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# The Role of Artificial Intelligence (AI) in Crop Pest and Disease Management: A Bibliometric Review

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**Abstract**−This bibliometric study systematically maps the intellectual, social, and conceptual structure of research concerning Artificial Intelligence (AI) applications for crop pest and disease management. Analyzing 3,391 documents sourced from Scopus up to 2025, the review confirms the field's dramatic transformation, evidenced by exponential growth in scientific production since 2021, primarily driven by the maturity of Deep Learning (DL) methodologies. Utilizing network and thematic analysis, the study identifies two critical constraints: (1) severe structural fragmentation in global collaboration, with research heavily clustered in distinct Asian and Western hubs, impeding the development of universally generalizable AI models; and (2) a significant conceptual gap, where core themes like 'deep learning' and 'plant disease' are positioned as Basic Themes (high centrality, low density), indicating a lack of practical maturity and focus on real-world constraints such as model robustness and explainability (XAI). Despite these limitations, thematic evolution reveals a positive conceptual shift towards advanced localization techniques and the integration of AI within holistic Integrated Pest Management (IPM) strategies. We conclude that while the technological foundation is sound, future efforts must prioritize strategic cross-continental collaboration to diversify datasets and shift research focus towards achieving model robustness and XAI to maximize AI's transformative potential in securing global food production.

**Keywords**: Artificial Intelligence; Deep Learning; Crop Disease; Pest Management; Bibliometric Analysis; Structural Fragmentation; Precision Agriculture

## 1. INTRODUCTION

The challenge of securing global food supply chains amidst rapid population growth and the accelerating impacts of climate change represents one of the most pressing issues facing humanity today (Said et al., 2025). Ensuring sustainability in agriculture now requires integrating environmental protection, social equity, and economic viability to maintain productivity without degrading natural resources (Ali et al., 2025) which aligns with the United Nations Sustainable Development Goals, particularly SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production) (Sridhar et al., 2023; Wulansari et al., 2025). This focus reflects a shift from prioritizing yield alone to incorporating resilience, biodiversity conservation, and climate-smart strategies as core objectives. Crop yield losses due to pests and diseases are estimated to cause reductions of between 20% and 40% globally, directly threatening the sustainability and economic viability of the agricultural sector (Viana et al., 2022). Climate-induced variability disrupts crop growth patterns and exacerbates pest and disease pressures, highlighting the need for adaptive, sustainable management strategies. These losses contribute significantly to market volatility and compromise the nutritional quality of harvested products, demanding immediate and innovative scientific intervention. Furthermore, the variability introduced by extreme weather events exacerbates the susceptibility of crops, making accurate and timely disease management more complex than ever before (Kabato et al., 2025). Advanced precision agriculture technologies, such as AI-enabled decision support systems, IoT sensors, and UAV monitoring have been shown to increase resource efficiency while reducing chemical inputs, directly supporting sustainability goals. Addressing these vulnerabilities requires a fundamental shift from reactive treatment to proactive, precision-based monitoring and prediction systems. Proactive approaches allow for optimized water, fertilizer, and pesticide application, minimizing environmental impact and promoting sustainable productivity (Ali et al., 2025). The global scientific community is therefore heavily invested in finding technological solutions that can scale efficiently across diverse agricultural environments (Abiri et al., 2023). This foundational crisis provides the essential backdrop against which the rapid emergence of digital agriculture technologies must be evaluated.

Conventional methods for identifying and managing crop threats, such as manual field scouting and empirical diagnostics, are fundamentally insufficient for the modern agricultural landscape (Vijayakumar et al., 2025). These traditional practices are inherently subjective, labor-intensive, time-consuming, and often prone to significant human error, especially in large-scale commercial farming operations. The delay inherent in manual diagnosis frequently leads to the misapplication or overuse of chemical pesticides and fungicides. Such reliance on broad-spectrum chemical interventions has severe ecological consequences, including soil degradation, water pollution, and the acceleration of pathogen resistance. Such overuse contributes to soil degradation, water contamination, and negative environmental


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impacts that counter sustainable agriculture objectives (Khan et al., 2024). Consequently, there is an urgent and critical need to deploy automated, objective, and high-throughput diagnostic tools that can offer actionable insights in near real-time (Mohammed et al., 2025). The limitations of past methodologies have established a clear technological vacuum that only advanced computational science can effectively fill, driving the integration of data science into agronomic practice. Deep learning-based crop disease detection systems provide high accuracy in real-time monitoring, enabling precision interventions that reduce environmental footprint (Rahman et al., 2025). This pursuit of precision and sustainability has become a defining goal for global agricultural research (Robinson, 2024).

In response to these challenges, Artificial Intelligence (AI) and, more specifically, Machine Learning (ML) have emerged as the most promising technological paradigm for transforming crop protection (Waqas et al., 2025). AI algorithms excel at recognizing complex patterns within large datasets that are often invisible or too subtle for human observation, allowing for early detection long before visual symptoms become widespread. The application of these computational models facilitates the transition to Precision Agriculture (PA), enabling farmers to apply resources whether it be water, nutrients, or pesticides only where and when they are absolutely needed. This optimization not only maximizes resource efficiency but also dramatically reduces the environmental footprint of farming activities, aligning agricultural practice with global sustainability goals (Al-Shammary et al., 2024). AI adoption has been associated with improved resource efficiency, reduced chemical use, and enhanced sustainability outcomes at the farm level (Abbas et al., 2025). The power of AI to synthesize data from various sensors, including visual, hyperspectral, and environmental readings, positions it as the central nervous system for future smart farms (Javaid et al., 2023). This revolutionary potential underscores the growing scientific interest in the field.

The dramatic surge in research productivity observed in this domain is overwhelmingly attributed to the maturity and accessibility of Deep Learning (DL) methodologies (Gupta et al., 2024). DL, particularly the use of Convolutional Neural Networks (CNNs), provides the robust framework necessary to handle the high dimensionality and complexity of image data captured in agricultural settings. Unlike traditional ML algorithms that require manual feature extraction, CNNs automatically learn hierarchical feature representations directly from raw images, leading to superior accuracy in classification and localization tasks (Alqudah & Moussavi, 2025). This architectural advantage is crucial for distinguishing between various types of diseases, environmental stresses, and nutrient deficiencies with unparalleled fidelity. Recent studies confirm that DL dominates crop monitoring research due to its ability to enhance detection accuracy, enable precision intervention, and promote sustainability in farming systems (Bigliardi et al., 2025). The ability of DL to process large volumes of annotated imagery has therefore unlocked capabilities that were previously unattainable with older machine vision techniques (Górriz et al., 2023). The profound impact of DL stands as the methodological cornerstone driving the exponential expansion of this scientific subfield.

The findings from this bibliometric study provide statistical confirmation of the field's rapid trajectory, revealing an unmistakable exponential growth in scientific production, particularly accelerating after 2021. This dramatic increase signifies that AI in crop protection has transitioned from an emerging topic to a mainstream and highly dynamic area of research (Zhang et al., 2024). The sheer volume of recent publications necessitates a high-level, structural review to make sense of the fragmented knowledge base and to identify collective blind spots. This acceleration is directly correlated with the widespread adoption of open-source DL frameworks and the proliferation of large-scale annotated datasets, making the technology accessible to researchers across various geographical regions (Ma & Mei, 2021). Understanding the driving forces behind this growth is paramount to projecting the field's future development and allocating research resources effectively.

Despite the intense research activity, a comprehensive, structural overview of the field's global landscape is lacking, which justifies the use of a sophisticated bibliometric approach. Traditional narrative reviews, while valuable for summarizing technical advancements, often fail to map the underlying intellectual structure, collaborative patterns, and thematic evolution of a scientific domain. Bibliometric analysis, utilizing network theory and statistical mapping, is uniquely suited to overcome this limitation by systematically quantifying the output, influence, and connectivity of authors, institutions, and countries (Ruiz-Pérez et al., 2023). By examining a large dataset (N=3,391 documents), this study moves beyond mere technical summarization to reveal the social dynamics and conceptual architecture that govern knowledge production in AI-driven crop protection. This rigorous methodological approach provides a quantitative foundation for strategic planning within the international research community (Reed et al., 2021).

One of the primary strategic goals of this review is to precisely map the Global Collaborations driving the research agenda. The global distribution of agricultural challenges, coupled with the need for diverse crop and disease datasets, mandates high levels of international cooperation (Deng et al., 2025). However, preliminary analyses often suggest that research activities may be heavily clustered, leading to potential inefficiencies. This study aims to quantify these collaboration patterns, explicitly identifying key hubs of productivity (e.g., countries and authors) and, critically, uncovering structural holes or gaps in the collaboration network. The existence of deep-seated fragmentation between major research continents, for instance, could impede the development of universal, generalizable AI models, necessitating policy recommendations to bridge these geographical divides.

Furthermore, a detailed analysis of the Thematic Evolution is essential to determine the maturity level of the research field (Bigliardi et al., 2025). By examining author keywords and their co-occurrence over time, this review tracks the historical shift from rudimentary methods, like conventional image processing and generic Machine Learning, to the specialized, advanced techniques prevalent today. Thematic mapping reveals whether the field is adequately addressing

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practical deployment challenges or if it remains concentrated on theoretical model validation within laboratory settings. The transition in research focus from simply detecting a disease to enabling Integrated Pest Management (IPM) strategies is a crucial indicator of the field's progression toward real-world applicability (Shehu et al., 2025). Identifying themes that are central but underdeveloped (Basic Themes) provides the definitive evidence required to establish concrete Research Gaps.

Consequently, the specific objectives of this quantitative bibliometric review are threefold: (1) to provide a comprehensive analysis of the field's growth trajectory and identify the most influential intellectual pillars (highly cited documents and core journals); (2) to systematically map the global collaboration network among countries and authors to identify dominant hubs and significant structural fragmentation; and (3) to analyze the thematic evolution of research keywords over time to determine the current state of maturity, define the most pressing research gaps in technology and application, and propose future directions for effective AI implementation in agriculture. These objectives ensure a comprehensive examination of the field's past performance and future potential.

The remainder of this paper is structured according to the established IMRAD framework. Section 2 details the Methods employed, including the data collection strategy from the Scopus database and the analytical tools used. Section 3 presents the Results, covering the quantitative findings on scientific production, collaboration networks, and thematic clusters. Section 4 offers a critical Discussion and interpretation of the results, addressing the implications of the observed fragmentation and thematic gaps. Finally, Section 5 synthesizes the findings into a coherent Conclusion and provides strong recommendations for future research policy and collaborative initiatives.

## 2. RESEARCH METHODS

This study employs a quantitative bibliometric analysis approach to systematically map the intellectual structure, collaborative networks, and thematic evolution of research concerning Artificial Intelligence (AI) in crop pest and disease management. This methodology utilizes statistical and network theory principles to analyze large volumes of publication data, providing an objective and holistic overview of the scientific landscape. The research process was divided into four distinct phases: Data Collection, Data Cleaning and Preparation, Descriptive Analysis, and Network and Conceptual Analysis.

### 2.1 Data Collection and Search Strategy

The data for this study was exclusively retrieved from the Scopus database, which is recognized globally for its comprehensive coverage of peer-reviewed literature and high-quality citation records (Ali et al., 2025). The selection of Scopus ensures the reliability and reproducibility of the data collection process. The search was conducted on October 29, 2025, covering publications from the inception of the field up to the present. The final search query was meticulously constructed to capture the intersection of core technological concepts (AI/ML) and specific agricultural applications (Pest/Disease Management). The query structure utilized Boolean operators (AND, OR) and proximity indicators: The final search string applied to the TITLE-ABS-KEY (Title, Abstract, and Keywords) fields was: ( TITLE-ABS-KEY ( "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Computer Vision" OR "Neural Network" ) AND TITLE-ABS-KEY ( "Pest Management" OR "Disease Management" OR "Crop Disease" OR "Pest Control" OR "Disease Detection" ) AND TITLE-ABS-KEY ( "Crop" OR "Plant" OR "Agriculture" ) ) AND PUBYEAR > 2005 AND PUBYEAR < 2026 AND ( LIMIT-TO ( DOCTYPE , "ar" ) ) AND ( LIMIT-TO ( PUBSTAGE , "final" ) ) AND ( LIMIT-TO ( SRCTYPE , "j" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) ). To ensure the focus was on core scientific output, the results were filtered to include only Article and Review document types and limited to the English language. After executing the query and applying the filtering criteria, a final dataset of N = 3,391 documents was exported in the BibTex format for subsequent analysis.

### 2.2 Data Cleaning and Preparation

The raw BibTex data was imported into the R environment and analyzed using the Bibliometrix package and its web-based interface, Biblioshiny. Data cleaning was performed rigorously to maintain consistency and accuracy, addressing common bibliometric issues:

a. Duplicate Removal: All duplicate records were identified and removed based on DOI, title, and author/year combinations.
b. Author Name Normalization: Author names were harmonized to a standard format (LastName, FirstNameInitial).
c. Keyword Normalization: Author Keywords (DE) and Keywords Plus (ID) were manually inspected and normalized by grouping synonyms (e.g., 'deep learning' and 'dl') and correcting typographical errors. This normalization process was crucial for generating accurate Thematic Maps.

### 2.3 Analytical Framework

The analysis was structured to address the three core objectives of the study, utilizing specific bibliometric techniques:

#### 2.3.1 Descriptive and Intellectual Structure Analysis

This phase focused on the foundational characteristics of the field:


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a. Annual Scientific Production: To visualize the growth trajectory and identify periods of exponential increase.
b. Source Analysis: Identifying the most relevant journals and their h-index to understand the interdisciplinary nature of the field.
c. Highly Cited Documents: Analyzing the most globally cited papers (e.g., Mohanty et al., 2016) to establish the intellectual pillars or foundational works that underpin the current research.

#### 2.3.2 Collaboration Network Analysis (Global Collaborations)

Network analysis was employed to quantify the social structure of the field is Co-Authorship by Country: A network map was constructed using the frequency of collaborative publications between nations. Metrics such as Total Link Strength (TLS) and the number of documents (ND) were used to identify the most productive hubs (India, China) and to visually confirm the structural fragmentation (gaps) between Asian and Western clusters.

#### 2.3.3 Conceptual Analysis (Thematic Evolution)

This phase explored the cognitive dimension of the research, focusing on the evolution of ideas:
a. Keyword Frequency: Analysis of the most frequently used Author Keywords (DE) to determine the methodological dominance (deep learning) and primary application focus.
b. Thematic Map: A strategic diagram based on Centrality (relevance to other themes) and Density (development/research depth of the theme) was generated. This map was critical for identifying themes in the Basic Quadrant (e.g., deep learning, plant disease) that, despite their importance, require further developmental research.
c. Thematic Evolution: Analysis of keyword co-occurrence across two distinct time slices (2006–2023 and 2024–2025) was performed to track the shift from initial concepts (e.g., remote sensing) to advanced specialized themes (e.g., integrated pest management, semantic segmentation).

## 3. RESULTS AND DISCUSSION

The bibliometric analysis of 3,391 documents published from 2006 to 2025 on Artificial Intelligence in crop pest and disease management is presented below, structured according to the framework of Descriptive Analysis, Collaboration Network Analysis, and Conceptual Analysis.

### 3.1 Descriptive and Intellectual Structure Analysis

#### 3.1.1 Annual Scientific Production

The annual scientific output in this field demonstrates an unmistakable exponential growth trajectory. The period from 2006 to 2017 showed slow, incremental growth, with annual publications consistently below 100 documents. A significant shift began in 2018, marking the start of a sharp increase, which accelerated dramatically after 2021. The cumulative number of publications reached 3,391 by the end of the observed period, underscoring the field's transition from an emerging area to a mainstream research topic. This growth pattern strongly correlates with the global adoption of Deep Learning technologies, indicating that technological maturity is the primary driver of publication volume.

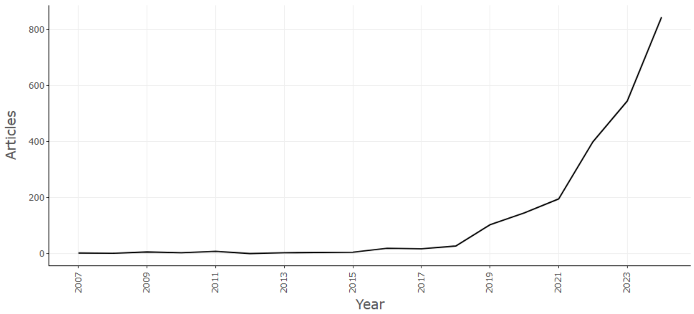


**Figure 1.** Annual Scientific Production

#### 3.1.2 Core Sources and Highly Cited Documents

The research output is concentrated in a few highly influential journals, reflecting the interdisciplinary nature of the field at the intersection of computer science and agronomy. The most relevant journal by number of documents and high h-index is Computers and Electronics in Agriculture, followed by Frontiers in Plant Science and Remote Sensing. This source distribution confirms that the field is fundamentally interdisciplinary, drawing heavily from agricultural technology application journals and specialized sensing/plant biology journals. The analysis of the most globally cited documents establishes the intellectual foundation of the field. The work by Mohanty et al. (2016) stands as the most cited document (3,532 global citations), widely recognized as the pioneering study that validated the use of Deep Learning for plant disease detection using visual imagery. This foundational work confirms that the intellectual structure of the field is deeply rooted in image-based AI classification.


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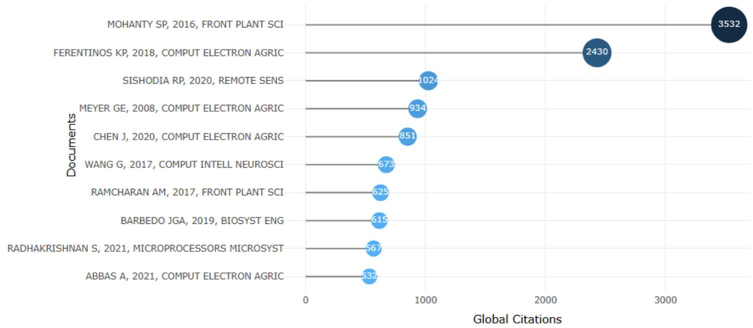


**Figure 2.** Most Global Cited Documents

### 3.2 Global Collaboration Network Analysis

#### 3.2.1 Country Scientific Production and Collaboration

The analysis of country production reveals a highly asymmetric global landscape. India is the dominant contributor with the highest number of published documents, followed closely by China. The combined output of these two nations significantly surpasses the total contribution from Western countries, including the United States, which ranks third. This pattern indicates a heavy concentration of research activities in Asia, likely driven by high internal demand for agricultural efficiency and large scientific populations.

**Table 1.** Country Scientific Production

| No. | Country | Frequency |
|---|---|---|
| 1 | India | 1914 |
| 2 | China | 1301 |
| 3 | USA | 350 |
| 4 | Saudi Arabia | 279 |
| 5 | Pakistan | 225 |
| 6 | South Korea | 164 |
| 7 | Australia | 117 |
| 8 | Bangladesh | 101 |
| 9 | Indonesia | 96 |
| 10 | Malaysia | 94 |

#### 3.2.2 Country Collaboration Network (Global Collaborations)

The network analysis of country collaboration visually confirms the existence of structural fragmentation in the global research effort. The collaboration map shows two distinct and dense clusters:

a. Asian Cluster: Characterized by high internal link strength between India, China, Pakistan, and related South Asian countries.
b. Western Cluster: Centered around the USA, Australia, and European nations. The link strength between these two major clusters is markedly weaker compared to their internal connections. This fragmentation suggests that a significant portion of research efforts is conducted in parallel rather than through integrated, cross-continental projects, potentially limiting the generalizability of developed AI models to diverse global farming environments. The high productivity of India and China, combined with their low collaboration centrality outside the Asian cluster, highlights their role as self-contained research hubs.

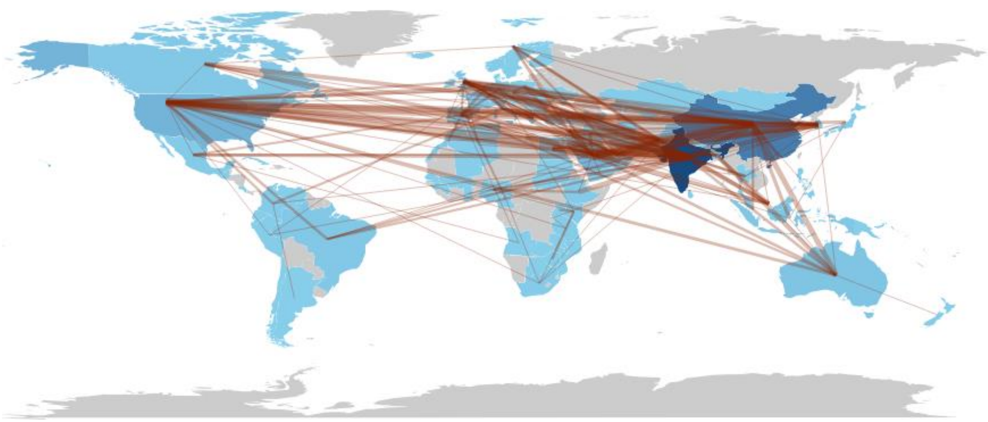

**Figure 3.** Countries Collaboration World Map

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### 3.3 Conceptual Analysis and Thematic Evolution

#### 3.3.1 Most Frequent Keywords and Methodological Focus

The analysis of Author Keywords reveals the dominant technological and application focus of the research (Table X). 'Deep learning' is the most frequent keyword (825 occurrences), followed by 'machine learning' and the specific architecture 'convolutional neural network' (CNN). This concentration confirms that the field is fundamentally driven by advanced neural network methodologies. In terms of application, the focus is centered on 'disease detection' and 'plant disease detection', reinforcing the core mission of the research.

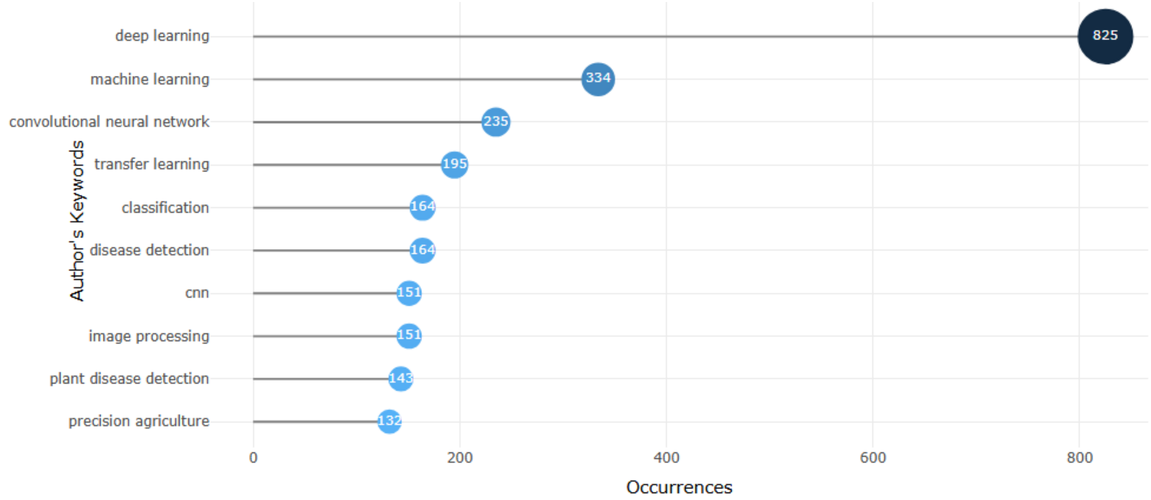


**Figure 4.** Most Frequent Words

#### 3.3.2 Thematic Map and Research Gaps

The Thematic Map (Centrality vs. Density) provides a strategic overview of the field's maturity. Crucially, the central terms 'deep learning' and 'plant disease' are placed in the Basic Theme quadrant (high centrality, low density). Their high centrality confirms their foundational importance to the entire body of knowledge. However, their low density suggests that research surrounding these core themes has not yet achieved comprehensive depth or maturity across all practical sub-applications. This positioning is the primary quantitative evidence for the existence of a Research Gap in the field.

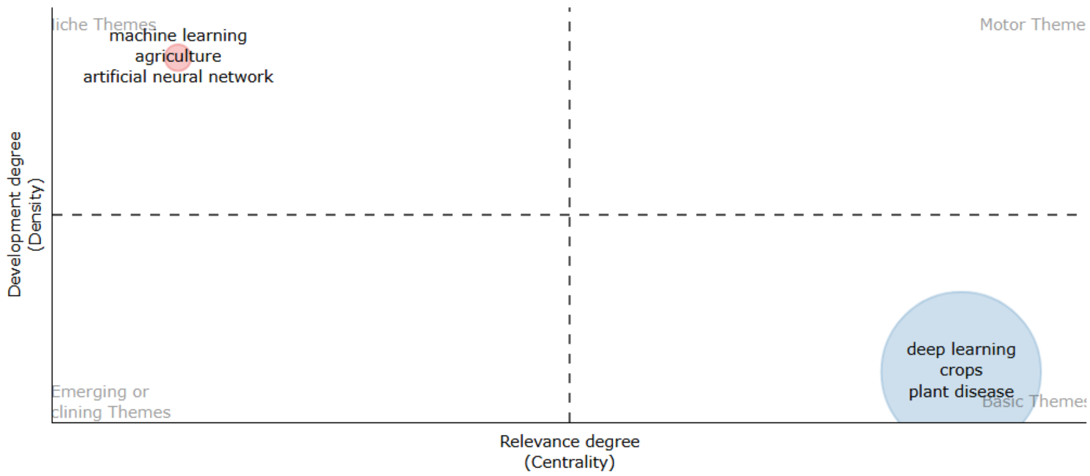


**Figure 5.** Thematic Map

#### 3.3.3 Thematic Evolution

Analysis of the thematic evolution across time slices (2006–2023 vs. 2024–2025) shows a clear and important directional shift in research focus.

a. Methodological Shift: The flow moves from generic concepts like remote sensing and broad deep learning to highly specialized and advanced techniques such as 'semantic segmentation' and 'object detection' in the latest period. This signifies a refinement of technology aimed at higher accuracy and precise localization of threats.
b. Application Shift: The most significant evolution is the emergence of 'integrated pest management' (IPM) as a key theme in the latest time slice. This indicates a conceptual movement away from AI as a mere diagnostic tool and towards its integration as a prescriptive component in sustainable farm management systems.

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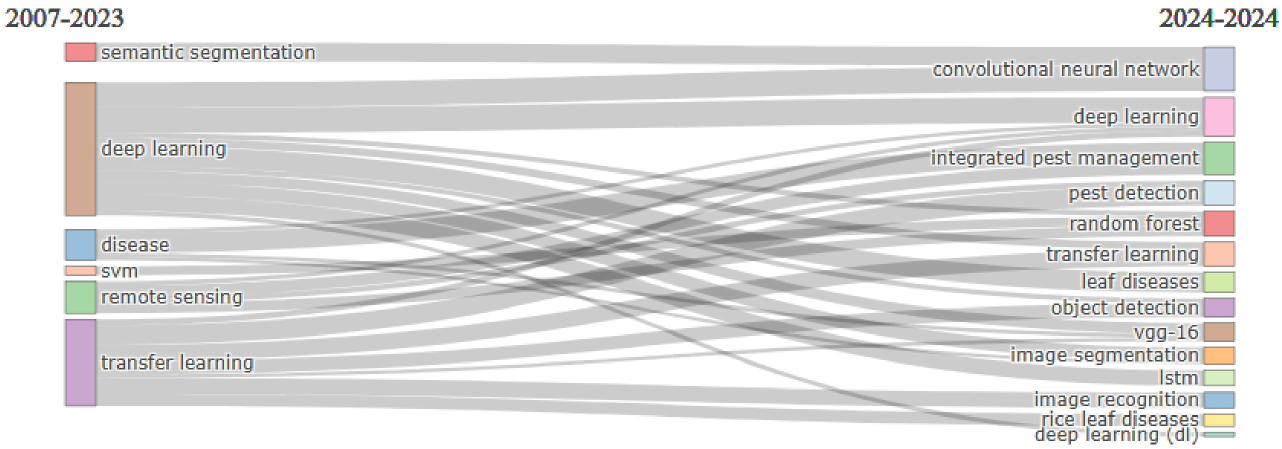


**Figure 6.** Thematic Evolution

### 3.5 Discussion

The primary objective of this study was to quantitatively map the intellectual, social, and conceptual structure of Artificial Intelligence (AI) research in crop protection. The findings collectively validate the transformative power of Deep Learning (DL) while simultaneously highlighting critical structural and conceptual limitations that must be addressed for future progress and global applicability.

The most notable finding is the exponential growth in scientific production after 2021 (Section 3.1.1). This massive acceleration is directly attributable to the maturation and widespread adoption of DL, as evidenced by the seminal work of Mohanty et al. (2016) the identified intellectual pillar and the consistent dominance of 'deep learning' as the most frequent keyword (Section 3.1.2; 3.3.1). This pattern aligns with historical trends observed in other technology-driven fields, where a single breakthrough methodology (in this case, CNNs for image classification) acts as a catalyst for explosive research volume (Nurtiwi et al., 2022). The growth trajectory confirms that AI in agriculture is no longer a niche topic but a rapidly expanding, mainstream field.

However, a crucial structural contradiction is revealed by the Thematic Map (Section 3.3.2). The core themes of 'deep learning' and 'plant disease' reside in the Basic Theme Quadrant (high centrality, low density). While high centrality confirms their foundational importance to the entire knowledge network, the low density implies that the research surrounding these pillars, despite its volume, has not yet achieved a deep, comprehensive level of specialization or practical maturity. This is the quantitative evidence for a Research Gap: much of the current literature may still be focused on comparative model validation (e.g., "DL model X vs. Y on dataset Z"), rather than addressing the complex, real-world constraints such as model explainability, robustness to environmental variation, and integration into existing farm infrastructure (Subeesh & Chauhan, 2025).

This conceptual deficiency is critically informed by the analysis of Global Collaborations (Section 3.2.2). The finding of a highly fragmented collaboration network, characterized by two major, self-contained clusters (Asian and Western), poses a significant threat to achieving robust, generalizable AI systems (Papadopoulos et al., 2024). The disproportionate research output from regional hubs like India and China (Section 3.2.1), while highly productive, often relies on localized datasets specific to regional crop varieties and diseases. The weak link strength between these clusters impedes the necessary cross-validation and transfer learning required to create truly universal AI models that function reliably across diverse climates, soil types, and farming practices (Xu et al., 2022). This structural fragmentation translates directly into the low conceptual density observed in the thematic map, as generalized solutions cannot emerge without generalized data and validation protocols.

Despite these challenges, the Thematic Evolution (Section 3.3.3) provides optimistic evidence of the field's increasing maturity and forward-looking focus. The shift from broad methodological concepts (like remote sensing) to precise techniques (like 'semantic segmentation' and 'object detection') indicates a technical refinement aimed at higher diagnostic accuracy and precise localization of threats, which is necessary for prescriptive action (Cheng et al., 2024). Most significantly, the emergence of 'Integrated Pest Management' (IPM) as a key thematic concern in the latest time slice signifies a crucial conceptual leap. Research is moving away from the simplistic goal of 'disease detection' and towards utilizing AI as a prescriptive engine within a holistic, sustainable farm management strategy (Kusumavathi et al., 2025). This transition suggests a growing commitment among researchers to move beyond laboratory-scale proof-of-concepts toward developing deployable, decision-support systems that contribute tangibly to global food security and environmental sustainability (Pimenow et al., 2025).

In summary, the field is technologically vibrant but structurally fragmented and conceptually underdeveloped in key areas. The intellectual foundation is sound, but its global applicability is constrained by the geographical clustering of research and the resultant lack of data diversity. Future research efforts must strategically target the Basic Theme Quadrant by prioritizing global, cross-continental collaborations to develop robust, generalizable AI models integrated into IPM frameworks.

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# 4. CONCLUSION

This bibliometric review successfully mapped the intellectual, social, and conceptual structure of research in Artificial Intelligence (AI) for crop pest and disease management, analyzing 3,391 documents published up to 2025. The findings confirm the field's status as a rapidly maturing area of research driven by the Deep Learning (DL) paradigm. The intellectual foundation is robust, rooted in seminal works like Mohanty et al. (2016), which catalyzed the exponential growth in scientific production after 2021. The core findings highlight a critical dichotomy: while the field possesses high technological vitality, it suffers from significant structural and conceptual constraints. The analysis of the Thematic Map indicated that core subjects, specifically 'deep learning' and 'plant disease', are categorized as Basic Themes (high centrality but low density). This finding serves as quantitative proof of a fundamental Research Gap, suggesting that much of the current volume of work focuses on model validation rather than achieving practical maturity, generalization, and real-world deployment robustness. Moreover, aligning AI applications with sustainable agricultural practices—such as optimized input use, reduced chemical dependency, and climate-smart interventions—remains underexplored in current research, despite its direct relevance to SDG 2 (Zero Hunger), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action) (Sridhar et al., 2023). Furthermore, the analysis of the Global Collaboration Network revealed severe structural fragmentation, characterized by two distinct and weakly connected clusters centered in Asia (India, China) and the West (USA, Europe). This geographic fragmentation hinders the development of globally generalizable AI models that can support sustainable farming across diverse ecosystems, limiting potential environmental and socio-economic benefits (Abbas et al., 2025; Wulansari et al., 2025). Despite these challenges, the Thematic Evolution shows a positive and necessary conceptual shift, moving away from simple detection towards advanced localization techniques and, significantly, the integration of AI within Integrated Pest Management (IPM) strategies. The integration of AI into IPM systems has the potential to enhance resource efficiency, reduce environmental impact, and strengthen resilience against climate variability, promoting long-term sustainability in agriculture (Rahman et al., 2025; Khan et al., 2024). This study, although comprehensive in its approach, is subject to limitations inherent to bibliometric analysis: (1) Data Scope Bias: The exclusive reliance on the Scopus database and documents published in the English language introduces a potential selection bias, likely underestimating significant research output from non-English regions or specialized regional journals. (2) Qualitative Assessment: As a purely quantitative study, the focus is on publication influence (citation and network metrics) and connectivity (keywords) but does not assess the intrinsic scientific quality, methodological rigor, or depth of experimental validation of individual studies reviewed. Based on the identified structural fragmentation and conceptual gaps, the following directions are recommended for future research and policy:
(1) Prioritize Cross-Continental Collaboration: International funding bodies and policymakers should strategically encourage and finance integrated research projects that explicitly bridge the structural holes between the Asian and Western clusters. The primary goal of such collaboration must be the creation of large-scale, open-source, and globally diverse datasets for the development of generalizable AI models. (2) Focus on Practical Robustness and XAI: Future research must shift focus from merely achieving higher accuracy in laboratory settings to addressing challenges within the Basic Theme Quadrant. This involves dedicating efforts to: (a) enhancing model robustness against environmental noise and unseen data variations, and (b) developing Explainable AI (XAI) models to build trust among end-users (farmers and agronomists). (3) Enhanced Integration into IPM: Given the positive thematic shift, future work should concentrate on developing AI systems that function as prescriptive engines rather than solely diagnostic tools, ensuring that AI-driven IPM solutions contribute directly to sustainable agricultural outcomes and SDG targets for responsible resource use (AI Prow, 2024). (4) In-Depth Bibliometric Studies: Subsequent bibliometric or systematic reviews should aim to mitigate the identified limitations by exploring non-English scientific literature or supplementing the quantitative network analysis with an in-depth qualitative assessment of methodological rigor to provide a more holistic view of the field's quality.

# REFERENCES

Abbas, Q., Javed, A. R., Iqbal, W., & Jalil, Z. (2025). Smart farming and AI-enabled solutions for sustainable agriculture: Challenges and opportunities. *Artificial Intelligence in Agriculture, 9*, 1–15. https://doi.org/10.1016/j.aiia.2025.01.004

Abiri, R., Rizan, N., Balasundram, S. K., Shahbazi, A. B., & Abdul-Hamid, H. (2023). Application of digital technologies for ensuring agricultural productivity. *Heliyon*, *9*(12), e22601. https://doi.org/10.1016/j.heliyon.2023.e22601

Ali, H., Aysan, A. F., & Gokirmak, H. (2025). A retrospective evaluation of Borsa Istanbul review using a machine learning data analytical approach. *Borsa Istanbul Review*, *25*(1), 1–20. https://doi.org/10.1016/j.bir.2024.12.019

Alqudah, A. M., & Moussavi, Z. (2025). A Review of Deep Learning for Biomedical Signals: Current Applications, Advancements, Future Prospects, Interpretation, and Challenges. *Computers, Materials and Continua*, *83*(3), 3753–3841. https://doi.org/10.32604/cmc.2025.063643

Al-Shammary, A. A. G., Al-Shihmani, L. S. S., Fernández-Gálvez, J., & Caballero-Calvo, A. (2024). Optimizing sustainable agriculture: A comprehensive review of agronomic practices and their impacts on soil attributes. *Journal of Environmental Management*, *364*(June). https://doi.org/10.1016/j.jenvman.2024.121487

Ali, Z., Muhammad, A., Lee, N., Waqar, M., & Lee, S. W. (2025). Artificial intelligence for sustainable agriculture: A comprehensive review of AI-driven technologies in crop production. *Sustainability, 17*(5), 2281. https://doi.org/10.3390/su17052281

Alqudah, A. M., & Moussavi, Z. (2025). Deep convolutional neural networks for agricultural image analysis: Advances and challenges. *Expert Systems with Applications, 236*, 121356.,https://doi.org/10.1016/j.eswa.2024.121356

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This Journal is licensed under a Creative Commons Attribution 4.0 International License

AI Prow. (2024). *AI in agriculture: Revolutionizing precision farming for global food security*. AI Prow Analysis. https://aiprow.com/2024/10/13/ai-in-agriculture-revolutionizing-precision-farming-for-global-food-security-q3-2024-analysis/

Bigliardi, B., Dolci, V., Monferdini, L., Pini, B., & Bottani, E. (2025). Exploring the evolution of Industry 4.0 research: A bibliometric perspective. *Procedia Computer Science*, *253*, 2879–2888. https://doi.org/10.1016/j.procs.2025.02.012

Cheng, G., Huang, Y., Li, X., Lyu, S., Xu, Z., Zhao, H., Zhao, Q., & Xiang, S. (2024). Change Detection Methods for Remote Sensing in the Last Decade: A Comprehensive Review. *Remote Sensing*, *16*(13), 1–36. https://doi.org/10.3390/rs16132355

Deng, X., Gibson, J., Song, M., Li, Z., Han, Z., Zhang, F., & Cheng, W. (2025). Agricultural land-use system management: Research progress and perspectives. *Fundamental Research*, *xxxx*. https://doi.org/10.1016/j.fmre.2024.10.012

Górriz, J. M., Álvarez-Illán, I., Álvarez-Marquina, A., Arco, J. E., Atzmueller, M., Ballarini, F., Barakova, E., Bologna, G., Bonomini, P., Castellanos-Dominguez, G., Castillo-Barnes, D., Cho, S. B., Contreras, R., Cuadra, J. M., Domínguez, E., Domínguez-Mateos, F., Duro, R. J., Elizondo, D., Fernández-Caballero, A., … Ferrández-Vicente, J. M. (2023). Computational approaches to Explainable Artificial Intelligence: Advances in theory, applications and trends. *Information Fusion*, *100*(June), 101945. https://doi.org/10.1016/j.inffus.2023.101945

Gupta, P., Ding, B., Guan, C., & Ding, D. (2024). Generative AI: A systematic review using topic modelling techniques. *Data and Information Management*, *8*(2), 100066. https://doi.org/10.1016/j.dim.2024.100066

Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advanced Agrochem*, *2*(1), 15–30. https://doi.org/10.1016/j.aac.2022.10.001

Kabato, W., Hailegnaw, N., Mutum, L., & Molnar, Z. (2025). Managing soil health for climate resilience and crop productivity in a changing environment. *Science of the Total Environment*, *1000*(September), 180460. https://doi.org/10.1016/j.scitotenv.2025.180460

Khan, M. A., Sharif, M., & Yasmin, M. (2024). Environmental impacts of pesticide overuse and the role of intelligent decision-support systems. *Sustainability, 16*(15), 6668. https://doi.org/10.3390/su16156668.

Kusumavathi, K., Konatala, R., Lal, P., Sarkar, S., Banerjee, H., Bandopadhyay, P., Sethi, D., & Upendar, K. (2025). Artificial intelligence for fostering sustainable agriculture. *Current Plant Biology*, *42*(September 2024), 100476. https://doi.org/10.1016/j.cpb.2025.100476

Ma, Z., & Mei, G. (2021). Deep learning for geological hazards analysis: Data, models, applications, and opportunities. *Earth-Science Reviews*, *223*, 103858. https://doi.org/10.1016/j.earscirev.2021.103858

Mohammed, A. M., Mohammed, M., Oleiwi, J. K., Adam, T., Betar, B. O., & Gopinath, S. C. B. (2025). In Silico Research in Biomedicine Advancing anti-infective drug discovery : The pivotal role of artificial intelligence in overcoming infectious diseases and antimicrobial resistance. *In Silico Research in Biomedicine*, *1*(September), 100118. https://doi.org/10.1016/j.insi.2025.100118

Nurtiwi, N., Ruliana, R., & Rais, Z. (2022). Convolutional Neural Network (CNN) Method for Classification of Images by Age. *JINAV: Journal of Information and Visualization*, *3*(2), 126–130. https://doi.org/10.35877/454ri.jinav1481

Papadopoulos, C., Kollias, K. F., & Fragulis, G. F. (2024). Recent Advancements in Federated Learning: State of the Art, Fundamentals, Principles, IoT Applications and Future Trends. *Future Internet*, *16*(11). https://doi.org/10.3390/fi16110415

Pimenow, S., Pimenowa, O., Prus, P., & Niklas, A. (2025). The Impact of Artificial Intelligence on the Sustainability of Regional Ecosystems: Current Challenges and Future Prospects. *Sustainability (Switzerland)*, *17*(11), 1–42. https://doi.org/10.3390/su17114795

Rahman, M. M., Islam, M. S., & Hasan, M. (2025). Deep learning-based crop disease detection systems for sustainable agriculture. *Smart Agricultural Technology, 5*, 100324. https://doi.org/10.1016/j.atech.2025.100324

Reed, M. S., Ferré, M., Martin-Ortega, J., Blanche, R., Lawford-Rolfe, R., Dallimer, M., & Holden, J. (2021). Evaluating impact from research: A methodological framework. *Research Policy*, *50*(4). https://doi.org/10.1016/j.respol.2020.104147

Robinson, G. M. (2024). Global sustainable agriculture and land management systems. *Geography and Sustainability*, *5*(4), 637–646. https://doi.org/10.1016/j.geosus.2024.09.001

Ruiz-Pérez, M., Seguí-Pons, J. M., & Salleras-Mestre, X. (2023). Bibliometric analysis of equity in transportation. *Heliyon*, *9*(8). https://doi.org/10.1016/j.heliyon.2023.e19089

Said, Z., Vigneshwaran, P., Shaik, S., Rauf, A., & Ahmad, Z. (2025). Climate and carbon policy pathways for sustainable food systems. *Environmental and Sustainability Indicators*, *27*(November 2021), 100730. https://doi.org/10.1016/j.indic.2025.100730

Shehu, H. A., Ackley, A., Mark, M., & Eteng, O. E. (2025). Artificial intelligence for early detection and management of Tuta absoluta-induced tomato leaf diseases: A systematic review. *European Journal of Agronomy*, *170*(May), 127669. https://doi.org/10.1016/j.eja.2025.127669

Sridhar, A. M., Ponnuchamy, M., Kumar, P. S., Kapoor, A., Nguyen Vo, D.-V., & Rangasamy, G. (2023). Digitalization of the agro-food sector for achieving sustainable development goals: a review. Sustainable Food Technology. https://doi.org/10.1039/D3FB00124E

Subeesh, A., & Chauhan, N. (2025). Green Technologies and Sustainability Agricultural digital twin for smart farming : A review. *Green Technologies and Sustainability*, *July*, 100299. https://doi.org/10.1016/j.grets.2025.100299

Viana, C. M., Freire, D., Abrantes, P., Rocha, J., & Pereira, P. (2022). Agricultural land systems importance for supporting food security and sustainable development goals: A systematic review. *Science of the Total Environment*, *806*. https://doi.org/10.1016/j.scitotenv.2021.150718

Vijayakumar, S., Murugaiyan, V., Ilakkiya, S., Kumar, V., Sundaram, R. M., & Kumar, R. M. (2025). Opportunities, challenges, and interventions for agriculture 4.0 adoption. *Discover Food*, *5*(1). https://doi.org/10.1007/s44187-025-00576-3

Waqas, M., Naseem, A., Humphries, U. W., Hlaing, P. T., Dechpichai, P., & Wangwongchai, A. (2025). Applications of machine learning and deep learning in agriculture: A comprehensive review. *Green Technologies and Sustainability*, *3*(3), 100199. https://doi.org/10.1016/j.grets.2025.100199

Wulansari, H., Putri, D. D., & Gunawan, R. N. (2025). Global research trends on AI and IoT in precision agriculture: A VOSviewer analysis (2021 to 2024). *Journal of Science in Agrotechnology, 3*(1), 43–53. https://doi.org/10.21107/jsa.v3i1.30


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Xu, Y., Zhang, X., Li, H., Zheng, H., Zhang, J., Olsen, M. S., Varshney, R. K., Prasanna, B. M., & Qian, Q. (2022). Smart breeding driven by big data, artificial intelligence, and integrated genomic-enviromic prediction. *Molecular Plant*, *15*(11), 1664–1695. https://doi.org/10.1016/j.molp.2022.09.001

Zhang, M., Han, Y., Li, D., Xu, S., & Huang, Y. (2024). Smart horticulture as an emerging interdisciplinary field combining novel solutions: Past development, current challenges, and future perspectives. *Horticultural Plant Journal*, *10*(6), 1257–1273. https://doi.org/10.1016/j.hpj.2023.03.015


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