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A Bibliometric Analysis of Knowledge Distillation in Medical Image Segmentation

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ABSTRACT

This study conducts a bibliometric analysis and systematic review to examine research trends in the application of knowledge distillation for medical image segmentation. A total of 806 studies from 343 distinct sources, published between 2019 and 2023, were analyzed using Publish or Perish and VOSviewer, with data retrieved from Scopus and Google Scholar. The findings indicate a rising trend in publications indexed in Scopus, whereas a decline was observed in Google Scholar. Citation analysis revealed that the United States and China emerged as the leading contributors in terms of both publication volume and citation impact. Previous research predominantly focused on optimizing knowledge distillation techniques and their implementation in resource-constrained devices. Keyword analysis demonstrated that medical image segmentation appeared most frequently with 144 occurrences, followed by medical imaging with 110 occurrences. This study highlights emerging research opportunities, particularly in leveraging knowledge distillation for U-Net architectures with large-scale datasets and integrating transformer models to enhance medical image segmentation performance.

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1. INTRODUCTION

Image segmentation is one of the main tasks for medical image analysis needs and as a diagnostic support tool for health workers [1]. Accurate segmentation is essential in the clinical application of disease diagnosis and treatment planning [2]. Medical image segmentation has been used to identify lesions of clinical value in medical images. For example, accurate vascular boundaries, exact lesion areas, and complete anatomical segmentation are essential for the clinical assessment of various diseases, including glaucoma, diabetic retinopathy, prostate, polyps, brain tumors, and other diseases [3].

Medical image segmentation is the process of dividing each pixel in an image into appropriate categories [4]. This is one of the most important steps in medical image analysis. Medical image segmentation helps extract detailed information from various tissues, organs, pathologies, and biological structures for medical diagnosis, surgical planning and treatment.

In recent years, segmentation methods based on deep neural networks (CNNs) have gradually attracted widespread attention due to their excellent segmentation performance. CNNs can generalize the distribution of samples and automatically extract target features from a large amount of data, which reduces the difficulty of manually setting image features [5]. More recently, deep neural networks have been used to build medical image segmentation models. Various new models such as U-Net, DeepLab V3+, SegNet, RefineNet, and PSPNet have achieved accurate segmentation of diverse medical images for clinical diagnosis [3].

Knowledge distillation is a method in machine learning in which a larger, more complex model (referred to as a "teacher") is taught to a smaller model (referred to as a "student") to improve its performance [6]. The goal is to transfer the knowledge contained in large models to smaller models so that smaller models can achieve similar or even better performance. In general, the process of this method consists of Teacher Training and Student Training [7]. Larger, more complex teacher models are trained on training datasets for specific tasks. This model has higher abilities and greater complexity than the smaller student model [8]. The smaller student model is then trained using the same dataset, but in this case, the targets or labels used for training come not only from the original label of the dataset, but also from the output of the teacher model (referred to as "soft targets") [9]. This output is in the form of a probability distribution of the classes generated by the teacher model. This method has been applied to a variety of machine learning tasks, including image classification, object detection, and natural language processing, and has been shown to be effective in improving the performance of student models [10].

Knowledge distillation in deep learning is an approach used to compress larger and more complex models into smaller and lighter models [11][12][13]. The goal is to transfer the knowledge contained in the larger model to the smaller model so that the smaller model can achieve good performance [14][15]. This approach is often used in the context of model compression and model deployment on resource-limited devices, such as mobile devices or edge devices [16][17]. The advantages of knowledge distillation on deep learning include reduced model size [18], increased efficiency [19], and the ability to transfer knowledge from a larger model to a smaller model [20]. This approach can be very useful when we need to implement the model on a resource-constrained device, without sacrificing good prediction performance.

Knowledge distillation has several significant benefits when applied to the medical field [21][22][23]. Some of these benefits involve the use of lighter models, better interpretability, and the ability to transfer knowledge from larger models to smaller models. Models generated through knowledge distillation are generally smaller and more efficient in the use of resources. This is particularly beneficial in implementations on medical devices, such as mobile devices, edge devices, or embedded systems, which often have limitations in terms of computing power or storage capacity. Lighter and more efficient models can provide faster response in medical image processing. It can be critical in medical emergency situations or real-time observation of patients. Smaller models have a tendency to use less energy, which can be an important consideration in the development of battery-powered medical devices or portable devices. Knowledge distillation allows transferring knowledge from a larger model to a smaller model without losing much performance or accuracy. This is especially important in a medical context where predictive accuracy can have a major impact on clinical decision-making.

Knowledge distillation in medical image segmentation can help create smaller, more efficient models without sacrificing segmentation accuracy [19]. This can be beneficial when applied to medical devices that have limited resources or when a quick response to medical image processing is required. This article discusses various studies that use the Knowledge Distillation method on medical image segmentation. The analysis technique used is the bibliometric method on similar research articles within a period of 5 years from Scopus and Google Scholar. The results of this analysis are to determine the potential for new research from the Knowledge Distillation method, especially in medical image segmentation.

2. METHODS

As a research method, bibliometric (or bibliometrics) analysis has been widely used in library and information science [24]. Bibliometric analysis is a research method used to measure, analyze, and understand the impact and development of scientific literature in a field of knowledge or discipline [25]. This method involves collecting and analyzing data related to scientific publications, such as journals, articles, and citations, to gain insight into the structure and trends of research developments. Bibliometric analysis involves a series of steps to collect, manage, and analyze bibliographic data in order to gain insight into the development of scientific literature in a field of knowledge or discipline [26]. Bibliometric analysis has advantages in predicting the future trend of a discipline. It is widely applied to analyze the research status, frontier directions and development trends of certain disciplines [27]. The following are the general steps in the bibliometric analysis in this study:

1. Data collection through systematic literature search within the target range of 5 years
2. Comprehensive analysis of the collected publications

3. Discussion of results, limitations, and future research directions

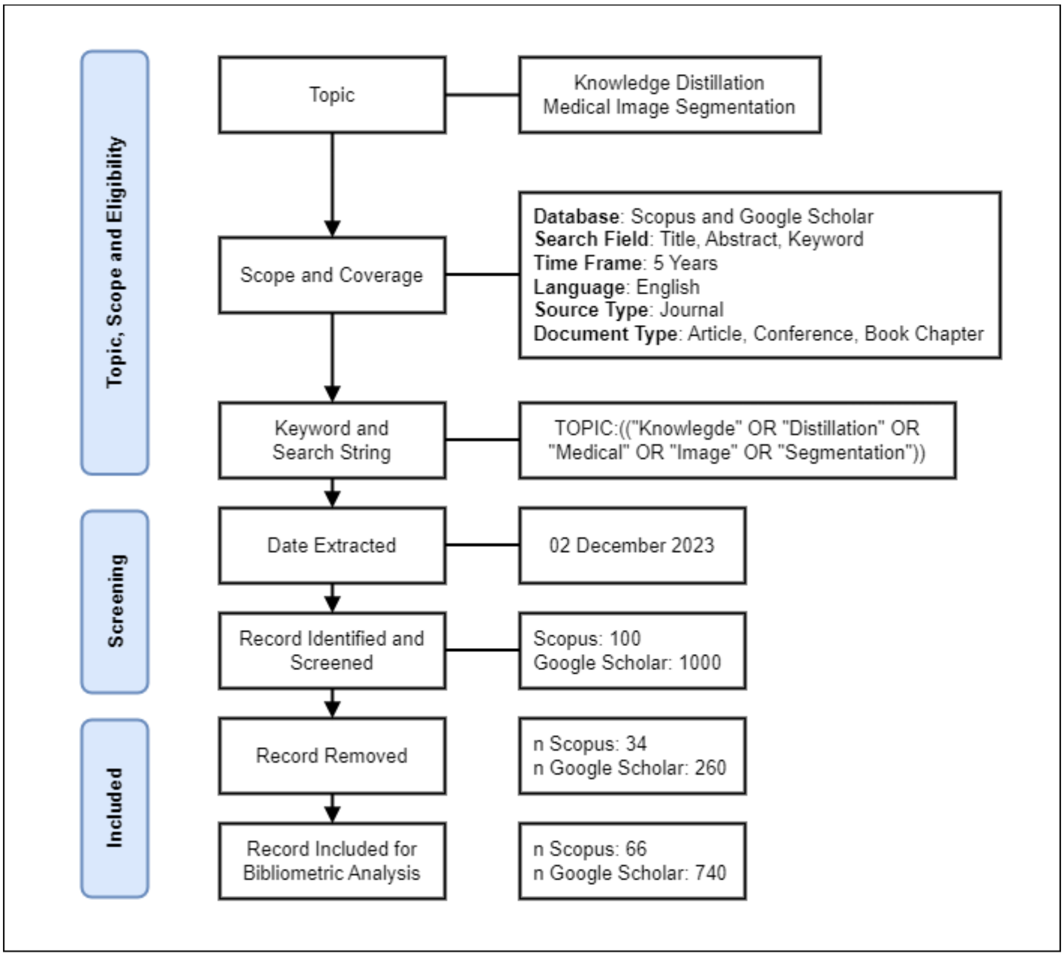

Fig 1. Bibliometric data extraction method

2.1. Bibliographic Data Extraction

Figure 1 shows the steps and details of the process of searching and extracting target datasets to perform bibliometric analysis. This study uses the Publish or Perish application, Vos Viewer and Biblioshiny to get research related to the research theme raised. The topics analyzed were Knowledge Distillation, Medical Image Segmentation. The scope and coverage in this article are sourced from the Scopus and Google Scholar databases. The search field focuses on Title, Abstract and Keywords with a Time Frame of 5 years. More specifically, we are looking for journal articles related to the English language. The documents used are Articles, Conferences or Proceedings and Book Chapters. The keywords used in this study are Knowledge, Distillation, Medical, Image and Segmentation. Based on the data successfully extracted with the Publish or Perish application, 100 related Scopus articles and 1000 Google Scholar articles were obtained. The article data obtained is then filtered again by deleting articles that are considered irrelevant. The final result of this data extraction resulted in 66 Scopus articles and 740 Google Scholar articles.

2.2. Bibliometric Analysis Methodology

Bibliometric analysis is a process of reviewing academic literature that relies on quantitative analysis of publications. A bibliometric study can be more reliable and detail-oriented than some other literature review techniques. Reviews that use bibliometric analysis are systematic, transparent, and reproducible if done correctly. Bibliometric analysis was initially very limited and was only used for citation summaries and publications. However, recent advances in bibliometric analysis tools, such as Biblioshiny, have allowed any research area to be analyzed using more complex matrices, such as co-citing, cross-collaboration between authors, institutions, and countries, source growth matrices, and historiography. In bibliometric analysis, it is a common observation that most scientific contributors offer only one manuscript, and a small but active percentage of authors are disproportionately productive [28].

3. ANALYSIS AND RESULTS

This study conducted a comprehensive analysis of bibliometrics and general information for all publications included in this study. The main information is obtained not using bibliometrix software, general information from selected documents is collected and analyzed. Table 1 shows the key information taken from all the studies included in the dataset. A bibliometric review was conducted from 806 documents from 343 sources and written by 798 different authors. The production of scientific articles on Scopus has increased in the last 5 years, but on Google Scholar there has been a decline. From the last 5 years, Scopus articles in 2023 show the highest number of publications with 30 different studies and Google Scholar articles show the highest number of publications in 2021 with 227 articles.

Table 1. Annual Publication Rate

Scopus					
Year	**2019**	**2020**	**2021**	**2022**	**2023**
Article	2	6	12	16	32
Google Scholar					
Year	**2019**	**2020**	**2021**	**2022**	**2023**
Article (n)	115	174	227	134	90

Figure 2 shows the annual publication rate from 2019 to 2023 of Scopus articles and Figure 3 shows the publication rate on Google Scholar in the range of 2019 to 2023. The Scopus article shows that in 2023 there will be a 2-fold increase compared to the previous year. In contrast to the Scopus article, in the Google Scholar article, the research trend continues to decline from 2021 to 2023. The increase in Scopus articles shows that the interest in research to be published on reputable publishers continues to increase among researchers, academics, and medical practitioners. The decline in Google Scholar publications is something worth discussing.

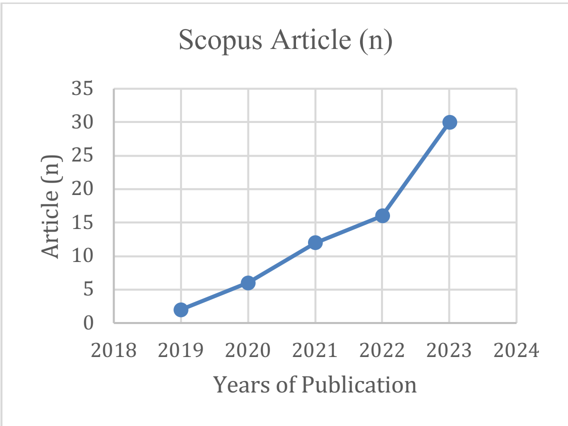

Fig. 2. Annual Publication of Scopus Article

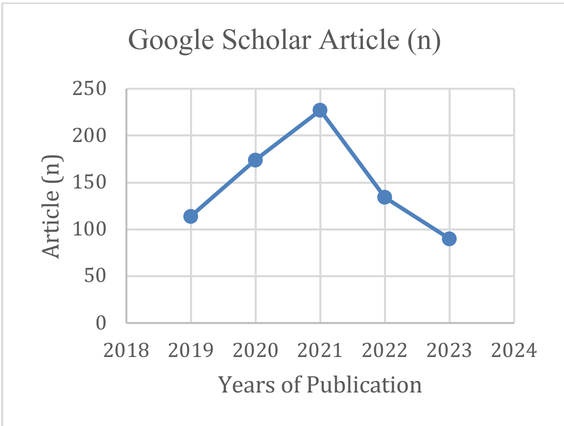

Fig. 3. Annual Publication of Google Scholar Article

3.1. Top 10 Most Cited Publications

Figure 4 and Figure 5 respectively show the most cited documents from both Scopus and Google Scholar articles. Global citations refer to the annual citation rate at the time the dataset used in this study is extracted. Based on Figure 4, The Scopus article titled "SimCVD: Simple Contrastive Voxel-Wise Representation Distillation for Semi-Supervised Medical Image Segmentation" [29] became the article with the highest number of citations, which was 76. This article discusses the issues of the need for a simple and effective framework for voxel representation learning in medical image segmentation and the need for training stability and performance improvement on unlabeled circuits in semi-supervised learning. The method proposed in the study is to use an unattended training strategy that takes two views of the input volume and predicts a signed distance map of the object's boundary in contrasting destinations. In addition, dropout is also used as a form of data augmentation to create a strong network against the collapse of representations and structural distillation is carried out by distillation of paired equations. The results of the study show that SimCVD has achieved a dice coefficient score of 90.85% and 89.03% in the Left Atrial Segmentation Challenge (LA) dataset with labeled ratios of 20% and 10%, respectively, showing an increase of 0.91% and 2.22% compared to the previous best results. The SimCVD framework also significantly advances advanced learning of sophisticated voxel representation in medical image segmentation.

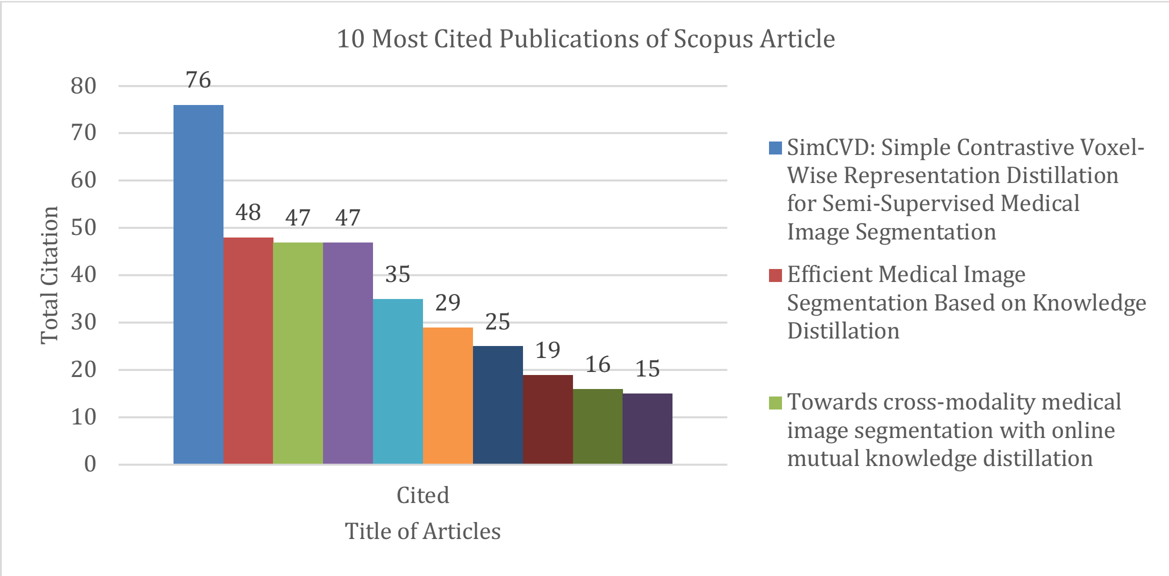

Fig. 4. 10 Most Cited Publications of Scopus Article

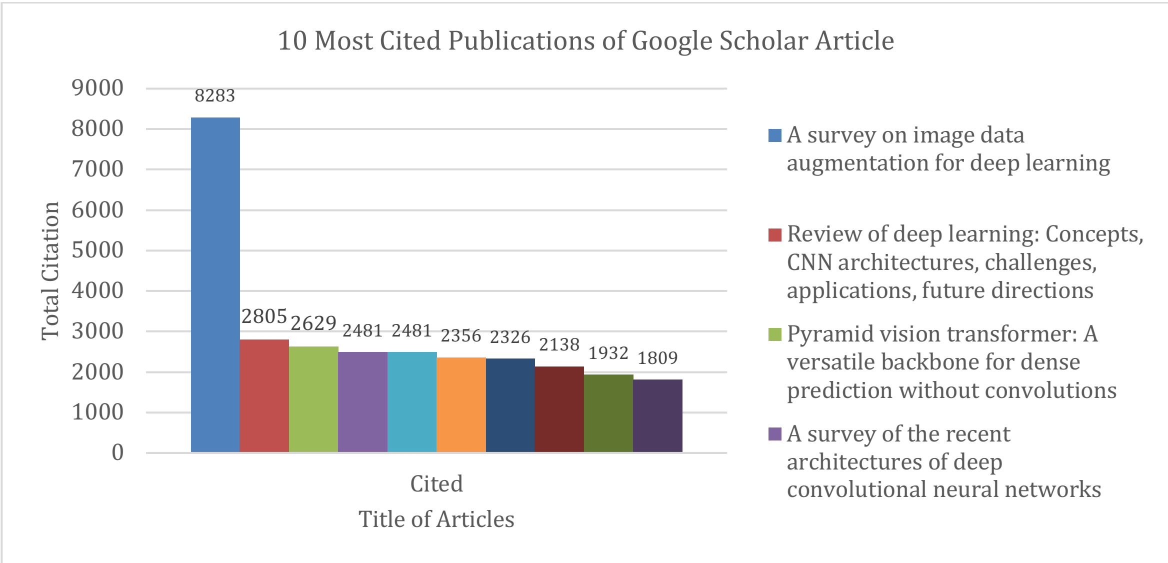

Fig. 5. 10 Most Cited Publications of Google Scholar Article

Based on Figure 5, A Google Scholar article titled "A survey on image data augmentation for deep learning" [30] became the article with the highest total citations. This certainly cannot be one of the results of a useful analysis. The article data generated from Publish or Perish, although specifically using special keywords, is apparently still not fully reliable, so advanced filters are needed so that researchers can really find the essence of the existing research data.

The next filtering technique is applied by utilizing the filter feature owned by Microsoft Excel. The filter with the contain "Knowledge Distillation" found one article that was quite specific with the title "Structured knowledge distillation for semantic segmentation" [31]. The number of citations from the article is 633. The article discusses the purpose of knowledge distillation which is useful for improving the performance of image segmentation networks by filtering structured knowledge from complex networks. The knowledge distillation method can achieve performance comparable to complex networks while being more computationally efficient.

3.2. Most Productive Countries

The top 10 countries with the highest productivity in terms of publications are presented in Table 2. Based on the table, China adheres to the most publications in the frequency of Scopus articles with a total of 35 and Google Scholar articles as many as 268. China is the contributor of the most articles with the topic "Knowledge Distillation Medical Image Segmentation" of all types of publications. The second place is the USA with 6 Scopus articles and 126 Google Scholar articles.

Table 2. Top 10 Country's Publication Frequency

Scopus		Google Scholar	
Region	**Frequency**	**Region**	**Frequency**
China	35	China	268
USA	6	USA	126
Canada	4	India	33
Hong Kong	2	Germany	30
Germany	2	Australia	29
Singapore	2	U.K	29
Tiongkok	2	Republic of Korea	22
South Korea	2	Canada	18
U.K.	2	Switzerland	12
Austria	1	Pakistan	12

The countries with the most cited articles in the last 5 years can be seen in Table 3. In articles sourced from Google Scholar, the USA has the highest number of citations, which is 21543 cited articles, followed by China with 14378 citations. In the article sourced from Scopus China, apparently it got the highest citations of 181 cited articles, followed by Belgium with 113 citations. This data shows that, although China has the highest frequency of publications, in terms of citations it is still below the USA on Google Scholar, while in Scopus China and the USA are not even in the top 10 countries with high citations.

Table 3. Top 10 Country' Publication Cited

Google Scholar		Scopus	
Region	**Cited**	**Region**	**Cited**
USA	21543	Tiongkok	181
China	14378	Belgium	113
Australia	6159	South Korea	72
Germany	5605	Australia	26
U.K.	4914	Canada	15
Republic of Korea	2441	U.K.	14
Pakistan	2327	Vietnam	10
Hong Kong	2220	Swiss	6
India	1885	India	4
Singapore	1264	Pakistan	12

3.3. The Most Productive Affiliation Between Institutions

Figure 6 Describes the institution that has the highest publication frequency in Scopus and Figure 7 describes the institution that has the highest publication frequency on Google Scholar. Based on Fig. 6, Shenzen University is the institution that produces the most Scopus publications on the topic of knowlegde distillation medical image segmentation as many as 3 specific articles and other institutions also produce the number of publications as many as 2 articles. The most interesting thing is that all institutions are from China. One of the articles from Shenzen University with the highest number of citations is "Real-time Colonoscopy Image Segmentation Based on Ensemble Knowledge Distillation" [32]. The article proposes an ensemble knowledge distillation approach for real-time colonoscopy image segmentation. The model is capable of detecting polyps, Merkel's diverticula, ulcers, and bleeding simultaneously from colonoscopy images. The model's performance has been tested on both public and real datasets, and it has been found to achieve acceptable results. This model has the potential to help doctors make decisions in practice, improving the detection of various intestinal diseases during colonoscopy.

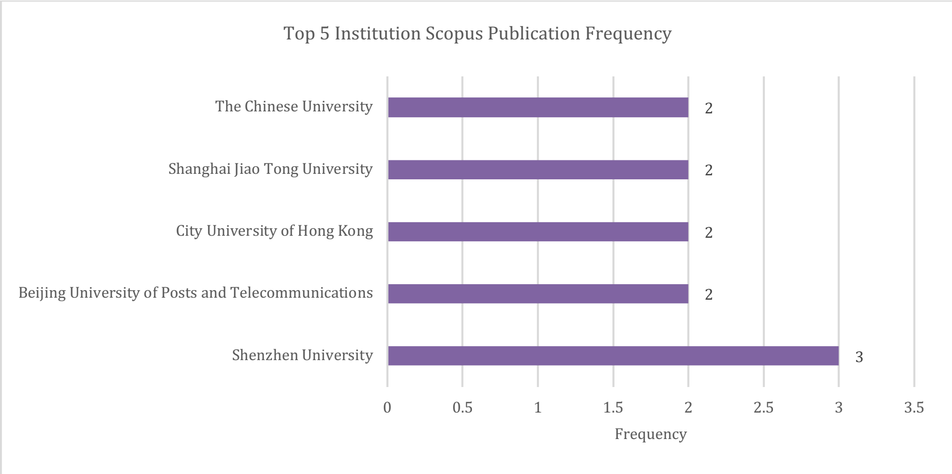

Fig. 6. Top 5 Institution Scopus Publication Frequency

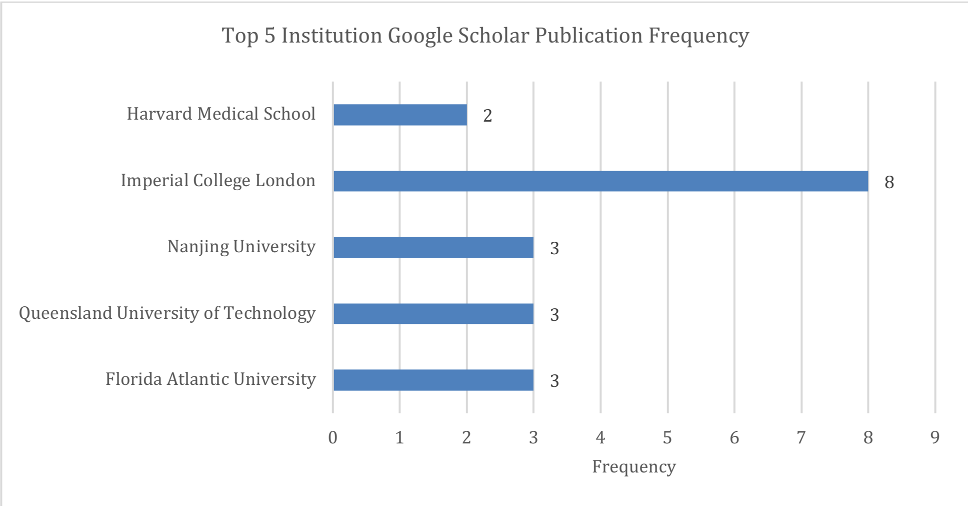

Fig. 7. Top 5 Institution Google Scholar Publication Frequency

Based on Figure 7, Imperial College London is the institution with the highest frequency of publications on Google Scholar. This institution has successfully published 8 articles related to knowledge distillation in medical image segmentation. One of the articles with the topic of knowledge distillation is "Unpaired multi-modal segmentation via knowledge distillation" [33].

Table 4 represents the number of institutions that have the most publication citations on Scopus Google Scholar. Based on Table 4, Yale University ranks first in the most Scopus document citations with 78 citations followed by The Chinese University in second place with 72 citations. In the Google Scholar publication, Florida Atlantic University received the highest number of citations, namely 8818 citations, followed by the Queensland University of Technology. One of the articles from Yale University titled "SimCVD: Simple Contrastive Voxel-Wise Representation Distillation for Semi-Supervised Medical Image Segmentation" [29] became the largest contributor of citations, as many as 76. In data sourced from Google Scholar, an article by the Queensland University of Technology titled "Optimizing the performance of breast cancer classification by employing the same domain transfer learning from hybrid deep convolutional neural network model" [34] proposes a new model to optimize performance by using transfer learning techniques, that is, deep learning models train a task, and then refine the model for other tasks. The results of the study empirically prove that the same domain transfer learning can optimize performance.

Table 4. Top 5 Institution Publication Cited

Scopus		Google Scholar	
Institution	**Cited Documents**	**Institution**	**Cited Documents**
Yale University	78	Queensland University of Technology	2962
The Chinese University	72	Nanjing University	2772
Zhejiang University	48	Imperial College London	2686
Harbin Institute of Technology	47	Harvard Medical School	2584
Shanghai Jiao Tong University	36	DCIS	2481

3.4. Most Frequent Keywords

The emergence and relevance of keywords that are widely used in selected publications can be analyzed using the Vos Viewer application. Table 5 is a list of the most searched keywords by researchers interested in the topic "Knowledge Distillation Medical Image Segmentation". Based on Table 5, the keyword medical image segmentation had the highest occurrenceences of 144 followed by medical imaging with 110 occurrenceences. Of the 10 popular keywords, prior knowledge appears which is one part of the topic of knowledge distillation in medical image segmentation. Research related to knowledge distillation has apparently begun to be interesting, especially in the field of deep learning.

Table 5. Top 10 Most Searched Keywords

Term	Occurences
Medical image segmentation	144
Medical Imaging	110
Image Processing	83
Semantic Segmentation	74
Processing	67
Transformer	50
Medical Image Processing	49
Prior Knowledge	41
Convolutional Neural Network	36
Artificial Intelligence	36

3.5. Network Keyword Analysis

The extraction of research data sourced from Scopus and Google Scholar is then visualized using the Vos Viewer application. Sourced from the analysis of keywords that are widely used by researchers, we visualize the relationship between the keyword "Knowledge Distillation" and other keywords. Figure 8 is the result of visualization that has been successfully obtained.

Based on Figure 8, The keyword "knowledge distillation" is connected to several other keys such as machine learning, deep learning model, self, convolutional neural network, medical image segmentation, semantic segmentation, medical imaging, medical image processing, object detection, u-net, semi, state, and transformer. The graph opens up new insights that knowledge distillation has begun to be widely applied to the field of medical image segmentation. U-net, which is one of the semantic segmentation architectures [35][36] is one of the architectures that emerges and is related to knowledge distillation.

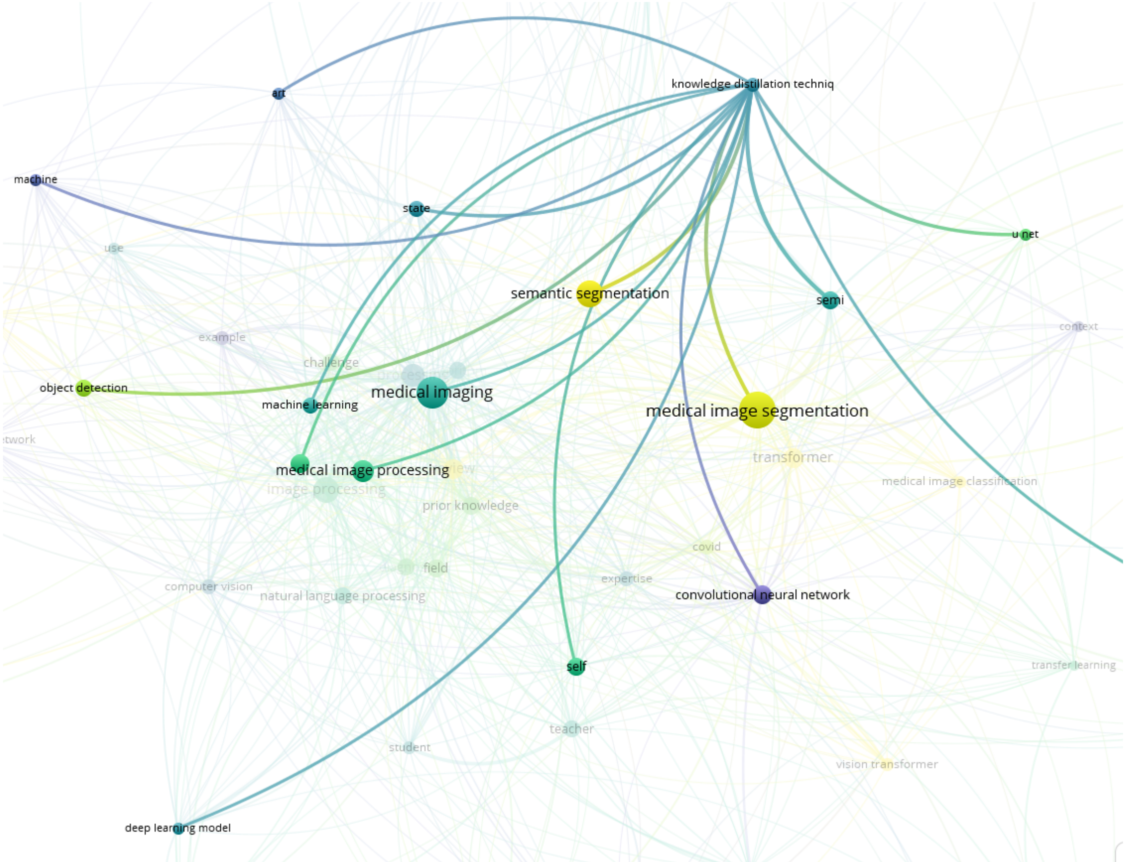

Fig. 8. Keyword Visualization Related to Knowledge Distillation

4. STATE OF THE ART

The state of the art *search method* in this study involves bibliometric analysis of Scopus and Google Scholar article data that has been selected and analyzed. Knowledge distillation is one of the interesting topics and is starting to attract a lot of attention because of its ability to compress large deep learning models so that it can be applied to various small devices without reducing the ability of the teacher model [37][38][39]. This knowledge distillation ability finally has the potential to be developed in the deep learning model in the medical field [40][41][42][43][44].

The level of publication in reputable international journals on this topic continues to increase, this shows that the interest in research to be published on reputable publishers continues to increase among researchers, academics, and medical practitioners. The Scopus article with the highest number of citations, "SimCVD: Simple Contrastive Voxel-Wise Representation Distillation for Semi-Supervised Medical Image Segmentation", has been proven to improve the knowledge distillation process. The highest-cited Google Scholar article, "Structured knowledge distillation for semantic segmentation", discusses the purpose of knowledge distillation which is useful for improving the performance of image segmentation networks by filtering structured knowledge from complex networks. The knowledge distillation method can achieve performance comparable to complex networks while being more computationally efficient.

Some of the keywords used by previous researchers show that knowledge distillation is widely used in deep learning, especially in segmentation of medical images. The interesting thing is the emergence of the transformer keyword which is included in the top 10 most searched keywords. If you look for more, apparently the transformer in knowledge disstillation can also be one of the interesting topics that can be tested in a study. For example, research conducted by [45][46][47][48] has used transformers and knowledge distillation. Knowledge distillation cannot be separated from general deep learning models such as Convolutional Neural Networks. This shows that knowledge distillation can be a new method that produces 'novelty' if applied to certain parts of deep learning.

Based on network keyword analysis visualized using Vos Viewer, knowledge distillation is connected to medical image segmentation, especially semantic segmentation. U-nets with small probabilities also seem to be connected to knowledge distillation. This means that the U-Net architecture if it uses big data can be compressed with the concept of knowledge distillation. In this way, U-Net can be applied to small devices such as mobile phones or IoT devices [49][50][51].

5. STUDY LIMITATIONS AND FUTURE DIRECTION

In this study, only Scopus and Google Scholar were used for bibliometric dataset extraction. Future research could use reports from various digital libraries, including PubMed and Web of Science, and build a single dataset from multiple sources. Thus, the target dataset for analysis will be much larger, thus providing a broader overview. Second, the next research can apply a 5-year period as a limitation in search conditions when extracting datasets from Scopus, PubMed, WoS and Google Scholar. Broader research findings can be found over longer spans, such as 10-year publications. Finally, documents that are not written in English are not extracted or selected, thus aiding in automated bibliometric analysis. However, language bias may occur in the analysis efforts in this study. Language translators can be used to translate non-English publications, so the report can also be included in the dataset.

6. CONCLUSION

Bibliometric analysis of publications on knowledge distillation methods in medical image segmentation was carried out with a collection of research data reported from 2019 to 2023. Scopus and Google Scholar are used to extract the target dataset. The USA, China, Australia, Germany, China and Belgium are among the most influential and productive countries, with the highest number of publications. The growth of research on Scopus data shows a fairly high increase from year to year, but there is a decrease if we look at the Google Scholar graph. The publication with the highest citations on Scopus proposes optimization for the knowledge distillation method and the article with the highest citations on Google Scholar discusses the purpose of knowledge distillation which is useful for improving the performance of image segmentation networks by filtering structured knowledge from complex networks. The most prolific affiliates are from the State of China. This can be seen from several of its institutions being the institutions that publish the most publications with the topic "knowledge distillation medical image segmentation". The keyword "medical image segmentation" is the most searched keyword when it is related to knowledge distillation. Of the 10 popular keywords, prior knowledge appears which is one part of the topic of knowledge distillation in medical image segmentation. The visualization of network keyword analysis opens up new insights that knowledge distillation has begun to be widely applied in the field of medical image segmentation.

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