Original Article
Food Science and Technology

ISSN 0101-2061 (Print)
ISSN 1678-457X (Online)

DOI: https://doi.org/10.1590/fst.72322

A bibliometric and visual analysis of fruit quality detection research

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Abstract

To understand the research status and current dynamics of fruit quality detection and objectively reflect the influence of different countries, research institutions and authors in this field, the software CiteSpace was used to bibliometrically and visually analyze the relevant literature on fruit quality detection in Web of Science (WoS) database from 1982 to 2021. The results showed that the number of publications on fruit quality detection showed a trend of slow in the early stage, rapid in the middle stage and intensified in the late stage. China has the largest number of international publications, accounting for 21.80% of the WoS database, but its intermediary centrality is inferior to that of the United States, Germany, Italy and Spain; the United States is at the core of international cooperation, establishing cooperative relations with most countries; through keywords co-occurrence network and keyword clustering, it is concluded that the research mainly focuses on fruit quality detection based on spectral technology or electronic nose technology, fruit composition detection based on high-performance liquid chromatography (HPLC), fruit edible safety detection, and genetic analysis of fruit quality-related traits. Bibliometrics and visual analysis of this fruit quality detection research can provide a certain reference for relevant researchers.

Keywords: fruit quality detection; CiteSpace; research trend; bibliometric analysis.

Practical Application: There have been many reviews on fruit quality detection. Although these reviews can provide relevant researchers with valuable information, most of the reviews are based on a specific research direction of fruit quality detection based on limited literature. Its development history and research trends cannot be good displays. The bibliometric method based on CiteSpace summarizes this research field in the form of visual and quantitative analysis, and the information is intuitive and easy to understand. We must conduct a comprehensive review of current fruit quality detection based on the existing rich literature to clarify the evolution and the future development direction of this field.

1 Introduction

With the development of the global economy and the improvement of overall consumption level, consumers' requirements for fruit quality have gradually increased. Under the dual influence of huge production and improved demand standards, how to realize accurate quality classification by convenient and quick fruit quality detection methods is an urgent need for researchers in the fruit industry (Choi et al., 2018).

The improvement of fruit quality detection ability is not only conducive to the development of the fruit industry but also conducive to enhancing the competitiveness of fruit export. Voss et al. (2019) showed that the development of a non-destructive testing system could improve the detection efficiency of peach quality and reduce production costs. Fruit quality detection includes external quality detection and internal quality detection. The external quality includes fruit size, shape, color, luster, surface damage, etc. The internal quality includes sugar content, acidity, soluble solids, internal defects, etc. Zhang et al. (2017) detected the external mechanical damage of blueberry based on hyperspectral imaging technology, which showed that the technology was feasible within 30 minutes after blueberry mechanical damage, and the average accuracy was 94.5%. Zhao et al. (2021) developed a robot system for apple internal quality detection based on visible and near-infrared spectroscopy technology for apple grading, which can quickly and accurately detect the soluble solids content of apples. Sun et al. (2020) also successfully detected pear black heart disease and soluble solids by visible near-infrared spectroscopy.

After years of development, the research on fruit quality detection has been extended to different perspectives, such as pesticide residue detection (Fu et al., 2019; Jia et al., 2018), quality detection model research (Li et al., 2021a; Wu et al., 2020; Yang et al., 2022), and the development of quality rapid classification system (Mazen & Nashat, 2019; Van De Looverbosch et al., 2020; Munawar et al., 2021). The research focuses are also increasingly diversified. Therefore, it is necessary to make a comprehensive review of the current fruit quality detection based on our current knowledge, to clarify the evolution of this field and its future development direction.

In recent years, various scholars have conducted a large number of literature reviews and qualitative classification studies on fruit quality detection from a specific perspective. For example, some scholars pay attention to the application of non-destructive testing technology in quality evaluation

Received 15 June, 2022
Accepted 01 Aug., 2022
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(Brosnan & Sun, 2004; Cubero et al., 2016; Jie & Wei, 2018), and some scholars pay attention to the specific application of certain detection technology in the field of fruit (Kanchanomai et al., 2020; Pathmanaban et al., 2019; Salehi, 2020), and some scholars pay attention to the detection of a certain quality item of fruit (Ahmad et al., 2018; Hussain et al., 2018; Magwaza & Opara, 2015; Li et al., 2021b). The scope and quantity of literature are limited. It can neither comprehensively and objectively reflect the whole picture of fruit quality detection research, nor systematically display the development process of fruit quality detection. Although these existing reviews are very valuable for scholars to understand the development of fruit quality detection, they mainly rely on qualitative methods to review the content of existing literature.

Given the extensive literature on fruit quality detection, it is more suitable to use bibliometric methods to systematically and accurately evaluate the literature on fruit quality detection (Song et al., 2021). CiteSpace is a visual analytic tool that can analyze the relationships between popular frontier research topics on a subject, the evolution of topics, and the determination of the knowledge base. It is a popular visualization analysis software for scientific research (Jia et al., 2019). Therefore, this study conducts data mining and visual quantitative analysis of the research literature on fruit quality detection based on CiteSpace, and obtains the development history and current situation, which provides important reference for relevant researchers to determine the research direction.

2 Materials and methods

2.1 Data collection

The related publications collected in Web of Science database (WoS) from 1982 to 2021 were searched using "fruit quality detection" as the topic word. The publication search was performed on March 20, 2022. In this study, only English publications were included (Table 1). A total of 1692 publications were obtained. After the duplicate publications were removed, 1683 were left. (The data in this research comes from public databases, so it does not involve ethical approval.)

2.2 Research method

Bibliometrics is a science of quantitative analysis of literature information (Huang et al., 2021), which can objectively and quantitatively analyze the impact of academic research. It is widely used in various fields such as publication statistics, impact assessment of research institutions, academic hotspot tracking, and future research directions (Silva et al., 2022). Word frequency analysis is a commonly used method in bibliometrics, which can be used to determine research hotspots and frontiers. Keywords reflect the core content of research publications, and their importance can be measured by their frequency and centrality. If the centrality of a keyword is greater than that of other keywords, it means that the keyword has a more important position in the research field (Ribeiro et al., 2022). High-frequency keywords can highlight the key issues in the research field, and keyword clustering can summarize the main contents of the research field (Cruz et al., 2022). In this study, Citespace software, which is widely used in bibliometrics, was selected for the quantitative analysis of sample publications (Lim et al., 2022).

Table 1. Publication data retrieval conditions setting the table.

Literature retrieval item	Literature retrieval settings
Document database	Web of Science core collection
Retrieval mode	TS
Retrieval terms	fruit quality detection
Timespan	1982-2021
Genre	All document types
Language	English

3 Results

3.1 Descriptive statistical analysis of the research literature

Trends in the number of published papers

The number of publications published annually in specific research areas can reflect the degree of development of research in this field, and therefore is an important indicator of its development and evolution (Cui et al., 2018). Figure 1 indicates that the publications on fruit quality detection in the past 30 years showed an overall growth trend, which was roughly divided into infancy, growth and outbreak periods. As of 2021, 1683 related publications were retrieved. From 1982 to 2002, there were 91 publications in this field, accounting for 5.41% of all WoS publications. The number of publications was small, which was the infancy of fruit detection development. The research field received limited attention during this period. From 2003 to 2014, there were 559 publications in this field, accounting for 33.21. The number of publications increased significantly compared with the previous stage. It was the growth period of fruit quality detection, and the research field received rapid attention during this period. From 2015 to 2021, there were 1033 publications in this field, accounting for 61.38%. It was the outbreak period of the development of fruit quality detection, and the field was widely concerned by scholars during this period. With the continuous development of related research, the research on fruit quality detection is expected to be more in-depth and perfect.

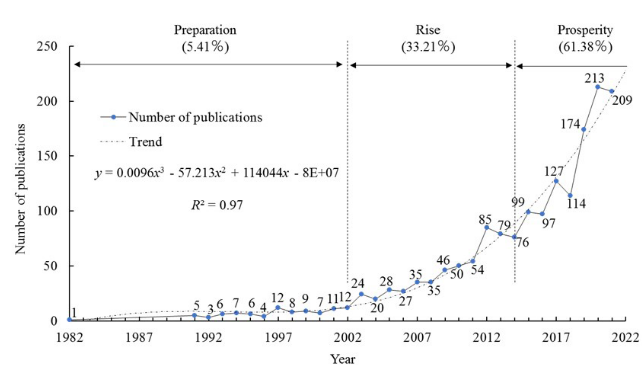


Figure 1. Publication outputs and growth forecast.

National distribution characteristics

The analysis of national publications in a certain field can reveal the scientific research strength of each country in this field and the cooperative relationship between countries (Liao et al., 2019). It provides a new perspective for evaluating the academic influence of a country, helps to find national institutions worthy of attention, and has a macro understanding of the spatial distribution of countries in the research field. In Figure 2, each node represents a country or region. The size of the node represents the number of publications. The larger the node is, the more publications are published in the country. The connection between nodes represents the cooperation between countries. The more connections, the closer cooperation between countries. Nodes with purple rings have intermediate centrality values greater than 0.1.

Figure 1 shows that China's node circle is significantly larger than other countries, and the number of publications is far ahead. According to the retrieved data, publications on fruit quality detection come from 112 countries or regions. Table 2 lists the top 10 countries with high-yield publications. The total number of publications in these 10 countries is 1350, accounting for 64.53% of the total publications, and most of them are developed countries. It should be noted that one publication may involve multiple countries, so the total number of publications counted by the country is greater than that published. China has the largest number of publications in the field of fruit quality detection, which is 456, accounting for 21.80% of the total. It shows that China pays more attention to the research, which is related to China's large fruit industry. Followed by the United States, with 243 publications, accounting for 11.62%. Spain ranked third with 177 publications, accounting for 8.46%. Subsequently, Italy, India and Brazil had publications of 110, 88 and 69, accounting for 5.26%, 4.21% and 3.30%, respectively. However, although China has the largest number of publications, the value of intermediary centrality is low, only 0.03, which is much smaller than that of the United States, Spain, Italy and Germany. It shows that China's scientific research influence is not as good as the above several countries, and still needs to strengthen the quality of research.

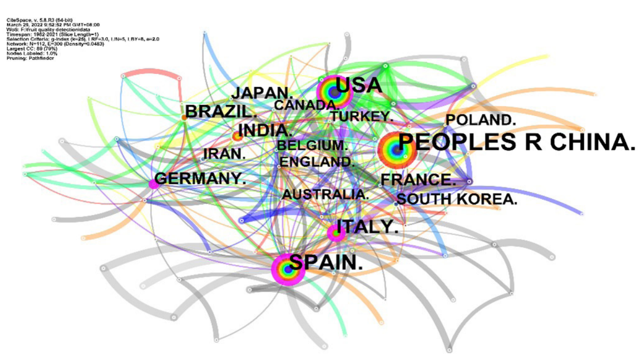


Figure 2. Map of the international situation on fruit quality detection research between 1982 and 2021.

In addition, it can be seen from Figure 2 and Table 2 that the cooperation between countries is relatively close (Density = 0.0483). Among the top 10 countries, the United States has cooperated with nine other countries and is at the core position in the field of fruit quality detection. The cooperation between Brazil and France, France and Spain, China and Japan is close, thus is conducive to further achieving good results in this research field.

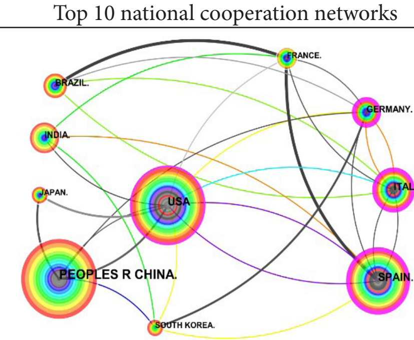
Analysis of institutional cooperation and institutional documents characteristics

Academic cooperation between institutions is of great significance to strengthen exchanges between scholars and the dissemination of advanced experience. This study uses CiteSpace software to analyze the network co-occurrence of institutions. The node type is set as an institution, and the institutional cooperation network map of fruit quality detection is obtained (Figure 3). Table 3 lists the top ten institutions with the most publications. It can be seen from Figure 3 that there are many core institutions around the world, such as Zhejiang University, ARS, Minist Agr, Nanjing University and so on, and take the above institutions as the core to establish cooperative relations with other institutions. It can be seen from Table 3 that among the top 20 institutions, the number of institutions from China accounts for the largest proportion. In terms of the number of publications, Zhejiang University of China ranks first, with 56 publications.

Analysis of author collaboration and author co-citation

The authors' cooperation map can identify the core authors of a discipline or field and their cooperation intensity and mutual

Table 2. The 1982-2021 high-yielding countries of international fruit quality detection research.

Rank	Country	Centrality	Count	Proportion	Top 10 national cooperation networks
1	China	0.02	456	21.80%	
2	USA	0.2	243	11.62%	
3	Spain	0.36	177	8.46%	
4	Italy	0.21	110	5.26%	
5	India	0.03	88	4.21%	
6	Brazil	0.05	69	3.30%	
7	Germany	0.22	63	3.01%	
8	France	0.06	50	2.39%	
9	Japan	0.05	50	2.39%	
10	South Korea	0.07	44	2.10%	

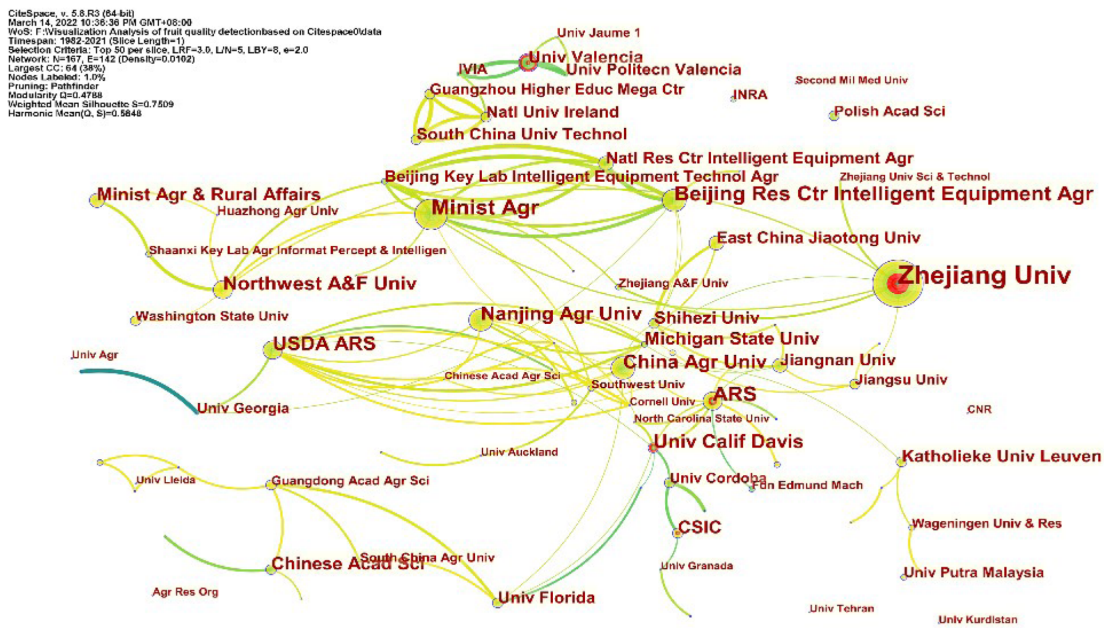


Figure 3. Institutional cooperation network.

Table 3. Top 20 most productive institutions in the fruit quality detection research area.

Rank	Institutions	Count	Proportion	Centrality
1	Zhejiang Univ	56	5.78%	0.01
2	ARS	27	2.79%	0.02
3	Minist Agr	27	2.79%	0.02
4	USDA ARS	24	2.48%	0.04
5	Beijing Res Ctr Intelligent Equipment Agr	24	2.48%	0.01
6	China Agr Univ	24	2.48%	0.05
7	Chinese Acad Sci	22	2.27%	0.02
8	CSIC	21	2.17%	0.04
9	Northwest A&F Univ	20	2.06%	0.01
10	Nanjing Agr Univ	19	1.96%	0
11	Michigan State Univ	19	1.96%	0.01
12	Univ Calif Davis	19	1.96%	0.08
13	Katholieke Univ Leuven	17	1.75%	0.02
14	Univ Valencia	15	1.55%	0.02
15	Agr Res Org	14	1.44%	0.05
16	Minist Agr & Rural Affairs	14	1.44%	0
17	CNR	13	1.34%	0.03
18	Shihezi Univ	13	1.34%	0
19	Univ Florida	13	1.34%	0.04
20	East China Jiaotong Univ	12	1.24%	0

citation relationship. The co-citation of authors is an important index to measure the academic influence of an author. According to the citation frequency, the author's influence in their research field can be analyzed. The literature published by the core authors has a certain key role and turning significance in its research field (Wang et al., 2019). Based on the CiteSpace software, we processed the literature data on fruit quality detection in WoS and obtained the network map of author cooperation and author co-citation. The relevant information was counted on the list of the top 15 authors (Figure 4, Figure 5, Table 3).

In the author cooperation map, there are 239 nodes and 397 connections, and the network density is 0.014. The two authors with the largest number of publications are JIANGBO LI and SHUXIANG FAN, reaching 22 and 19, respectively. In addition, 10 authors (such as WENQIAN HUANG, XI TIAN, DAWEN SUN and RENFU LU) published articles more than 10 times. At the same time, it can be seen from the spatial structure and connection distribution of the author map that the researchers of fruit quality detection have formed multiple author cooperation groups, but the relationship between groups is not close.

A total of 1169 nodes and 1488 connections were generated in the author's cited analysis map. Based on the analysis of Figure 5 and Table 4, Nicolai BM, Li JB and ElMasry G are the most frequently cited, with 130, 92 and 80 respectively, followed by Qin JW, Wu D and fan SX. Nicolai BM, Qin JW, Lu R, Wang J and others have high intermediary centrality, indicating that these authors have great communication influence. In addition, almost all of the top 15 authors are from China, indicating that China attaches great importance to fruit quality detection.

Subject category distribution

Subject categories represented the highest level of the specialty. The topics addressed in fruit quality detection papers from 1982 to 2021 can be visualized in the form of co-occurring subject categories (Figure 6). Each category refers to a topic associated with the journals in the WoS database. The analysis identified 186 topics and 557 edges. The labels are written over the circles

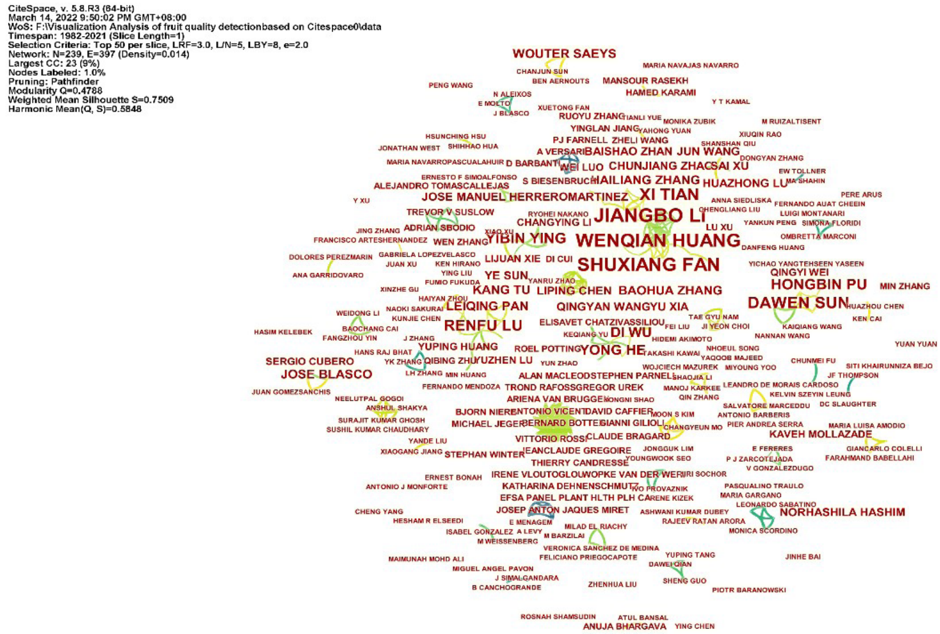


Figure 4. Author cooperation network map.

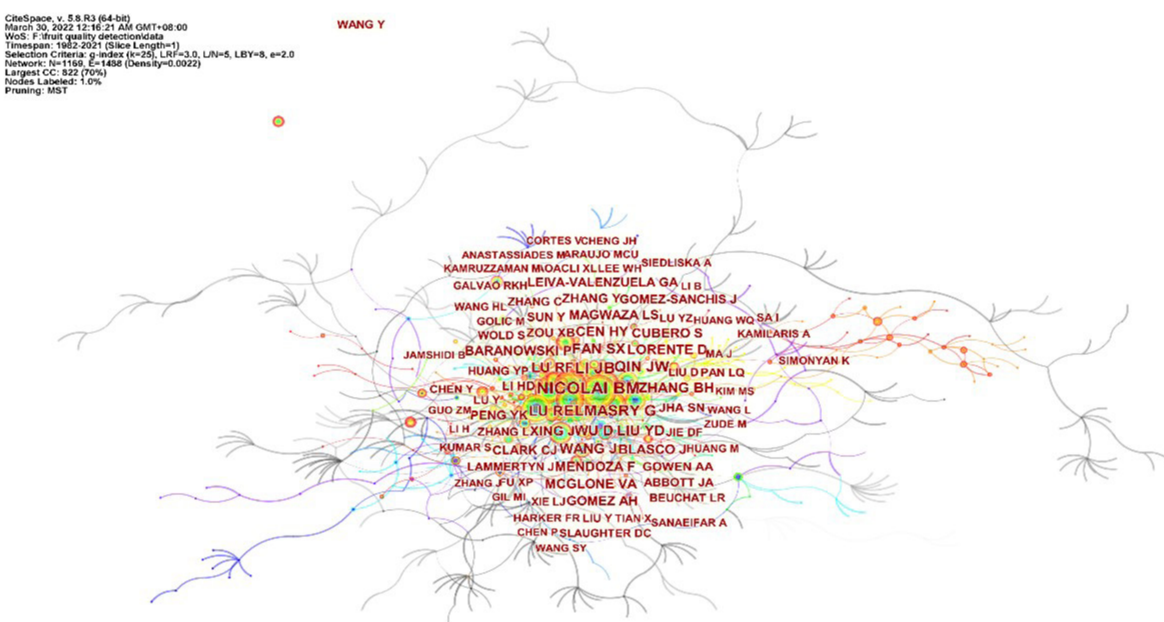


Figure 5. Author co-citation network map.

on the map. The size of each circle is proportional to the number of papers attributed to the respective category (Li et al., 2019).

Table 5 lists the first 20 Web of Science categories associated with fruit quality detection. The table also gives the cumulative number of publications under the category, the betweenness value and the year of the first occurrence in the dataset. The six highest-ranking categories were: Food Science &Technology, Chemistry, Agriculture, Horticulture, Agronomy, Engineering. Of the top 20 categories, Food Science & Technology has the largest number of publications, while Chemistry had the most significant betweenness value (0.4), denoting its influence on the dissemination of research in fruit quality detection.

3.2 Analysis of research hotspots

Keywords condense the theme of an article with concise words, which is the core and essence of the article. The analysis of high-frequency keywords can determine the hotspots in a

Table 4. Top 15 authors and co-cited authors.

Rank	Author	Count	Centrality	Rank	Co-cited Author	Count	Centrality
1	JIANGBO LI	22	0	1	Nicolai BM	130	0.07
2	SHUXIANG FAN	19	0	2	Li JB	92	0.03
3	WENQIAN HUANG	19	0	3	ElMasry G	80	0.05
4	XI TIAN	13	0	4	Qin JW	72	0.07
5	DAWEN SUN	12	0	5	Wu D	57	0.01
6	RENFU LU	10	0	6	Fan SX	55	0.02
7	YIBIN YING	9	0	7	LU R	55	0.08
8	HONGBIN PU	9	0	8	Liu YD	53	0.03
9	YONG HE	8	0	9	Zhang BH	51	0.01
10	DI WU	8	0	10	Lu RF	51	0.02
11	BAOHUA ZHANG	6	0	11	Wang J	49	0.07
12	KANG TU	6	0	12	Cen HY	47	0.04
13	JOSE BLASCO	6	0	13	Xing J	45	0.05
14	HAILIANG ZHANG	6	0	14	Lorente D	44	0.03
15	LEIQING PAN	6	0	15	McGlone VA	42	0.03

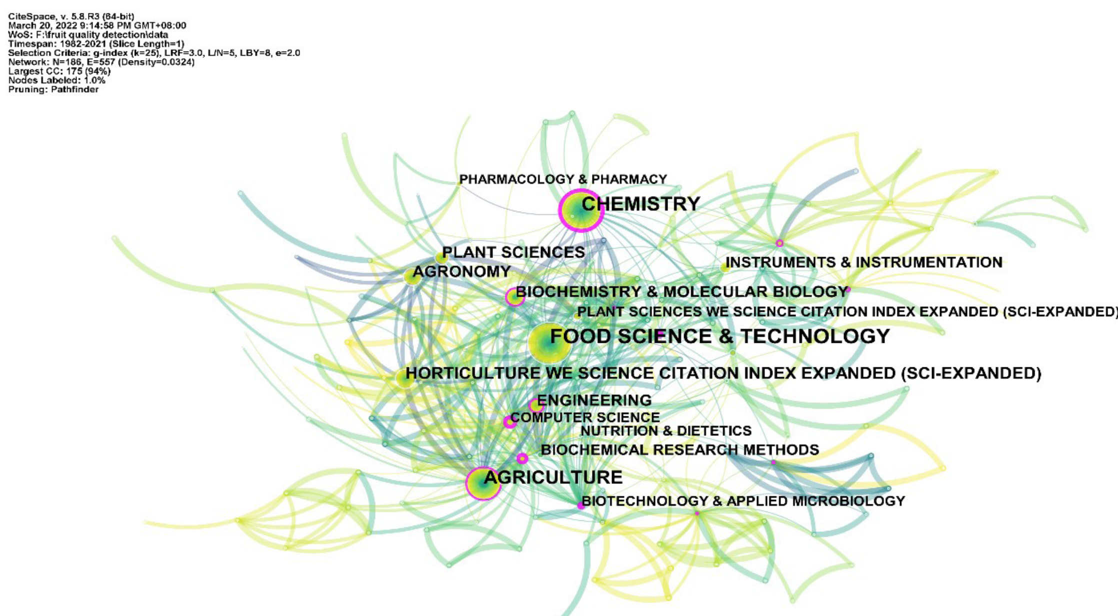


Figure 6. Co-occurring subject categories during 1982-2021.

research field and help to predict the development trend of the research field (Gao et al., 2019). This study sets the period from 1982 to 2021, and takes one year as a time slice to obtain the keyword co-occurrence map (Figure 7). The map consists of 755 nodes and 2766 lines. The number of nodes represents the number of keywords, the size of tags represents the frequency of keywords, and the connection represents the connection between keywords. Table 6 shows keyword information for the top 30. Combined with Figure 8 and Table 6, in addition to the keywords contained in the retrieval theme 'fruit quality detection', 'identification', 'classification', 'food', 'apple' and 'system' are the keywords with high frequency. The emergence of such keywords reflects the research hotspots of fruit quality detection. Preliminary results show that fruit quality classification, detection system development and fruit quality detection based on spectral detection technology are the research hotspots in the field of fruit quality detection.

A keyword clustering network can further detect the distance and affinity between high-frequency keywords, excavate hidden information, and present hotspots of fruit quality detection research. To obtain research hotspots more clearly, a K-means clustering analysis of keywords was carried out by CiteSpace. The results showed that the Q value of the clustering map was 0.5551, and the S value was 0.8097. When the Q value is greater

Table 5. Top 20 subject categories in the dataset.

Rank	Frequency	Centrality	Year	WoS category
1	671	0.07	1991	Food science & Technology
2	560	0.4	1991	Chemistry
3	420	0.12	1982	Agriculture
4	192	0.03	1991	Horticulture
5	162	0.01	1994	Agronomy
6	143	0.12	2004	Engineering
7	141	0.07	1992	Plant science
8	140	0.16	1991	Biochemistry & Molecular biology
9	101	0.07	1995	Instrument & Instrumentation
10	99	0.04	1991	Biochemistry Research Methods
11	82	0.25	1995	Computer Science
12	78	0.06	2000	Nutrition & Dietetics
13	70	0.23	1999	Biotechnology & Applied microbiology
14	64	0.03	1992	Pharmacology & Pharmacy
15	51	0.33	1999	Environmental Sciences & Ecology
16	50	0.05	2003	Science & Technology – other topics
17	49	0.16	1995	Physics
18	44	0.03	1994	Microbiology
19	36	0	1982	Agricultural Engineering
20	36	0.03	2001	Spectroscopy

than 0.3, it means that the divided clustering structure is obvious. When the S value is greater than 0.7, the clustering is efficient and convincing, so the clustering results can be accepted here. We use LLR algorithm to generate clustering labels based on keyword naming. By clustering, eight categories of research topics were formed, including 'hyperspectral imaging', 'phenolic compounds', 'Salmonella', 'electronic nose', 'pesticide residue', 'expression', 'Sers', 'vitamin content', 'metabolism', 'ascorbic acid', 'linkage map' (Figure 8). At the same time, the clustering is modified twice by tracing and reading the original literature (Table 7).

Based on Table 7, the current research hotspots of fruit quality detection were further integrated and summarized in the following five aspects.

Study on fruit quality detection based on spectral technology (clustering 0 + clustering 4 + clustering 6 + clustering 7)

According to the existing literature, the research on fruit quality detection based on spectral technology plays an important role in the research field of fruit quality detection. It mainly focuses on the selection of spectral types and modeling methods to detect the related quality of fruits. According to the specific application classification, the research of spectrum in fruit is roughly divided into qualitative detection and quantitative detection. Including pathogen detection (Ilic et al., 2018), origin traceability (Pang et al., 2018), acidity detection (Assis et al., 2018), brittleness and hardness detection (Onda et al., 1994), shelf life detection (Taghoy & Villaverde, 2018), external damage (Blasco et al., 2009), pesticide residue detection (Wang et al., 2021).

1. Sugar acidity detection. Taste is one of the bases for people to select fruits, and sugar content and acidity are important factors affecting taste. In recent years, it has been used as

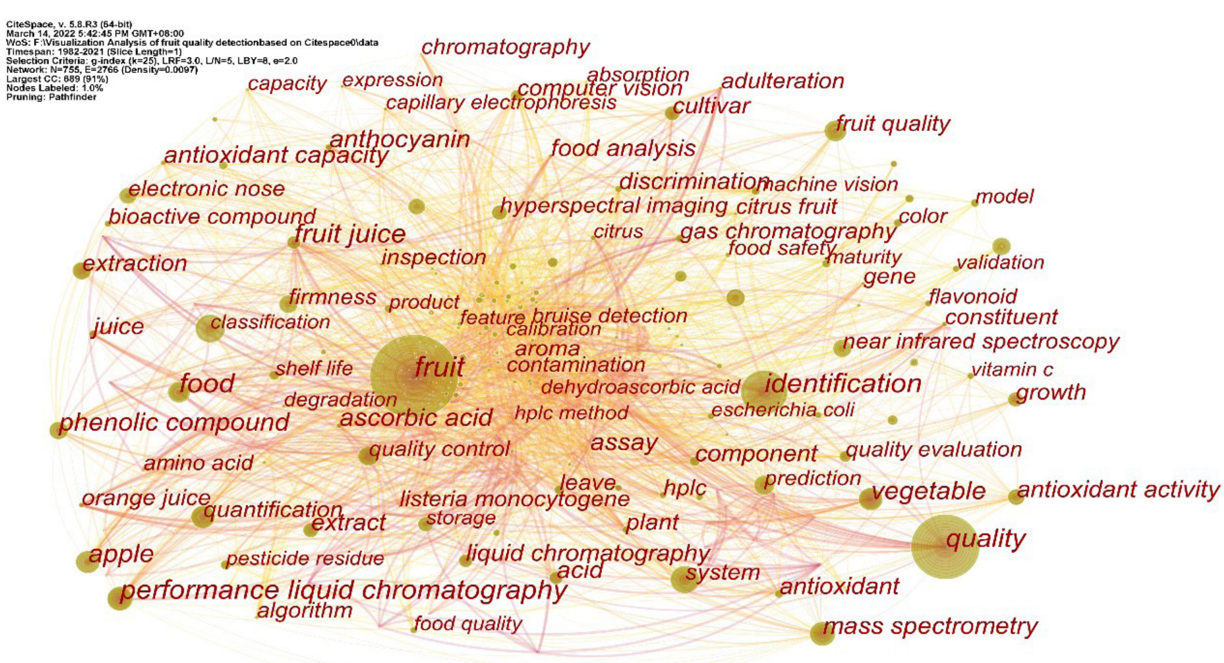


Figure 7. Keywords co-occurrence network map.

Table 6. Top 30 high-frequency keywords.

Keywords	Frequency	Centrality	Keywords	Frequency	Centrality
fruit	475	0.2	firmness	60	0.02
quality	362	0.11	quantification	60	0.03
identification	171	0.12	extraction	58	0.03
classification	121	0.01	soluble solids content	57	0.01
food	83	0.12	antioxidant activity	56	0.04
apple	81	0.1	spectroscopy	53	0.02
system	73	0.05	hyperspectral imaging	52	0.02
prediction	72	0.02	electronic nose	51	0.03
mass spectrometry	70	0.04	storage	48	0.02
near infrared spectroscopy	70	0.03	computer vision	47	0.03
performance liquid chromatography	68	0.09	fruit juice	47	0.09
fruit quality	68	0.06	liquid chromatography	46	0.03
vegetable	66	0.08	quality control	46	0.03
phenolic compound	61	0.05	acid	43	0.05
nir spectroscopy	61	0.01	extract	42	0.03

Table 7. Results of keyword cluster analysis.

Cluster ID	Size	Silhouette	Key keywords	LLR Clustering	Manual naming
0	142	0.774	hyperspectral imaging; soluble solids content; computer vision; pear; nir spectroscopy	hyperspectral imaging	Detection of Fruit Quality Based on Spectral Imaging
1	115	0.726	phenolic compounds; antioxidant activity; quality control; bioactive compounds; hplc-dad	phenolic compounds	Detection of Fruit Components Based on HPLC
2	78	0.729	salmonella; food safety; microbiological quality; microbial quality; microflora	salmonella	Detection of edible safety of juice
3	68	0.82	electronic nose; fruit juice; amino acids; fruit juices; hyperspectral imaging	electronic nose	Study on Fruit Quality Detection Based on Electronic Nose Technology
4	49	0.902	pesticide residue; pesticide residues; fruit; solid phase extraction; tandem mass spectrometry	pesticide residue	Study on Detection of Pesticide Residues in Fruits
5	47	0.818	expression; biosynthesis; ethylene; agricultural products	expression	Study on the relationship between fruit characteristics and gene expression
6	44	0.857	sers; machine learning; statistical features; core-shell nanoparticles; residue detection	Sers	Study on Fruit Quality Detection Based on Raman Spectroscopy
7	40	0.833	vitamin content; principal component analysis (PCA); energy value; Minas Gerais; behavior	vitamin content	Study on the detection of fruit nutrient content

an important reference for fruit taste. Zhang et al. (2021) showed that the combination of visible and near-infrared spectroscopy with a competitive adaptive weighted sampling method could effectively select the characteristic wavelength and improve the speed and accuracy of predicting the sugar content and acidity of apples.

2. Brittle hardness detection. The texture of fruit mainly includes brittleness, hardness and so on, which reflects the physical characteristics and organizational structure of fruit and affects the eating taste. The traditional fruit texture detection method adopts destructive detection methods such as pressure hardness tester or texture analyzer, which is inefficient and damages the commodity value of apple after detection. Sheng et al. (2019) established the prediction model of Korla fragrant pear hardness by near-infrared diffuse reflectance spectroscopy, and successfully predicted the hardness of fragrant pear.

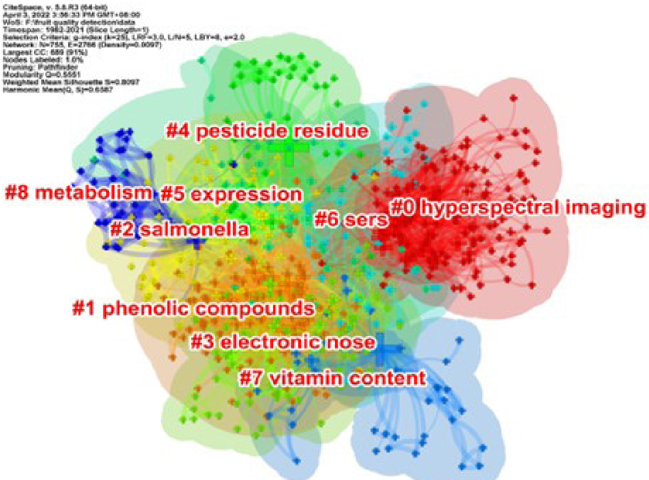


Figure 8. Keywords clustering map.

3. Shelf life detection. Shelf life is an important index to measure the life of fruits. Accurately judging its shelf life can better grasp the information about fruit storage life and quality, and provide an important reference for sales planning. Arias et al. (2018) explore here the potential of digital measurement of browning for determining the acceptability and shelf life of two varieties of fresh-cut pear (Conferencia and Decana del Comicio). The potential of browning digital measurement in determining the acceptability and shelf life of two kinds of fresh-cut pears (Conferencia and decana del comicio) was discussed. Samples were evaluated over two weeks by three methods. Human evaluation and image analysis showed that there were significant differences and similar trends in different storage conditions. The image analysis of browning is consistent with the shelf life. Under different atmospheric conditions, the correlation coefficient between the percentage of the brown area and shelf life is 0.867 to 0.979 for conferencia and 0.753 to 0.997 for decana del comicio.

4. External damage detection. Fruits due to picking, handling and other processes by bumping, extrusion leading to skin decay or rupture, part of the weak damage to the naked eye are difficult to identify, resulting in discoloration, and decay. Early detection and elimination are the main measures at present. Munera et al. (2021) used visible light (VIS) and near-infrared (NIR) hyperspectral imaging technology to identify common external and internal defects of loquat varieties and showed that XGBoost classifier was the best method to identify external damage.

5. Pathogen detection. The disease is one of the serious threats to fruit quality, which directly affects fruit grading. Prevention of diseases and timely elimination of disease fruits are currently powerful measures. Zeng et al. (2016) systematically reviewed the immunological detection methods, molecular biological detection methods and control research progress of melon bacterial fruit spot pathogens at home and abroad, which provided a good reference for pathogen detection.

6. Origin traceability. The perfect traceability system of agricultural products can greatly guarantee the quality of fruit and promote the sale of fruit. Wu et al. (2021) took Chinese jujube as the research object. Based on Physical and Nutritional Characteristics, eight main parameters were simplified by multiple comparisons, correlation analysis and principal component analysis algorithm, and the accuracy of traceability was 100%. This is of great significance to the protection of regional advantages of jujube.

7. Pesticide residue detection. Excessive application of pesticides by fruit farmers in the planting process will lead to excessive pesticide residues in fruits and affect consumer food safety. Chen et al. (2021) detected the residual pesticides on fruit surfaces based on a novel thermal desorption probe integrated with the corona-discharged assisted paper-spray mass spectrometry (PS-MS).

Study on fruit quality detection based on electronic nose technology (cluster 3)

The working principle of the electronic nose is to simulate the human olfactory organ through the gas sensor array and to perceive and analyze the odor. It is composed of three parts: sensor, signal processing system and pattern recognition system. The overall information of the tested sample is obtained through the sensor and pattern recognition system (Cao et al., 2022). In the field of fruit detection, the electronic nose is mainly used to detect and judge the storage period, freshness, maturity and whether the fruit is infected by pests and diseases (Adedeji et al., 2020; Salehi, 2020).

1) Detection of fruit pests and diseases infection. Most fruits are easy to be damaged in the picking process and form wounds. These wounds are easily infected by pathogens or pests, resulting in the decay and damage of fruits after harvest. Therefore, rapid, accurate and non-destructive detection of whether fruits are infected is one of the current research hotspots. Using electronic nose technology to detect and analyze the volatile substances of fruits after harvest can effectively distinguish the infected fruits. Wen et al. (2019) developed a scanning electronic nose system (SENS) to detect early infection caused by Hendel in citrus fruits. The results showed that SENS could successfully detect early B. dorsalis infection in citrus fruits.

2) Fruit storage period and freshness detection. Preservation and storage is an important technology to ensure fresh fruit supply. There is no obvious difference between the appearance of most fruits at the beginning of storage and after a period of storage, so it is very difficult for consumers and merchants to judge the storage time or remaining shelf life of fruits. Electronic nose technology can determine

the storage time and freshness of fruit through the change of fruit odor during storage. Pu et al. (2018) studied the effects of drying and storage on jujube volatiles by electronic nose and GC-MS technology. Studies showed that esters, aldehydes, furans and pyrazines decreased significantly with the extension of storage time, while acids and terpenes increased.

3) Detection of fruit maturity for timely harvesting. Too early harvest will lead to low fruit yield and poor fruit flavor. Too late harvest will lead to fruit storage difficulties and short shelf life. Therefore, it is necessary to correctly judge the maturity of fruit to determine the appropriate harvest period. The electronic nose technology was applied to the detection of fruit maturity. According to the change of fruit odor under different maturity, the change rule of fruit volatile substances with time was analyzed to judge the maturity of the fruit. Chen et al. (2018) used the electronic nose (E-nose) based on metal oxide semiconductors as a non-destructive monitoring system for monitoring the changes in the yield of volatile organic compounds during fruit ripening. PCA analysis can be used to distinguish different ripening stages, and the average accuracy is up to 90%.

Research on fruit component detection based on high-performance liquid chromatography (HPLC) (cluster 1)

With the progress of science and technology and the improvement of economic level, people began to focus on the research of fruit components, such as functional components and harmful components. High-performance liquid chromatography (HPLC) is a widely used method for accurate measurement of a component in fruits. The method takes the solution as the mobile phase and uses the high-pressure infusion system to pump the mixed solvent of different proportions of the mobile phase or the single solvent of different polarity into the fixed chromatographic column to complete the separation of each component in the column, and finally enters the detector for detection, to realize the analysis of the sample. This method is widely used in the detection of fruit pesticides and functional components. Huang et al. (2019) determined the contents of nomilin and limonin in different citrus varieties during fruit development and ripening by HPLC. The results showed that the contents of limonin and nomilin in most citrus fruits increased first and then decreased during fruit growth and ripening, and the content of limonin in citrus fruits was the highest at maturity.

Fruit edible safety detection (cluster 2)

Fruits may be contaminated by microorganisms or pathogens in various ways, especially the use of contaminated raw materials and washing water of processing machinery in the process of fruit juice processing, which may eventually lead to foodborne diseases. Therefore, it is necessary to control the microbial contamination of juice. Lee et al. (2021) purchased 100 kinds of fresh fruit and vegetable juices from online and offline stores in Korea, and quantitatively and qualitatively monitored the general microbial quality and foodborne pathogens. Through selective agar evaluation, coliform group, Bacillus cereus, Staphylococcus aureus, Escherichia coli, etc., this study can be used as the basic data for technological development to ensure the microbial quality and safety of fresh fruit and vegetable juice.

Genetic analysis of fruit quality-related traits (cluster 5)

The research on the genetic basis of fruit quality can provide new information on fruit biology, promote genome-assisted breeding, and provide technical support for improving fruit quality through the control of environmental conditions. In recent years, to improve fruit quality, some scholars carried out genetic analyses on fruit quality-related traits (fruit shape, acidity, single fruit weight, etc.). QTL mapping is a common method to determine the location of quantitative shape genes on chromosomes, and QTL analysis based on a genetic map is a common method for the study of fruit quality-related traits. Wang et al. (2020) analyzed the genes related to single fruit weight, peel color, kernel size, fruit diameter, soluble solids content and flesh firmness of pear based on this method, and identified QTLs for these traits. The Forcada et al. (2019) conducted population structure analysis and genome-wide association analysis (GWAS) of 4558 peach genomes and finally identified 347 significant associations between markers and traits, which provided technical support for improving peach quality.

4 Conclusion

Based on CiteSpace software and the bibliometric method, this study conducted a visual analysis of the research on fruit quality detection, focusing on the number of publications, the publication status of countries, institutions and authors, the publication characteristics of different subject categories, keywords co-occurrence and clustering, and quantitatively described the development process and dynamics of research in this field. Over the years, the number of publications on fruit quality detection has been increasing, and international research in this field has been paid more and more attention. In the field of research, the cooperation between countries is relatively close, especially the United States, as the core country in this field, has established cooperative relations with many countries. Among these countries, the majority with high intermediary centrality are developed countries. Although Chinese scholars are active in the research field of fruit quality detection and have published many articles, the intermediary centrality is low and the influence is not high. Food Science & Technology has the largest number of publications. Fruit quality detection based on spectral or electronic nose technology, fruit composition detection based on high-performance liquid chromatography (HPLC), fruit edible safety detection and genetic analysis of fruit quality-related traits are the main research topics in this field.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest

The authors declare no conflict of interest.

Availability of data and material

The data used in this article all came from the Web of Science.

Funding

Supported by the National Natural Science Foundation of China (11964030), the Open Project of Key Laboratory of Modern Agricultural Engineering in Colleges and Universities of the Department of Education of the Autonomous Region (TDNG2021201).

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