



REVIEW ARTICLE

Artificial intelligence for crop disease detection and management: A bibliometric analysis of global research trends

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Abstract

Artificial intelligence (AI) has emerged as a transformative technology for crop disease detection and management by enabling rapid, accurate and automated disease diagnosis to support sustainable agricultural production. This study presents a bibliometric analysis of global research trends in AI-based crop disease detection and management from 2016 to 2026. Bibliographic data were retrieved from the Scopus database using a structured search strategy. A total of 3729 records were initially identified and 605 publications were retained after applying predefined inclusion and exclusion criteria. Bibliometric indicators and VOSviewer software were employed to analyse annual publication trends, leading contributors, collaboration networks, keyword co-occurrence patterns, bibliographic coupling relationships and co-citation structures. The results reveal a substantial increase in research output, particularly after 2021, indicating growing scientific interest in AI-enabled crop protection technologies. Keyword analysis identified deep learning, machine learning, computer vision, transfer learning and plant disease detection as the dominant research themes. In contrast, co-authorship and co-citation analyses revealed strong international collaboration and a well-established intellectual foundation. The literature indicates that AI-based crop disease detection has the potential to improve early disease diagnosis, support timely management decisions, reduce unnecessary pesticide application and enhance precision agriculture. However, limited field validation, scalability and economic evaluations remain important research gaps. Future research should focus on field-based validation, explainable AI, multimodel learning, deployment under real farming conditions and comprehensive assessments of cost-effectiveness and operational efficiency.

Keywords: computer vision; explainable artificial intelligence; knowledge mapping; scientometric analysis; sustainable agriculture; transfer learning

Introduction

Agriculture plays a vital role in global food security, yet crop productivity is severely affected by plant diseases caused by fungal, bacterial, viral and other pathogens. Early and accurate disease detection is essential to minimise yield losses, reduce unnecessary pesticide application and support sustainable crop production. Conventional disease diagnosis relies primarily on visual inspection by farmers and plant pathologists, which is often labour-intensive, time-consuming, subjective and less effective for large-scale monitoring or early-stage disease identification (1, 2).

Traditionally, plant disease diagnosis has relied on visual inspection performed by farmers, agronomists and plant pathologists. Although expert-based diagnosis can provide reliable results, these approaches are often labour-intensive, time-consuming, subjective and difficult to implement over large cultivation areas. Furthermore, many diseases exhibit similar visual symptoms during their early stages, making accurate identification challenging even for experienced specialists. Delayed or inaccurate diagnosis frequently results in disease progression, increased crop

damage, excessive pesticide application and economic losses. These limitations have motivated researchers to explore automated disease detection systems capable of providing timely and accurate diagnostic information to support crop management decisions (1).

Recent advances in artificial intelligence (AI) have transformed agricultural research and practice by enabling automated analysis of large and complex datasets. Artificial intelligence encompasses a broad range of computational techniques, including machine learning (ML), deep learning (DL), computer vision (CV), artificial neural networks (ANNs) and more recently, vision transformers (ViTs). These technologies have demonstrated remarkable capabilities in extracting disease-related features from plant images, sensor data, hyperspectral imagery and remote sensing platforms. Among these techniques, DL methods have gained particular attention because of their ability to automatically learn hierarchical features from raw data without extensive manual feature engineering. As a result, AI-driven systems have achieved unprecedented levels of accuracy in disease identification, classification and severity assessment across various crops (2,3).

Convolutional neural networks (CNNs) have emerged as one of the most widely adopted architectures for plant disease detection due to their superior performance in image recognition tasks. Numerous studies have reported classification accuracies exceeding 90 % when CNN-based models are applied to benchmark datasets such as PlantVillage. Transfer learning approaches utilising pre-trained architectures, such as ResNet, EfficientNet, VGGNet, DenseNet and MobileNet, have further improved detection accuracy while reducing computational requirements. More recently, vision transformer-based models have demonstrated promising results by capturing long-range dependencies and global contextual information within plant images, thereby expanding the capabilities of AI-based disease diagnosis systems (2, 3).

The integration of AI with emerging digital agriculture technologies has significantly enhanced crop health monitoring and disease management. Internet of things (IoT) devices, unmanned aerial vehicles (UAVs), wireless sensor networks, cloud computing platforms and mobile applications are increasingly being combined with AI algorithms to facilitate real-time disease surveillance. Such intelligent systems support precision agriculture by enabling early disease detection, disease forecasting, targeted pesticide application and decision-support mechanisms. These innovations not only improve crop productivity but also contribute to environmental sustainability by reducing unnecessary agrochemical usage and optimising resource allocation (1, 4).

Despite remarkable progress, several challenges continue to limit the practical implementation of AI-based crop disease detection systems. One major limitation is the widespread reliance on controlled laboratory datasets, particularly PlantVillage, which often fail to represent the variability encountered under real field conditions. Variations in lighting conditions, background complexity, disease severity levels, environmental stress factors and crop growth stages can substantially affect model performance. Consequently, models demonstrating exceptional accuracy in laboratory environments may experience performance degradation when deployed in agricultural fields. Researchers have therefore emphasised the need for more diverse, realistic and challenge-oriented datasets to improve model robustness and generalisability (5).

Another critical challenge relates to model interpretability and transparency. Although DL models often achieve superior predictive performance, they are frequently criticised as "black-box" systems because the reasoning behind their predictions is not easily understandable. This limitation raises concerns regarding trust, reliability and adoption among agricultural stakeholders. To address these issues, recent studies have increasingly explored explainable artificial intelligence (XAI) approaches that provide visual and interpretable explanations for disease predictions. Simultaneously, researchers are investigating lightweight architectures, edge computing and federated learning techniques to facilitate deployment in resource-constrained agricultural environments (1, 6).

The growing body of literature on AI-enabled crop disease detection and management reflects the rapid evolution of this research domain. Recent studies have expanded beyond disease classification to include disease severity estimation, disease forecasting, intelligent decision-support systems, autonomous monitoring and precision crop protection. Moreover, advances in multimodal learning, hyperspectral imaging, transformer architectures and explainable AI are creating new opportunities for developing more robust and practical disease management

solutions (7, 8).

Although several review articles have examined specific aspects of AI-based plant disease detection, the literature remains fragmented due to the rapid emergence of novel algorithms, datasets and application domains. A comprehensive bibliometric assessment of recent developments is therefore essential to understand current research trends, evaluate methodological advancements, identify existing challenges and highlight future research opportunities. Accordingly, this bibliometric study aims to critically examine the application of AI in crop disease detection and management, with particular emphasis on AI techniques, datasets, performance outcomes, implementation challenges and future research directions. The findings are expected to provide valuable insights for researchers, practitioners, policymakers and technology developers seeking to advance intelligent and sustainable crop protection systems.

Problem focus

Artificial intelligence (AI) has emerged as one of the most promising technological approaches for crop disease detection and management, resulting in a rapid increase in scientific publications over the last decade. Researchers have extensively explored ML, DL, CV, transfer learning and emerging transformer-based architectures to improve disease diagnosis, classification, forecasting and decision-support systems in agriculture. Consequently, the research landscape has expanded significantly across multiple disciplines, including plant science, computer science, agricultural engineering and precision agriculture.

Despite this rapid growth, the existing literature remains fragmented and dispersed across various journals, institutions, countries and research domains. Although numerous studies have reported advances in AI-based disease detection models, limited attention has been given to understanding the overall structure and evolution of the research field. Information regarding publication trends, influential authors, leading countries, collaborative networks, dominant research themes and intellectual foundations remains scattered, making it difficult to obtain a comprehensive overview of the field's development. Furthermore, the increasing emergence of advanced technologies such as VITs, XAI, edge computing, multimodal learning, remote sensing and smart agriculture has transformed the research landscape. The rapid expansion of these technologies necessitates a systematic mapping of global research activities to identify major contributors, emerging themes, knowledge structures and future research directions.

Therefore, a comprehensive bibliometric analysis is required to evaluate the development of AI-based crop disease detection and management research. By analysing publication trends, collaboration networks, keyword co-occurrence patterns, bibliographic coupling relationships and co-citation structures, this study aims to provide a holistic understanding of the global research landscape. The findings are expected to assist researchers, policymakers and agricultural technology developers in identifying research gaps, fostering scientific collaboration and guiding future innovations in intelligent crop protection and sustainable agriculture.

Methodology

This study employed a bibliometric research design to examine the global scientific literature on AI applications in crop disease detection

and management. Bibliometric analysis is a quantitative approach used to evaluate research productivity, publication trends, collaboration patterns, intellectual structures and emerging themes within a specific research domain. The method facilitates the systematic mapping of scientific knowledge through the analysis of bibliographic metadata and citation relationships, thereby providing insights into the development and evolution of a research field. The bibliographic data was retrieved from the Scopus database, which was selected due to its extensive coverage of peer-reviewed literature across agriculture, plant science, AI, computer science and related disciplines. The literature search was conducted on June 18, 2026, using a structured search strategy designed to capture publications related to AI-based crop disease detection and diagnosis. The search string used was ("Artificial Intelligence" OR AI OR "Machine Learning" OR "Deep Learning") AND ("Crop Disease Detection" OR "Plant Disease Detection" OR "Plant Disease Diagnosis"). The initial search yielded 3729 records. To ensure the quality and relevance of the retrieved publications, predefined

inclusion and exclusion criteria were established based on the publication period, document type, language, source type and research focus. The detailed inclusion and exclusion criteria adopted in this study are presented in Table 1, whereas the literature screening and selection process is illustrated in the Preferred reporting items for systematic reviews and meta-analyses (PRISMA) flow diagram (Fig. 1). The bibliometric analysis was performed on the complete dataset of 605 Scopus-indexed publications. However, only representative references relevant to the study background, methodology and discussion are cited in the manuscript in accordance with the journal guidelines. The retrieved records were exported from the Scopus database in Comma-Separated Values (CSV) format and processed for bibliometric evaluation. Descriptive bibliometric indicators were used to analyse annual publication trends, leading countries, authors, institutions, source journals and citation performance. Bibliometric analysis and network visualisation were conducted using VOSviewer software (version 1.6.20), a widely used tool for constructing and visualising

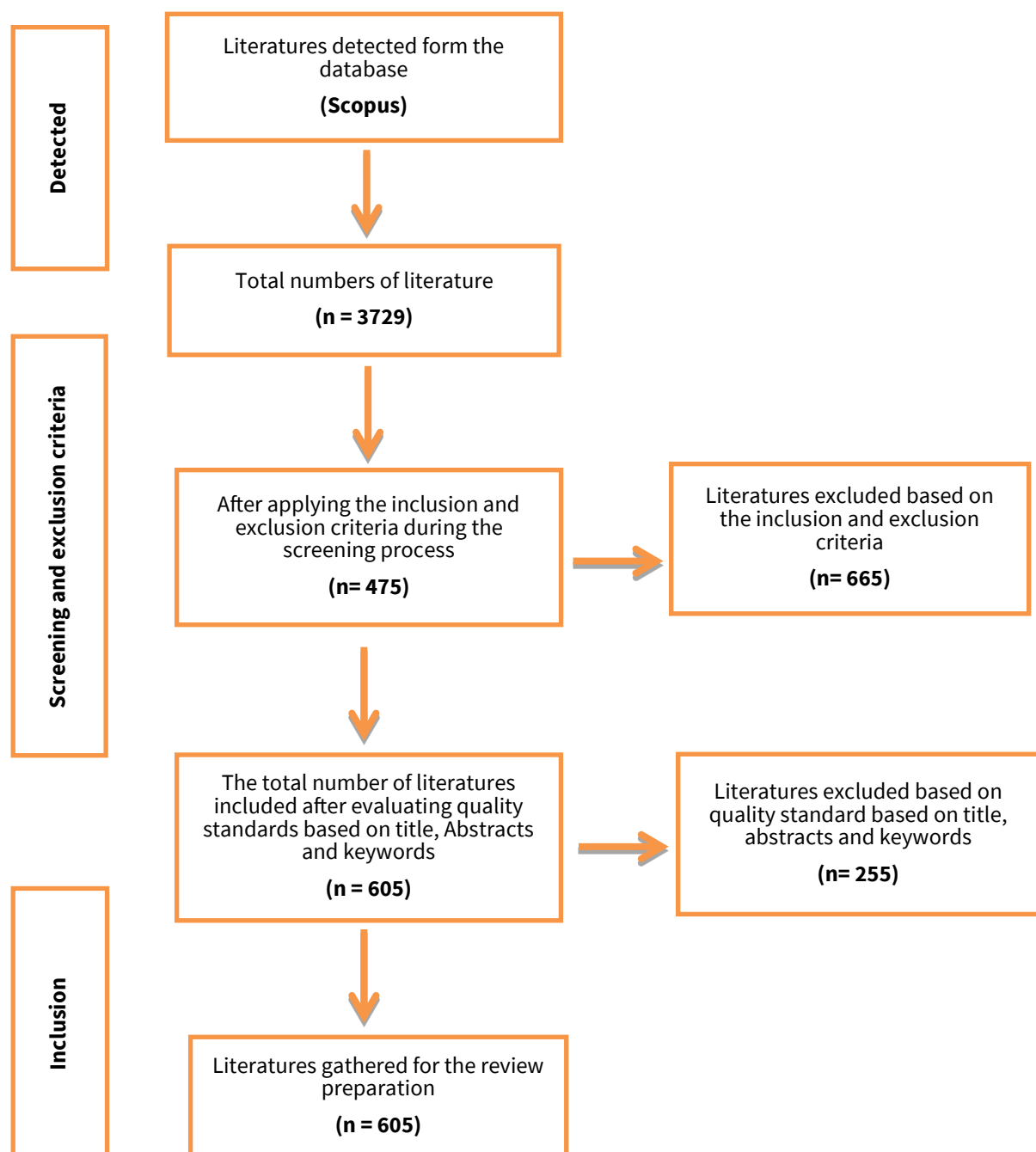


Fig. 1. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) flowchart.

Table 1. Inclusion and exclusion criteria

Databases	Inclusion	Exclusion
Time span	2016–2026	< 2016
Document type	Articles, Review	Conference papers, Book chapters, Books, Editorials, Conference reviews
Languages	English	Non- English And others all
Source type	Journal	Trade journal Book series Book
Publication stage	Final	Conference proceeding
Open access	All open access	Article in press Others

bibliometric networks. Four complementary bibliometric techniques were employed in this study. Co-authorship analysis was used to examine international collaboration patterns among countries and identify major research contributors. Keyword co-occurrence analysis was performed to reveal dominant research themes, emerging topics and conceptual structures within the field (Table 2). Bibliographic coupling analysis was applied to assess intellectual similarities among countries based on shared references, thereby highlighting common research interests and knowledge foundations. Co-citation analysis was conducted to identify influential publications and reveal the intellectual structure underpinning AI-based crop disease detection and management research. The resulting bibliometric networks were visualised using VOSviewer maps, where node size represented the relative importance or frequency of occurrence of an item, link thickness indicated the strength of relationships between items and colours represented clusters of closely related entities. These visualisations facilitated the interpretation of collaboration patterns, thematic developments and knowledge structures within the field. The dataset used for the analysis was retrieved from the Scopus database on 18 June 2026 and the processed data and VOSviewer output files are available from the corresponding author upon reasonable request.

Results and Discussion

Annual publication trends

The annual publication trend provides insight into the growth and evolution of research on AI for crop disease detection and management. As presented in Table 3, research output remained relatively low between 2016 and 2020, with fewer than 20 publications annually. However, publication activity increased substantially from 2021 onwards, reflecting growing interest in the application of ML, DL, CV and precision agriculture technologies. The highest number of publications was recorded in 2025 (193 publications), followed by 2024 (115 publications). The consistent upward trend indicates the increasing importance of AI-driven disease diagnosis systems in addressing challenges related to crop health monitoring, disease management and sustainable agricultural production.

Most productive countries

Geographical publication analysis was conducted to identify the major contributors to AI-based crop disease detection research. As presented in Table 4, India emerged as the most productive country

Table 3. Annual publication trend in AI-based crop disease detection and management research (2016–26)

Year	Number of publications
2016	1
2017	2
2018	2
2019	16
2020	12
2021	30
2022	56
2023	94
2024	115
2025	193
2026	84
Total	605

with 444 publications, followed by China (205 publications) and Saudi Arabia (111 publications). Pakistan, South Korea and the United States also demonstrated substantial research contributions. The high publication output from these countries indicates strong research interest and investment in AI-based crop disease detection and management. However, publication productivity alone does not confirm the practical adoption, field-level implementation, or economic feasibility of these technologies. Many published studies are based on laboratory experiments, benchmark datasets, simulation models, or CV approaches, while comparatively fewer studies validate AI models under real farming conditions. Therefore, future research should place greater emphasis on field-based validation, economic feasibility, scalability and adoption among small and marginal farmers to facilitate the practical deployment of AI technologies in agriculture.

Most productive authors

Analysing author productivity helps identify the research community driving advancements in AI-based crop disease detection and management. As presented in Table 5, the field is characterised by a group of highly productive researchers, reflecting sustained scientific contributions and active collaboration in this domain. The author productivity pattern indicates continuous research efforts in areas such as DL, CV, disease classification and intelligent crop protection. This distribution also demonstrates the interdisciplinary and globally collaborative nature of AI research for crop disease detection and management, contributing to the rapid advancement of innovative technologies for sustainable agriculture.

Most productive source journals

The analysis of publication sources provides insight into the journals that disseminate research on AI-based crop disease detection. As

Table 2. The list of keywords employed during the database literature searches

Databases	Keywords	Total number of articles
Scopus	("Artificial Intelligence" OR AI OR "Machine Learning" OR "Deep Learning") AND ("Crop Disease Detection" OR "Plant Disease Detection" OR "Plant Disease Diagnosis")	3729

Table 4. Top contributing countries in AI-based crop disease detection and management research

Rank	Country	Publications
1	India	444
2	China	205
3	Saudi Arabia	111
4	Pakistan	91
5	South Korea	77
6	United States	76
7	Malaysia	55
8	Australia	55
9	Bangladesh	54
10	Egypt	46

Table 5. Most productive authors in AI-based crop disease detection and management research

Rank	Author	Publications
1	Wang Y.	10
2	Kumar S.	7
3	Li Y.	6
4	Mridha M.F.	6
5	Kumar R.	6
6	Sharma P.	6
7	Wang X.	5
8	Liu J.	5
9	Ali F.	5
10	Zhou J.	5

presented in Table 6, the publications are distributed across agricultural, plant science, engineering and computer science journals, highlighting the interdisciplinary nature of the field. Although this diversity has accelerated methodological innovation, future studies should increasingly focus on translational research that validates AI technologies under field conditions and assesses their technical, economic and operational feasibility for practical agricultural applications.

Most influential publications

Citation analysis was performed to identify the publications that have had the greatest impact on the development of AI-based crop disease detection and management research. As shown in Table 7, the study entitled Using DL for image-based plant disease detection received the highest citation count (4230 citations), making it the most influential publication in the field. Several review articles and methodological studies also received substantial citation counts, indicating their importance in shaping subsequent research. The highly cited publications primarily focus on DL architectures,

Table 6. Most productive source journals

Rank	Journal	Publications
1	Frontiers in Plant Science	57
2	IEEE Access	48
3	Smart Agricultural Technology	19
4	Agriculture	19
5	AgriEngineering	18
6	International Journal of Advanced Computer Science and Applications	16
7	Sensors	15
8	Computers, Materials and Continua	14
9	Agronomy	13
10	Engineering, Technology and Applied Science Research	13

image-based disease diagnosis and automated crop health monitoring systems, which form the intellectual foundation of contemporary AI-driven agricultural research.

Co-authorship analysis of countries

International collaboration plays a crucial role in advancing research on AI for crop disease detection and management. The country-level co-authorship network reveals a highly interconnected research landscape characterised by extensive collaboration among countries across Asia, Europe, North America and Oceania (Fig. 2). In the network, node size represents the publication output of a country, while the links indicate collaborative relationships among countries. The thickness of the connecting lines reflects the strength of collaboration and the different colours represent distinct collaboration clusters.

Among the contributing countries, India occupies the most influential position within the network, as indicated by its largest node size and extensive collaborative linkages. The country demonstrates strong research partnerships with China, Pakistan, Bangladesh, Egypt, Canada and the United States, highlighting its central role in global scientific collaboration related to AI-based crop disease detection and management. The prominence of India suggests a substantial research output and increasing emphasis on the application of AI technologies in agriculture.

China also emerges as a major contributor, exhibiting a large node size and strong collaborative relationships with several countries, including India, the United States, Bangladesh, Australia and Iran. The country's strategic position within the network reflects its growing influence in AI-driven agricultural research and its active engagement in international scientific partnerships. Likewise, the United States serves as a key collaboration hub connecting multiple countries and clusters, demonstrating its significant contribution to

Table 7. Most influential publications in AI-based crop disease detection and management research

Rank	Article title	Citations
1	Using deep learning for image-based plant disease detection	4230
2	Plant disease detection and classification by deep learning: A review	928
3	Plant disease detection and classification by deep learning	753
4	Deep learning for image-based Cassava disease detection	715
5	Recent advances in image processing techniques for automated leaf pest and disease recognition: A review	539
6	An advanced deep learning models-based plant disease detection: A review of recent research	520
7	Solving current limitations of deep learning based approaches for plant disease detection	488
8	Plant disease detection using hybrid model based on convolutional autoencoder and CNN	384
9	Automatic and reliable leaf disease detection using deep learning techniques	383
10	AI-Powered banana diseases and pest detection	382

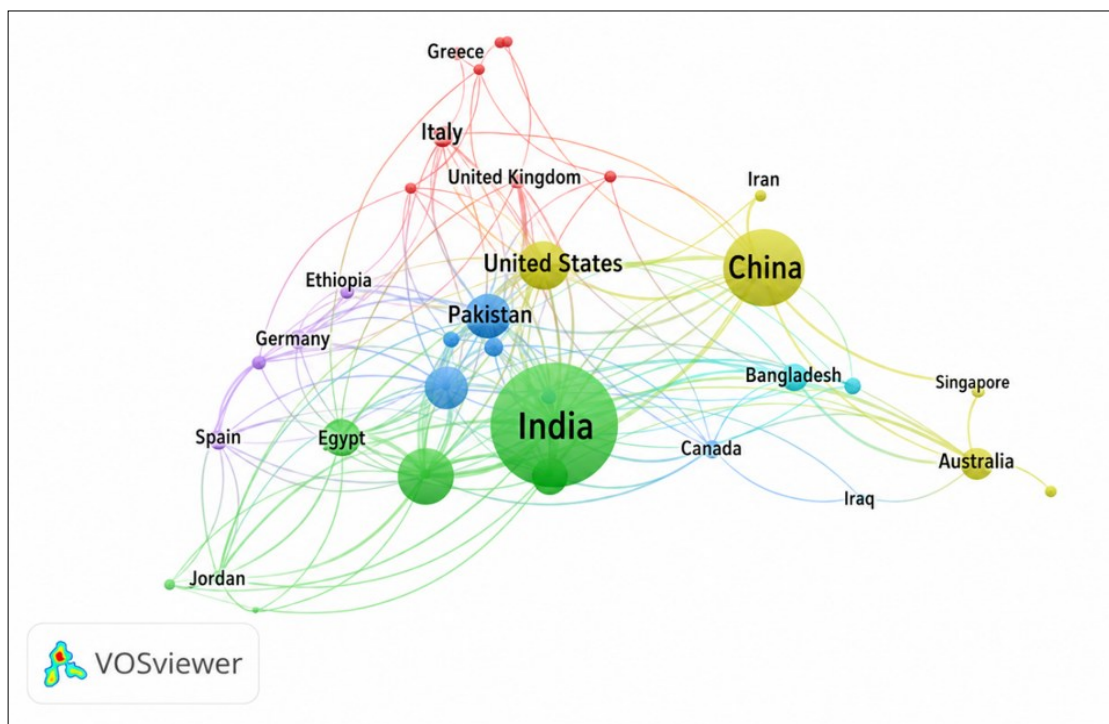


Fig. 2. Co-authorship analysis of countries.

technological advancements and interdisciplinary research in this field.

Pakistan and Bangladesh represent important contributors within the Asian research cluster. Pakistan maintains strong collaborative links with India, China and the United States, indicating increasing research activity in AI-enabled crop disease diagnosis and precision agriculture. Similarly, Bangladesh exhibits notable collaboration with India, China, Australia and Canada, reflecting the expanding participation of developing countries in agricultural AI research.

A distinct European collaboration cluster is observed, comprising countries such as the United Kingdom, Italy, Greece, Germany and Spain. Within this cluster, the United Kingdom acts as a prominent collaborative node and maintains strong connections with both European and non-European countries. Italy and Greece also exhibit active research partnerships, while Germany and Spain contribute through moderate yet meaningful collaborative interactions. These connections indicate the growing involvement of European research institutions in the development of AI-based solutions for crop disease management.

Several other countries, including Egypt, Ethiopia, Jordan, Iran, Iraq, Singapore, Canada and Australia, occupy relatively smaller yet strategically important positions within the network. Although their publication outputs are comparatively lower, their collaborative connections demonstrate active participation in international research efforts. Australia, in particular, exhibits strong collaborative relationships with China, Bangladesh and Singapore, suggesting its increasing contribution to global agricultural technology research. Overall, the co-authorship network highlights a strong culture of international scientific collaboration in the field of AI-based crop disease detection and management. India, China and the United States emerge as the dominant research hubs, serving as major centres of knowledge generation and international cooperation. The extensive collaborative linkages observed across countries indicate that research in this domain is increasingly global in nature, facilitating knowledge exchange, technological innovation

and the development of advanced AI-driven solutions for sustainable crop protection and agricultural productivity.

Co-occurrence analysis of author keywords

The co-occurrence analysis of author keywords provides insights into the major research themes, emerging topics and conceptual structure of AI-based crop disease detection and management research. The keyword network demonstrates the frequency of keyword occurrence and the relationships among research concepts, where larger nodes indicate higher occurrence frequencies and stronger links represent greater co-occurrence relationships between keywords. The network is organised into multiple clusters representing distinct yet interconnected research domains within the field, as shown in Fig. 3.

Among all keywords, "deep learning" emerges as the most dominant and influential research theme, as indicated by its largest node size and central position within the network. Its strong connections with keywords such as plant disease detection, ML, transfer learning, image processing, CNN and ViTs suggest that DL has become the primary technological approach for developing automated disease detection systems. The prominence of this keyword reflects the increasing adoption of advanced neural network architectures for accurate and efficient plant disease diagnosis.

The keyword "plant disease detection" also occupies a central position in the network, indicating its role as the primary application area of AI technologies in agriculture. Its extensive linkages with ML, DL, image processing, smart agriculture and plant disease classification highlight the multidisciplinary nature of research in this domain. The strong association between plant disease detection and AI-based methodologies demonstrates the growing emphasis on automated disease identification systems to support precision agriculture and sustainable crop management.

The ML represents another major research cluster and is strongly associated with keywords such as feature extraction, remote sensing, hyperspectral imaging and transfer learning. This suggests that ML techniques continue to play a significant role in

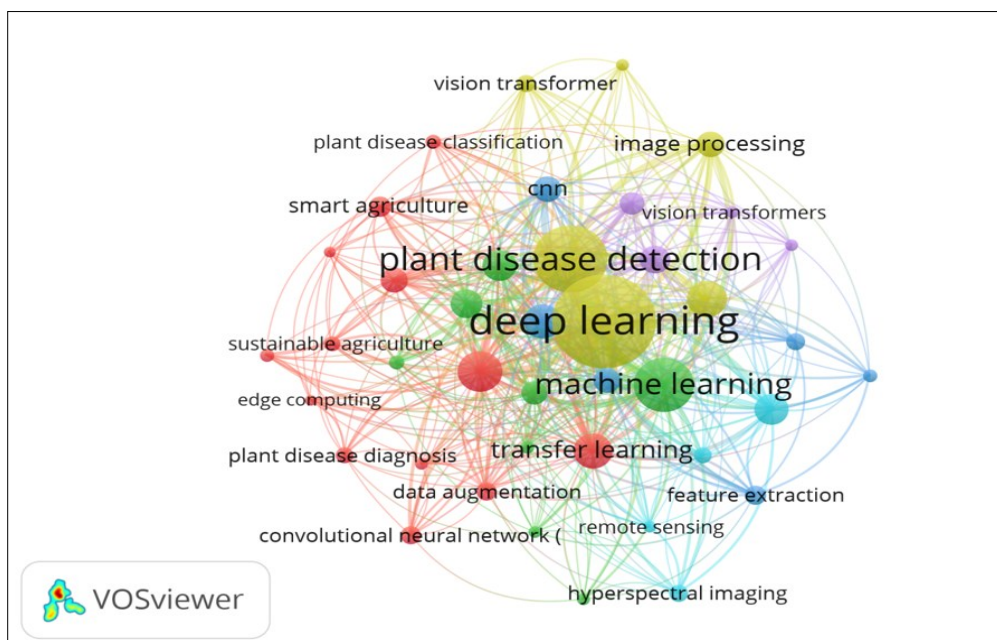


Fig. 3. Co-occurrence analysis of author keywords.

disease prediction, classification and image analysis applications. The presence of these interconnected keywords indicates the integration of advanced sensing technologies and data-driven approaches for improving disease detection accuracy and monitoring crop health under diverse environmental conditions.

Several emerging technologies are also visible within the network. Keywords such as "ViTs," and "image processing" form a distinct cluster closely linked with DL and plant disease detection. The appearance of transformer-based architectures highlights a recent shift toward advanced DL models capable of capturing complex image features and improving disease classification performance. This trend reflects the growing interest in next-generation AI models that can overcome some of the limitations associated with conventional CNNs.

The network further reveals the importance of supporting techniques such as transfer learning, data augmentation and CNNs. These keywords are strongly connected with plant disease diagnosis and DL, indicating their widespread application in addressing challenges related to limited datasets and improving model generalisation. Transfer learning, in particular, has emerged as an important strategy for enhancing classification performance while reducing training time and computational requirements.

In addition to disease detection technologies, the presence of keywords such as smart agriculture, sustainable agriculture, edge computing, remote sensing and hyperspectral imaging demonstrates the expanding scope of AI applications in agriculture. These keywords indicate increasing research interest in integrating AI with precision agriculture and real-time crop monitoring. However, the co-occurrence analysis reflects research trends rather than practical implementation under field conditions. Although these technologies have shown promising results in controlled environments, their large-scale adoption remains constrained by factors such as field variability, infrastructure requirements, implementation costs and limited validation under diverse farming conditions. Future research should therefore prioritise field-based validation, cost-effectiveness, scalability and farmer adoption to facilitate the practical deployment of AI-based crop disease management systems.

Bibliographic coupling analysis of countries

Bibliographic coupling analysis was performed to examine the intellectual connections among countries contributing to research on (AI)-based crop disease detection and management. Bibliographic coupling occurs when publications from different countries cite similar references, indicating shared research interests, common knowledge bases and comparable scientific orientations. In the network, node size represents the influence and publication strength of a country, while the links indicate the degree of shared references between countries. Stronger linkages reflect greater similarity in research foundations and thematic focus. The overlay visualisation further illustrates the temporal evolution of research activity, with colours ranging from blue (earlier average publication years) to yellow (more recent average publication years), as shown in Fig. 4.

The analysis reveals that India occupies the most prominent position within the network, indicating its substantial contribution to the scientific literature and its strong intellectual connections with numerous countries. The large node size and extensive linkages suggest that Indian researchers frequently utilise similar knowledge sources and research frameworks as scholars from other leading countries. This finding highlights India's growing influence in shaping research directions related to AI applications in crop disease detection and precision agriculture.

China emerges as another major research hub, demonstrating strong bibliographic coupling relationships with India, the United States, Japan, Bangladesh and several other countries. The prominent position of China reflects its significant research output and its active involvement in advancing AI-driven agricultural technologies. The strong coupling observed between China and other leading countries indicates a high degree of similarity in research themes, methodologies and reference patterns.

The United States also occupies a central position within the network and exhibits extensive bibliographic connections with countries across multiple regions. Its strong links with India, China, Germany, Italy and the United Kingdom suggest that researchers from these countries frequently draw upon similar scientific

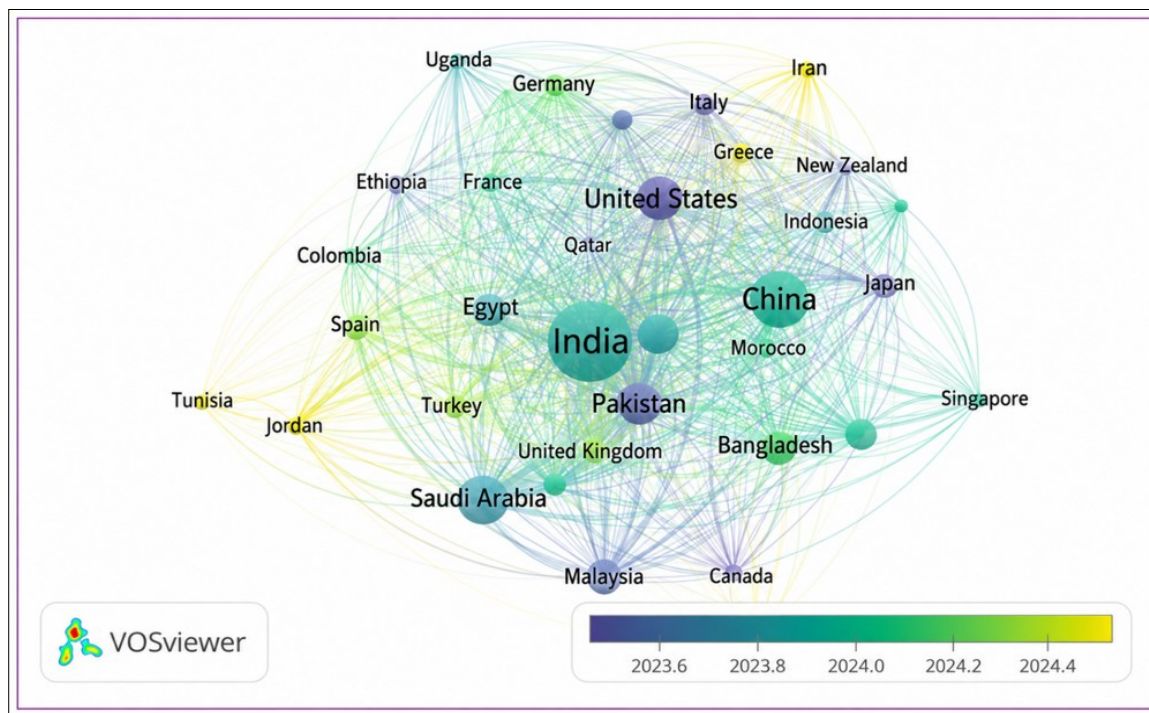


Fig. 4. Bibliographic coupling analysis of countries.

foundations and contribute collectively to the advancement of AI-based crop disease detection research. The central role of the United States further emphasises its importance in the global dissemination of knowledge and technological innovation.

Several Asian countries, including Pakistan, Bangladesh, Malaysia, Saudi Arabia, Japan, Singapore and Indonesia, demonstrate substantial bibliographic coupling with the major research hubs. Pakistan and Bangladesh, in particular, show strong connectivity with India and China, indicating shared research interests in ML, DL, image processing and precision agriculture applications. The presence of these countries within the core network reflects the increasing contribution of developing nations to agricultural AI research.

European countries such as Germany, Italy, Spain, Greece, France and the United Kingdom also form an important component of the bibliographic coupling network. Germany exhibits relatively strong coupling relationships with multiple countries, suggesting active participation in the development of AI-enabled agricultural technologies. Similarly, Italy and Greece maintain significant intellectual linkages with both European and non-European countries, highlighting the international nature of research collaboration and knowledge exchange within the field.

The overlay visualisation further illustrates the temporal evolution of research activities across countries. Nations represented by blue and purple colours, such as the United States, Malaysia, Canada and Ethiopia, indicate relatively earlier contributions to AI-based crop disease detection research. In contrast, countries shown in green and yellow, including Jordan, Tunisia, Iran and Spain, represent more recent research activity, reflecting the continued expansion of this field. The temporal distribution suggests that research on AI applications in crop disease detection has gradually diversified, with increasing participation from a broader range of countries over time. This evolution indicates the growing global adoption of AI technologies for sustainable crop protection and highlights the emergence of new research contributors that are

strengthening the international knowledge base in this domain.

Co-citation analysis of cited references

Co-citation analysis was performed to identify the most influential and frequently cited references that have shaped the development of research on AI-based crop disease detection and management. Co-citation occurs when two references are cited together by subsequent publications, indicating their intellectual relationship and contribution to the knowledge structure of a research field. In the network, node size represents the citation influence of a reference, while the links indicate the frequency with which references are cited together. Stronger connections reflect a higher degree of intellectual association and different colours represent distinct thematic clusters within the literature, as shown in Fig. 5.

The co-citation network reveals several highly influential studies that constitute the foundational knowledge base of AI-driven crop disease detection research. Among the most prominent references are the works of (9–14), which have been extensively cited together by subsequent researchers. The large node sizes associated with these references indicate their substantial impact on the advancement of DL and ML applications in agricultural disease diagnosis.

One of the major clusters is centred around studies related to DL-based plant disease classification, including the influential work of Ferentinos and related studies on CNN (10). These references have played a crucial role in demonstrating the effectiveness of DL algorithms for identifying plant diseases from image datasets. Their strong co-citation relationships indicate that they are frequently used as foundational references when developing and evaluating AI-based disease detection models.

Another prominent cluster comprises studies associated with deep residual learning, CNNs and image classification architectures. References linked to residual learning frameworks and very deep convolutional networks exhibit strong interconnections, highlighting the importance of advanced DL architectures in improving disease classification performance. The frequent

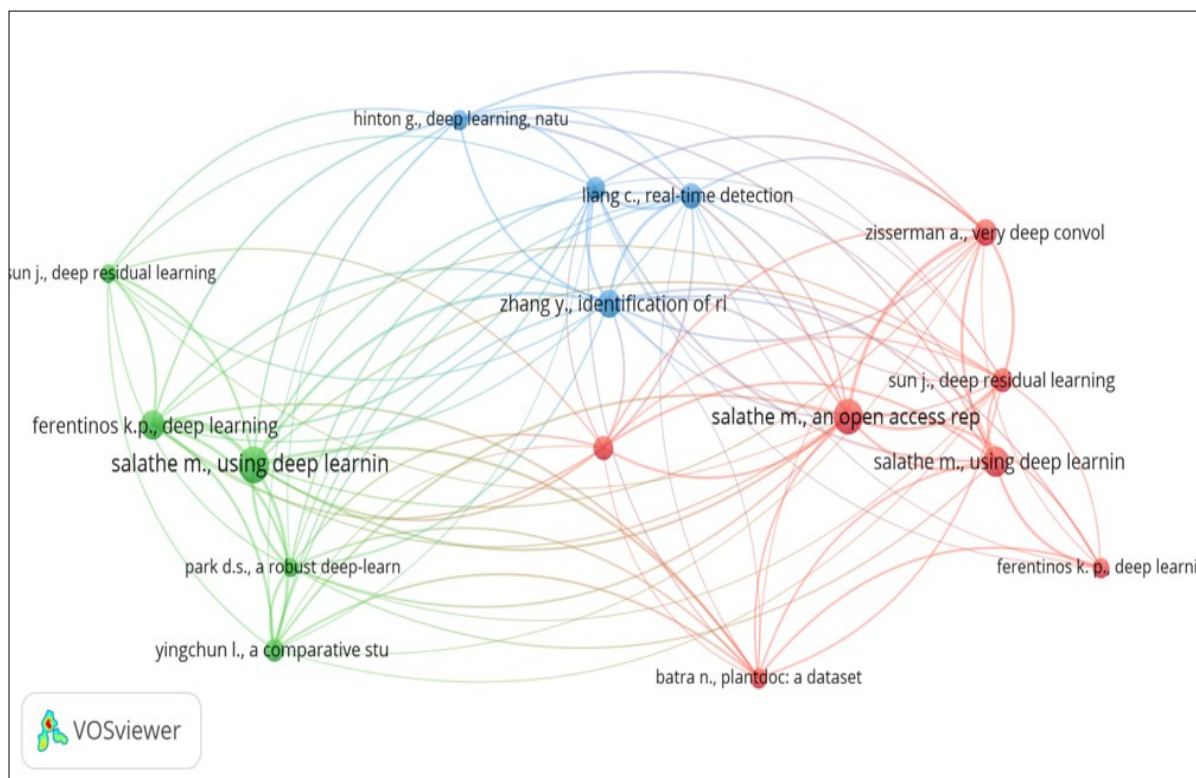


Fig. 5. Co-citation analysis of cited references.

co-citation of these studies suggests that researchers commonly rely on these foundational CV methodologies when designing crop disease detection systems.

The network also highlights the significance of studies focusing on real-time disease detection, transfer learning and robust DL frameworks. References authored by Liang, Zhang, Park and others occupy important positions within the network and demonstrate strong intellectual connections with both traditional DL studies and emerging AI applications in agriculture. These studies have contributed significantly to improving model accuracy, computational efficiency and practical applicability under real-world agricultural conditions. Furthermore, references related to publicly available disease datasets, including PlantDoc and other benchmark image datasets, form an important component of the co-citation structure. The presence of these references indicates the critical role of standardised datasets in facilitating model training, validation and comparative performance evaluation. Their frequent co-citation reflects the widespread use of benchmark datasets in AI-based plant disease detection research.

The clustering pattern observed in the network suggests that the intellectual foundation of this research field is primarily built upon three major themes: DL-based disease classification, advanced CV architectures and dataset-driven model development. The strong interconnections among these clusters indicate that contemporary research increasingly integrates multiple AI techniques and computational approaches to enhance disease detection accuracy and support precision agriculture applications.

Challenges and limitations of AI-based crop disease detection and management

Despite significant advancements in AI-based crop disease detection and management, several limitations continue to hinder the widespread adoption and practical implementation of these

technologies. One of the major limitations lies in the availability of high-quality and diverse datasets. Most AI models are trained using publicly available datasets collected under controlled laboratory conditions with uniform backgrounds, consistent lighting and clearly visible disease symptoms. These datasets often fail to represent the variability encountered under real agricultural environments, such as varying illumination, complex backgrounds, overlapping leaves, multiple disease symptoms, environmental stress and different crop growth stages, resulting in reduced model performance under field-highlighted conditions (14, 15).

Dataset imbalance and the limited availability of annotated images for economically important crops and region-specific diseases further restrict model generalisability and prediction accuracy (16, 17). In addition, advanced DL models require substantial computational resources, large training datasets and specialised hardware such as graphics processing units (GPUs), which limit their adoption in resource-constrained agricultural settings (18, 19). The limited interpretability of DL models, generalisation issues across different environmental conditions and the lack of standardised evaluation protocols further constrain their practical implementation. Moreover, challenges related to internet connectivity, sensor integration, infrastructure, technological literacy and maintenance continue to limit large-scale field deployment, particularly among small and marginal farmers (19, 20–22).

Future perspectives

Future research should focus on developing diverse field-based datasets that better represent real agricultural conditions and improve the robustness of AI models. Greater emphasis should also be placed on XAI, multimodal learning, edge computing, transfer learning and transformer-based architectures to enhance model transparency, computational efficiency and decision support. Furthermore, large-scale field validation, economic feasibility assessments and scalability studies are essential to bridge the gap between laboratory research and practical agricultural applications.

Future investigations should also evaluate the adoption of AI technologies among farmers under different socio-economic and farming conditions to facilitate sustainable crop disease management (22).

Mitigation strategies

Several strategies can enhance the practical feasibility and adoption of AI-based crop disease detection systems. Developing region-specific and balanced datasets, establishing standardised benchmarking protocols and improving model interpretability through explainable AI can increase model reliability and user confidence. The integration of lightweight AI models with mobile devices, edge computing, IoT platforms and cloud-based advisory systems can improve accessibility for resource-limited farming communities. Strengthening collaborations among researchers, extension agencies, policymakers and technology developers, together with farmer training, infrastructure development and affordable digital solutions, will further support the successful deployment of AI technologies under real farming conditions and promote sustainable agricultural production (22).

Conclusion

This bibliometric analysis provides a comprehensive overview of global research trends in AI-based crop disease detection and management during 2016–26. The findings demonstrate a substantial increase in scientific publications, reflecting the growing adoption of Artificial Intelligence (AI) technologies for crop health monitoring, disease diagnosis and sustainable agricultural production. India, China and the United States emerged as the leading contributors, while co-authorship analysis highlighted strong international collaboration in advancing AI-driven agricultural research. Keyword co-occurrence analysis identified deep learning (DL), machine learning (ML), computer vision (CT), image processing and plant disease detection as the dominant research themes, with emerging interest in vision transformers (ViTs), explainable AI, remote sensing and smart agriculture. Bibliographic coupling and co-citation analyses revealed a well-developed intellectual foundation supported by influential studies that have accelerated advancements in AI-based disease detection. Despite this progress, challenges such as limited field-based validation, dependence on controlled datasets, computational complexity and model interpretability continue to hinder large-scale practical implementation. Future research should prioritise the development of diverse field datasets, improve model explainability and computational efficiency and promote the integration of AI with edge computing, the internet of things (IoT), multimodal learning and precision agriculture technologies. Overall, this study offers a comprehensive understanding of the evolution and emerging directions of AI-based crop disease detection research and provides a valuable reference for researchers, policymakers and technology developers working toward intelligent and sustainable agricultural systems.

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Authors' contributions

DS contributed to article collection, analysis and interpretation. AR contributed to idea development, validation and manuscript review. DM contributed to drafting the manuscript. MS contributed to manuscript review and MV contributed to validation. All authors have read and approved the final manuscript.

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Declaration of generative AI and AI-assisted technologies in the writing process:

While preparing this work, the authors used the Grammarly AI tool to improve grammar and increase the article's readability. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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