Artificial Intelligence in Agriculture: Benefits, Challenges, and Trends

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Review

Artificial Intelligence in Agriculture: Benefits, Challenges, and Trends

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Abstract: The world's population has reached 8 billion and is projected to reach 9.7 billion by 2050, increasing the demand for food production. Artificial intelligence (AI) technologies that optimize resources and increase productivity are vital in an environment that has tensions in the supply chain and increasingly frequent weather events. This study performed a systemic review of the literature using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology on artificial intelligence technologies applied to agriculture. It retrieved 906 relevant studies from five electronic databases and selected 176 studies for bibliometric analysis. The quality appraisal step selected 17 studies for the analysis of the benefits, challenges, and trends of AI technologies used in agriculture. This work showed an evolution in the area with increased publications over the last five years, with more than 20 different AI techniques applied in the 176 studies analyzed, with machine learning, convolutional neural networks, IoT, big data, robotics, and computer vision being the most used technologies. Considering a worldwide scope, the countries highlighted were India, China, and the USA. Agricultural sectors included crop management and prediction and disease and pest management. Finally, it presented challenges and trends that are promising when considering the future directions in AI for agriculture.

Keywords: artificial intelligence; agriculture; machine learning; convolutional neural networks; agricultural applications

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1. Introduction

Geopolitical events are causing supply chain strains, and climatic events are impacting the food systems' resilience [1]. The challenges to ending hunger and food insecurities keep growing, and the COVID-19 pandemic has further highlighted fragilities in our agrifood systems and inequalities in our societies [2]. This scenario becomes more urgent with the growing food demand. The Food and Agriculture Organization (FAO) has stated that by 2050 there will be around 10 billion people, and the food demand will grow by 70% [3]. Artificial intelligence (AI) techniques applied in agriculture can optimize agricultural processes by food system resilience increases.

AI is an evolving set of technologies that are used to solve a variety of applied problems and has been extensively applied in farming recently [4]. This work's purpose is to make a systematic review of the current studies and research in agriculture that employ the recent practices of AI technologies to solve several relevant problems.

Reviews of the literature are important for synthesizing the existing knowledge base: in [5], the authors conducted a review about crop yield prediction using machine learning; in [6], advanced agricultural disease image recognition technologies were explored; IoT solutions for smart farming were researched in [7]; big data in agriculture in [8]; and agriculture 4.0 in [9,10]. This work presents extensive research on the latest application of

AI in agriculture to alleviate problems in the seven main agriculture domains identified: crop management, water management, soil management, fertirrigation, crop prediction, crop classification, disease, and pest management. In the 176 studies selected for descriptive analysis, more than 20 different artificial intelligence techniques were identified. After the qualitative analysis, 17 articles were selected and described their application in agriculture, challenges, and benefits.

The outline of this paper proceeds with the research methodology, which follows the PRISMA steps with the selected criteria and data collected; Section 3 presents the bibliometric analysis results; Section 4 presents the relevant articles selected with a quality appraisal regarding their main agriculture domains and the AI technologies used; Section 5 presents the challenges, benefits, trends, and research directions identified. Finally, Section 6 shows some conclusions.

2. Methodology

This section presents the review principles of the systematic literature review (SLR), study selection criteria, and the quality appraisal of the studies selected.

2.1. Review Principles

This systematic review was defined by [11] as a review that uses systematic methods to collate and synthesize the findings of studies that address a formulated question, and this should be reported in sufficient detail for the review findings to be replicated.

This SLR aimed to identify and analyze recent studies relating to the artificial intelligence techniques applied in agriculture, answering specific questions and recognizing trends. The methodological steps included their identification, screening, eligibility, and inclusion. Firstly, we defined the research questions, followed by the criteria for studies inclusion and exclusion. Later the research in scientific databases extracted the relevant studies, and finally, the results identified were analyzed to answer the research questions. The SLR ensured clarity and transparency through a four-phase verification flowchart adapted from [12]. This work sought to expand current research knowledge focusing on AI technologies applied in agriculture. Table 1 presents the questions formulated.

Table 1. Research questions.

ID	Research Question	Justification
RQ1	What are the most influential countries, research institutions, journals, and principal papers in AI techniques applied to agriculture?	The purpose is to supply the context related to the research of AI applied to agriculture.
RQ2	What are the principal AI techniques applied for domains of agriculture tasks?	AI techniques identification applied for principal agriculture domains.
RQ3	What are the main benefits and challenges of adopting AI for agriculture?	Identifies the opportunities and gaps for research and development, indicating challenges and trends.

By answering the research question in Q1, this work aimed to identify the context related to the topics addressed in AI and agriculture. To answer the research questions, Q2 and Q3, adapted a framework proposed by [9]. The intersections in Figure 1 represent AI technology's potential impact on agriculture applications, Q2, and identify the challenges and benefits arising from Q3. Based on Figure 1, the framework focused on AI technologies, application domains, and challenges and benefits [9,11].

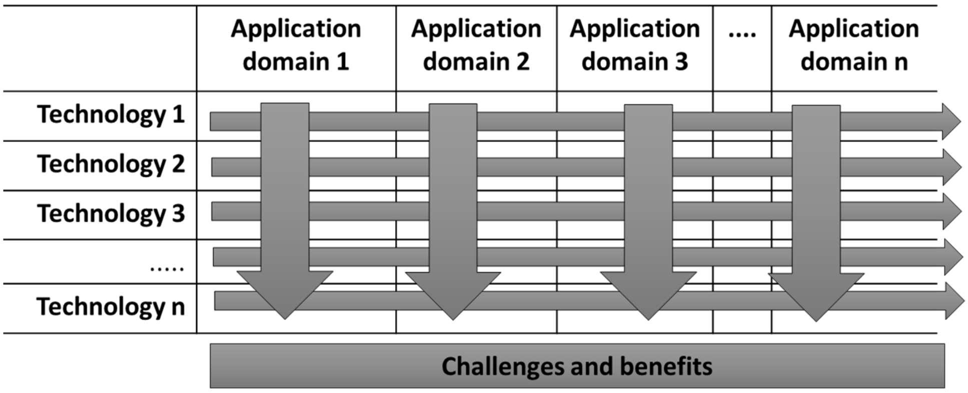

Figure 1. Theoretical framework. Adapted from [9].

2.2. *Study Selection Criteria*

SLR steps were identified and screened for eligibility and inclusion. This could be correlated to a PRISMA flow diagram (Figure 2). This paper's identification considered the current knowledge published in scientific journals in English, disregarding book chapters, annals, and abstracts of events. Table 2 presents the inclusion indicator for the data collection phase.

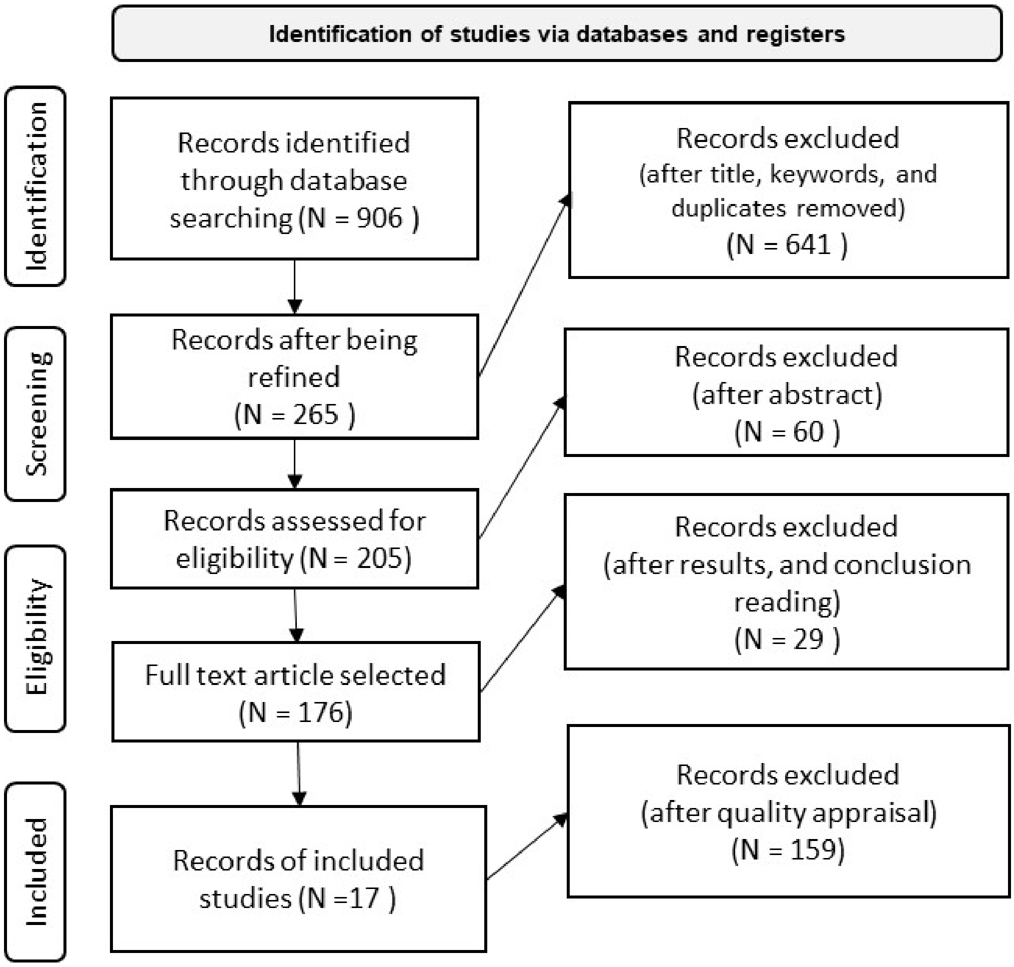

Figure 2. Methodology flow diagram. Adapted from [12].

Table 2. Data collection indicator.

Indicator	Description
Search interval	2017 to 2022
Databases	ScienceDirect; Scopus; Springer; IEEE Xplore; MDPI
Screening	Title, abstract, DOI and year
Document types	Review and original article
Language	English
The proposed solution	Applied on agriculture

The literature databases used to search for scientific information were: ScienceDirect, Scopus, Springer, IEEE Xplore, and MDPI. A search string combined the keywords for artificial intelligence, agriculture, synonyms, and subareas, using logical operators such as OR and AND. Table 3 presents the search strings that were defined considering the inclusion criteria. This query string was inserted in an advanced search camp of the databases consulted.

Table 3. Search string.

Search String
(Artificial intelligence OR Computer vision OR Machine learning) AND (Agriculture OR Culture Selection OR Land preparation OR Seeding OR Irrigation OR fertilization OR Culture maintenance OR Harvest OR Precision Agriculture)

At the identification stage, considering the areas of exact and natural sciences, engineering, and agronomy confined, the research focus on artificial intelligence applied to agriculture, bringing the number of studies to 906. In the screening stage, these studies were verified based on their titles and keywords, and by removing duplicates, 265 records were obtained. After reading the abstract, results, and conclusion, 176 papers went to the eligibility stage and were fully read (Figure 2). These studies were bibliometrically evaluated to obtain indicators on the area (Section 3). In the inclusion stage, 13 paper records were selected considering the quality assessment, and these selected records are discussed in Sections 4 and 5.

2.3. Quality Appraisal

The quality assessment evaluates the aspects relevant to the SLR in each paper, considering the evaluation score for which each paper would be included or excluded in the inclusion phase. The qualitative analysis aimed to classify and prioritize the articles analyzed in the SLR. There were five quality evaluation criteria; three were quantitative and correlated with the Journal: Impact Factor, Citescore, and Citations. The AI technologies and the agriculture domain applications are characteristics related to the paper content and how they are related to the objective of this study. Each indicator has its measure; therefore, we grouped the criteria into three response options: "high", "medium", and "low" (Table 4).

In the eligibility analysis stage, the ranges of values were identified from the analysis of the distribution of the 176 studies selected. For example, records with an impact factor between 11.8 and 6.1 were evaluated as high and received 1.0 points in this criterion (Table 5). In quantitative criteria, each analyzed record could have points from 0 to 3.

Table 4. Quality evaluation criterion.

Criterion	Measure Description
Impact Factor	Evaluate the scientific journals' importance
Citescore	Represents the average number of citations
Citations	Mean how many times a publication has been cited
Artificial intelligence technologies	Importance of artificial intelligence technology considering methodology, references, application and results.
Agriculture domain applications	Importance in agriculture application considering methodology, references, application and results.

Table 5. Evaluation quantitative criterion.

Criterion	High	Medium	Low
Impact Factor	[11.8–6.1]	[6.0–3.1]	[3.0–1.58]
Citescore	[18.7–6.5]	[6.4–4.0]	[3.9–2.7]
Citations	[1195–100]	[99–10]	[9–0]

To balance the journal's impact criteria and the adherence of the records to the work objective, the qualitative criteria had a scale of 1.5, 1, and 0.5 (Table 6), and original articles whose AI application and agriculture were described with quality in the methodology, results, and conclusion, obtained the highest evaluation. In the qualitative criteria, each analyzed record could have a minimum of 1 and a maximum of 3 points. Papers that did not have AI applications in agriculture in their introduction or conclusion were eliminated in the eligibility stage. Each record could have points from 1 to 6.

Table 6. Evaluation qualitative criterion.

Criterion	High	Medium	Low
AI Technology Application domain	Original papers | Methodology | Results | Conclusion	Review | Introduction | Conclusion	Introduction | Conclusion

The 176 papers selected in the eligibility stage were read in their entirety for a quality appraisal. Table 7 shows the papers with the highest scores.

Table 7. Papers with the highest score in the quality assessment.

References	AI Technology	Application Domain	Impact Factor	Citescore	Citations	Scores
[13]	Computer vision; Convolutional neural network	Crop classification	6.757	11.8	289	6.0
[14]	Robotics; Unmanned aerial vehicles (UAVs)	Water management; Crop management	7.5	9.4	166	6.0
[5]	Machine learning	Crop prediction	6.757	11.8	283	6.0
[15]	Artificial neural network (ANN); Internet of things (IoT)	Water management	6.757	11.8	127	6.0
[16]	Convolutional neural network (CNN); Computer vision	Disease and pest management	7.5	9.4	26	5.5
[17]	Deep learning (DL)	Disease and pest management; Soil management	10.238	17.1	14	5.5
[18]	Deep learning (DL); Computer vision	Disease and pest management	6.757	11.8	26	5.5

Table 7. *Cont.*

References	AI Technology	Application Domain	Impact Factor	Citescore	Citations	Scores
[19]	Robotics and automation; Computer vision; Convolutional neural network	Crop management	5.002	8.7	135	5.5
[20]	Genetic algorithm; Internet of things (IoT)	Fertigation management	11.072	15.8	25	5.5
[21]	Machine learning	Water management	6.757	11.8	40	5.5
[22]	Digital twins	Crop management	6.757	11.8	63	5.5
[23]	Machine learning	Crop prediction	8.171	12	12	5.5
[24]	Machine Learning (ML); Internet of Things (IoT)	Crop management	3.476	7	12	5.0
[8]	Big data; Robotics	Crop management	6.765	9.7	1195	5.0
[25]	Machine learning; Computer vision	Crop management	6.757	11.8	70	5.0
[26]	Deep learning; Computer vision	Crop classification	3.889	5.0	19	4.5
[6]	Deep learning; computer vision	Disease and pest management	6.409	12	11	4.5

3. Descriptive Analysis (RQ1)

This section quantitatively describes the 176 selected studies considering the publications and citations volume; the method of the studies identified; and the most influential countries, journals, and institutions. Figure 3 shows the distribution of papers and citations per year.

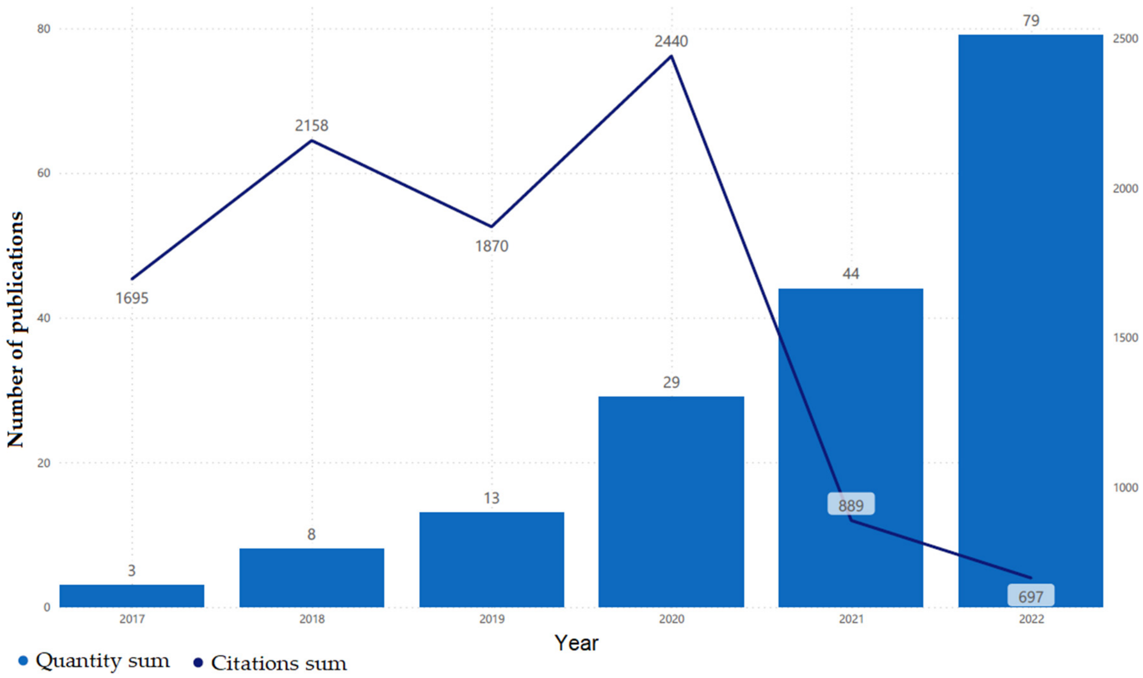

Figure 3. Distribution of papers and citations per year.

The publications number and citations in the area have tripled over the last three years; the data collected in December 2022, reached a peak of 2440, referring to the 2020 publications. That is, the 2021 and 2022, publications were already citing the 2020 publications, showing the dynamism of feedback from this line of research. Studies were classified as either theoretical or empirical (Table 8). Theoretical studies were classified as reviews or SLRs. Additionally, empirical studies were classified as modeling and simulation, surveys, or case studies.

Table 8. The studies identified.

Studies	Category	Total	%
Theoretical	Reviews	59	34
	Systematic literature reviews	16	9
	Total	**75**	**43**
Empirical	Modelling and simulations	68	39
	Case studies	13	7
	Surveys	20	11
	Total	**101**	**57**
	Overall total	**176**	**100**

The number of studies was balanced, with 43% classified as theoretical and 57% as empirical. Theoretical studies had an emphasis on reviews of the literature, with 59 papers representing 34%, and in between empirical studies, these stood out in modeling and simulation, with 68 papers representing 39%. The most representative articles in quality appraisal steps reflect this distribution, such as [13,15] which developed, respectively, robot strawberry-picky and smart irrigation systems.

When studying a research paper's relevance, bibliometric analysis can consider several indicators. This research shows the volume and impact of the publications concerning citation numbers. The Netherlands is the most influential country in this research scope, with 5 publications and 1629 citations, closely followed by India, with 37 publications and 1499 citations. Greece had only 3 publications and 1002 citations, and China had 23 publications with 899 citations. Table 9 shows the countries with more than 100 citations.

Table 9. Most influential countries.

Score	Country	Publications	Citations
1	The Netherlands	5	1629
2	India	37	1499
3	Greece	3	1002
4	China	23	899
5	Spain	5	868
6	USA	10	679
7	Australia	5	649
8	Brazil	9	556
9	France	2	232
10	Egypt	3	185
11	New Zealand	2	168
12	Italy	7	157
13	Pakistan	5	144
14	Malaysia	7	115
15	Portugal	2	107
16	Canada	3	105
17	Chile	4	100

Computers and Electronics in Agriculture led the ranking with 4206 citations and 55 publications, followed by Agricultural Systems (1195), Sensors (1012), and Artificial Intelligence in Agriculture (592). Table 10 shows the Journals with more than 100 citations; those with the greatest impact factor are Computers in Industry (11.245), IEEE the Internet of Things Journal (10.238), Computers and Electronics in Agriculture (6.757), Agricultural Systems (6.765), and Information Processing in Agriculture (6.409).

Table 10. Journals and impact factors.

Score	ISSN	Journal	Impact Factor	Citescore	Publications	Citations
1	0168-1699	Computers and Electronics in Agriculture	6.757	11.8	55	4206
2	0308-521X	Agricultural Systems	6.765	9.7	1	1195
3	1424-8220	Sensors	3.847	5.8	7	1012
4	2589-7217	Artificial Intelligence in Agriculture	7.5	9.4	7	592
5	2073-4395	Agronomy	3.949	3.9	10	339
6	0166-3615	Computers in Industry	11.245	16.9	2	242
7	2214-3173	Information Processing in Agriculture	6.409	12	3	229
8	2169-3536	IEEE Access	3.476	6.7	10	196
9	2071-1050	Sustainability	3.889	5.0	7	196
10	1537-5110	Biosystems Engineering	5.002	8.7	2	189
11	2095-3119	Journal of Integrative Agriculture	4.384	5.6	1	185
12	2543-1536	Internet of Things	5.711	10.2	3	173
13	2079-9292	Electronics	2.690	3.7	3	115
14	2076-3417	Applied Sciences	2.838	3.7	4	111
15	2327-4662	IEEE Internet of Things Journal	10.238	17.1	2	110

Table 11 shows the ten institutions with the highest citation volume. This ranking was led by universities from the USA, The Netherlands, three universities from China, India, Chile, and two universities from Malaysia and Brazil.

Table 11. Institutions promoting research.

Score	Institution	Country	Publications	Citations
1	University of Florida	USA	7	326
2	Wageningen University & Research	The Netherlands	5	1629
3	China Agricultural University	China	4	365
4	Vellore Institute of Technology	India	2	138
5	Universidad Católica del Maule	Chile	2	75
6	Universiti Teknologi Malaysia	Malaysia	2	73
7	Dalian University of Technology	China	2	58
8	Shihezi University	China	2	51
9	University of Campinas	Brazil	2	48
10	Universiti Putra Malaysia	Malaysia	2	29

Finding 1: The publications and citations of artificial intelligence techniques applied to agriculture increased almost six times over the last three years, demonstrating the importance and timeliness of this research line. The most influential countries identified were among the world's largest food producers, and there were different Journals with high-impact factors in publishing in this field.

4. Artificial Intelligence in Agriculture (RQ2)

Agriculture, meaning land cultivation, is the science of raising livestock and producing crops. The principal resource base for agriculture is the physical environment, and the cultivated crop plant is their production unit. The challenge of agriculture is to efficiently manage the physical environment to provide for the biological demands of the crop plant [27]. The principal factors that impact crop yield are soil productivity, the accessibility of water, climate, and pests or diseases [28].

4.1. Main Agriculture Domains

Artificial intelligence is transforming the agricultural sector by optimizing processes and resources. This review identified seven main agricultural applications, as shown in Figure 4, and are summarized in Table 12. The objective of crop management is to rationalize resource use [29,30]. Water management aims to optimize the irrigation process and water use on the farm [31,32]. Soil management is an important component of the success of site-specific cropping systems management. Chemical application in proper proportions is of environmental and economic concern to farmers [33].

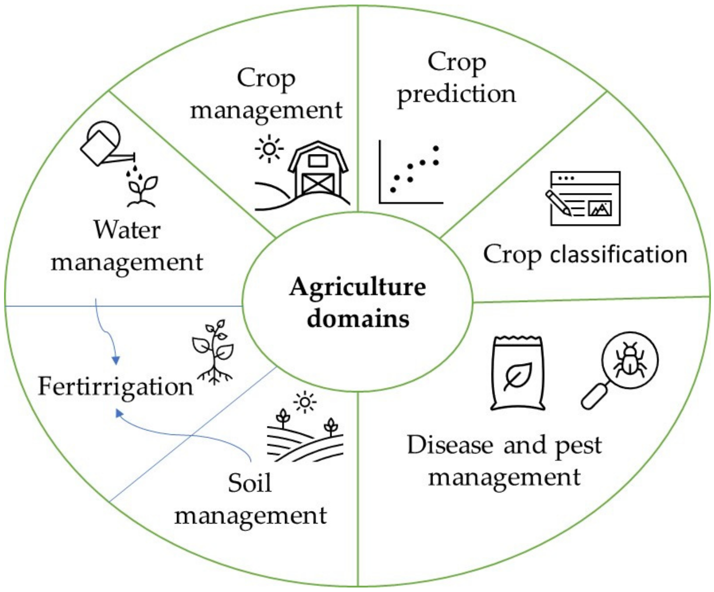

Figure 4. Agriculture domains.

Fertigation uses an irrigation system for fertilizers too. It has been observed that fertigation helps to improve fertilizer effectiveness [34]. Crop prediction or crop yield prediction is an important subject for effective and sustainable resource utilization [35]. Crop classification refers to which crops are grown and can combine image processing and deep learning [36]. Finally, diseases and pests impact crop yield and quality, and their management can improve production and make a substantial contribution to food security [37]. Table 12 shows the applications in the agriculture domains identified with references consulted and the papers correlated with the highest score in the quality assessment.

Table 12. Applications in agricultural domains.

Application Domain	Description	References
Crop management	Covers seed sowing, maintenance, harvesting, storage, and distribution.	[8,14,19,22,24,25,27,38]
Water management	Optimizing water usage through irrigation techniques and processes.	[14,15,21,27,28,39]
Soil management	Assuring plant nutritional sufficiency.	[17,24,27]
Fertirrigation	Technology that aims at the application of fertilizers via irrigation water.	[20,40]
Crop prediction	Crop production prediction is fundamental for the producer's logistic planning.	[5,23]
Crop classification	Crop classification aims to offer a global understanding of crop distribution and information for another application domain.	[13,26,41]
Disease and pest management	Affect crop yields and quality and reduces resource use efficiency. The wide variety of weeds, animals, and microorganisms that threaten agricultural crops requires technology for their protection.	[6,16–18,27,37]

4.2. Artificial Intelligence Technologies

Artificial Intelligence began in the 1950s inspired by cognitive processes and neurobiology [42]. The major challenge for this originated in analyzing AI technologies when applied to agriculture and increasing food production while confronting climatic changes.

There are four categories of intelligent systems: systems that think like humans, systems that act like humans, systems that think rationally, and systems that act rationally [43]. These categories refer to thinking and behavior, measuring their success in terms of fidelity to human performance or rationality. An AI system can store and manipulate data and the acquisition, representation, and manipulation of knowledge. Manipulation includes the ability to deduce (infer) new knowledge from existing knowledge.

This section concerns the artificial intelligence technologies that were identified in the papers included in the SLR. The identified technologies were grouped into three main groups: cognitive science applications, robotics applications, and natural interface applications. Figure 5 shows the technologies identified in the 176 articles analyzed. IoT, big data, and cloud computing technologies served as a support for the implementation of specific AI techniques such as computer vision, robotics, machine learning, augmented reality, and virtual reality (AR & VR).

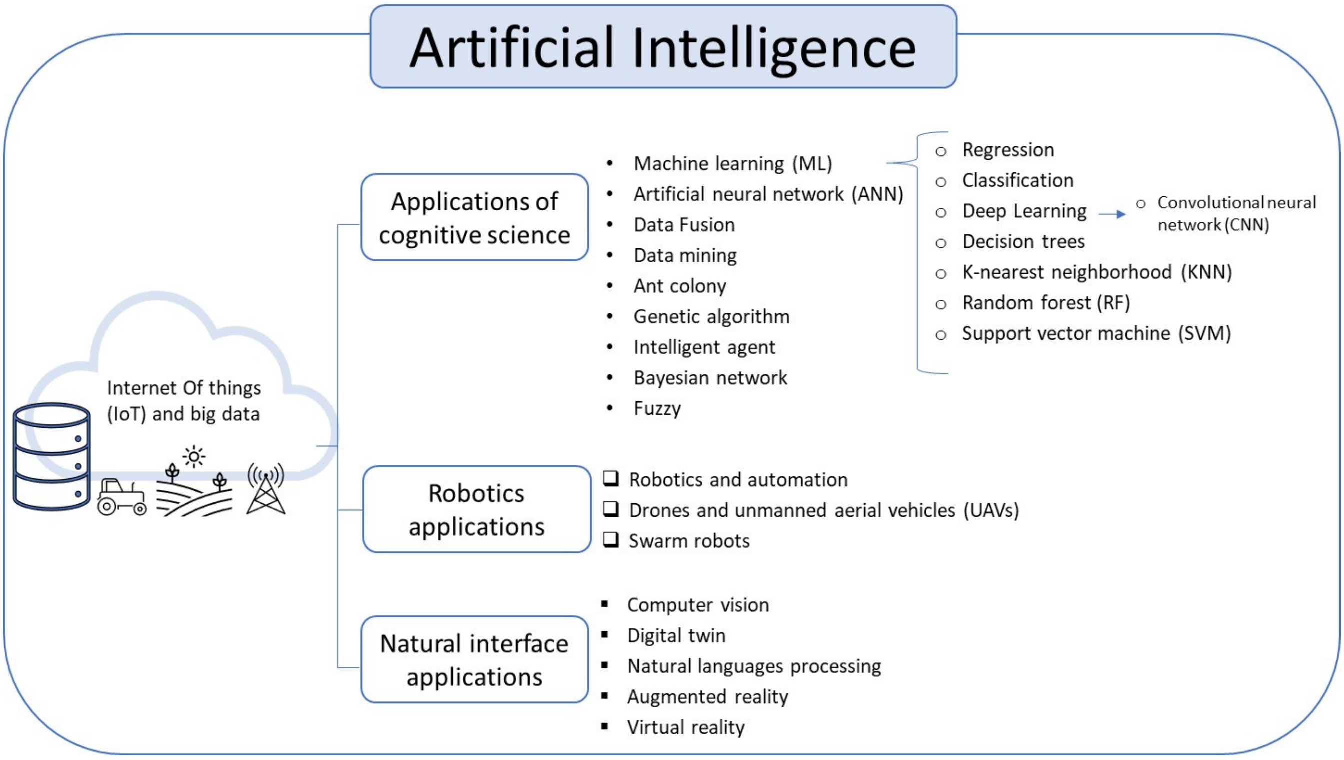

Figure 5. Identified AI technologies in descriptive analysis.

Table 13 presents the main technologies identified in the 17 articles selected in the quality assessment stage and their applications. Table 14 shows the objective of this work which was to identify AI technologies and agricultural applications in selected articles. In [14], an application for irrigation, disease, and pest management stood out, [5] presented with a review of this field, and [15] developed a smart irrigation system. New technologies like agricultural digital twins were also analyzed. Agricultural digital twins are challenged to capture the interactions between living systems and their environment [22].

Table 13. Identified AI technologies in the papers selected.

Technology	Description	References
Robotics and automation	Use of machines, computer software, and other technologies to perform tasks that substitute or replicate human actions.	[8,14,19]
Drones and unmanned aerial vehicles (UAVs)	Aircraft without pilot on board that can be remote-controlled.	[14,25]
Machine learning (ML)	It is a system that can autonomously modify its behavior based on its own experience with several different algorithms that can be employed for prediction accuracy and performance evaluation.	[5,21,23–25]
Artificial neural networks (ANNs)	Computing systems inspired by the human brain, which can learn new things, and adapt to new and changing environments.	[15,19]
Deep learning: convolutional neural network (CNN)	It is based on a set of algorithms related to machine learning. CNNs algorithms find patterns in images to recognize objects, classes, and categories.	[6,13,16–18,26]
Genetic algorithm (GA)	Algorithms widely used in machine learning that are inspired by the processes of biological evolution to solve problems and model evolutionary systems.	[20]
Computer vision	Computer Vision includes problems, such as object detection, motion tracking, and action recognition, using methods for acquiring, analyzing, and understanding images extracted automatically.	[6,13,16,18,19,25,26]
Digital twins	It is a virtual representation that seeks productivity and efficiency optimizations.	[22,44]
Internet of things (IoT)	Connects different intelligent equipment, facilitating the management of the crop.	[15,20,24,45]
Cloud computing	On-demand availability of resources such as data storage and computing power.	[25,46,47]
Big data	It collects, processes, and analyzes data.	[8,48]

Table 14. AI technologies in agriculture.

Technology	Crop Management	Water Management	Soil Management	Fertirrigation	Disease and Pest	Crop Prediction	Crop Classification
Robotics and automation	[8,14,19]	[14]					
Drones and Unmanned Aerial Vehicles	[14,25]	[14]					
Machine learning	[24,25]	[21]	[24]			[5,23]	
Artificial neural networks	[19]	[15]					
Deep Learning: Convolutional neural network			[17]		[6,16–18]		[13,26]
Genetic algorithm				[20]			
Computer vision	[19]				[6]		[13]
Digital Twins	[22]						
Internet of Things	[24]	[15]	[24]	[20]			
Cloud computing	[25]						
Data analytics and big data	[8]						

Finding 2: In the reviewed literature, we identified seven main applications: crop management, water management, soil management, fertigation, crop prediction, crop classification, disease, and pests. And twenty-four different artificial intelligence technics, including more big data, IoT, and cloud computation, were identified. Applications that were more frequent included crop management, water management, diseases and pests. The technics used the most were machine learning, robotics, deep learning, and the Internet of Things.

5. Benefits, Challenges and Trends (RQ3)

Table 15 shows an analysis of the selected studies in the quality assessment stage with a focus on the benefits and challenges in agriculture. Modeling and simulation papers, in general, used machine learning in the development of algorithms and systems to apply crop, water, and fertirrigation management [14,15,20,21]. In [13,16–18,26], we used crop classification and disease, and pest management with machine learning and computer vision.

Table 15. Benefits and challenges identified.

Benefits	Challenges	References
In an unstructured environment, the algorithm Mask-RCNN accurately recognized the categories of the objects.	The algorithms built into this work do not extract contour and shape information accurately.	[13]
Robots and drones optimized the use of water and pesticides and increased productivity and quality.	Low offer and high cost of cognitive solutions that need to be more affordable for their popularization.	[14]
Intelligent system tool for crop yield prediction.	System complexity.	[5]
A low-cost system with remote monitoring was portable, lightweight, and user-friendly.	The main challenges identified are related to the dissemination and commercialization of the developed technology.	[15]
The results showed that an increase in the dataset volume achieved better model performance.	The challenge is the use of Inception V3 and ResNet-based CNN models for a much deeper analysis of crop images is anticipated.	[16]
A responsive web application with deep learning that exploited the collected data.	This work was evaluated only on a small data set about coffee leaves	[17]
Intelligent system for classifiers for early diagnosis of plant pests, reducing the consumption of agricultural pesticides, saving costs, and reducing environmental pollution.	As challenges, they aim to implement an intelligent service for detecting citrus pests and extend the proposed architectures to detect more classes of pests.	[18]
As labor requirements in horticulture become more challenging, automated solutions, like the ones proposed in this work, are an effective approach to maintaining productivity and quality.	As challenges, measured the damage or effect on kiwi quality by the picker and reduce the losses, which currently stand at 24.5%.	[19]
The main benefit is promoting sustainable irrigation and fertilization management in precision agriculture.	Identify parameters like the ratios between water and fertilizers, their impact on the crop production function, and the costs of applying IoT technology.	[20]
ET_0 was estimated for water management using ANN, ELM, and MLR models.	Dissemination and use of ANN, ELM, and MLR models on a large scale in irrigation planning and management.	[21]
The benefits can include cost reductions, catastrophe prevention, positive economic impacts, and safer human–machine interactions.	Agricultural researchers often small and medium farms are more risk-averse.	[22]
Hybrid models and deep learning techniques are used for crop yield prediction.	The use of Neutrosophic sets to express indeterminate and inconsistent information that can be widely explored.	[23]
Intelligent systems use wireless sensor networks (WSNs) that exploit the acquisition, communication, and processing of data.	The acceptance of the precision agriculture solution considering privacy and security.	[24]
Intelligent systems use big data applications to predict insights into the food supply chain.	Challenges need to be addressed: data ownership and privacy; data quality in real-time; intelligent processing and analytics; sustainable integration of big data sources.	[8]
An intelligent system using the cloud was developed to accurately and rapidly process, analyze, and visualize data collected from UAVs.	Popularization and commercialization of the Agroview system.	[25]

Table 15. *Cont.*

Benefits	Challenges	References
Using the CNN model for image augmentation and the accuracy rate.	As challenges, increase date fruit varieties, and adapt the model for a mobile application.	[26]
Analysis of artificial intelligence techniques applied for agricultural disease image recognition.	Limitations like the training process being prone to over-fitting, and for each new dataset and task, the models need to be re-trained.	[6]

Robotics, deep learning, and computer vision were used in the case study paper on kiwifruit harvesting [19]. The case studies showed in [24,25] developed systems using machine learning and IoT for crop management. In reviews of the literature, [5,23] used machine learning techniques for crop yield prediction, [22] used digital twins for crop management, [8] studied big data for smart farming, and [6] used deep learning and computer vision for disease and pest recognition.

In the SRL analysis, we identified terms that used various AI technologies to optimize agricultural processes; the main terms identified were precision agriculture, agriculture 4.0, and smart farming. Precision agriculture is an approach in farm management that uses information technology (IT) to optimize resource usage and reduce environmental impacts [25,49]. Precision agriculture uses remote sensing approaches in the aerial monitoring of agricultural fields and provides real-time images collected from satellites, UAVs, or manned aircraft [50].

Agriculture 4.0 or Digital Agriculture is a term referring to Industry 4.0. It represents a more efficient industry that makes full use of Big Data and new technologies to benefit the entire supply chain and produce a greater and better quantity, with less, in search of increasing food supplies and reducing waste [10,51–54]. Described as precision farming evolution, agriculture 4.0 uses automated collection, integration, and data analysis [9]. Next-generation agriculture 5.0 and 6.0 uses a deep training data set and technological advancements through robots that can target achieving both production and environmental goals [24]. Already the term "Smart Farming" is to the application of intelligent systems and communication technologies such as sensors, IoT, cloud-based processes, artificial intelligence, and networking in the farming system to boost farm produce [55].

Finding 3: Artificial intelligence techniques applied in the main fields of agriculture were identified, with the main benefits being the optimization of agricultural management systems, irrigation, and the identification of diseases and pests. It was observed that the increase in intelligence in agriculture could be related to the digitization and manipulation of large volumes of data, enabling the use of intelligent techniques in system optimization and planning. Computer vision was used in conjunction with robotics and Unmanned Aerial Vehicles (UAVs) for classifying crops and identifying diseases and pests.

The present section provides insights into the technologies most researched. Based on the technologies identified in the 176 articles analyzed, Figure 6 shows the Top 10 most frequent technologies and terms identified. There is a relationship between the identified technologies: machine learning is the most used technique, and this technique, like deep learning and computer vision, needs data to obtain good results. We can see in the top 10: the Internet of Things, which is capable of collecting and transmitting data; big data, a knowledge area that studies how to treat, analyze and obtain information from large data sets; and cloud computing, which is a data center that makes data available over the Internet.

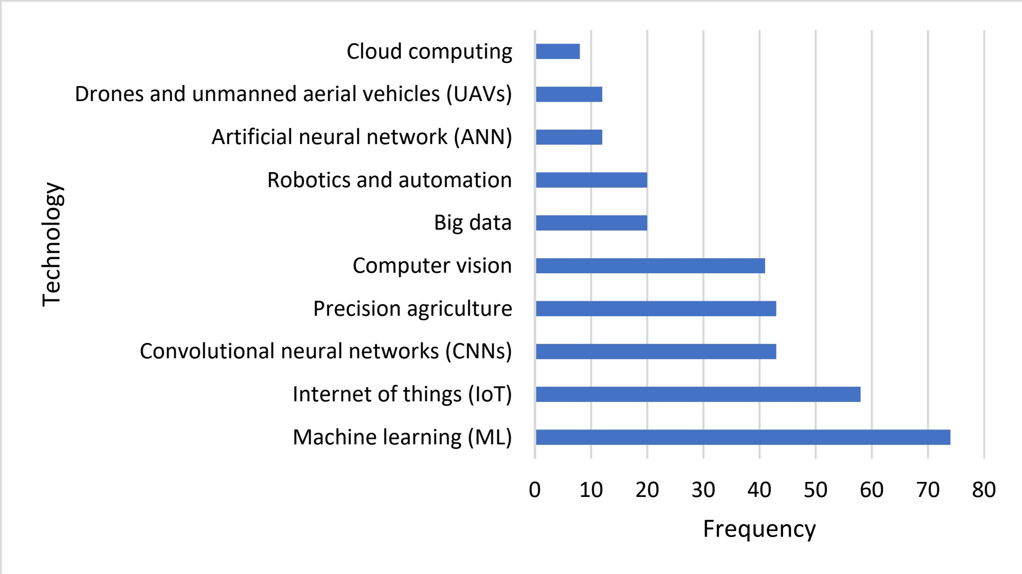

Figure 6. Top 10 most frequent technologies and terms resulting from the analysis of 176 papers.

Drones and unmanned aerial vehicles (UAVs) can collect a huge and complex amount of data, and using big data analytics tools and cloud computing could be utilized to increase data processing efficiency, provide data security and scalability, and reduce costs [25]. Machine learning, ANN-based, and deep learning techniques hold a promising future in crop prediction due to the amount of data from varied sources [23].

In addition to the most cited technologies presented in Figure 6, the emergence of new technologies was observed in the review, including Digital Twins (DT). Precision Agriculture (PA) was the term most frequent, but new terms like Agriculture 4.0 and smart farming are gaining space in reviews of the literature. This work analyzed the relevant studies on AI in agriculture. These findings identified summarize the analysis and possible future research directions stand out:

- Research needs to be adapted to the climate and crop of application regions; food-producing countries like Brazil are still not very expressive in their scientific production in the area.
- AI technologies can be applied in several areas of agriculture; it is necessary to understand the production chain of the crop analyzed to identify the best technique to be applied and its interrelationship with terms such as agriculture 4.0 and smart farming seek which can integrate these various technologies for the optimization of a production chain.
- The most applied technologies have in common digitized data needs; they are at the digital revolution heart, and, for future research, the interaction and need for technologies to enable the application and reach of results must be observed.

6. Conclusions

This survey has presented a systematic review of the literature, which was conducted by employing the PRISMA methodology, which aimed to identify the principal and recent artificial intelligence technologies that have been applied in the agricultural domain. This research selected 176 papers for bibliometric analysis and 17 papers for quality appraisal.

It was possible to identify seven main agriculture applications: crop management, water management, soil management, fertigation, crop prediction, crop classification, and disease and pest management. Beyond these, twenty-four different artificial intelligence technics were identified. The technics most used were machine learning, deep learning with a convolutional neural network, robotics, and the Internet of Things. The main benefits of this included the optimization of agricultural management systems, irrigation, and the identification of diseases and pests. It was observed that an increase in intelligence in agriculture could be related to the digitization and manipulation of large volumes of data, enabling the use of intelligent techniques in system optimization and planning.

In this context, a big challenge, especially for small and medium agricultural production units, is the mapping and digitization of production processes. Recently, the hardware and software costs required have decreased; however, these values are still prohibitive for many farmers. Labor qualification is also a challenge. In food-producing countries, public policies are necessary for the development of competitive technologies and workforce qualifications.

In these trends, computer vision has been used with robotics and unmanned aerial vehicles (UAVs) for classifying crops and identifying diseases and pests. New technologies like digital twins are promising for optimizing agricultural processes. And frequently used terms such as precision agriculture has been sharing a space with frameworks such as smart farming; agriculture 4.0, which uses telecommunications and data infrastructure for the agricultural supply chain; and agriculture 5.0, which incorporates AI and UAVs for more information.

This article provides a synthesis of the recent studies and technologies analyzed. This review has some limitations, such as the selection of articles from academic journals written in English and the findings being related to the reviewers' experiences. Some threats to the validity of these results are biases in the selection of digital libraries and the number of studies selected. For future work, the inclusion of other databases is planned.

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