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A data-driven analysis of global research trends in medical image: A survey

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A R T I C L E I N F O

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A B S T R A C T

With the development of artificial intelligence and high-performance computing equipment, new technologies have huge effects on medical image research. However, it is difficult to find out when new research topics appear, who those authors with influences are, and how relevant publications influence the academic community. In order to catch up with global research trends, traditional methods of literature review are inadequate to acquire information. In this case, a data-driven analysis offers a new quantitative approach to studying global research trends. Specifically, this paper used several basic bibliometric indexes to characterize the global trends of medical image research from 1993 to 2022, including yearly output, active journals, important authors, active institutions, and main countries. Furthermore, we utilized network-based methods to analyze the internal relations of co-word, co-authorship, and co-citation, so as to discover academic hotspots and clarify global research trends. Finally, some conclusions are drawn as follow: (1) The present medical image research is on an upward trend. The number of publications on medical image surged since 2015 due to advances in deep learning. Deep learning and convolutional neural networks (CNNs) are both popular research keywords in recent years. (2) *IEEE Transactions on Medical Imaging* is the most influential journal in view of Total Local Citation Score (TLCS) and Total Global Citation Score (TGCS), followed by *Medical Image Analysis*. *Neurocomputing* and *Information Fusion* are well-recognized in local research community. (3) Van Ginneken B and Aerts HJWL are representative scholars in consideration of TLCS and TGCS. (4) The USA is a leading country in medical image research. Other influential countries include China, India, UK, Germany, France, Canada, Netherlands, Australia, Italy, South Korea, Switzerland, etc. Most important institutions are from these countries, including *Harvard*, *UMich*, *Stanford*, *UPenn*, *UNC*, *CAS*, *SJTU*, *UCL*, *UofT*, *RU*, etc. (5) Application of artificial intelligence technologies, especially CNNs, has dramatically promoted global studies of medical image since 2015. Interdisciplinary collaborations become popular among experts with different disciplines backgrounds. We can infer that medical image analysis and application based on deep learning will still be a flourishing field in the near future with the improvement of algorithms and the application of high-performance computing equipment.

1. Introduction

Medical images describe distributions of various physical features measured from the human body [1]. Medical image research contains two relatively independent research directions: medical imaging system and medical image processing. Medical imaging has categories including ultrasound imaging, X-ray imaging, computed tomography (CT), magnetic resonance imaging (MRI), Positron Emission Tomography (PET), etc. [2] Medical image processing involves several tasks such as segmentation [3], registration [4], enhancement [5], conversion [2], clustering [6], etc.

When the medical images were first digitized and processed in a computer, scientists tried to analyze them automatically. Sets of rules were established for medical image processing in the early days. In the late 1990 s, pattern recognition and machine learning, especially supervised methods, enjoyed tremendous popularity among academics of medical image analysis [7,8]. In the early 2000 s, many researchers turned to optimize learning models according to specific problems [9,10]. Since the great success of AlexNet [11] in 2012, deeper convolutional networks have made

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great progress in computer vision [12]. Deep learning in medical image analysis appeared at international conferences soon and has grown dramatically since 2015.

A number of studies have made efforts to summarize literature on medical image (such as Litjens et al., 2017 [7], Ravi et al., 2017 [13], Mathur et al., 2019 [14], Haskins et al., 2020 [15], Sarvamangala et al., 2021 [16], Chen et al., 2022 [46]), based on which they describe the trends and supply expert insights for future researches. Nonetheless, this interdisciplinary scientific field covers a wide range of topics and research directions, and it is difficult for scholars to fully understand the situation. Further, expert opinions may be biased due to background, expertise, and view [17]. Hence, we need to investigate the research trends from another perspective.

The data-driven analysis is a more objective approach based on quantitative analysis. It can use basic bibliometric information, e.g., keywords, authors, citations, institutions, countries, and topics [18]. Two important metrics have been applied to the numerical analysis: total local citation score (TLCS) and total global citation score (TGCS) [19]. They represent the local and global influence of authors and journals. Other structure information can be extracted by network-based approaches such as co-author relations, co-word relations, and co-citation relations. These metrics have been proved effective for analyzing and understanding the scientific field, especially in areas where readers may require a great deal of expertise and corresponding background.

Several scientometric analyses have been conducted in previous work [18–20]. These analyses clearly show the local and global impacts of topics and journals. Also, internal structure information better reveals the interactions among topics. However, data-driven analysis is rarely adopted in the field of medical image research. With the rapid growth of the field, this type of data-driven analysis is becoming more and more necessary. Therefore, we propose the use of scientometric methods to help analyze trends in the field.

The main contributions can be summarized as a better roadmap for newcomers to the field; interdisciplinary research chances can be better identified; knowledge gaps can be found by seasoned experts to gain a more objective understanding of the field. The rest of this article is presented as follows. Section 2 gives the procedure of data acquisition. Section 3 elaborates the methodology of data-driven analysis. Numerical indexes and network-based methods are introduced in detail. Section 4 and 5 present bibliometric and network-based analysis. Section 6 discusses the subject category distribution and the reason why medical image research has become a hotspot in recent years. Section 7 concludes and points out future research directions.

2. Data acquisition

Several databases can be selected as data sources of bibliographic data such as Web of Science (WOS), Scopus, Embase, etc. In this work, data are acquired from the WOS Core Collection, a well-known comprehensive database that provides standardized academic publications [21]. Specifically, we retrieve data from the Science Citation Index Expanded database of WOS. The Science Citation Index (SCI) is recognized as an authoritative and high-quality scientific literature citation indexing tool due to its rigorous selection process [22]. Science Citation Index Expanded (SCI-E) is an expanded version of SCI covering some extra important papers that are not indexed by SCI. Furthermore, the aforementioned database has been used for the bibliometric analysis in past bibliometric review articles [17,21,22].

The search criteria used in this paper are shown in Table 1. We defined several phrases related to medical image as a search query. The timespan was restricted to the past thirty years from 1993 to 2022. We attempted to obtain "Article" type documents in the SCI-E database in all languages since most well-recognized academic papers are published in the form of articles [19]. The database was accessed on September 7th, 2022. Finally, a total of 19,762 records related to the medical image over the past three decades have been obtained from the WOS. Among the publications, 98.02 % of articles (19,371) are written in English. Other languages involve French (218), German (68), Chinese (50), Spanish (22), Dutch (9), Turkish (5), Korean (4), Portuguese (4), Japanese (3), Polish (3), etc.

Analysis and visualization of the extracted data can be handled by many bibliometric and network tools such as HistCite, Pajek, VOSviewer, Gephi, and CiteSpace. This work strives to explore the global trends in medical image research by programming and utilizing HistCite [23], VOSviewer [24], and CiteSpace [25].

3. Methodologies

Both basic bibliometric analysis and network analysis are exploited to reflect the global academic research trends and explore hotspots in the field of medical imaging. In this section, numerical indexes are first introduced to help readers comprehend some important concepts in subsequent analysis. Then network-based methods are presented with co-word, co-authorship, and co-citation analysis.

3.1. Numerical indexes

For most scholars in academia, the Impact Factor (IF) is a well-known metric for evaluating the impact of an academic journal. It is an instant index by calculating the yearly average number of citations gained by papers published in the journal [26]. Journals with high IF are cited more frequently and play a crucial role in scientific development and communication. However, the IF also has some disadvantages. For instance, biological science or medical journals typically have higher IF than computer science or engineering. Besides, open-access journals incline to have higher IF since they provide easy access to their academic publications. In these cases, the IF may not be effective to measure the true quality or impact of journals. Hence, it is essential to incorporate extra metrics for further assessing the quality of journals.

Two indexes are contained in the bibliometric tool HistCite [23]: TLCS and TGCS. TLCS and TGCS are abbreviations for Total Local Citation Score and Total Global Citation Score, respectively. TLCS describes the count of citations that a research article gains from the present data collection. In this study, local data collection is the data retrieved from the SCI-E database with specified search criteria. On the other hand, TGCS refers to the times that an article has been cited from the entire data collection. Taking this work as

Table 1
Search criteria given in this paper.

Search Query	Timespan	Document Types	Citation Indexes	Language
"medical image" OR "medical imaging" OR ("medical X-ray" OR "medical computed tomography" OR "medical MRI" OR "medical Positron Emission Tomography")	1993–2022	Article	SCI-E	All

an example, WOS is the whole database. By combining TLCS and TGCS indexes, it is possible to discover underlying research trends within the domain and throughout the entire science community.

3.2. Network-based methods

The numerical indexes above give straightforward rankings, but they are incapable of providing insights into the relations among the target papers, journals, or authors. Therefore, some network-based analysis approaches have been presented, including co-word [27], co-authorship [28], and co-citation network [29].

Co-word network. Co-word network method was proposed by French scholars and soon attracted the attention of numerous researchers [30]. The co-word relationship could be simply considered as the co-occurrence of keywords in academic publications. The co-word relation would be strong enough if every-two keywords appeared together with a high frequency. We can construct a co-word network by extracting the keywords of all papers in data collection and counting the co-occurrence relationship. By reducing links using minimum spanning tree and pathfinder network [31], crucial clusters of keywords are created for the analysis of research trends.

Co-authorship network. Compared to the co-word networks, the co-authorship networks reflect the relationship of co-author in the academic circle rather than groups of keywords. Authors and their co-author relations can be simplified as nodes and links in a co-authorship network. The weight of links denotes the strength of the scientific collaboration relation. When two scholars co-author a paper, the weight of the link will increase by one. The more frequent every-two scholars co-author, the stronger the co-author relation will be. Many scientific co-authorship networks have been created and applied in different fields of academic analysis [32].

Co-citation network. The co-citation network can be constructed based on the co-citation relationship. Similar to co-word and co-authorship network, the nodes and links of a co-citation network are the cited references and co-citation relations. This type of network investigates the bibliographic datasets based on the co-citation relationship. If a paper cites two other research articles in the reference, a link will be built between the two articles. The link strength represents the frequency that two articles are co-cited. The co-citation network studies research hotspots and trends from the perspective of domain knowledge, rather than the social relationships of authors. In addition, co-citation networks display more details than co-word networks that focus on the semantic level.

Experiments using both bibliometric and network analysis are elaborated in the following section. Simple numerical indexes like TLCS and TGCS will be applied to direct bibliometric analysis. Based on the network technologies, three methods of co-word, co-authorship, and co-citation network are given to illuminate the global research trends in the field of medical imaging. Moreover, the visualization of produced network helps to better understand important research communities.

4. Basic bibliometric analysis

4.1. Yearly output

Yearly output reflects the annual activity and impact of a research field. Here, we calculate the time distribution of yearly publication counts, TLCS, and TGCS to uncover the active and influential status of medical image research. The publication count directly reveals the number of records collected in the WOS database each year. TLCS and TGCS stand for the local and global impact of publications. Publication counts, TLCS, and TGCS of the medical image between 1993 and 2022 are shown in Fig. 1.

According to Fig. 1, before 2012, the annual publication count in the field of medical imaging was less than 600. However, this number began to increase dramatically in the past ten years due to the development of deep learning and high-performance computing equipment. The last decade witnessed an upward trend in the research of medical image, especially in the last three years. There are 1,470, 1,955 and 2,240 research articles published in 2019, 2020 and 2021, respectively. Because of incomplete data for 2022 when the database was accessed on September 7th, 2022, it explains the low record in 2022.

Even though publication count is a good indicator of activity, it does not represent the influence of papers. Two other metrics, TLCS and TGCS, can measure the degree of influence because they utilize the number of citations, which often reflects the impact of a journal or an author. TGCS is much larger than TLCS because TGCS gets references from the entire WOS database.

The TLCS peaked in 2019 (2,787), so the publications in 2019 have attracted huge attention from researchers in the local field. By examining the publications in 2019, we discovered two papers contribute a lot to this peak: "CE-Net: context encoder network for 2D medical image segmentation [33]" (129) and "Medical image

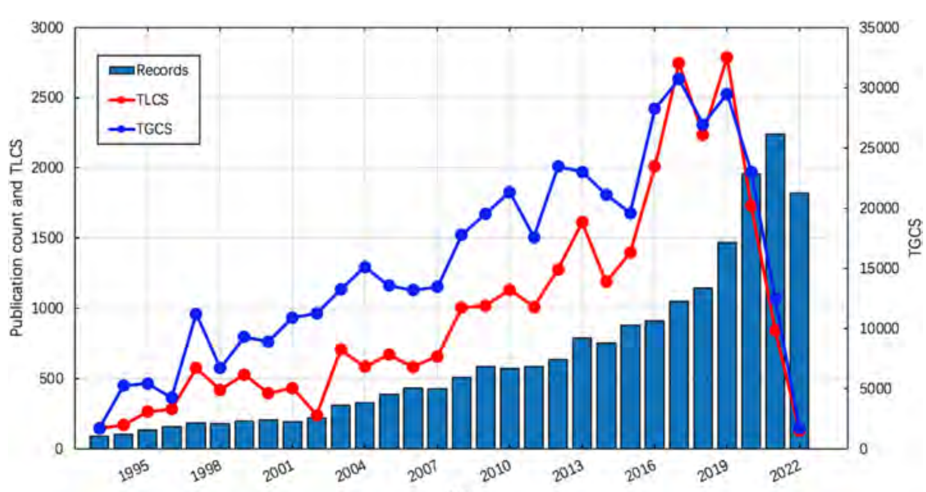


Fig. 1. Yearly output of medical image research in the WOS database from 1993 to 2022.

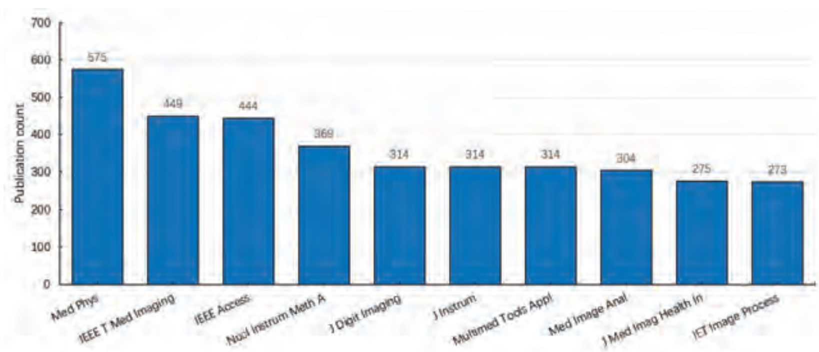
fusion with parameter-adaptive pulse coupled neural network in nonsubsampled shearlet transform domain [61]" (113). Both of them focus on the complicated neural network model in specific tasks of medical image. In addition, there was another local peak (2,745) in 2017. We found a paper named "A survey on deep learning in medical image analysis" [7] with the largest LCS (Local Citation Score) of 548, accounting for the peak. As deep learning has been a prevalent topic in recent years, a survey on deep learning in the field of medical image analysis naturally draws considerable attentions from the local community.

TGCS achieved its peak with a value of 30,698 in 2017. Four papers play a vital role: "A survey on deep learning in medical image analysis" [7]" (with a GCS of 4,615), "Computational radiomics system to decode the radiographic phenotype [34]" (with a GCS of 1,732), "Deep learning for health informatics [13]" (with a GCS of 725), and "Low-dose CT with a residual encoder-decoder convolutional neural network [35]" (with a GCS of 625). We also saw some local peaks in 2010, 2012, and 2019 due to the delay citation window effect [20]. Besides, it needs several years for a new paper to get citations, which also leads to a low value of TLCS and TGCS in 2020, 2021 and 2022.

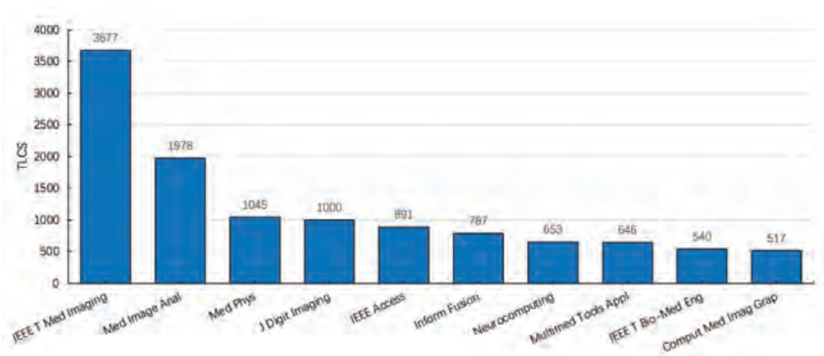
4.2. Active journals

Journals are often the conduits for well-recognized research results and academic activities [20]. The 19,762 downloaded articles are derived from 2,968 different journals. The top ten journals with the highest publication counts, TLCS, and TGCS are summarized in Fig. 2, respectively.

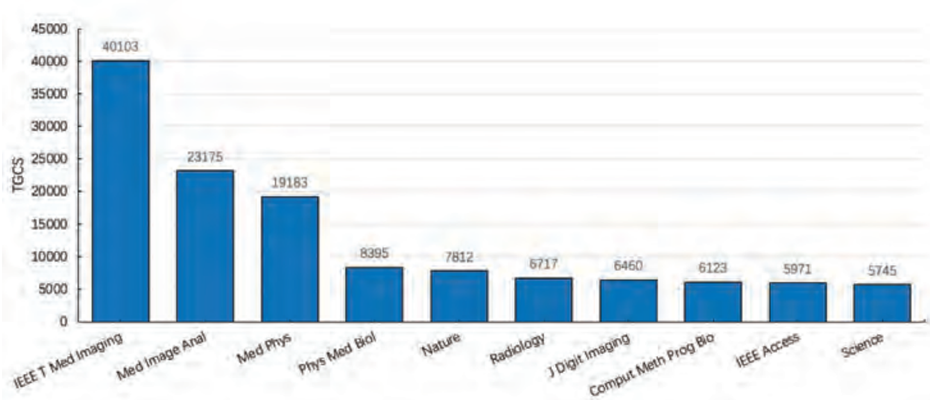
According to Fig. 2 (a), *Medical Physics* produces the largest number of publications. It is the most active journal in medical image research from the viewpoint of publication output. On the



(a) Top ten journals of publication count



(b) Top ten journals of TLCS



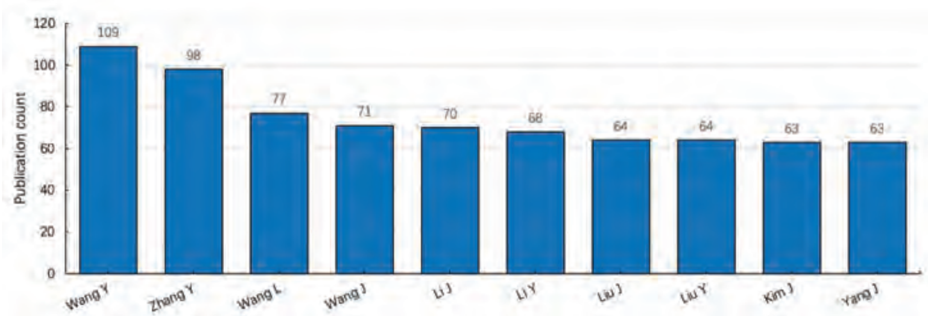
(c) Top ten journals of TGCS

Fig. 2. Publication count, TLCS, and TGCS per journal for medical image (1993–2022).

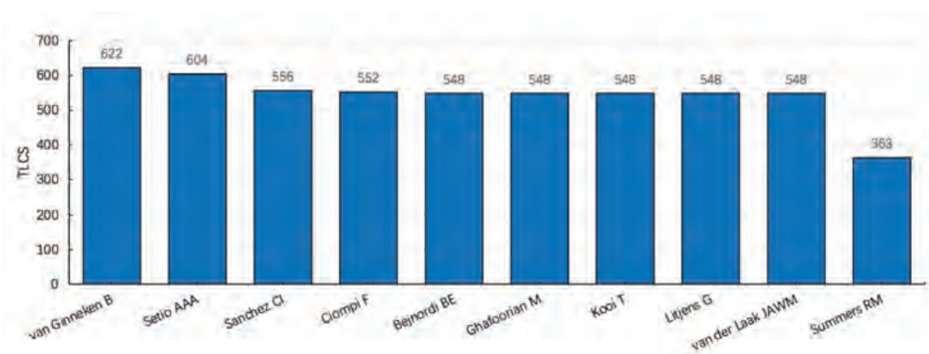
contrary, *IEEE Transactions on Medical Imaging* holds the highest TLCS and TGCS (see Fig. 2 (b) and Fig. 2 (c)), which means it gets cited by both in-domain and out-domain scholars. Therefore, this journal has a great influence on the local and the whole scientific community. Within the journal, a paper titled "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning [36]" maintains a maximum LCS of 195, whereas another paper titled "Multimodality image registration by maximization of mutual information [37]" has the largest GCS value of 3,312. *Medical Image Analysis* and *Medical Physics* are ranked second and third in view of TLCS and TGCS. Famous multidisciplinary journals, such as *Nature*, *Science*, etc., appear in the top ten TGCS rankings. This is partly because papers published in the world's leading journals have drawn more attentions from scholars outside medical image research. In contrast, *Information Fusion* and *Neurocomputing* possess larger TLCS (ranked sixth and seventh) but do not appear in the top ten journals of TGCS. These two journals focus more on computer science and artificial intelligence techniques in medical image processing, hence attracting researchers within the domain.

4.3. Important authors

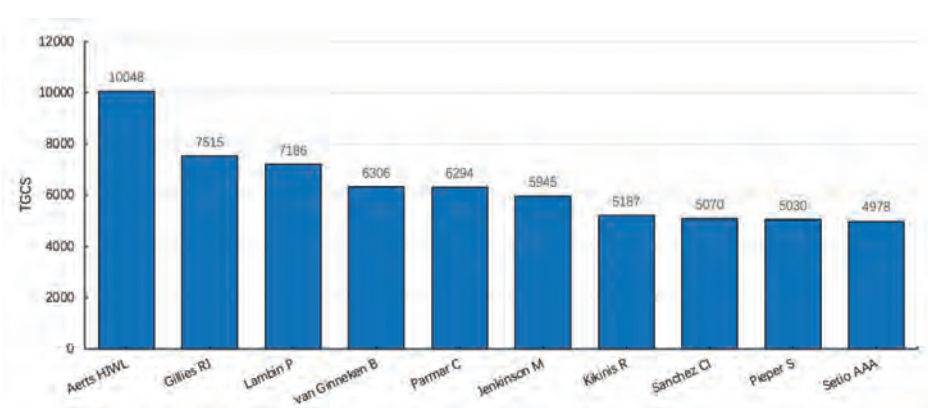
Important authors are significant indicators to assist scholars in academic research [19]. Newcomers can quickly follow the research hotspot by looking at the publications of the leading authors. In the field of medical image research, 58,933 different authors published 19,762 papers. All authors in the dataset are ranked by three metrics: publication count, TLCS, and TGCS. As depicted in Fig. 3 (a), many productive authors have written more than 60 articles, but none of them appears in the TLCS or TGCS rankings. The high number of publications is due to the ambiguity of Chinese personal names. For example, "Wang Y" may refer to Wang Yue (Beijing Institute of Petrochemical Technology), Wang



(a) Top ten authors of publication count



(b) Top ten authors of TLCS



(c) Top ten authors of TGCS

Fig. 3. Publication count, TLCS, and TGCS per author for medical image (1993–2022).

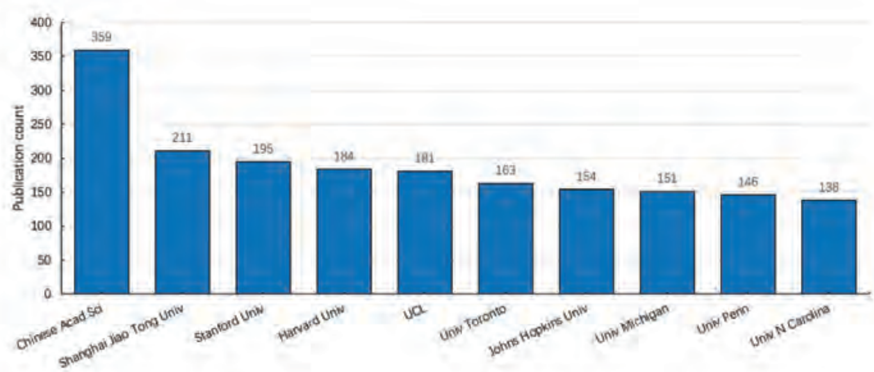
Yi (St. Francis Hospital), Wang Yu (North University of China), Wang Yi (Iowa State University), Wang Yan (University of California, San Francisco), etc. Therefore, TLCS and TGCS are more accurate to measure important authors in this case.

For TLCS in Fig. 3 (b), nine of the top ten TLCS authors (except Summers RM) co-authored a paper titled "A survey on deep learning in medical image analysis" [7] with the LCS of 548. Accordingly, they have a TLCS of at least 548 and belong to a highly influential group in the local research community. Furthermore, three of the nine authors appear in the TGCS ranking in Fig. 3 (c), involving Van Ginneken B, Setio AAA, and Sanchez CI. In other words, the three experts also play an important role in the all-science community.

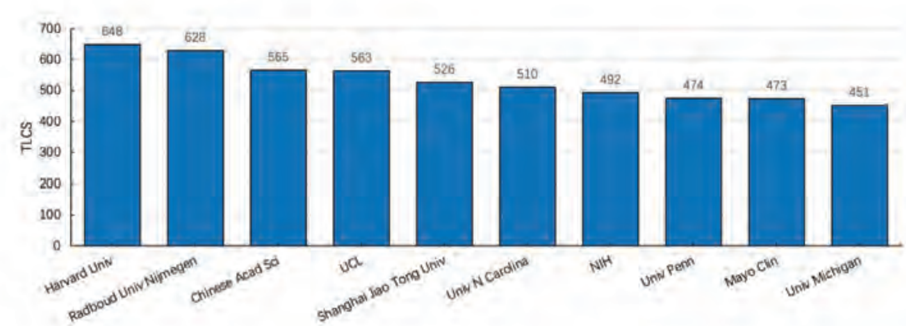
We investigated the top ten TGCS authors and discovered that Aerts HJWL has the largest influence from the standpoint of TGCS. He has many high GCS research articles and has contributed a lot to the global impact. One paper named "Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach" [38] published in 2014 achieves the highest GCS of 24,74.

4.4. Active institutions and main countries

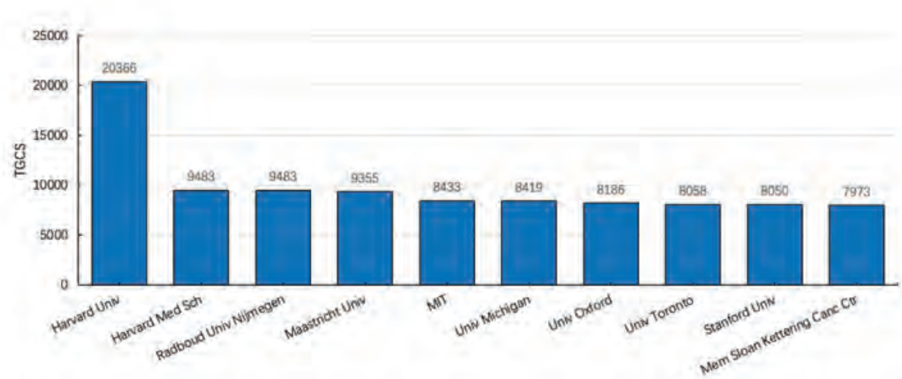
Institutions play a substantial role in analyzing global trends in the academic field. By counting the institutions of all authors, we gained 13,389 institutions. The publication counts of the top ten institutions account for 9.52 % of the total literature. Publication count, TLCS and TGCS per institution are illustrated in Fig. 4. *Chinese Academy of Sciences (CAS)* had 359 papers for publication, so it is the most active institution in consideration of the publication count. *Shanghai Jiao Tong University (SJTU)* and *Stanford University* rank second and third respectively. About 88.02 % of papers were published between 2013 and 2022 for *CAS*, compared to 81.04 % and 69.74 % for *SJTU* and *Stanford*, respectively.



(a) Top ten institutions of publication count



(b) Top ten institutions of TLCS



(c) Top ten institutions of TGCS

Fig. 4. Publication count, TLCS, and TGCS per institution for medical image (1993–2022).

As for TLCS, *Harvard University* achieves the best TLCS, followed by *Radboud University Nijmegen (RU)*. *Harvard* continuously published journals with local impact from 1997 to 2022. Most research concentrates on computer science methods in medical image analysis and processing. However, there are only 36 papers in the dataset for *RU*, among which the paper titled "A survey on deep learning in medical image analysis" [7] has the highest LCS of 548. This means that some influential papers play a pivotal role in improving the academic reputation of an organization. *CAS* and *SJTU* rank third and fifth in TLCS respectively.

Harvard University and *Harvard Medical School (HMS)* are the leading institutions from the perspective of TGCS as shown in Fig. 4 (c). Many scholars from *HMS* often use *HMS* rather than *Harvard University* as their institution. Consequently, *Harvard* plays an important role in all scientific areas. Nevertheless, *CAS* and *SJTU* fail to enter the TGCS rankings, which indicates the two Chinese universities are currently less influential than other top ten institutions in the entire science community.

Overall, only *Harvard University* and *University of Michigan (UMich)* appear in the top ten ranking list for publication count, TLCS and TGCS. Other active and important institutions appear twice in the three rankings, including *Stanford University*, *University of Pennsylvania (UPenn)*, *University of North Carolina (UNC)*, *University College London (UCL)*, *University of Toronto (UofT)*, *CAS*, *SJTU*, and *RU*.

Countries are another dimension for assessing academic activities in medical image research. The retrieved papers are from 134 different countries, suggesting many countries attach importance to this field. The top ten countries have occupied 89.30 % of the total publication count. Fig. 5 displays the top ten countries according to publication counts, TLCS, and TGCS.

Both the USA and China are in the top two positions in terms of three metrics. The USA is the leading country in terms of publication count, TLCS, and TGCS. Therefore, the USA maintains a dominant position in both the local and the whole scientific community. Seven countries appear in three rankings simultaneously, including the USA, China, India, UK, Germany, France, and Canada. Other influential countries include the Netherlands, Australia, Italy, South Korea, Switzerland, etc.

5. Network analysis

Numerical indexes used in bibliometric analysis reflect the activity and influence of authors, journals, institutions, countries, etc. However, these indexes are insufficient to describe the relationship within the target dataset. In this section, network-based approaches are exploited to analyze the co-word, co-authorship, and co-citation relations.

5.1. Co-word analysis for medical image

Co-word network reveals the topics and hotspots in a research community. Co-word network is created by extracting keywords as nodes and their co-occurrences in a paper as links. The minimum number of occurrences of a keyword is chosen as 5. In our analysis, 4,362 of the 53,689 keywords meet the threshold. 50 keywords with the greatest total link strength in 4,362 keywords are selected to highlight important keywords. Finally, we succeeded in obtaining a network with 50 nodes and 1,196 links, displaying the co-word network utilizing VOSviewer [24] in Fig. 6.

The node size reveals the occurrence frequency of a keyword. A larger node denotes the keyword has a higher occurrence rate in the dataset [18]. The link strength indicates how many articles two keywords co-occur in. Different clusters are represented by different colors. The color of a node implies which cluster it belongs to. According to Fig. 6, there are 4 clusters of different research themes. The largest cluster in red color incorporates keywords like "algorithm", "optimization", "registration", "segmentation", "models", etc. It can be inferred that the algorithm is important in this group. The segmentation and registration of medical images often need the design and use of complicated algorithms. Another cluster in green includes keywords such as "computed-tomography", "ct", "ultrasound", "PET", and "medical imaging". Many keywords are highly relevant to different categories of medical imaging. The remaining two clusters (blue and yellow) have similar keywords, like "medical image processing", "feature extraction", "classification", "machine learning", "deep learning", and "convolutional neural network". These two groups focus on a hot research area: the application of machine learning and deep learning in the field of medical image processing.

Since the co-word network cannot capture the temporal information, an improved co-word network considering time can be given to better understand the trends in medical image research. Fig. 7 presents the temporal co-word network with time as a parameter. Thirty years are separated into six periods. Each period contains five years, which is depicted in different color. In this work, the pathfinder method is used for pruning and filtering out small clusters.

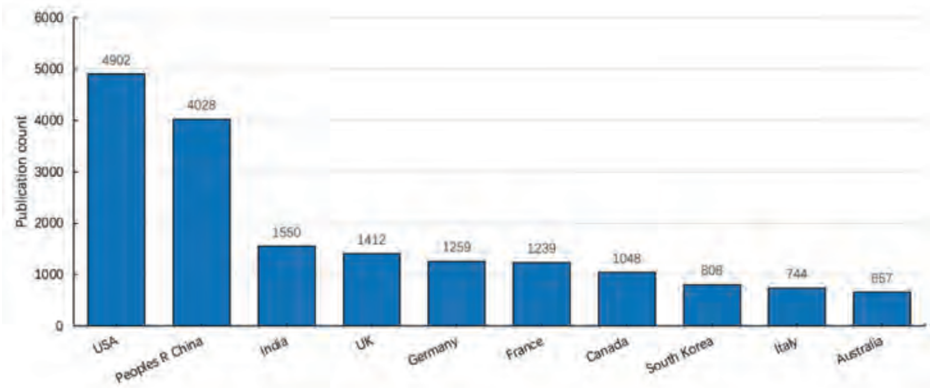
According to Fig. 7, there exists five crucial clusters in period 5 (2013–2017). It indicates that the most important keywords and famous concepts in medical image research emerged between 2013 and 2017. The keywords of "classification", "segmentation", "reconstruction", "registration", and "optimization" can indicate the popularity of medical image processing among researchers. In period 6 (2018–2022), keywords such as "deep learning" and "convolutional neural network" are the focus of most scholars in the field of medical imaging. Thanks to the advances in deep learning and high-performance computing equipment, medical image research has developed rapidly over the past decade [39–41]. The remaining two clusters are from period 1 (1993–1997) and period 2 (1998–2002).

Nevertheless, the keywords in period 3 (2003–2007) and period 4 (2008–2012) fail to form identifiable clusters because they are strongly linked to period 5. In these periods, "medical imaging" and "medical image processing" are prevalent keywords, as much work has been performed, such as face recognition [42,43]. Although many keywords first appear in period 3 and 4, they are widely used in period 5.

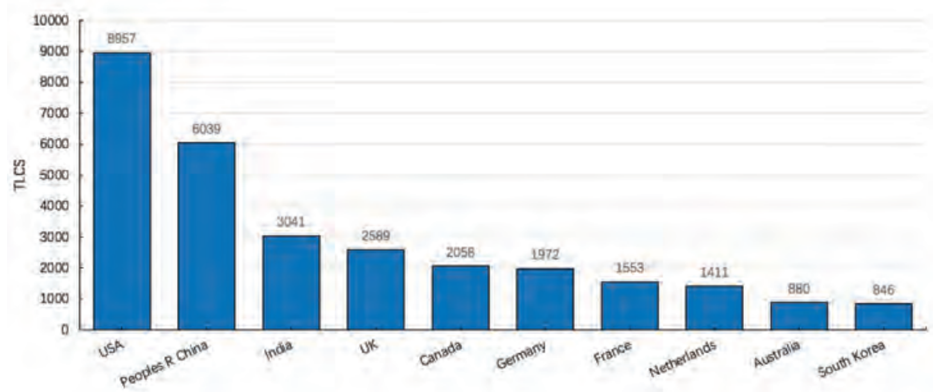
5.2. Co-author analysis for medical image

Co-authorship networks explore global research trends and hotspots by investigating different academic communities. The minimum publication count of each author was set to 5. By filtering small nodes and finding the largest connected component of the co-authorship network, a network of 223 authors was discovered. The number of links is 736, which stands for the number of times that two scholars co-author papers. A co-author density map for medical image research is shown in Fig. 8.

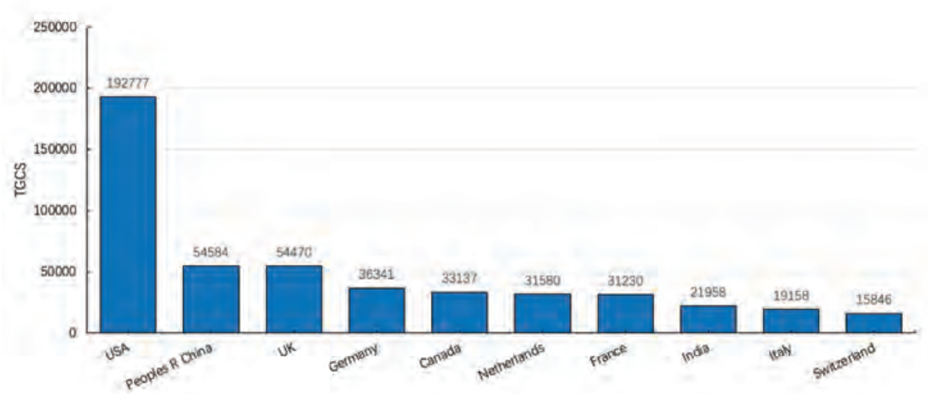
Although 22 clusters are found in our analysis, we tag five clusters in Fig. 8. Cluster #1 is composed of 6 authors. *Josien P.W. Pluim* frequently collaborates with *Bram van Ginneken* and *Marius Staring*. *Marius Staring* and *Josien P.W. Pluim* co-authored 7 papers in the dataset. For cluster #2, it is a research community of many Chinese scholars. *Shen Dinggang* has a total link strength of 62. *Wang Qian* and *Wu Guorong* are his co-authors, with 12 and 14 collaborations, respectively. Three people co-authored a high GCS paper titled "Scalable high-performance image registration framework by unsupervised deep feature representations learning" [44]. In the dataset, *Shen Dinggang* also cooperates with *Wang Lei*, *Zhang Yu*, etc. In cluster #3, *Sebastien Ourselin* published 8 papers and 7



(a) Top ten countries of publication count



(b) Top ten countries of TLCS



(c) Top ten countries of TGCS

Fig. 5. Publication count, TLCS, and TGCS per country for medical image (1993–2022).

papers with *Marc Modat* and *Jan Deprest* respectively. One high GCS paper is a collaboration between *Sebastien Ourselin* and *Marc Modat*: "Fast free-form deformation using graphics processing units" [45]. Also, *Sebastien Ourselin*, *Jan Deprest*, *Wang Guotai*, *Li Wenqi*, etc. co-authored a paper with a high GCS named "Interactive medical image segmentation using deep learning with image-specific fine tuning" [47]. Cluster #4 is a complete network of 13 scholars, as people within the community often collaborate to publish papers. Cluster #5 is a cluster containing 15 authors, but it is a loosely connected research community.

Co-author analysis assesses scientific collaborations of authors in the field. However, some important scientists may publish highly-cited research papers only by themselves. In this case, co-author analysis fails to evaluate such influential authors. This problem can be solved by co-citation analysis.

5.3. Co-citation analysis for medical image

Rather than scientific collaboration and semantic information, co-citation networks make use of citations to trace global research trends in medical imaging. A timeline map of co-citation networks for medical image research is drawn by CiteSpace [25]. Fig. 9 gives the visualization along with cluster information.

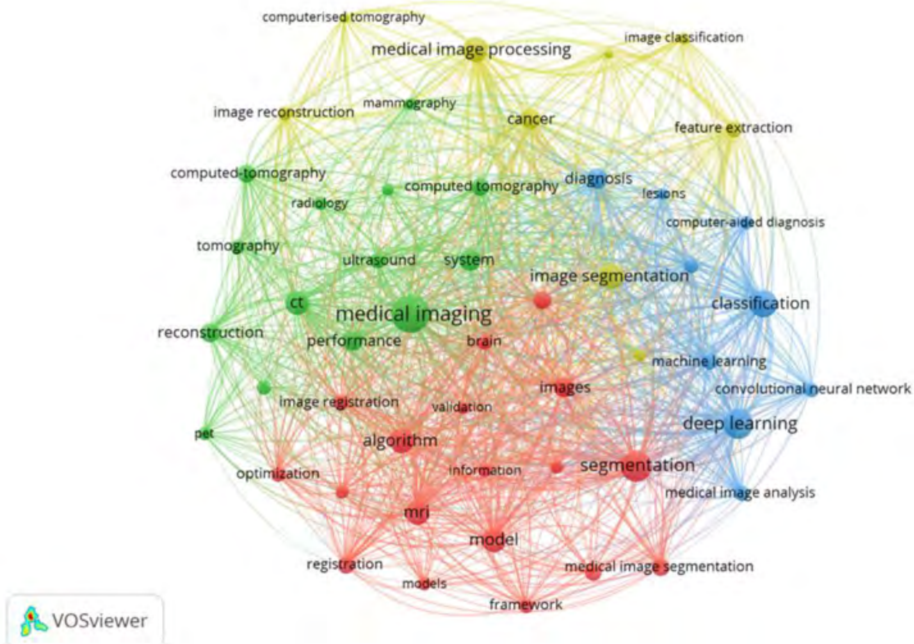


Fig. 6. Visualization of co-word network for medical image.

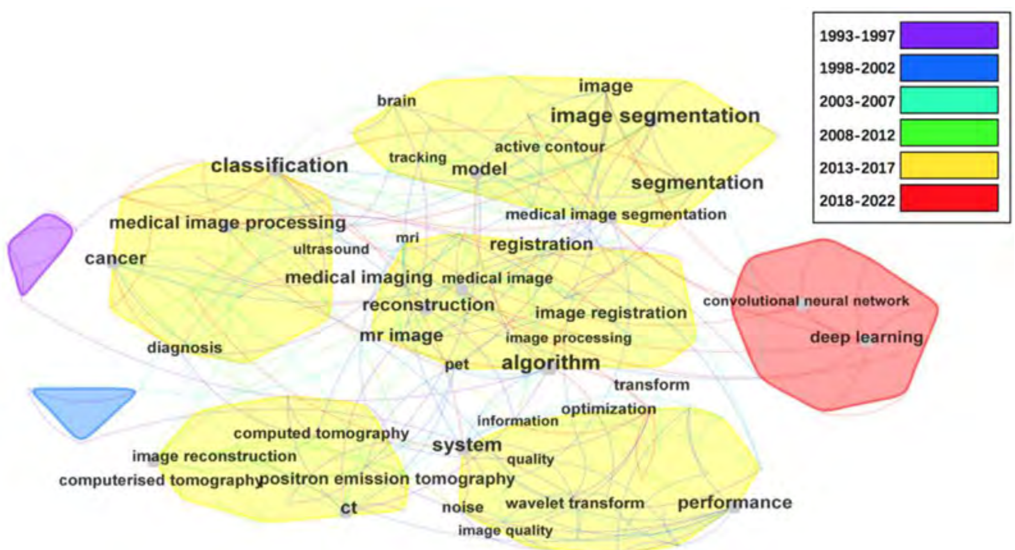


Fig. 7. Visualization of temporal co-word network for medical image.

As shown in Fig. 9, each line represents the timeline of a corresponding topic, labeled on the right. The basic method of topic generation is the automatic topic extraction method applied to a collection of topic texts. These text collections are mainly abstracts, titles, or keywords in co-cited reference clusters. From left to right, the colors from blue, green, yellow, to red stand for different periods from 1993 to 2022. The purple perimeter of a node implies the publication has high betweenness, which is defined as the fraction of the shortest path passing through the node [30]. A high-betweenness node can easily communicate with nodes in different communities [48]. The purple-colored node is often the starting point to initiate a new research direction [20], playing a crucial role in the subfield of medical imaging.

By removing small clusters, the top ten largest clusters are selected in the timeline map. Between 1993 and 1997, it was difficult to find large clusters through co-citation analysis owing to a tiny number of papers. When it comes to the period 1998–2002, cluster #8 was identified with the label of "3d differential operators". This topic was a hotspot during the 1990 s, but the number of papers declined after 2002. For cluster #3, "mutual information (MI)" was the major theme in the research community. MI was first introduced to the medical image field before 2000. Maintz et al. referred to the application of MI in a survey [49]. In the early 2000s, MI was widely exploited in medical image processing, especially in registration. For example, Pluim et al. expounded different types of MI-based registration methods in his article [50]. From 2003 to 2012, the main topics of the two clusters #5 and #9 were "radiation therapy" and "content-based image retrieval", respectively. In cluster #9, the paper of Mueller et al. in 2004 [51], discussing content-based image retrieval systems, was the most cited publication. Experts in clusters #5 and #9 focused on medical applications.

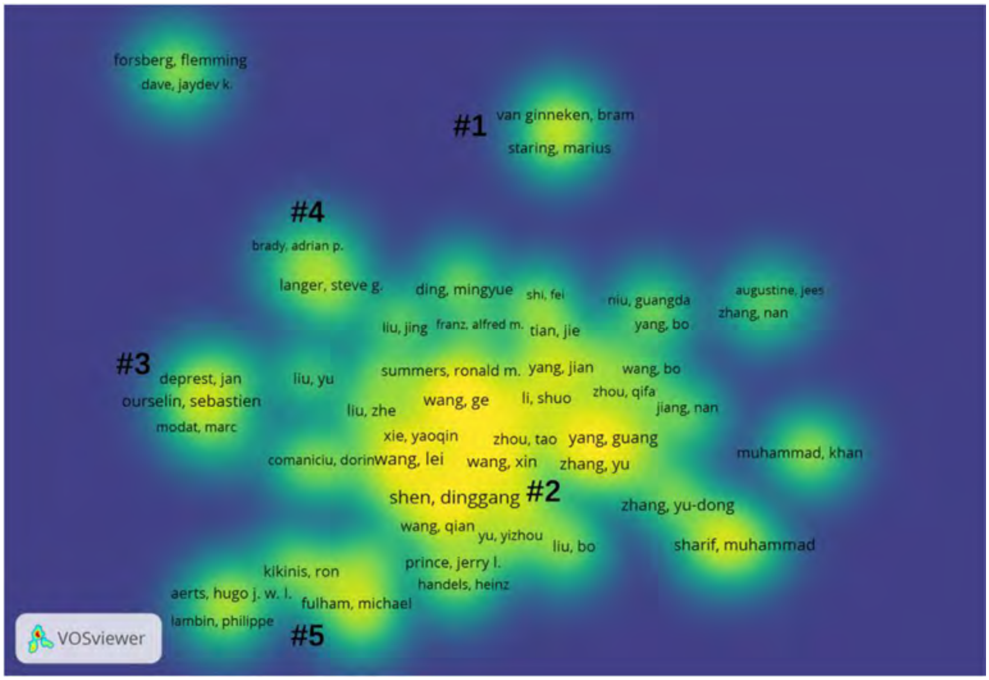


Fig. 8. Density visualization of co-authorship network for medical image.

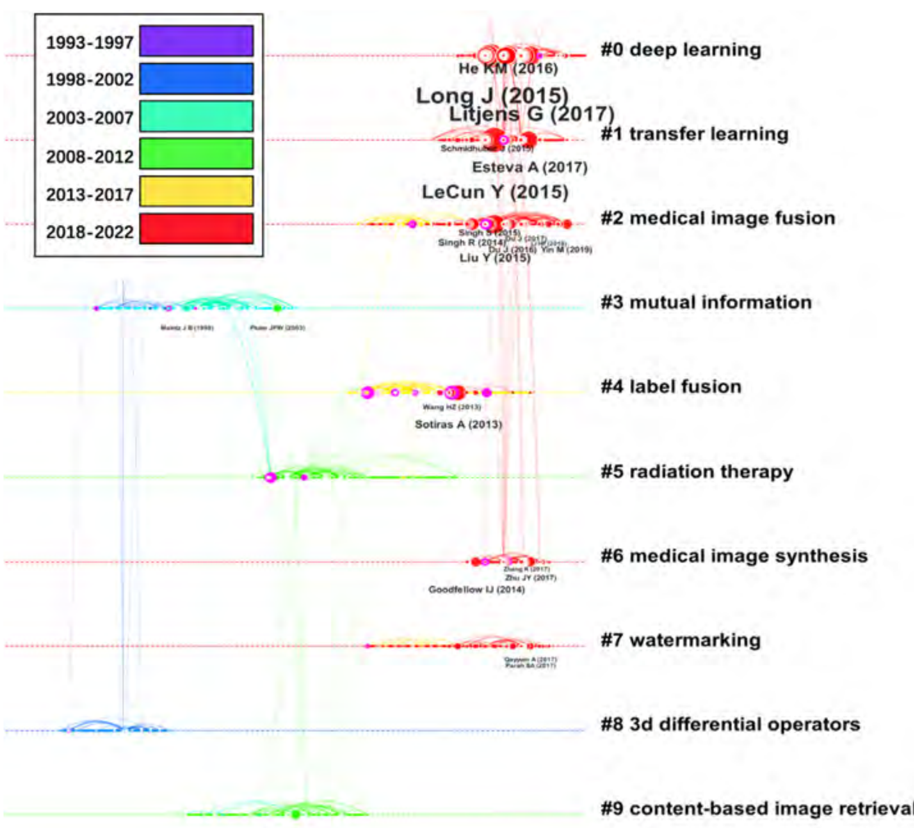


Fig. 9. Timeline visualization of co-citation network for medical image.

The period of 2013–2022 witnessed several emerging topics and a tremendous number of publications. For the period from 2013 to 2017, many nodes were aggregated into cluster #4, focusing on "label fusion". A node is colored with a purple perimeter, indicating a new branch of label fusion research. It was a study of multi-atlas segmentation by the use of joint label fusion, published by Wang et al., 2013 [52]. A highly cited article concerning this topic was written by Sotiras et al., 2013 [53].

In cluster #2 and # 7, researches started in the early 2010 s and then entered in new phase after 2015. For cluster #7, two highly cited papers on the "watermarking" topic were published in 2017, incorporating Qayyum et al., 2017 [54] and Parah et al., 2017 [55]. In cluster #2, "medical image fusion" is the core research topic of the authors. Major achievements before 2015 involve Wang et al., 2014 [56] and Singh et al., 2014 [57]. Due to the development of deep learning, most of the highly cited papers are published from 2015, including Liu et al., 2015 [58], Singh et al., 2015 [59], Du et al., 2017 [60], Li et al., 2018 [5], and Yin et al., 2019 [61]. These studies explore the theory and application of medical image fusion.

Three clusters, tagged as #0, #1, and #6, are composed of many fashionable topics such as "deep learning", "transfer learning", and "medical image synthesis". For cluster #0, the papers of Long et al., 2015 [62] and He et al., 2016 [63] are two high-citation papers from CVPR. Though they do not belong to the medical image research field, they appear with high frequency in citations of the downloaded WOS database. Hence, co-citation analysis can discover more information than co-word and co-author analysis. Another significant paper is a survey on deep learning in medical image analysis (Litjens et al., 2017 [7]), which has been discussed in the previous section. For cluster #1, the work of LeCun et al., 2015 [64] and Schmidhuber et al., 2015 [65] are two pivotal publications that build the theoretical foundation of medical image research based on transfer learning. The work of Esteva et al., 2017 [66] is the application of deep neural networks in dermatology. Finally, cluster #6 is concerned with the topic of medical image synthesis. Related studies are identified such as Goodfellow et al., 2014 [67], Zhu et al., 2017 [68], and Zhang, et al., 2017 [69]. They adopt deep learning for the task of image synthesis. Overall, deep learning plays a critical role in the advance of medical image research.

6. Discussions

The field of medical imaging covers interdisciplinary studies in medicine, computer science, mathematics, etc. For instance, the nuclear medicine imaging research may include subject areas such as radiology, biophysics, and oncology. Thus, subject categories in a publication are good indicators to help us learn more about cross-disciplinary topics. Web of Science provides more than 200 WOS subject categories, showing different disciplines of publications and specific areas of research. Each paper can be tagged with at least one subject category.

The subject category distribution of medical image research has been calculated according to the bibliographic data of WOS. The statistical results show that there are 141 subject categories in 19,762 publications concerning medical image research. That is to say, a wide range of research directions exist in this field, and there is a lot of interdisciplinary content in the publications. The top ten subject categories, publication counts, and percentages are listed in Table 2. As can be seen from the table, the number of publications for *Engineering* is the largest, followed by *Computer Science*. The imaging technique develops with the improvement of efficient analysis methods based on computer science and engineering. Pattern recognition, deep learning, artificial intelligence, and other engineering technologies are widely utilized in medical image research, which has contributed to the progress of medical imaging techniques in the last few years. The "*Radiology, Nuclear Medicine & Medical Imaging*" category ranks third. It is a cross-disciplinary research direction that integrates medical imaging and clinical treatment, which has developed rapidly in the past three decades.

The number of publications increased dramatically in medical image research since 2015. Both TLCS and TGCS showed similar trends from 2015 to 2019 (see Fig. 1). TLCS achieved a maximum score in 2019, whereas TGCS in 2017. The great success of deep learning in the field of computer vision has inspired many researchers to apply it to medical image analysis. After 2013, convolutional neural networks (CNNs) rapidly developed into a research hotspot in medical image analysis [70–72], which can automatically extract hidden features of the medical image and significantly improve the performance of classification, registration, conversion, etc. In 2017, a comprehensive summary of the research on deep learning in medical image analysis [7] contributed to the second highest score of TLCS and the highest score of TGCS, becoming a common reference for many scholars within the domain and throughout the entire science community. The application of deep learning, especially CNNs, accounts for the rise of publication count, TLCS, and TGCS. More and more papers are published in this field, contributing to the peak of TLCS in 2019. Moreover, many hospitals and medical schools begin to cooperate with experts in computer vision, which facilitates the sharing of medical image resources, thus promoting the flourishing of medical image research.

Table 2
Subject category distribution of medical image research (top ten listed).

Ranking	Subject Category	Publication Count	Percentage
1	Engineering	7209	36.45 %
2	Computer Science	6076	30.72 %
3	Radiology, Nuclear Medicine & Medical Imaging	3639	18.40 %
4	Physics	1710	8.65 %
5	Instruments & Instrumentation	1215	6.14 %
6	Mathematical & Computational Biology	1053	5.32 %
7	Optics	971	4.91 %
8	Materials Science	940	4.75 %
9	Science & Technology - Other Topics	910	4.60 %
10	Chemistry	840	4.25 %

Deep learning can automatically learn more discriminative features from datasets. After being applied to tasks of medical image classification, detection, segmentation, registration, and so forth, it has made significant breakthroughs compared with traditional approaches. This is the main reasons why deep learning and transfer learning are the most fashionable topics in temporal co-citation network (see Fig. 9). Medical image analysis and applications based on deep learning will show a continuous growth trend in the coming years with the improvement of deep learning algorithms, high-performance computing equipment, medical image quality, and labeling set.

We discussed global research trends in medical imaging based on the WOS data from 1993 to 2022, but there are some limitations of the analysis. It is impossible to retrieve all articles of a field by setting a keyword or a search query. Some papers may be neglected in this process. Therefore, we brought up a representative search query that can capture most mainstream papers in this field. In addition, other datasets were not used in this paper. Some previous work has proved that most research topics can be found overlapped in different datasets and the WOS database is a representative for studying the global research trends [20].

7. Conclusions

In this paper, we concentrated on the analysis of global research trends in medical image from 1993 to 2022 based on a data-driven method. Data acquisition was carried out through the Web of Science by setting some restricted search conditions. We successfully fetched 19,762 records. Further, both bibliometric indexes and network-based methods were taken to study the research hotspots and global trends. Taking into account the analysis presented above, we eventually reached the following conclusions:

(1) In the field of medical imaging, the overall number of papers has been increasing for nearly-three decades. In particular, the annual output skyrocketed from 635 to 2,240 in the past ten years due to the development of deep learning and high-performance computing equipment. *Medical Physics* is the most active journal from the standpoint of publication counts, while *IEEE Transactions on Medical Imaging* and *Medical Image Analysis* are the most influential journals in view of TLCS and TGCS. *Neurocomputing* and *Information Fusion* are well-recognized journals in the local research community.
(2) There are 141 subject categories discovered in the publications of medical image research. Engineering and Computer Science currently attract most scholars in medical image research. For active authors, Van Ginneken B and Aerts HJWL are representative researchers from the viewpoint of TLCS and TGCS, respectively.
(3) The USA leads in medical image research from the perspective of three metrics. Other influential countries include China, India, UK, Germany, France, Canada, Netherlands, Australia, Italy, South Korea, Switzerland, etc. Most leading institutions come from these countries such as *Harvard*, *UMich*, *Stanford*, *UPenn*, *UNC*, *CAS*, *SJTU*, *UCL*, *UofT*, *RU*, etc. However, only *Harvard* and *UMich* appear in the top ten of publication count, TLCS, and TGCS.
(4) Network-based methods succeed in extracting the main focus and discovering global research trends in the field of medical imaging. Segmentation, classification, registration, and algorithm are academia's adored research topics. In the past thirty years, various hotspots surfaced at different times. With the upgrading of deep learning algorithms such as convolutional neural networks, the application of artificial intelligence technologies has dramatically promoted global studies in this field since 2015. Scientific collaboration becomes incredibly popular among experts in medical image research. Many hospitals and medical schools cooperate with scholars who specialize in computer vision, facilitating access to medical image resources. Thus, the medical image will still be a thriving research direction in the near future.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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