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Review

Bibliometrics and Visual Analysis of Non-Destructive Testing Technology for Fruit Quality

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Abstract: This study examined the development and trends in non-destructive testing technology for fruit quality. The status of the research field and the application hotspots were investigated to provide a reference for future research in this field. Relevant studies on the non-destructive testing of fruit quality published between 1993 and 2022 were identified in the core database Web of Science. The temporal distribution, spatial distribution, literature features, research progress, and leading research hotspots were quantified and visualised using bibliometrics. The findings revealed that there continues to be active research and publications on non-destructive testing technology for fruit quality, with a good development trend. China and the USA are the major contributors to research on non-destructive testing technology for fruit quality. The major research institutions include Zhejiang University and the United States Department of Agriculture. The major papers are published in Postharvest Biology and Technology and Acta Horticulturae, among others. These studies mainly focus on agriculture, food, and gardening, among other topics. The detection indices mainly concern internal quality, such as sugar degree and soluble solids, and apparent quality, such as hardness. The detection technologies mainly include electronic nose (E-nose) technology, machine vision technology, and spectral detection technology. In the future, technological developments in artificial intelligence and deep learning will further promote the maturation and application of non-destructive testing technologies for fruit quality.

Keywords: fruit quality; non-destructive testing; bibliometrics; clustering mapping; CiteSpace

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1. Introduction

Fruits are an indispensable part of the human diet due to their rich nutrients and sweet taste. The increasing consumer demand for fruits, and their central role in a healthy diet, have contributed to the societal appreciation of high-quality fruits, which has led to increased research interest in the detection of fruit quality [1]. At present, fruit quality detection is restricted by the low efficiency of the available detection devices, the inapplicability of destructive testing technologies, and the low generalisation rate of non-destructive testing technologies. As a result, fruit quality grades are mixed, and insignificant price differences exist among different levels of fruits, resulting in damage to brand value [2]. Hence, there is a critical need to develop fruit quality detection technology within the forest and fruit industry to increase the economic value and market competitiveness of fruits.

Traditionally, fruit quality detection methods have mainly included the subjective experience-based judgement of orchard workers or the detection of the physiochemical properties of fruits based on local samples. However, the former approach is time-consuming and requires a large labour force for large-scale fruit detection; it also lacks uniform standards for accuracy. The latter approach can damage fruits and is limited by its detection cost and time requirements. As such, it is not suitable for large-scale fruit detection. To solve the above problems and meet the demands for fruit quality detection, non-destructive testing technologies are currently being developed. Non-destructive testing technology involves the application of external stimuli to test samples and the examination of the transmitted and reflected physical indices of the test objects [3]. The chemical and physical properties of the test samples can be evaluated without damaging the original state of the samples. Since non-destructive testing technology is simple, fast, highly efficient, and non-destructive, it has been extensively applied to fruit quality testing [4]. Common non-destructive testing methods for fruit quality include optical property detection [5–7], the machine vision test [8,9], magnetic resonance imaging (MRI) [10,11], the acoustic feature test [12,13], the mechanical property test [14,15], the dielectric property test [16,17], the e-nose test [18,19], and so on. Examining the research status and leading hotspots in the field of non-destructive testing technology can provide a reference for the future development of non-destructive testing methods for fruit quality. Bibliometrics refers to the science of quantitative analysis of the literature in a certain research field, which has the characteristics of objectivity, quantification, and modeling. It plays an important role in uncovering hotspots in research fields and identifying future research directions. Bibliometrics has been widely applied to many fields, including agriculture, economy, and ecology, among others [20,21].

In this study, a quantitative analysis of the research progress and development trend in the non-destructive testing of fruit quality was performed. Studies related to the non-destructive testing of fruit quality published between 1993 and 2022 were identified and analysed using bibliometrics. High-frequency keywords related to the non-destructive testing of fruit quality were analysed using the CiteSpace and Hiplot Pro visual literature analysis tools. The research progress and leading hotspots in the non-destructive testing of fruits were analysed [22].

2. Data Sources and Research Methods

2.1. Data Sources

All data for this study were derived from the core database Web of Science. This database has groundbreaking content, high-quality data, and a long history. It covers the most important and influential studies in the relevant research field [23].

Relevant non-destructive testing technologies for common fruits (e.g., peach, pear, and apple) were employed as the search terms. Specifically, the search terms were TI = (“apple*” OR “pear*” OR “peach*” OR “fruit*”) AND TI = (“Nondestructive*” OR “optical*” OR “visible*” OR “infrared*” OR “spectra*” OR “spectroscopy*” OR “vision*” OR “acoustic*” OR “scattering*” OR “mechanical*” OR “vibration*” OR “nuclear magnetic resonance*” OR “NMR*” OR “hardness*” OR “elasticity*” OR “impulse*” OR “dielectric*” OR “microwave drying*” OR “electronic noses*”) NOT TS = (“tree*” OR “leaf*” OR “root*” OR “pest*” OR “disease*” OR “fruit fly*” OR “ juice*” OR “pearl*” OR “Pearson*” OR “ cell*” OR “slice*”). Studies not relevant to the research topic, for example, where “peach” referred to “peach blossom” or “impulse” referred to “a sudden strong and unreflective urge or desire to act”, were deleted.

More than 1400 studies published between 1 January 1993 and 31 December 2022 were collected for bibliometric analysis. Subsequent search results may differ slightly due to updating of the database. Quantity changes may have a slight influence on the final research conclusions. Data searching was terminated on 8 May 2023.

2.2. Research Methods

The quantitative analysis of the identified studies was carried out using bibliometrics. The number of relevant studies and the development trends in non-destructive testing technology for fruit quality were analysed using Excel statistics. The statistical analysis of high-publication institutions, high-publication journals, frequently cited studies, and high-frequency keywords was carried out. A keyword clustering map, emergence map, time map, common creation country/region field Chordal graph, and keyword–journal double mode matrix were plotted using the knowledge mapping visualisation software CiteSpace (CiteSpace. 6.2.R2. March 2023. Chaomei Chen, Professor, Institute of Computer and Information Science, Drexel University, USA, https://citespace.podia.com/download accessed on 27 March 2023) and the visual analysis platform Hiplot Pro (https://hiplot.com.cn/home/index.html accessed on 27 March 2023). The temporal and spatial developments in the non-destructive testing of fruit quality were reviewed and visualised.

3. Descriptive Statistical Analysis of Identified Studies

The distributions of the identified studies in terms of time, space, and source were examined. The development timeline was investigated, and the major research countries/regions and institutions were analysed. The key publications and most influential studies in the field of non-destructive testing of fruit quality were identified.

3.1. Temporal Distribution

The quantity of publications in different years reflects the attention of researchers to the topic of non-destructive testing of fruit quality, to some extent. It also reflects the development process of the field and subjects [24]. The annual quantity of published papers on the non-destructive testing of fruit quality in the top 10 countries, and the publication growth trend, are shown in Figure 1.

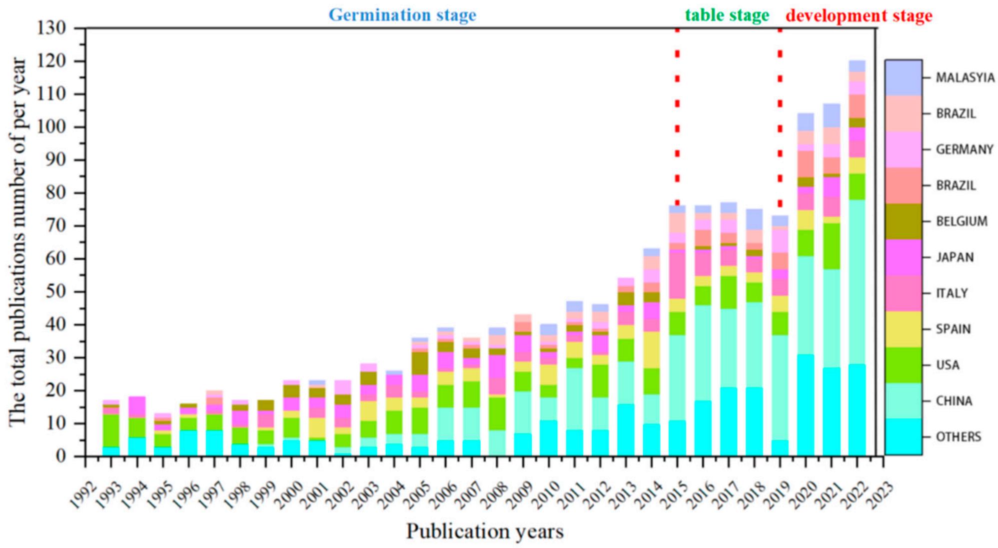

Figure 1. Cumulative histogram of the annual change in the number of publications for the top 10 countries in the field of non-destructive testing technology for fruit quality.

It can be seen from Figure 1 that the number of publications generally exhibited an increasing trend over the study period. The germination stage was evident from 1993 to 2014. At this time, few scholars studied the non-destructive testing of fruit quality, and these scholars were from a limited number of countries. However, there were many high-quality studies. For instance, Peris A et al. (2001) conducted a non-destructive test of the internal quality and optimal harvest period of apples using visible–near-infrared (Vis–NIR) spectral technology [25]. Li et al. (2002), from China Agriculture University, developed a new automatic screening experimental system for apple surface defects based on computer image technology. This system was able to simultaneously test and screen the four side surfaces of each apple online and was found to have relatively high practicability and feasibility [26]. Bart et al. (2007) reviewed the application of new technologies for fruit quality detection, such as spectral resolution spectra, near-infrared multispectral technology, and hyperspectral imaging technology. These technologies are highly relevant to the application of spectral technologies to the non-destructive testing of fruit quality [27].

Over time, the number of relevant papers increased slowly, year by year. An increasing number of scholars published papers in this field.

The stable stage was evident from 2014 to 2019. The number of research papers from China, Malaysia, and Belgium markedly increased, but the total quantity of relevant research papers exhibited little change. Cen et al. (2016) detected cold damage in cucumbers through hyperspectral imaging technology by combining feature selection and a supervised classification algorithm. They demonstrated the potential of hyperspectral imaging technology for cold damage detection in fruits [28]. Arendse et al. (2018) demonstrated that near-infrared spectra are feasible for studying the internal quality of fruits with thick pericarps [29]. Bhargava et al. (2018) carried out a critical comparison of several detection algorithms for fruit and vegetable quality proposed by researchers in recent years [30]. Zhang et al. (2014) described the latest development of a computer vision system for the external quality detection of fruits and vegetables and discussed its applications [31]. This particular study offers important guidance for the application of machine vision technology to the non-destructive testing of fruit quality.

Finally, the research field was observed to be in a fast development stage from 2019 to 2022. The number of publications increased significantly. More than 100 papers were published in 2020. The integrated application of multiple technologies was a prominent characteristic of the published research on non-destructive testing technology for fruit quality during this stage. For example, Kasampalis Dimitrios et al. (2021) evaluated the nutritional quality of pepper using colour, chlorophyll fluorescence, visible–near-infrared (Vis–NIR) spectra, red–green–blue (R–G–B) and red–green–near-infrared (R–G–NIR) digital imaging technology [32]. Tang et al. (2020) reviewed the application and research progress of harvest robots and vision technology in the harvest of fruits and described the fruit recognition and positioning technology based on digital image processing technology and deep learning algorithms. Moreover, they proposed future development trends in machine vision [33]. Wan et al. (2020) proposed a deep learning framework for the detection of different fruits based on an improved Faster R-CNN and evaluated its performance [34]. The development of digital image technology and deep learning technology has injected new vitality into studies on the non-destructive testing of fruit quality. It is expected that the number of publications will significantly increase in future years.

3.2. Spatial Distribution

3.2.1. Countries/Region

To determine the influential countries/regions in the field of non-destructive testing technology for fruit quality, and evaluate their cooperative relations, a chordal graph of countries/regions was plotted with Hiplot Pro. The node size expresses the quantity of studies, and the connected lines between two nodes express the cooperative relations. It can be seen from Figure 2 that more than 70 countries/regions have participated in this research field. Asia, Europe, and North America were the major contributors. This might be related to national policy orientations, economic development levels, agricultural development levels, and the climatic and geographical conditions being appropriate for the local development of the forest and fruit industry [35]. There was relatively frequent cooperation between China and the USA, between the USA and Canada, and between Spain and Iran. The top five countries/regions in terms of the number of publications were China, the USA, Spain, Italy, and Japan, which published 361 (25.79%), 199 (14.21%), 99 (7.07%), 98 (7%), and 91 (6.5%) papers, respectively. China accounted for 25.79% of papers, more than one-quarter of the total studies. This is mainly attributed to China's attention to agricultural development and the formulation and implementation of multiple supporting policies in recent years. In the "14th Five-Year Plan" of promoting agricultural and rural modernisation, China proposed the promotion of "diversified development of fruits, vegetables and tea, developing facility agriculture, and developing unique industries like forest and fruit industry, traditional Chinese medicines and edible mushrooms according to local conditions" [36]. Since 2020, the Ministry of Agriculture and Rural Affairs and the Ministry of Finance have been constructing dominant and unique industrial clusters, and have included 16 fruit industrial clusters in the construction range [37]. In 2021, the Ministry of Agriculture and Rural Affairs printed the "14th Five-Year Plan" on the Implementation Scheme of "Three Quality Indices and One Standard" in the planting industry, which aims to improve the development quality benefits and competitiveness of industries such as the fruit industry [38]. Scientific research funds for the forest and fruit industry have also continued to increase, bringing annual growth in the contribution of forest and fruit studies to academic development. There is no doubt that other countries have also made considerable contributions to the research progress on the non-destructive testing of fruit quality. It is likely that further developments in the non-destructive testing of fruit quality in the future will rely on collaborative endeavours between multiple countries and regions.

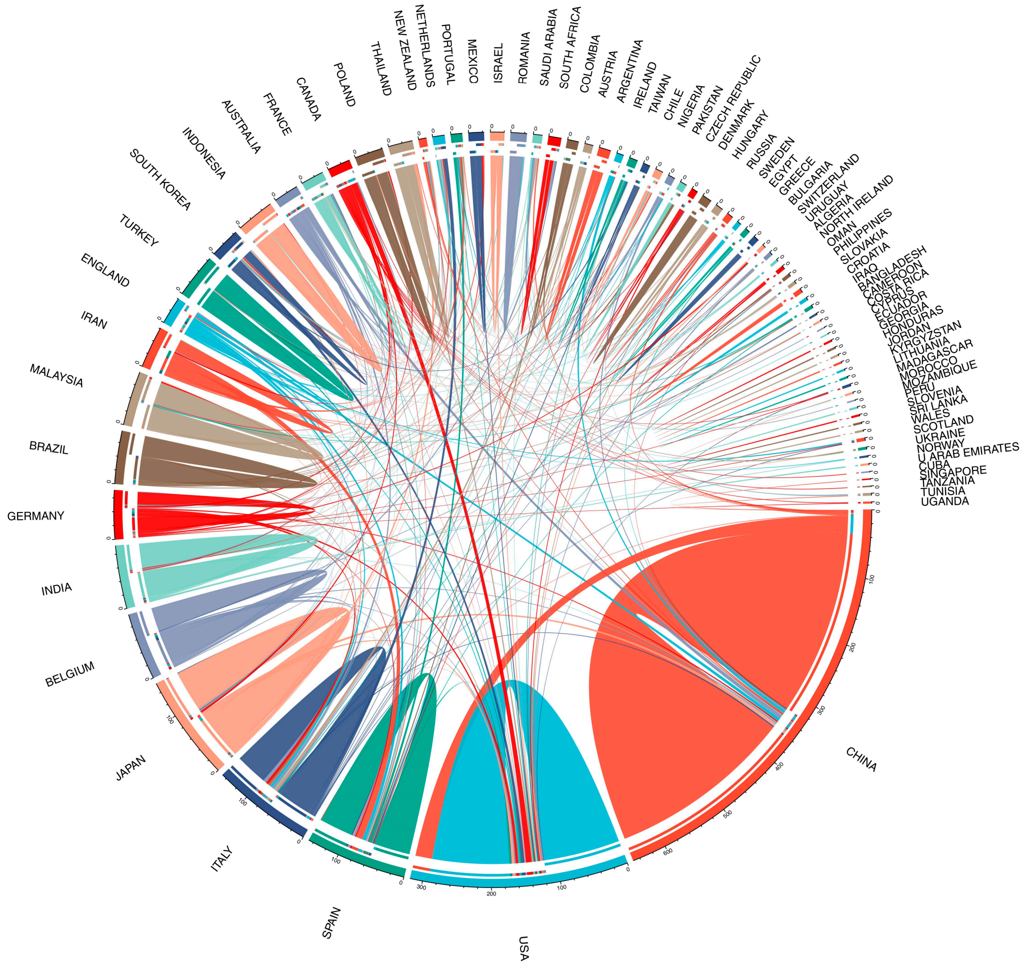

Figure 2. Mapping knowledge domains of co-authoring countries/regions.

In summary, a country's economic level is the basis for the development of non-destructive testing of fruit quality. Compared with economically underdeveloped countries/regions, economically developed ones have published more in-depth studies on the non-destructive testing of fruit quality and have achieved more research progress. Nevertheless, a high economic development level alone cannot bring considerable development to the field. This is because policy orientation determines the continuous economic inputs of the country/region to the field. Hence, development in the non-destructive testing of fruit quality cannot occur without economic support and policy guidance. Moreover, transbackground and transnational cooperation is conducive to the cooperation between different teams, facilitating leaps and diversified development in the field.

3.2.2. Institutions and Units

According to the analysis, more than 300 institutions were involved in studies on the non-destructive testing of fruit quality between 1993 and 2022. These institutions have made considerable contributions to the development of non-destructive testing technologies for fruit quality. The top 10 institutions in terms of the number of publications on the non-destructive testing of fruit quality in the Web of Science are listed in Table 1. Chinese and American institutions accounted for 7 of these 10 institutions, reflecting these countries' attention to and continuous efforts in this field. It is important to note that Zhejiang University achieved the most relevant scientific publications, with 71 papers published during the study period, accounting for 5.07% of the total publications. The United States Department of Agriculture published 63 papers, accounting for 4.5% of the total, ranking second.

Table 1. Top 10 institutions with a high number of publications in the Web of Science.

High-Volume Institutions Top 10	Number	Ratio (%)
Zhejiang University	71	5.07
United States Department of Agriculture	63	4.50
China Agricultural University	36	2.57
Ministry of Agriculture Rural Affairs	36	2.57
Ku Leuven	34	2.43
Consiglio Nazionale Delle Ricerche	32	2.29
Michigan State University	27	1.93
Washington State University	26	1.86
Northwest A&F University, China	24	1.71
National Agriculture and Food Research Organization, Japan	24	1.71

Among the global research institutions, Zhejiang University had the highest publication number in the Web of Science. This implies that the contribution of Zhejiang University to the non-destructive testing of fruit quality in China has been the most significant. This institution has strong scientific research power and an extremely strong influence on the field. The top 10 institutions comprised 6 universities and 4 research institutions. Based on the international scientific and technological development trend, the continued strengthening of scientific research cooperation among universities, research institutions, and enterprises is needed. This will facilitate the transformation of scientific research achievements.

3.3. Source Distribution

3.3.1. High-Publication Journals

Journals are the most important source of academic developments and scientific reports. Hot journals in the field can be identified by analysing the distribution of publications in journals. This is also applicable to the tracking of information in the most recently published studies. Journal distribution analysis is highly relevant to the information acquisition of researchers [39]. The top 10 journals in terms of the number of publications on the non-destructive testing of fruit quality in the Web of Science database are listed in Table 2. All journals published more than 20 papers. Specifically, *Postharvest Biology and Technology*, a journal from the Netherlands, achieved the top rank, with 85 papers (6%); this publication number is far higher than those of the other journals. Thus, this journal is the most influential journal in the field.

The above journals encompass several research fields, such as agriculture, food, optics, computer science, biology, gardening, etc. This means that the non-destructive testing of fruit quality is a multidisciplinary research field, and its development requires strengthened cooperation, exploration, and common progress across multiple disciplines.

Table 2. Top 10 high-publication journals in the Web of Science.

High-Published Journals Top 10	Number	Ratio (%)
Postharvest Biology and Technology	85	6.07
Acta Horticulturae	55	3.93
Horticulturae	46	3.29
Journal of Food Engineering	42	3.00
Computers and Electronics in Agriculture	34	2.43
Spectroscopy and Spectral Analysis	32	2.29
Transactions of the Asae	29	2.07
Journal of Agricultural and Food Chemistry	26	1.86
Food Chemistry	23	1.64
Biosystems Engineering	22	1.57

3.3.2. High-Citation Studies

The frequency of citation is an important evaluation index that provides an objective measure of the research influence, citation value, and degree of attention a paper has received in the field. A higher frequency of citations indicates higher attention to the paper and greater influence of the paper within scientific communication. High-citation studies are often those that focus on hotspot themes in the field, providing a guide on the academic frontier of the field. Analysing the high-citation studies on the non-destructive testing of fruit quality can provide researchers with a reference for the future research direction of the field. The top 10 high-citation studies on the non-destructive testing of fruit quality are listed in Table 3; all papers were cited more than 240 times.

Table 3. Top 10 high-citation studies in the Web of Science.

Top 10	Document	Frequency
1	DeepFruits: A Fruit Detection System Using Deep Neural Networks	482
2	Apple Detection during Different Growth Stages in Orchards Using the Improved YOLO-V3 Model	372
3	Advances in Machine Vision Applications for Automatic Inspection and Quality Evaluation of Fruits and Vegetables	329
4	NIR Spectroscopy Applications for Internal and External Quality Analysis of Citrus Fruit—A Review	300
5	Principles and Applications of Hyperspectral Imaging in Quality Evaluation of Agro-Food Products: A Review	284
6	Reflectance Spectral Features and Non-Destructive Estimation of Chlorophyll, Carotenoid and Anthocyanin Content in Apple Fruit	264
7	Measurement of the Optical Properties of Fruits and Vegetables Using Spatially Resolved Hyperspectral Diffuse Reflectance Imaging Technique	257
8	Non-destructive Measurement of Acidity, Soluble Solids, and Firmness of Jonagold Apples Using NIR-Spectroscopy	243
9	Principles, Developments and Applications of Computer Vision for External Quality Inspection of Fruits and Vegetables: A Review	240
10	A New Index Based on Vis Spectroscopy To Characterize the Progression of Ripening in Peach Fruit	240

In the Web of Science, "DeepFruits: A Fruit Detection System Using Deep Neural Networks", a study published by Sa, Inkyu et al. in 2016, was cited the most. This study proposed an accurate, fast, and reliable real-time fruit detection method based on deep convolutional neural networks [40]. According to the research results, the proposed detection method not only improves detection accuracy but can also be deployed to new fruit detection systems quickly. It began to attract significant attention after 2019, and the annual number of citations exceeded 100. The second most cited paper, "Apple Detection During Different Growth Stages in Orchards Using the Improved YOLO-V3 Model", was published by Tian et al. in 2019. In this study, an improved YOLO-V3 model was proposed for fruit quality detection under complicated conditions, such as illumination fluctuations, disordered backgrounds, overlapping apples, and different maturity stages [41]. This study also attracted extensive attention after 2019. This indicates that neural network technology became popular and began to attract significant attention in the field of non-destructive testing of fruit quality around 2019. Furthermore, "Advances in Machine Vision Applications for Automatic Inspection and Quality Evaluation of Fruits and Vegetables", a study published by Sergio Cubero in 2010, reviewed the development trend in machine vision technology for the internal and external quality inspection of fruits and vegetables [42]. This study has a high guiding role and reference value for the future study of non-destructive testing technologies for fruit quality.

These 10 studies have had significant influences on this research field. Their research directions and methods are representative. It is important to note that 5 of these 10 studies were published in the top 10 journals, and 3 were published in *Postharvest Biology and Technology*. This indicates that journals with a high number of publications on non-destructive testing technology for fruit quality are associated with high-citation publications, to some extent. This also verifies that *Postharvest Biology and Technology* is the most influential journal in the field. Moreover, the top 10 high-citation research hotspots in the field of non-destructive testing of fruit quality included spectral detection technology, machine vision technology, and neural networks. Common research indices included physical properties (e.g., the degree of maturity and hardness) and internal fruit quality (e.g., soluble solid content).

4. Research Progress and Leading Hotspots

Keywords in academic papers are tags indicating the research core and subject information. They provide a high-level summary of the major contents of a paper and can be used to identify the content characteristics and academic research direction of a paper. Here, clustering analysis and emergency analysis of the keywords, terms, and subject terms of studies on non-destructive testing technology for fruit quality were carried out using CiteSpace. Based on this analysis, the overall research progress in the field of non-destructive testing of fruit quality was analysed, the current research hotspots were identified, and the future development trend was predicted.

4.1. Statistical Analysis of Keywords

A statistical analysis of the frequency of keywords in high-publication journals was carried out. A high-frequency keyword–journal clustering tree was plotted by combining the high-frequency keywords with the high-publication journals (Figure 3). Furthermore, a hierarchical clustering analysis of high-frequency keywords and high-frequency journals was carried out. The hierarchical clustering analysis based on the bimodule matrix effectively improves the single-dimensional analysis of the traditional system clustering algorithm, achieving simultaneous clustering of topic keywords and journals [43]. The vertical clustering tree reveals the clustering results of high-frequency keywords, with 15 high-frequency keywords listed at the bottom of the graph. The horizontal clustering tree illustrates the clustering results of high-publication journals, with 12 high-publication journals listed on the right of the graph. Each box represents the high-frequency keyword–journal corresponding to the column and row. The colour depth reflects the frequency of co-occurrence in publications. The clustering results were interpreted, and hotspot research directions and popular journal groups in relation to the non-destructive testing of fruit quality were summarised.

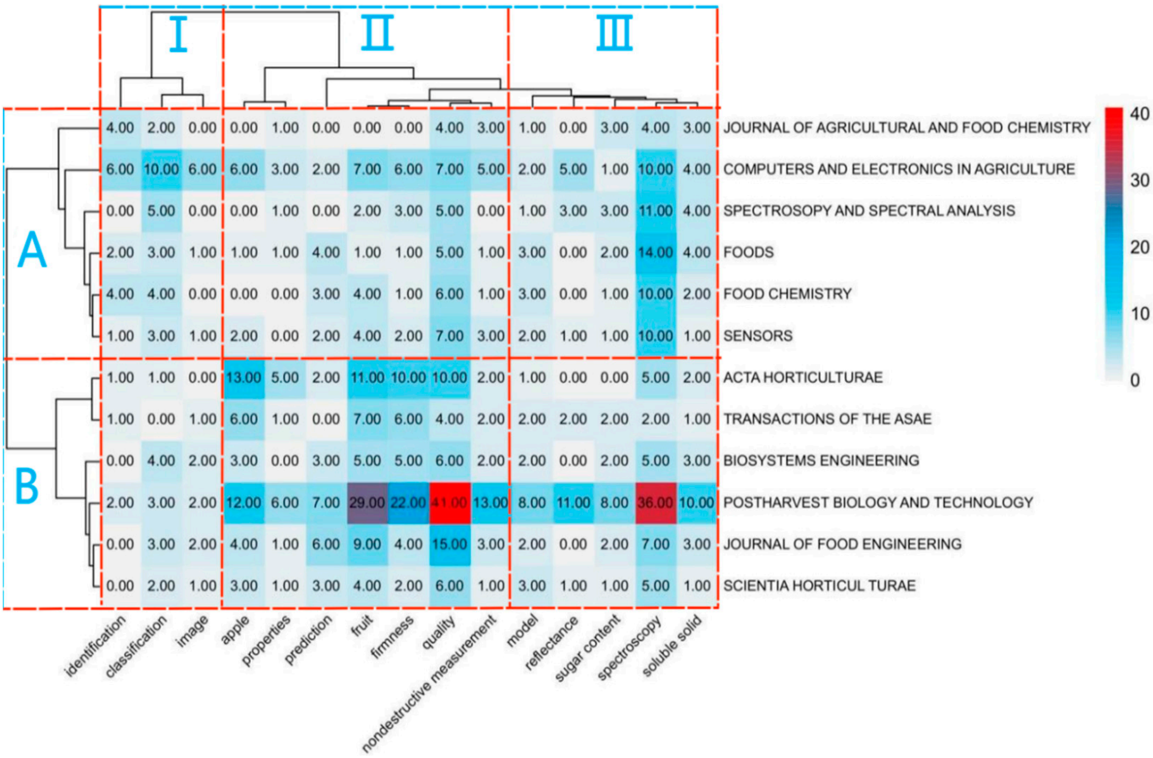

Figure 3. Knowledge domain mapping of hierarchical clustering trees based on keywords and bimodule matrix of journals.

Keywords that occurred frequently included apple, fruit, classification, quality, properties, prediction, and non-destructive measurement. This agrees well with the research topic of this study. Keywords like image, identification, spectroscopy, reflectance, and model also occurred relatively frequently. This demonstrates that these are currently popular research methods in the field of non-destructive testing of fruit quality. Moreover, words like firmness, sugar content, and soluble solids also occurred frequently, indicating that these are quality indices of interest in the field of non-destructive testing of fruit quality.

The research hotspots in this field can be divided into three main categories: (I) image recognition technology (image, classification, and identification); (II) general research objects and contents, including fruit, apple, non-destructive measurement, quality, properties, prediction, and firmness; and (III) traditional research methods and detection indices, including model, reflectance, spectroscopy, sugar content, and soluble solids. The journals can be divided into two major types according to the disciplines: (A) agriculture, food, and electronics; and (B) biology and gardening.

4.2. Clustering Maps of Keywords

A range of research topics were observed in the literature regarding the non-destructive testing of fruit quality. In this study, a clustering analysis of high-frequency keywords in relevant papers was carried out to identify the key research problems.

Clustering analysis of keywords is performed to investigate the contributions of keywords in relevant papers and the close relations among keywords. It is used to identify the core contents and structure of a specific field. The clustering analysis of keywords in relevant studies was carried out using CiteSpace. Nine colour-distinguished clustering maps were generated, as shown in Figure 4. The font size of the tags of the nodes represents the frequency. The quantity and width of the connecting lines represent the co-occurrence intensity among keywords. A smaller clustering number indicates that more keywords are included, and content closer to the centre of the cluster is more important.

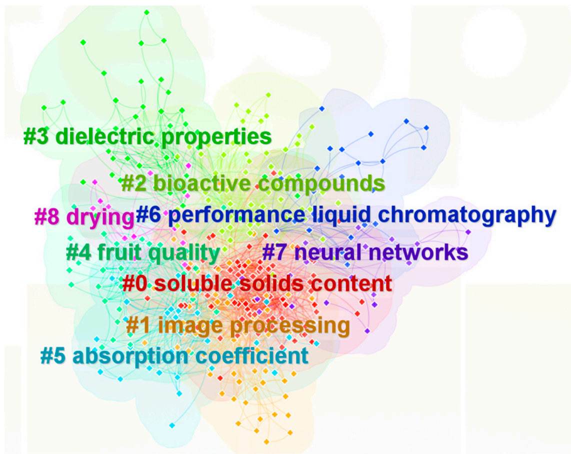

Figure 4. Clustering maps of keywords.

Clustering tags were divided into two types according to meaning: research object (#0 soluble solid content; #2 bioactive compounds; #3 dielectric properties; #4 fruit quality; and #5 absorption coefficient) and research method (#1 image processing; #6 performance liquid chromatography; #7 neural networks; and #8 drying).

4.3. Emergency Analysis of Keywords

An emergency word is one where the value of the keyword increases sharply into a hotspot over a short period. The emergency intensity of a keyword is proportional to the activity of the represented topic in the corresponding period. Here, an emergency analysis of keywords in relevant studies was carried out using CiteSpace. The results are shown in Figure 5. Deep learning, soluble solids, sugar content, internal quality, phenolic compounds, machine vision, and system were identified as emergency keywords with widespread interest and significant influence in this academic field. Moreover, the activity of the keywords corresponds with the growth trend of publications in Figure 1.

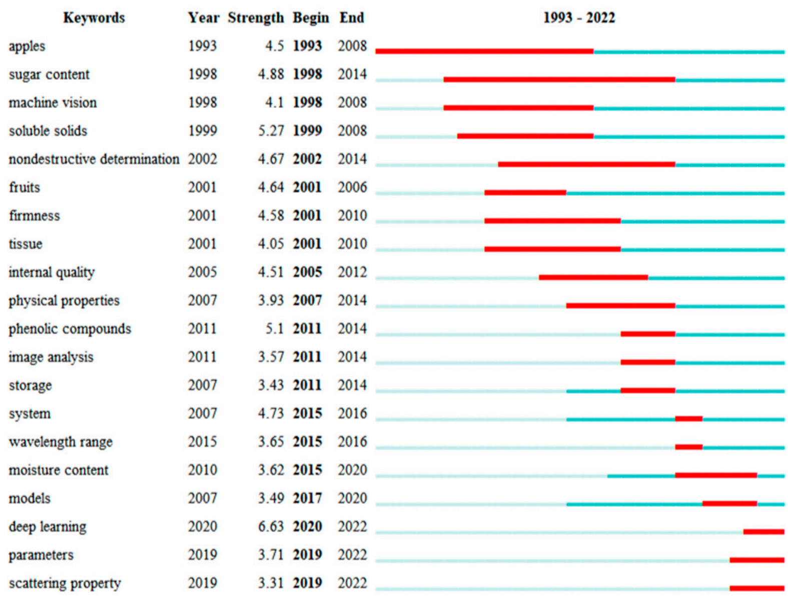

Figure 5. Evolution of emergency hotspots of keywords.

4.4. Temporal Analysis of Keywords

To further clearly and intuitively examine the development history of research on the non-destructive testing of fruit quality, a temporal map of keywords was plotted using

CiteSpace (Figure 6). The temporal map depicts keywords included in the clustering according to time. Each box in Figure 6 represents a keyword and the year of its first occurrence in the dataset. The box size represents the frequency of occurrence of the keyword, and the lines among keywords represent their connections. The development veins within the field of non-destructive testing technology for fruit quality were analysed. In combination with the number of publications and occurrence of keywords, the veins and leading points were further studied according to the time nodes and keywords.

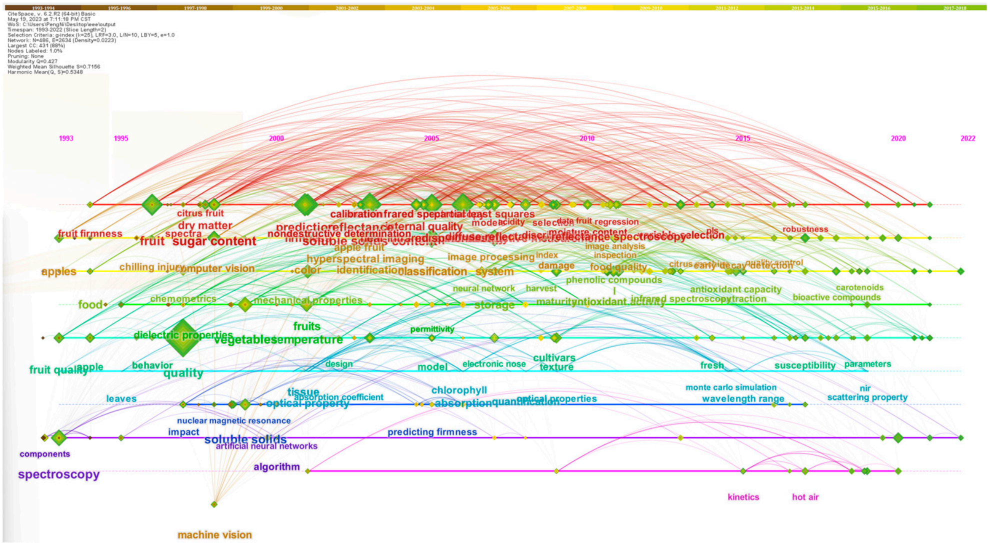

Figure 6. Temporal map of keywords.

The hotspot evolution of emergency keywords in Figure 5 and the growth trend of publications in Figure 1 were combined. The co-occurrence map of keywords was divided into three stages according to the timeline: the germination stage (1993–2014), the stable stage (2014–2019), and the development stage (since 2019). In the germination stage, texture analysis [44], sugar refractometry [45], analysis methods using optical instruments [46], and other traditional methods were used to test the physical properties (e.g., hardness) [47] and internal quality (e.g., sugar degree [48], soluble solids [49], and phenolic compound content [50]) of fruits. It is important to note that machine vision technology [51] began to be used for the inspection of the external quality of fruits in 1998. In the stable stage, most studies applied e-nose [52], diffuse reflection [53], and near-infrared spectra [54] technologies. Machine vision technology [55] was further developed. In the development stage, neural networks and deep learning technologies were developed and integrated with traditional technologies like machine vision and spectra [56–58]. This injected new vitality into the field of non-destructive testing technologies for fruit quality.

5. Conclusions

Journal papers on the non-destructive testing of fruit quality published in the Web of Science database between 1993 and 2022 were identified in this study. Using bibliometrics, the quantitative distribution and sources of the relevant studies were analysed. The research contents, content progress, leading hotspots, and development trends in the field of non-destructive testing of fruit quality were summarised based on knowledge maps. Moreover, the research dynamics in the field were investigated. The major conclusions are outlined below:

(1) Studies on the non-destructive testing of fruit quality were in the germination stage from 1993 to 2014. There were few published papers from a limited number of countries in 1993. Over time, the number of related papers gradually increased, year by year. More countries began to investigate and publish studies on the non-destructive testing of fruit quality. The field was in the stable stage from 2014 to

2019. During this time, there was continuous publication of relevant research papers. Finally, there was sharp growth in the number of studies from 2019 to 2022. Significant growth in the field is expected over the next few years.

(2) Research on non-destructive testing technology for fruit quality has mainly concentrated in Asia, North America, and Europe. China and the USA are the most active countries in this field. Furthermore, there has been close cooperation between China and the USA, the USA and Canada, and Spain and Iran. Continuous capital funding and policy support from these countries in addition to good transnational cooperation will further facilitate the diversified development of non-destructive testing technology for fruit quality.

(3) Major research institutions that have published in this field include Zhejiang University, the United States Department of Agriculture, China Agricultural University, the Ministry of Agriculture Rural Affairs, and so on. Zhejiang University has made a remarkable contribution and has a significant influence on the field.

(4) Relevant studies in the field have mainly been published in *Postharvest Biology and Technology*, *Acta Horticulture*, *Horticulturae*, *Computers and Electronics in Agriculture*, *Spectroscopy and Spectral Analysis*, and so on. They have mainly been focused on agriculture, food, electronics, biology, gardening, etc.

(5) The primary evaluation indices in the published studies include internal quality (e.g., sugar degree and soluble solids) and physical properties (e.g., hardness). The research methods mainly include e-nose technology, machine vision technology, and spectral detection technology (including hyperspectra and visible/near-infrared spectra), etc. Recently, neural networks and deep learning have undergone significant development. They have been combined with spectral technology and machine vision technology. As a result, non-destructive testing technology for fruit quality has entered a new development stage.

This paper provides an overview of the data recorded in the Web of Science on non-destructive testing of fruit quality from 1993 to 2022 for a total of 30 years, mainly relying on the pioneering content of the Web of Science, high-quality data, long history, and authority, covering the most important and influential research in related research fields [59]. However, a variety of disciplines may also be included in other databases, resulting in data omissions [60]. Therefore, even if the use of multiple databases will bring problems such as overlapping samples, it should also be considered so as to expand the research scope, which is an aspect that should be considered in future bibliometric research [61].

There is currently significant research and publication activity in the field of non-destructive testing technology for fruit quality. There remains a good development trend. Studies on the application of non-destructive testing technology for fruit quality to agricultural production and agricultural product processing are becoming increasingly mature. In particular, non-destructive testing technology for fruit quality has promising application prospects in agricultural product processing, and its application is booming. Moreover, technological developments, such as sensors, the Internet of Things (IoT), big data, machine vision, artificial intelligence, and deep learning will promote the maturity and application of non-destructive testing technology for fruit quality. This technology can also be applied to the whole process of fruit production, transportation, and marketing, meeting the market needs for fruit quality detection.

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