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REVIEW ARTICLE

The evolution of Artificial Intelligence in agriculture: A bibliometric analysis

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Abstract

Artificial Intelligence (AI) has emerged as a revolutionary force, fundamentally reshaping conventional practices and opening new avenues for growth across various sectors. In agriculture, AI is transforming practices by addressing key challenges such as soil health, maximising production and alleviating labour shortages. AI helps farmers gain insights into crop management, optimise resources and improve efficiency. However, high initial costs and the need for specialised knowledge pose barriers, particularly for small-scale farmers. Despite these challenges, the future of AI in agriculture appears promising, with advancements in autonomous systems and AI-driven precision farming poised to boost productivity and sustainability. This systematic review evaluates AI implementation in agriculture over the past decade through a bibliometric analysis of 70 research papers from the Scopus database. It highlights contributions such as computer vision and deep learning, which enhance crop management by enabling real-time health monitoring, early disease detection and data-driven decisions that boost yields. The bibliometric analysis also explores co-authorship networks, illustrating collaborative efforts among researchers and institutions in the agricultural domain. The analysis of annual research patterns reveals a steady increase in AI-related publications, reflecting a growing interest and investment in this field. Furthermore, the assessment of global scientific outputs underscores the widespread adoption of AI technologies, highlighting their potential to revolutionise agriculture and contribute to food security in an era of increasing demand. Overall, this review illustrates the dynamic nature of AI in agriculture and its promising future.

Keywords

computer vision; crop management; deep learning; sustainability; systematic review

Introduction

Artificial Intelligence (AI) empowers machines to think, learn and solve problems similar to humans (1). This rapidly evolving field involves developing intelligent agents that possess the ability to perceive, reason, learn, communicate and operate in intricate environments (2). AI is revolutionising various sectors by optimising processes, driving innovation and enhancing productivity while addressing complex challenges and improving efficiency (3, 4). Beyond its widespread use in various fields, it is playing a pivotal role in agriculture addressing critical challenges including climate change, resource limitations and food security. Technologies such as biofuels, nanoparticles, nutrient recycling and biochar have long been at the forefront of sustainable agriculture (5, 6), with AI now emerging as a complementary technology to further enhance these efforts. This shift towards AI in agriculture is expected to bring about numerous benefits, including resource and labour cost savings, reduced working hours and lessened soil compaction (7). AI is playing a crucial role in innovation, serving as both an originator and facilitator of new ideas and products (8). As AI continues to evolve, it promises to transform agriculture, making it more productive, sustainable and attractive to future generations.

The feasibility of AI in agriculture is especially pertinent to developing countries, where agriculture forms the backbone of the economy. Here, AI technologies can aid in tackling region-specific challenges, such as irregular rainfall patterns, pest infestations and inefficient irrigation systems (9, 10). However, for smallholder farmers, barriers such as the high initial investment, limited access to digital infrastructure and lack of technical expertise pose significant obstacles (11). In response to the escalating challenges of agricultural productivity and sustainability, this review highlights the importance of AI trends in shaping the future of agriculture. By conducting an extensive bibliometric analysis, the study illuminates the advancements, collaborative networks and patterns shaping the dynamic research landscape of AI in agriculture.

Methodology

A Systematic Literature Review (SLR) was conducted to explore the applications of AI in the agricultural sector over the last decade. Systematic reviews play a crucial role in the exploration of a field by providing a comprehensive and methodical synthesis of existing evidence (8). A systematic search was carried out using the Scopus database, reputed for the best coverage of peer-reviewed literature. Relevant keywords were chosen based on their applicability in the context of AI and agriculture, ensuring that studies relevant to the application of AI in farming would be retrieved. The selected keywords are:

- "artificial intelligence" and "machine intelligence": Core terms representing different aspects of AI.
- "applications": To emphasize practical uses of AI.
- "agriculture": To narrow the focus to our field of interest.
- "farming": Included to capture a broader scope of agricultural practices.
- "ai": To encompass studies that may refer to artificial intelligence using this abbreviation.

Specific Boolean operators (e.g., AND, OR) were used to focus searches. For example, the keywords "applications AND artificial AND intelligence AND agriculture" were used to find studies that aimed at the practical applications of AI in agriculture.

Initial screening of articles

Inclusion and exclusion criteria are crucial in systematic reviews as they determine the scope and validity of the results. Only research articles published in English from 2013 to 2023 were considered. Studies that did not provide significant findings or lacked sufficient data on AI applications in agriculture were excluded. These criteria, along with a clear search strategy, are essential for the methodical and replicable nature of systematic reviews (12). Building on these insights, a set of inclusion and exclusion criteria were designed for the review which are presented in Table 1.

The systematic review's inclusion criteria placed a strong emphasis on research publications that were published in peer-reviewed journals in order to ensure the inclusion of novel findings and rigorous methodology.

Results and Discussion

The application of AI in agriculture was examined using a variety of algorithms and the desired result was utilised as

Table 1. Inclusion and exclusion criteria for screening of articles

Criteria	Inclusion	Exclusion
Initial identification		
Publication type	Research articles	Review papers, conference proceedings, book chapters, series
Source type	Journal	Trade journal
Publication stage	Final	Press
Access type	Open access	Restricted access such as Hybrid gold, Green, Gold and Bronze
Language	English	Non-English
Timeline	2013–2023	<2013
Screening		
Title and abstract	Existence of predefined keywords in the title, abstract or keywords in part of the paper	
Full text	Included articles with at least one remarkable outcome of AI in agricultural context	

an input to find relevant research articles. Different keyword combinations related to AI and agriculture were explored to find relevant papers as shown in Table 2.

Table 2. Keywords used and the total number of publications from the Scopus database

Sl. No	Search strings	Number of publications
1	"applications" AND "artificial" AND "intelligence" AND "agriculture"	2134
2	"artificial" AND "intelligence" AND "agriculture"	5154
3	"artificial" AND "intelligence" AND "farming"	1579
4	"applications" AND "ai" AND "agriculture"	984
5	"applications" AND "machine" AND "intelligence" AND "agriculture"	895
Total (N)		10,746

From an initial pool of 10746 articles, 10143 were excluded based on these criteria. Further screening for duplicates and relevance reduced the count to 331. The full-text evaluation resulted in the final inclusion of 70 studies. The process is summarised using a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram in Fig. 1, which illustrates the systematic filtering of publications. It is a key component of systematic reviews that is crucial for transparently documenting the review process and attrition of irrelevant records (13).

Bibliographic data of the selected papers were extracted from databases in a compatible format, including authors, publication years, titles, abstracts and keywords. They were processed systematically using R Studio and VOSviewer. R's open-source ecosystem offers researchers robust tools for bibliometric and co-citation analysis (14). This makes it an ideal platform for analysing publication

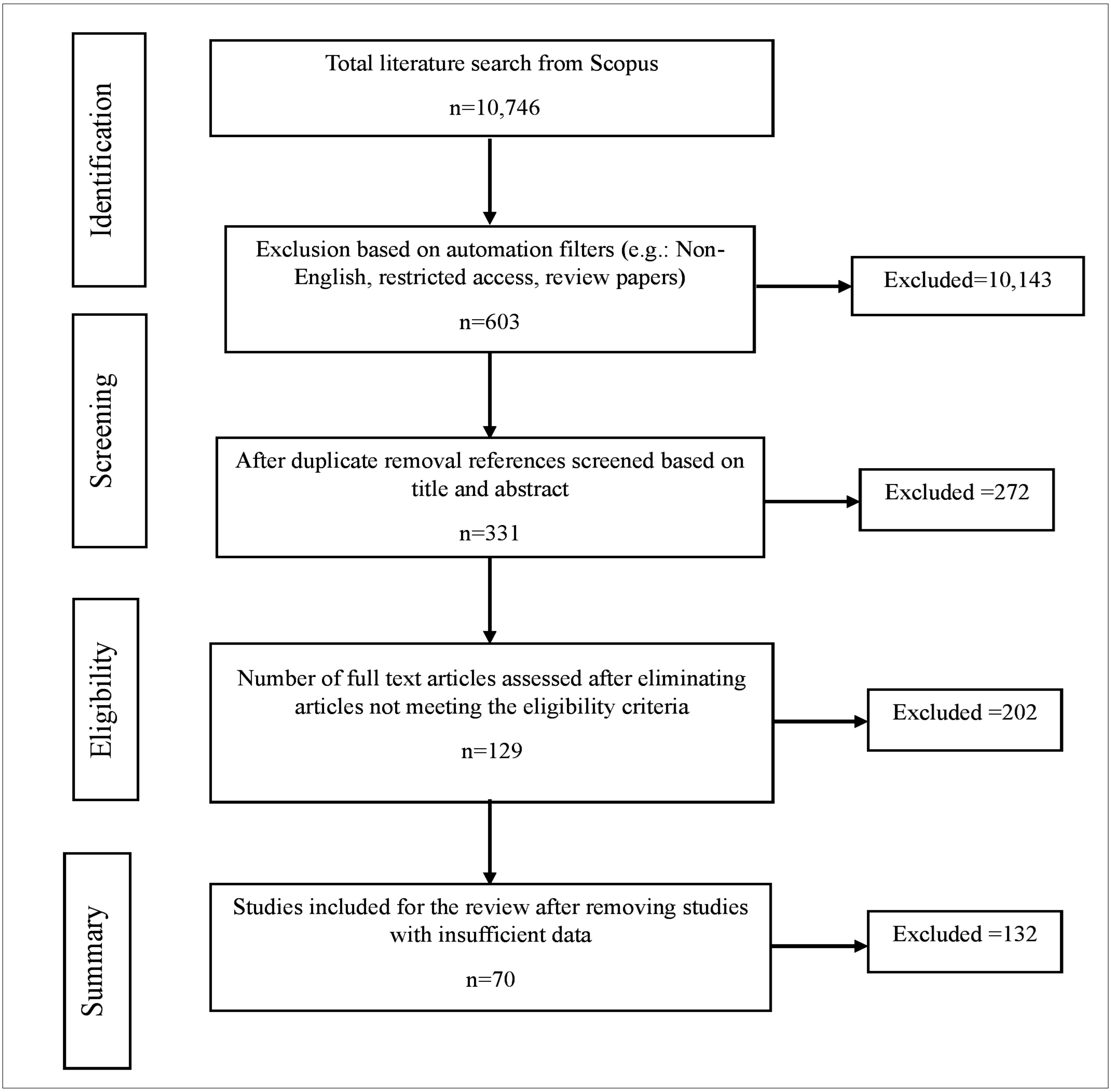

Fig. 1. The PRISMA Flow diagram depicting the number of studies included and excluded for systematic review.

trends and exploring emerging research topics. In R Studio, the bibliometrix package was employed to clean the data by removing duplicates, standardising author names and filtering irrelevant studies. Descriptive statistics were generated to summarise publication trends and citation counts. The cleaned data were then exported to VOS viewer, where co-authorship networks, citation networks and keyword co-occurrence maps were created. This integration facilitated a comprehensive analysis of trends and relationships, enhancing the understanding of AI applications in agriculture.

Co-occurrence network

The co-occurrence network displayed in Fig. 2 was developed using VOSviewer, capturing the interplay between major themes and connecting various terms within an agricultural AI context. Co-occurrence networks exhibit small-world features and power-law degree distribution, indicating the presence of meaningful communities.

such as disease detection, plant classification and fruit counting (16). The integration of computer vision and deep learning in agriculture is expected to revolutionise the industry, with applications ranging from crop health monitoring to yield prediction (17).

AI seeks to replicate human intelligence in machines, enabling them to think, learn and solve problems like humans (18). This enables nearly human-free plant species identification, pathogen diagnosis and crop maturity estimation. Terms like "farming" and "smart agriculture" signify not merely trends but also a vision of future farms operating as integrated systems. The next stage of AI implementation in agriculture is expected to be comprehensive, utilising data from various sources related to soil and weather to optimise resource utilisation and reduce environmental impact.

The terms "machine learning", "artificial neural networks" and "remote sensing" appear in a greenish cluster,

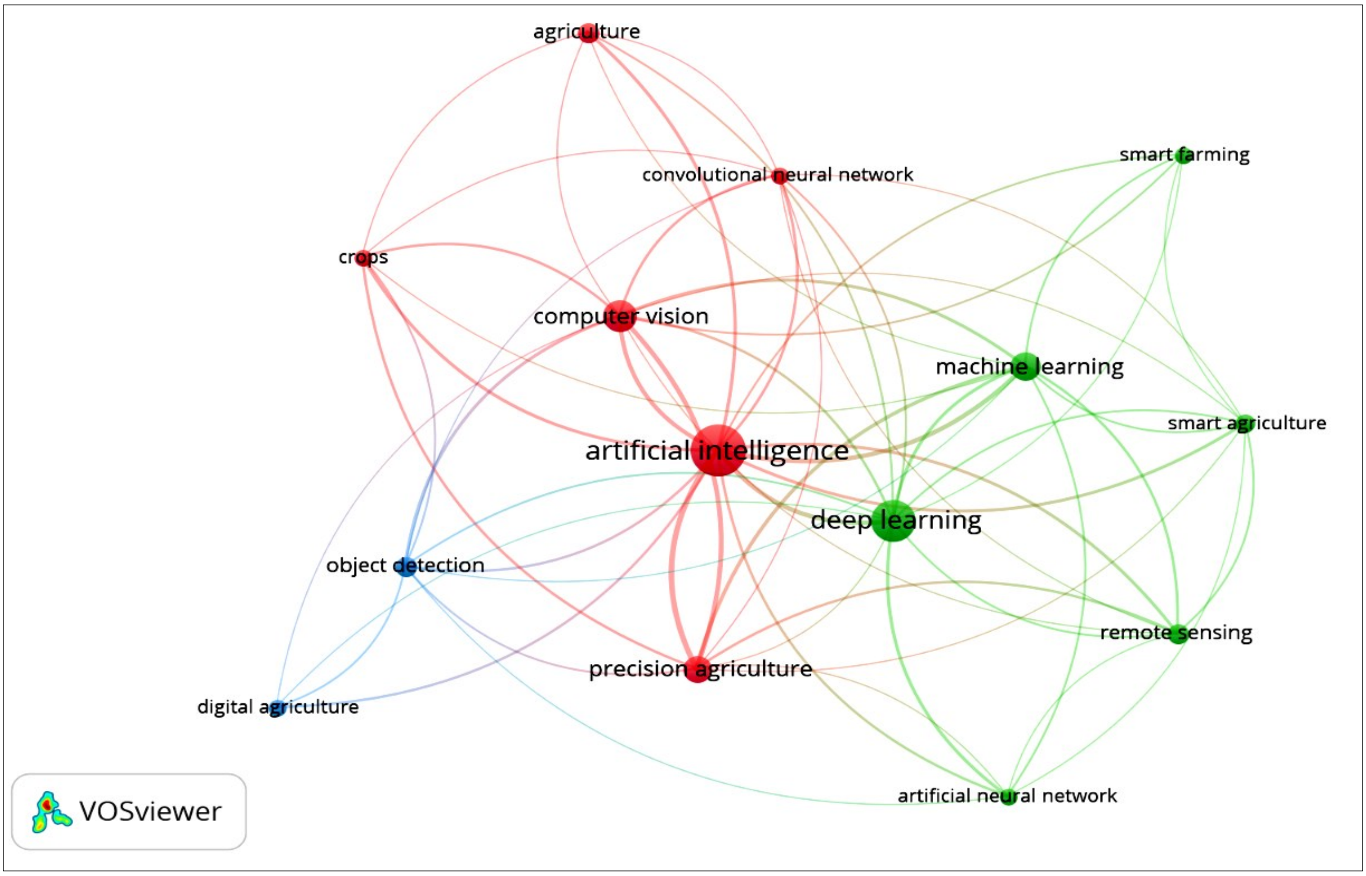

Fig. 2. Co-occurrence network of keywords highlighting the key research themes.

The key technology highlighted here is "Artificial Intelligence". This represents a paradigm shift in methodologies, where AI, in conjunction with computer vision and deep learning, achieves precision at scales beyond human capability. Computer vision is revolutionising agriculture by providing valuable insights into crop growth and health while optimising farming practices. These technologies have demonstrated significant potential in enhancing crop management and disease detection, enabling early identification of plant diseases through image analysis of leaves, which allows farmers to take prompt action and reduce crop losses (15). Deep learning techniques consistently outperform traditional image processing methods in tasks

representing their augmented capabilities to analyse data from multiple sources, such as satellite imagery, to support decision-making in agriculture. These technologies are employed to analyse and interpret a wide range of data, from crop disease prediction to crop quality classification (19). "Precision agriculture" is inherently linked to these concepts, emphasising a shift toward more accurate and meticulous approaches in farming.

The red group, comprising "agriculture" and "crops", denotes the specific application of AI technologies, providing practical evidence of where farming activities are directly involved. The blue grouping of "digital agriculture" alongside "object detection" suggests that the agricultural sector is undergoing digital transformation, focusing on object identification and classification within the farming environment for automation and monitoring purposes.

The co-occurrence network reveals a strong focus on 'smart agriculture' and 'digital transformation', highlighting an industry-wide shift toward integrating AI with sustainable practices. Niche themes like genetic algorithms and decision-making, though underdeveloped, hold significant potential for innovation in farm management. AI-driven agriculture is poised to address challenges like climate change, population growth and food scarcity by developing solutions that enhance sustainability and resilience. This analysis offers a glimpse into a future where AI and agriculture co-evolve, fostering ecological and social impacts.

Thematic map

Thematic maps are essential in bibliometric analysis as they visually depict the thematic structure of a bibliographic database. In this analysis, R-Studio was utilised to generate the thematic map, which stratifies research themes based on their centrality and level of development. The map, illustrated in Fig. 3, categorises the applications of AI in agriculture into four distinct groups, highlighting their significance and implications for future research.

Motor Themes

Centrally located 'Motor Themes' include Artificial Intelligence, deep learning and computer vision represent the core of contemporary agronomic research. Artificial Intelligence serves as the foundation for innovative applications, utilising various algorithms to facilitate agricultural practices.

Deep learning has demonstrated remarkable capability in analysing large-scale datasets, significantly improving crop yield prediction model (20). This underscores its potential to extract valuable insights from complex agricultural data. The integration of AI and big data-driven technologies, as demonstrated in industrial sectors (21). By enhancing farming practices, predictive maintenance and resource management, these technologies have the potential to improve sustainability and efficiency in agricultural systems as well (22).

Computer vision plays a pivotal role in real-time monitoring, contributing to advancements in plant phenotyping, disease diagnosis and yield prediction (23). Its central position reflects the reliability of image-based research and underscores its importance in modernising agricultural methodologies. These motor themes indicate a trend where AI is not merely an auxiliary tool but a fundamental element driving agricultural modernisation. The prevalence of these technologies suggests a future where their

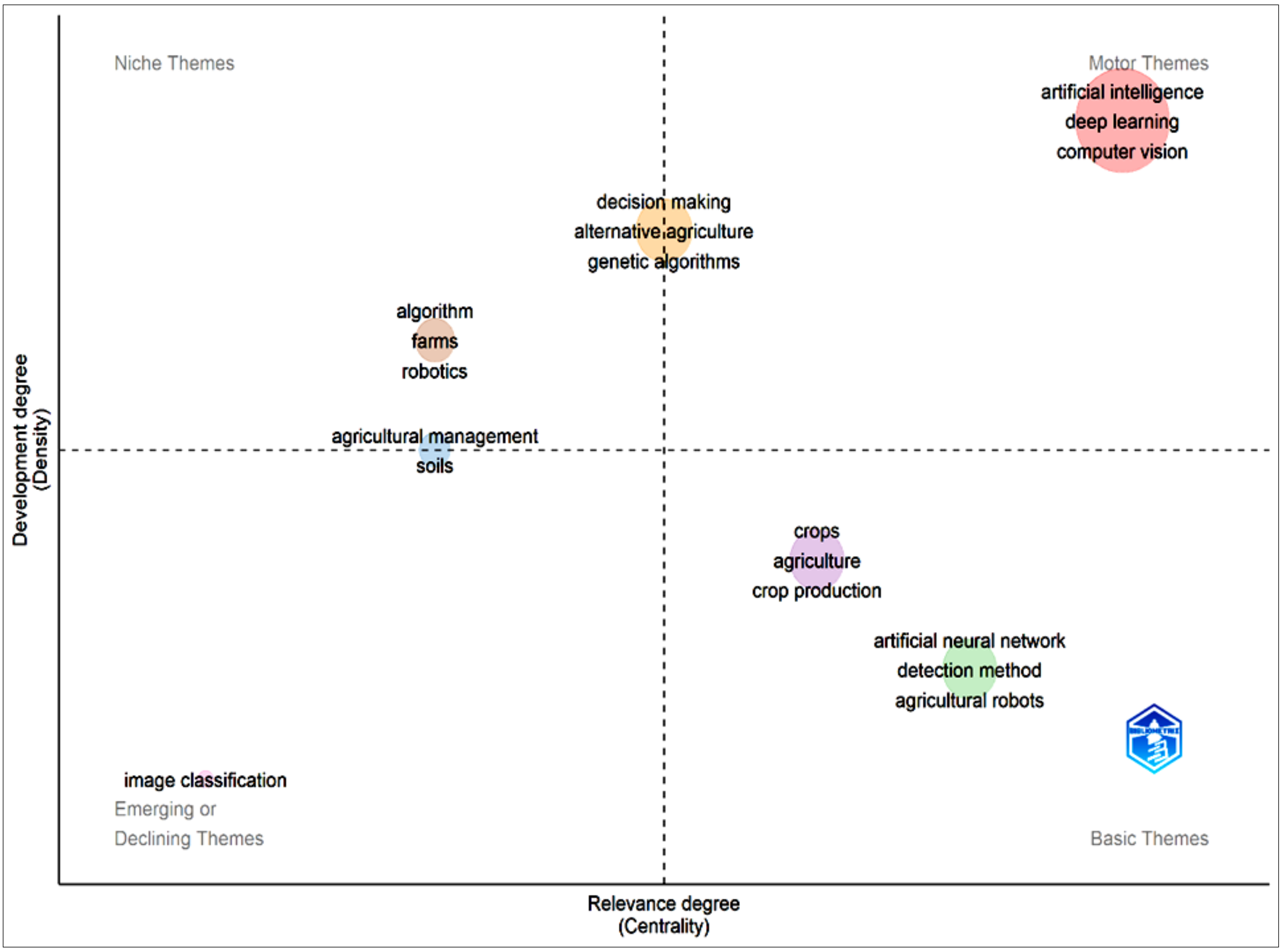

Fig. 3. Thematic analysis of research topics in applications of AI in agriculture.

integration into agricultural practices deepens, enhancing efficiency and productivity.

Niche Themes

In less explored areas of research, themes such as decision -making, alternative agriculture and genetic algorithms remain relatively underdeveloped yet critical. They are integral to the niche of study where innovation first flourishes before rapidly advancing the field. AI-driven decision-making in farming is in its early stages of revolutionising farm management. Alternative agriculture encompasses new practices like urban farming or organic agriculture. Although not widespread, AI could significantly impact their scalability and sustainability.

Genetic algorithms, a subset of AI, are increasingly utilised across various fields due to their ability to handle complex optimisation problems. They replicate the natural selection process to improve plant breeding. Their niche status indicates they are pioneers in integrating computer intelligence with genetics, potentially leading to new agricultural methodologies. Overall, the research themes are converging into one scientific area, which may rapidly accelerate as they integrate with credible new approaches.

Basic Themes

'Basic' themes, including crops, agriculture and crop production, typically exhibit low developmental density, suggesting they are primary focuses of agricultural research but have lagged in AI integration. These areas seem to harbour unexploited resources that could leverage AI technologies, facilitating a paradigm shift. AI tools in these domains could open new perspectives for crop management, significantly impacting global food security by enhancing availability, accessibility, utilisation and stability (24). This indicates a future where AI and agriculture interact closely.

Emerging or Declining Themes

The 'Emerging or Declining Themes' reflect the dynamic and shifting nature of AI in agricultural research. Image classification appears prominently in this quadrant, suggesting it may be a highly competitive research area. Image classification holds significant potential, playing a critical role in grading and sorting agricultural products. New imaging techniques aiding in disease and stress identification provide rapid and accurate solutions for farmers, especially in rural areas with limited access to agricultural experts. It is also possible that after an initial peak, research in this field may decline, paving the way for more advanced AI methods. This thematic map represents the current state of AI in agriculture and serves as a foundation for envisioning its future applications.

Country-wise scientific production

Global scientific accomplishments are shown in Fig. 4, with the US and China leading due to their extensive R and D investments, infrastructure and strong innovation ecosystems. Brazil, India and Pakistan also contribute significantly, driven by expanding research networks, skilled researchers and policies fostering international collaboration and publishing. Their contributions signal a shift in the global research landscape, with emerging nations playing a more prominent role in scientific advancement.

Countries like Canada, France and the UAE prioritise high-impact or specialised research, leveraging niche expertise and strategic resource allocation. The US and China not only dominate AI development but also act as innovation hubs, fostering technologies that influence various sectors, including agriculture.

Middle-tier nations like Brazil and India are becoming focal points for AI innovation, particularly in agriculture, where AI-driven solutions boost productivity, optimise resource use and support sustainable practices. These technologies are critical for addressing challenges like water scarcity, soil degradation and population growth. Meanwhile, countries with lower scientific productivity, though not leading in AI development, are pivotal in

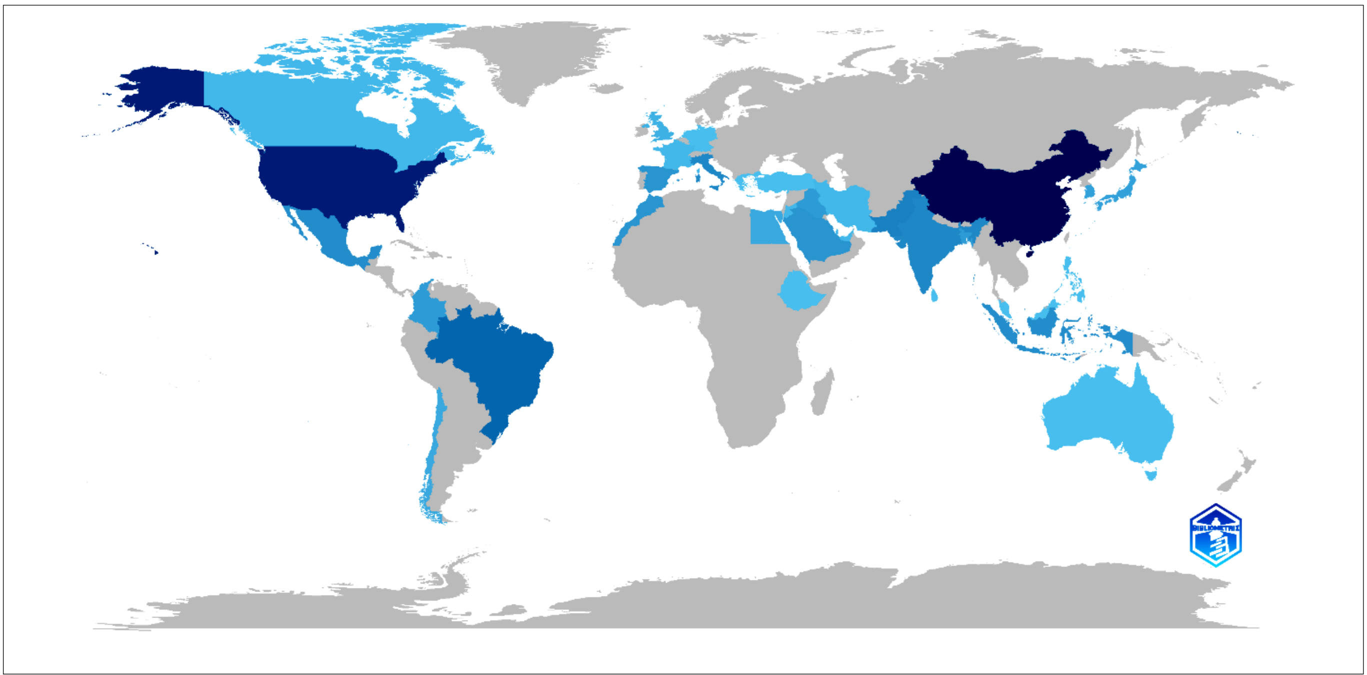

Fig. 4. Scientific production from different countries. Darker shades indicate a higher number of publications.

adapting and localising technologies, often addressing region-specific challenges.

An emerging insight is the role of cross-border collaborations in democratising AI, enabling smaller nations to benefit from shared knowledge and resources. Integrating AI into agriculture goes beyond modernisation; it provides solutions to global food security challenges, enhances resilience to climate change and promotes balanced technological advancement across the world.

Annual scientific production over the years

Fig. 5 below illustrates annual scientific production with lines of advancement showing how quickly the research efforts are stepping up. This line graph demonstrates the yearly output of research in the field of AI in agriculture in Y-axis over a period of 7 years from 2017 to 2023 represented in X-axis.

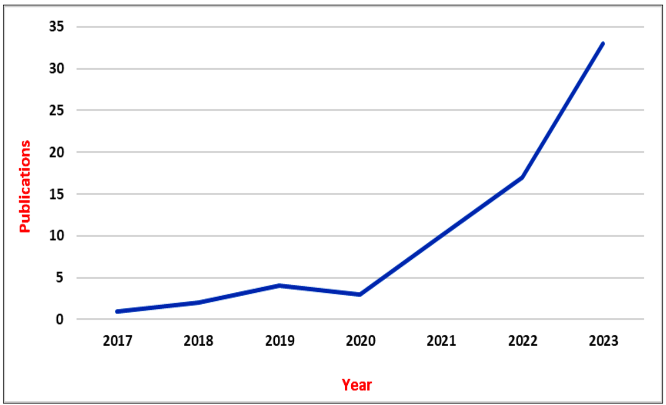

Fig. 5. Annual scientific production.

It is evident from the figure that there is a steady upward trend due to various factors that kindle the sector's progress. The expanding population drives up the demand for food, catalysing the pursuit of advanced techniques such as AI which optimises yield, reduces loss and enhances resource utilisation (25). Moreover, financing from the public and private sectors supports research, development and pilot projects all of which accelerate the technology's growth. Overall, the rising trend reflects the promising potential of AI in revolutionising agricultural practices.

Co-authorship network

The network visualisation in Fig. 6 visualises country-level co-authorship in AI applications in agriculture, with shadowed lines representing shared collaborations and node sizes proportional to publication volume. The United States is central, reflecting its foundational role. Strong links with South Korea and Taiwan highlight shared interests in AI-driven innovations addressing global agricultural needs. These collaborations could advance precision agriculture, enhancing crop yields, resource management and sustainable farming practices.

China's partnerships with Egypt and Morocco suggest a strategic focus on contextualising AI technologies to address diverse agricultural challenges, such as water scarcity. These alliances may lead to region-specific AI solutions for arid and semi-arid farming conditions, showcasing how North African collaboration could set a model for adaptive agricultural technologies in response to climate change.

The network reveals a dual approach: bilateral and regional problem-solving alliances alongside a global collaborative network that includes emerging actors like Bangladesh. Bangladesh's nascent presence highlights its potential as a growth area in AI-driven agriculture, offering a prototype for other nations in the early stages of integrating AI into farming systems.

The future of AI in agriculture lies in cross-border research collaborations addressing local and global needs. Joint problem-solving, technological exchange and strategic alliances will drive innovation, enhancing agrarian efficiency, food security and sustainable development amidst growing environmental challenges.

AI techniques employed in diverse agricultural fields

While the bibliometric analysis reveals significant trends in AI applications in agriculture. Table 3 summarises the key findings derived from a review of 70 selected articles. This section categorises the various areas of application, detailing how AI techniques and models have been employed to address specific agricultural challenges.

Limitations of the study

This study relied solely on a literature search within the Scopus database, limiting the scope to English-language, peer-reviewed publications. The process of selecting keywords was systematic, but some studies may have been overlooked due to unconventional terminology use. Future reviews could include multiple databases, consider various languages and include grey literature to provide a more comprehensive understanding of the field of AI in agriculture.

Conclusion

This review highlights the transformative potential of AI in agriculture, advancing productivity, efficiency and sustainability. Key technologies particularly deep learning, revolutionise agriculture by enhancing decision-making capa-

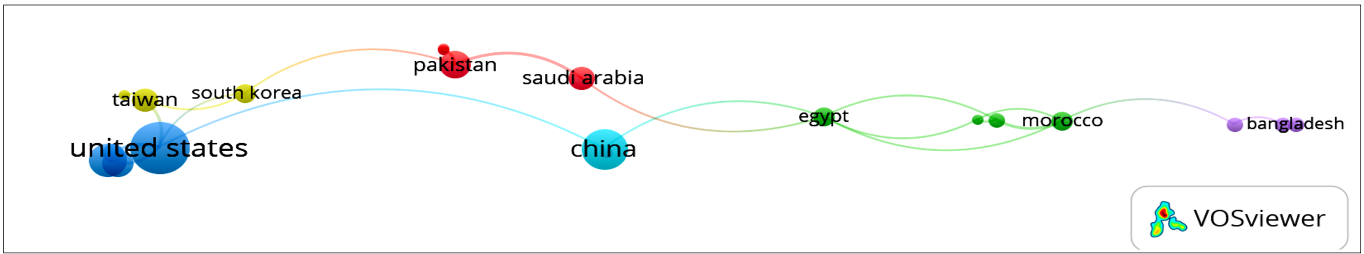

Fig. 6. Co-authorship network.

bilities and optimising farming practices. Machine learning and computer vision have shown great promise in applications like disease detection, crop monitoring and yield prediction. However, challenges include accuracy issues, such as AI "hallucinations" and ethical considerations related to data security, privacy and equitable access, particularly for smallholder farmers. Addressing these requires robust model training, diverse datasets and ethical implementation strategies. A strategic approach is necessary for integrating AI into agriculture sustainably and ethically, maximising its potential while fostering inclusivity and resilience in food systems.

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We sincerely acknowledge Dr. Paul Mansingh for his inval-

Table 3. Various AI techniques/modules/algorithms used in specific fields

Field of AI application	AI techniques/models/algorithms used	Source
Disease management	• Convolutional Neural Networks (CNNs) • Generative Adversarial Networks (GANs) • Deep Learning • Transfer Learning • Ulti-Context Fusion Network (MCFN) • Machine Learning (ML) • Image classification • MobileNet • SqueezeNet Models • Improved YOLOv5 model • RNN and CNN combination • Conditional Generative Adversarial Network (C-GAN) • Efficient detection model (EFDet) • VGG16 model • LeafNet model • VGG-19 • ResNet-50 architectures • BiGRU: Bidirectional Gated Recurrent Unit • CBAM: Convolutional Block Attention Module	(26–39)
Counting, classification and yield estimation	• SPD-Conv module • C3SE module • Context augmentation module • CoordConv • YOLOv4 • Deep learning • Computer vision • CNNe • Machine learning • SpikeSegNet • Faster R-CNN • Efficientnet • RetinaNet • Single Shot Detector (SSD) • YOLO • Artificial Neural Networks (ANN) • Long Short-Term Memory (LSTM) • Recurrent Neural Network (RNN) • Deep Neural Network • YOLOv3 • Faster Region-Based Convolutional Neural Networks (Faster R-CNN) • AlexNet	(40–54)

Pest management	• Computer vision • Machine learning • CNN • Deep Learning • Hybrid Artificial Intelligence • Deep learning Convolutional Neural Networks (DCNNs) • Transfer learning	(55–61)
Crop monitoring and management	• Deep Learning • Transfer Learning • Computer vision • Machine Learning • CNN • Faster R-CNN • Mask • R-CNN, YOLOv3 • CropClassiNet • CanopySegNet • PlantCountNet • InsectNet • LeafNet-based model • YOLOv4 • DeepSORT • Back Propagation neural network • Deep neural networks • Intelligent plant monitoring system	(24, 62–70)
Weed management	• CNN • Object detection algorithms like YOLO (You Only Look Once) • DCNN • Unsupervised learning for weed detection in line crops	(71, 72)
Soil health management	• ANN • CNN • Deep Neural Network (DNN) • Adaptive Neuro-Fuzzy Inference System (ANFIS)	(73–76)
Crop nutrition management	• Deep learning CNN • Long-short term memory (LSTM) • DCNN • ANN	(77–79)
Energy optimisation	• Machine Learning	(80)
Weather	• Machine Learning • Deep Learning • Anomaly Detection • LSTM • Recurrent Neural Networks (RNN)	(81–83)

uable guidance in imparting the principles of Systematic Literature Review (SLR), which significantly contributed to

Information services	• Natural Language Processing (NLP) • Machine Learning • Artificial Intelligence Markup Language (AIML)	(84, 85)
Irrigation management	• LSTM neural network • WLSTM: Wavelet Long Short-Term Memory • WGMDH: Wavelet Group Method of Data Handling and WGAANFIS: Wavelet-Adaptive Neuro-Fuzzy Inference System	(86, 87)
Automation	• CNN • Machine Learning	(88, 89)

the rigor of this review. We also extend our deepest appreciation to Dr. Karthikeyan Chandrasekaran for facilitating aseries of workshops that provided essential writing skills, further enriching the quality of this article.

Authors' contributions

MV led the review process, conceptualized the study and drafted the manuscript. SM provided critical revisions, contributed to the study design and guided the methodology. JP supported in literature collection and analysis, while TJ supported data organization and contributed to the manuscript's refinement. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

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

During the preparation of this work, the author used ChatGPT for minor tasks such as grammar checks, formatting assistance and language refinements. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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