

AI-Powered Early Detection of Crop Diseases and Pest Infestations: A New Paradigm for Plantation Risk Management

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Abstract: Crop diseases and pest infestations remain persistent threats to plantation productivity, with pests estimated to destroy up to 40% of global crop production and plant diseases and invasive insects imposing substantial economic losses worldwide (Food and Agriculture Organization of the United Nations [FAO], 2019). Climate change is intensifying these risks by altering the geographic range, seasonality, and population dynamics of pathogens and pests (Gullino et al., 2021; Skendžić et al., 2021). This paper examines how artificial intelligence (AI) — including convolutional neural networks (CNNs), vision transformers (ViTs), unmanned aerial vehicle (UAV)-based multispectral and hyperspectral sensing, and Internet of Things (IoT)-enabled monitoring — can strengthen the early detection of biotic stress in plantation crops and thereby support plantation risk management. Drawing on recent peer-reviewed and industry literature, the paper synthesises evidence on detection performance, deployment modalities, and pathways for integration into enterprise risk-management systems. It proposes a conceptual framework in which AI-enabled early-warning systems operate as a continuous, spatially explicit risk-sensing layer linking agronomic observations with operational, financial, and insurance decision-making. AI can improve the timeliness, spatial precision, and consistency of surveillance; however, its risk-management value depends on field validation, representative training data, reliable infrastructure, affordable deployment, and appropriate governance. AI should therefore currently be positioned as decision support that augments, rather than replaces, agronomic expertise and ground-truthing.

Keywords: artificial intelligence; plant disease detection; pest infestation; precision agriculture; plantation risk management; machine learning; remote sensing.

1. INTRODUCTION

Background

Plantation agriculture — encompassing large-scale production systems such as oil palm, rubber, tea, coffee, and rice — is structurally exposed to biotic risk. A single unmanaged disease outbreak or pest incursion can propagate rapidly across contiguous stands, eroding yield, quality, and asset value before the damage becomes readily visible to the naked eye. The FAO estimates that pests destroy between 20% and 40% of global crop production each year, with plant diseases costing the world economy more than USD 220 billion annually and invasive insects a further USD 70 billion (FAO, 2019). Climate change can expand the geographic and seasonal range within which pests and pathogens establish themselves (Gullino et al., 2021), while warming can alter pest generation cycles, distribution, and voltinism — the number of generations a pest population produces per year (Skendžić et al., 2021). Taken together, these dynamics mean that the biotic-risk environment facing plantation operators is not static: it is expanding in both geographic reach and seasonal duration, which places a growing premium on surveillance systems capable of keeping pace with a moving threat rather than being calibrated to historical risk patterns alone.

Traditional disease and pest surveillance relies heavily on manual scouting, visual inspection, and reactive treatment. These approaches can be labour-intensive and spatially incomplete, and by their nature they may detect infestations only after visible symptoms have already emerged — by which point yield loss, pathogen spread, or pest reproduction may already be well underway. AI offers a different surveillance paradigm: repeated observation across space and time and, where

suitable sensors and validated models are available, the identification of physiological or spectral anomalies before symptoms become obvious to a human scout. This paper argues that AI-based detection technologies can be understood not merely as agronomic tools, narrowly focused on crop protection, but as an emerging risk-management infrastructure for plantation enterprises — one that connects field-level observation to the operational, financial, and insurance decisions made further up the organisation.

Purpose of the Study

The purpose of this paper is to examine how AI-based detection technologies can strengthen plantation risk management, not simply plant-level diagnosis. It sets out to (1) synthesise the technological literature on AI-based disease and pest detection across the three principal modalities currently in use — image-based classification, UAV-based remote sensing, and IoT-enabled ground monitoring; (2) propose a conceptual framework for embedding these technologies into enterprise risk management as a continuous, spatially explicit sensing layer; (3) illustrate plausible plantation-crop applications; and (4) identify the methodological, infrastructural, and governance barriers that currently limit the translation of laboratory and pilot performance into reliable operational value.

Research Questions

This study is organised around two guiding questions:

1. How can AI-based disease and pest detection technologies be reframed from isolated agronomic tools into a coherent, continuous risk-sensing layer that supports enterprise decision-making?
2. What technical, infrastructural, and governance conditions must be satisfied before AI-generated risk signals can be responsibly incorporated into operational, financial, and insurance decisions?

Significance

The significance of this paper lies in connecting two literatures that are typically kept separate: the technical literature on AI-based plant disease and pest detection, which is concerned primarily with classification accuracy, and the risk-management literature, which is concerned with how organisations detect, quantify, and respond to threats to asset value. By positioning AI-based detection explicitly as risk-management infrastructure, the paper aims to give plantation executives, agronomists, and risk officers a shared vocabulary for evaluating these technologies — one that asks not only “how accurate is this model?” but “does this system shorten the interval between risk emergence and verified response, and does it do so reliably enough to inform decisions with financial consequences?” The remainder of the paper reviews the technological literature, proposes a conceptual framework for embedding AI into plantation risk management, illustrates plantation-crop applications, discusses adoption barriers, and concludes with implications and priorities for future research.

2. LITERATURE REVIEW

2.1 Deep Learning for Plant Disease Classification

The dominant technical approach to AI-based plant disease detection is supervised image classification using CNNs, which learn discriminative visual features directly from labelled leaf or canopy imagery (Nyawose et al., 2025). CNN and CNN-long short-term memory (CNN-LSTM) approaches have been applied to potato, apple, tomato, rice, and other crop-disease classification problems (Alzakari et al., 2024; Ahmed & Yadav, 2024; Ananthi et al., 2024; Andrianto et al., 2020; Arora et al., 2024). These applications typically report classification accuracy in the range of 90% or higher under controlled test conditions, illustrating that the underlying computer-vision techniques are technically mature for the narrow task of distinguishing known disease categories within curated image sets.

Vision transformers have emerged as an alternative to conventional CNN backbones, offering different trade-offs between representational capacity, data requirements, and computational cost (Dosovitskiy et al., 2020; Liu et al., 2021). However, high benchmark accuracy does not necessarily transfer to field conditions. Models trained on curated imagery may inadvertently exploit background or lighting artefacts — such as a consistent photographic backdrop associated with diseased samples in a training set — rather than robust disease features, producing performance degradation when the same model is applied to real-world images collected under variable field lighting, occlusion, and cultivar diversity (Nyawose et al., 2025). This lab-to-field generalisation gap therefore remains a central limitation of the current literature, compounded by small or imbalanced datasets and limited transferability of trained models across crops and production environments (Chouhan et al., 2019; Nyawose et al., 2025).

Beyond visible-symptom classification, image-based machine learning is increasingly being integrated with genomic and phenomic data to support disease-resistance prediction, extending AI's potential role beyond detection of existing outbreaks toward predictive breeding and longer-term resistance management (Dolatabadian et al., 2025). This convergence suggests that the value of AI in plant-health management may ultimately extend upstream, into breeding and cultivar-selection decisions, rather than being confined to reactive detection once a crop is already in the ground.

2.2 UAV-Based Remote Sensing for Early Detection

UAVs equipped with multispectral, hyperspectral, or thermal sensors can provide plot- or plantation-scale surveillance that would be impractical to achieve through manual scouting alone. Pest and pathogen activity can alter chlorophyll content, water status, canopy temperature, and canopy structure; consequently, spectral and thermal measurements may reveal physiological stress before obvious visual discolouration becomes apparent to a human observer walking the same rows.

Reported applications in the wider literature span pest detection in field and orchard crops, insect-population monitoring, and combined hyperspectral and light detection and ranging (LiDAR) approaches to forest and tree-crop health assessment, reflecting a broader trend toward multi-sensor UAV platforms in precision agriculture. For plantation risk management, the value of this modality lies not in detection accuracy considered in isolation, but in whether the resulting signal improves the timing and spatial precision of verified intervention and reduces avoidable treatment costs or downstream liabilities. A highly accurate model that flags anomalies too late, or across too coarse a spatial resolution to guide targeted treatment, delivers limited risk-management value even if its classification statistics are impressive on paper.

2.3 IoT and Sensor Networks in Plantation Monitoring

IoT sensor networks provide a complementary, ground-based monitoring layer that operates continuously rather than at the scheduled intervals of a UAV flight or a manual scouting round. In oil palm, an integrated IoT and supervised machine-learning decision-support system has been reported for real-time monitoring of soil, environmental, and equipment parameters, with prediction accuracy exceeding 95% for the reported model and support for fertilisation, irrigation, and maintenance decisions (Puangsuwan et al., 2025). Together, the literature reviewed in this section suggests three complementary technological pillars for plantation biotic-risk surveillance: image-based classification for symptomatic diagnosis, UAV-based spatial sensing for plot- and estate-scale surveillance, and IoT-enabled continuous monitoring for ground-truthed environmental and physiological context. No single pillar is sufficient on its own; their combination is what allows the risk-sensing architecture proposed in Section 3 to function across spatial scales and temporal frequencies simultaneously.

3. TOWARD A NEW PARADIGM: AI AS A CONTINUOUS RISK-SENSING LAYER

This paper proposes reframing AI-based detection as a continuous risk-sensing layer that converts observations of biotic threats into quantifiable, spatially referenced risk data, rather than treating each detection event as an isolated diagnostic output. The framework involves three related shifts in how surveillance is conceived and organised: from lagging to leading indicators, from uniform to spatially differentiated risk, and from episodic to repeated or continuous assessment.

3.1 From Lagging to Leading Indicators

Traditional visual scouting is, almost by definition, a lagging indicator: it identifies disease or pest damage only once visible symptoms have appeared, at which point biological processes such as pathogen spread or pest reproduction may already be well advanced. Where validated spectral or physiological anomalies precede visible symptoms, AI-enabled detection can shift surveillance toward earlier, leading indicators of stress. The practical value of this shift is the possibility of shortening the interval between risk emergence, verification, and response — potentially allowing intervention while the affected area is still small and containment is still feasible, rather than after an outbreak has already spread across a block.

3.2 From Uniform to Spatially Differentiated Risk

Plantation-wide averages, of the kind typically reported in routine agronomic monitoring, can conceal substantial within-estate heterogeneity driven by microclimate, drainage, soil variability, management history, and proximity to inoculum sources such as previously infected blocks or neighbouring properties. UAV- and IoT-derived spatial data can support differentiated allocation of scouting and treatment resources — directing limited field-scouting labour toward the blocks flagged as higher risk rather than spreading effort evenly across an estate — and can improve the documentation of high-risk zones for both operational planning and, where relevant, insurance or certification reporting.

3.3 From Episodic to Continuous Assessment

Manual scouting is necessarily periodic, constrained by available labour and physical access to often difficult terrain. IoT networks and scheduled UAV flights can instead generate repeated data streams that support time-series indicators such as rate of spread, cumulative exposure, and recurrence across seasons — indicators that are simply not observable from a single scouting visit, however thorough. This shift from episodic snapshots to continuous or near-continuous assessment is, in many respects, the most consequential of the three, because it is what allows the other two shifts (earlier indicators, spatial differentiation) to be sustained over time rather than captured only occasionally, provided that the underlying measurements and models have been properly validated for the conditions in which they are deployed.

3.4 Proposed Risk-Management Architecture

Synthesising the three shifts described above, a four-layer architecture is proposed for embedding AI-based detection into plantation risk management:

1. **Sensing** — data acquisition through UAVs, IoT devices, and handheld or vehicle-mounted imaging systems, capturing the raw visual, spectral, and environmental signals that underpin all downstream analysis.
2. **Detection and classification** — CNN/ViT, regression, or anomaly-detection models applied to sensed data, producing candidate flags for disease or pest presence, severity, or physiological stress.
3. **Aggregation** — the combination of validated model outputs into block- or estate-level risk indicators, integrating information across sensing modalities and time points rather than treating each detection event in isolation.
4. **Decision** — a layer in which aggregated risk information informs agronomic response, contingency planning, and, where technically and contractually appropriate, insurance or risk-transfer decisions.

AI outputs are therefore positioned throughout this architecture as inputs to enterprise risk management, feeding into a decision layer that retains human judgement and verification, rather than as standalone diagnoses that trigger automatic action. This framing is deliberate: it reflects the paper's central argument that AI's current risk-management value lies in improving the timeliness and precision of information available to decision-makers, not in replacing the decision-makers themselves.

4. ILLUSTRATIVE APPLICATION DOMAINS IN PLANTATION CROPS

The technological pillars reviewed in Section 2 have plausible application across a range of plantation-crop contexts, though the maturity of evidence varies considerably by crop and modality. Oil palm applications include IoT-integrated decision support for fertilisation, irrigation, and maintenance, reported with prediction accuracy exceeding 95% in at least one published system (Puangsuwan et al., 2025). Rice applications include smartphone-deployable CNN disease diagnosis, illustrating that image-based classification models can, in principle, be delivered through devices already available to smallholder and estate field staff rather than requiring specialised hardware (Andrianto et al., 2020). Apple and potato studies illustrate the transferability of CNN and CNN-LSTM architectures across different crop systems, suggesting that model architectures developed for one crop may provide a useful technical starting point for adaptation to plantation tree crops, subject to retraining on crop-specific imagery (Ahmed & Yadav, 2024; Alzakari et al., 2024).

Hyperspectral and LiDAR-based approaches developed for forestry and orchard health assessment may be similarly relevant to rubber, tea-shade, and other agroforestry-adjacent plantation systems, given the structural and canopy similarities between these production systems and forest stands; confirming this relevance, however, requires locating and validating the specific primary studies before any operational or investment assumptions are drawn from them, and this remains an item for the author's continuing literature search. Across all of these domains, the recurring lesson from Section 2 applies: local field validation under the specific cultivar, climate, and management conditions of the target plantation is essential before reported model performance from the published literature is translated into operational or investment assumptions.

5. CHALLENGES AND LIMITATIONS

AI adoption in plantation biotic-risk surveillance faces methodological, infrastructural, financial, and governance constraints that will determine whether it produces genuine risk reduction or merely adds cost and complexity to existing operations.

5.1 Lab-to-Field Generalisation

Reported benchmark accuracy should not be treated as equivalent to operational accuracy. Models can underperform on field-collected imagery because of background, lighting, cultivar, and acquisition differences relative to the curated datasets on which they were originally trained and validated (Nyawose et al., 2025). Field validation under representative plantation conditions — including the specific cultivars, growth stages, and seasonal lighting conditions the plantation actually experiences — is therefore required before AI outputs are allowed to support consequential agronomic, financial, or insurance decisions. A model that has never been tested against the plantation's own imagery carries meaningfully greater operational risk than its published accuracy figures might suggest.

5.2 Infrastructure, Cost, and the Digital Divide

AI-enabled precision agriculture depends on reliable power, connectivity, sensors, UAV platforms, data infrastructure, and technical capability, none of which can be assumed to be uniformly available across plantation geographies. Infrastructure gaps, cost, skills shortages, and training-data representativeness remain important barriers in developing regions (Center for Strategic and International Studies [CSIS], 2026). As a result, the benefits described in Sections 2 through 4 may not be available at the same cost, reliability, or scale in emerging-market plantation systems as they are in the better-resourced settings in which much of the underlying research was conducted.

5.3 Data Governance and Model Equity

Plantations located outside the geographic, climatic, cultivar, or crop conditions represented in a model's training dataset may experience materially lower detection performance than the published literature would suggest, simply because their local conditions were not represented during model development. This raises questions of data ownership, model transparency, accountability, and equitable access to locally calibrated models — questions that become substantially more consequential if AI outputs are subsequently used to inform insurance underwriting, sustainability certification, credit assessment, or other decisions with direct financial consequences for the plantation operator.

6. DISCUSSION: IMPLICATIONS FOR PLANTATION RISK MANAGEMENT

AI-based detection is best understood as a risk-timing and risk-targeting technology rather than a risk-elimination technology. Its potential contribution is to shorten the interval between biological onset and operational detection, and to narrow the spatial footprint requiring verification and intervention, rather than to prevent disease and pest pressure from occurring in the first place. If demonstrated reliably under field conditions, these improvements can strengthen contingency planning, resource allocation, and risk reporting — allowing plantation managers to move scouting and treatment resources toward genuinely elevated-risk areas rather than distributing effort uniformly, and allowing risk officers to document exposure with a level of spatial and temporal granularity that manual scouting records cannot easily provide.

Given the generalisation and governance limitations discussed in Section 5, AI outputs should currently be treated as decision-support inputs that augment, rather than replace, agronomic judgement and ground-truthing. A practical near-term operating model is a tiered response protocol, in which AI-flagged anomalies trigger targeted human verification — a field visit by an agronomist or trained scout to the specific coordinates flagged by the system — before large-scale treatment or insurance-relevant reporting decisions are made. This tiered structure allows plantations to capture the surveillance-efficiency benefits of AI (directing scarce human attention toward the locations most likely to need it) while retaining a human check against false positives and locally atypical conditions that an imperfectly generalised model might misclassify.

The uneven distribution of infrastructure discussed in Section 5.2 also means that the benefits of AI-enabled surveillance may accrue unevenly across the sector unless deliberately addressed through shared infrastructure, locally calibrated model development, training programmes, and financing mechanisms that lower adoption barriers for smallholder-linked and emerging-market operations (CSIS, 2026). Left unaddressed, this dynamic risks widening the gap between large, well-capitalised plantation groups capable of building bespoke, locally validated systems and smaller operators dependent on generic, unvalidated tools.

7. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

AI-powered disease and pest detection represents a meaningful departure from purely reactive, visually triggered plantation surveillance. Reconceptualising these technologies as a continuous, spatially differentiated risk-sensing layer — rather than as a collection of individually impressive classification models — offers a pathway toward more precise surveillance, better-targeted intervention, and better-informed contingency planning at the enterprise level. Realising this potential requires closing the benchmark-to-field performance gap identified throughout this paper, addressing infrastructure and cost barriers

that currently limit deployment in less-resourced settings, and ensuring that the models plantations rely on actually represent the crops, cultivars, and conditions under which they are grown.

Future research should prioritise field-validated longitudinal studies conducted under real plantation operating conditions rather than curated benchmark datasets; direct evaluation of whether earlier AI-assisted detection measurably reduces yield loss and intervention cost relative to conventional scouting, rather than assuming this follows automatically from improved detection timing; integration of validated AI outputs into financial and insurance risk models, with appropriate attention to the governance questions raised in Section 5.3; and context-specific model development for smallholder-linked and emerging-market systems that are currently under-represented in the training data underlying most published models. Until this evidence base is stronger, AI should be regarded as a decision-support layer within plantation risk management rather than an autonomous substitute for agronomic expertise and field verification.

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