Computer Vision for Food Nutrition Assessment: A Bibliometric Analysis and Technical Review

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***Abstract*—This study examines the latest trends, challenges, and advances in food image segmentation and computer vision-based nutritional analysis. Traditional nutritional assessment methods such as food diaries and questionnaires are limited by their reliance on participant recall and manual processing, which reduces their accuracy and efficiency. As an alternative, advances in machine learning and deep learning have shown potential in automating food identification and estimating nutrient content, such as calories, protein, carbohydrates, and fat. This study was conducted through bibliometric analysis and technical review of publications from the Scopus database, using a structured search strategy and applying inclusion and exclusion criteria. Articles were selected based on topic relevance, use of machine learning or deep learning methods, publication in English, and publication between 2020 and 2024. The review identified key research trends, key contributors, popular methods such as CNN and YOLO, and the most frequently reported limitations, including lack of dataset diversity, inaccuracy in food volume estimation, and the need for real-time integrated systems. These limitations were analyzed based on the methodology and findings of the reviewed studies. This review is expected to be a comprehensive reference for researchers and practitioners in developing food image segmentation technology for more accurate and applicable nutritional assessment.**

Keywords*—*Bibliometric Analysis; Food Image Segmentation; Nutrition Analysis; Computer Vision; Research Trends.

I. Introduction

Child malnutrition is a pressing global health problem. Insufficient and inappropriate food provision is a major contributor to the deterioration of children's health [1]. Nutritional assessment plays a vital role in preventing stunted growth and malnutrition from an early age [2], [3]. It enables early detection, personalized interventions, and continuous monitoring, all of which are essential for ensuring optimal growth and development in children [4], [5]. By addressing nutritional deficiencies early, long-term health problems can be avoided, thereby improving the overall quality of life of children [6].

Traditional nutritional assessment methods, such as food diaries, questionnaires, and dietary recalls, are still widely used in research but have several limitations [7], [8]. These approaches require considerable time and effort from both participants and researchers, as they often involve extensive food recording and participant interviews. They also rely heavily on memory and honesty, which can lead to recall bias or socially desirable responses, resulting in inaccurate data [9]. In addition, sample preparation in nutritional studies is often destructive, costly, and time-consuming, particularly for large-scale assessments [10]. Challenges such as incorrect portion size estimation, data processing delays, and nutrient variations due to different cooking methods further hinder the reliability and efficiency of traditional dietary assessments [11].

To address these limitations, computer vision technology has emerged as a promising solution for conducting rapid, noninvasive, and automated nutritional analyses using food images. Various literature reviews have explored the use of computer vision for food recognition and nutrient estimation. For instance, Subhi *et al.* [12] provided a comprehensive overview of food recognition and volume estimation techniques but did not cover the latest deep learning-based approaches or the practical implementation challenges of these techniques. Lo *et al.* (2020) [13] compared image-based classification and volume estimation algorithms, focusing on technical performance and accuracy. Devi *et al.* [14] reviewed CNN-based diet system architectures with a focus on transfer learning, while Rathod *et al.* (2024) [15] highlighted the effectiveness of deep learning models for classification but did not address the full pipeline from classification to nutrient estimation. Notably, these studies tend to overlook the segmentation stage, which is a crucial step in food-image analysis.

Identifying food types from images is an essential first step, as it enables the system to estimate the nutritional content, such as calories, protein, carbohydrates, and fat, by analyzing the size and area of the food items [16]-[18]. Some systems also incorporate before-and-after meal images to improve the accuracy of nutritional calculations [19]. However, the performance of such systems largely depends on the availability of diverse and well-annotated datasets. Datasets such as Nutrition5k provide rich resources, including images, videos, and accurate nutritional data [20]; however, many others still lack sufficient diversity and precise labelling [20]-[22]. These deficiencies hinder the model's ability to generalize across various food types, especially those that appear visually similar [23], [24]. Food image segmentation presents unique challenges. Complex dishes with mixed ingredients and overlapping components are difficult to segment and recognize accurately [24]. Although incorporating additional data, such as text or sensors, may improve performance, it often increases the system complexity [24]. Despite these challenges, the use of computer vision in nutritional analysis continues to advance rapidly, enabling faster and contactless evaluation through deep learning techniques, such as convolutional neural networks (CNNs) [19], and enabling quick and contactless nutritional analysis through digital image processing [10], [25], [26]. This technology can identify and separate food objects in images, which are then used to recognise the food type and estimate its nutritional value [19], [27]-[29]. This approach leverages convolutional neural networks (CNNs) and other image-processing methods to enhance detection accuracy. As the demand for accurate and practical nutritional monitoring increases, the development of robust food-image analysis systems has become increasingly important. Therefore, this review aims to provide a comprehensive overview of the current segmentation methods used in food image analysis, evaluate their effectiveness for nutritional estimation, and highlight existing challenges and future research opportunities. Unlike previous studies, this review offers a systematic classification of food image segmentation techniques, emphasizing their role as critical components in automatic recognition and analysis pipelines. It further examines technical obstacles, such as diverse presentation styles, overlapping food elements, and the lack of high-quality datasets, which continue to limit segmentation performance.

Specifically, this study contributes in three key ways.

- Segmentation methods are classified based on the techniques used, providing a structured understanding of their development.
- It identifies common limitations in existing studies, such as the poor segmentation of complex meals and a shortage of high-precision annotations.
- Future research directions are proposed, including the development of multimodal segmentation approaches, improved model generalization through data augmentation, and exploration of lightweight models suitable for real-time and mobile applications.

In addition, this study incorporates a bibliometric analysis of literature published from 2020 to 2024 sourced from the Scopus database. The analysis captured trends in publication volume, key contributors, frequently used keywords, segmentation method classifications, and limitations. Through this structured review and data-driven insights, we aim to support researchers and practitioners in advancing the development of more effective and deployable food-image segmentation systems.

II. Materials and Methods

This study employed bibliometric analysis and technical review methods, applying article selection and evaluation criteria adapted from Kitchenham's guidelines [30], [31], as illustrated in Fig. 1, and the preferred reporting items for systematic reviews and meta-analyses 2020 (PRISMA) guidelines [32] which provide a structured approach for the design, execution, and reporting of systematic reviews and meta-analyses. PRISMA serves as the central framework for ensuring that the literature review process is both systematic and transparent. By incorporating PRISMA, this study aims to enhance the rigor and replicability of the review process, ensuring that all relevant studies are comprehensively identified, assessed, and synthesized. This approach not only strengthens the reliability of the findings but also ensures that the review aligns with current best practices for conducting systematic reviews, providing a solid foundation for future research in the field.

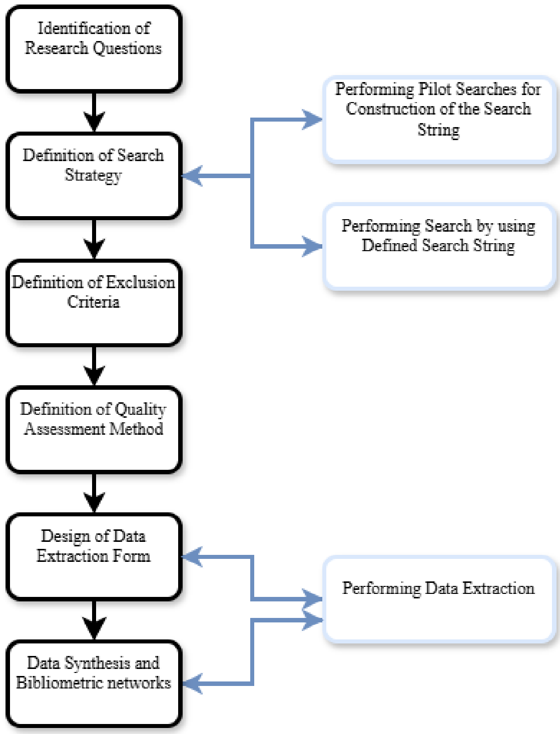

Fig. 1. This review protocol refers to the guidelines from Kitchenham [30], [31]

Fig. 1 illustrates a structured workflow for conducting a bibliometric analysis and technical literature review, following the guidelines established by Kitchenham [30], [31]. The process began with the identification of research questions, which served as the foundation for the entire review. This was followed by the definition of a search strategy, including the construction of search strings through pilot searches and the execution of the main search using the finalised strings. Subsequently, exclusion criteria were established to filter out irrelevant studies, and a quality assessment method was defined to ensure the inclusion of only high-quality publications. The next step involved designing a data extraction form to systematically gather relevant information from the selected studies. Data extraction was then performed, followed by data synthesis and bibliometric network analysis to identify research trends, collaborations, and knowledge gaps. According to Kitchenham, the strength of the SLR methodology lies in its transparency, objectivity, and reproducibility, making it a reliable approach for generating comprehensive and credible insights for future research endeavours. Each stage of the systematic review process is elaborated in the subsequent sections to ensure clarity and transparency.

A. Research Question

In this study, we examined the latest trends and developments in food image segmentation and nutrition analysis based on computer vision using a bibliometric approach. The analysis process began by formulating six key research questions that served as the foundation for collecting and filtering the relevant literature.

- *RQ1: What are the research trends in food image segmentation based on computer vision during 2020–2024?*
- *RQ2: Who are the main contributors (authors, institutions, or countries) in the field of food image segmentation based on computer vision during 2020–2024?*
- *RQ3: How are the approaches to food image segmentation classified based on the methods used in the literature from 2020 to 2024?*
- RQ4: What are the most frequently reported limitations in the studies?
- *RQ5: What future research directions have been proposed in the literature related to food image segmentation?*

B. Search Strategy and Selection Criteria

A systematic literature search was conducted using the Scopus database with the application of a Boolean search strategy. The keywords used in this search were: "food segmentation" OR "food image analysis" OR "nutrition analysis" OR "nutrition" OR "food assessment" OR "food evaluation" OR "food analysis" OR "nutritional assessment" AND "machine learning" OR "deep learning". The search focused on publications from 2020 to 2024, without restricting the type of scientific documents, except based on relevance criteria. The initial search yielded 1,574 articles, which were further filtered according to the inclusion and exclusion criteria. This strategy was designed to reach literature relevant to the topic of nutrition assessment based on food-image segmentation and computer vision.

C. Definition of Exclusion Criteria

To ensure the quality and relevance of the literature analysed in this study, a filtering process was conducted based on a set of exclusion criteria developed by adapting the article quality assessment guidelines from Kitchenham [30], [31]. These criteria were used to evaluate whether the articles found aligned with the research focus, which is food image segmentation and nutrition analysis based on computer vision with machine learning or deep learning approaches. Table I summarizes the exclusion criteria applied during the article selection phase.

Table I presents the exclusion criteria used to select the relevant articles for this study. Articles were excluded if the title and abstract did not match the purpose of the article, were published outside the 2020-2024 timeframe, were not in English, were duplicate articles, or were published in unsuitable journals or proceedings [10], [32]–[113]. The purpose of these exclusion criteria was to ensure that the articles used in the research were suitable for the topic, time relevance, standardised language, and originality.

TABLE I. EXCLUSION CRITERIA

ID	Criterion
1	Title and abstract are not consistent with the purpose of the article.
2	Year published outside 2020-2024 (RQ 1-5)
3	Article not in English
4	Duplicate article
5	In addition, journals and proceedings

D. Definition of Quality Assessment Method

The selected articles were then evaluated using the quality assessment method described by Muttaqien *et al.* [114]. To ensure objectivity, the evaluation was independently conducted by five reviewers, and the final score of each article was based on a consensus of their assessment. Table II lists the questions used to assess the quality of the articles. Articles with scores below eight were excluded to narrow the search results. A total of 149 articles were included in the analysis.

Table II contains the Quality Evaluation Questions used to assess the quality of the studies. Each question was answered with "Yes" (score 2), "Partial" (score 1), or "No" (score 0). The questions included the clarity of study objectives, definition of scope, explanation of solutions tested, validity of variables, documentation of the process, whether all questions were answered, presentation of negative findings, and clarity of key findings. The purpose of this evaluation was to assess the quality and credibility of the study, as illustrated in Fig. 2.

TABLE II. QUALITY EVALUATION QUESTION. YES, SCORE 2; PARTIAL, SCORE 1; NO, SCORE 0

ID	Questions	Yes (2)	Partial (1)	No (0)
Q1	Are the aims of the study clearly stated?			
Q2	Are the scope and context of the study clearly defined?			
Q3	Is the proposed solution clearly explained and validated by an empirical study?			
Q4	Are the variables used in the study likely to be valid and reliable?			
Q5	Is the research process documented adequately?			
Q6	Are all study questions answered?			
Q7	Are the negative findings presented?			
Q8	Are the main findings stated clearly in terms of creditability, validity, and reliability?			

Fig. 2 shows the results of the article quality assessment based on Q score. This graph shows the number of articles (Paper Count) in each Q-score range: 7-8, 9-10, 11-12, 13-14, and 15-16. Articles with scores of 7-8 (orange) have the lowest number, while articles with scores of 15-16 have the highest number, indicating better quality. The dashed red line indicates the limit at which low-scoring articles can be filtered out of the analysis. This graph provides an overview of the distribution of the quality of articles assessed by the Q-score, as well as separates articles that meet certain quality criteria from those that do not, as illustrated in Fig. 3.

Fig. 3 shows the study selection process using the PRISMA method, with the aim of screening and selecting relevant studies for systematic review based on eligibility, accessibility and quality criteria.

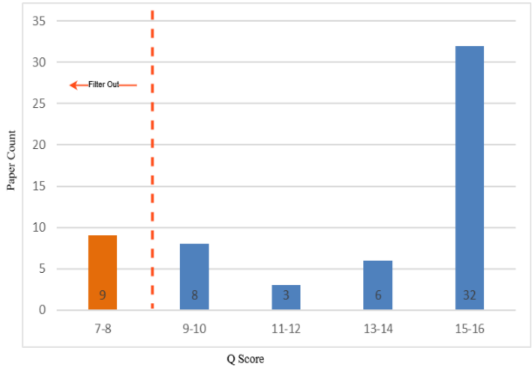

Fig. 2. Quality assessment result

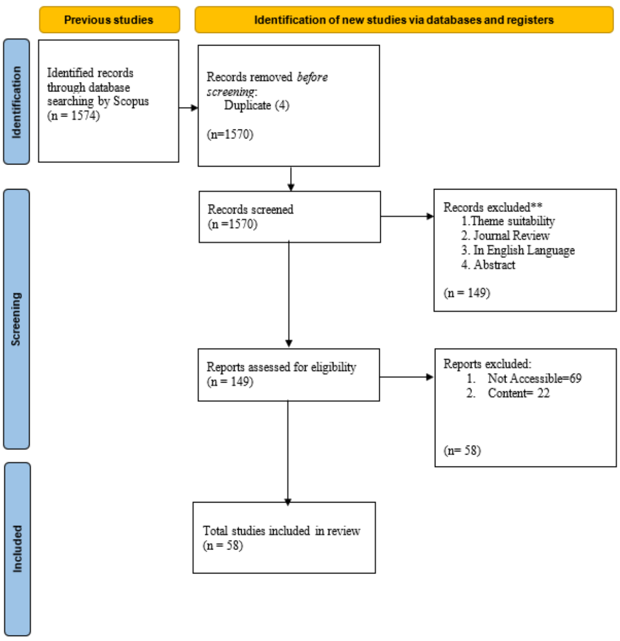

Fig. 3. Selection results using PRISMA

E. Design of Data Extraction Form

The form or template for recording important data from the selected articles, using the PRISMA method in paper selection, aimed to systematically organise information. The recorded data included the author's name, year of publication, methods used in the research, results obtained, and the main conclusions of the article. The PRISMA method assists in screening and selecting relevant articles based on eligibility, accessibility, and quality criteria, thus ensuring that only articles that meet the standards are included in the review. Using this template, the recording process becomes more structured, facilitating analysis and allowing for more efficient comparisons between articles.

F. Data Synthesis and Bibliometric Networks

Once the relevant articles are extracted, the next step is to analyse and synthesise the obtained data, including by using bibliometric analysis (e.g. through Bibliophagy in R). This helps identify major research trends, find key contributors, and map collaboration networks between authors or institutions. In addition, an in-depth review of the selected papers was conducted to obtain important information required in a Systematic Literature Review (SLR), such as key findings, methodologies used, and potential gaps that need to be further explored.

III. Results and Discussion

A. Results

This section presents the answers to the research questions of this study, where each answer is supported by articles obtained from our search results.

1) *RQ1. What are the research trends in image segmentation-based food nutrition assessment in the period 2020-2024 based on bibliometric analysis?*

Based on the graph in Fig. 4, there is a significant upward trend in the number of publications per year. This trend indicates that in the past five years, interest and attention to the application of machine and deep learning for image-based nutritional analysis has increased rapidly, in line with technological developments and the need for innovative solutions in the field of health and nutrition.

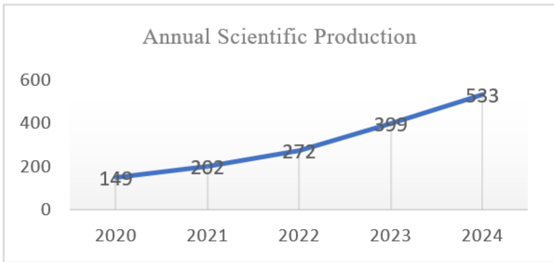

Fig. 4. Research trends 2020-2024

Fig. 5 depicts the trend in the development of research topics from 2020 to 2024 in the field of image-based nutrition analysis and artificial intelligence technologies. Machine learning, deep learning, and food recognition dominated the frequency of term occurrence, with machine learning being the most frequently used. Other terms, such as food nutrition assessment, food segmentation, and obesity prediction, began to appear consistently towards 2024, reflecting the increasing research focus on the application of AI techniques in nutrition evaluation and health prediction. Topics such as diet, computer vision, and natural language processing also showed associations but with lower frequencies. Overall, this graph indicates that the use of machine learning and deep learning-based technologies for nutrition applications has increasingly taken center stage in scientific research in recent years.

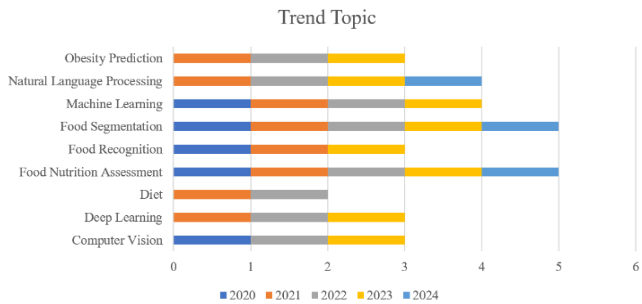

Fig. 5. Topic trends 2020-2024

2) ***RQ2:*** *Who are the main contributors (authors, affiliations or countries) in image segmentation-based food nutrition assessment based on bibliometric data?*

Fig. 6 shows a list of the top 10 most relevant authors based on the number of documents published on topics related to image-based nutritional analysis and artificial intelligence. Author Wang Y takes the top spot with 28 documents, showing a dominant contribution compared to other authors. This is followed by Wang X with 19 documents, and Zhang and Liu Y who produced 18 and 17 documents respectively. Other authors such as Li J, Li Y, Chen Y, and Li S also showed a fairly high level of productivity, with the number of documents ranging from 15 to 18. Meanwhile, He and Huang contributed 12 documents each. This data shows that research contributions in this field are largely driven by the most active group of authors, who play an important role in the development of research related to the application of machine learning and computer vision in nutrition analysis.

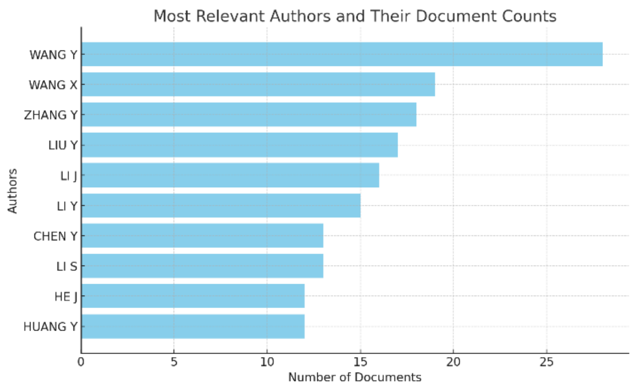

Fig. 6. Top 10 key contributors

Fig. 7 shows the relationship between the author's home institution (AU_UN), author (AU), and home country (AU_CO) for research topics related to image-based nutrition analysis and artificial intelligence. It can be seen that most of the top 10 authors, such as Wang Y, Wang X, Li S, Liu Y, and Zhang Y, are affiliated with institutions in China, such as the University of Electronic Science and Technology of China and Capital Medical University. The majority of the scientific work produced by these authors comes from China, followed by contributions from the United States and a small number from Germany, Canada, the United Kingdom, and Italy. This graph shows that China is the largest contributor to this field of research, with the United States as the second largest contributing country. This highlights the dominance of Chinese institutions and researchers in the development of machine- and DL-based research for nutrition analysis.

Fig. 8 shows that the darker the color, the higher the number of publications in that year. From this map, it can be observed that China, India, and the United States are the countries with the highest scientific contributions, as represented by the darkest blue shades. Countries such as South Korea, Brazil, the United Kingdom, and Australia also appear relatively active, as shown in medium blue tones. In contrast, most countries in Africa, the Middle East, and parts of Southeast Asia, including Indonesia, show low or undetected levels of contribution (represented in gray), indicating limited involvement in the scientific publications on this topic. This visualization reinforces that global scientific production in this field remains concentrated in developed countries and several Asian nations with strong research capabilities.

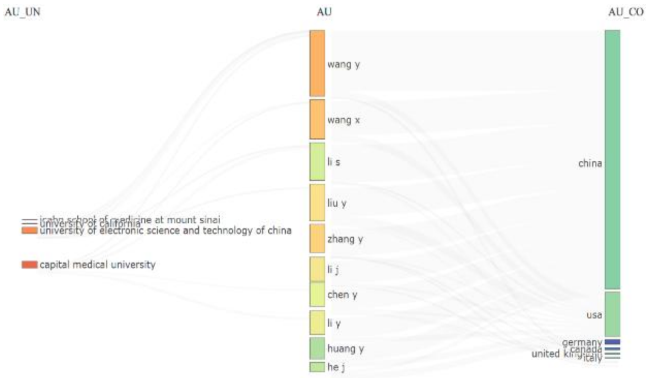

Fig. 7. Relationship between author, affiliate and country

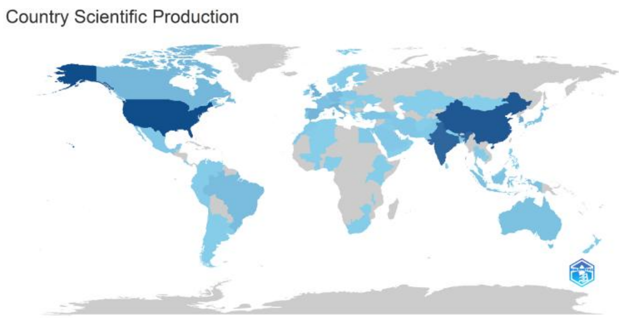

Fig. 8. Country scientific production

3) *RQ3: What are the common and current methods used for image segmentation-based food nutrition assessment in the current literature during the period 2020-2024?*

Table III lists the methods commonly used in studies related to Deep Learning and Machine Learning. In the Deep Learning category, the most commonly used algorithms include convolutional neural networks (CNNs) with various variations, such as ResNet 50, ResNet 101, ResNet 152, and ResNet 18, as well as the You Only Look Once (YOLO) algorithm with various versions (v4-v8), Faster RCNN, MobileNet, and Inception V3 and V4. These methods have been widely applied in various studies [35] [76].

TABLE III. COMMONLY USED METHODS

Metode	Study ID	Top Used Algorithms
Deep Learning	[33], [36]–[40], [49]–[52], [57]–[61], [64], [65], [67]–[71], [73], [87]–[89], [91]–[94], [97]–[101], [103], [105], [108]–[110], [113], [114]	CNN, ResNet 50, ResNet 101, ResNet 152, ResNet 18, YOLO (v4-v8) Faster RCNN, MobileNet, Inception V3, Inception V4,
Machine Learning	[33], [35], [36], [50]–[53], [57]–[59], [61]–[65], [67], [69], [71], [87]–[91], [93], [95]–[99], [103], [105], [108], [110], [113], [114]	Neural Network, Random Forest, KNN, SVM, K-Means, Naïve Bayes, XGBoost.

In the machine learning category, the methods used are more varied, ranging from neural network, random forest, Knearest neighbours (KNN), support vector machine (SVM), K-Means, Naïve Bayes, to the XGBoost algorithm. These algorithms are widely applied in research recorded between. These two methods demonstrate the importance of using the correct technique according to the characteristics of the data and research objectives.

4) *RQ4: What are the most commonly reported limitations of studies?*

An analysis of 49 studies showed that the main limitations of image segmentation-based nutrition assessment include limited datasets, low segmentation accuracy, especially for overlapping foods, and difficulty in estimating volume without depth information. Many models still rely on manual annotation, lack generalisability, and are not integrated in an end-to-end manner. In addition, most studies have not been validated under real-world conditions and have only focused on specific types of food, limiting their wide applicability in daily dietary practices. A full description of these limitations can be seen in Table IV.

TABLE IV. STUDY LIMITATIONS ANALYSIS RESULTS

Categories of Limitations	Description	Studies
Limited Datasets (Size and Variety)	The food datasets used are small, unrepresentative and lack cultural diversity	[96], [52], [114], [101]
Errors in Food Segmentation/Detection	Difficulty in detecting foods with complex shapes, occlusion, or similar visuals	[89], [92], [93]
Inaccurate Volume and Weight Estimation	Difficulty estimating food volume/weight from 2D images without depth information	[69], [70], [113], [73]
Reliance on Manual or Semi-Automatic Annotation	Some models still need manual labeling (bounding box or food class)	[63], [89]
Limitations of Model Generalization	Model works well on own dataset but performs poorly on other public datasets	[93], [109], [90], [114]
Absence of Precision Nutrition Ground Truth	Nutritional information comes from lookup tables, not actual measurements, leading to inaccuracies	[49], [92], [97], [59], [91], [110]
Nutrition Estimation Not Real-time or Not Integrated	Pipeline is still separate: lookup classification detection, not yet end-to-end	[33], [39], [58], [62], [73], [87]
Limited to Certain Food Categories	The system is only able to recognize certain types of food (for example: only Thai, Indian, etc.)	[33], [37], [59], [69], [71], [96], [103], [109], [69], [93], [103]
Lack of Field Validation (Real World)	Models have not been tested in real environments such as restaurants, homes, or mobile applications	[62], [33], [63], [67], [89]

The following table summarises the results of the analysis of the limitations found in various studies related to food detection and nutrition estimation. One of the main limitations is the limited size and variety of datasets, where many studies rely on small or homogeneous datasets that are not culturally representative, affecting the generalisability of models across different populations and food types. Studies by [82], [73], [43], and [76] emphasised the need for diverse datasets to make food detection systems more robust and applicable across different cultures. Another challenge is segmentation or detection difficulties for foods with complex shapes or occlusions, especially when foods have irregular shapes or are partially hidden. Research by [61], [59], and [54] highlights that models struggle to detect foods that look visually similar or when multiple food items are placed together, leading to detection or segmentation errors.

Additionally, estimating food volume and weight is often inaccurate, particularly when using 2D images without depth information. Studies by [35], [40], [44], and [41] show that such estimates can be significantly inaccurate, undermining the practical application of these systems for nutritional assessment, especially when depth sensors are unavailable. Another limitation is the reliance on manual or semi-automatic annotation. Many models still depend on manually annotated datasets or semi-automatic methods, such as bounding boxes or food class labels. Research by [77], [61], and others shows that this approach is time-consuming and prone to human error, limiting the scalability and accuracy of the food detection models. Many models perform well on specific datasets but poorly on others, indicating poor cross-dataset performance. Studies by [43], [54], [64], and [80] highlight that food detection systems are often overfitted to the datasets on which they were trained and do not generalise well to diverse, real-world data. Nutritional information inaccuracies also pose a problem, particularly those derived from lookup tables, which can lead to inaccuracies in nutritional estimation. Studies by [45], [53] [55], [59], [65] and [66] have pointed out that reliance on lookup tables often results in imprecise estimates because the data in these tables are often outdated or incomplete. Furthermore, many food detection systems are still not real-time or integrated, with separate pipelines for detection, classification, and nutritional information lookup. Research by [36], [41], [47], [48], [70], and [81] identifies this issue, where having separate processes for each step hinders the practical use of these systems in dynamic environments. Limited food category recognition is also an issue, with some models capable of recognising only specific food categories, such as Thai or Indian foods. Studies by [40], [42], [54], [64], [65], [67], [70], [72], and [82] show that such limitations restrict the general applicability of food detection systems, making them less useful for broader and more diverse food recognition tasks. Finally, the lack of field validation in real-world environments, such as restaurants, homes, or mobile apps, remains a significant issue. Research by [61], [69], [70], [77], and [81] emphasises the importance of testing food detection and nutrition estimation systems in real-world settings to ensure that they perform as expected outside controlled environments.

5) *RQ5: What future research directions have been proposed in the literature related to food image segmentation?*

Future research on food image segmentation should focus on several key areas to overcome these challenges. First, the datasets used in these systems must be improved to make them more diverse and representative of different food types from various cultures, as emphasised by [24], [25]. Additionally, segmentation algorithms must be refined to detect foods with complex or occluded shapes more accurately. This improvement is essential to ensure that the system can handle a wider range of food types in the future. Furthermore, the estimation of food volume and weight needs to be enhanced, potentially by incorporating 3D technology to achieve more precise results, as suggested by studies such as [43], [54], [64], and [80]. This would provide a more accurate assessment of food quantities, which is crucial for nutritional analysis. Another crucial area for development is reducing the reliance on manual annotations. Instead, systems that can autonomously estimate nutrient content in real time and in an integrated manner are required. This could involve combining the detection, classification, and nutrient lookup processes into a seamless pipeline, as noted by [36], [41], [47], [48], [70], and [81]. Moreover, future systems should be designed to recognise a broader range of food types, including foods from various countries, to ensure universal applicability and cultural inclusivity. Finally, real-world validation of these findings is crucial. Testing models in everyday environments, such as restaurants, or through mobile apps is essential to ensure that these systems perform effectively in real-life situations, as highlighted in [61], [69], [70], [77], and [81]. This would help identify and address any limitations when the system is used outside a controlled environment.

IV. Conclusions

This study highlights the critical role of food image segmentation as a foundational component of computer vision-based automated nutritional assessment systems. Through a systematic analysis of literature published between 2020 and 2024 sourced from the Scopus database, we observed a significant increase in the adoption of deep learning technologies, particularly convolutional neural networks (CNN) and YOLO, for image-based food recognition and nutrient estimation. Research in this field is predominantly driven by institutions and researchers from China, indicating high productivity but also raising concerns regarding regional publication bias and limited global representativeness. This review also identifies several recurring limitations in existing studies, including small and culturally homogeneous datasets, challenges in segmenting visually complex or overlapping foods, and inaccurate volume and nutrient estimations due to the lack of depth information in two-dimensional (2D) images. Many systems continue to rely on manual annotation, lack end-to-end integration, and have not been validated in real-world settings, factors that significantly constrain their applicability in everyday nutritional monitoring. This review provides a structured classification of segmentation methods and outlines strategic directions for future research. These include the development of more inclusive and culturally representative datasets, enhancement of segmentation algorithms capable of handling shape variation and occlusion, incorporation of 3D imaging technologies for more accurate volume estimation, and design of lightweight models suitable for real-time mobile deployment. Furthermore, practical validation in real-world environments, such as restaurants, households, and healthcare settings, is essential to ensure usability and impact. This study also explicitly acknowledges methodological limitations, such as potential selection bias in the screening process, subjectivity in quality assessments (despite being independently conducted by five reviewers), and the constraints of relying solely on Scopus-indexed bibliometric data, which may affect the findings' completeness and generalizability. For future research, we recommend strengthening interdisciplinary collaboration between computer science, nutrition, cultural anthropology, and public health to ensure that the systems developed are technically robust and socially and culturally relevant. Future food image segmentation systems should aim to develop fully integrated architectures that operate efficiently and in real time. User-centred testing in real-world environments is strongly encouraged to assess the usability, accuracy, and acceptance of the system. In addition, establishing standardized evaluation metrics and open benchmarking protocols will be crucial for enabling fair comparisons across different models and approaches. With these developments, food image segmentation technology can evolve into a more inclusive, adaptive, and impactful tool for addressing global nutritional challenges.

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