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Original Research Paper

Artificial Intelligence Based Crop Disease Detection and Agricultural Productivity with Environmental Improvement Using Machine Learning

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ABSTRACT

Artificial intelligence (AI) and machine learning are increasingly used to identify visible crop disease symptoms and support timely crop-management decisions. Agricultural productivity or environmental sustainability, however, does not follow naturally from high image-classification performance. A critical narrative review was undertaken to explore the relationship between diagnostic reliability, field deployment, agronomic decision making, farmer adoption, and environmental outcomes. It reflects twenty selected publications about image classification and segmentation, smartphone diagnosis, precision spraying, adoption, pesticide management, and environmental accounting from 2016 to 2026. Only targeted searching and purposive selection were used; it is not a systematic review or meta-analysis, and no experiments or pooled effect estimates are reported.

High accuracy on controlled image datasets can be reduced in field conditions due to changing lighting and backgrounds, crop cultivars, symptoms, and sampling. Designs on mobile diagnostic systems and recent crowd-management studies address real opportunities but sometimes no longer separate the extra value of AI from treatment, training or extension support. Similarly, reports of reductions in pesticide application due to better management practices are not necessarily follow-on effects of disease-detection technologies. Hence a framework of representative field observations, uncertainty assessment, agronomic verification, feasible farmer adoption, targeted management, and independent measurement of outcomes is proposed by the present review. Pesticide risk, resource use, and equitable access shall be considered at the same time as diagnostic performance, marketable yield and farm profitability.

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1. INTRODUCTION

1.1 Background of the Study

Crop diseases reduce crop yield and quality and can stimulate rapid diagnosis and efficient disease management. Savary et al. (2019) estimated aggregated pathogen and pest losses for the principal crops, such as potato (17.2% loss) and rice (30.0% loss). These expert-based estimates represent a broader biological burden and do not characterize disease losses or amounts that can be recovered using AI.

While machine learning can help with observation, productive intervention requires considering crop, weather, availability of treatments, and agronomic judgment. Relevant unit of success is thus a farm decision and its consequences, not an image label in isolation.

1.2 Problem Statement

Image classification addresses the question of whether a photo is similar to known categories. The farmer must understand whether the disease is actionable or not, what response is appropriate and whether the likely return is likely to be worth the cost. A proper label may come too late, trigger an incorrect treatment or simply not be used. Management changes also affect environmental outcomes. Using less pesticide does not guarantee less toxicity, and extra sensing or computing requires resources. Clear specification of comparator and measurement boundary is required when the claim is about sustainable improvement.

1.3 Objectives of the Study

The objective is to examine the trench and level of deployment evidence, consider the relationships between automatic recognition and management outcomes and to describe the remaining research need while suggesting a framework for operational use that connects reliability, uptake, productivity, profitability and environmental assessment.

1.4 Research Questions

The following four questions direct the review:

(RQ1) To what extent do published diagnostic performances reflect field conditions?

(RQ2) What are the management processes that link diagnosis to productivity?

(RQ3) What are the favorable conditions for better environmental outcomes?

(RQ4) What criteria are used to assess combined effectiveness, affordability, and equitable access?

2. REVIEW OF LITERATURE

2.1 Previous Reviews and the Distinct Contribution of the Present Study

H. Barbedo (2016) highlights capture situation, complex backgrounds and symptom ambiguity, while Liu and Wang (2021) presents a comparison of deep learning tasks, datasets and detection challenges. These reviews make clear the importance of technical generalisation.

Precision farming at the production-environment interface: economic and adoption conditions (Finger, et al., 2019) Bahmutsky et al. (2024) summarize life cycle impacts and costs, revealing the significance of accounting boundaries. This paper does not argue that sustainability was overlooked in previous reviews, even though it does follow the disease-specific decisions through the stages of agronomic verification and adoption to the jointly assessed results.

2.2 Machine Learning and Diagnostic Capability

Feature-based classifiers are built by teaching a set of engineered colour, texture, or shape features. Object detectors locate instances, segmentation draws boundaries between adjacent pixels, and convolutional neural networks learn representations of images. They are distinct tasks, not tiers of precision (Liu and Wang, 2021). Barbedo (2018) presents the rationale behind the effects that the characteristics of data sets and the presentation of symptoms have for the performance of deep learning.

Mohanty et al. (2016) obtained 99.35% accuracy on 54,306 images from 38 crop/condition classes, while around 31% on out-of-distribution images. The difference highlights the distribution shift, not a general accuracy assurance. Classification performance does not measure pathogen confirmation, treatment appropriateness, or yield protection.

Beyond image classification frameworks, advanced agricultural and environmental modeling frequently relies on stochastic metaheuristic optimization techniques Rejo et al (2021) have worked on Genetic Algorithms (GA) and genetics-based harmony search algorithms—for robust parameter tuning and predictive forecasting. Understanding the convergence behavior and computational trade-offs of these optimization algorithms is essential when scaling machine learning models from controlled computational environments to complex agricultural deployment scenarios.

2.3 Datasets and Field Representation

PlantDoc has 2,598 images for thirteen plant species and up to seventeen disease classes (Singh et al., 2020). Its complexity expands the concept of evaluation beyond controlled backgrounds, but data gathered on the internet cannot replace prospective sampling between farms, seasons, cultivars, and disease status.

PlantSeg offers 7,774 diseased images and their correspondent segmentation marks (Wei et al., 2026). Lesion limits can be used for localisation research but visible affected area does not necessarily equal whole-plant severity, pathogen load, or yield loss. Those interpretations depend on independent measurements and crop-specific relationships.

2.4 Mobile Diagnosis, Adoption, and Deployment

Ramcharan et al. (2019) assessed mobile cassava diagnosis using field images and video. Edge inference only requires intermittent connectivity, while cloud processing provides the capacity for more sophisticated models but comes with limits on transmission, availability, and privacy. Feasibility for deployment should be evaluated on a real device and workflow.

Mrisho et al. 2020 reported 65% symptom recognition for the evaluated version of Nuru, in comparison to extension officers (40-58%) and farmers (18-31%) on plant level, which was increased to 74-88% by assessment through six leaves. These are not yield results; they are diagnosis data. However, in Benin, Ahoya et al. (2024) found that Nuru adoption was linked to training and smartphone ownership, highlighting implementation barriers but not necessarily productivity.

2.5 Management, Productivity, and Environmental Evidence

AI-related systems are already linked to management through evidence. Pear-canopy segmentation & variable-flow spraying, canopy targeting vs. disease triggered treatment: field tested by Seol et al. (2022). Jadesha et al. (2026a) assessed disease, grain yield, and cost-benefit aspects of a maize downy mildew advisory and fungicide package versus an untreated control across two seasons. Incremental AI benefits remain unresolved without a similar fungicide programme with less or zero AI.

Jadesha et al. (2026b) specifically tested fungicide efficacy without relying on AI outputs for southern corn leaf blight. On a non AI basis, Lechenet et al. (2017) estimated how much pesticides could be reduced on 946 French farms without affecting productivity or profitability, and found that 59% could cut use by 42%. Guinet et al. (2023) correlated crop diversification efforts and heterogeneous pesticide responses, such as increased herbicide use with cover crops.

In addition to digital disease management and precision spraying, sustainable agricultural productivity is heavily influenced by innovative pre-sowing agronomic interventions. Rejo et al (2022) have experimented and shown that physical pre-treatment methods such as high-voltage electrostatic field treatments have been shown to significantly enhance seed germination, seedling vigor, and overall crop productivity in pulses like Bengal gram (Cicer arietinum) without relying on artificial chemical fertilizers or pesticides. Evaluating such physical management techniques alongside AI-driven decision support systems provides a more holistic view of agricultural sustainability.

2.6 Research Gap and Analytical Propositions

Among the chosen literature, there is relatively little evidence that expressly separates the benefit of AI based disease decisions from simultaneous farm and environmental measurements in representative scenarios. Integrated studies are available, however, different comparators and populations are frequently used to assess technical performance, treatment efficacy, adoption, and environmental accounting. Their discoveries can not simply be joined to a proven causal sequence.

The review suggests that benefits will rely on accurate observations, calibrated uncertainty, appropriate agronomic guidance, potential adoption, and sound management. Additionally, environmental improvement relies on the treatment policy and its implications. These are not tested hypotheses or claims of absolute novelty; rather, they are propositions for guiding evaluation.

3. RESEARCH METHODOLOGY

3.1 Research Design and Selection of Studies

It is not a systematic review, a meta-analysis, a model development study, or a field experiment, as it is a critical narrative review and conceptual synthesis. The argument draws upon 20 purposively selected publications dating from 2016 to 2026. The complete retrieval denominator or the formal screening flow was not utilities.

Original diagnostic or deployment studies and relevant prior reviews, management studies with measured outcomes, and methodological evidence required to interpret uncertainty or environmental effects were selected. Promotional claims and unsupported numerical generalisations excluded. Non-crop machine learning studies were kept only if their methodological function, as machine learning tools to help the systems, was very explicit.

3.2 Data Sources and Collection Procedures

Targeted web searches and publisher records were done on 20 October 2026. Searches were conducted on plant disease detection, field validation, precision spraying, adoption, yield, profitability, and environmental outcomes; then title-specific verification was performed. Records referred to were Frontiers, Springer Nature, PLOS, ScienceDirect, MDPI, PMLR, ACL Anthology and author repositories. These were web searches and not documented exhaustive searches anywhere else.

The concepts discovered were cropping, setting, task, data source, design, comparator, measured outcome, reported finding, and interpretative limitation. Specifically, the searches focused on studies that linked recognition, management, and quantifiable benefits. Bibliographic data has been verified through information from other publishers or authors; in the case of unavailable full texts, appraisal was carried out from accessible information or manuscripts. Representative search terms included: plant disease detection, field validation, variable-rate spray application, pesticide reduction and crop results/field application. Iterative alteration of search combinations; no retainable database search history, no deduplication record, no screening counts were made. As such, the selection does not reflect the extent of literature completeness, but rather enables critical comparison.

3.3 Analytical Categories and Interpretive Procedure

Evidence was categorised into diagnostic reliability, operational implementation, agricultural performance, and environmental outcomes. Percentages for different tasks and sampling units were kept in context, not ranked. Grain yield and marketable yield were considered separate endpoints, as were profitability, spray coverage, quantity of pesticide use, and environmental risk; hence, a pooled estimate was not calculated.

Interpretation asked whether each design allowed for prediction, association, treatment efficacy, or an incremental AI effect. For instance, a fungicide-versus-untreated comparison tests a management package; it does not isolate the treatment effect from the diagnostic effect. Future metrics and future framework links are presented as recommendations. Where a statement implied a broader comparison than was actually undertaken by the study, interpretation was based on the study design and measurement endpoints rather than upon a broad claim in a study's title or abstract.

3.4 Reliability, Scope, and Ethical Considerations

The review has been conducted with traceable citations and clear causal boundaries, but lacks a registered review protocol, independent duplex screening, or a formal risk-of-bias analysis. Accessible positive studies may be favored through purposive selection, availability in English and access restrictions. In addition to this, deployment recommendation requires informed participation, responsible data handling and access to agronomic escalation.

4. SYNTHESIS AND DISCUSSION

4.1 Profile of the Comparative Evidence

Table 1 presents sixteen empirical or methodological studies in the categories of diagnosis, implementation, agronomy, and environmental assessment. Section 2.1 compares four prior reviews. Outcomes and limitations are paired together to avoid giving the impression of incompatible technical and farm results.

Table 1. Comparative Evidence: Measured Outcomes and Interpretive Boundaries

Source and design	Crop setting and method	Outcome actually measured	Finding and interpretive boundary
Mohanty et al. (2016); model evaluation	Multiple crops; image classification	Image accuracy: 99.35% internal; approximately 31% external	Distribution shift; no farm outcomes.
Singh et al. (2020); dataset	PlantDoc; complex images	Classification and detection benchmarks	2,598 images; not prospective farm validation.
Wei et al. (2026); dataset	PlantSeg; diseased images	Pixel-level segmentation	7,774 images; no validated yield-loss relationship.
Ramcharan et al. (2019); deployment	Cassava; mobile detection	Field image/video diagnostic performance	Operational evaluation; no causal yield evidence.
Mrisho et al. (2020); evaluation	Cassava; smartphone diagnosis	Symptom and plant-level accuracy	Sampling affects diagnosis; no harvest endpoint.
Lechenet et al. (2017); observational	946 French arable farms	Pesticide use, productivity, profitability	Estimated reduction potential; not an AI intervention.
Guinet et al. (2023); observational	French cropping systems	Diversification and pesticide use	Responses vary; not AI-attributable effects.
Savary et al. (2019); expert assessment	Five major food crops	Estimated pathogen and pest losses	Production context; not preventable AI losses.
Guo et al. (2017); methodological	Neural classification benchmarks	Confidence calibration	Supports calibration evaluation; no crop outcomes.

Strubell et al. (2019); methodological	Natural language processing	Training energy and financial costs	Accounting relevance; numerical results not transferable.
Barbedo (2018); model analysis	Plant disease imagery	Factors affecting recognition	Dataset and symptom constraints; no farm impact.
Seol et al. (2022); field experiment	Pear orchard; canopy segmentation	Spraying and variable-flow performance	Targets canopy, not diagnosed disease; no causal yield evidence.
Ahoya et al. (2024); adoption analysis	Benin cassava farmers; Nuru	Factors associated with adoption	Access and training matter; no causal productivity estimate.
Jadesha et al. (2026a); field comparison	Maize downy mildew; advisory package	Disease, grain yield, cost-benefit	Treated versus untreated; AI contribution not isolated.
Jadesha et al. (2026b); separate evaluations	Maize leaf blight; AI and fungicides	Image diagnosis; treatment yield and economics	Fungicide trial independent of AI outputs.
Schulz et al. (2021); longitudinal analysis	US pesticide use and toxicity	Applied toxicity across non-target groups	Mass and toxicity diverge; not observed AI impact.

4.2 Diagnostic Reliability and Decision Support

Field evaluation should first rule out poor images and exclude symptoms of disease from symptoms of nutrient deficiency, injury, senescence, and other lookalikes. Chronic problems identified by Barbedo (2016) include non-discriminating symptoms and challenging capture conditions. Reference diagnoses should be based on plant pathology assessment value, provided by independent adjudicator, and where suitable, confirmation from the laboratory, not on model agreement.

The expression of one's confidence is not necessarily the probability of being correct. Guo et al. (2017) showed that modern neural networks can be miscalibrated and estimated temperature scaling. Crop use should be calibrated on separate validation data and revaluated under field shift. The abstention thresholds are to be based on consequences, available referral capacity, and not arbitrary confidence cut-off.

Diagnostic reporting proposed such as sensitivity, specificity, precision, macro-average of F1, calibration, and error rate on accepted predictions for disease specific reporting. Precision is a function of prevalence: balanced benchmark results can misrepresent low-prevalence deployment. Class counts and confusion matrices reveal failure in minority classes. If there are repeated leaves, they should be shown as clustered observations, not as individual farms.

Compare feature-based baselines, convolutional models, detectors, and segmenters with equivalent data partitions and task-appropriate endpoints. Detection requires localisation assessment, segmentation requires mask agreement (plus a separately validated measure of severity if one exists). When comparing edge and cloud, factor in latency, memory, connectivity outages, and time to acquisition. Context-aware models that incorporate image and context need to be compared with image-only and context-only baselines. Multi-modal inputs can provide information that is not obtained from the photograph, or imply location or seasonal shortcuts. Regional differences, delayed weather data and missing sensor values should therefore also be tested as operational failure cases and not dropped silently out of evaluations.

Split datasets by farm, acquisition session and season if possible; avoid near-duplicate leakage. Save outside spots and future seasons for trial. Explicitly state report unfamiliar diseases, mixed symptoms, device variation and missing context. Negative cases and uncertain diagnoses are important, as very clean evaluation sets obscure errors that lead to true decisions about treatments.

4.3 Implications for Agricultural Productivity and Environmental Outcomes

4.3.1 Productivity Benefits and Risks of Overreliance

The proposed productivity pathway should be recognized early enough to alter an effective action. Management could be specific treatment, sanitary measures, resistant material, or additional investigation. The two maize studies show why treatment results are important; however, the control groups do not highlight the added value of bespoke AI.

Future studies must identify marketable yield per ha, quality grades, gross margin in advance. Cost accounting should include diagnosis, labour, equipment depreciation, connectivity, and treatment. Price and assumptions transparently; grain yield/treatment cost-benefit ratios may exclude marketability and digital infrastructure costs.

Not only can a false negative lead to inaction, but a false positive can create an unnecessary cost item. Record recommendations, actual farmer actions, reasons for non-adoption, and timing of application. These intermediate observations help to understand failure in terms of recognition, advice, affordability, execution and ineffective agronomy. There are also costs to referral: additional visits, postponed decision-making, and the burden on limited extension personnel. An abstaining system should therefore be observed as an overall service, assessing whether farmers who are referred are being advised in a timely way, and whether cases that haven't been resolved are being funnelled through to disadvantaged users.

4.3.2 Environmental Performance and Equitable Access

Environmental assessment in the future should document application frequency, active ingredients per hectare, and a scientifically defensible hazard- or toxicity-weighted indicator. Schulz et al. (2021) identified opposing trends in pesticide mass and toxicity, illustrating that quantity alone is insufficient. When possible, collect data on water residues, soil impacts, or non-target organisms; risk indicators are still proxies for an ecological effect.

Use per hectare to explain local pressure and per tonne to connect burden with production. These indicators can move in different directions with yield changes. Boundaries should encompass pertinent input production, application and digital resources, and sensitivity analysis of assumptions should be conducted, as addressed in the broader accounting concerns from Bahmutsky et al. (2024).

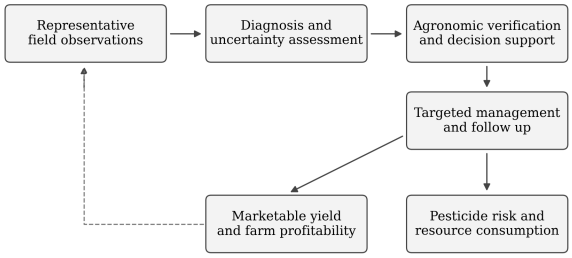
Strubell et al. (2019) reported energy- and cost-related factors associated with natural language processing. They should not be used directly in crop application based on their numerical estimates. Instead, assess energy use during training and inference, device needs, and transmission needs for the proposed deployment, while transparently mapping transmission demand onto shared infrastructure.

Assessment of device ownership, language, connectivity, trainings and device extension support are required for affordability and equitable access. The barriers detailed by adoption associations reported by Ahoya et al. (2024) are worth exploring. Monitor participation and performance in relevant farmer groups, including those who do not have access to the application themselves.

4.4 Proposed Relationship Between Detection, Productivity, and Environmental Outcomes

Figure 1 is a conceptual illustration that has not been validated. Image quality and representative sampling condition diagnosis; uncertainty means repeat observation or referral. Agronomic verification is the link between diagnosis and the right action. Implementation is mediated by adoption—affordability, trust, available inputs, and extension access. Each relationship may be altered by weather, crop stage, and disease pressure.

Figure 1. Proposed Conceptual Framework: Hypothesised Links and Feedback from Agricultural and Environmental Outcomes



The feedback arrow can be understood as learning from both agricultural and environmental outcomes. Follow-up should document accepted advice, actions taken, diagnostic corrections, harvest results, and environmental indicators. The diagram does not imply causation, but rather describes observations that feed into further sampling, model assessment, and revisions to the management plan.

A contextual module might include rainfall, temperature, cultivar, stage of growth, and disease pressure. Any added value should be tested in the future, even if there is an input which is missing or incorrect. When the recommended remedial action is beyond the scope of evidence provided by observable signs, it should be made available for expert verification.

A suitable prospective design would involve comparing equivalent extension and treatment access with and without the use of AI support and would randomise farm or clusters when possible. Track more than one season, document spillover and attrition, and evaluate real management. An untreated comparator can only measure treatment effectiveness and does not adequately measure incremental diagnostic value. Analyse participants based on their attributed service, if applicable, and conduct transparent implementation analyses. Record where advice has been dropped without initially assuming that it is farmer fault. Similar access to inputs, independent assessment of outcomes, and stratification for common environmental or infectious exposure could improve interpretation of treatment differences.

Establish joint success criteria and acceptable tradeoffs in advance of analysis. A yield non-inferiority margin, an economic threshold, and an environmental target

should be explained to agronomists and farmers who participate. Express confidence intervals and bad outcomes; gains in one endpoint should not mask deficits in another. Environmental targets should specify type of indicator, baseline, time horizon, and relevant organism or compartment. But if it looks better, look for another input, crop stage or position. Don't offer one sustainability rating but rather explain uncertainty throughout the measured outcomes and accounting assumptions.

4.5 Findings Against the Research Questions

RQ1: Controlled-image accuracy does not fully characterize field reliability. The external-image deterioration and mobile sampling effect, respectively, explain why independent and representative evaluation is required (Mohanty et al., 2016; Mrisho et al., 2020). Regard for dependability across different seasons and regions is still a gamble.

RQ2: Actions mediate productivity, while diagnosis can influence timely treatment and follow-up. Integrated maize studies present management outcomes without separating the effects of AI, represented by Jadesha et al., (2026a) and (2026b). Equivalent-care comparators are required.

RQ3: Environmental improvement needs beneficial changes in input use and risk. Canopy-directed spraying provides operational evidence, whereas toxicity suggests that less mass does not mean less harm (Seol et al., 2022; Schulz et al., 2021). The ecological benefits for the disease are unknown.

RQ4: Assess collectively technical reliability, marketable yield, gross margin, environmental indicators. Attention to implementation and accounting boundaries is supported by adoption and life cycle reviews (Ahoya et al., 2024; Bahmutsky et al., 2024). Prospective assessment of transferability is needed in farmer groups.

5. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

5.1 Conclusions

AI detection of disease can provide valuable diagnostic tools and viable implementation sites, yet sustainability benefits are contingent upon suitable and accepted management. AI independently enhancing yield, profitability, and environmental performance is still not demonstrated in the existing integrated studies.

This paper provides an outcome-based interpretation that links field reliability, uncertainty, agronomic verification, adoption, and measured outcomes. It extends technical and precision agriculture reviews by making causal boundaries and evaluation requirements explicit. The framework is a research proposal, not a validated intervention.

5.2 Limitations of the Study

Coverage is limited by purposive selection and accessibility in English. Pooled conclusions are precluded because of heterogeneous crops, sampling units, comparators, and endpoints. Only accessible records or manuscripts were available for some studies and no formal risk of bias assessment was performed. The framework has not yet been tested, and the lack of selected evidence does not imply that it lacks research.

5.3 Future Research

Future research should involve prospective, multiple-season trial comparisons with independent diagnoses and comparable agronomic assistance. They should be measured together with the marketable yield and gross margin, along with predefined analysis and clear accounting for pesticide use and environmental indicators. Log adoptions, barriers to accessing, referral outcomes, attrition, and unintentional harm.

New diseases, cultivars, devices, and changing prevalence should be monitored through longitudinal evaluation. Renewed validation is required when the model is used for recalibration and updates. The publication of negative results, failures in implementation, and reproducible protocols of success would help distinguish technical promise from hardnosed agricultural and environmental usefulness. Shared evaluation resources should hold farm and season IDs, uncertainty labels and allowed re-use conditions so that external checks can be performed without identifiable farmer records being exposed.

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