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Artificial Intelligence and Machine Learning for Crop Disease Detection: A Systematic Review and Research Agenda

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Abstract

Crop diseases constrain global agricultural productivity and food security, particularly for smallholder farmers who lack timely, affordable diagnostic tools. Artificial intelligence and machine learning have transformed automated crop disease detection, but much reported performance rests on controlled laboratory datasets that may not reflect field conditions. This systematic review, following PRISMA 2020 guidelines, synthesizes 35 peer-reviewed studies drawn from 1,210 records across six databases, published 2015–2025 and covering 22 crop species across 17 countries. Convolutional neural networks remain dominant, although Vision Transformers, lightweight architectures, explainable AI, federated learning, and hybrid models are emerging alternatives. Most studies relied on laboratory datasets, reported accuracy alone, and lacked external validation, producing a consistent laboratory-to-field performance gap, particularly in African smallholder contexts. The review identifies gaps in dataset diversity, reporting transparency, and deployment feasibility, and proposes a four-pillar research agenda spanning data, algorithms, deployment, and policy to guide field-ready AI development.

Keywords: artificial intelligence, machine learning, crop disease detection, systematic review, smallholder agriculture

Introduction

Agriculture is central to global food security, yet crop diseases remain a major constraint on productivity and farmer livelihoods. The Food and Agriculture Organization (FAO, 2021) estimates that pests and diseases cause substantial global crop losses, with impacts felt most severely

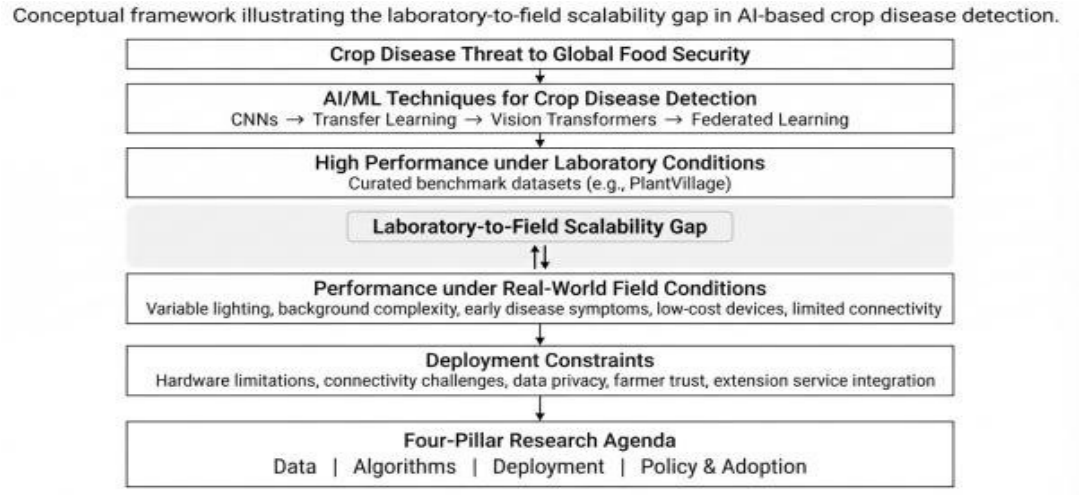
by smallholder farmers in regions where diagnostic services and agricultural support systems remain limited.

Conventional diagnosis methods, including visual inspection and laboratory techniques such as PCR and ELISA, are costly, time-consuming, and difficult to scale in smallholder systems (Isinkaye et al., 2024). Advances in AI, ML, smartphones, and digital imaging have enabled automated disease-detection systems; Mohanty et al. (2016) demonstrated the potential of convolutional neural networks (CNNs), achieving 99.35% accuracy on a benchmark dataset and accelerating research in this area.

Recent systematic reviews have highlighted rapid growth in AI-based crop disease detection while identifying persistent challenges, including limited field validation, inconsistent evaluation metrics, dataset limitations, and inadequate evidence of real-world deployment (Majdalawieh et al., 2025; Ngugi et al., 2024; Nyawose et al., 2025). However, limited attention has been given to whether existing evidence reflects the realities of smallholder farming, particularly in Sub-Saharan Africa. This review addresses that gap by synthesizing 35 peer-reviewed studies, evaluating methodological practices, identifying limitations, and proposing priorities for scalable, practical AI-enabled disease detection. By combining quantitative synthesis with a structured quality assessment, the review moves beyond cataloguing reported accuracies to examine whether the underlying evidence base is good enough to guide real-world deployment decisions. This distinction between demonstrated laboratory performance and validated field performance underpins the analysis that follows.

The review is guided by a conceptual framework integrating the Technology Acceptance Model with principles of reproducibility and methodological transparency (Davis, 1989; Ioannidis et al., 2014; OECD, 2023). The framework proposes that high laboratory accuracy may not translate into field performance because of environmental variability, image quality, device limitations, and connectivity constraints. Studies were therefore evaluated on performance, ecological validity, transparency, and deployment suitability (Figure 1). The objective of this review was to synthesize AI/ML applications in crop disease detection, evaluate model performance and methodological practices, identify key research gaps, and develop a research agenda for field-ready deployment.

Figure 1: Conceptual framework illustrating the laboratory-to-field scalability gap in AI-based crop disease detection.



Source: Authors conceptualization based on Davis (1989) Ioannidis et al. (2014), OECD (2023), and the reviewed literature

LITERATURE REVIEW

AI and ML applications in crop disease detection evolved considerably between 2015 and 2025, shifting from laboratory-focused classification toward more field-oriented applications.

Early studies relied on CNNs trained on curated datasets, with Mohanty et al. (2016) and Ferentinos (2018) reporting accuracies above 99% using the PlantVillage dataset; however, dependence on controlled images limited transferability to real farming environments.

Research between 2019 and 2022 expanded transfer learning and field-collected datasets, particularly in African smallholder contexts. Ramcharan et al. (2017, 2019), Selvaraj et al. (2019), and Mrisho et al. (2020) showed that performance often declines under field conditions due to lighting, background complexity, image quality, and disease severity. More recent work has introduced Vision Transformers, lightweight YOLO models, federated learning, and explainable AI to improve efficiency, privacy, transparency, and deployability (Aggarwal et al., 2024; Akter et al., 2024; Kabala et al., 2023; Mayo et al., 2024; Pan et al., 2024; Prince et al., 2024; Shehu et al., 2025).

Despite these advances, evidence remains uneven across crops and regions. Rice, tomato, maize, wheat, and potato dominate the literature, while smallholder-relevant crops such as cassava, banana, common bean, cocoa, yam, and millet remain underrepresented (Majdalawieh et al., 2025; Ngugi et al., 2024; Nyawose et al., 2025). Continued reliance on benchmark datasets such as PlantVillage (Hughes & Salathé, 2015) also limits ecological validity, alongside persistent gaps in field validation, evaluation consistency, and deployment reporting.

Prior systematic reviews have identified important methodological challenges. Majdalawieh et al. (2025) highlighted the computational efficiency of CNNs relative to Vision Transformers; Ngugi et al. (2024) reported increasing architectural diversity but limited field validation and inconsistent evaluation; and Nyawose et al. (2025) emphasized the need for larger, more representative datasets. However, limited attention has been given to reporting quality, the applicability of AI models to African smallholder systems, and structured priorities for field deployment. This review addresses these gaps through a systematic synthesis and a four-pillar research agenda for field-ready AI-based crop disease detection.

Review Design

This review followed PRISMA 2020 guidelines (Page et al., 2021) to identify, screen, and synthesize evidence on AI/ML applications in crop disease detection. The PICO framework guided eligibility: Population, diseased crops across agroecological regions; Intervention, AI/ML methods for detection, classification, or severity assessment; Comparison, variation in models, datasets, validation approaches, and deployment contexts; Outcomes, performance metrics, dataset characteristics, validation methods, deployment feasibility, and computational requirements. This structured approach helped ensure that eligibility decisions were applied consistently across the six databases searched and reduced the risk that studies were included or excluded on an ad hoc basis.

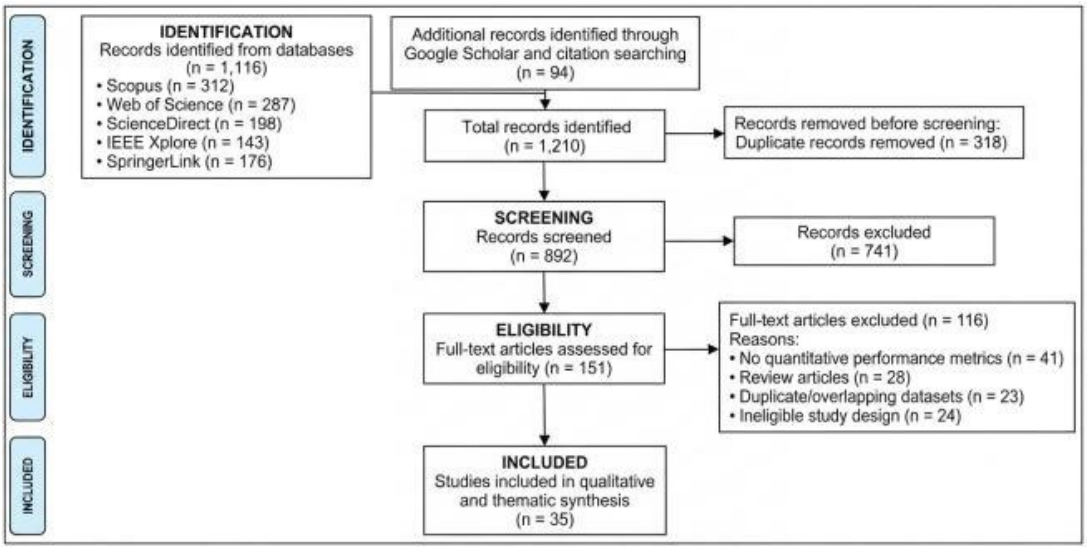
Search Strategy

Searches were conducted across Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink, and Google Scholar, for studies published 2015-2025, combining AI/ML terms (e.g., deep learning, CNN, YOLO, Vision Transformer, federated learning) with crop disease terms (e.g., plant disease, disease classification, diagnosis) using Boolean operators with database-specific adaptations.

Screening and Selection

Records were managed in Zotero (v6.0) with duplicates removed. Of 1,210 records identified, 318 duplicates were removed, leaving 892 studies for title/abstract screening. Following eligibility review of 151 full-text articles, 116 were excluded for lack of quantitative metrics (n=41), review design (n=28), duplicate datasets (n=23), or ineligible design (n=24). Thirty-five peer-reviewed studies (2015-2025) were retained for synthesis (Figure 2).

Figure 2: PRISMA 2020 flow diagram of study selection.



Source: Adapted from Page et al. (2021); study selection data compiled by the authors.

Studies were included if peer-reviewed, published in English, applied AI/ML to crop disease detection, identification, classification, or severity assessment, and reported at least one quantitative performance metric. Studies were excluded if non-peer-reviewed (conference abstracts, theses, preprints, grey literature), non-English, duplicative, based on overlapping datasets without new findings, focused on unrelated tasks (e.g., weed detection, yield prediction), or were themselves reviews.

Quality Assessment and Data Extraction

Methodological quality and reporting completeness were assessed using nine criteria adapted from the AXIS tool (Downes et al., 2016), agricultural ML reporting recommendations (Kapoor et al., 2022), and Majdalawieh et al. (2025), covering dataset characteristics, external validation, performance reporting, data/code availability, computational requirements, inference speed, and deployment specifications. Each study was scored 0-9; scores informed evaluation of transparency and deployment readiness rather than exclusion. Full per-study scores and the complete data-extraction record for all 35 studies are provided in Supplementary Appendix A.

Statistical Synthesis

Because of substantial heterogeneity in crops, diseases, datasets, and evaluation metrics, meta-analysis was not performed. Narrative and thematic synthesis were used instead; descriptive statistics (mean, median, min, max, SD) were calculated for studies reporting extractable accuracy using unweighted arithmetic means, as design variation made weighted pooling unsuitable.

Overview of Included Studies

The 35 included studies were published 2015-2025; 28 (80%) from 2019 onward and 21 (60%) between 2022 and 2025, consistent with accelerating adoption of deep learning in agriculture (Majdalawieh et al., 2025). The studies covered 22 crop species across 17 countries or multi-country regions, though coverage remained uneven, with limited representation of smallholder-focused African crops. Table 1 presents a representative sample.

Table 1: Representative sample of included studies.

Study	Crop	AI/ML Method	Dataset	Key Accuracy Finding
Mohanty et al. (2016)	14 crops	CNN (AlexNet, GoogLeNet)	PlantVillage, 54,306 lab images	99.35% on curated test set; benchmark performance under controlled conditions.
Ramcharan et al. (2019)	Cassava	SSD MobileNet (on-device)	Field photos/video, Tanzania	80.6% pronounced / 43.2% mild symptoms; 37 pp lab-to-field drop documented.
Selvaraj et al. (2019)	Banana	Faster R-CNN + MobileNetV1	30,952 images, Africa + India	90%+ across 18 classes; largest multi-country African field dataset in sample.
Long et al. (2023)	Wheat	CerealConv CNN (field images)	Real field + glasshouse, UK	97.05%; outperformed trained pathologists by 2% on independent subset.
Pan et al. (2024)	Cotton	CDDLite-YOLO (lightweight YOLOv8)	Field images, China	mAP 90.6% at 1.8M parameters, 222 FPS; designed for embedded devices.
Shehu et al. (2025)	Tomato	Vision Transformer (ViT-Base)	PlantVillage + Nigerian farms	99.17% on PlantVillage vs. 77.27% on field images; large gap documented.

Source: Authors compilation from the reviewed literature (2015-2025)

Characteristics and Descriptive Statistics

Deep learning dominated the evidence base: CNNs were used in 17 studies (49%), object-detection approaches (YOLO, SSD MobileNet, Faster R-CNN) in 8 (23%), and emerging methods, including Vision Transformers, federated learning, hybrid ML, and segmentation models, appeared in the remainder, reflecting increasing architectural diversity. This dominance reflects the suitability of CNN architectures for image-based classification; however, continued reliance on CNN-based approaches also highlights the field's dependence on architectures developed primarily under controlled conditions rather than diverse agricultural environments.

PlantVillage served as the primary or sole dataset in 9 studies (26%); 21 studies (60%) used field-collected images and 5 used hybrid datasets. Although the increasing use of field-collected images suggests progress toward realistic evaluation, continued reliance on benchmark datasets such as PlantVillage raises concerns regarding model generalizability across diverse agricultural environments. Among the 27 studies reporting extractable accuracy, the mean was 94.51% (SD = 6.32), median 96.50%, maximum 99.67%, and minimum 76.50%. However, variations in dataset characteristics,

disease severity, and validation strategies indicate that accuracy values reflect study-specific conditions rather than directly comparable measures of field performance.

Cassava and banana were prominent in African studies, while rice, wheat, and cotton dominated Asian research; cocoa, cowpea, common bean, yam, millet, coffee, and mango remained comparatively underrepresented. Table 2 summarizes dataset types and validation strategies.

Table 2: Dataset types and validation strategies across included studies.

Category	Studies (n = 35)	Notes
PlantVillage as sole/primary dataset	9 (26%)	Controlled images; limited representation of field conditions.
Custom field-collected dataset	21 (60%)	Variable quality and geographic coverage; improved ecological validity.
Hybrid (curated + field)	5 (14%)	Combines benchmark comparability with field diversity.
External validation reported	8 (23%)	Independent test set, multi-site, or expert benchmark.
Disaggregated metrics (P/R/F1) reported	8 (23%)	Majority of studies report accuracy only.
African/smallholder context data	21 (60%)	Greater representation than reported in some prior reviews.

Source: Authors compilation from the included studies (2015-2025)

Quality Assessment

Quality assessment revealed limited validation and reporting transparency: only 8 studies (23%) reported external validation and 8 (23%) reported metrics beyond accuracy (e.g., precision, recall, F1). Although 21 studies (60%) used field images, few demonstrated deployment readiness through independent validation or computational reporting. Per-study scores (range 0–5.5 of 9) are provided in Supplementary Appendix A.

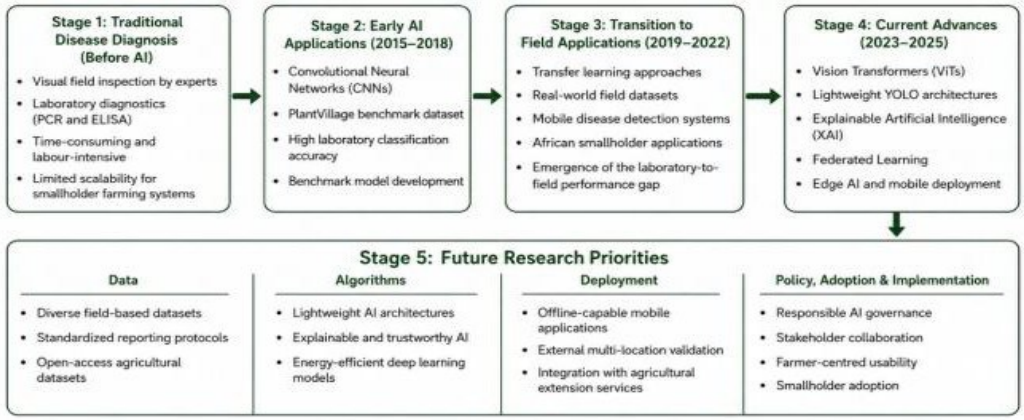
Thematic Findings

Performance frequently declined when models moved from controlled to field settings. Ramcharan et al. (2019) reported a 37-percentage-point reduction for cassava disease detection on mild-symptom field images; Mrisho et al. (2020) recorded field accuracy as low as 21% for cassava brown streak disease; and Shehu et al. (2025) observed a decline from 99.17% on PlantVillage to 77.27% on Nigerian field images using the same Vision Transformer model. Deployment constraints further widened this gap: Sanga et al. (2020) found that although ResNet152 achieved 99.2% accuracy, its computational demands limited deployment on affordable devices, requiring the lighter but less accurate InceptionV3 (95.41%).

CNNs remain dominant because of their efficiency and suitability for limited-data settings, while Vision Transformers, lightweight YOLO models, and hybrid approaches are emerging to improve scalability (Mayo et al., 2024; Akter et al., 2024; Pan et al., 2024; Zhao et al., 2023), as demonstrated by Mahmood et al. (2025) and Ishengoma and Lyimo (2024), who reported strong performance under constrained computational resources and limited datasets. Explainability and privacy are also gaining attention:

Grad-CAM approaches improve interpretability (Prince et al., 2024; Topal et al., 2024), and federated learning offers privacy-preserving potential (Aggarwal et al., 2024; Kabala et al., 2023), though both require further field validation. Figure 3 summarizes the evolution of AI- and ML-based crop disease detection from traditional diagnostic methods to contemporary AI approaches and synthesizes the future research priorities identified in this review.

Figure 3: Evolution of Artificial intelligence and Machine Learning for Crop Disease Detection (2015-2025) and Future Research Priorities



Source: Authors compilation from the reviewed literature (2015-2025)

Research Gaps

Five priority gaps emerged from the synthesis: (1) dataset geographic and ecological bias, with 9 of 35 studies (26%) relying solely on PlantVillage, highlighting the need for diverse, open-access field datasets; (2) limited field validation, as only 8 studies (23%) reported external validation despite laboratory-to-field declines of up to 37 percentage points, emphasizing the need for independent, multi-location testing; (3) inconsistent metric reporting, with only 8 studies (23%) reporting disaggregated metrics, limiting cross-study comparison and supporting the need for standardized reporting frameworks; (4) a smallholder deployment gap, as few studies reported computational requirements, inference speed, or hardware constraints, indicating the need for models balancing accuracy, affordability, and scalability; and (5) limited policy and adoption research, requiring greater attention to explainability, uncertainty estimation, usability, and human-centred design.

Comparison with Prior Reviews

These findings align with earlier reviews (Majdalawieh et al., 2025; Ngugi et al., 2024; Nyawose et al., 2025) regarding CNN dominance and reporting limitations but extend existing evidence in four ways: by showing that model suitability depends on deployment factors (data availability, computational demand, hardware, and user context) as much as accuracy; demonstrating stronger representation of African and smallholder-focused research (21 of 35 studies, 60%); quantifying reporting gaps through a nine-criterion quality assessment; and proposing a four-pillar research agenda linking evidence gaps to improved datasets, algorithms, deployment, and implementation. These contributions suggest that future systematic reviews in this area should treat deployment readiness as a distinct outcome to be assessed alongside predictive accuracy, rather than as a secondary consideration reported only when convenient.

CONCLUSION

This systematic review analyzed 35 studies on AI/ML-based crop disease detection across 22 crop species and 17 countries or regions. Although AI models achieve high laboratory accuracy, performance frequently declines under field conditions due to dataset limitations, environmental variability, and deployment constraints, particularly in African smallholder contexts. Limited external validation and reporting transparency remain major barriers to reliable assessment. Addressing gaps in datasets, validation, reporting, and deployment is essential for developing reliable, explainable, and field-ready AI systems that support practical agricultural decision-making. Realizing the potential of AI-based crop disease detection for smallholder farmers will depend as much on closing these evidence gaps as on further improving model accuracy.

RECOMMENDATIONS

Pillar 1, Data (short-term, 1-3 years): Develop and share diverse field-based datasets covering underrepresented crops, environments, and smallholder systems, with standardized reporting of datasets, validation, and performance metrics. Priority should be given to crops and regions currently underrepresented in the literature, including cassava, banana, common bean, cocoa, yam, and millet production systems.

Pillar 2, Algorithms (medium-term, 3-5 years): Advance lightweight, efficient, and explainable AI models for affordable devices and expand federated learning research toward practical agricultural applications. Particular attention should be paid to models that can run on low-cost smartphones without reliable internet connectivity, since this remains the primary hardware constraint reported across the included field studies.

Pillar 3, Deployment (medium to long-term, 3-10 years): Develop offline-capable, multi-crop diagnostic tools and integrate AI disease detection with extension services and digital advisory platforms. Pilot programmes co-designed with agricultural extension officers would help identify practical barriers to adoption before large-scale rollout is attempted.

Pillar 4, Implementation and user-centered design (long-term, 5-10 years): Promote responsible data-sharing, stakeholder collaboration, and evaluation of usability, cost-effectiveness, and adoption barriers to ensure AI solutions meet farming needs**.** Longitudinal studies tracking farmer adoption and outcomes over multiple growing seasons would provide stronger evidence of real-world impact than single-season accuracy snapshots.

LIMITATIONS

This review was limited to English-language publications, which may have excluded relevant non-English studies. Publication bias may have favoured studies reporting higher performance, while exclusion of conference papers may have omitted emerging developments. Heterogeneity in crops, datasets, and evaluation protocols precluded meta-analysis, and incomplete reporting and limited external validation constrained synthesis. Despite these limitations, the PRISMA-guided approach and structured quality assessment provide a robust synthesis of current evidence and research priorities.

Note: Supplementary Appendix A (Containing complete data-extraction table and full nine-criterion quality scores for all 35 studies) is available.

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