Artificial Intelligence in Agriculture: Benefits, Challenges, and Trends

Subjects: Computer Science, Artificial Intelligence

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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.

artificial intelligence | agriculture | machine learning | convolutional neural networks

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 the agrifood systems and inequalities in the 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].

2. Descriptive Analysis (RQ1)

Reserachers 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 1** shows the distribution of papers and citations per year.

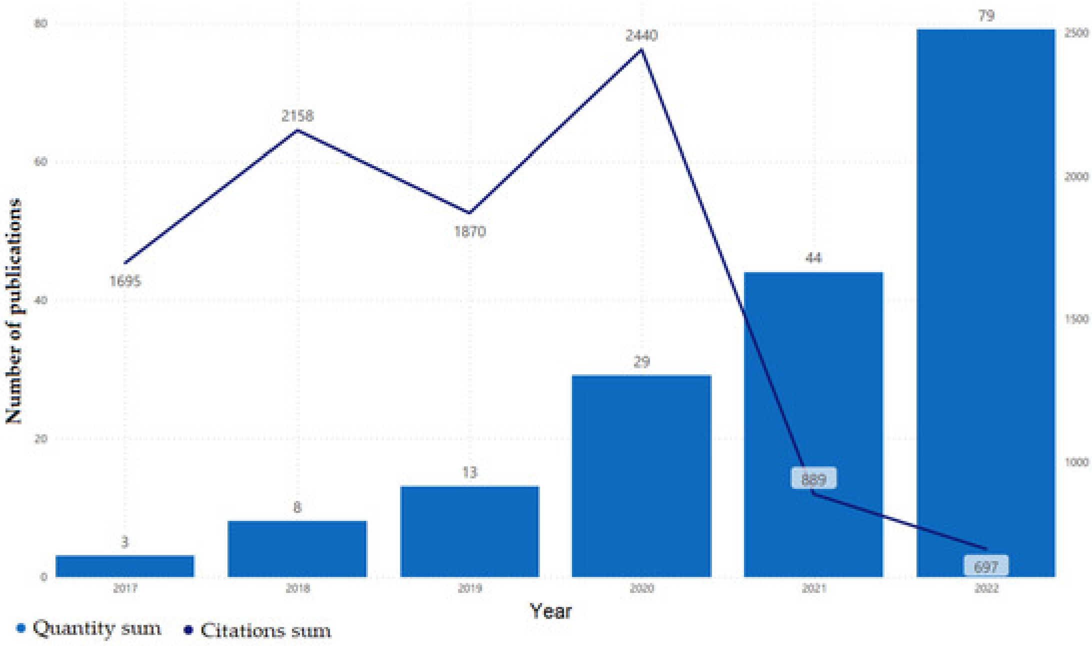

Figure 1. Distribution of papers and citations per year.

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 1**). Theoretical studies were classified as reviews or SLRs. Additionally, empirical studies were classified as modeling and simulation, surveys, or case studies.

Table 1. 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 [11][12] which developed, respectively, robot strawberry-picky and smart irrigation systems.

When studying a research paper's relevance, bibliometric analysis can consider several indicators. It is showed that the volume and impact of the publications concerning citation numbers. The Netherlands is the most influential country in the 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 2** shows the countries with more than 100 citations.

Table 2. 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 3. 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-	IEEE Internet of Things Journal	10.238	17.1	2	110

Table 4 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.

Score	ISSN	Journal	Impact Factor	Citescore	Publications	Citations
	4662					

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. 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 [13]. The principal factors that impact crop yield are soil productivity, the accessibility of water, climate, and pests or diseases [14].

Finding 2: In the reviewed literature, researchers 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 5 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 [12][15][16][17]. In [11][18][19][20][21], researchers used crop classification and disease, and pest management with machine learning and computer vision.

Table 5. 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.	[11]
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.	[15]
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.	[12]
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.	[18]
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	[19]
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.	[20]
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%.	[22]
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.	[16]
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.	[17]
The benefits can include cost reductions, catastrophe prevention, positive economic	Agricultural researchers often small and medium farms are more risk-averse.	[23]

Benefits	Challenges	References
impacts, and safer human–machine interactions.		
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.	[24]
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.	[25]
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.	[26]
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.	[21]
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]

In the SRL analysis, researchers 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 [26][27]. 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 [28].

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][29][30][31][32]. 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 [25]. 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 [33].

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 2** 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. Researchers 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.

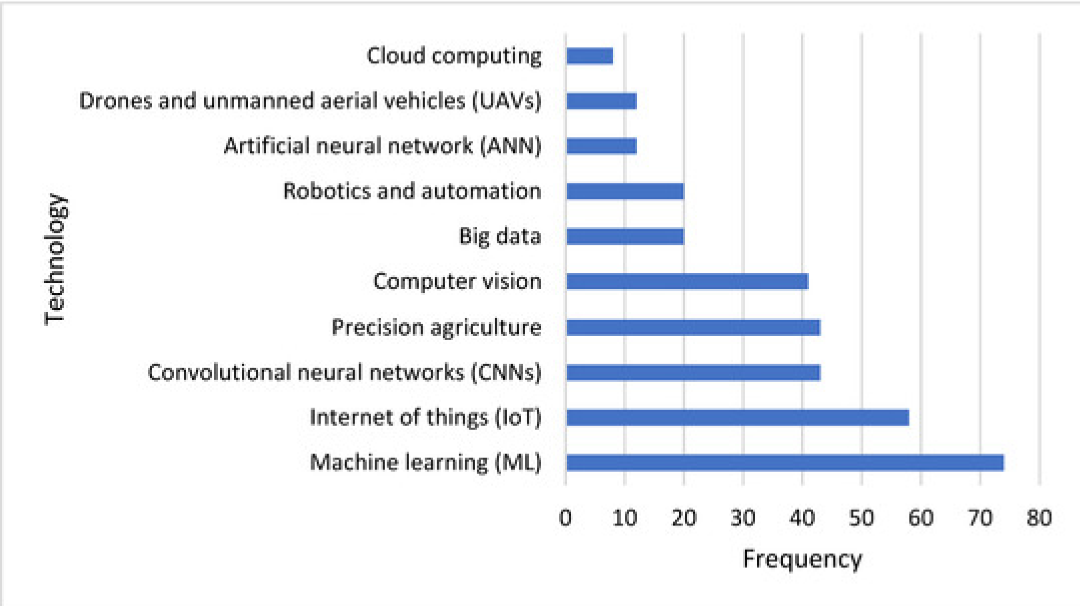

Figure 2. Top 10 most frequent technologies and terms resulting from the analysis of 176 papers.

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 [26]. Machine learning, ANN-based, and deep learning techniques hold a promising future in crop prediction due to the amount of data from varied sources [24].

In addition to the most cited technologies presented in **Figure 2**, 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. Researchers 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.

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