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Visual Analysis of Research in the Field of Food Target Detection

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Abstract: *Based on CiteSpace, this study conducts a bibliometric visualization analysis of 401 research articles related to food target detection from the Web of Science, covering the period from 2014 to 2024. It explores the research progress, hotspots, and limitations in this field in recent years. The results indicate that there is close international collaboration in food target detection, forming a core cooperative network. The cited references are categorized into 8 clusters, with a majority of highly cited works focusing on theoretical research, specifically on the algorithms themselves. In contrast to the cited references, the documents from research sample are categorized into10 clusters based on keywords, predominantly focusing on the identification and detection of food components. However, the study also reveals certain limitations, such as the absence of a core group of authors in the field, a lack of diverse authorship, and the absence of an interdisciplinary collaborative network. In light of this, The paper proposes corresponding solutions from the perspective of resource sharing and co-construction.*

Keywords: *Target detection, Food, Visualization, CiteSpace*

1. Introduction

As people's awareness of food safety increases, ensuring food quality and identifying harmful substances has become particularly important. Target detection technology can assist in automatically monitoring food and identifying potential issues with it [1], Object detection is currently one of the hottest and most challenging core issues in the field of computer vision. Its main tasks, in addition to focusing on classifying different images, also involve accurately estimating the concepts and locations of the objects contained in each image to achieve a comprehensive understanding of the image. [2]。 Object detection algorithms mainly consist of two methods: traditional detection and deep learning detection. Among them, traditional detection methods primarily rely on manually designed feature extraction. However, manual feature extraction is inadequate for large-scale data and has weak generalization ability, which may result in incomplete and inaccurate recognition. In response to this issue, many scholars and technology researchers have begun to apply deep learning algorithms. In the field of object detection, deep learning algorithms are mainly divided into Two-Stage Detection and Single-Stage Detection. The commonly used two-stage detection algorithms for food detection include Faster R-CNN[3] and R-FCN[4]. Two-stage algorithms offer high accuracy and robustness, making them particularly suitable for complex real-world application scenarios. However, due to the high computational complexity of the models, they are less suitable for real-time applications and devices with limited hardware resources[5]. Compared to two-stage detection algorithms, single-stage detection algorithms do not require the generation of regional proposals, making their algorithm flow more straightforward and clear. Common single-stage algorithms applied in the field of food object detection include the YOLO[6] (You Only Look Once) series of algorithms and SSD[7] (Single Shot Multibox Detector), with the YOLO series being the most representative.

2. Data Collection and Research Method

2.1. Data Collection

The literature database is sourced from the Web of Science Core Collection. The search period is set

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from 2014 to 2024, using Topic search criteria that include both "Food" and "Object Detection." The Research Areas are limited to Computer Science, Food Science Technology, Imaging Science Photographic Technology, Chemistry, or Materials Science. A total of 401 articles were obtained from the search, comprising 260 Articles, 91 Proceedings Papers, and 39 Reviews.

2.2. Research Method

This study conducts a bibliometric analysis using CiteSpace 6.3.R1 software on the filtered sample. Bibliometric analysis is a quantitative method primarily employed to investigate and evaluate academic literature, along with its impact and development trends in specific fields. Co-occurrence analysis is one of the most crucial modules within this framework[8]. It reflects the strength of relationships between article keywords and cited literature, allowing for the identification of research hotspots and key themes in the academic domain. Important indicators for analyzing co-occurrence results include centrality, density, frequency, burst strength, and sigma. Cluster analysis is a vital component of co-occurrence analysis, commonly used to categorize literature with similar research themes. This helps scholars gain a clearer understanding of the development trends within the field and its inherent connections[9]. Modularity and silhouette scores are key indicators for assessing clustering effectiveness.

This paper first conducts a co-occurrence analysis of the research collaboration network, followed by a co-citation and co-occurrence analysis of research keywords. It ultimately summarizes the shifts in research hotspots concerning object detection algorithms in food-related studies from 2014 to the present, as well as their potential future trends.

3. Results

3.1. Collaboration Network

3.1.1. Co-authorship Network Analysis

In this section, we utilized CiteSpace software to conduct a co-authorship analysis of the research sample. The filter settings were configured to display only the top 30 most closely related author collaboration networks, resulting in the generation of the author co-occurrence map shown in Figure 1. The final synthesized map includes a total of 299 authors and 165 collaboration lines, with a collaboration network density of 0.0037. From the map, it can be observed that between 2014 and 2024, a co-authorship network was formed around core authors such as "Zhang, Yanhua," "Kim, Moon S," "Xu, Lu," and "Cao, Jie." Among them, the most densely connected group consists of authors "Zhong, Wei" and "Yang Tian-Ming," which collectively produced 10 collaboration routes.

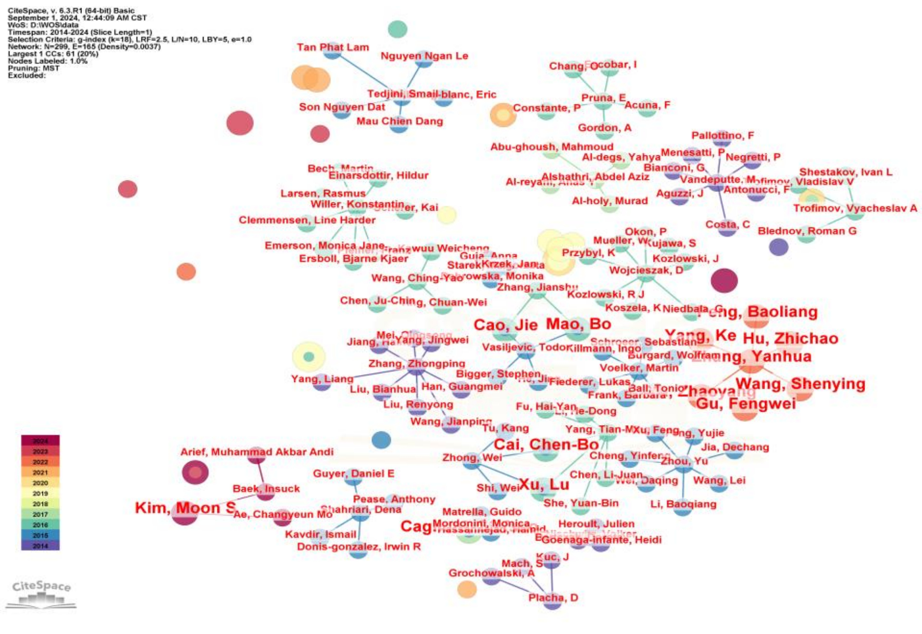

Figure 1: Collaboration network map of authors

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Table 1 lists the publication volume, with the authors having the highest number of publications being "Yanai, Keiji" and "Belhadj, Djallel," each with three publications. According to Price's Law formula[10], as shown below, it is possible to extract the range of core authors in any research field.

$$A = 0.749 \times \sqrt{B_{max}} \tag{1}$$

Where A represents the minimum number of publications by authors in the field, and B_{max} refers to the publication count of the scholar with the highest number of publications in that field. When a scholar's publication volume exceeds A, they are considered a core author in this domain. If the total publication volume of all core authors exceeds 50% of the total literature in that field, it is indicative of a core author group within the domain. From Table 1, we find that B_{max} is 3, and it can be concluded that A equals 1.297. Since the number of publications must be rounded up, the value of A becomes 2. According to the output, there are a total of 27 authors with no fewer than 3 publications, with a total of 56 articles published, which only accounts for 13.965% of the total number of literature (401 articles). This indicates that there has not yet formed a core author cluster in the field of food object detection, and the collaboration relationships among authors are relatively weak.

Table 1: Number of publications by authors

No.	Author	Count
1	Yanai, Keiji	3
2	Belhadj, Djallel	3
3	Yang, Ke	2
4	Nuzillard, Danielle	2
5	Wang, Shenying	2
6	Gu, Fengwei	2
7	Lu, Renfu	2
8	Amelin, V G	2
9	Lu, Yuzhen	2
10	Xu, Lu	2
11	Mao, Bo	2
12	Kim, Moon S	2
13	Hu, Zhichao	2
14	Cao, Jie	2
15	Haddad, Madjid	2

3.1.2. National Collaboration Network Analysis

This section conducts a co-occurrence analysis of the nationalities of the authors using CiteSpace software. Consistent with the previous section, the top 30 countries with the most intense collaboration were selected, as shown in Figure 2. The co-occurrence map includes a total of 75 institutions, with 103 collaboration links, leading to a collaboration network density of 0.0371, which represents a sharp increase compared to the collaboration density among the authors. From 2014 to 2024, a research cluster primarily consisting of countries such as China, USA, India, Germany, England, and South Korea has formed.

According to Table 2, the country with the highest publication volume is China (116 publications), followed by the USA (45 publications) and India (41 publications). Similarly, based on Price's Law formula[10], the B_{max} is 116, and the calculated value of A is 8.07, which rounds up to 9. There are 17 countries with a publication volume of at least 9, and their total number of published articles is 383, accounting for 95.5% of the total number of sample literature. Therefore, a core publishing cluster of countries has formed in the field of food object detection, indicating a strong collaborative relationship among the publishing countries. The table shows that most publications are concentrated in China, the USA, and India, with China's publication volume being more than double that of the other countries. The level of betweenness centrality reflects the critical role of that node in information dissemination, resource allocation, or collaborative networks[11]. From the table, it can be seen that the countries with strong centrality are USA (0.41), Spain (0.33), India (0.21), and China (0.20). Although China and India have a high volume of publications, their betweenness centrality is not the highest. This may be

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due to the authors from China and India tending to focus more on publishing research related to their own countries, with less collaboration with researchers from other countries, thereby reducing their bridging role in the international research network.

Figure 2: Collaboration network map of countries

Table 2: Number of publications by countries

No.	Country	Count	Centrality
1	PEOPLES R CHINA	116	0.2
2	USA	45	0.41
3	INDIA	41	0.21
4	SOUTH KOREA	21	0.06
5	JAPAN	20	0.06
6	RUSSIA	20	0.05
7	ITALY	16	0.11
8	SAUDI ARABIA	16	0.19
9	SPAIN	14	0.33
10	ENGLAND	13	0.02

3.2. Research Topic

3.2.1. Co-cited Network Analysis

In bibliometric analysis, when two or more documents are cited by one or more documents simultaneously, it is referred to as a co-citation relationship. Cluster analysis uses clustering algorithms to categorize related keywords, thereby deriving different thematic clusters of content. Together, these methods can provide insights into current research hotspots from different perspectives[11]. This section first conducts a co-citation analysis of the references using CiteSpace, followed by a cluster analysis of the cited document. It generates a co-citation clustering map of the references, as shown in Figure 3, along with a table (Table 3) summarizing the top ten highly cited references. The modularity and silhouette values are 0.6604 and 0.9027, respectively, both exceeding their critical thresholds of 0.3 and 0.5, indicating that the structure of the co-cited reference is significantly robust and the clustering effect is significant.

The cited references is divided into eight distinct clusters, each clearly reflecting the current hot topics within the field of food object detection. Based on the magnitude of centrality, core references for each cluster can be identified. Overall, the most extensively covered topic among the cited references is "garlic root cutting," which has the greatest overlap with "imaging" and intersects with "Machine Vision," "semantic segmentation," "multi-scale," and "smart traps." The most isolated cluster, however, is "smart agriculture," which shows no intersection with any other clusters.

In terms of each cluster, the cluster centered on the research theme of "Machine Vision" features the

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work of Redmon J[12], who proposed the significant improvement model YOLO v3 in 2018. The YOLO series of algorithms is one of the primary single-stage algorithms in the field of object detection. Next is the "semantic segmentation" cluster, with its center being the article by Sandler[13], which introduced a new mobile architecture called MobileNetV2, enhancing the performance of mobile models across multiple tasks and benchmarks while accommodating various model sizes. The clusters "faster R-CNN" and "multi-scale" are centered around Kamilaris[14], who primarily discusses the application of object detection algorithms in agriculture from a literature review perspective. The "garlic root cutting" cluster is centered on Thuyet[15], whose work developed a CNN-based software for garlic image processing, achieving an overall sorting accuracy of 89% for three types of garlic. The most central reference in the "imaging" theme cluster comes from Krizhevsky [16], who, along with his team, trained a large deep convolutional neural network and employed a recently developed regularization method called "dropout" to reduce overfitting in fully connected layers, thereby decreasing the error rate in recognition. The cluster centered on "smart traps" features the work by He et al.[17], which proposed an instance segmentation method called "Mask R-CNN" that effectively detects objects in images while generating high-quality segmentation masks for each instance, serving as an extension of "Fast R-CNN." Finally, the center of the "smart agriculture" cluster, represented by Hussain[18], discusses the evolution from YOLO v1 to YOLO v8 and its applications in digital manufacturing and industrial defect detection. The "foreign body detection" cluster is centered on Djekic[19], whose work explores the various foreign objects reported in the Rapid Alert System for Food and Feed (RASFF) from 1998 to 2015. It discusses and analyzes aspects such as the types of foreign objects, the foods involved, and their geographical distribution across designated regions in Europe, including algorithms for detecting food defects and pests.

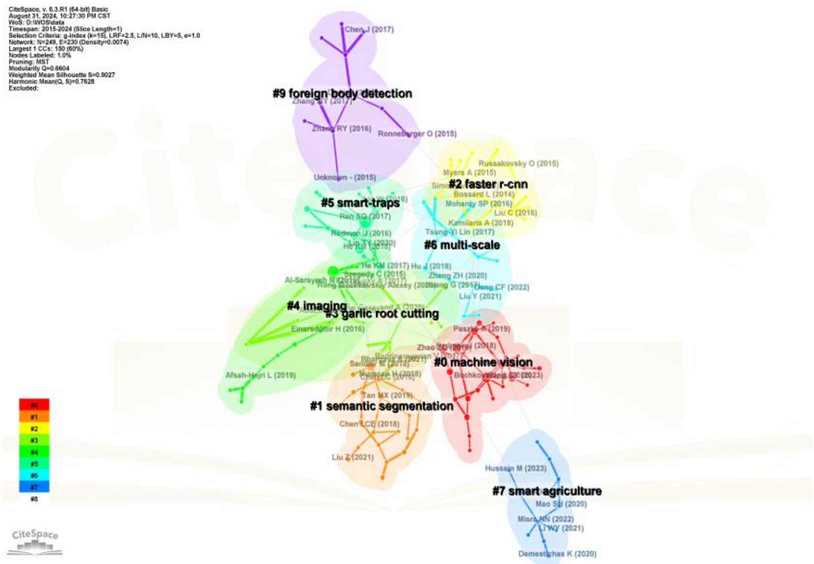

Figure 3: Co-citation network map of references

Table 3: The top 10 high-cited references

No.	Title	Author	Freq.	Centrality
1	ImageNet classification with deep convolutional neural networks	Krizhevsky *et al.*	36	0.08
2	Deep Residual Learning for Image Recognition	He *et al*	26	0.16
3	YOLOv4: Optimal Speed and Accuracy of Object Detection	Bochkovski *et al.*	24	0.05
4	YOLOv3: An Incremental Improvement	Redmon *et al.*	18	0.14
5	Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks	Ren *et al.*	18	0.03
6	Mask R-CNN	He *et al.*	17	0.11
7	SSD: Single Shot MultiBox Detector	Liu, W. *et al.*	16	0.06
8	Deep learning in agriculture: A survey	Kamilaris	15	0.1
9	Feature Pyramid Networks for Object Detection	Lin *et al.*	14	0.06
10	You Only Look Once: Unified, Real-Time Object Detection	Redmon *et al.*	14	0.04

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From Table 3, it can be seen that the most cited reference is the work of Krizhevsky et al.[16], which has been cited as many as 36 times. Following this, we have He et al.[20] with 26 citations and Bochkovskiy et al.[21] with 24 citations. Notably, among the top ten most cited references, four are related to the YOLO series of algorithms, highlighting their significance in the field of object detection algorithms. The remaining references pertain to CNN and R-CNN series algorithms. Almost all authors of these cited works are either the founders of the respective algorithms or scholars with significant contributions, indicating that these references primarily discuss the theoretical aspects of object detection algorithms.

3.2.2. Keyword Co-occurrence Analysis

Figure 4 shows the keyword clustering of the study, where all sampled keywords have been categorized into 9 clusters: #0 deep learning, #1 artificial intelligence, #2 3D printing, #3 edge detection, #4 hyperspectral imaging, #5 1-4-benzenedithiol, #6 food safety, #7 object recognition, #8 bacterial detection, and #9 leaf stress. It is evident that, unlike the cited references, the documents themselves are more application-oriented. One part of the themes includes the identification of food components and the detection related to food safety, while another part leans more towards the description and use of the entire industry and mainstream algorithms.

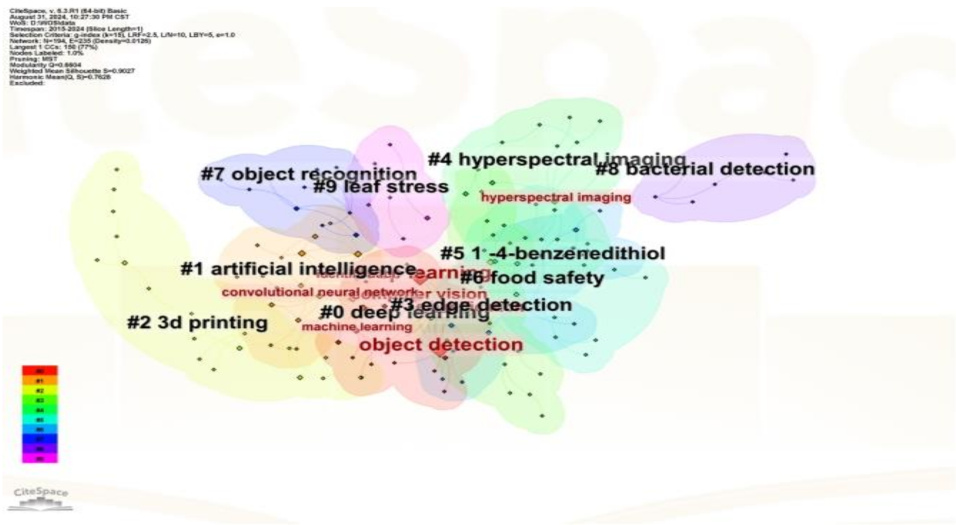

Figure 4: Co--occurrence network map of keywords

The following table also illustrates the current hot topics in the field of food object detection. "Deep learning," "machine learning," and "convolutional neural network" are the theoretical hotspots of current research, whereas "computer vision," "classification," "food," "hyperspectral imaging," "identification," and "system" are the application hotspots in ongoing research.

Table 3: The top 10 keywords with the most co-occurrence frequency

No.	Keywords	Number of publications	Centrality
1	deep learning	78	0.1
2	object detection	78	0.16
3	computer vision	34	0.13
4	classification	32	0.23
5	food	22	0.11
6	convolutional neural network	15	0.1
7	hyperspectral imaging	15	0.15
8	identification	14	0.15
9	machine learning	13	0.06
10	system	11	0.18

4. Conclusions

This article conducts an analysis of 401 publications in the field of food object detection indexed in the Web of Science from 2014 to 2024 using bibliometric analysis methods combined with CiteSpace software. The results reveals the current research development processes, hotspots, and limitations

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within this domain. Overall, the number of studies in food object detection has been increasing in recent years alongside the advancement of deep learning technologies, with close research collaboration networks forming among various countries, leading to the establishment of a core collaboration network. The co-cited references are categorized into 8 clusters, with highly cited documents leaning towards theoretical research, focusing on the algorithms themselves. In contrast, the research sample literature is divided into 10 keyword clusters, predominantly oriented towards the identification and detection of food components.

However, there are certain limitations within the research field. There is no formation of a core group of authors, and the authorship tends to be somewhat singular, lacking an intersecting collaborative network. Based on this analysis, the following suggestions are proposed:

Firstly, it is essential to strengthen collaboration within the field. On one hand, establishing open-source code repositories and technical platforms is encouraged to invite developers and scholars to contribute to and improve object detection algorithms and related tools. On the other hand, establishing joint laboratories across institutions or universities is important for sharing datasets and data resources, encouraging researchers from different disciplines to engage in collaboration.

Secondly, collaboration across disciplines should be enhanced. Academic institutions should strengthen partnerships with industries, facilitating the sharing of data and technological resources between academia and industry. This will promote the practical application of object detection algorithms in sectors related to food, agriculture, and healthcare, aiming to expand their use in more fields.

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