Research hotspots and development trends of harvesting robots based on bibliometric analysis and knowledge graphs

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Abstract: Over the past 30 years, there has been continuous progress in global science and technology. However, many agricultural products still heavily rely on traditional methods of manual and mechanical harvesting, facing challenges such as high costs and low efficiency. To address these challenges, researchers have developed various harvesting robots to handle diverse tasks in complex farm environments. This study analyzed pertinent papers on harvesting robots retrieved from the Web of Science (WOS) core database and the China National Knowledge Infrastructure (CNKI) database, spanning the years 1993 to 2022. Using specialized software such as CiteSpace and VOSviewer, a bibliometric analysis was conducted to examine the research progress and hotspots in the field of harvesting robots. The analysis of 517 English papers indicated a continuous expansion in the research scale of harvesting robots. Furthermore, the research history can be divided into three distinct periods. Currently, research on harvesting robots is experiencing a rapid growth phase, with the number of related papers steadily increasing each year. In the year 2022 alone, 151 English papers were published. This growth is attributed to close collaborations among different countries/regions, institutions, and authors. China, the United States, and Japan play crucial roles in the research of harvesting robots. Notably, China has published 326 English papers, ranking first globally. Through analysis, it was also found that Chinese papers focused on harvesting robots earlier, thereby promoting the development of agricultural robots. Additionally, bibliometric analysis revealed that the research hotspots of harvesting robots mainly include system and structure design, object recognition and localization, and multi-robot coordination, among others. In the future, development trends of harvesting robots will focus on: 1) diversifying robot types, 2) expanding application scenarios, 3) enhancing overall performance to reduce losses, and 4) reducing manufacturing costs. In conclusion, through a comprehensive bibliometric analysis, this study has provided valuable insights to advance the automation of harvesting.

Keywords: harvesting robots, crops harvesting, bibliometric analysis, research hotspots, development trends.
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1 Introduction

As global science and technology advance, the planting area and yield of agricultural products continue to expand, leading to an increasing demand for efficient harvesting[1]. After the mechanical harvesting problems of staple crops such as wheat and corn were basically solved, research and application hotspots shifted to economic crops such as vegetables, flowers, and fruits. However, due to the complex growth environment of these economic crops, traditional large-scale machines are no longer feasible. As a consequence, many fruits and vegetables still rely heavily on manual harvesting. However, manual harvesting faces multiple challenges such as high labor costs and low work efficiency[2,3]. Furthermore, with the increasing trends of population aging and young people migrating, the agricultural workforce continues to decrease[4]. To address this situation, there is an urgent need for research in automated harvesting, with robotic harvesting proving to be more adaptable and viable.

For a considerable duration, researchers have been dedicated to developing technology related to harvesting robots, achieving significant progress in this field[5-8]. The application scenarios for harvesting robots are constantly expanding, including greenhouses[9,10], standardized farmlands[11,12], hilly areas[13,14], orchards[15,16], tea gardens[17,18], and other complex environments. Moreover, the variety of harvesting objects is continuously increasing, including cucumbers[19,20], tomatoes[21,22], eggplants[23,24], sweet peppers[25,26], strawberries[27,28], citrus[29,30], kiwifruit[31,32], apples[33,34], and other agricultural products. As for the harvesting methods, they are also constantly evolving, including pulling[35,36],

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suctioning[37,38], twisting[39,40], cutting[41,42], and other forms. Therefore, the research on harvesting robots is gaining much more attention.

Analyzing identified topics using bibliometric methods can aid in uncovering research trends and frontier areas[43,44]. Moreover, bibliometric analysis has been widely employed across diverse research fields, encompassing agriculture, industry, education, and medical treatment. For instance, Bertoglio et al.[45]summarized the current state of the digital agriculture using bibliometric methods, and predicted that the Internet of Things (IoT) and Artificial Intelligence (AI) will constitute development trends in the future. Jiang et al.[46] conducted a bibliometric analysis on the research progress of Unmanned Aerial Vehicles (UAVs), summarizing the current research hotspots and technological challenges. Through a bibliometric analysis, Ni et al.[47] found that research on non-destructive testing of fruit quality is highly active and that the technology is progressively maturing.

At the same time, researchers have conducted summarization and analysis of the research progress in agricultural robots[48,49]. For instance, Bechar and Vigneault[50] conducted an analysis of recent progress and limitations in agricultural robot research. They emphasized the necessity to improve the design of intelligent systems for robots and enhance capabilities to operate in complex environments. In addition, Liu et al.[51] presented a summary of the research status of various agricultural robots, categorizing them based on different application scenarios and operation links. They also conducted a detailed analysis of key technologies and development trends. Furthermore, Wang et al.[52] analyzed the structures and functions of harvesting robots designed for different crops, such as apples, tomatoes, kiwifruits, and cucumbers. Nevertheless, currently, there are few papers conducting bibliometric analyses on harvesting robots. Therefore, this study is considered both necessary and innovative, contributing to the current understanding of harvesting robots.

In summary, this study utilizes bibliometric methods to analyze the current research status and identify frontier hotspots in the field of global harvesting robots. Research hotspots such as robot design, object recognition, and collaborative work have garnered significant attention. Additionally, this study forecasts future development trends, providing a valuable reference for subsequent research.

2 Materials and methods

2.1 Bibliometric materials and search process

This study aims to explore the current global development status of harvesting robots. Over the past three decades, numerous researchers have predominantly published papers on harvesting robots in English. Consequently, this study selected the Web of Science (WOS) core database as the source for bibliometric materials[53,54].

To ensure sufficiency, accuracy, reliability, and credibility of the analysis results, this study utilized the advanced function of the database to search for English papers. According to WOS search rules, the search subject was set as: ALL = (“harvest* robot*”) OR = (“pick* robot*”) OR = (“robot* harvest*”) OR = (“robot* pick*”). The time range was set from January 1st, 1993, to December 31st, 2022. The paper type was restricted to articles and reviews. Initially, 728 English papers were retrieved, and after screening, 517 English papers were identified as relevant to harvesting robots. Each paper record included essential information, such as title, publication time, journal, country/region, institution, author, and keywords. All this information was used in the bibliometric analysis.

To gain a deeper understanding of the development status of harvesting robots in China, this study also conducted searches for relevant Chinese papers in the China National Knowledge Infrastructure (CNKI) database. Using identical search settings and filtering procedures, 227 Chinese papers related to harvesting robots were obtained.

2.2 Bibliometric methods and analysis software

This study used several bibliometric analysis software, including MS Excel, CiteSpace, and VOSviewer. As traditional data analysis software, MS Excel possesses powerful functionalities and can conduct accurate statistical analysis of research progress. In contrast, CiteSpace and VOSviewer are comprehensive bibliometric analysis software[55,56]. In particular, CiteSpace is highly suitable for keyword clustering, while VOSviewer is good at visually representing research collaborations.

Consequently, this study conducted a comprehensive and multi-level bibliometric analysis based on the above retrieval results and software tools. These analyses aimed to reveal research hotspots and development trends of harvesting robots. MS Excel was used to analyze the distribution of papers in terms of time, journals, countries/regions, institutions, and authors. Based on the temporal and spatial distribution of these papers, the analysis revealed the evolution of research on harvesting robots. In addition, CiteSpace and VOSviewer were employed to investigate research collaborations, keyword clustering, as well as highly cited papers. Specifically, the analyses also reflected the level of attention dedicated to harvesting robots in various countries/regions.

3 Results and discussion

3.1 Time distribution of English papers

Examining the time distribution of published papers reflects the prevalence of research on harvesting robots. As illustrated in Figure 1, the number of papers in this field has markedly increased over the past three decades, reaching a total of 517. Notably, in 2022 alone, the number of published papers accounted for 29.21% of the total. The consistent increase in the number of papers aligns with the growing demand for harvesting robots[57,58]. Furthermore, it is anticipated that this growth trend will persist.

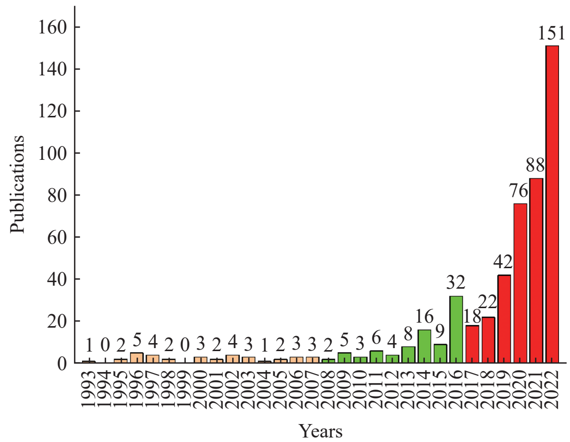

Figure 1 English papers on harvesting robots published from 1993 to 2022

Based on these findings, the research history of harvesting robots from 1993 to 2022 can be divided into three distinct periods. The first period, from 1993 to 2007, was characterized by a slow exploration period. As the research was in its nascent stages, technological developments progressed slowly[59,60]. Consequently, the number of published papers remained consistently low during this period. The second period was a fluctuating rising period between 2008 and 2016. This period was characterized by the maturation of robot technology[61,62], leading to a steady increase in the number of papers published within this timeframe. Finally, the period from 2017 to 2022 can be defined as a period of rapid growth, during which harvesting robots have emerged as a research hotspot. With new technologies and methods constantly evolving[63-65], the number of published papers in this field has been increasing exponentially every year.

3.2 Space distribution of English papers

Analyzing the spatial distribution of papers helps in comprehending the research scale of harvesting robots across various countries/regions. Simultaneously, it is possible to identify key institutions and essential authors in this field. Furthermore, this analysis can establish international cooperation networks among countries/regions, institutions, and authors. It is noteworthy that a higher number of connections in the network indicates a closer level of collaborative relationships.

3.2.1 Country/region distribution and cooperation networks

Papers on harvesting robots have been published by a total of 45 countries/regions. As observed in Figure 2, the three countries with the highest number of papers are China, the United States, and Japan. Specifically, China exhibits the most extensive research efforts, dominating paper publications with a share of 63.06%. Moreover, the United States and Japan also demonstrate a notable interest in harvesting robots and display impressive levels of technological advancement[66]. Meanwhile, England and Germany conduct research on harvesting robots and have published several papers[67], significantly enhancing agricultural technology.

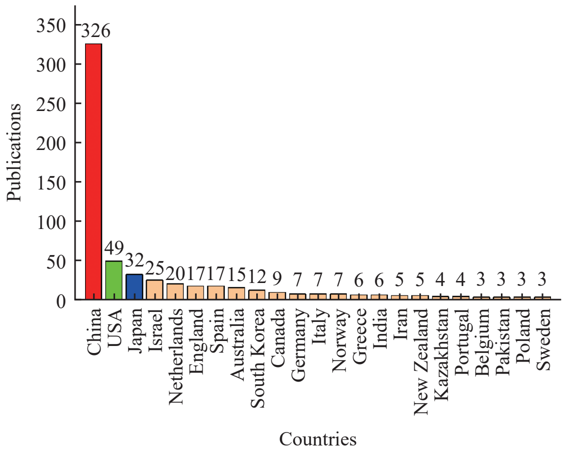

Figure 2 English papers on harvesting robots published by the top twenty countries

As illustrated in Figure 3, the degree of collaboration among China, the United States, and Japan is the highest. This cooperation aligns with the number of papers published by these three countries. In addition to the trilateral cooperation among these three countries, there are also substantial collaborations involving China, England, and Australia[68,69], as well as among the United States, Israel, and the Netherlands[70,71], and among Japan, Kazakhstan, and South Korea[72,73]. Furthermore, collaborative efforts are frequent among Spain, Italy, and Canada[74,75], as well as among the Netherlands, Germany, and France[76]. The substantial progress in harvesting robots can be attributed to extensive collaborations among these countries.

3.2.2 Institution distribution and cooperation networks

A total of 421 institutions have published papers related to harvesting robots. According to Table 1, the top ten institutions in terms of publication volume collectively have contributed to 266 papers, accounting for 51.45%. Among them, the top three institutions are Jiangsu University, South China Agricultural University, and Northwest A&F University, all situated in China. This data indicates that Chinese institutions place significant emphasis on harvesting robots[77]. It is noteworthy that average cited times of papers related to Wageningen University, Ben-Gurion University, and Washington State University are significantly higher than those of Chinese institutions. The average cited times are obtained by dividing the total number of cited times by the total number of papers. This data implies that research outcomes from these institutions carry greater credibility.

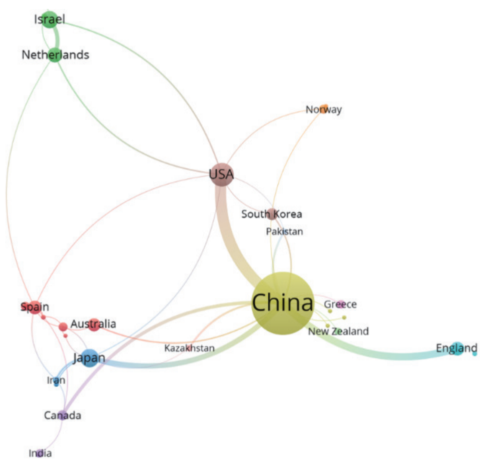

Figure 3 Cooperation networks among different countries/regions

Table 1 English papers on harvesting robots published by the top ten institutions

Ranks	Institutions	Countries	Publications	Cited times	Average cited times
1	Jiangsu University	China	49	877	17.90
2	South China Agricultural University	China	48	1634	34.04
3	Northwest A&F University	China	37	627	16.95
4	Ministry of Agriculture and Rural Affairs of China	China	22	324	14.73
4	Zhongkai University of Agriculture and Engineering	China	22	791	35.95
6	China Agricultural University	China	19	404	21.26
7	Wageningen University	Netherlands	17	1088	64.00
8	Ben Gurion University	Israel	16	795	49.69
9	Nanjing Agricultural University	China	14	233	16.64
10	Shandong Normal University	China	11	204	18.55
10	Washington State University	USA	11	692	62.91

With reference to Figure 4, the top three institutions that exhibit the highest level of collaboration in the research on harvesting robots are South China Agricultural University, Northwest A&F University, and Jiangsu University. This finding is in line with the number of papers published by these three institutions. Moreover, widespread internal collaborations among Chinese institutions are observed. In contrast, Pennsylvania State University and Washington State University have established close partnerships with numerous international institutions. This indicates that the research capabilities of these institutions have been widely recognized. Therefore, Chinese institutions need to strengthen international cooperation to expand their influence[78,79].

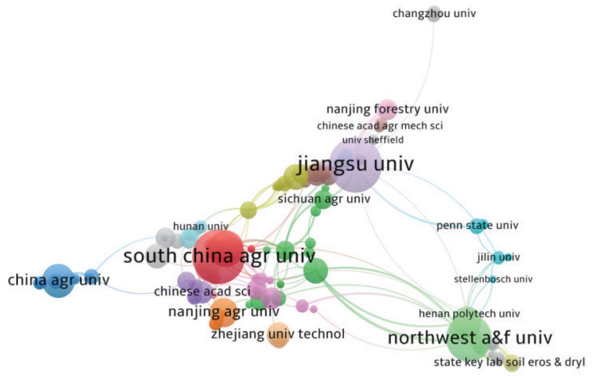

Figure 4 Cooperation networks among different institutions

3.2.3 Author distribution and cooperation networks

A total of 1435 authors have published papers on harvesting robots. As shown in Figure 5, 16 authors have published more than ten papers, with 11 of these authors coming from China. This indicates that Chinese authors have made significant contributions to this field. Moreover, Edan Y from Ben-Gurion University and Chen C from Monash University rank fourth and fifth in terms of publication quantity. Dividing the total number of cited times by the total number of papers yields the average cited times for papers published by these authors. Apparently, Van Henten EJ and Hemming J from Wageningen University have produced widely cited works. In particular, Kondo N from Kyoto University is recognized as an early pioneer in harvesting robots[80,81], accelerating the development of related technologies. Overall, the research outcomes of these authors have significant practical implications and reference value.

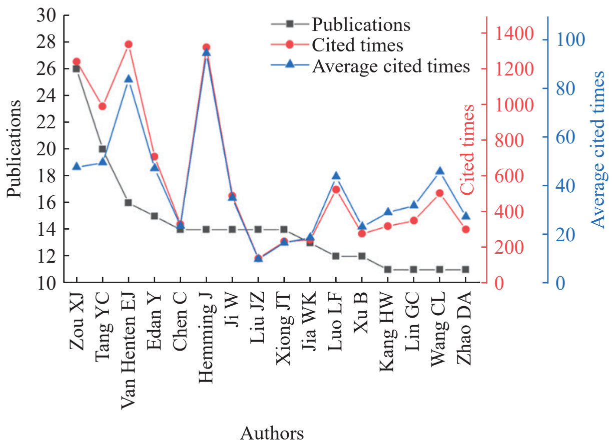

Figure 5 Authors who have published more than ten English papers

With reference to Figure 6, the collaborative relationships among authors are very active and close. In particular, Chinese authors have exhibited a high level of internal cooperation, forming several research groups. Examples include the team led by Zou X J and Xiong J T[16,82] from South China Agricultural University, the team led by Ji W and Zhao D A[33,69] from Jiangsu University, and the team led by Cui Y J[31] from Northwest A&F University. Furthermore, the team led by Chen C[83] from Monash University and the team led by Zhang Q[84] from Washington State University have established robust collaborations with international authors. This indicates that these teams have a significant impact in the field of harvesting robots[84,85].

3.3 Analysis of sources and citations in English papers

3.3.1 Journal distribution of English papers

An analysis of journal distribution can aid in identifying popular journals. 517 papers on harvesting robots have been published in a total of 107 journals. Referring to Figure 7, the top ten journals collectively published 302 papers, accounting for 58.41% of all published papers. These journals receive widespread attention and wield considerable influence[86]. Remarkably, the journals "Computers and Electronics in Agriculture" (Comput Electron Agr), "Biosystems Engineering" (Biosyst Eng), and "Sensors" are ranked among the top three in both the number of published papers and the number of citations. Furthermore, the journal "International Journal of Agricultural and Biological Engineering" (IJABE) has placed significant emphasis on research related to harvesting robots, bearing important implications for future work[82].

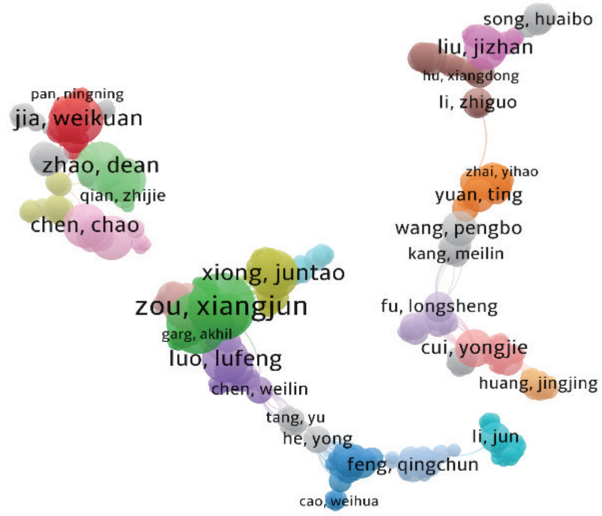

Figure 6 Cooperation networks among different authors

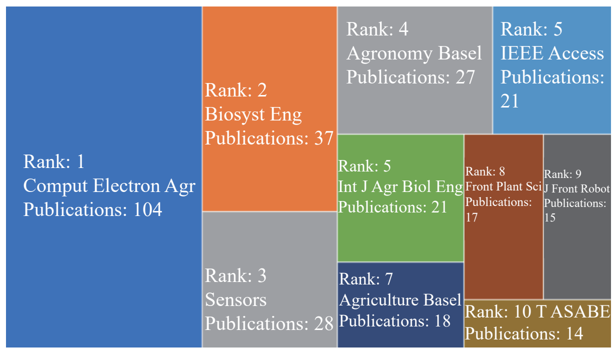

Figure 7 English papers on harvesting robots published by the top ten journals

3.3.2 Highly cited English papers

Examining citations is a useful method for identifying the most important research papers on harvesting robots. Referring to Table 2, the top ten English papers were cited between 161 to 486 times, with an average of 180. As for the research topics, these papers comprise four reviews and six articles. Specifically, one review paper summarized the key technologies and development trends of harvesting robots[48]. Moreover, three articles respectively discussed the structure design and actual testing of harvesting robots for cucumbers, apples, and strawberries[10,15,33]. The remaining three reviews and three articles all focused on the theme of detecting, recognizing, and localizing harvestable objects[61,86-90]. The themes of these papers highlight the current research hotspots in the field of harvesting robots, providing significant reference value.

Table 2 Top ten English papers with the most citations

Rank	Title	Journal	Paper type	Cited times
1	DeepFruits: a fruit detection system using deep neural networks[87]	Sensors	Article	486
2	Harvesting robots for high-value crops: state-of-the-art review and challenges ahead[48]	J Field Robot	Review	293
3	Sensors and systems for fruit detection and localization: A review[61]	Comput Electron Agr	Review	260
4	An autonomous robot for harvesting cucumbers in greenhouses[10]	Auton Robot	Article	237
5	Fruit detection for strawberry harvesting robot in non-structural environment based on Mask-RCNN[86]	Comput Electron Agr	Article	220
6	Design and control of an apple harvesting robot[33]	Biosyst Eng	Article	181
7	Evaluation of a strawberry-harvesting robot in a field test[15]	Biosyst Eng	Article	178
8	Recognition and localization methods for vision-based fruit picking robots: A review[88]	Front Plant Sci	Review	176
9	Faster R-CNN for multi-class fruit detection using a robotic vision system[89]	Comput Netw	Article	169
10	A review of key techniques of vision-based control for harvesting robot[90]	Comput Electron Agr	Review	161

3.4 Bibliometric analysis of Chinese papers

3.4.1 Time distribution of Chinese papers

Through rigorous retrieval and screening, this study has obtained 227 Chinese papers related to harvesting robots. As shown in Figure 8, the number of Chinese papers has been steadily increasing since 2003, reaching its peak in 2015. Especially since 2008, the number of Chinese papers on harvesting robots has significantly increased, averaging 13 papers per year. The growth trend is primarily due to the rapid development of robotics technology and the policy support from government agencies. It is evident that, despite China initiating its research on harvesting robots relatively late, the gap with agriculturally developed countries has progressively narrowed in recent years. China's research interest in the field of harvesting robots has been continuously strengthening, leading to significant progress and fostering international collaborations.

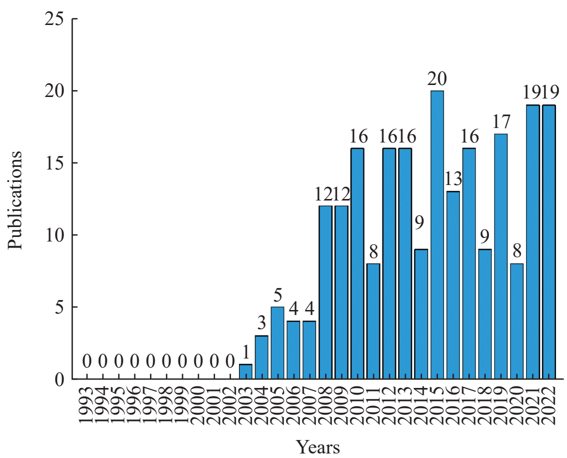

Figure 8 Chinese papers on harvesting robots published from 1993 to 2022

3.4.2 Journal distribution of Chinese papers

A total of 15 journals have published 227 Chinese papers on harvesting robots. As shown in Table 3, the top five journals in terms of paper count collectively published 217 papers, accounting for over 95.60% of the total. Notably, the journals "Transactions of the Chinese Society for Agricultural Machinery" (Transactions of the CSAM) and "Transactions of the Chinese Society of Agricultural Engineering" (Transactions of the CSAE) collectively published 206 papers, constituting over 90.74%. These two journals hold significant influence and expertise in the field of agricultural engineering in China, demonstrating comprehensive attention and support for research on harvesting robots.

Table 3 Chinese papers on harvesting robots published by the top five journals

Rank	Journals	Publications	Percentage
1	Transactions of the CSAM	116	51.10%
2	Transactions of the CSAE	90	39.64%
3	Journal of Jiangsu University (Natural Science Edition)	4	1.76%
4	Journal of Huazhong University of Science and Technology (Natural Science Edition)	3	1.32%
5	ROBOT	2	0.88%
5	Journal of Mechanical Engineering	2	0.88%

3.4.3 Highly cited Chinese papers

Table 4 displays the top ten Chinese papers based on the number of citations, ranging from the highest count of 376 to the lowest of 162, with an average of 233. These papers comprise four reviews and six articles. Among them, the four reviews discussed the research progress of harvesting robots[91-94], two articles covered the system design of harvesting robots[95,96], three articles focused on the recognition and positioning of harvesting objects[97-99], and one article presented the optimization of end-effectors[100]. These topics reflect the research hotspots in the field of harvesting robots.

Table 4 Top ten Chinese papers with the most citations

Rank	Title	Journal	Paper type	Cited times
1	Research actuality and prospect of picking robot for fruits and vegetables[94]	Transactions of the CSAM	Review	376
2	Research progress and problems of agricultural robot[93]	Transactions of the CSAE	Review	324
3	Apple positioning based on YOLO deep convolutional neural network for picking robot in complex background[98]	Transactions of the CSAE	Article	257
4	Design and experiment of intelligent mobile fruit picking robot[96]	Transactions of the CSAM	Article	230
5	Present situation and development of mobile harvesting robot[92]	Transactions of the CSAE	Review	222
6	Robotics for fruit and vegetable harvesting: A review[91]	ROBOT	Review	197
7	Development and performance analysis on cucumber harvesting robot system in greenhouse[95]	ROBOT	Article	192
8	Recognition of mature oranges in natural scene based on machine vision[97]	Transactions of the CSAE	Article	190
9	Identification and location system of multi-operation apple robot based on vision combination[99]	Transactions of the CSAM	Article	180
10	Hardware design of the end-effector for tomato-harvesting robot[100]	Transactions of the CSAM	Article	162

3.5 Discussion of keywords clustering and research hotspots

The analysis of keywords distribution can provide insights into the research hotspots. As shown in Figure 9, the frequency of keywords is depicted by the intensity of color, where darker hues correspond to a higher occurrence frequency. The data analysis indicates that the most frequently used keywords are: (1) harvesting robot, (2) design, (3) recognition, (4) machine vision, (5) system, (6) fruit, (7) positioning, (8) deep learning, (9) detection, and (10) color. This signifies that the associated keywords garner a heightened level of attention. Over time, "deep learning" is becoming the latest research hotspot for harvesting robots.

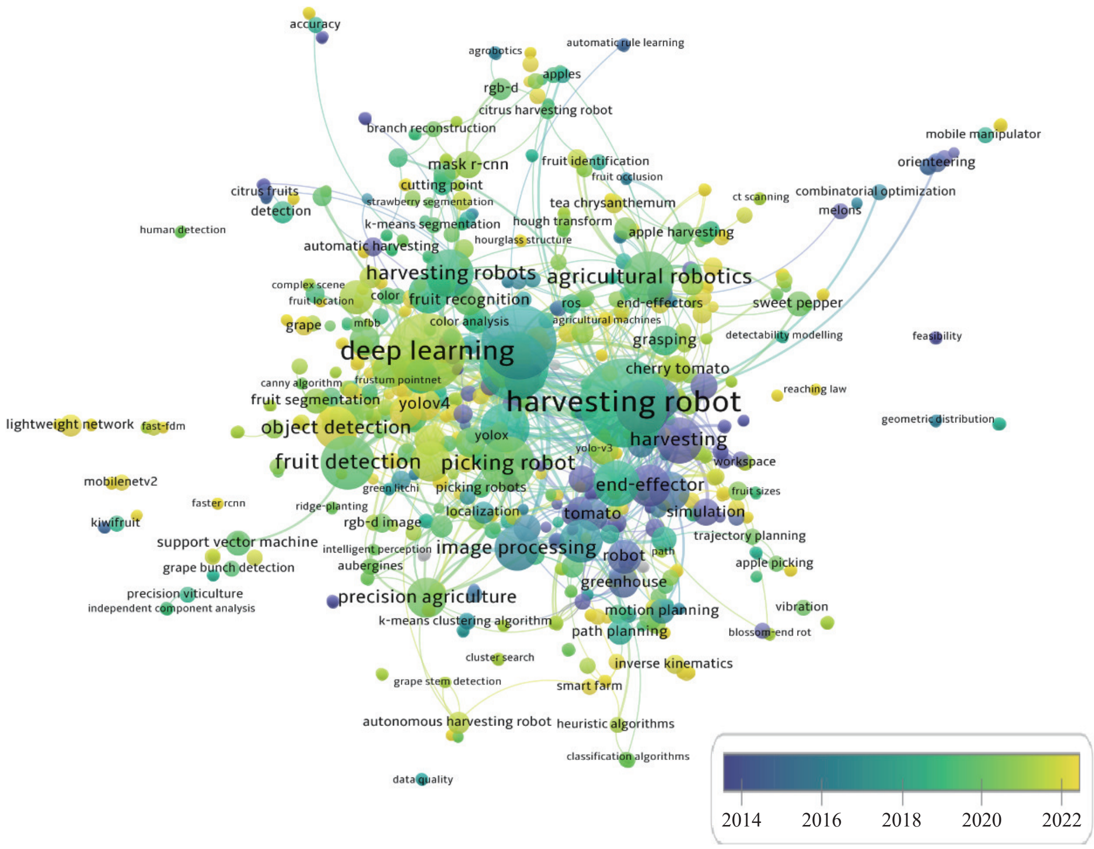

Figure 9 Keyword appearance popularity

Furthermore, clustering analysis of keywords can reveal the interrelationships among research hotspots. As shown in Figure 10, this study obtained the following clustering results. The analysis indicates that the research hotspots of harvesting robots are primarily centered around the following themes.

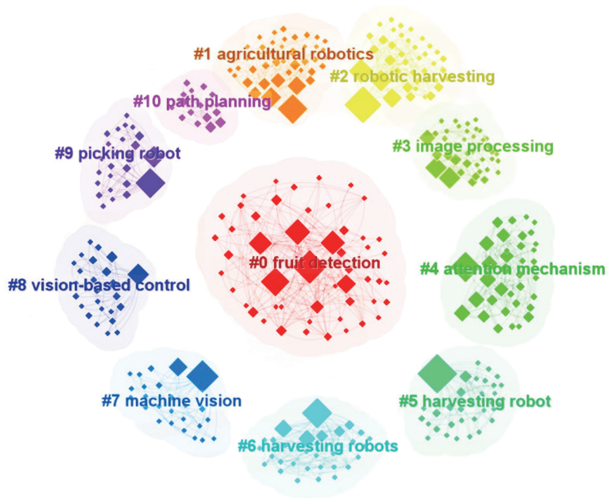

Figure 10 Keyword clustering results

(1) System design of harvesting robots

Owing to the expansion of the agricultural cultivation areas and rising labor costs, the adoption of robots for crops harvesting has become an increasingly popular approach. Consequently, the system design of harvesting robots has emerged as a prominent research hotspot in recent years[37,84,101]. A standard harvesting robot comprises components such as a locomotion device, a decision-making module, a visual recognition unit, a robotic arm, and an end effector. Researchers are focusing on optimizing structural design of robots to enhance performance during the harvesting process. For instance, in addition to the traditional fixed-sliding structure as a locomotion device, wheeled and tracked self-propelled designs have also gained prevalence for robots. Furthermore, high-performance computers are commonly used in the decision-making module to improve planning and control capabilities. Visual recognition units primarily rely on a variety of sensors and depth cameras. Lastly, the robotic arm manifests in various forms, including single-arm, double-arm, and multi-arm designs.

(2) Recognition and localization of objects

Precise recognition and localization of objects are crucial for the efficient operation of harvesting robots. Researchers have dedicated significant efforts to the development of recognition methods. These methods include traditional digital image processing, machine learning-based image recognition, and deep learning-based neural network recognition[102-104]. In the realm of localization, certain researchers obtain 2D localization information by analyzing object centroids, contours, and symmetry axes. Meanwhile, other researchers utilize tools such as multi-eye cameras, depth cameras, and ranging sensors to acquire 3D localization information. In addition, various influencing factors, such as lighting conditions, occlusion, overlap, and vibrations have been considered by researchers. Considering the complexity and diversity of application scenarios for harvesting robots, it is expected that research on object recognition and localization will continue.

(3) Navigation and path planning of robotic arms

The research hotspot in this field mainly focuses on robot navigation and the path planning of robotic arms[105-107]. In terms of robot navigation, researchers aim to achieve efficient obstacle avoidance and motion path planning. Accurate motion navigation enhances the safety and stability of robot operations. The global navigation satellite system (GNSS) and various advanced sensors, such as lidar, and industrial cameras, are extensively used to achieve this objective. As for the path planning of robotic arms, researchers primarily emphasize structural design with varying degrees of freedom, to enable effective obstacle avoidance and sequence planning for harvesting. A well-planned harvesting sequence is crucial for improving work efficiency. Researchers have meticulously compared the advantages and limitations of various path planning algorithms.

(4) Design and optimization of end effectors

The end effector establishes direct contact with the harvested object, and its reliability influences the harvesting efficiency and the quality of agricultural products. Researchers have designed various types of end effectors[38,108,109]. Researchers also utilize theoretical analysis, simulations, and practical experiments to optimize processes. Claw-type end effectors, including three-fingered, four-fingered, and multi-fingered, all demonstrate excellent gripping performance. Furthermore, cutting end effectors are suitable for agricultural products that cannot be directly grasped. In addition, suction end effectors operate in a faster way, and the accuracy and stability of airflow are crucial.

(5) Collaborative operation of multiple robots

Multi-robot coordination is also a crucial research hotspot in the field of harvesting robots[71,90]. A single robot working independently cannot meet the practical harvesting demands. Multi-robot collaborative operations not only fully unleash the potential of robots but also significantly increase harvesting efficiency. Simultaneously, multi-robot coordination holds significant strategic value for advancing sustainable development in agricultural production. It contributes to reducing energy consumption and maximally preserving ecological balance.

(6) Extensive application of deep learning

Deep learning and artificial intelligence have been extensively employed in the research of harvesting robots, significantly enhancing the autonomy of this field[74,110]. By applying deep learning to process vast agricultural datasets, harvesting robots receive more precise information for decision-making. Artificial intelligence enables real-time perception of environmental information, enabling harvesting robots to adapt to various planting conditions and crop characteristics. The continual evolution of these advanced technologies will further drive innovation in the field of harvesting robots.

3.6 Discussion of development trends

Based on the above analysis, it is evident that the research on harvesting robots has made some strides. However, the application of harvesting robots is still constrained by various issues, requiring further development in the following areas:

(1) Diversifying robot types to relieve labor shortages

Incorporating robotic technology into agricultural practices has multiple benefits, including relieving labor shortages, reducing reliance on seasonal labor, and easing the workload for farmers. Looking ahead, the focus will be on developing various types of harvesting robots[4,41], including those for mountain and hill terrains, those with multi-arm capabilities, and all-encompassing harvesting robots. This concerted effort aims to bring about a more sustainable and innovative era in agricultural development.

(2) Expanding application scenarios to improve efficiency

With the ongoing expansion of agricultural production, the demand for efficient harvesting is ever-increasing. In the future, it will be imperative to plan the harvesting sequence[68,83]. Integrating robot design with planting agronomy is crucial for enhancing adaptability to complex environments. In the research on harvesting robots, full integration of technologies, such as big data, deep learning, and artificial intelligence, is imperative. These initiatives aim to boost harvesting efficiency and expand operation area.

(3) Enhancing overall performance to reduce losses

Currently, precise control over the working process of harvesting robots remains a challenge[95,110]. Specifically, it is necessary to further enhance the recognition capabilities of harvesting robots for accurate identification. Optimizing path planning capabilities contributes to improving operational efficiency. Moreover, it is also crucial to accelerate research of multi-arm collaborations and multi-robot collaborations. Further diversifying the types of end effectors enables the harvesting of a greater variety of agricultural products. Such endeavors are of paramount importance for achieving low-loss harvesting.

(4) Reducing manufacturing costs to promote application

The current high manufacturing cost is impeding the development of harvesting robots[72,74]. To address this issue, future research should focus on exploring new technologies to enhance the design of hardware and software systems at a lower cost. Additionally, there should be efforts to develop new materials to reduce the cost of essential components, such as vision cameras and robotic arms. Moreover, new production methods should be studied to balance the relationship between cost and precision. These efforts would significantly contribute to the promotion and adoption of harvesting robots.

4 Conclusions

Utilizing bibliometric methods and knowledge graphs, this study has conducted an analysis of the developmental history and research hotspots relative to harvesting robots. The primary findings are summarized as follows:

(1) Research on harvesting robots has been receiving growing attention. The developmental history can be divided into three distinct periods: a slow exploration period from 1993 to 2007, a fluctuating rising period from 2008 to 2016, and a rapid growth period from 2017 to 2022. It is expected that this rapid development trend will continue for a long time.

(2) Collaborations among different countries/regions, institutions, and authors are becoming increasingly close. In this context, research institutions and authors in China mainly engage in domestic collaborations. Washington State University and Wageningen University maintain relatively frequent collaborations with other international institutions.

(3) This study retrieved a significant number of English and Chinese papers on harvesting robots. Bibliometric analysis reveals that the current research hotspots on harvesting robots encompass multiple aspects. It is particularly noteworthy that recognition methods based on deep learning have become a frontier research direction. Looking ahead, to promote the development of agricultural automation, efforts should be made to increase the variety of harvesting robots as much as possible.

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