THE USA JOURNALS
THE AMERICAN JOURNAL OF AGRICULTURE AND BIOMEDICAL ENGINEERING (ISSN – 2689-1018)
VOLUME 06 ISSUE07

PUBLISHED DATE: - 27-07-2024
DOI: - https://doi.org/10.37547/tajabe/Volume06Issue07-03 **PAGE NO.: - 11-28**

RESEARCH ARTICLE **Open Access**

EXPLORING BENEFITS, OVERCOMING CHALLENGES, AND SHAPING FUTURE TRENDS OF ARTIFICIAL INTELLIGENCE APPLICATION IN AGRICULTURAL INDUSTRY

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Abstract
The global population, now at 8 billion and projected to reach 9.7 billion by 2050, necessitates a significant increase in food production. This escalating demand underscores the importance of artificial intelligence (AI) technologies in agriculture, which enhance resource optimization and productivity amid supply chain pressures and more frequent extreme weather events. A systematic literature review (SLR), conducted using the PRISMA methodology, examined AI applications in agriculture, encompassing 906 relevant studies from five electronic databases. From these, 176 studies were selected for bibliometric analysis, with a quality appraisal further refining the selection to 17 key studies. The review highlighted a notable rise in publications over the past five years, identifying over 20 AI techniques, including machine learning, convolutional neural networks, IoT, big data, robotics, and computer vision, as predominant. The research emphasized significant contributions from India, China, and the USA, focusing on sectors like crop management, prediction, and disease and pest management. The study concluded with an analysis of current challenges and future trends, pointing to promising directions for AI in agriculture to meet global food production demands.

Keywords Artificial intelligence, Agriculture, Systematic literature review, Bibliometric analysis, Challenges and future trends.

INTRODUCTION

Geopolitical events and climatic disruptions are increasingly straining supply chains and undermining the resilience of food systems, presenting significant challenges to global efforts to end hunger and food insecurity [1]. The COVID-19 pandemic has exacerbated these vulnerabilities, exposing critical weaknesses in agri-food systems and deepening societal inequalities [2]. As the global population is projected to reach around 10 billion by 2050, the Food and Agriculture Organization (FAO) estimates that food demand will surge by 70% [3]. This dramatic rise necessitates innovative solutions to enhance food production and distribution. Artificial intelligence (AI) offers a promising avenue for addressing these challenges by optimizing agricultural processes. AI techniques can improve crop yields, reduce waste, and streamline supply chains, thereby enhancing the overall resilience of food systems. By leveraging AI, we can develop more efficient and sustainable agricultural practices that are better equipped to meet the growing food demands of the future while mitigating the impacts of geopolitical and climatic disruptions.

AI, a key discipline within computer science, focuses on developing algorithms that mimic the cognitive, physiological, or evolutionary phenomena observed in nature and human beings [4]. Unlike traditional models that require explicit knowledge of problem-solving paths, AI relies on data, examples, and relationships to facilitate diverse problem resolutions. This approach allows AI to exhibit intelligent behavior akin to human experts in specific tasks. Presently, AI is predominantly directed towards solving problems involving large, dynamic data sets that often contain inaccuracies and contradictions. Techniques such as iterative methods and interconnected neural network architectures, commonly referred to as "Machine Learning" and "Deep Learning," form the backbone of modern AI [5-7]. These methods are widely applied across various domains, unified by their ability to analyze vast and complex data structures influenced by temporal and uncertain factors.

Agriculture, an intricate sector blending science, engineering, and economic principles, has undergone significant advancements through the integration of AI. Comprehensive reviews by Ruiz-Real, et al. [8] and Jha, et al. [9] highlight the transformative impact of expert systems and decision support systems in optimizing agricultural processes and supply chain management. These systems simulate agricultural operations, enhancing resource allocation and process efficiency. AI's applications in quality control, as explored by Nair and Mohandas [10], enable precise monitoring through artificial vision systems. Additionally, AI facilitates policy formulation, exemplified by Bryceson and Slaughter [11] analyzed AI as a collaborative tool among agri-food chain stakeholders. Economic studies applying neural networks and machine learning techniques to agri-food product pricing reveal AI's potential in predicting and stabilizing market fluctuations. In climate science, researchers like Siegert, et al. [12] and Kosovic, et al. [13] used AI to model and predict solar radiation, aiding in climate management and agricultural planning.

The interest in AI's agricultural applications has surged due to its robust data analysis capabilities. The rise of Agriculture 3.0 introduced robotics and automation, revolutionizing traditional practices with sophisticated machinery capable of autonomous planting, spraying, and harvesting [14-16]. Agriculture 4.0 further enhances efficiency through intelligent farms and interconnected systems, focusing on precision agriculture to optimize water, fertilizer, and phytosanitary product use [17-19]. This approach, combined with genetic engineering and big data analytics, addresses challenges like climate change adaptation and resource optimization. The technification of agriculture, driven by Industry 4.0 concepts, has heightened AI's role, enabling agri-food companies to streamline operations and drive economic growth [20, 21]. This technological evolution not only meets the rising demand for richer diets but also enhances employment and economic activities in industrial regions, solidifying AI's crucial role in modern agriculture and global food security.

Bibliometric studies that connect various disciplines have become increasingly significant in understanding the impact and future potential of interdisciplinary synergies within the research community. These studies serve as vital indicators of interest and engagement in specific fields, offering a comprehensive view of scientific production and collaboration patterns. For instance, Gu [22] demonstrated the global structure of scientific output, highlighting the intricate relationships between quality, references, and author synergies. In the realm of artificial intelligence (AI), Cobo, et al. [23] delved into its evolution using various bibliometric indicators, focusing on citations related to knowledge-based systems. Despite the wealth of research in AI, similar bibliometric studies in the agri-food industry or agriculture are less common. Nevertheless, the growing number of publications in these fields, as evidenced by trends in Google Scholar over the past five years, suggests a burgeoning interest and a promising future for interdisciplinary studies that explore the interplay between AI and agriculture.

Literature reviews play a crucial role in synthesizing the existing knowledge base, offering insights into the application of AI in agriculture [24]. Notable reviews include works on crop yield prediction using machine learning [25], advanced agricultural disease image recognition technologies [26], IoT solutions for smart farming, and big data applications in agriculture [27-29]. These reviews highlight the diverse and innovative applications of AI aimed at addressing various agricultural challenges. In our study, we conducted extensive research on AI applications in agriculture, identifying seven key domains: crop management, water management, soil management, fertilization, crop prediction, crop classification, and disease and pest management. From 176

studies selected for descriptive analysis, over 20 different AI techniques were identified. A subsequent qualitative analysis distilled 17 articles that provided detailed insights into the application, challenges, and benefits of AI in agriculture, underscoring the significant potential and ongoing advancements in this field.

Research Purpose

SLR, as defined by [11], utilizes systematic methods to collate and synthesize the findings of studies addressing a formulated question, reported in sufficient detail to enable replication of the review's findings. This SLR aims to identify and analyze recent studies on AI techniques applied in agriculture, addressing specific questions and recognizing emerging trends. The methodological steps involved identification, screening, eligibility, and inclusion of relevant studies. Initially, research questions were defined, followed by the establishment of criteria for study inclusion and exclusion. A comprehensive search in scientific databases was then conducted to extract relevant studies, which were subsequently analyzed to answer the research questions. The SLR ensured clarity and transparency through a four-phase verification flowchart adapted from [12]. This work aims to expand current research knowledge by focusing on AI technologies in agriculture. Table 1 presents the questions formulated for this review.

Table 1. Questions for study

ɔ	esearch question	ıstification
1	/hich nations have had the most impact in the field of research universities, publications, and seminal works in AI approaches used in agriculture?	o provide the necessary background information regarding AI research in the agricultural sector.
2	/hat are the most common AI methods used for agricultural work?	pplication of AI methods for identifying key areas of agriculture.
3	/hen it comes to using AI in agriculture, what are the biggest pros and cons?	ighlights trends and problems while revealing potential avenues for future research and improvement.

This research aimed to contextualize the topics of AI and agriculture by addressing the research question posed in Q1. To tackle Q2 and Q3, a framework adapted from existing literature was employed. Figure 1 illustrates the intersections between AI technology's potential impacts on agricultural applications (Q2) and highlights the associated challenges and benefits (Q3). The framework concentrates on AI technologies, their application domains, and the ensuing challenges and benefits, building on the methodologies proposed by previous studies.

METHODOLOGY

This section outlines the review principles of the Systematic Literature Review (SLR), the criteria for selecting studies, and the quality assessment of the chosen studies. To examine the evolution of AI in the agricultural industry as reflected in scientific publications, a comprehensive bibliometric analysis was conducted. The study employs a systematic bibliographical approach centered on a specific topic, adhering to a sequence of methodical steps. These steps include: (a) defining the search criteria, keywords, and time frame; (b) selecting relevant databases; (c) refining the research criteria; (d) exporting the full set of results; and (e) analyzing and discussing the findings (see Figure 1). This structured process ensures a rigorous and thorough exploration of the literature, facilitating a clear understanding of AI's impact on agriculture over time.

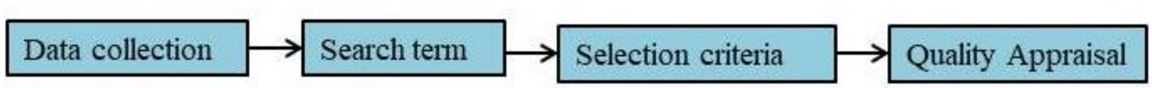

Figure 1. Stages of bibliometric analysis

DATA COLLECTION

For the systematic exploration of scientific information, a comprehensive array of literature databases was meticulously utilized. These databases, including ScienceDirect, Scopus, Springer, IEEE Xplore, and MDPI, were selected for their expansive coverage across various disciplines and their robust repositories of scholarly works. Each database was meticulously navigated to ensure a thorough search for pertinent research material. Table 2 serves as a crucial guide, presenting the inclusion indicator for the data collection phase, thus ensuring a systematic and transparent approach in the retrieval and selection of relevant literature. This meticulous selection process underscores the commitment to rigor and comprehensiveness in acquiring the necessary foundation for the subsequent stages of analysis and synthesis.

Table 2. Data collection source

ıdicator	escription
Search interval	)17 to 2022
Databases Screening	:ienceDirect; Scopus; Springer; IEEE Xplore; MDPI
Document types	itle, abstract, DOI, and year
Language	eview and original article
The proposed solution	nglish
Screening	pplied on agriculture

Search term

The search string devised for querying databases on artificial intelligence and its applications in agriculture incorporates a nuanced blend of keywords, synonyms, and logical operators to optimize the retrieval of relevant literature. By amalgamating terms like "artificial intelligence" and "agriculture" with synonyms and subarea descriptors, the search aims to cast a wide net, capturing varied perspectives and facets within the intersection of these domains (see Table 3). The strategic use of logical operators such as OR and AND enhances the precision of the search, allowing for the inclusion of diverse terms while maintaining coherence in the retrieved results. Employing this comprehensive query string in advanced search fields of databases ensures a systematic exploration of pertinent literature, facilitating a robust understanding of the advancements, challenges, and potential applications of artificial intelligence in agricultural contexts.

Table 3. Search term of this study

Search term
TITLE-ABS-KEY (agriculture*) AND (TITLE-ABS-KEY (artificial* AND intelligence*) OR TITLE-ABS-KEY (AI*) AND TITLE-ABS-KEY (machine* AND learning*) AND TITLE-ABS-KEY (deep* AND learning*)) AND PUBYEAR > 2012 AND PUBYEAR < 2022 AND (LIMIT-TO (DOCTYPE , "review") AND (DOCTYPE , "original article")) AND (LIMIT-TO (LANGUAGE , "English"))

Selection criteria

The systematic literature review (SLR) followed a meticulous process of identification and screening to ensure the inclusion of pertinent studies, as depicted in Figure 2 of the PRISMA flow diagram.

This paper's identification phase meticulously considered contemporary knowledge disseminated through peer-reviewed scientific journals in English. Notably, exclusion criteria were applied to filter out sources such as book chapters, annals, and abstracts, thereby maintaining a focus on robust, scholarly publications. By adhering to these rigorous standards, the SLR aimed to synthesize a comprehensive understanding of the topic under investigation, rooted in the latest empirical research findings available in the academic landscape.

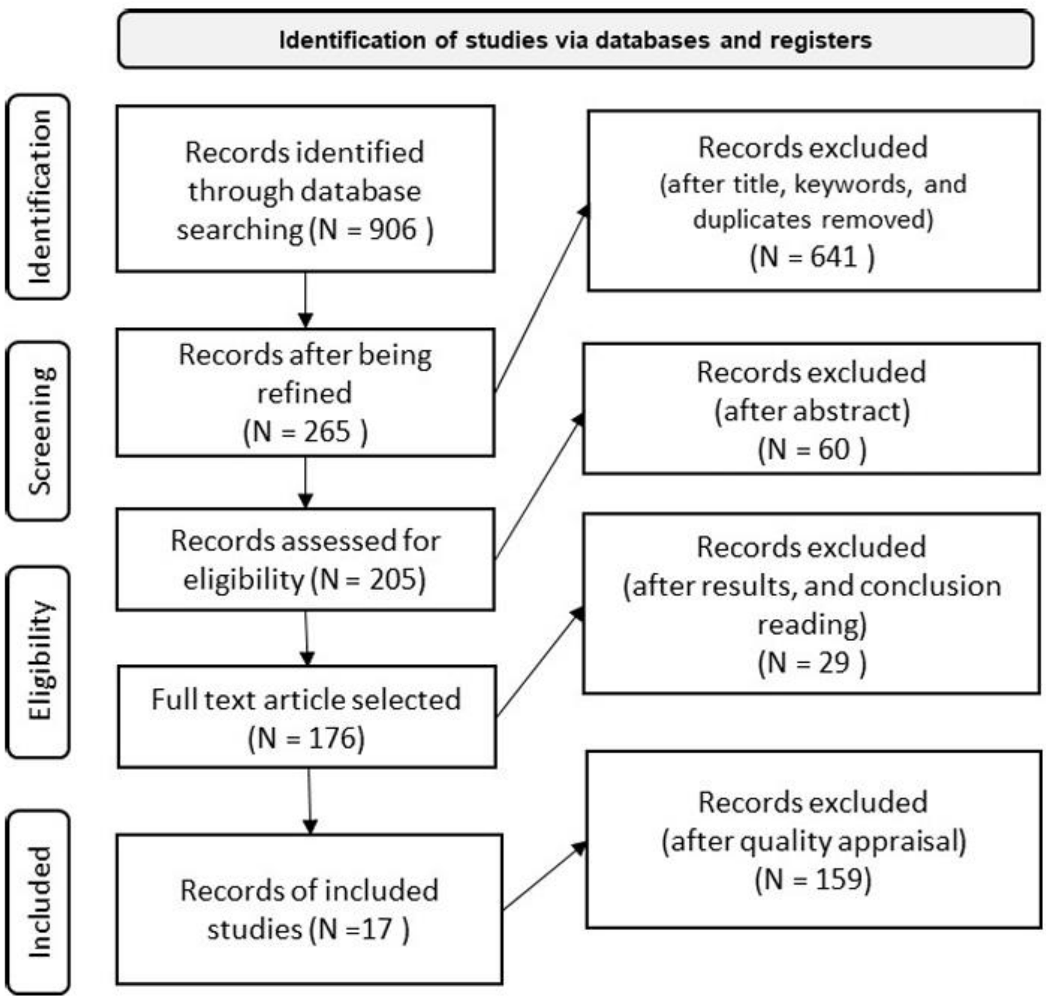

Figure 2. PRISMA flow diagram of this study

Selection criteria

The quality assessment of papers within the SLR encompassed an in-depth evaluation of various pertinent aspects, crucial for determining their inclusion or exclusion during the screening phase. This qualitative analysis was designed to meticulously categorize and prioritize the articles scrutinized within the SLR framework. Five distinct quality evaluation criteria were employed, encompassing both quantitative and content-related dimensions. Among these criteria, three were quantitative, directly linked to journal metrics such as Impact Factor, Citescore, and Citations, serving as indicators of scholarly impact and relevance. Additionally, qualitative aspects, notably the integration of AI technologies and applications within the agriculture domain, were assessed for their alignment with the study's objectives. Each criterion was assigned one of three response options—high, medium, or low—based on predefined thresholds, ensuring a comprehensive and standardized assessment process (see Table 4).

Table 4. Quality appraisal criteria

ıdicator	escription
Impact Factor	Assess the significance of scientific publications
Citescore	Stands for the typical amount of references
Citations	The number of times a publication has been referenced
Artificial intelligence technologies	ıking into account the technique, citations, usage, and outcomes, artificial intelligence technology is of extreme significance.
Agriculture domain applications	ıking into account the technique, citations, usage, and outcomes, agriculture application is of extreme significance.

During the eligibility analysis phase, thorough scrutiny of the 176 selected studies revealed distinct ranges of values pertinent to various criteria. For instance, in assessing the impact factor, a spectrum from 11.8 to 6.1 delineated high-quality studies, each garnering 1.0 points in this criterion, as outlined in Table 5. This quantitative approach facilitated a nuanced evaluation, wherein each record could amass points ranging from 0 to 3 across multiple criteria. By meticulously delineating such ranges and assigning corresponding point values, the eligibility analysis not only ensured a comprehensive assessment but also facilitated a structured comparison among the diverse pool of studies under consideration.

Table 5. Quantitative assessment criteria

Criterion	High	Medium	Low
ImpactFactor	[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]

For a quality appraisal, all 176 papers that were chosen during the eligibility stage were reviewed in their entirety. The papers with the highest scores are shown in Table 7.

Table 7. Quality assessment with a high score

References	AI technology	Application domain	Citescore	Impact Factor	Citation	Score
[30]	Robotics and automation; Computer	Crop management	5.002	8.7	135	5.5

	vision; Convolutional neural network					
[31]	Genetic algorithm; Internet of Things (IoT)	Fertigation management	11.072	15.8	25	5.5
[32]	Machine learning	Water management	6.757	11.8	40	5.5
[33]	Digital twins	Crop management	6.757	11.8	63	5.5
[34]	Machine learning	Crop prediction	8.171	12	12	5.5
[35]	Machine Learning (ML); Internet of Things (IoT)	Crop management	3.476	7	12	5.0
[27]	Bigdata; Robotics	Crop management	6.765	9.7	1195	5.0
[36]	Machine earning; Computer vision	Crop management	6.757	11.8	70	5.0
[37]	Deep learning; Computer vision	Crop Classification	3.889	5.0	19	4.5

RESULTS AND DISCUSSION

Descriptive Analysis(R1)

This section provides a quantitative analysis of the 176 selected studies, encompassing their publication and citation volumes, the methodologies employed in their identification, and the predominant countries, journals, and institutions driving their research. Figure 3 visually represents the distribution of papers and citations per year, offering insight into the temporal trends of scholarly activity within the field. Through meticulous examination, this section illuminates the landscape of research, shedding light on the prolific contributors, influential publications, and the evolving discourse surrounding the subject matter. By delineating these key metrics, it affords a comprehensive understanding of the breadth and impact of the studies under scrutiny, thereby facilitating informed interpretation and guiding future inquiry.

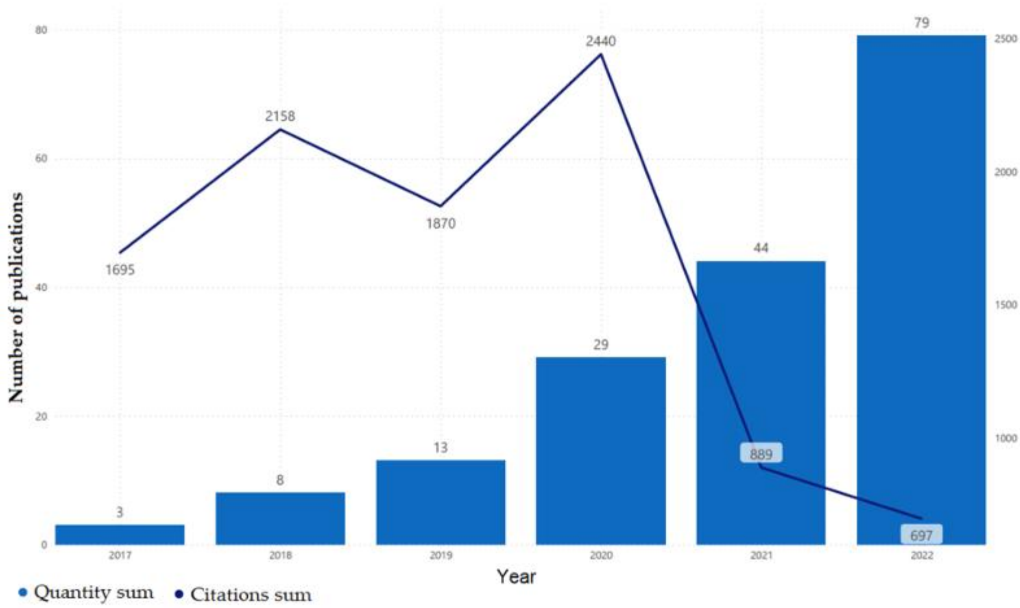

Figure 3. Publications and citations per year

Over the past three years, there has been a remarkable surge in both the number of publications and citations within the field, indicating a substantial growth in research activity and scholarly engagement. Data collected up to December 2022 revealed a peak of 2440 publications referencing works from 2020. This surge underscores the dynamic feedback loop prevalent in this area of research, with subsequent years building upon and citing earlier findings. These studies have been systematically classified into theoretical and empirical categories (see Table 8). Theoretical inquiries encompass reviews and SLRs, while empirical investigations include modeling and simulation studies, surveys, and case studies. This structured classification offers valuable insights into the diverse methodologies employed within the field, reflecting its multidisciplinary nature and the breadth of approaches undertaken to advance knowledge and understanding.

Table 8. Identified studies

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

The distribution of studies was balanced, with 43% classified as theoretical and 57% as empirical. The theoretical studies predominantly focused on literature reviews, accounting for 34% of the total with 59 papers. Among the empirical studies, modeling and simulation were particularly prominent, comprising 39% of 68 papers. This distribution is mirrored in the quality appraisal steps, where notable articles such as [38] and [39] exemplify the applied research in the field. These studies respectively developed innovative systems for robotic strawberry picking and smart irrigation, highlighting the practical implications of both theoretical and empirical research in advancing technological applications.

When evaluating the significance of a dissertation Bibliometric analysis sheds light on the quantity and influence of publications by use of citation metrics; it assesses the relevance of research articles by means of a number of variables. The Netherlands stands out as the most influential country in this domain, achieving 1629 citations from only 5 publications. India is a close contender with 37 publications accumulating 1499 citations. Greece, although contributing just 3 publications, has a substantial impact with 1002 citations. China, with 23 publications, has garnered 899 citations. Table 9 provides a comprehensive overview of countries with more than 100 citations, highlighting the global reach and influence within this research area.

Table 9. Quality assessment with a high score

Score	Country	Publications	Citations
1	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

Over the last three years, the publications and citations of artificial intelligence (AI) techniques applied to agriculture have increased almost sixfold, underscoring the growing significance and relevance of this research area. The most influential countries in this domain are among the world's largest food producers, highlighting the global recognition of AI's potential to revolutionize agricultural practices. Additionally, numerous high-impact journals have emerged as key platforms for disseminating groundbreaking research in this field, further demonstrating the scholarly and practical importance of integrating AI in agriculture.

Artificial Intelligence in Agriculture (R2)

Agriculture domain

Agriculture, defined as the science of cultivating land and raising livestock, is essential for producing the food and resources necessary for human survival. Central to this practice is the physical environment, which serves as the foundational resource base, and the cultivated crop plant, which is the primary unit of production [40]. The success of agricultural endeavors hinges on the effective management of the physical environment to meet the biological demands of these crops. Key factors influencing crop yield include soil productivity, water availability, climate conditions, and the control of pests and diseases [41]. Mastering these variables is crucial for optimizing agricultural output and ensuring the sustainability and resilience of food systems.

Artificial intelligence is revolutionizing the agricultural sector by optimizing processes and resources. This review identified seven key applications: crop management, water management, soil management, chemical application, fertigation, crop prediction, and crop classification, as summarized in Table 10. The primary goal of crop management is to rationalize resource use [42]. Water management focuses on optimizing irrigation and water use on farms, while soil management is crucial for the success of site-specific cropping systems. Proper chemical application is vital for environmental and economic sustainability [43]. Fertigation, the use of irrigation systems for fertilizer application, has been shown to enhance fertilizer effectiveness. Crop prediction and classification, utilizing image processing and deep learning [44], are essential for sustainable resource utilization. Effective management of diseases and pests is critical for improving crop yield, quality, and overall food security.

Table 10. Uses in the agricultural sector

References	Domain	Details
[45]	Crop management	Included are planting, tending, harvesting, storing, and distributing seeds
[46]	Water management	Streamlining irrigation methods and processes to maximize utilization of water
[47]	Soil management	Make sure plants get enough nutrients.
[48]	Fertirrigation	Technology with the goal of providing data for a different application sector and a worldwide perspective on crop distribution
[34]	Crop prediction	The logistical management of farmers relies heavily on crop productivity projection
[49]	Crop classification	The purpose of crop categorization is to provide a comprehensive picture of crop dispersion and related data for a different field of usage
[50]	Disease and pest management	Impair crop yields and quality while decreasing the efficiency of resource utilization. Protecting agricultural crops from the many different kinds of weeds, animals, and microbes necessitates technological solutions.

Artificial Intelligence Technologies

The integration of AI into agriculture, aimed at enhancing food production while mitigating the effects of climate change, poses significant challenges rooted in the analysis of AI technologies. Originating from the conceptualization of cognitive processes and neurobiology in the 1950s, AI's evolution has delineated four distinct categories of intelligent systems: those that emulate human thought, behavior, rational thinking, and rational action. Success in these categories is gauged by their fidelity to human performance or rationality [8]. AI systems are proficient in data storage, manipulation, knowledge acquisition, representation, and deduction of new knowledge from existing information. Within the realm of agriculture, AI technologies are diverse, encompassing cognitive science, robotics, and natural interface applications. These technologies, as identified across numerous studies, are bolstered by auxiliary technologies like IoT, big data, and cloud computing, enabling the implementation of specific AI techniques such as computer vision, robotics, machine learning, augmented reality, and virtual reality.

The analysis of 17 selected articles in the quality assessment stage revealed a spectrum of AI technologies and their applications in agriculture, as summarized in Table 11. Notably, the focus encompassed innovations such as irrigation, disease, and pest management systems, which emerged prominently in the literature. Additionally, a comprehensive review of these advancements, as presented in [24], provided valuable insights into the field's progression. Furthermore, the development of a smart irrigation system, detailed in [39], showcased practical implementations of AI in enhancing agricultural practices. Moreover, the exploration of emerging technologies like agricultural digital twins, highlighted in [33], underscored the ongoing efforts to capture the intricate interactions between living systems and their environment.

Table 10. AI technologies that were mentioned in the chosen papers

References	Domain	Details
[30]	Robotics and automation	The utilization of machinery, software, and other technology to carry out activities that replace or mimic human movements
[51]	Drones and unmanned aerial vehicles (UAVs)	Unmanned aerial vehicles that are capable of being commanded remotely
[32]	Machine learning (ML)	This system has the ability to adapt its behavior on its own using various algorithms that can be used to evaluate performance and make accurate predictions.
[52]	Artificial neural networks(ANNs)	Computer systems that mimic human intelligence, which is able to acquire new knowledge and adjust to novel and ever-changing circumstances.
[37]	Deep learning: convolutional neural network CNN)	A collection of algorithms connected to machine learning forms its basis. CNNs use picture patterns to identify objects, classifications, and categories.
[30]	Genetic algorithm (GA)	Machine learning algorithms that simulate evolving processes and resolve issues by studying biological evolution.
[31]	Computer vision	Automatic picture acquisition, analysis, and comprehension are all part of computer vision, which includes issues like object detection, motion tracking, and action recognition.

[53]	Digital twins	The goal of this virtual representation is to maximize efficiency and production
[36]	Internet of Things (IoT)	Establishes connections between various intelligent devices, making crop management easier
[54]	Cloud computing	Assets like storage for information and computer power are made available on request
[55]	Big data	Information is gathered, processed, and analyzed

In our comprehensive review of the literature, we have discerned seven primary applications that underscore the diverse utility of artificial intelligence (AI) in agricultural contexts. These applications encompass crop management, water management, soil management, fertigation, crop prediction, crop classification, and the identification and mitigation of diseases and pests. Furthermore, our analysis has unveiled a rich tapestry of AI techniques, numbering twenty-four distinct methodologies. Notably, prevalent among these techniques are big data analysis, Internet of Things (IoT) integration, and cloud computation. Of these applications, crop management, water management, and disease and pest control emerge as the most prevalent areas of focus, indicating their significance in addressing contemporary agricultural challenges. Within the realm of AI techniques, machine learning, robotics, deep learning, and IoT technologies stand out as the most frequently employed tools, underscoring their pivotal role in advancing agricultural innovation and sustainability.

Benefits, Challenges and Trends (RQ3)

The integration of machine learning, deep learning, and computer vision techniques within agriculture has heralded a transformative era known as Agriculture 4.0 or Digital Agriculture. This paradigm shift leverages advanced technologies like precision agriculture, IoT, and cloud computing to revolutionize farming practices. Precision agriculture optimizes resource utilization and minimizes environmental impact through real-time monitoring aided by remote sensing technologies. Agriculture 4.0, akin to Industry 4.0, harnesses big data and novel technologies across the supply chain, aiming to enhance productivity while reducing waste. Moreover, the emergence of next-generation agriculture, denoted as 5.0 and 6.0, emphasizes deep learning and robotic advancements to balance production and environmental sustainability. Underpinning these advancements is the pervasive use of artificial intelligence, facilitating efficient crop management, irrigation, and disease detection by processing vast datasets. This synergy of technologies underscores a pivotal shift towards intelligent farming systems, where data-driven insights empower farmers to make informed decisions, fostering agricultural sustainability and productivity.

UAVs have revolutionized data collection in agriculture, offering vast and intricate datasets. Leveraging big data analytics tools and cloud computing can markedly enhance data processing efficiency, bolster data security, ensure scalability, and reduce operational costs. Furthermore, the integration of ML, ANN-based, and deep learning techniques shows promise, particularly in crop prediction, owing to the abundance of data from diverse sources. Amidst these advancements, emerging technologies like DT are reshaping the agricultural landscape. While PA remains prominent, newer terms such as Agriculture 4.0 and smart farming are gaining traction in scholarly discourse. Notably, there's a call for tailored research endeavors, considering regional climate and crop specifics, particularly in countries like Brazil, which are yet to fully harness their scientific potential in this domain. Additionally, understanding the intricacies of crop production chains is crucial for effectively applying AI technologies and optimizing production (see Figure 4). These technologies, with their common reliance on digitized data, lie at the heart of the digital revolution in agriculture. As we chart future research trajectories, it's imperative to focus on enabling technologies that facilitate the practical application and dissemination of research outcomes.

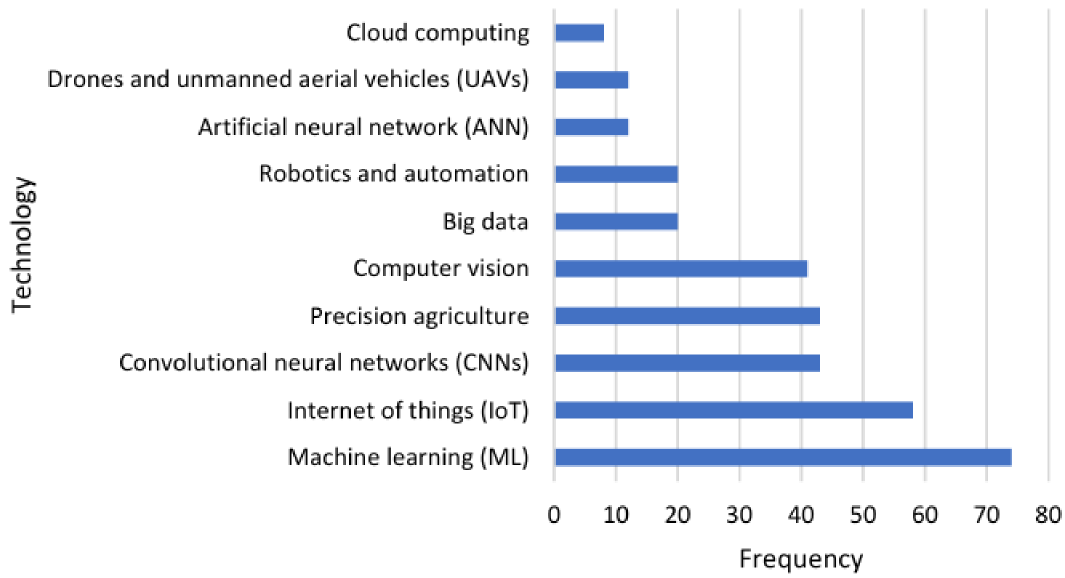

Figure 4. The top 10 technologies and phrases that emerged from the examination of 175 publications

CONCLUSIONS

This systematic literature review, conducted using the PRISMA methodology, comprehensively examines the application of artificial intelligence (AI) technologies in agriculture. Analyzing 176 papers through bibliometric analysis and assessing 17 papers for quality, the review identifies seven primary agricultural applications: crop, water, soil management, fertigation, prediction, classification, and disease/pest management. Notably, twenty-four AI techniques, prominently including machine learning, deep learning with convolutional neural networks, robotics, and the Internet of Things, are identified as pivotal in advancing agricultural practices. These technologies offer substantial benefits such as optimizing management systems, irrigation, and disease identification. However, challenges persist, particularly in digitizing production processes and addressing the associated costs, which remain prohibitive for many farmers. Labor qualification and the need for supportive public policies in food-producing nations are also highlighted. Moreover, the integration of computer vision with robotics and UAVs for crop classification and disease detection, alongside emerging technologies like digital twins, signifies promising avenues for agricultural optimization. As precision agriculture transitions towards smart farming frameworks, incorporating telecommunications and data infrastructure, the advent of agriculture 4.0 and 5.0 further underscores the evolving landscape driven by AI and UAV technologies. Despite these insights, the review acknowledges limitations such as language bias and database selection, suggesting avenues for future research to enhance the comprehensiveness and validity of findings.

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