Plant diseases remain persistent biological constraints on crop yield, quality, profitability, and food security. Their global burden is substantial, yet the magnitude and spatial distribution of losses vary with crop, pathogen, climate, market access, and management intensity [1–4].

Disease epidemics arise from interacting host, pathogen, environment, and management processes. Tempera-

ture, relative humidity, rainfall, leaf wetness, soil moisture, crop phenology, cultivar susceptibility, inoculum pressure, and field operations influence infection and epidemic development. Climate change adds nonstationarity by shifting pathogen ranges, host phenology, overwintering, and the frequency of conducive weather windows [5–7].

Visual scouting, laboratory diagnostics, resistant cultivars, sanitation, cultural practices, biological control, and chemical protection remain indispensable. Their limitations are nevertheless familiar: scouting is episodic and observer dependent; confirmatory diagnostics can be slow or costly; and calendar-based or uniform pesticide programs can waste inputs, increase non-target exposure, and intensify resistance selection [8–10].

Precision agriculture introduced site-specific management, whereas smart and digital agriculture extended this logic to connected sensing, predictive analytics, cyber-physical systems, and partial automation [11–15]. In plant health, however, technical capability is not equivalent to management value. A classifier is useful only if it improves a diagnostic or scouting decision; a sensor network is useful only if its data alter risk assessment or intervention timing; and an autonomous platform is useful only if the complete sensing-to-action chain is safe, reliable, and economically justified.

Previous reviews have catalogued sensing, machine-learning, IoT, and robotic technologies, but many treat components separately or emphasize algorithmic performance without testing whether outputs are integrated into disease decisions [16–19]. The distinctive contribution of this review is therefore decision-centered and cross-technology: it reorganizes the evidence around four research questions rather than around devices alone, applies an explicit deployment-oriented quality rubric, synthesizes quantitative field results, and proposes a maturity model for integrated plant-health systems.

Research questions:

RQ1. What operational value do intelligent technologies add beyond conventional scouting, laboratory diagnosis, and uniform intervention? RQ2. How reliable is the supporting evidence under real production conditions? RQ3. Which technical, economic, social, and institutional barriers prevent routine adoption? RQ4. Which research directions are most likely to improve field value rather than merely increase technical sophistication?

2. Review Design and Methodology

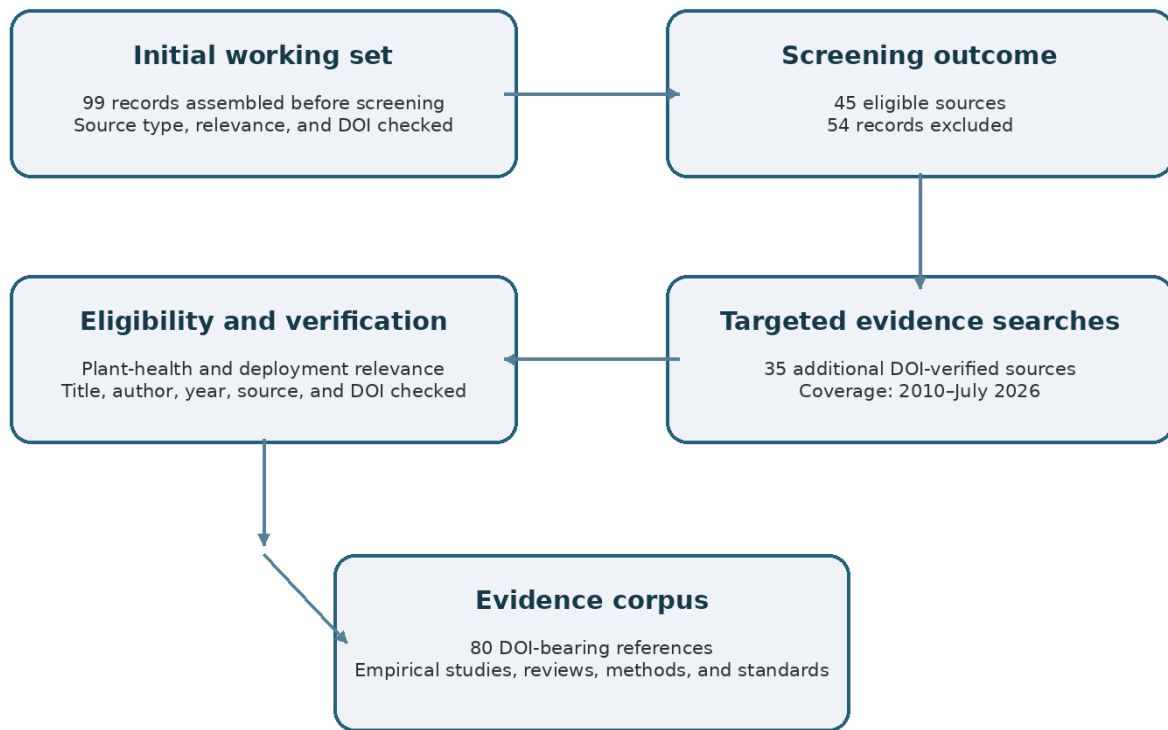
2.1. Review Type and Reporting Approach

This article is a critical narrative review using structured literature screening, targeted evidence searches, and deployment-oriented appraisal elements. It is not a registered systematic review or meta-analysis because the objective is conceptual synthesis across heterogeneous study designs rather than estimation of a pooled intervention effect. Reporting choices were informed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement and its literature-search extension (PRISMA-S), and by the Scale for the Assessment of Narrative Review Articles (SANRA) [20–22].

2.2. Information Sources and Search Strategy

An initial 99-record working bibliography was screened line by line. Records that were non-source objects, off-scope, duplicated, or supported by unreliable bibliographic metadata were excluded. Targeted searches covered publications from 2010 through July 2026; earlier foundational work was retained when it defined widely used epidemiological, precision-agriculture, forecasting, or sensing concepts. Source discovery and verification used Crossref/DOI records, PubMed, IEEE Xplore, and journal or publisher search portals, including ScienceDirect, SpringerLink, Wiley Online Library, and MDPI, together with backward and forward citation chaining. Search concepts combined plant-health terms with technology and deployment terms; the source channels and representative strings are reported in **Appendix A Table A1**. Because this is a critical narrative review and no contemporaneous systematic-review export log was available, retrospective database-hit and deduplication counts are not reported. **Figure 1** summarizes the auditable corpus-development workflow: 99 initial records, 45 eligible sources, 54 excluded records, 35 additional DOI-verified sources, and 80 references in the final corpus.

The diagram summarizes screening of the initial 99-record working set and targeted identification of 35 additional DOI-verified sources, yielding an 80-source corpus. Counts describe corpus development for a critical narrative review and are not PRISMA denominators for a registered systematic review.



Excluded records were non-source objects, off-scope or duplicate items, or entries with unreliable or mismatched bibliographic metadata. The diagram reports corpus development for a critical narrative review, not a PRISMA denominator for a registered systematic review.

Figure 1. Literature identification and corpus-development workflow.

2.3. Eligibility, Screening, and Evidence Extraction

Eligible publications were peer-reviewed articles, reviews, or DOI-bearing conference papers that addressed plant disease detection, surveillance, environmental monitoring, disease forecasting, decision support, precision intervention, robotics, system integration, or adoption. Studies focused only on yield prediction, irrigation, food processing, non-agricultural sectors, or generic algorithms without a plant-health application were excluded. Potentially relevant English-language sources were assessed against these criteria, and the final list was checked for title, authorship, year, source, DOI, and direct relevance to the review questions. E.B. organized the candidate literature and evidence matrix; Y.G. verified the final inclusion set, and differences were resolved by discussion. For each empirical study, the extraction form captured crop, pathogen or stress, technology, environment, dataset or trial scale, validation design, comparator, quantitative performance, operational outcome, cost evidence, and limitations.

2.4. Deployment-Oriented Quality Appraisal

A deployment-oriented appraisal rubric was used because clinical tools such as the Newcastle-Ottawa Scale are not well matched to heterogeneous engineering, agronomic, sensing, field-deployment, and adoption studies (**Table 1**). Five domains were rated from 0 to 2 as an interpretive aid: representativeness and external validation; quality of disease ground truth; appropriateness of comparator or baseline; reporting of uncertainty and failure cases; and measurement of operational, economic, or environmental outcomes. Ratings were not summed into universal quality classes or used as an exclusion threshold because evidentiary requirements differ across classifiers, sensing systems, forecasts, intervention trials, robotics, and social research. Reviews, standards, and conceptual papers were assessed for scope, source transparency, and relevance.

2.5. Synthesis and Limitations of Comparability

Because studies differed in crops, pathogens, units of analysis, disease prevalence, train-test partitions, sensors, treatment programs, and economic contexts, effect sizes were not pooled. Quantitative results are presented as study-specific evidence and are interpreted in relation to validation design. Accuracy from balanced image datasets,

for example, is not compared directly with F1 scores from open-set commercial-field detection or with fungicide reductions in prospective advisory trials.

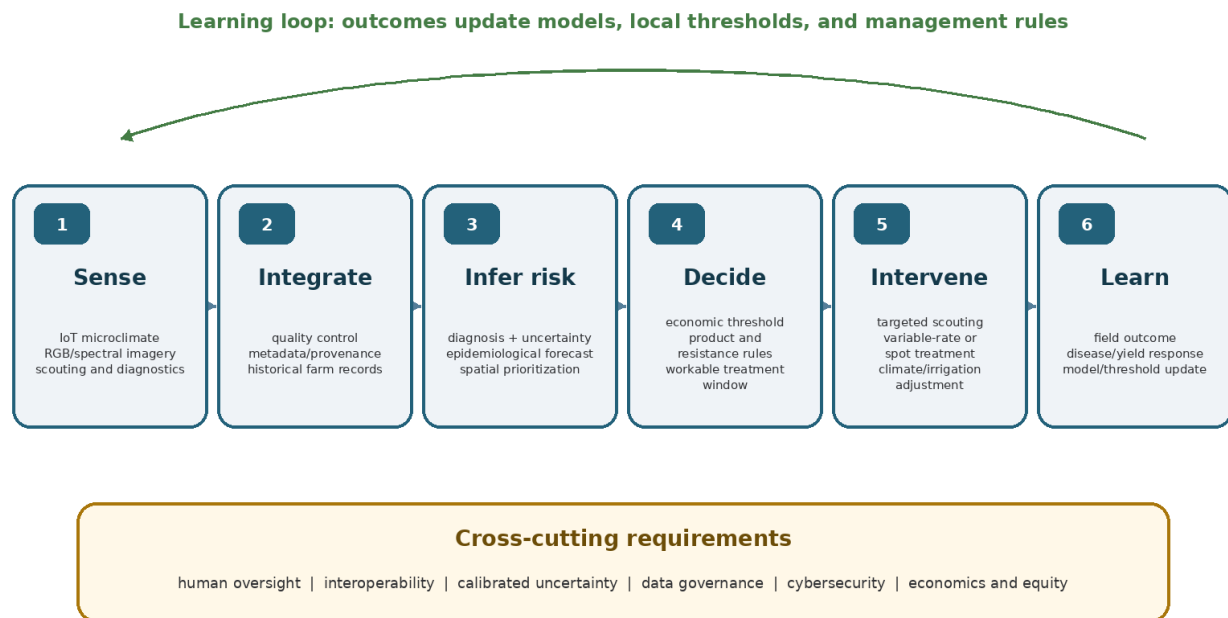
Table 1. Deployment-oriented evidence appraisal rubric.

Domain	0 Points	1 Point	2 Points
Field representativeness	Curated or controlled data only	Limited field data or one site/season	Independent farms, seasons, regions, devices, or open-set testing
Disease ground truth	Visual labels without confirmation	Expert scoring or partial diagnostic confirmation	Independent expert, molecular, culture, or validated severity reference
Comparator	No meaningful baseline	Internal model or conventional baseline	Best available practice, human expert, or prospective management comparator
Uncertainty and failures	Only best aggregate metric	Some class-wise errors or confidence estimates	Calibration, false alarms/misses, failure cases, missing-data or uptime reporting
Operational outcomes	No decision outcome	Proxy such as speed, map quality, or input estimate	Disease, yield, treatment, labor, cost, environmental, or adoption outcome

3. Analytical Framework: Intelligent Agriculture as a Plant-Health Ecosystem

Plant disease management is not a single prediction task. It is a sequence of decisions under biological, temporal, economic, and regulatory constraints: where to inspect, whether symptoms require confirmation, whether infection conditions occurred, when an intervention remains useful, which action is compatible with resistance and residue rules, and whether the outcome justifies updating the recommendation. Effective systems therefore need coordinated intelligence across leaf, canopy, field, farm, and regional scales [6,23,24].

The architecture in **Figure 2** links six functions. IoT sensors, proximal red-green-blue (RGB) cameras, unmanned aerial vehicles (UAVs), satellites, scouting, and laboratory diagnostics provide observations. Data integration supplies quality control, metadata, provenance, and historical context. Models then estimate diagnosis, severity, spread, or infection risk. A DSS combines those estimates with crop stage, cultivar, economics, product constraints, resistance management, and workable weather windows. Intervention may range from targeted scouting or environmental adjustment to variable-rate treatment. Finally, post-intervention observations return to the learning loop. Farm software ecosystems and data standards are essential because value is lost when these functions remain isolated [25,26].



Operational value is created only when the complete chain is timely, auditable, and linked to a feasible crop-protection decision.

Figure 2. Intelligent plant-health ecosystem.

The evidence-to-action chain connects sensing, integration, risk inference, decision support, intervention, and feedback learning. Human oversight, interoperability, uncertainty, governance, cybersecurity, economics, and equity are cross-cutting requirements.

This ecosystem framing also clarifies responsibility. A disease map is not a recommendation; a recommendation is not an intervention; and an intervention is not evidence of benefit unless the outcome is measured. Each transition can introduce delay, uncertainty, or bias. The review therefore distinguishes component performance from workflow performance and uses the latter as the primary definition of deployment readiness.

4. RQ1: Operational Value beyond Conventional Practice

4.1. Earlier and More Scalable Detection

AI has demonstrated that visual symptom patterns can be learned at scale. Curated-dataset studies reported very high classification performance: Mohanty et al. achieved 99.35% on held-out PlantVillage images, Ferentinos reported 99.53% across 87,848 images and 58 crop-disease classes, and fine-tuned deep networks frequently exceeded 99% in benchmark settings [27–30]. The operational advantage is speed and consistency: a smartphone or edge device can triage many images, standardize symptom recording, and prioritize expert attention.

The value proposition is strongest when sensing reveals information before symptoms are readily visible. Airborne hyperspectral and thermal data have detected disease-associated physiological changes in olive and *Xylella*-infected trees, while recent controlled studies reported more than 90% previsual detection of sugarcane smut and mosaic and successful early discrimination of tomato fungal and bacterial diseases using hyperspectral or handheld spectroscopy [31–35]. Multispectral segmentation and transformer descriptors have also been applied to early *Botrytis* detection [36,37].

These results show that intelligent sensing can shift plant health from symptom confirmation toward anomaly detection and risk prioritization. They do not, by themselves, prove that treatment can be advanced or losses reduced. Previsual detection is actionable only when it is pathogen-specific enough, arrives before an effective intervention window closes, and is linked to confirmatory or precautionary rules appropriate to the cost of error.

4.2. Continuous Risk Monitoring and Forecasting

IoT monitoring adds temporal resolution that periodic scouting cannot provide. Leaf wetness, temperature, humidity, rainfall, soil moisture, and canopy conditions can identify infection periods and update disease forecasts continuously. Low-power wireless networks and long-range communication technologies make local monitoring feasible, although energy, calibration, and connectivity remain design constraints [38–40].

The most convincing management evidence comes from prospective disease-warning and DSS trials. In 83 French vineyard plots over four years, the Mildium system maintained protection while reducing fungicide treatments by 30–50% relative to grower practice. A Chilean powdery-mildew strategy maintained severity below 3% with two to three treatments and reduced cost by 40–60%. A 2024 vineyard study combining a predictive model with targeted biological control reported more than 75% reduction in synthetic fungicide use while maintaining satisfactory control [41–43]. A recent IoT apple-orchard pilot reported reductions of up to 50% in pesticide use for codling moth and more than 33% in fungicide use for powdery mildew, illustrating the potential of integrated monitoring rather than sensing alone [44].

Forecasting therefore creates value by changing the timing or necessity of action. Useful performance metrics include warning lead time, false-alarm and missed-event rates, number of treatments avoided, disease severity, yield, labor, and cost. Statistical accuracy without an explicit decision threshold is insufficient because the same forecast can be valuable in a high-value greenhouse crop and unusable in a low-margin rainfed crop.

4.3. Spatially Targeted Intervention and Robotics

Remote sensing provides spatial coverage that manual scouting rarely achieves. Satellite platforms offer repeated regional observations, while UAV and ground systems provide flexible, high-resolution mapping. Sentinel-2 red-edge information is useful for chlorophyll and canopy traits, but spatial resolution, clouds, revisit intervals, and disease specificity determine whether satellite products can guide crop protection [45–47]. Vegetation and thermal signals reflect stress rather than pathogen identity; drought, nutrient deficiency, heat, herbicide injury, insects, and

disease can overlap spectrally [48,49].

Robotics closes part of the gap between detection and action by standardizing scouting or delivering localized treatment. Agricultural robots can reduce repetitive labor and improve measurement density, but field navigation, throughput, occlusion, illumination, battery life, and safe actuation remain limiting [50–52]. Variable-rate spraying has been demonstrated in nursery and specialty-crop systems, and newer camera-DSS-sprayer architectures can geolocate disease detections for spot-specific treatment [53,54].

Recent evidence shows a progression from prototypes toward supervised field operation. PhytoPatholoBot was deployed in research and commercial vineyards and reported disease detection and severity estimates comparable to experienced human scouts while operating with low-power onboard processing [55]. Such systems are likely to enter high-value, structured crops before broad-acre systems because the economic value per hectare is higher and row geometry is more predictable (Table 2).

Table 2. Representative quantitative evidence for intelligent plant disease management.

Study	Technology and Setting	Quantitative Result	Management Implication	Important Limitation
Mohanty et al. (2016) [27]	Deep CNN; PlantVillage plus external web images	99.35% held-out accuracy; 31.4% on external images	Fast image triage is feasible	Large domain-shift penalty; external set not a prospective farm trial
Ferentinos (2018) [28]	Deep CNNs; 87,848 images, 58 classes	Best accuracy 99.53%	Broad multi-crop recognition in curated data	Controlled image distributions; no intervention outcome
Polder et al. (2025) [54]	Embedded RGB camera in commercial grape, apple, and carrot fields	Closed-set F1 66.3/45.1/42.1%; open-set F1 34.8/5.5/4.2%; 31 h without hardware/software failure	Direct evidence that field transfer, not benchmark ranking, is decisive	Disease-specific F1 remained too low for unsupervised treatment
Bao et al. (2024) [33]	Hyperspectral imaging + spectral-spatial deep learning; inoculated sugarcane	>90% detection before visible smut and mosaic symptoms	Previsual surveillance is technically possible	Controlled trial; cost and disease-management benefit not tested
Reis-Pereira et al. (2024) [35]	Handheld ultraviolet-visible (UV-Vis) spectroscopy; tomato bacterial disease	100% sensitivity in training and validation sets before macroscopic lesions	Potential low-cost anomaly triage	Controlled inoculation and limited external validation
Deliere et al. (2015) [41]	Mildium DSS; 83 vineyard plots over 4 years	30–50% fewer treatments while maintaining protection	Prospective, multi-site treatment reduction	Region- and disease-specific expertise rules
Valdes-Gomez et al. (2017) [42]	Powdery-mildew DSS; two Chilean vineyards, four seasons	Severity <3%; 2–3 treatments; 40–60% lower cost	Demonstrates agronomic and economic value	High-value perennial crop; transfer requires local calibration
Altieri et al. (2024) [43]	Forecast model + targeted biocontrol; vineyards	>75% reduction in synthetic fungicide use with satisfactory control	Links forecast to lower-chemical intervention	Biocontrol efficacy remains environment dependent
Jamshidi et al. (2025) [44]	Integrated IoT orchard monitoring and management; pilot	Up to 50% pesticide and >33% fungicide reduction	Shows value of multi-function farm platform	Pilot scale; long-term maintenance and return on investment unclear
Liu et al. (2026) [55]	Autonomous ground robot; research and commercial vineyards	Detection/severity comparable to experienced scouts	Near-real-time autonomous scouting is emerging	Specialty-crop platform; large-scale economics not yet established

4.4. Comparative Value and Current Readiness

Across technologies, added value falls into three categories: information that is earlier than routine observation; information that is more frequent or spatially complete; and action that is more targeted (Table 3). Readiness is highest where the biological decision rule is already established and technology improves measurement or delivery. It is lower where the system must infer pathogen identity from ambiguous signals or make unsupervised treatment decisions in heterogeneous environments. Closed-loop autonomous disease management therefore remains at low readiness and is better represented by the maturity model in Figure 3 than as a routine field technology.

Table 3. Comparative contribution and deployment readiness by technology.

Technology	Distinct Operational Contribution	Strongest Current Evidence	Main Unresolved Risk	Indicative Readiness
Image AI/smartphone	Rapid triage and standardized symptom recording	Curated multi-crop classification; growing open-set evidence	Dataset shift, unknown classes, mixed stresses	Moderate for human-assisted triage; low for stand-alone diagnosis
Hyperspectral/thermal/proximal sensing	Previsual anomaly detection and physiological characterization	Controlled early-detection studies; selected field demonstrations	Specificity, calibration, cost, environmental sensitivity	Moderate for research/high-value crops

Table 3. *Cont.*

Technology	Distinct Operational Contribution	Strongest Current Evidence	Main Unresolved Risk	Indicative Readiness
Satellite/UAV surveillance	Spatial hotspot mapping and epidemic tracking	Repeated canopy-scale coverage with targeted ground truth	Clouds, revisit, confounding stress, processing delay	Moderate to high for surveillance; lower for diagnosis
IoT microclimate + forecast	Continuous infection-risk estimation and timely warning	Prospective disease-warning systems with treatment reduction	Sensor drift, missing data, local calibration, alert fatigue	High for well-studied diseases and supported regions
DSS	Combines biology, economics, product rules, and feasibility	Established vineyard and orchard examples	Poor interoperability, opaque thresholds, weak maintenance models	Moderate to high when locally supported
Robotic scouting	Repeatable high-density observations with geolocation	Commercial-field prototypes and specialty-crop robots	Navigation, throughput, perception, capital and service cost	Moderate in structured high-value crops
Smart/variable-rate intervention	Targets product to mapped risk	Selected nursery, orchard, and vineyard systems	Missed disease, drift, resistance, liability	Moderate to high in selected systems

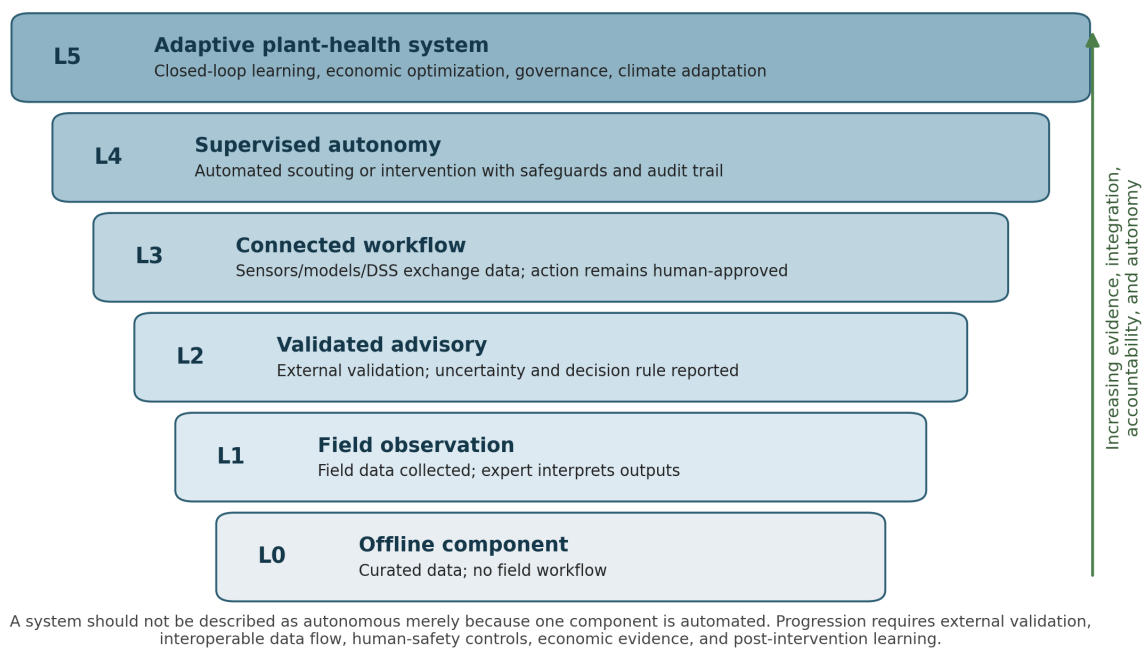


Figure 3. Deployment maturity model for intelligent disease management.

Progression from an offline component to an adaptive plant-health system requires external validation, interoperable workflows, accountable human or automated action, economic evidence, and feedback learning.

5. RQ2: Reliability under Real Production Conditions

5.1. Dataset Shift, Leakage, and Open-Set Recognition

The dominant reliability problem in image-based diagnosis is distribution shift between development data and deployment environments. Random image splits can place near-duplicate leaves, backgrounds, or acquisition conditions in training and test sets. Models may exploit background color, imaging artifacts, or cultivar-specific symptom expression rather than disease biology. Dataset size helps, but diversity in geography, cultivar, season, growth stage, symptom severity, camera, and co-occurring stress is more important for transferability [56,57].

The contrast between benchmark and external performance is stark. Mohanty et al. reported 99.35% on held-out PlantVillage images but only 31.4% on external images. Polder et al. observed major F1 declines when models were moved from closed-set to commercial-field open-set data [27,54]. These results do not invalidate AI; they show that random-split accuracy is an incomplete readiness metric.

Field validation should separate farms, seasons, regions, and devices between training and testing. Results should be stratified by disease stage, cultivar, image quality, and confounding stress. Open-set or out-of-distribution (OOD) detection is essential because a field image may contain an untrained disease, insect damage, nutrient deficiency, or no interpretable symptom. The safe output in such cases is uncertainty and escalation, not a confident forced label.

5.2. Convolutional Neural Networks, Vision Transformers, and Multimodal Models

Convolutional neural networks (CNNs) remain attractive because they are efficient, well characterized, and compatible with edge deployment. Vision transformers (ViTs) can model longer-range relationships and have produced strong smartphone-based disease classification, but often require more data or pretraining [58]. Architecture comparisons are meaningful only when train-test separation and field conditions are equivalent; a small benchmark improvement is less valuable than robust calibration or a lower false-negative rate at early infection.

Multimodal and vision-language approaches are expanding the task from image labeling toward context-aware explanation. Recent studies combine images with text or sensor information, support few-shot learning, and generate question-answering outputs [59–61]. Foundation models may reduce task-specific labeling and support transfer, but their benefits depend on agricultural pretraining data, domain adaptation, compute, licensing, and expert validation [62,63]. Their explanations should not be accepted as agronomic reasoning merely because they are fluent.

5.3. Explainability, Calibration, and Diagnostic Pathways

Explainable AI methods can reveal whether a model attends to lesions, leaf margins, or irrelevant background regions [64,65]. However, saliency and attention maps are not causal proof and can be unstable. Explanations should be evaluated by plant pathologists against symptom biology and should indicate uncertainty, alternative causes, and the next safe action.

A realistic diagnostic pathway is tiered. AI may prioritize scouting, standardize image capture, suggest likely causes, and connect symptoms to weather-based risk. Expert or laboratory confirmation remains appropriate for quarantine organisms, first reports, visually ambiguous syndromes, or decisions with high financial or regulatory consequences. The objective is not to replace diagnostics but to allocate diagnostic effort more efficiently.

5.4. Specificity and Ground Truth in Remote Sensing

Disease, drought, nutrient deficiency, heat, herbicide injury, and insects can all alter chlorophyll, canopy temperature, water status, and reflectance. Remote sensing therefore often detects stress before it identifies cause. Disease-specific claims require spatially and temporally matched ground truth, healthy and abiotic-stress controls, severity ratings, and diagnostic confirmation [16,17].

A visually compelling map is not validation. Ground-truth points should sample the full severity range and include areas predicted as healthy, uncertain, and stressed for other reasons. Sensor specifications, radiometric calibration, illumination, weather, spatial resolution, preprocessing, and map-generation thresholds should be reported. Temporal trajectories and sensor fusion can improve specificity because disease progression differs from transient water or heat stress, but these benefits require prospective testing.

5.5. Forecast, IoT, and Robotic Reliability

Forecasting reliability depends on biological validity, local calibration, weather quality, and lead time. Empirical models may be transparent but region-specific; mechanistic models are interpretable but parameter intensive; data-driven models can capture nonlinear relationships but can learn spurious correlations; and hybrid models can combine epidemiological structure with adaptive calibration [23,66]. Climate change makes historical thresholds progressively less stationary.

IoT studies should report sensor uptime, calibration drift, missingness, battery replacement, communication loss, maintenance time, and alert delivery, not only architecture. Robotics studies should add navigation failures, coverage, throughput, occlusion, safety stops, processing latency, crop damage, false-negative escape, and intervention accuracy (Table 4). A 31-h malfunction-free camera test is useful hardware evidence, but low open-set disease F1 still limits autonomous treatment. Reliability is the joint probability that every required component

works within the biological decision window.

Table 4. Common sources of overestimation and recommended validation corrections.

Threat	How Performance Is Inflated	Operational Consequence	Recommended Correction
Random image split/ near-duplicate leakage Late, obvious symptoms	Acquisition-specific cues appear in both training and test sets Easy cases dominate datasets	Unexpected failure on new farms or devices Missed early intervention window	Farm-, season-, region-, and device-independent testing Severity-stratified sampling; latent/early samples with confirmation
Closed-set classification	Every image is forced into a known class	Confident error on unknown disease or abiotic stress	Open-set/OOD testing and abstention thresholds
Sparse or biased ground truth	Only obvious hotspots are confirmed	Remote-sensing specificity appears higher than it is	Balanced healthy/diseased/abiotic controls and independent diagnosis
Single-site weather calibration	Local correlations are treated as universal	Forecast false alarms or misses elsewhere	External regional validation and recalibration protocol
Short IoT deployment	Maintenance and drift are not observed	System fails after research support ends	Multi-season uptime, drift, battery, and total-maintenance reporting
Robot evaluated only on detection	Navigation and actuation are ignored	Map cannot be converted safely into treatment	End-to-end coverage, latency, treatment, crop-safety, and failure tests
Aggregate accuracy only	Rare classes and calibration are hidden	False reassurance for emerging disease	Class-wise sensitivity, calibration, cost-weighted errors, confidence intervals

6. RQ3: Barriers to Routine Adoption

6.1. Interoperability and Workflow Fragmentation

Interoperability is a structural barrier because sensors, imagery platforms, farm-management systems, DSS, and machinery often use incompatible data models and proprietary interfaces. A disease map that cannot be imported into a sprayer controller or advisory platform has limited operational value. Reference architectures and farm software ecosystems provide a conceptual basis for modular integration [25].

Internationally recognized approaches should be used where applicable. International Organization for Standardization (ISO) 11783 enables standardized communication with agricultural machinery; OPC Unified Architecture (OPC UA) has been evaluated as a gateway for remote access to ISO 11783 process data [67]. The DEMETER architecture demonstrated interoperability across heterogeneous hardware and software in large agricultural pilots [68]. AgGateway resources such as the Agricultural Data Application Programming Toolkit (ADAPT) can support translation among field-operation data formats, while findable, accessible, interoperable, and reusable (FAIR) principles require transparent data and metadata stewardship [69–71].

Interoperability is not only a file-format problem. Disease systems also need shared semantics for crop, cultivar, pathogen, symptom, severity scale, sensor, observation time, geolocation, diagnostic method, forecast version, treatment, and outcome. Provenance must identify which model, threshold, weather forecast, and product rules produced a recommendation. Without this audit trail, accountability and learning are weak even when data can be transferred.

6.2. Economics and Business Models

Many studies report model accuracy or sensor design without total cost of ownership. Adoption depends on capital cost, installation, calibration, batteries, connectivity, data plans, subscriptions, software updates, repair, operator training, insurance, downtime, and integration with existing machinery. Benefits may include fewer treatments, lower product use, improved timing, avoided loss, reduced scouting labor, better documentation, and reduced exposure. These benefits are crop- and risk-specific.

The decision-support trials summarized above show that economic evidence is feasible: Valdes-Gomez et al. [42] reported 40–60% lower treatment cost, whereas Deliere et al. [41] documented treatment reductions over four years. Yet economic transfer is not automatic. A system justified in vineyards, nurseries, or protected crops may not pay in broad-acre crops with low disease prevalence. Research should report break-even area, sensitivity to disease incidence, service lifetime, labor assumptions, and who bears the cost and captures the benefit.

6.3. Human Factors, Explainability, and Responsibility

Adoption is socio-technical. Farmers and advisers need outputs in familiar agronomic language, visible uncertainty, and recommendations that fit equipment, labor, weather, product availability, and legal constraints. Partici-

patory design is particularly important because technology may otherwise add data entry, alert fatigue, or recommendations that cannot be acted upon [14].

Responsibility should be explicit. The model developer is responsible for validated claims and documentation; the platform provider for data integrity, availability, and version control; the adviser for context-specific interpretation; the applicator for compliant operation; and the farmer for final management under current supervised models. Liability becomes ambiguous when automated decisions cross organizational boundaries. Human-in-the-loop approval is therefore not merely a transitional inconvenience; it is a practical control for uncertain or high-consequence decisions.

6.4. Data Governance, Cybersecurity, and Trust

Digital plant-health data can reveal disease risk, yield potential, management practices, or commercially sensitive field conditions. Farmers may be reluctant to share data when ownership, access, portability, deletion, secondary use, and benefit sharing are unclear. Surveys and legal analysis have linked opaque data licenses and weak governance to reduced trust [72,73].

Cybersecurity is also an agronomic issue. Compromised sensor data can trigger false warnings; unavailable cloud services can delay treatment; and manipulated prescription maps can cause crop damage. Minimum controls include authentication, role-based access, encryption, secure updates, logging, backup and offline modes, incident response, and separation between advisory and actuation permissions. Blockchain can support auditability in some traceability settings, but it does not correct poor data quality, unclear incentives, or unsafe decision logic [74].

6.5. Developing-Country and Smallholder Contexts

Smallholder systems face distinctive constraints: fragmented fields, lower ability to absorb capital risk, intermittent electricity and connectivity, limited repair services, language and literacy barriers, and fewer extension personnel (Table 5). Reviews emphasize that sustainable digital agriculture for smallholders requires affordable devices, shared services, local language, training, participatory design, and viable institutional support [75,76]. Empirical evidence from Vietnam found that education, age, farm size, training, scientist interaction, extension contact, and membership in community organizations influenced adoption [77].

Table 5. Adoption barriers and implementation responses.

Barrier	Failure Mechanism	Evidence or Standard to Use	Priority Response
Interoperability	Proprietary formats and disconnected sensing/DSS/machinery	ISO 11783, OPC UA, DEMETER, AgGateway/ADAPT, FAIR	Open application programming interfaces (APIs), shared ontologies, versioned metadata, exportability
Total cost of ownership	Pilot benefits disappear after research support ends	Multi-year cost, uptime, maintenance, and break-even analysis	Service-level agreements, repair pathways, sensitivity analysis
Rural connectivity and power	Warnings or maps arrive too late; data loss	Low-power wide-area networking and edge-computing design with offline testing	Local processing, store-and-forward, energy budget, graceful degradation
Trust and explainability	Users reject black-box or excessive alerts	Calibrated uncertainty; agronomist-validated explanations	Action-oriented messages, evidence trace, escalation rules
Data governance	Fear of secondary use, lock-in, or unequal benefit	FAIR data management plus transparent contractual governance	Consent, portability, deletion, role-based access, benefit sharing
Cybersecurity	Manipulated or unavailable data affect decisions	Threat modeling and secure software lifecycle	Authentication, encryption, updates, audit logs, manual override
Liability and regulation	Responsibility is unclear across model, adviser, and machinery	Documented model scope and decision authority	Human approval for high-risk actions; incident and recall procedures
Smallholder access	High fixed cost, language, training, and service constraints	Participatory design and extension evidence	Shared infrastructure, local-language/offline tools, public-good weather and advisory services

A “low-cost sensor” is not low cost when replacement parts, calibration, smartphones, data plans, and technical support are unavailable. Promising models include cooperative weather stations, extension-operated diagnostic hubs, pay-per-use UAV services, offline-capable applications, and regional DSS delivered through trusted advisers. Equity evaluation should ask who is represented in training data, who can act on a warning, who owns the resulting data, and whether benefits accrue to farmers or primarily to platform providers.

7. RQ4: Research Priorities That Increase Field Value

7.1. Replace Benchmark-Centric Evaluation with Decision-Centered Validation

Future studies should preregister the intended use: triage, diagnosis, severity estimation, hotspot mapping, forecast, treatment recommendation, or autonomous actuation. The validation population must match that use. Minimum reporting should include data origin, diagnostic confirmation, cultivar, growth stage, severity, co-occurring stress, train-test separation, external sites, devices, model version, computational requirements, calibration, abstention policy, and failure cases. Model cards and deployment datasheets should state where the system must not be used.

Evaluation should weight errors by management consequence. A false negative before a rapidly spreading epidemic may cost more than confusion among late-stage symptoms; a false positive can cause unnecessary pesticide use and erode trust. Decision-curve analysis, cost-sensitive metrics, lead time, and uncertainty calibration can therefore be more informative than overall accuracy.

7.2. Develop Multimodal and Biologically Constrained Models

Images should be combined with information that plant pathologists already use: crop stage, cultivar, recent weather, leaf wetness, field history, symptom distribution, and pathogen prevalence. Multimodal transformers and vision-language models provide mechanisms for combining image, text, and sensor data [59,61,63]. Their output should be constrained by curated disease knowledge and should cite the evidence used for recommendations.

Hybrid forecasting is particularly promising. Mechanistic epidemiology can define infection processes and biologically plausible relationships, while machine learning can update local parameters, detect residual patterns, and assimilate sensor data. This reduces the risk that a high-capacity model learns short-lived correlations and provides a path for climate adaptation.

7.3. Foundation Models, Federated Learning, and Privacy-Preserving Adaptation

Agricultural foundation models may support transfer across crops, sensors, and tasks, but their current readiness is moderate rather than mature. Key requirements are representative pretraining data, transparent licensing, agricultural vocabulary, robust fine-tuning, out-of-distribution detection, and field benchmarks [62]. Few-shot and vision-language studies show potential for data-scarce classes, yet comparative field trials remain limited [60].

Federated and privacy-preserving learning can help multi-farm collaboration where raw data cannot be centralized. Research should not assume that privacy alone creates participation: communication efficiency, non-identical farm data, model poisoning, incentives, and governance must also be solved. Local adaptation should preserve a validated global baseline and record when a model changes sufficiently to require revalidation.

7.4. Climate-Adaptive Disease Forecasting and Digital Twins

Climate change creates a moving target for models calibrated on historical weather and pathogen distributions. Systems need rolling recalibration, scenario testing, uncertainty under novel extremes, and explicit monitoring for performance drift [5,26]. Digital twins can integrate crop state, microclimate, pathogen processes, and management scenarios, but agricultural twins remain limited by model calibration, semantic interoperability, and real-time data quality [78–80].

A disease-management digital twin should be judged by whether it changes a decision—not by visual realism. Useful outputs include expected disease trajectory under alternative spray dates, consequences of a missed weather window, trade-offs between ventilation and energy in protected crops, or the value of additional scouting. Uncertainty must propagate through the twin so that scenario differences are not presented with false precision.

7.5. Move from Components to End-to-End Trials

The most important benchmark is a prospective end-to-end field trial against best available conventional practice. Such a trial should track data capture, model inference, advisory delivery, farmer action, treatment execution, disease severity, yield, product use, labor, cost, environmental indicators, trust, and failures. It should record when a recommendation was ignored and why. A technically correct warning that arrives after the workday or cannot be implemented with available machinery has no operational value.

The maturity model prevents inflated claims of autonomy. A system with an automated classifier but manual data transfer and no validated action rule remains at Level 1. A connected platform that provides externally validated advice with uncertainty may reach Level 2 or 3. Level 4 requires supervised automated action, safeguards, audit logs, and demonstrated safety. Level 5 additionally requires outcome-based adaptation, governance, and climate-aware recalibration.

7.6. Stakeholder Action Agenda

To translate these research priorities into actionable roles, **Table 6** outlines the priority actions, evidence expectations, and long-term responsibilities for the main stakeholder groups involved in the development, deployment, and governance of intelligent plant-health systems.

Table 6. Priority actions by stakeholder group.

Stakeholder	Immediate Priority	Evidence Expected before Scaling	Longer-Term Responsibility
Researchers	Use external and open-set validation; report failures and uncertainty	Prospective multi-site evidence and reproducible datasets/metadata	Maintain benchmarks that reflect crops, regions, devices, and emerging diseases
Technology developers	Design for interoperability, offline operation, maintenance, and human override	Uptime, calibration, cybersecurity, latency, and total-cost documentation	Lifecycle support, model monitoring, recall/update procedures
Plant pathologists and advisers	Define decision context, ground truth, escalation, and safe abstention	Agronomically meaningful error analysis and treatment thresholds	Steward disease knowledge and evaluate explanations
Farmers and producer organizations	Participate in co-design and define acceptable data terms	Demonstrated local benefit, workflow fit, portability, and service support	Collect outcome feedback and negotiate equitable data value
Policymakers and funders	Support public-good weather, extension, testbeds, and open standards	Independent field trials and equity assessment	Clarify liability, data rights, cybersecurity, and access for smallholders

8. Limitations of This Review

This review has four principal limitations. First, it is a critical narrative review based on structured literature screening and targeted evidence searches rather than a registered systematic review; its broad cross-disciplinary scope and the absence of a contemporaneous database-export log mean that retrieval cannot be considered exhaustive. Second, only English-language, DOI-verifiable publications were retained, which improves reference integrity but may exclude useful regional reports, theses, standards, commercial evaluations, and non-English evidence. Third, heterogeneous metrics and trial designs precluded meta-analysis; quantitative results are therefore illustrative and study specific. Fourth, commercial performance, prices, and platform availability change rapidly and are often incompletely documented in peer-reviewed literature. The maturity classifications are evidence-based judgments, not product certifications.

These limitations reinforce rather than weaken the main conclusion: strong claims should be tied to the conditions under which evidence was generated. The review does not rank vendors or assert universal superiority of one architecture. It identifies where credible evidence exists and where field, economic, or governance evidence is still missing.

9. Conclusions

This review answers the four research questions as follows. For RQ1, intelligent agriculture adds value when it supplies earlier, more frequent, or spatially complete information and converts that information into a better-timed or more targeted action. The clearest quantitative benefits currently come from established disease-warning and DSS programs and from selected precision-application systems; AI and advanced sensing have strong diagnostic potential but less frequent evidence of downstream disease or economic benefit.

For RQ2, reliability under production conditions is uneven. Curated image accuracy is often high, but external and open-set studies expose major performance losses. Remote sensing is effective for surveillance but can confuse biotic and abiotic stress. IoT and forecasts require calibration, maintenance, local validation, and timely alerts. Robotic scouting is approaching operational use in structured high-value crops, whereas unsupervised end-to-end disease management remains immature.

For RQ3, the main barriers are not a lack of algorithms or sensors. They are fragmented workflows, incom-

patible formats, weak metadata, uncertain total cost of ownership, rural connectivity, maintenance, limited economic evidence, poor uncertainty communication, unclear liability, data-governance concerns, cybersecurity, and inequitable access. These barriers interact; a technically accurate tool may fail because advice is late, untrusted, unaffordable, or impossible to execute.

For RQ4, research should prioritize external multi-season validation, open-set and cost-sensitive evaluation, biologically constrained multimodal models, climate-adaptive hybrid forecasts, Findable, Accessible, Interoperable, and Reusable (FAIR) data architectures, participatory design, and prospective end-to-end trials. The appropriate near-term objective is context-sensitive, supervised autonomy. Some farms need only a reliable local warning; others can benefit from UAV mapping, edge diagnostics, prescription maps, or robotic scouting. Full autonomy should be reserved for settings where the entire decision chain has been validated and can fail safely.

Researchers should report evidence that supports management decisions; developers should build maintainable and interoperable systems; policymakers should fund independent testbeds, open standards, and equitable advisory infrastructure; and farmers and advisers should remain active co-designers and decision owners. Journals and reviewers should require DOI verification, transparent data provenance, deployment-relevant validation, economic reporting, and clear limitations rather than rewarding benchmark-only novelty. Intelligent agriculture is most credible when it strengthens plant pathology and farmer expertise rather than obscuring them behind automation. Success should be measured by healthier crops, fewer unnecessary inputs, timely and defensible decisions, lower total risk, and benefits that persist after the research project ends.

Author Contributions

Conceptualization, G.Y. and B.E.; methodology and review framework, G.Y. and B.E.; literature collection and organization, B.E.; critical analysis and interpretation, G.Y. and B.E.; writing—original draft preparation, B.E.; writing—review and editing, G.Y. and B.E.; supervision, G.Y.; project administration, G.Y. Both authors have read and agreed to the published version of the manuscript.

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No new data were created or analyzed. The literature-selection counts, source channels, representative search concepts, and evidence-appraisal fields are reported in **Appendix A**.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

AI-assisted tools were used only to support language editing, readability, document formatting, and DOI cross-checking during manuscript preparation. The authors reviewed, verified, and approved all scientific content, inter-

pretations, references, and conclusions, and they take full responsibility for the final manuscript.

Appendix A

Table A1. Source channels, core search concepts, and representative Boolean strings.

Concept Block	Representative Query
Source channels	Crossref/DOI records; PubMed; IEEE Xplore; ScienceDirect; SpringerLink; Wiley Online Library; MDPI and other journal sites; backward and forward citation chaining
Plant health	("plant disease" OR phytopath* OR pathogen OR "crop disease" OR "disease forecasting")
AI and diagnosis	AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR CNN OR "vision transformer" OR "foundation model" OR "vision-language")
Sensors and surveillance	AND (IoT OR sensor* OR "remote sensing" OR hyperspectral OR multispectral OR thermal OR UAV OR satellite OR "proximal sensing")
Decision and intervention	AND ("decision support" OR forecast* OR warning OR robot* OR "smart sprayer" OR "variable rate" OR "precision intervention")
Deployment and adoption	AND (field OR farm OR commercial OR external validation OR open-set OR transferability OR cost OR adoption OR interoperability OR smallholder)
Limits	Search window: 2010-July 2026; English; peer reviewed; DOI verified. Foundational earlier studies retained. Narrative synthesis; no claim of exhaustive bibliometric coverage.

Table A2. Data extraction fields used in the evidence matrix.

Category	Fields
Bibliographic	Authors, year, title, source, DOI, publication type
Biological context	Crop, cultivar, pathogen/disease, growth stage, symptom stage, co-occurring stress
Technology	Sensor/platform, model, communication, cloud/edge configuration, intervention hardware
Study design	Laboratory/greenhouse/field/commercial, locations, seasons, sample or plot size, comparator
Validation	Train-test separation, external/open-set testing, diagnostic ground truth, uncertainty/calibration
Outcomes	Accuracy/sensitivity/F1, lead time, uptime, disease severity, yield, treatment number, product use, labor, cost
Deployment	Maintenance, connectivity, interoperability, user role, data governance, limitations and failure cases

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