11-24-2020

A Systematic Literature Review With Bibliometric Meta-Analysis Of Deep Learning And 3D Reconstruction Methods In Image Based Food Volume Estimation Using Scopus, Web Of Science And IEEE Database

Prachi Kadam
Symbiosis Institute of Technology, prachi.kadam@sitpune.edu.in

Nayana Petkar
Symbiosis Institute of Technology, nayana.petkar.mtech2019@sitpune.edu.in

Shraddha Phansalkar Dr.
Symbiosis Institute of Technology, shraddhaphansalkar@gmail.com

A Systematic Literature Review With Bibliometric Meta-Analysis Of Deep Learning And 3D Reconstruction Methods In Image Based Food Volume Estimation Using Scopus, Web Of Science And IEEE Database

Prachi Kadam
Research Scholar and Assistant Professor, Symbiosis Institute of Technology (SIT), Symbiosis International Deemed University, Pune, India
Email: prachi.kadam@sitpune.edu.in

Nayana Petkar
Postgraduate Student, Symbiosis Institute of Technology (SIT), Symbiosis International Deemed University, Pune, India
Email: nayana.petkar.mtech2019@sitpune.edu.in

Dr. Shraddha Phansalkar
Associate Professor, Symbiosis Institute of Technology (SIT), Symbiosis International Deemed University, Pune, India
Email: shraddhaphansalkar@gmail.com

A Systematic Literature Review With Bibliometric Meta-Analysis Of Deep Learning And 3D Reconstruction Methods In Image Based Food Volume Estimation Using Scopus, Web Of Science And IEEE Database

Abstract

Purpose- Estimation of food portions is necessary in image based dietary monitoring techniques**.** The purpose of this systematic survey is to identify peer reviewed literature in image-based food volume estimation methods in Scopus, Web of Science and IEEE database. It further analyzes bibliometric survey of image-based food volume estimation methods with 3D reconstruction and deep learning techniques.

Design/methodology/approach- Scopus, Web of Science and IEEE citation databases are used to gather the data. Using advanced keyword search and PRISMA approach, relevant papers were extracted, selected and analyzed. The bibliographic data of the articles published in the journals over the past twenty years were extracted. A deeper analysis was performed using bibliometric indicators and applications with Microsoft Excel and VOS viewer. A comparative analysis of the most cited works in deep learning and 3D reconstruction methods is performed.

Findings: This review summarizes the results from the extracted literature. It traces research directions in the food volume estimation methods. Bibliometric analysis and PRISMA search results suggest a broader taxonomy of the image-based methods to estimate food volume in dietary management systems and projects. Deep learning and 3D reconstruction methods show better accuracy in the estimations over other approaches. The work also discusses importance of diverse and robust image datasets for training accurate learning models in food volume estimation.

Practical implications- Bibliometric analysis and systematic review gives insights to researchers, dieticians and practitioners with the research trends in estimation of food portions and their accuracy. It also discusses the challenges in building food volume estimator model using deep learning and opens new research directions.

Originality/value- This study represents an overview of the research in the food volume estimation methods using deep learning and 3D reconstruction methods using works from 1995 to 2020. The findings present the five different popular methods which have been used in the image based food volume estimation and also shows the research trends with the emerging 3D reconstruction and deep learning methodologies. Additionally, the work emphasizes the challenges in the use of these approaches and need of developing more diverse, benchmark image data sets for food volume estimation including raw food, cooked food in all states and served with different containers.

Keywords: Image based food volume estimation, 3D reconstruction, Deep Learning, Bibliometric analysis, PRISMA.

1. Introduction

With increase in stress at work and hectic lifestyle, there is rising threat of lifestyle disorders. However, with rise in alarming health issues, there is an awareness to monitor and control the adverse effects on health. There is rise in awareness and importance of maintaining health via good eating habits and exercise. This is achieved by using various dietary assessment tools [1].

For dietary monitoring, the dieticians or nutritionists would ask the patient to maintain food diaries which had self-logged entries of food consumed in entire day. One such dietary assessment system is 24-hour dietary recalls (24 HR). This is used to monitor daily food consumption. But there are limitations to this self-logged method – erroneous recording of data or inaccurate entry of portion size thus leading to incorrect calculations of calorie count [2]. A textual entry of food logs like most of the applications such as HealthifyMe needs user interaction and manual inputs of food items to enter type of food or volume/quantity of food consumed [3].With explosion in various digital devices like – tabs, mobiles, digital wearable devices, and smartphones, the usage of digital and automated methods also have become abundant [4]. There are various applications which provide an automated platform for maintaining diet logs.

Food portions refer to the quantity of food consumption during meals. For packed foods, package sizes are definite and portions are calibrated in terms of net weights. The energy is then measured in terms of calories. For non-packaged food, portion size needs to be estimated. Some of the dieticians and practitioners log the food quantity in terms of container sizes (bowls, teaspoons, table spoons). Most of these containers are mapped to some approximate weights and nutrition labels. There is absence of standardization in calibrations of food portion. Hence there is a need of estimating the food portions in terms of weight or volume.

An image based Food Volume Estimation (FVE) aims to take images or videos of food images to perform image based modelling techniques including segmentation, depth measurement, displacement and calibrate the quantity of the food using image. Most of these techniques estimate the food quantity with its volumetric measures. However, there is a need to look at the accuracy of these estimates. A precise volumetric estimation relies on proper image acquisition, image processing and volume calibration. An image-based food logging method and its variants are discussed in [5] where user takes a picture of the food-dish eaten in a day through a dietary assessment application. This application then identifies a food item, estimates its volume and calculates the calorie count. This is subject to limitations of lesser variations, less accuracy and robustness.

Accuracy of image based dietary assessment and food quantity estimation can be increased with the help of advanced methods in computer vision and deep learning methods [5]. Computer vision methods are backbone of image-based dietary assessment tools which allow more precise estimate of food intake with nutrition and calorie assessment. The fact that these automated methods have least human intervention, subject to lesser perception errors, increases the probability of exact estimate of consumed food and its equivalent calories. But implementation of such image-based dietary assessment tools depends on computer vision based learning algorithms for an automated flavor [6].

1.1 Significance and Objectives

A study of image based FVE methods is thus necessary for analysis of accurate, precise and user-friendly dietary management methods. Besides a taxonomy of the existing estimation methods needs to be surveyed for selecting a better model. 3D reconstruction and Deep Learning (DL) methods are the emerging areas and show rising applications in other use cases of dietary management like food classification. Hence there is also need to see the applicability of these methods in food portion estimation.

3D reconstruction method uses depth camera to reconstruct the food item or cameras placed at various angles to reproduce a 3D image of the food item [7]. Deep learning has emerged as one of the best methods applied to computer vision on various image types. Deep learning methods have ability to learn from the existing image dataset (train data set), extract features from constructed images like depth, texture, boundaries of the food image and estimate its volume [8].

Besides learning algorithm, an important factor for accurate estimation of food volume from image sets, is the robust image data set that is used for training the model used in the application. The presented work evaluates the literature with the richness of the data set. Higher errors in estimation will highlight need for a robust and diverse dataset that encompasses wide range and coverage of food-item images.

Although there has been significant works done in food volume estimation, a review on image based food volume estimation and analyzing its accuracy is important. Secondly with the recent 3D modelling techniques and deep learning approaches, a deeper review of the work in this field will elicit the research opportunities and scope of future work. The following systematic literature review is complementary to the existing literature and provides contributions to the researchers, practitioners, dieticians, application developers interested in dietary management with respect to qualitative and quantitative meta- analysis of image based food volume estimation approaches. The research work undertaken can be summarized precisely by answering the formulated research questions as shown in the Table 1.

Table 1. Research question with its significance

Research Question	Significance of research question
What are the state-of-art strategies in image-based food volume estimation in the literature?	A clustering of similar strategies will help analyze the performances for different food types.
What are the research trends in the literature of food volume estimation methods?	The popularity and recentness of the area will be established with PRISMA search. Bibliometric analysis will elicit research trends
What are the different 3D reconstruction methods used in food volume estimation?	3D reconstruction is model based approach to FVE. Different methods will help in analyzing the applications and evaluate the performances
What are the different deep learning methods used in food volume estimation?	Deep Learning techniques have been already established in dietary monitoring. Deep Learning techniques is emerging area that can be applied for image based FVE.

Understanding a research area and evaluating its scope, is necessary to perform a systematic review to uncover the trends, challenges and future work. The paper is organized as – systematic review of existing research in the area of FVE by using PRISMA methodology and Bibliometric analysis which is discussed in section 2 and section 3 followed by detailed discussion of the outcome from the review and detailed answers of the research questions in section 4; future works is discussed in section 5 followed by limitations of the study are mentioned in section 6 to explain the scope of the study.

2. Research Methodology

For analyzing a research topic, with its recentness, research trends and scope of further research, a systematic literature review is desirable. For finding answers to the research questions laid, in the objectives two standard methods are applied – PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) and Bibliometric Analysis.

We used the PRISMA approach to select the works in the image based food volume estimation from popular scientific data bases with clear inclusion and exclusion criteria and quality assessment.

A bibliometric study was then carried out on shortlisted works for meta-analysis in terms of geographical distribution, affiliation, top citations in Scopus and Web of Science. It is desirable to have complete knowledge about the authors, citations and affiliations. This offers clarities to researchers in knowing current state-of-art and strategizing future goals in the research field. Here bibliometric analysis was done in two phases:

Phase 1: Bibliometric Analysis of Image-based Food Volume Estimation using Scopus and WoS

This phase aims to show the research trends in the food volume estimation with image based approaches. Only peer viewed original articles, application papers were included in the study. The search keyword used for this purpose were – Food Volume Estimation.

Phase 2: Analysis of Food Volume Estimation on 3D reconstruction and Deep learning method using Scopus and WoS

This phase aims to show research trends in deep learning and 3D reconstruction methods for image based food volume estimation methods. The search keywords were augmented with these qualifiers.

2.1 PRISMA Approach

PRISMA is a standard method to give a systematic review for existing research. We adopted this method to conduct a systematic review and evaluated the research in the area of – *Food Volume Estimation* for food images. PRISMA flow chart is as shown in the figure 1.

A) Screening Criteria Strategy

The articles are reviewed over the period of 1950 to 2020, across databases like:

- Web of Science
- KCI
- Russian Science Citation Index
- SciELO
- Scopus
- IEEE Xplore Digital Library

The keyword search was “Image based food volume estimation”. (*food volume estimation* OR *image based* OR *dietary management*)

The searches were run against the title, keywords, abstract of the works in different databases separately. They were conducted on 20 Oct 2020 and we have included all the studies till Oct 2020.

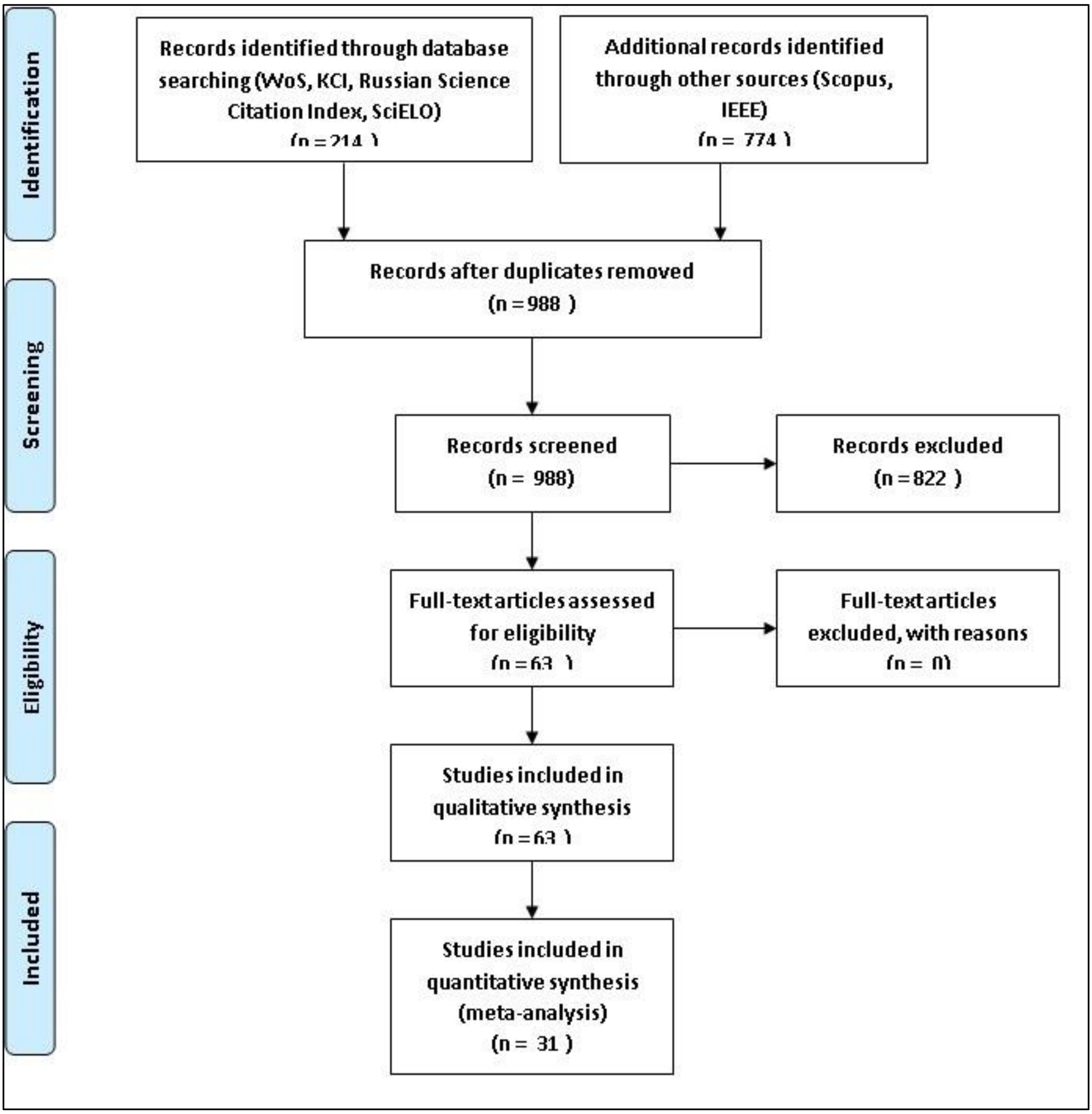

Figure 1. PRISMA flowchart for Systematic Review of Food Volume Estimation

B) Inclusion and Exclusion Criteria

Only peer-review articles, and articles written in English were taken. The papers focusing on image based food volume estimation for dietary management were included. All the papers which referred to non-image based approaches to the food volume estimation were excluded. The databases furnished results with the search – food volume estimation of 988 publications, out of which the duplicates were removed. These duplicates consisted of same articles with varied reference format of author details. Once the duplicates were removed, the search results were screened on the basis of articles related to food volume estimation done on the basis of food images and related to dietary assessment only. Thus out of total 978 articles 822 articles were excluded which were not from the area of interest and whose full articles were not available. The focus was on 63 articles found from the screening process.

Total 63 articles were included for further study from the previous screening process. From a detailed study of these articles, it was found that 3D reconstruction and deep learning methods were the recent cutting edge areas in the literature. The study shows results that could be further deliberated in this area. Thus, only the 31 articles which included the 3D reconstruction method and deep learning methods for image-based food volume estimation were included for meta-analysis.

C) Quality Assessment

The quality assessment process was carried out to see the efficacy of the searched works. This was done manually and the following criteria were used:

1) Dietary Management: Paper focusses on the dietary management were considered, as the calorific conversion of the volume was the context of our work.
2) Image based estimation approaches: The paper must emphasize and discuss a method for an image based approach to food volume estimation.
3) Data sets: The details on how data was acquired, diversities of the image data set were analyzed.
4) Performance: As the domain targets estimation, accuracy in prediction was the main performance criteria for assessing the work.

A critique to our findings is discussed in discussion section.

3. Bibliometric Analysis

Phase A: Bibliometric Analysis of Image-based Food Volume Estimation using Scopus and Web of Science

From PRISMA methodology of systematic review the articles to be included for further study were found. But to answer the research questions on qualitative and quantitative categories, we conducted meta-analysis of the works. To understand the importance of the topic with respect to – number of publications per year, per country, per subject area, number of citations could be carried out in more depth by supporting this systematic review with bibliometric analysis. Thus, in this section, a detailed bibliometric analysis of articles received from SCOPUS and Web of Science (WoS) is focused upon.

3.1 Analysis of Keywords

Table 2. List of all Keywords

Keywords Sets	Keywords
Keywords_Set1	“dietary assessment” OR “volume estimations” OR “Diet” OR “dietary intake” OR “nutritional assessment” OR “food intake” OR “obesity” OR “adult”
Keywords_Set2	“image processing” OR “estimation” OR “image segmentation” OR classification” OR “food segmentation” OR “diet records” OR “segmentation” OR “mobile devices” OR “human” OR “portion size”
Keywords_Set3	“food volume estimation” OR “3D reconstruction” OR “calorie intake” OR “cameras” OR “computer vision” OR “dietary intakes” OR “controlled study” OR “protein”
Keywords_Set4	“environmental exposure” OR “analysis” OR “smartphone” OR “risk assessment” OR “deep learning” OR “energy intake” OR “medical records” OR “diseases” OR “food recognition” OR “feature extraction” Or “mobile applications” OR “image texture”
Keywords_Set5	“portion size estimation” OR “single image” OR “food analysis” OR “parameter estimation” OR “vision-based approaches” OR “2D images” OR “calcium intake” OR “calibration” OR “body weight”

The list of all keywords is derived from notable databases like Scopus and Web of Science. Here, the primary keywords are food volume estimation and deep learning, and the secondary keywords are dietary assessment, food recognition, calorie intake, 3D reconstruction. The keywords used in this bibliometric analysis regarding food volume estimation are depicted on the above Table 2, in which the set of keywords are used with “AND” or “OR”.

3.2 Analysis of Publication in Food Volume Estimation

Scopus database generated around 103 publications which were in English, Chinese and German languages. Before 2009, there were relatively low publications regarding food volume estimation, but steadily increase from year 2009 to 2020. Whereas, WoS database generated around 66 publications which were in English and German languages. As compared to Scopus, in WoS, before 2011, there were relatively low publications regarding food volume estimation. From country-wise publications, it is concluded that India’s publication in WoS is relatively low. Table 3 shows the country-wise publication for Scopus. Table 4 shows the country-wise publication for WoS.

Table 3. Top 10 Countries in Publications for Scopus

Country	No. Of Publications
United States	31

China	12
Japan	9
Switzerland	8
Australia	6
India	5
Italy	5
United Kingdom	5
Germany	4
Taiwan	4

Table 4. Top 10 Countries in Publications for WoS

Country	No. Of Publications
United States	28
England	7
Australia	6
China	6
Switzerland	5
Spain	4
Italy	3
Japan	3
France	3
Norway	3

Publication types published in this research field in Scopus are article, book chapter, conference review, review, and conference paper. In this review analysis, publications were 103 out of which 48 articles, 48 conference paper and 4 conference review, 2 review and 1 book chapter documents were there. However, publication types in this research field in WoS are articles, review, meeting abstract, proceedings paper and correction. In WoS, publications published were 66 out of which 59 articles, 5 reviews,1 meeting abstract, 1 proceedings paper and 1 correction documents were there. Figure 2 and 3 shows the document type indexed by Scopus and WoS respectively.

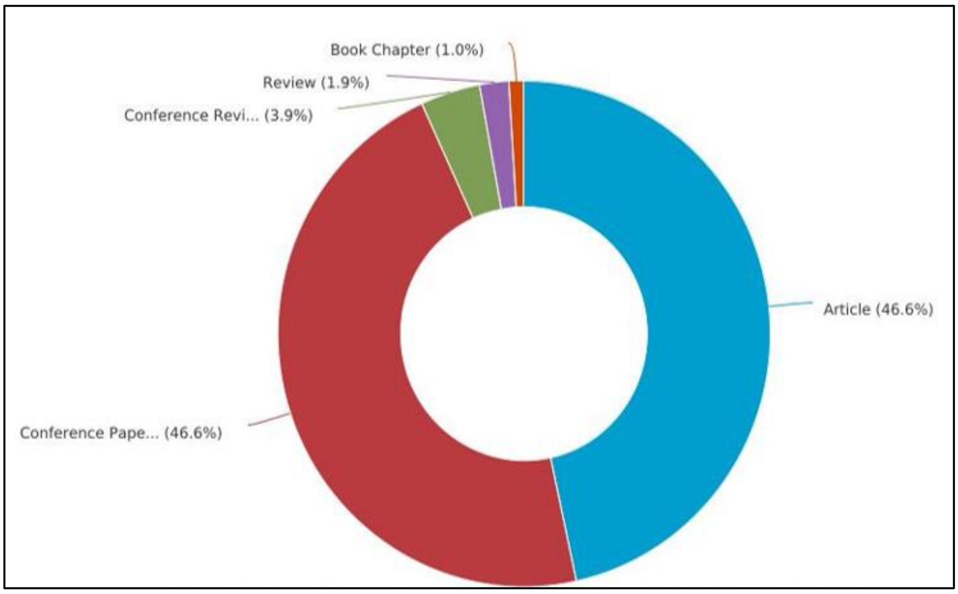

Figure 2. Publication types indexed Scopus

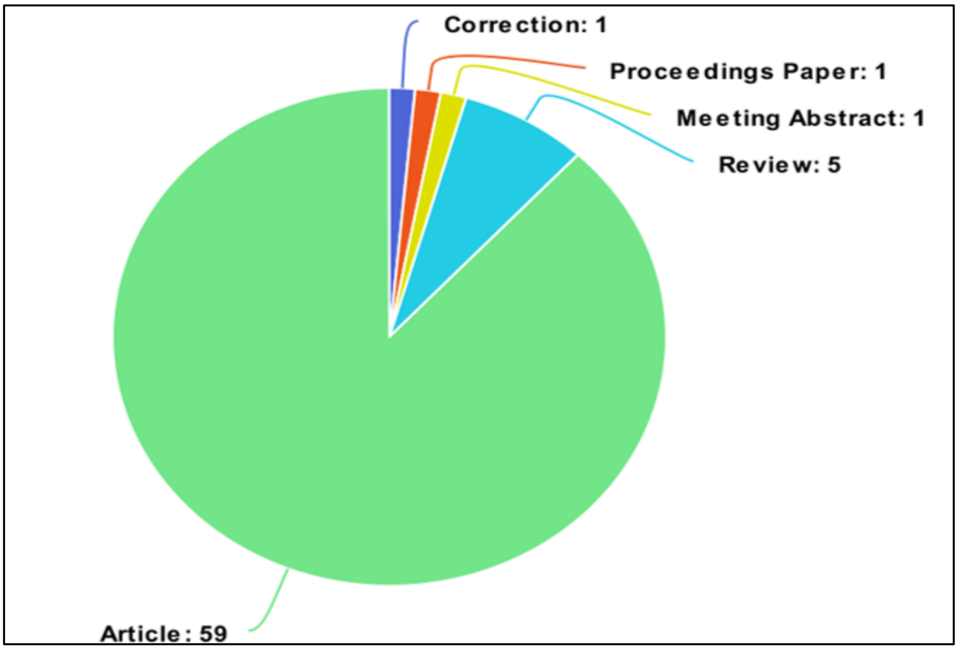

Figure 3. Publication types indexed by WoS

3.3 Analysis by Year

The document published in Scopus before 2009 were relatively low because of following reasons - less awareness of health, fewer applications to monitor health related parameters and lesser technological advancement to support the field of food volume estimation. After this period, there were slightly increase in the growth of machine learning which results in more publications than earlier years. The average publication is made after 2009. The highest number of publications were in 2019 and the number is increasing. In WoS, document published before 2011 is relatively low. After 2011, there is steadily increase in publication. The highest number of publications were in 2019 and the number is increasing. Figure 4 and 5 shows the publications per year in Scopus and WoS respectively.

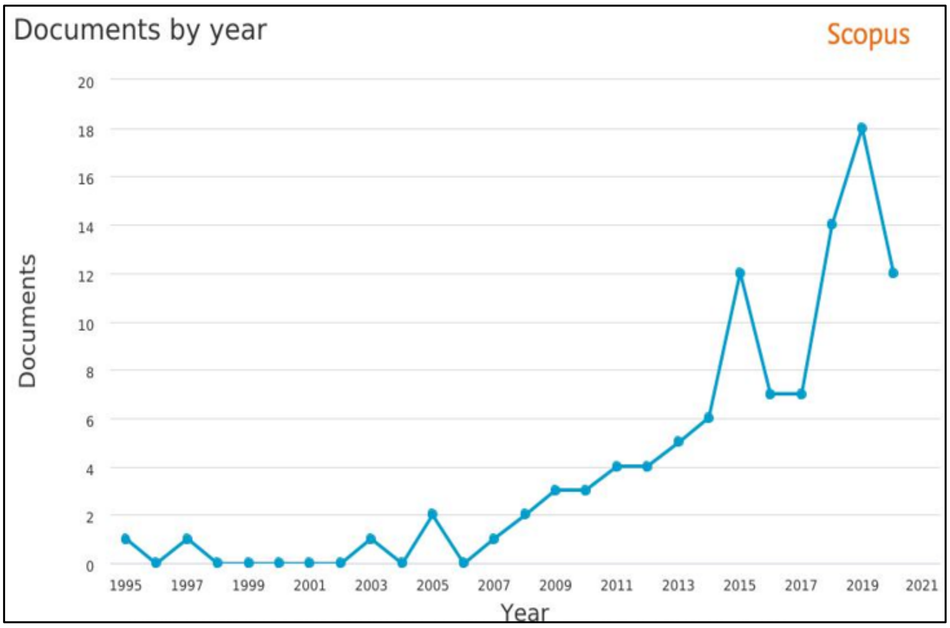

Figure 4. Number of publication indexed by Scopus

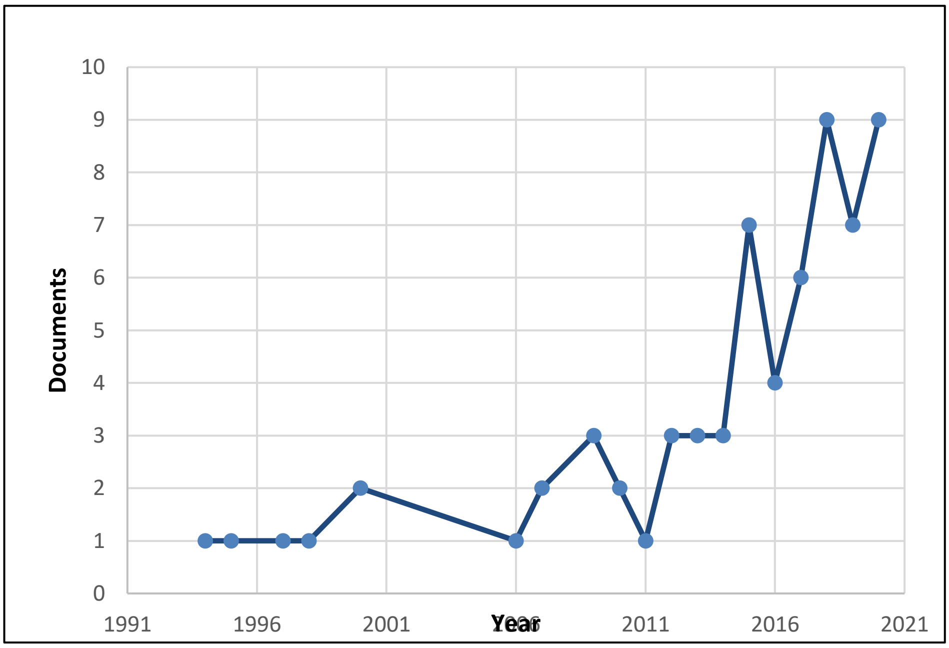

Figure 5. Number of publication indexed by WoS

3.4 Analysis by Geographic Location

The geographical location of published paper is drawn by using imapbuilder tool. This map shows countries along with their respective number of publications. Figure 6 and 7 shows the Satellite view of the geographical location of the research areas. From the figures, it is observed that research publication in Scopus is found across all continents, whereas in WoS, European countries has highest number in publication in this research field.

Figure 6. Satellite view of Geographical Locations of research areas for Scopus

Figure 7. Satellite view of Geographical Locations of research areas for WoS

3.5 Analysis by Subject Area

Figure 8 and 9 shows the subject area-wise distribution in the field of FVE for Scopus and WoS respectively. In Scopus, computer science has highest number of publications were 53 documents followed by engineering with 47 documents, mathematics with 20 documents etc. In WoS, engineering has the highest number of publications with 21% of overall documents followed by food science technology with 17%, computer science with 9 %, Nutrition Deictics with 8% and rest less than 7%.

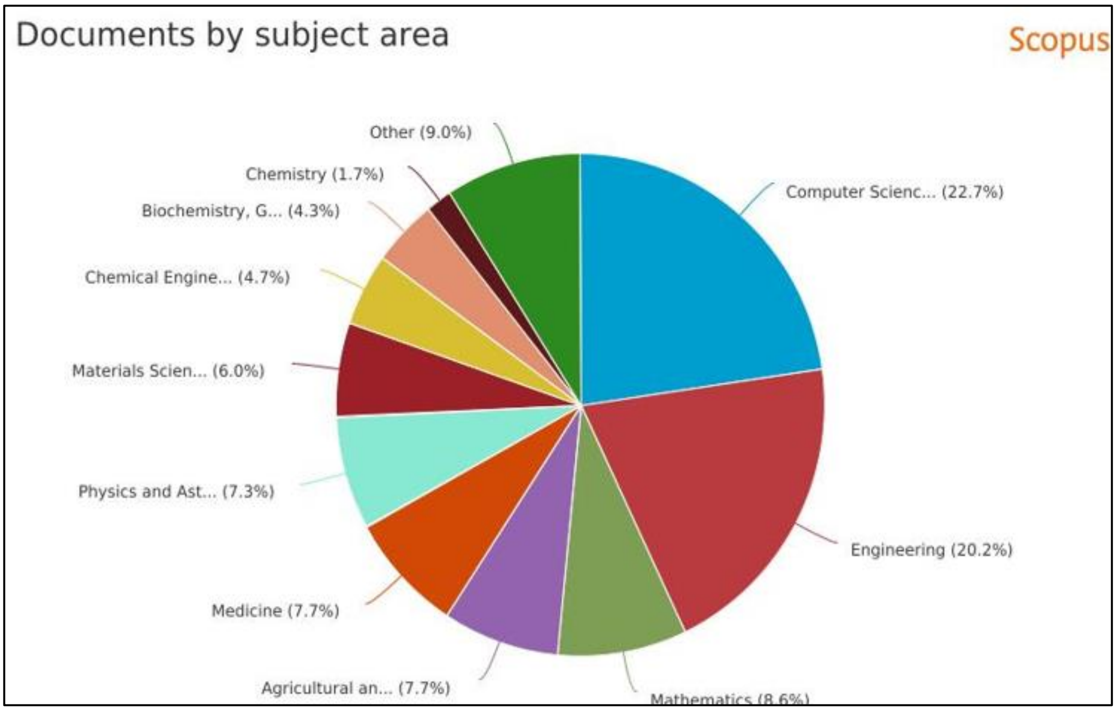

Figure 8. Analysis of documents by subject areas for Scopus

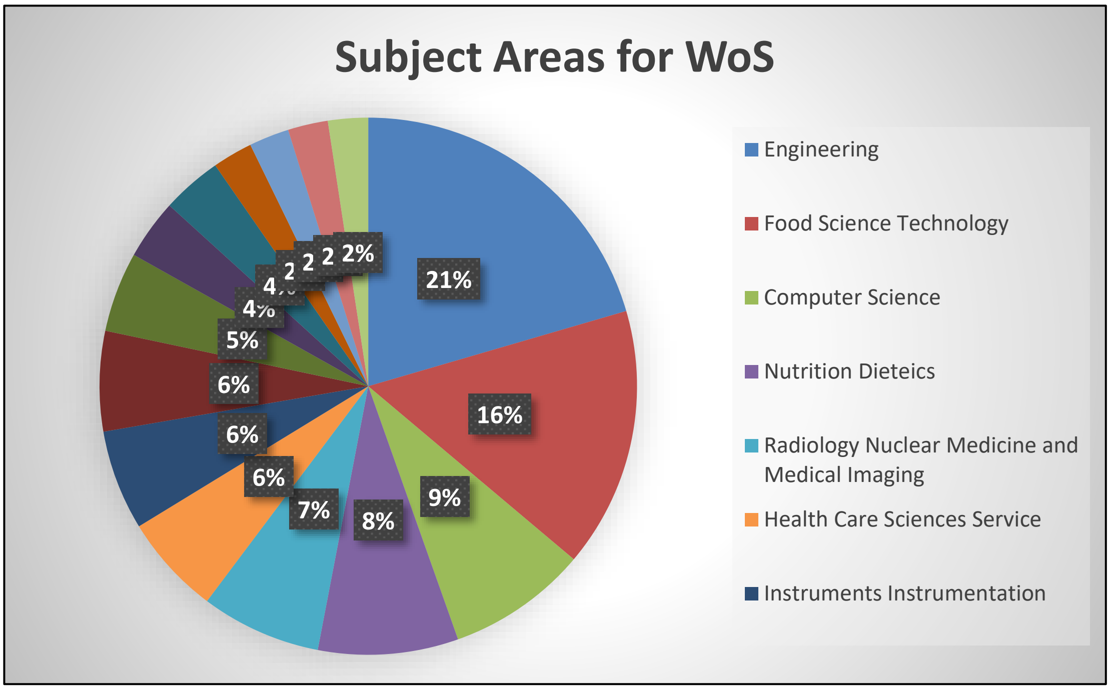

Figure 9. Analysis of documents by subject areas for WoS

3.6 Network Analysis

Analysis of networks in bibliometric research is very important. Network analysis is a collection of graphs which represents association between various factors. Gephi, Table2Net, and VOS viewer are the tools used to drawn different types of networks regarding food volume estimation. The data which is used to drawn this network representation was extracted from popular databases Scopus and WoS. All data files imported in this tool are in Comma Separated Values (.csv) format. Figure 10 and 11 shows the contribution of authors in the research field which is drawn using VoS viewer. Figure 12 and 13 shows the affiliation for organization or universities contributing in this research field which is drawn using Gephi and Table2Net.

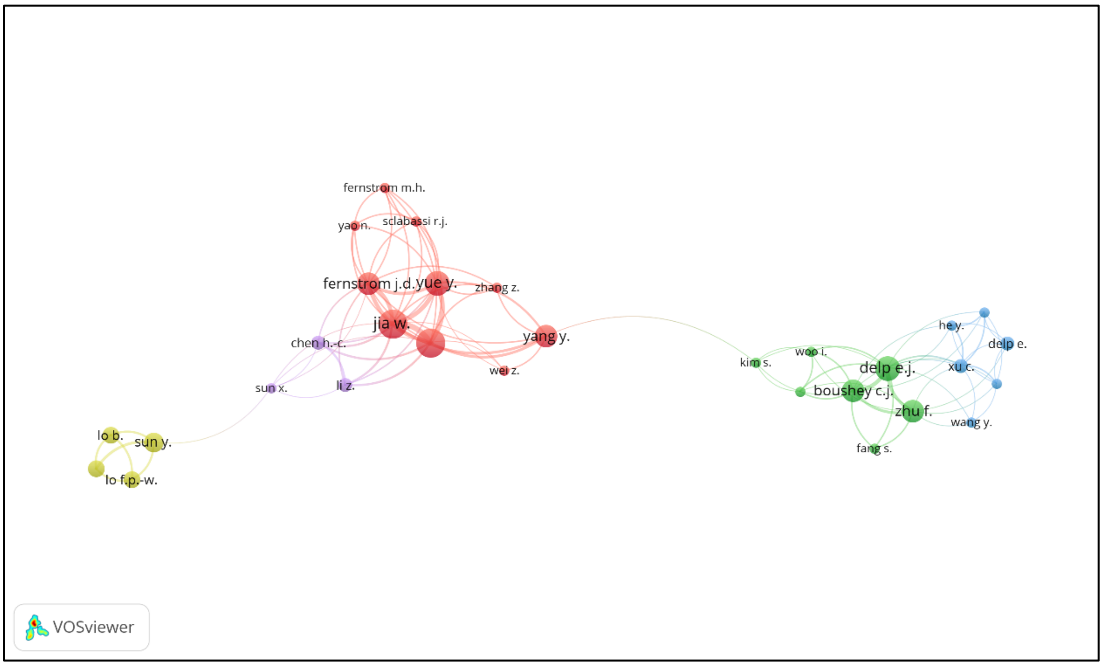

Figure 10. Analysis of Author's Contribution for Scopus

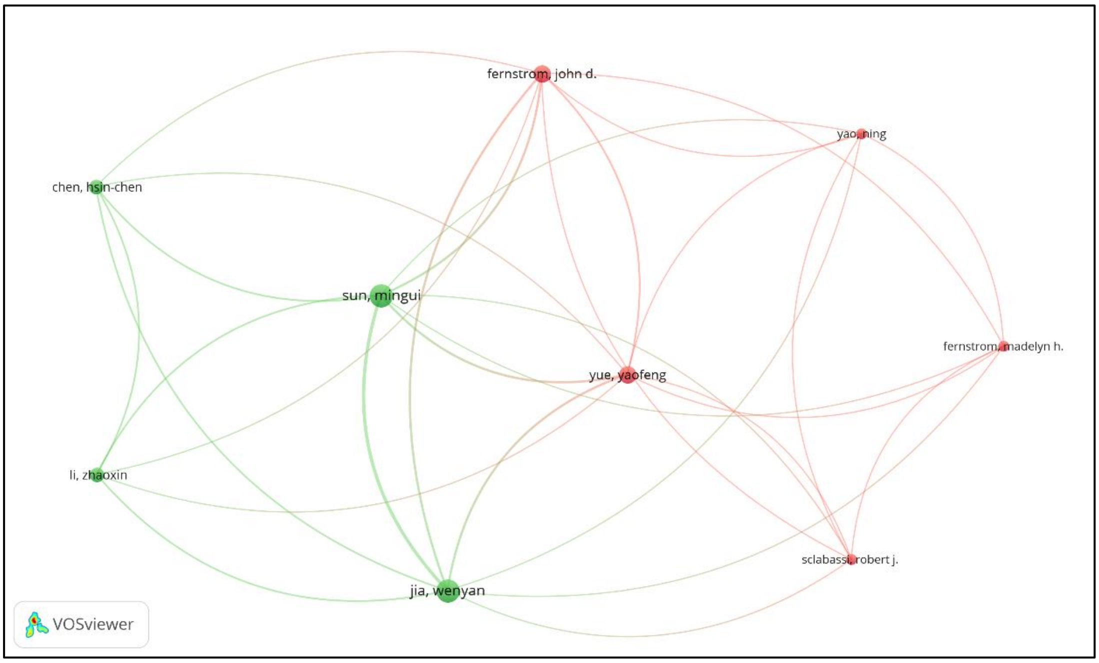

Figure 11. Analysis of Author's Contribution for WoS

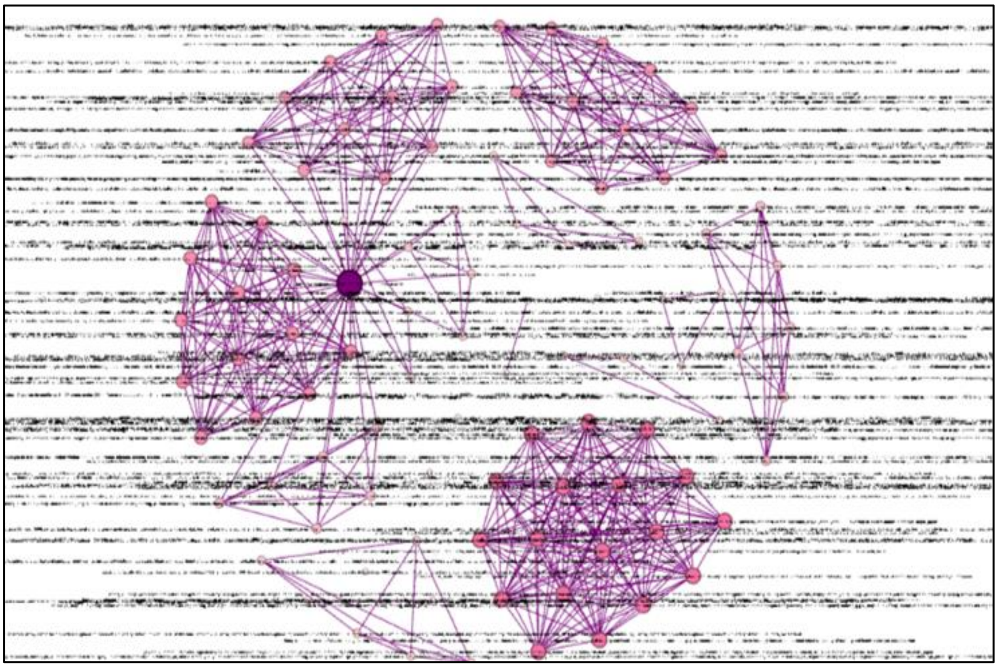

Figure 12. Analysis of Affiliation for Scopus

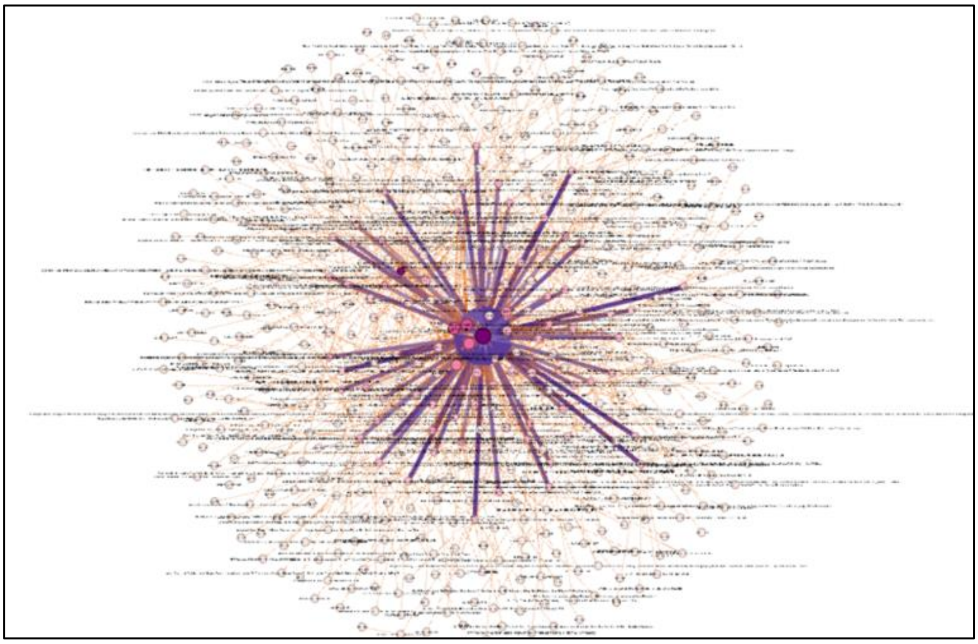

Figure 13. Analysis of Affiliation for WoS

While drawing a network representation of Author's keywords (Figure 14 and 15), the type of analysis was co-occurrence. The minimum number of occurrences of a keyword was set to 2. For Scopus out of 285 keywords, 37 keywords meet the threshold. The largest set of connected items consist of 36 items/keywords. For WoS out of 267 keywords, 35 keywords meet the threshold. The largest set of connected items consist of 28 items/keyword.

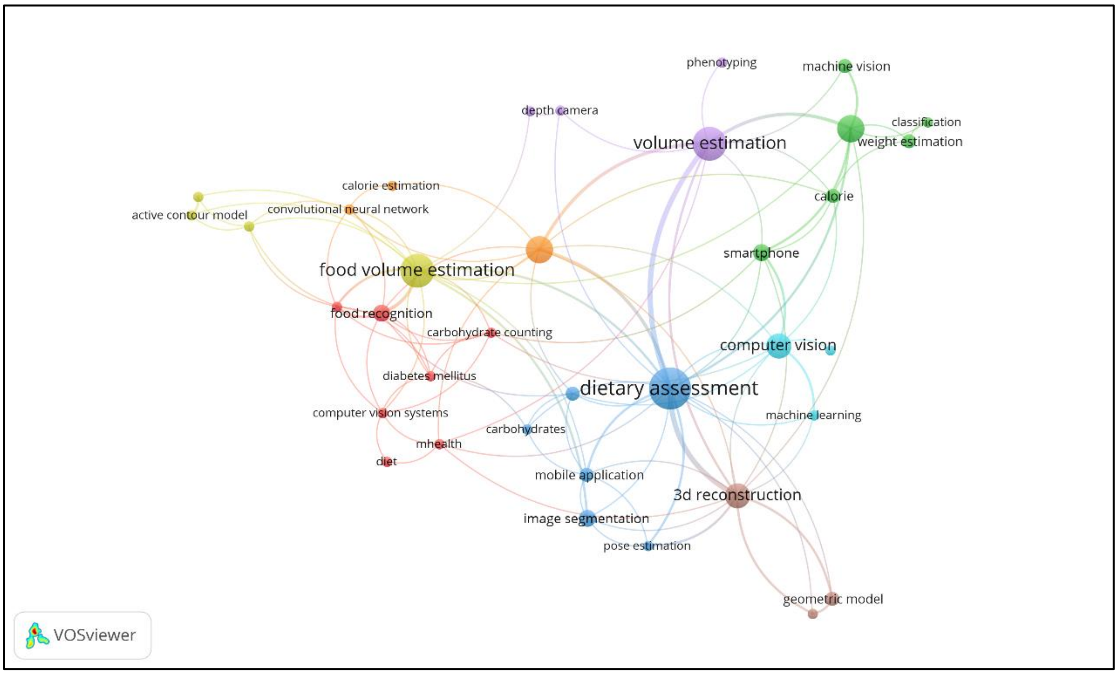

Figure 14. Analysis of Author's keywords for Scopus

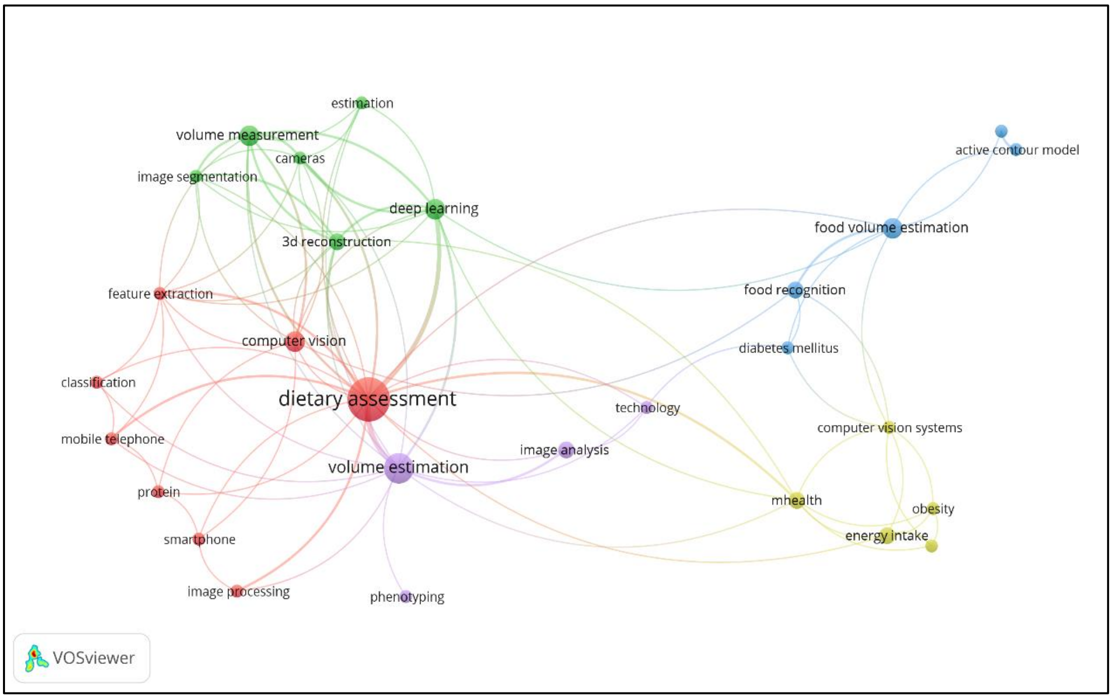

Figure 15. Analysis of Author's keywords for WoS

Figure 16 and 17 shows the Bibliometric Coupling and the unit of analysis was documents. The Bibliometric coupling analysis tells that the relations of items is determined based on the number of references they share. For Scopus, out of 103 documents, some are not connected to each other. The largest set of connected items consists of 47 items. For WoS, out of 66 documents, some are not connected to each other. The largest set of connected items consists of 29 items.

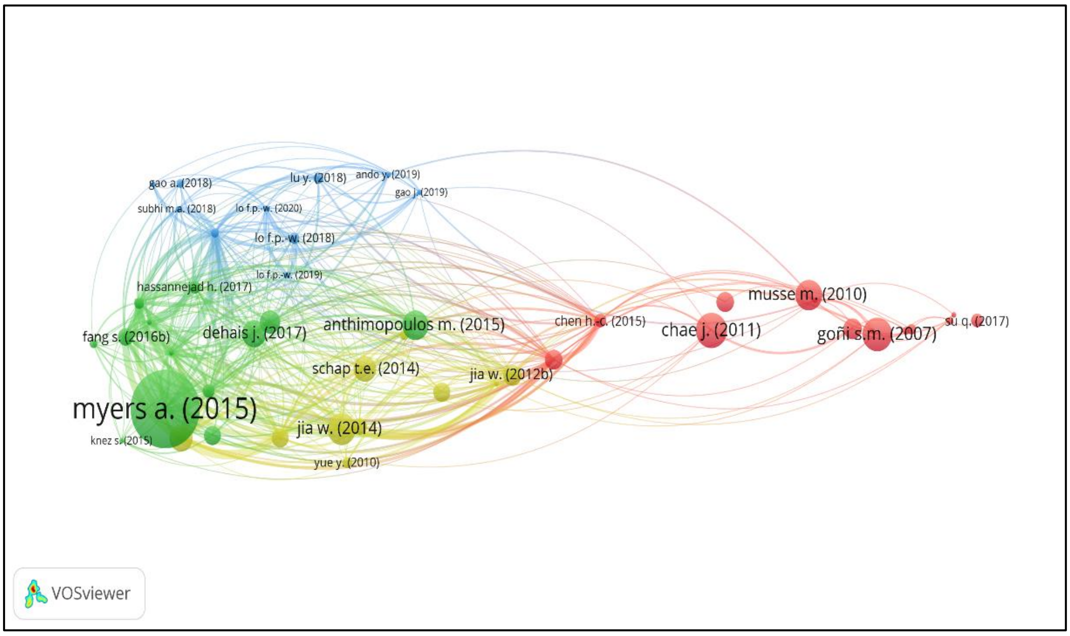

Figure 16. Bibliometric Coupling of documents for Scopus

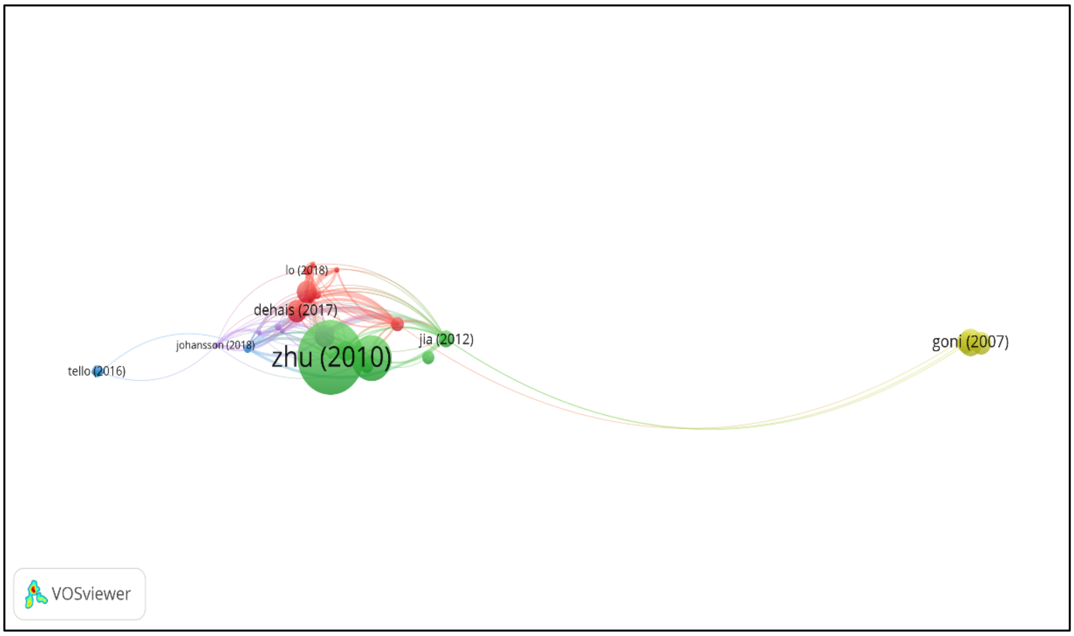

Figure 17. Bibliometric Coupling of documents for WoS

Figure 18 and 19 shows the analysis of citations where unit of analysis was set to documents. For Scopus, out of 103 documents, some of documents are not connected. Hence, only 25 documents were selected for citations. For WoS, out of 66 documents, some of documents are not connected. Hence, only 16 documents were selected for citations.

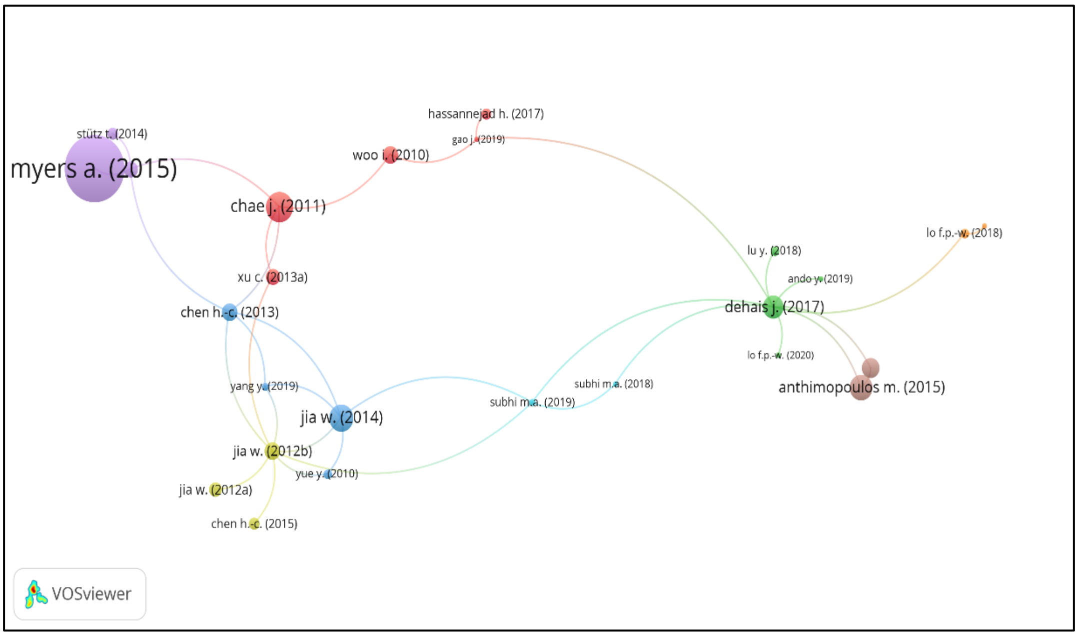

Figure 18. Analysis of Citations by document type for Scopus

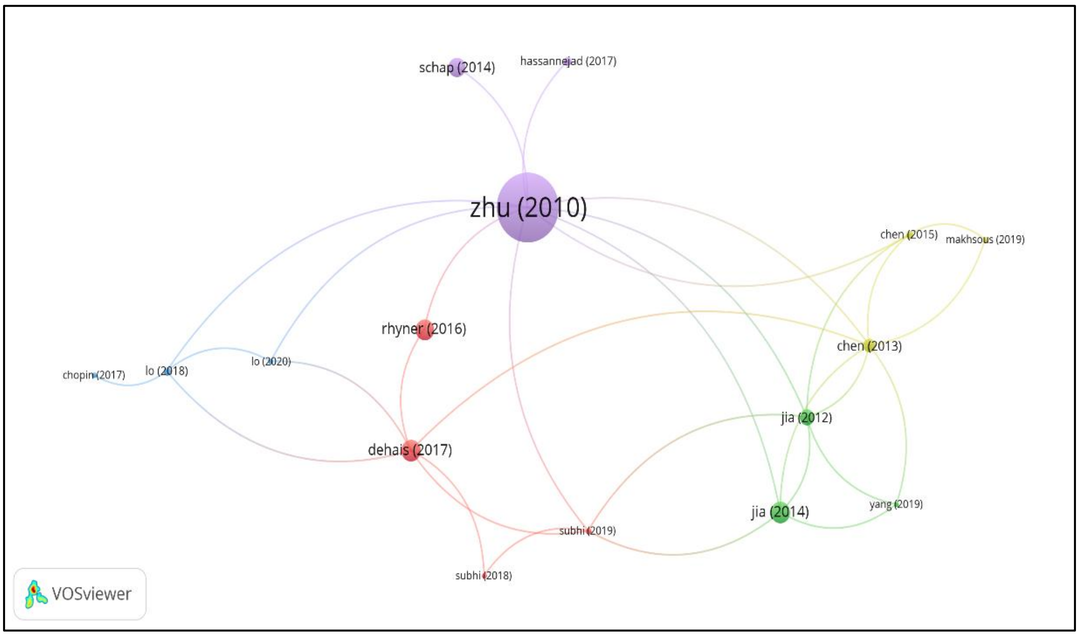

Figure 19. Analysis of Citations by document type for WoS

3.7 Citation Analysis

The analysis of citation plays a very significant role in bibliometric research. The citations tell which publications have more credibility towards research domains. Citation analysis is done by counting the number of times the individual publication is cited or referred by other publications. Table 5 and 6 shows the citation done in all years in the area of research. In Scopus, the total citation count of 103 publications is 1108 till date whereas, In WoS, the total citation count of 66 publications is 976 till date.

Table 5. Analysis of Citations for Publications by Year for Scopus

Year	>2020	2020	2019	2018	2017	2016	2016>	Total
No of Citations	2	200	203	171	147	104	281	1108

Table 6. Analysis of Citations for Publications by Year for WoS

Year	>2020	2020	2019	2018	2017	2016	2016>	Total
No of Citations	1	123	155	147	112	78	360	976

Table 7 and 8 shows the most cited top 10 publications in the field of food volume estimation. Table 9 and 10 shows the most cited top 10 journals along with the number of citations done regarding food volume estimation.

Table 7. Top 10 Publications Cited by Scopus

Year	No of Citations	References
2015	164	[9]
2011	51	[10]
2015	49	[11]
2008	48	[12]
2007	47	[13]
2014	44	[14]
1997	43	[15]
2010	41	[16]
2015	40	[17]
2017	35	[18]

Table 8. Top 10 Publications Cited by WoS

Year	No of Citations	References
2010	178	[19]
2012	88	[20]
2013	57	[21]
2007	42	[13]
1997	42	[15]
2015	41	[11]
1994	33	[22]
2014	32	[14]
2017	31	[18]
2006	31	[23]

Table 9. Top 10 Cited by Scopus

Journal Title	Total no. of Citations
Proceedings of the IEEE International Conference on Computer Vision	164
Proceedings of SPIE - The International Society for Optical Engineering	82
Journal of Food Engineering	71
Public Health Nutrition	52
Plant Methods	49
Proceedings - International Conference on Pattern Recognition	48

Magnetic Resonance Imaging	43
Journal of Diabetes Science and Technology	40
Journal of Medical Internet Research	32
Computers and Electronics in Agriculture	21

Table 10. Top 10 Journal Cited by WoS

Journal Title	Total no. of Citations
IEEE Journal Of Selected Topics In Processing	178
Journal Of Food Engineering	128
Journal Of Medical Internet Research	119
Psychiatry Research-Neuroimaging	57
Applied And Environmental Microbiology	42
Plant Methods	41
Public Health Nutrition	35
Neurogastroenterology And Motility	33
IEEE Transactions On Multimedia	31
World Journal Of Gastroenterology	29

Phase B: Analysis of Food Volume Estimation on 3D reconstruction and Deep learning method using Scopus

This bibliometric analysis performed using Scopus Database. This keyword analysis performed mainly on 3D reconstruction method and deep learning method.

3.8 Analysis by Keyword for 3D reconstruction and Deep learning method

Table 11. Analysis on Keywords

3D reconstruction method		Deep learning method	
Keyword Sets	Keywords	Keyword Sets	Keywords
Keywords Set1	“3D reconstruction” AND “mobile technology” “computer vision” And “Dietary assessment” AND “machine learning” AND “object recognition”	Keywords Set1	“Deep learning” OR “Dietary assessment” OR “Digital health” OR “Food volume estimation” OR “Personalized nutrition” OR “Public health”

Keywords Set2	“3D laser scanning” AND “Cooking loss” AND “Volume Pose estimation” AND “Cameras” AND “Estimation” AND “Image processing”	Keywords Set2	“calorie estimating” OR “deep learning” OR “diabetes” OR “Food recognition”
Keywords Set3	“3d reconstruction” AND “Depth measurement” AND “Dietary measurement” AND “Image segmentation” AND “Mobile structured light system” AND “Volume measurement”	Keywords Set3	“Deep learning” OR “Food image processing” OR “Food volume estimation” OR “Monocular depth estimation”
Keywords Set4	“3D model rendering” AND “3D reconstruction” AND “dietary assessment” AND “image segmentation” AND “pose estimation”	Keywords Set4	“Calorie estimation” OR “Convolutional neural network” OR “Deep learning” OR “IoT” OR “3D reconstruction” OR “AlexNet” OR “Hue Saturation Value (HSV)” OR “Matrix laboratory (MATLAB)” OR “Mesh”
Keywords Set5	“3-d modeling” AND “3D graphical models;” AND “3D reconstruction” AND “3D reconstruction from multiple views” AND “Camera calibration” AND “Dietary assessments” AND “Model based approach” AND “Image segmentation” AND “Mobile devices” AND “Three dimensional computer graphics” AND “Three dimensional”	Keywords Set5	3D reconstruction” OR “mobile technology” OR “computer vision” OR “Dietary assessment” OR “machine learning” OR “object recognition”

The list of all keywords are derived from notable databases like Scopus. For deep learning, the primary keywords are food volume estimation and deep learning, and the secondary keywords are dietary assessment, food recognition, calorie intake, 3D reconstruction etc. For 3D reconstruction method, the primary keywords are food volume estimation and 3D reconstruction and the secondary keywords are dietary assessment, food recognition, calorie intake, image segmentation, etc.

3.9 Analysis by Publication on 3D reconstruction and Deep learning method

After comparing the number of publications, 3D reconstruction has more number of publication than deep learning method. There are 15 documents published in the Scopus Database regarding 3D reconstruction method, whereas 14 documents published for deep learning method. India has published 2 documents each in 3D reconstruction as well as deep learning method. Figure 20 shows, United States has published 7 documents which is highest number of publication. By looking at Figure

21, United Kingdom has published 4 documents, which is the highest number of publication.

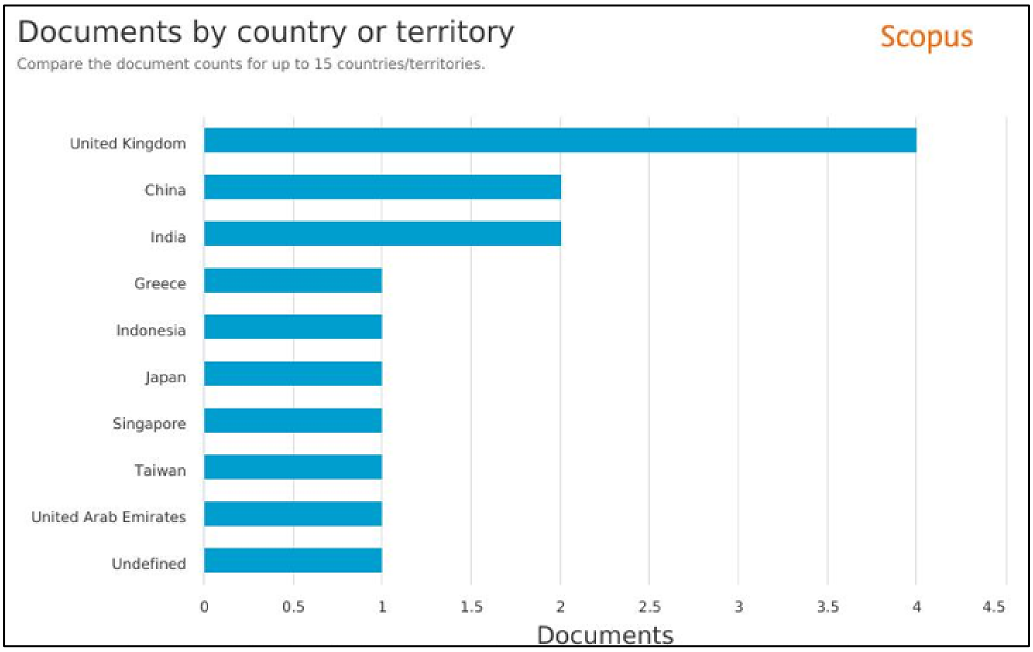

Figure 20. Analysis of Countries in Publication for 3D reconstruction

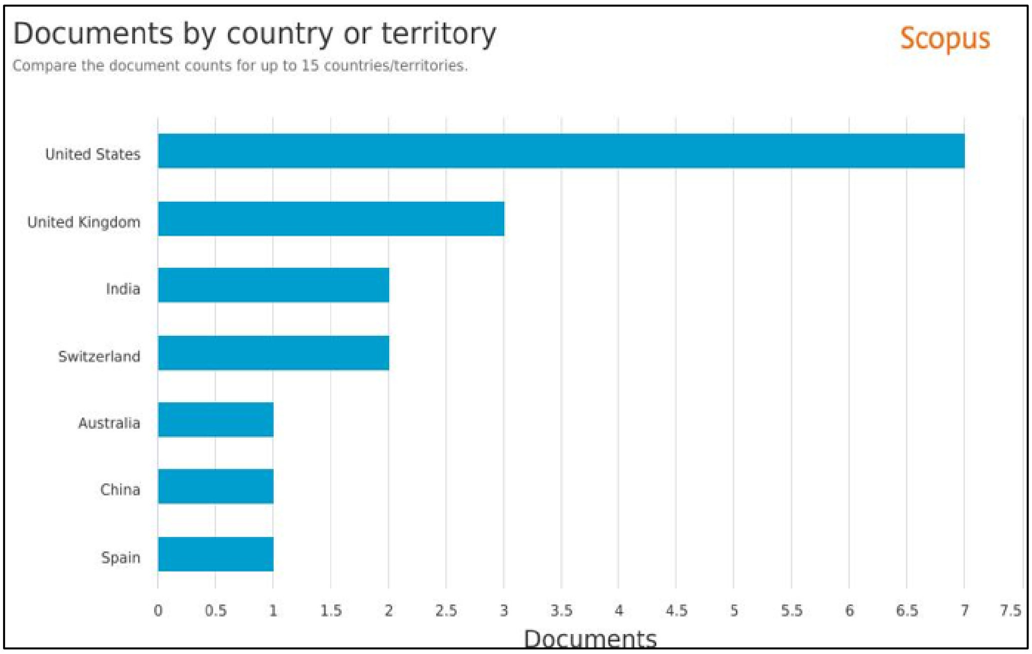

Figure 21. Analysis of Countries in Publication for Deep learning

3.11 Analysis by Year

Figure 22 and 23 show the number of publication count per year for Food image volume estimation using 3D reconstruction and Deep Learning method. From both the figures it is conclusive that 3D reconstruction method being older than deep learning method, shows a greater number of publications till 2013 and there by decline in the number. Whereas, since then, the Deep learning method shows increase in number of publications since the method started evolving around that year.

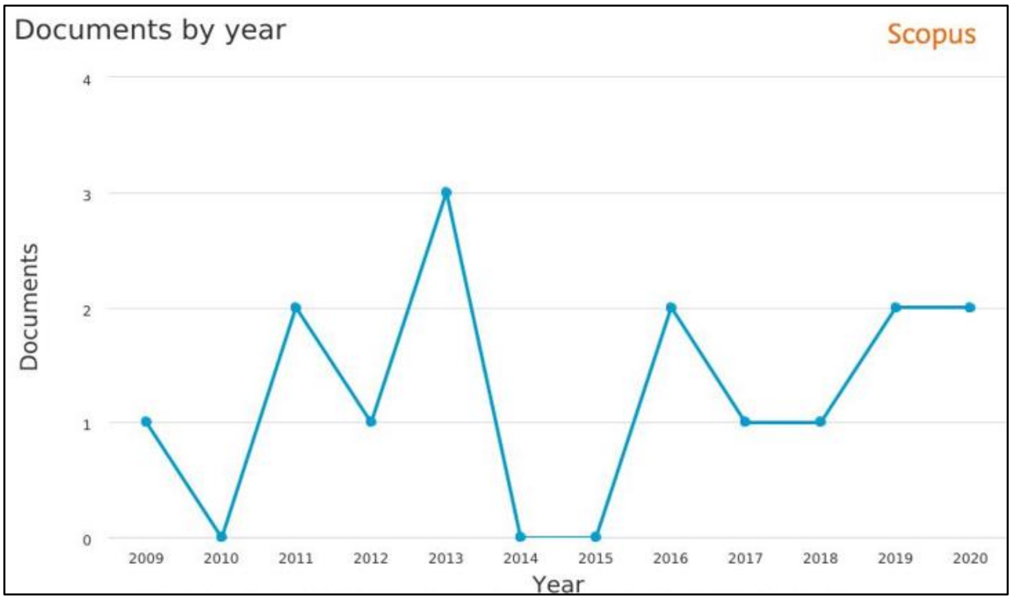

Figure 22. Analysis of Year for 3D reconstruction

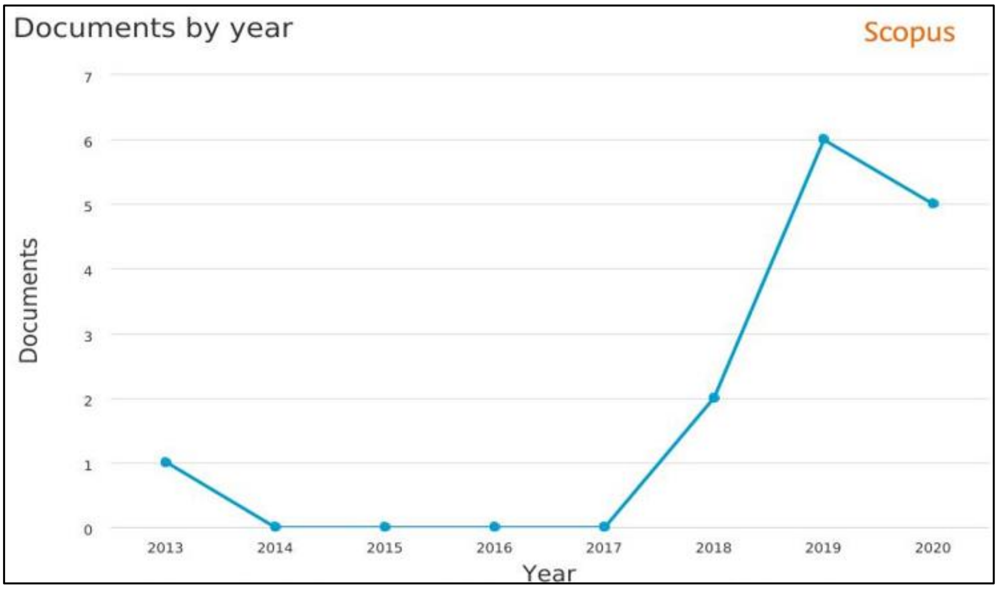

Figure 23. Analysis of Year for deep learning

3.12 Analysis by Citations

Below Table 12 shows the analysis of citations along with the total number of citations throughout the years from 2009 to 2020. In this research field, total of publications are only 15. Hence, the total of citations are 276. Below Table 13 shows the analysis of citations along with the total number of citations throughout the years from 2013 to 2020. In this research field, total of publications are only

14. Hence, the total of citations are also less.

Table 12. Analysis of Citations for Publications by Year on 3D reconstruction method

Year	2020	2019	2018	2017	2016	2013	2012	2011	2009	Total no of Citations
No of Citations	0	8	7	32	29	73	4	21	102	276

Continued.

Table 14. Analysis of Citations for Publications by Year on Deep learning method

Year	2020	2019	2018	2013	Total no. of Citations
No of Citations	3	4	9	0	16

Table 13. Publications Cite by Scopus using 3D reconstruction method

Year	No of Citations	References
2020	0	[2]
2020	0	[24]
2019	2	[8]
2019	6	[25]
2018	7	[26]
2017	32	[18]
2016	13	[27]
2016	16	[28]
2013	20	[29]
2013	21	[30]
2013	32	[31]
2012	4	[32]
2011	20	[33]

Table 15. Publications Title cited by Scopus using Deep learning method

Year	No of Citations	References
2020	1	[34]
2020	0	[2]
2020	0	[35]
2020	0	[36]
2020	2	[37]
2019	1	[38]
2019	0	[39]
2019	2	[8]
2019	0	[40]
2019	1	[41]

Table 14 shows the list of all publications title along with their respective citations for 3D reconstruction. Table 15 shows the list of all publications title along with their respective citations for Deep learning method.

Phase C: Analysis of Food Volume Estimation on 3D reconstruction and Deep learning method using Web of Science

This bibliometric analysis performed using Web of Science Database. This keyword analysis performed mainly on 3D reconstruction method and deep learning method.

3.13 Analysis by Keyword for 3D reconstruction and Deep learning method

Table 16. Analysis on Keywords

3D reconstruction method		Deep learning method	
Keyword Sets	Keywords	Keyword Sets	Keywords
KeywordsSet1	"Computer vision" AND "diabetes" AND "stereo vision" AND "volume measurement"	KeywordsSet1	"Dietary assessment" OR "volume estimation" OR "deep learning" OR "image rendering" OR "3D reconstruction"
KeywordsSet2	"3D reconstruction" AND "Dietary assessment" OR " volume estimation" OR "deep learning" OR "image rendering" OR "3D reconstruction"	KeywordsSet2	"Three-dimensional displays" OR "Solid modeling" OR measurement" OR "Deep Learning" OR "Cameras" OR "Estimation" OR "Data models" OR "dietary assessment" OR "point cloud completion" OR "(3-D) reconstruction" OR estimation"
KeywordsSet3	"3D reconstruction" AND "volume estimation" AND "Dietary assessment" AND "image processing" AND "Depth measurement"	KeywordsSet3	"food volume estimation" OR assessment;" OR :public health" OR "digital health" OR "personalized nutrition"

The list of all keywords are derived from notable databases like Web of Science. For deep learning, the primary keywords are food volume estimation and deep learning, and the secondary keywords are dietary assessment, food recognition, calorie intake, 3D reconstruction etc. For 3D reconstruction method, the primary keywords are food volume estimation and 3D reconstruction and the secondary keywords are dietary assessment, food recognition, depth measurement image segmentation, etc.

3.14 Analysis by Publication

After comparing the number of publications, 3D reconstruction has 13 publications whereas, deep learning method has 6 publications. In Web of Science, it considered UK and England are different countries, similarly it considered China and Peoples R China are different countries. Hence, its shows two bars for UK as well as for England, similarly for China or Peoples R China. UK or England, China or Peoples R China, Norway, Spain, USA has published 2 document and Australia, Japan and South Africa has published 1 document in 3D reconstruction. For deep learning method, England has published 3 document and China, Taiwan and Singapore has published 1 document.

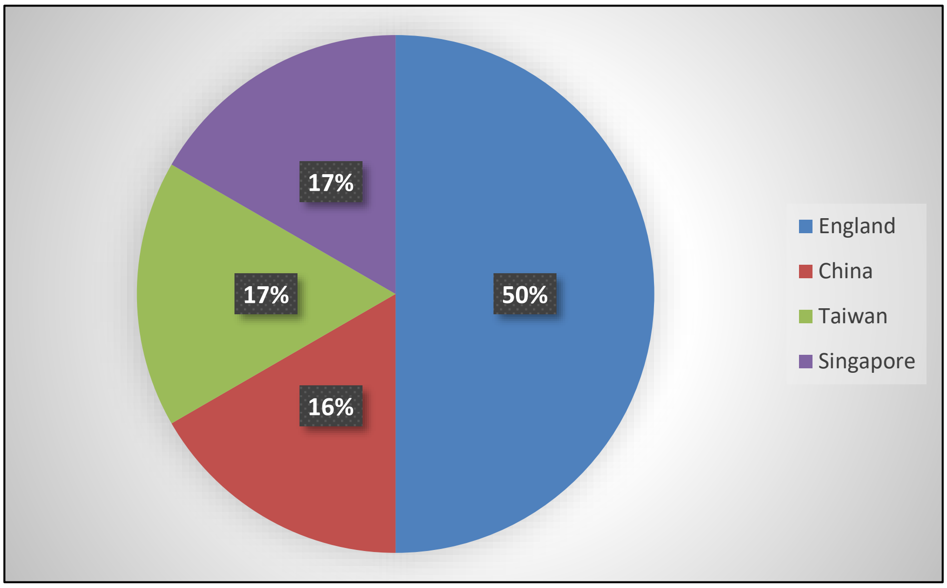

Figure 24. Analysis of Countries in Publication for 3D reconstruction

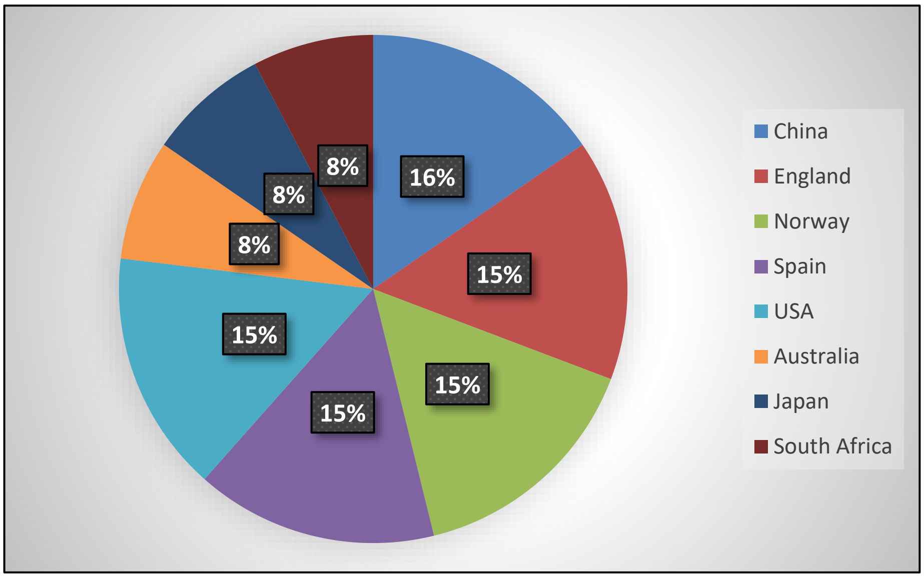

Figure 25. Analysis of Countries in Publication for deep learning

3.15 Analysis by Year

Figure 26 and 27 how the number of publications count per year for Food image volume estimation using 3D reconstruction and Deep Learning method. From both the figures it is conclusive that 3D reconstruction method being older than deep learning method, shows a less number of publication around the year and there by decline in the number. Whereas, since then, the Deep learning method shows increase in number of publications since the method started evolving around that year.

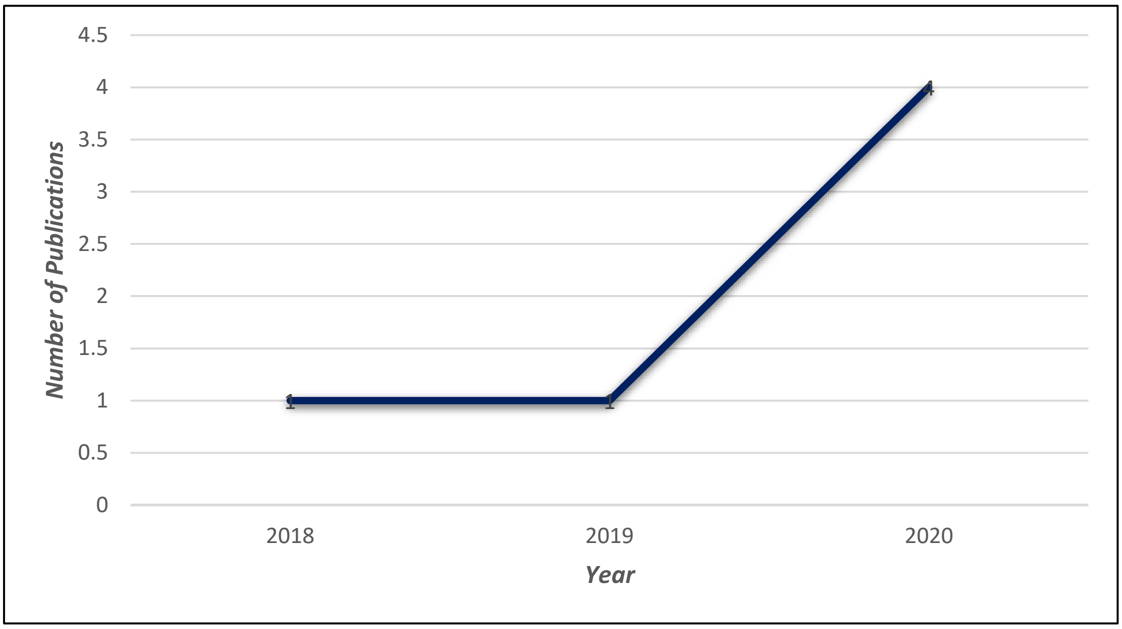

Figure 26. Analysis of Year for 3D reconstruction

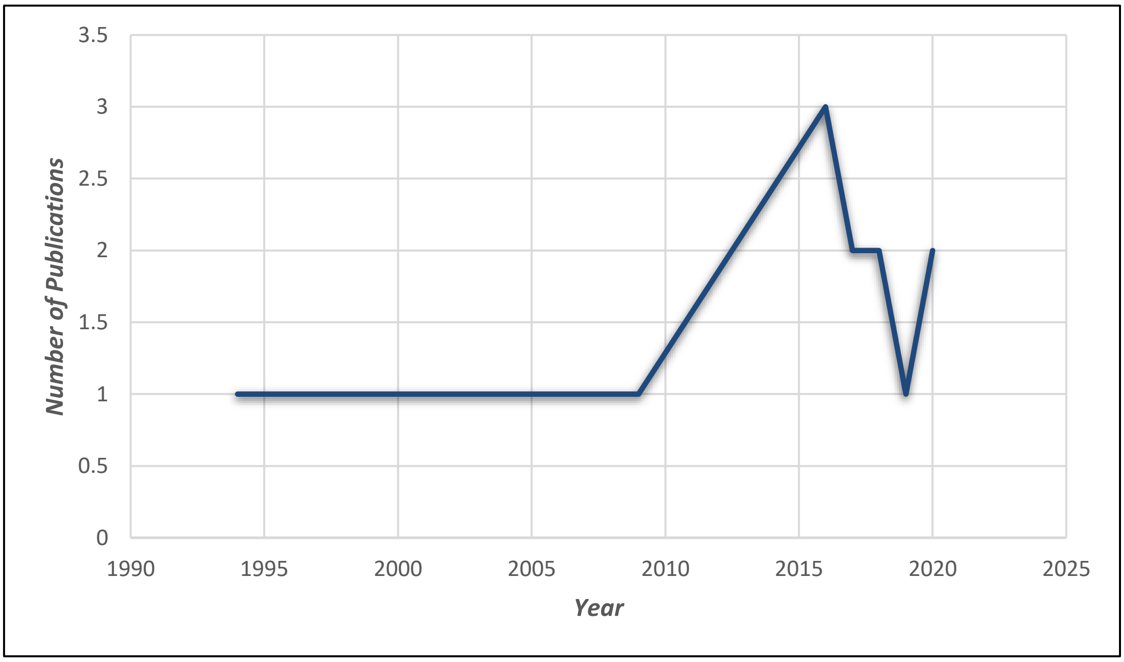

Figure 27. Analysis of Year for deep learning

3.16 Analysis by Citations

Below Table 17 shows the analysis of citations along with the total number of citations throughout the years from 2017 to 2020. In this research field, total of publications are only 13. But, the total of citations are 294. Table 18 shows the analysis of citations along with the total number of citations throughout the years from 2019 and 2020. In this research field, total of publications are only 6. Hence, the total of citations are 12. Table 19 shows the list of all publications title along with their respective citations. Table 20 shows the list of all publications title along with their respective citations.

Table 17. Analysis of Citations for Publications by Year on 3D reconstruction method

Year	2020	2019	2018	2017	<2017	Total no of citations
No of Citations	30	43	30	13	178	294

Table 18. Analysis of Citations for Publications by Year on Deep learning method

Year	2020	2019	Total no of citations
No of Citations	8	4	12

Table 19. Publications Title cited by WOS using 3D reconstruction method

Year	No of Citations	References
1997	98	[42]
2009	80	[43]
1994	33	[22]
2017	32	[18]
2016	13	[27]
2016	12	[44]
2018	8	[45]
2019	6	[25]
2016	6	[46]
2018	4	[47]
2017	2	[48]
2020	0	[2]
2020	0	[24]

Table 20. Publications Title cited by WOS using Deep Learning method

Year	No of Citations	References
2018	8	[45]
2020	3	[37]
2019	1	[41]
2020	0	[2]
2020	0	[49]
2020	0	[35]

4. Discussion

The methodology for review is phased out with:

1. Systematic literature review with PRISMA approach.
2. Bibliometric analysis of the works in the area of image based food volume estimation using 5 databases

3. Bibliometric analysis of the works in the area of image based food volume estimation using deep learning and 3D reconstruction using Scopus and WoS

We discuss how these findings help address our research questions:

RQ1. What are the state-of-art strategies in Image-based Food Volume Estimation in the literature?

We carried out the analysis of the term – Food volume analysis in the phase II of bibliometric study. The literature was clustered based on five methods from the literature reviews: Stereo-based [50][51][18][26][19][7], Model-based (3D reconstruction) [10][29][14][52], Perspective Transformation [53][54][55][56][57], Depth camera [33][58] and Deep learning [9][59][45][60][8][37]. Our findings echoed the discussions in the review [2] and the recent trends like deep learning and 3D reconstruction are promising better results.

The number of publications in each method from search of SCOPUS and WoS databases based on the search criteria described in the section 3, is shown in the table 21 below.

Table 21. Image Based Food Volume Estimation Methods with number of publication from SLR

Image-based Food Volume Estimation Methods	**Number of Publications**
Stereo-based Approach[2]	6
Model based Approach (3D reconstruction)[2]	21
Perspective Transformation[2]	5
Depth Camera method[2]	13
Deep learning[2]	14

We also enumerated number of citations for each method and found that papers in 3D reconstruction show maximum 38 citations [18][45]. This proves 3D reconstruction method is more popular in estimating volume of food. Further, recent advances in deep learning techniques show potential of computer vision based methods in food volume estimation. This is conclusive from the increasing number of publications of volume estimation in this area as shown in Figure 28. The trends of publications in these methods was carried out. The number of articles published per year was found. Figure 28 shows that 3D reconstruction food volume estimation method has more number of publications from 2009 towards 2016. Whereas, with the advent of deep learning algorithms, the trends of number of publications show considerable growth from 2017 since 2020 and shows upward trend.

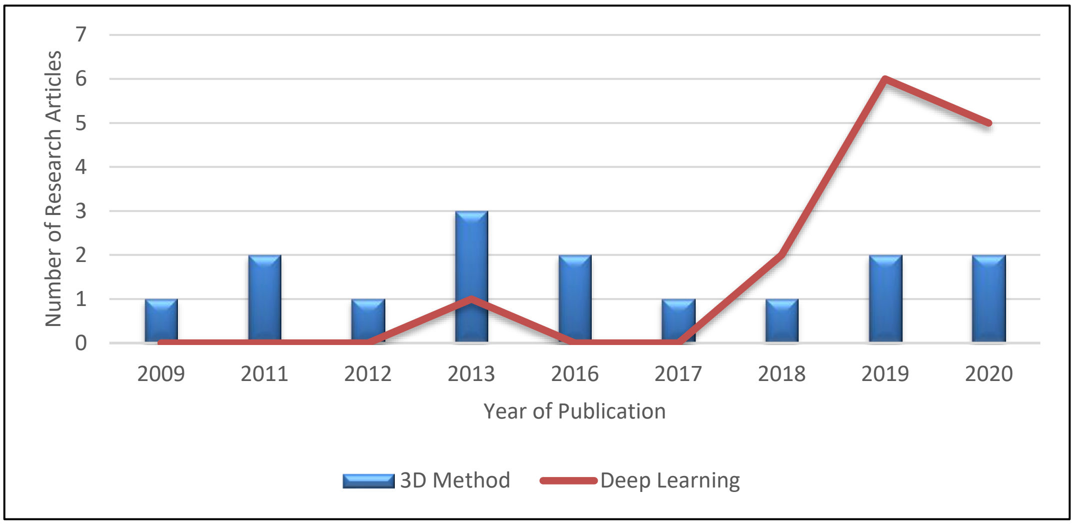

Figure 28. Articles published for 3D reconstruction and Deep Learning methods per year

RQ.2 What are the research trends in the literature of Food Volume Estimation methods?
The 3D reconstruction method gained popularity in food volume estimation methods. From bibliometric analysis of individual methods – 3D reconstruction methods show more number of publications till year 2020, the top three countries with added research were seen in US, UK and India, However the number of citations in this method has shown steady decline after the advent of Deep learning algorithms. The most cited paper of conventional method – 3D reconstruction is "*Two-View 3D Reconstruction for Food Volume Estimation*", 2017, authored by J. Dehais, et. al [18].
Deep learning method shows annual increase in number of publications. The top three countries working in Deep learning are UK, China and India and number of citations are now showing increasing trend. The most cited work in deep learning method is "*Food Volume Estimation Based on Deep Learning View Synthesis from a Single Depth Map*", 2018, authored by Lo W. et. al [45].

RQ3. What are the different 3D reconstruction methods used in food volume estimation?

For 3D reconstruction further meta-analysis of the 15 publications is summarized in the Table 22. The analysis is done on the basis of estimation accuracy and details of datasets. From the table, it is observed that 3D reconstruction is specialized model-based approach. The error rate in estimation is as low as 3.6% and the methods are applied on various datasets. Some of the data sets are publicly available food image data sets [61]. Whereas some of them are synthetic datasets [9] created for experimentations. The data set consists of raw foods, fruits, packaged meals and very meagre varieties of cooked food.

Table 22. Detailed analysis on 3D Reconstruction Papers

Methods in 3D reconstruction	**Accuracy**	**Dataset**	**Ref**
A review paper (CNN, FCNN, GAN, Point cloud	1.62% Error rate for DL	A review paper (YCB, NYU depth V2, Nfood etc.)	[2]

completion model)			
Terrestrial 3D laser scanning technology	94% perimeter shrinkage	Pork Cuboids	[24]
Point completion network	95.41% Accuracy	YCB dataset	[8]
Mobile Structured Light System (SLS)	40% Accuracy	White Rice, Carrots, Yellow Rice, White Rice+ Turkey, Carrots+Turkey, Peppers+Carrots, Celery+Peppers, Mixed Rice, Yellow Rice+Turkey, Celery+Carrots, Celery, Peppers, Turkey+Yellow Rice, Turkey+Celery, Turkry, Carrots+Peppers, Celery+Broccoli, Yellow Rice+Celery, Peppers+Celery	[25]
Simultaneous Localisation and Mapping (SLAM)	83% Accuracy	Mini Cake, Sandwich, Sausage	[26]
Two-view dense stereo 3D reconstruction	Less than 10% Error Rate	Meals-45, Angles-13, Plates-18, Meals-14	[18]
Geometric reconstruction	96% Accuracy	Eight different grapevine cultivars(Aramon, Bobal, Cabernet Franc, Danugue, Derechero de Muniesa, Monastrell, Moravia Agria and Ruby Seedless)	[27]
Single-view 3D scene reconstruction based on shape templates and prism model	Less than 6% Error Rate	Milk, Orange Juice, Strawberry Juice, Margarine, Lettuce, Coke, Chocolate Cake, French Dressing, Ketchup, Sausage, Scrambled egg, White Toast, Garlic Bread, Sugar Cookie, Spaghetti, French Fries, Peaches, Pear Halves, Cheeseburger	[28]
3D model generation and pose estimation	3.6% to 12.3% Error Rate	Banana, Bagel, Orange juice, Orange, Rice Krispy Treat	[29]
Multi-view dense stereo reconstruction	90% Accuracy	Chicken, Spaghetti and Fusilli	[30]
Single image and a multi-view 3D reconstruction using “Shape from Silhouettes”	10% Error Rate	Banana, Bagel, Orange juice, Rice Krispy Treat	[31]
Diet Data Recorder System (DDRS)	Less than 2% Error Rate	Sandwich and muffin	[32]
Mobile Structured Light System (SLS)	The performance of the system is not presented	Images of mango	[33]

Iterative Closest Point (ICP)	High in Accuracy	Grain Storage	[62]
Multi-view dense stereo reconstruction	2.0% to 9.5% Error Rate	FNDDS	[50]

RQ.4 What are the different deep learning methods used in food volume estimation?

From the trend depicted in Figure 28, it is perceptible that deep learning methods with computer vision are increasingly accepted in the field. There were only one or two publications in the area of food volume estimation in the year 2013 to 2018 but from the year 2019, there is substantial rise in the research in this area with deep learning.

We carry out a qualitative meta-analysis on the works in Deep learning methods. Table 23 shows a detailed analysis of the 14 works from the search. From the table, it is pragmatic that lowest estimation error rate is 1.62% for deep learning methods.

The training data sets show standard and benchmarked data sets, but they show lesser data size. Also there are limited diversities with food types, meals and states (liquids /solids). This shows need for a robust and more diverse data sets for a well-trained estimation model.

Table 23. Detailed analysis on Deep Learning Papers

Methods in DL	Accuracy	Dataset	Ref
SSD_Mobilenet object detection model	9% Avg Error Rate	The dataset contains a total of 633 original images in 11 categories, averaging nearly 60 images in each category	[34]
A review paper (CNN, FCNN, GAN, Point cloud completion model)	1.62% Error rate for DL	A review paper (YCB, NYU depth V2, Nfood etc.)	[2]
A review paper (CNN model)	Avg accuracy of 92% and 98%	A review paper (Food X, RGB-D images etc.)	[35]
Mask R-CNN for training and water displacement method for testing	±20 mL	EPIC-Kitchens dataset and own food videos dataset for training the model, UNIMIB2016 dataset and COCO dataset for food segmentation, 16 different foods and combined meals for testing	[36]
Point completion network UNet	92.29% Accuracy	Eight food categories, including banana, apple, burger, cake, pizza, orange, rice, and donuts	[37]
CNN model	90.69% Accuracy	10 food items, including Samosa, vegetable rice, sandwich, donuts, chocolate cake, apple, aloo paratha, vegetable salad, pizza and spaghetti	[38]
Mask R-CNN	97.48% Accuracy	Fried Tofu, Fried Tempeh, Braised Spiced Tofu, Braised Spoced Tempeh, White Bread	[39]
Point completion network	95.41% Accuracy	YCB dataset	[8]

Alexnet	46.53% Accuracy	Multi-color Salad, Dry fruits and Bread	[40]
Mask R-CNN	95% Accuray from the vertical angle and 80% Accuracy from horizontal angle	Four types of hams with different length, height, and thickness	[41]
linear regression model	MAE 2.5% Error Rate	One dataset was damaged field data acquired in 2018 (2170 fields). The other was undamaged field data acquired in 2017 (1358 fields). They used RapidEye and SPOT-6 satellite images in 2017 and 2018, respectively.	[63]
Point Cloud Completion and Iterative Closet Point(ICP)	93% Accuracy	YCB dataset	[45]
Faster R-CNN	±20 Error Rate	Four different types of food shapes	[64]

5. Future Work

The study of food volume estimation algorithms with systematic literature review and bibliometric meta- analysis shows need of future work:

1) Lesser work in developing countries like India where obesity and lifestyle disorders are prominent.
2) Computer vision based approach to food image volume estimation shows scope of better accuracy.
3) Deep learning approaches learn with training data sets. The available data sets are more local and do not show diversities with respect to food-types, serving styles and food states. Also, we see lesser work with volume estimation of cooked dishes.
4) From table 22 and 23, it is observed that there is absence of single, standard data set for comparing the performance of estimation methods. This necessitates developing robust datasets which include cooked or uncooked food items; food items with definite and indefinite shape; local and global cuisine; single food and multi-food dishes. Such a data set will offer a benchmark to compare the performance of these estimation methods.

6. Limitations of Survey

The current section identifies limitations within this study that might need enhancement. The search is limited to food volume estimation methods in dietary management perspective only. It excludes other prominent areas like culinary. Although there are established methods of food volume estimation methods, our work emphasizes on the potential of deep learning and 3D reconstruction.

In this systematic review, search is limited to the literature in Web of science, Scopus and IEEE databases. Whereas, for Bibliometric analysis only two databases – WoS and Scopus are considered. For meta-analysis we reviewed 31 papers based on 3D reconstruction and deep learning methods. The survey may be limited by introduction of bias in the selection of literature. Literature works focus on methods in food identification and segmentation in dietary management. We emphasize only on the food-portions estimation and neglect other contributions for discussions here.

7. Conclusion

This review assesses image-based food volume estimation methods for dietary management. Increasing number of publications in this area reflects the interests in the areas for dietary management. This review evaluates current state-of-art in image-based food volume estimation. It studies 63 literary works between 2009- 2020.

We have revolved the survey to answer the four research questions. We first clustered the works in five main methods: Stereo-based approach, Model-based approach, Perspective transformation approach, Depth camera-based approach and deep learning approach. Then we investigated the trends in research and research outcomes with bibliometric survey. Here we see increase in the research works in the area especially in 3D reconstruction and deep learning methods. Finally, we carried out qualitative meta-analysis of deep learning and 3Dreconstruction method. This is done on basis of models, size and structure of data sets and accuracy of the estimation models. The study gives insights to the researchers, practitioners and dietitians for understanding current status and possible research directions in image-based food volume estimation techniques for dietary management.

References

[1] Y. Ji, H. Plourde, V. Bouzo, R. D. Kilgour, and T. R. Cohen, "Validity and Usability of a Smartphone Image-Based Dietary Assessment App Compared to 3-Day Food Diaries in Assessing Dietary Intake Among Canadian Adults: Randomized Controlled Trial," *JMIR mHealth uHealth*, vol. 8, no. 9, p. e16953, 2020, doi: 10.2196/16953.

[2] F. P. W. Lo, Y. Sun, J. Qiu, and B. Lo, "Image-Based Food Classification and Volume Estimation for Dietary Assessment: A Review," *IEEE J. Biomed. Heal. Informatics*, vol. 24, no. 7, pp. 1926–1939, 2020, doi: 10.1109/JBHI.2020.2987943.

[3] F. Cordeiro *et al.*, "Barriers and negative nudges: Exploring challenges in food journaling," *Conf. Hum. Factors Comput. Syst. - Proc.*, vol. 2015-April, pp. 1159–1162, 2015, doi: 10.1145/2702123.2702155.

[4] E. Mendi, O. Ozyavuz, E. Pekesen, and C. Bayrak, "Food intake monitoring system for mobile devices," *Proc. 2013 5th IEEE Int. Work. Adv. Sensors Interfaces, IWASI 2013*, pp. 31–33, 2013, doi: 10.1109/IWASI.2013.6576082.

[5] K. H. Yu, A. L. Beam, and I. S. Kohane, "Artificial intelligence in healthcare," *Nat. Biomed. Eng.*, vol. 2, no. 10, pp. 719–731, 2018, doi: 10.1038/s41551-018-0305-z.

[6] C. J. Boushey, M. Spoden, F. M. Zhu, E. J. Delp, and D. A. Kerr, "New mobile methods for dietary assessment: Review of image-assisted and image-based dietary assessment methods," *Proc. Nutr. Soc.*, vol. 76, no. 3, pp. 283–294, 2017, doi: 10.1017/S0029665116002913.

[7] I. Woo, K. Otsmo, S. Kim, D. S. Ebert, E. J. Delp, and C. J. Boushey, "Automatic portion estimation and visual refinement in mobile dietary assessment," *Comput. Imaging VIII*, vol. 7533, p. 75330O, 2010, doi: 10.1117/12.849051.

[8] F. P. W. Lo, Y. Sun, J. Qiu, and B. Lo, "A novel vision-based approach for dietary assessment using deep learning view synthesis," *2019 IEEE 16th Int. Conf. Wearable Implant. Body Sens. Networks, BSN 2019 - Proc.*, vol. i, no. 5, pp. 1–4, 2019, doi: 10.1109/BSN.2019.8771089.

[9] A. Meyers *et al.*, "Im2calories: Towards an automated mobile vision food diary. Proceedings of the IEEE International Conference on Computer Vision," *Iccv*, no. December, p. pp.-1233–1241, 2015.

[10] J. Chae *et al.*, "Volume estimation using food specific shape templates in mobile image-based dietary assessment," *Comput. Imaging IX*, vol. 7873, p. 78730K, 2011,

doi: 10.1117/12.876669.
[11] A. Das *et al.*, “Digital imaging of root traits (DIRT): A high-throughput computing and collaboration platform for field-based root phenomics,” *Plant Methods*, vol. 11, no. 1, pp. 1–12, 2015, doi: 10.1186/s13007-015-0093-3.
[12] O. D. Leinhard *et al.*, “Reprint from Proceedings of the 19th International Conference on Pattern Quantitative abdominal fat estimation using MRI,” *Image (Rochester, N.Y.)*, pp. 1–4, 2008.
[13] S. M. Goñi, E. Purlis, and V. O. Salvadori, “Three-dimensional reconstruction of irregular foodstuffs,” *J. Food Eng.*, vol. 82, no. 4, pp. 536–547, 2007, doi: 10.1016/j.jfoodeng.2007.03.021.
[14] W. Jia *et al.*, “Accuracy of food portion size estimation from digital pictures acquired by a chest-worn camera,” *Public Health Nutr.*, vol. 17, no. 8, pp. 1671–1681, 2014, doi: 10.1017/S1368980013003236.
[15] J. Pernthaler, A. Alfreider, T. Posch, S. Andreatta, and R. Psenner, “In situ classification and image cytometry of pelagic bacteria from a high mountain lake (Gossenkollesee, Austria),” *Appl. Environ. Microbiol.*, vol. 63, no. 12, pp. 4778–4783, 1997, doi: 10.1128/aem.63.12.4778-4783.1997.
[16] C. H. Burton, “Reconciling the new demands for food protection with environmental needs in the management of livestock wastes,” *Bioresour. Technol.*, vol. 100, no. 22, pp. 5399–5405, 2009, doi: 10.1016/j.biortech.2008.11.018.
[17] M. Anthimopoulos *et al.*, “Computer vision-based carbohydrate estimation for type 1 patients with diabetes using smartphones,” *J. Diabetes Sci. Technol.*, vol. 9, no. 3, pp. 507–515, 2015, doi: 10.1177/1932296815580159.
[18] J. Dehais, M. Anthimopoulos, S. Shevchik, and S. Mougiakakou, “Two-view 3D reconstruction for food volume estimation,” *IEEE Trans. Multimed.*, vol. 19, no. 5, pp. 1090–1099, 2017, doi: 10.1109/TMM.2016.2642792.
[19] E. Zhu, F., Bosch, M., Woo, I., Kim, S., Boushey, CJ., Ebert, DS., Delp, “The use of mobile devices in aiding dietary assessment and evaluation.,” *IEEE Signal Process. Lett.*, vol. 4, no. 4, pp. 756–766, 2010.
[20] B. L. Daugherty *et al.*, “Novel technologies for assessing dietary intake: Evaluating the usability of a mobile telephone food record among adults and adolescents,” *J. Med. Internet Res.*, vol. 14, no. 2, pp. 156–167, 2012, doi: 10.2196/jmir.1967.
[21] A. links open overlay panelIdoiaMarqués-I.-G. S.-P.-V. ÁngelesJurado, “Frontal cortical thinning and subcortical volume reductions in early adulthood obesity,” *Sci. Direct*, vol. 214, no. 2, pp. 109–115, 2013, doi: https://doi.org/10.1016/j.pscychresns.2013.06.004.
[22] N. T. Trygve Hausken, Odd Helge Gilja, Knut Matre, “Volume estimation of the gastric antrum and the gallbladder in patients with non-ulcer dyspepsia and erosive prepyloric changes, using three-dimensional ultrasonography,” *ResearchGate*, pp. 263–270, 2008, doi: 10.1111/j.1365-2982.1994.tb00192.x.
[23] M. P. J. Eifert, G. Sanglay, D. Lee, S. Sumner, “Prediction of raw produce surface area from weight measurement,” *J. Food Eng.*, doi: 10.1016/J.JFOODENG.2005.02.030.
[24] R. Vaskoska, M. Ha, H. T. T. Tran, K. Khoshelham, J. D. White, and R. D. Warner, “Evaluation of 3D Laser Scanning for Estimation of Heating-Induced Volume Shrinkage and Prediction of Cooking Loss of Pork Cuboids Compared to Manual Measurements,” *Food Bioprocess Technol.*, vol. 13, no. 6, pp. 938–947, 2020, doi: 10.1007/s11947-020-02421-0.
[25] S. Makhsous, H. M. Mohammad, J. M. Schenk, A. V. Mamishev, and A. R. Kristal, “A novel mobile structured light system in food 3D reconstruction and volume estimation,” *Sensors (Switzerland)*, vol. 19, no. 3, 2019, doi: 10.3390/s19030564.

[26] A. Gao, F. P. W. Lo, and B. Lo, “Food volume estimation for quantifying dietary intake with a wearable camera,” *2018 IEEE 15th Int. Conf. Wearable Implant. Body Sens. Networks, BSN 2018*, vol. 2018-Janua, no. March, pp. 110–113, 2018, doi: 10.1109/BSN.2018.8329671.

[27] I. J. Tello J., Cubero S., Blasco J., Tardaguila J., Aleixos N., “Application of 2D and 3D image technologies to characterise morphological attributes of grapevine clusters,” *J. Sci. Food Agric.*, vol. 96, no. 13, pp. 4575–4583, 2016, doi: 10.1002/jsfa.7675.

[28] S. Fang, C. Liu, F. Zhu, E. J. Delp, and C. J. Boushey, “Single-View Food Portion Estimation Based on Geometric Models,” *Proc. - 2015 IEEE Int. Symp. Multimedia, ISM 2015*, pp. 385–390, 2016, doi: 10.1109/ISM.2015.67.

[29] C. Xu, Y. He, N. Khanna, C. J. Boushey, and E. J. Delp, “MODEL-BASED FOOD VOLUME ESTIMATION USING 3D POSE School of Electrical and Computer Engineering , Purdue University Department of Electronics and Communication Engineering , Graphic Era University , Dehradun , India Cancer Epidemiology Program , University,” pp. 2534–2538, 2013.

[30] M. S. G. Dehais J., Shevchik S., Diem P., “Food volume computation for self dietary assessment applications,” 2013, doi: 10.1109/BIBE.2013.6701615.

[31] C. Xu, Y. He, A. Parra, E. Delp, N. Khanna, and C. Boushey, “Image-based food volume estimation,” *CEA 2013 - Proc. 5th Int. Work. Multimed. Cook. Eat. Act.*, pp. 75–80, 2013, doi: 10.1145/2506023.2506037.

[32] J. Shang *et al.*, “Dietary intake assessment using integrated sensors and software,” *Multimed. Mob. Devices 2012; Multimed. Content Access Algorithms Syst. VI*, vol. 8304, p. 830403, 2012, doi: 10.1117/12.907769.

[33] J. Shang *et al.*, “A mobile structured light system for food volume estimation,” *Proc. IEEE Int. Conf. Comput. Vis.*, pp. 100–101, 2011, doi: 10.1109/ICCVW.2011.6130229.

[34] H. Liang, Y. Gao, Y. Sun, and X. Sun, “CEP: calories estimation from food photos,” *Int. J. Comput. Appl.*, vol. 42, no. 6, pp. 569–577, 2020, doi: 10.1080/1206212X.2018.1486558.

[35] W. Tay, B. Kaur, R. Quek, J. Lim, and C. J. Henry, “Current developments in digital quantitative volume estimation for the optimisation of dietary assessment,” *Nutrients*, vol. 12, no. 4, pp. 8–15, 2020, doi: 10.3390/nu12041167.

[36] A. Graikos, V. Charisis, D. Iakovakis, S. Hadjidimitriou, and L. Hadjileontiadis, “Single image-based food volume estimation using monocular depth-prediction networks,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 12189 LNCS, pp. 532–543, 2020, doi: 10.1007/978-3-030-49108-6_38.

[37] F. P. W. Lo, Y. Sun, J. Qiu, and B. P. L. Lo, “Point2Volume: A vision-based dietary assessment approach using view synthesis,” *IEEE Trans. Ind. Informatics*, vol. 16, no. 1, pp. 577–586, 2020, doi: 10.1109/TII.2019.2942831.

[38] P. Kamakshi Priyaa, S. Sathyapriya, and L. Arockiam, “Nutrition monitoring and calorie estimation using internet of things (IoT),” *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 11, pp. 2669–2672, 2019, doi: 10.35940/ijitee.K2072.0981119.

[39] R. D. Yogaswara, E. M. Yuniarno, and A. D. Wibawa, “Instance-Aware Semantic Segmentation for Food Calorie Estimation using Mask R-CNN,” *Proc. - 2019 Int. Semin. Intell. Technol. Its Appl. ISITIA 2019*, no. August, pp. 416–421, 2019, doi: 10.1109/ISITIA.2019.8937129.

[40] S. K. Gaikwad and A. R. Karwankar, “Food image 3D reconstruction using image processing,” *Proc. Int. Conf. Trends Electron. Informatics, ICOEI 2019*, vol. 2019-April, no. Icoei, pp. 618–621, 2019, doi: 10.1109/icoei.2019.8862615.

[41] S. T. Liong, Y. S. Gan, and Y. C. Huang, “Automatic surface area and volume prediction on ellipsoidal ham using deep learning,” *J. Food Process Eng.*, vol. 42, no. 5, pp. 1–16, 2019, doi: 10.1111/jfpe.13093.

[42] D. E. S. J. O H Gilja, P R Detmer, J M Jong, D F Leotta, X N Li, K W Beach, R Martin, “Intragastric distribution and gastric emptying assessed by three-dimensional ultrasonography,” *Natl. Cent. Biotechnol. Inf.*, pp. 38–49, 1997, doi: 10.1016/s0016-5085(97)70078-7.

[43] J. O.-C. G.P. Moreda, Francisco Javier García Ramos, Margarita Ruiz-Altisent, “Non-destructive technologies for fruit and vegetable size determination – A review,” *J. Food Eng.*, pp. 119–136, 2009, doi: 10.1016/j.jfoodeng.2008.11.004.

[44] L. O. Ebrahiema Arendse, Olaniyi Amos Fwole, Lembe Samukelo, Magwazac Umezuruike, “Estimation of the density of pomegranate fruit and their fractions using X-ray computed tomography calibrated with polymeric materials,” *Biosyst. Eng.*, vol. 148, pp. 148–156, 2016, doi: https://doi.org/10.1016/j.biosystemseng.2016.06.009.

[45] F. P. W. Lo, Y. Sun, J. Qiu, and B. Lo, “Food volume estimation based on deep learning view synthesis from a single depth map,” *Nutrients*, vol. 10, no. 12, pp. 1–20, 2018, doi: 10.3390/nu10122005.

[46] Z. H. Shao Qing, Xu Tao, Yoshino Tatsuo, Zhao Yujie, Yang Wenting, “Point cloud simplification algorithm based on particle swarm optimization for online measurement of stored bulk grain,” *Int. J. Agric. Biol. Eng.*, vol. 9, no. 1, 2016, doi: 10.3965/j.ijabe.20160901.1805.

[47] F. T. Fumihiko Tanaka, “Determination of thermal diffusivity of persimmon flesh tissue using three-dimensional structure model based on X-ray computed tomography,” *J. Food Eng.*, pp. 151–157, 2018, doi: 10.1016/j.jfoodeng.2017.10.021.

[48] Z. Q. Jie Li, “The Application of Image Acquisition and Analysis Techniques to the Field of Drying,” *Food Eng. Rev.*, pp. 13–35, 2016, doi: 10.1007/s12393-016-9146-2.

[49] Q. G. Y. L. Shichao Jin, Yanjun Su, Shilin Song, Kexin Xu, Tianyu Hu, Qiuli Yang, Fangfang Wu, Guangcai Xu, Qin Ma, Hongcan Guan, Shuxin Pang, “Non-destructive estimation of field maize biomass using terrestrial lidar: an evaluation from plot level to individual leaf level,” *Plant Methods*, 2020, doi: 10.1186/s13007-020-00613-5.

[50] M. Puri, Z. Zhu, Q. Yu, A. Divakaran, and H. Sawhney, “Recognition and volume estimation of food intake using a mobile device,” *2009 Work. Appl. Comput. Vision, WACV 2009*, 2009, doi: 10.1109/WACV.2009.5403087.

[51] M. H. Rahman *et al.*, “Food volume estimation in a mobile phone based dietary assessment system,” *8th Int. Conf. Signal Image Technol. Internet Based Syst. SITIS 2012r*, no. June 2014, pp. 988–995, 2012, doi: 10.1109/SITIS.2012.146.

[52] M. Sun *et al.*, “An exploratory study on a chest-worn computer for evaluation of diet, physical activity and lifestyle,” *J. Healthc. Eng.*, vol. 6, no. 1, pp. 1–22, 2015, doi: 10.1260/2040-2295.6.1.1.

[53] Y. He, C. Xu, N. Khanna, C. J. Boushey, and E. J. Delp, “FOOD IMAGE ANALYSIS : SEGMENTATION , IDENTIFICATION AND WEIGHT ESTIMATION School of Electrical and Computer Engineering , Purdue University Department of Electronics and Communication Engineering , Graphic Era University Cancer Epidemiology Program , Univ.”

[54] W. Jia *et al.*, “Imaged based estimation of food volume using circular referents in dietary assessment,” *J. Food Eng.*, vol. 109, no. 1, pp. 76–86, 2012, doi: 10.1016/j.jfoodeng.2011.09.031.

[55] Y. Yue, W. Jia, and M. Sun, “Measurement of food volume based on single 2-D image without conventional camera calibration,” *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, no. 2, pp. 2166–2169, 2012, doi: 10.1109/EMBC.2012.6346390.

[56] P. Pouladzadeh, S. Shirmohammadi, and R. Al-Maghrabi, “Measuring calorie and nutrition from food image,” *IEEE Trans. Instrum. Meas.*, vol. 63, no. 8, pp. 1947–1956, 2014, doi: 10.1109/TIM.2014.2303533.
[57] Y. Yang, W. Jia, T. Bucher, H. Zhang, and M. Sun, “Image-based food portion size estimation using a smartphone without a fiducial marker,” *Public Health Nutr.*, vol. 22, no. 7, pp. 1180–1192, 2019, doi: 10.1017/S136898001800054X.
[58] “A COMPARISON OF FOOD PORTION SIZE ESTIMATION USING GEOMETRIC MODELS AND DEPTH IMAGES Shaobo Fang , Fengqing Zhu , Chufan Jiang † , Song Zhang † , Carol J . Boushey ‡ and Edward J . Delp School of Electrical and Computer Engineering , Purdue University Sch.”
[59] P. F. Christ *et al.*, “Diabetes60 - Inferring Bread Units From Food Images Using Fully Convolutional Neural Networks,” *Proc. - 2017 IEEE Int. Conf. Comput. Vis. Work. ICCVW 2017*, vol. 2018-Janua, pp. 1526–1535, 2017, doi: 10.1109/ICCVW.2017.180.
[60] S. Fang *et al.*, “SINGLE-VIEW FOOD PORTION ESTIMATION : LEARNING IMAGE-TO-ENERGY MAPPINGS USING GENERATIVE ADVERSARIAL NETWORKS School of Electrical and Computer Engineering , Purdue University , West Lafayette , Indiana , USA School of Public Health , Curtin University , ,” *2018 25th IEEE Int. Conf. Image Process.*, pp. 251–255, 2018.
[61] B. Calli, P. Abbeel, S. Member, A. M. Dollar, and S. Member, “The YCB Object and Model Set :,” 2015.
[62] X. Liang and W. Sun, “A fast 3D surface reconstruction and volume estimation method for grain storage based on priori model,” *Int. Symp. Photoelectron. Detect. Imaging 2011 Laser Sens. Imaging; Biol. Med. Appl. Photonics Sens. Imaging*, vol. 8192, p. 81923X, 2011, doi: 10.1117/12.901036.
[63] J. Yawata, K., Hitachi, Ltd, 1-280, Higashi-koigakubo, Kokubunji-shi, Tokyo, 185-8601, Japan; Yamamoto, T., Hitachi, Ltd, 1-280, Higashi-koigakubo, Kokubunji-shi, Tokyo, 185-8601, Japan; Hashimoto, N., Hitachi, Ltd, 1-280, Higashi-koigakubo, Kokubunji-shi, T, “Mixed model estimation of rice yield based on NDVI and GNDVI using a satellite image,” in *Remote Sensing for Agriculture, Ecosystems, and Hydrology XXI*, 2019, p. 48, doi: 10.1117/12.2532108.
[64] L. J.-H. Liang Y.-C., “Food Calorie Estimation Method Based on Deep Learning,” *Scopus*, vol. Volume 44, no. Issue 2, p. 6, 2018, doi: 10.14135/j.cnki.1006-3080.20170313006.