Bibliometric analysis and short survey in CT scan image segmentation: identifying ischemic stroke lesion areas

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ABSTRACT

Ischemic stroke remains one of the leading causes of mortality and long-term disability worldwide. Accurate segmentation of brain lesions plays a crucial role in ensuring reliable diagnosis and effective treatment planning, both of which are essential for improving clinical outcomes. This paper presents a bibliometric analysis and a concise review of medical image segmentation techniques applied to ischemic stroke lesions, with a focus on tomographic imaging data. A total of 2,014 publications from the Scopus database (2013–2023) were analyzed. Sixty key studies were selected for in-depth examination: 59.9% were journal articles, 29.9% were conference proceedings, and 4.7% were conference reviews. The year 2023 marked the highest volume of publications, representing 17% of the total. The most active countries in this area of research are China, the United States, and India. "Image segmentation" emerged as the most frequently used keyword. The top-performing studies predominantly used pre-trained deep learning models such as U-Net, ResNet, and various convolutional neural networks (CNNs), achieving high accuracy. Overall, the findings show that image segmentation has been widely adopted in stroke research for early detection of clinical signs and post-stroke evaluation, delivering promising outcomes. This study provides an up-to-date synthesis of impactful research, highlighting global trends and recent advancements in ischemic stroke medical image segmentation.

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1. INTRODUCTION

Stroke is the sudden onset of a focal neurological deficit of vascular origin, it can be ischemic in 80% or hemorrhagic in 15% [1]. It causes motor deficits and loss of sensitivity or language disorders [2]. It is the second leading cause of death worldwide, with 87% of cases occurring in developing countries [3]. In sub-Saharan Africa, numerous studies present biases and offer inaccurate estimates of stroke incidence and prevalence [4]. Mortality rates are higher than in developed countries, strokes occur at a younger age, and hypertension is the leading risk factor [5]. However, the distribution of ischemic strokes does not appear to be very different from that observed in developed countries. This is a diagnostic and therapeutic emergency requiring rapid, multidisciplinary, and multi-professional care, requiring better coordination to reduce both mortality and disability linked to this pathology [6].

Establishing neurovascular units has significantly enhanced the early management of ischemic stroke. However, the subjective identification of the affected brain area often poses challenges, complicating accurate localization. Therefore, ensuring early diagnosis through scanner-type imaging sequences is crucial to mitigate these difficulties and facilitate precise determination of the affected region. To better explore medical imaging segmentation techniques and methods, conducting a bibliometric study to assess overall research trends on ischemic stroke imaging segmentation using documents published in the Scopus database from 2013 to 2023 is important.

This paper principally aims to highlight the most relevant research (authors, articles, and productivity trends) and future research directions on ischemic stroke through bibliometric analysis. Thus, this work provides an updated overview of the evolving research on image segmentation after stroke but specifically focuses on stroke image segmentation for identifying damaged areas using deep learning techniques [7], Bayesian capsules, and Bayesian networks [8] using the Scopus database. This article primarily focuses on the research development trends in stroke image segmentation, including the most productive authors, sources, countries, collaborations, and various other aspects, as well as an examination of the state-of-the-art in stroke image segmentation. The rest of the paper is organized as follows: in section 2, we present the results of the bibliometric analyses, followed by a review of state-of-the-art image segmentation in section 3, where we discuss preprocessing, segmentation, and the proposed methodology.

2. METHOD

The research methodology involved an analysis of international publications concerning stroke image segmentation over the past decade, spanning from January 2013 to December 2023. This period was deliberately selected to encompass the rapid development of novel technologies and methodologies in stroke image segmentation, thereby allowing for a comprehensive assessment of recent research trends and their evolving impact. Research data were retrieved from the Scopus database using a predefined search string executed in December 2023. The search string included the following terms: "(stroke AND image AND segmentation) OR (stroke AND image AND Bayesian AND capsule AND image AND segmentation) OR (stroke AND image AND CNN AND image AND segmentation) OR (stroke AND images AND lesion AND image AND segmentation) OR (stroke AND images AND region AND image AND segmentation)." A bibliometric analysis was conducted using the analytical tools available in the Scopus interface, in combination with the VOSviewer application [9]. VOSviewer facilitates the visualization of bibliometric networks, including associations among researchers, institutions, countries, affiliations, publication volume, keywords, research collaborations, emerging trends, key concepts, highly cited studies, and less explored research themes.

To clarify the methodology adopted in this study, a flowchart was developed to illustrate the various steps of the data collection process in Figure 1. An initial search, conducted without applying any filters, identified 2,059 publications. This dataset was then refined by applying specific inclusion and exclusion criteria to ensure the relevance of the selected documents.

Only publications released between January 2013 and December 2023 were retained to focus on recent research and technological advances in image segmentation for ischemic strokes. The selection was further restricted to articles written in English or French, thus ensuring the accessibility of results to an international scientific audience. Regarding document types, only scientific journal articles, systematic reviews, and indexed conference proceedings were included, excluding editorials, non-indexed abstracts, and unpublished theses. Additionally, only peer-reviewed publications were retained to ensure the scientific rigor of the sources. The thematic scope was clearly defined: selected documents had to deal specifically with medical image segmentation in the context of ischemic stroke.

Although no geographical filters were applied during the initial search, a secondary analysis allowed for the identification of the most active regions in this research domain. The United States, China, and India stood out as the main contributors in terms of publication volume. This information was used to assess the geographical distribution of research efforts.

After applying all filters, the refined dataset comprised 2,014 publications. Bibliometric analysis was then conducted using the bibliometrix package in RStudio and the VOSViewer tool. It is important to note that our analysis focused exclusively on the quantitative aspects of the publications (volume, temporal trends, sources, keywords, and contributing countries) and did not include in-depth qualitative analysis, such as citation content evaluation or detailed study of co-author collaboration dynamics.

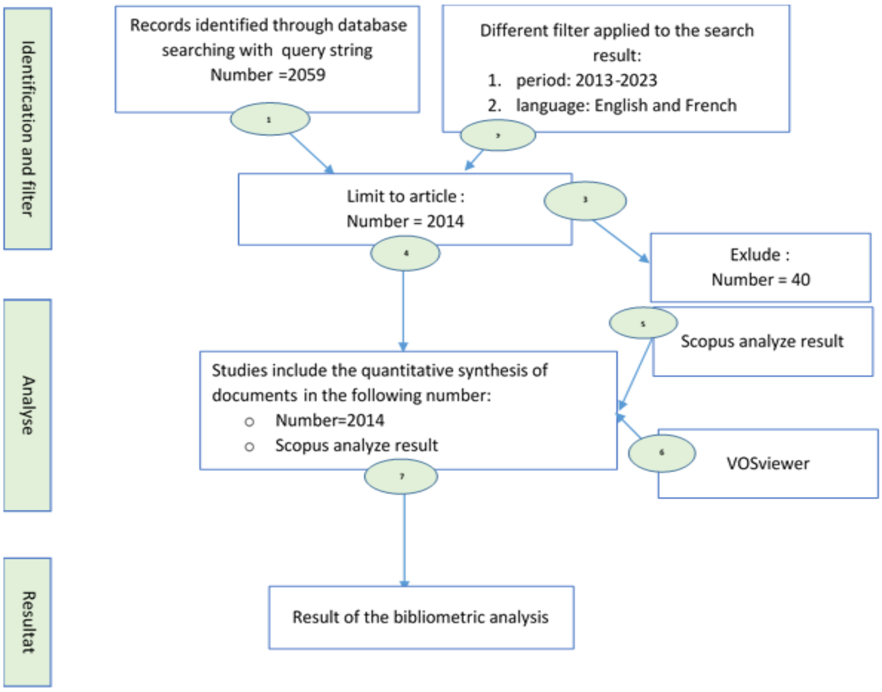

Figure 1. Literature search in the Scopus database

3. RESULTS AND DISCUSSION

The analysis of the publications highlights a strong interest from the scientific community in medical image segmentation for ischemic strokes over the past decade. The results of this analysis are detailed in the following subsections. This growing attention reflects both the clinical importance of early and accurate stroke detection and the rapid evolution of deep learning techniques that have significantly advanced the field.

3.1. Analysis of scientific production

Since 2018, there has been an increase in annual scientific productivity related to the segmentation of computed tomography (CT) images for identifying ischemic stroke lesion areas, reaching a peak in 2023 with approximately 350 publications. Figure 2 indicates a variation from less than 20 articles published in 2013 to around 60 in 2023. This explains the interest shown by researchers in our research subject.

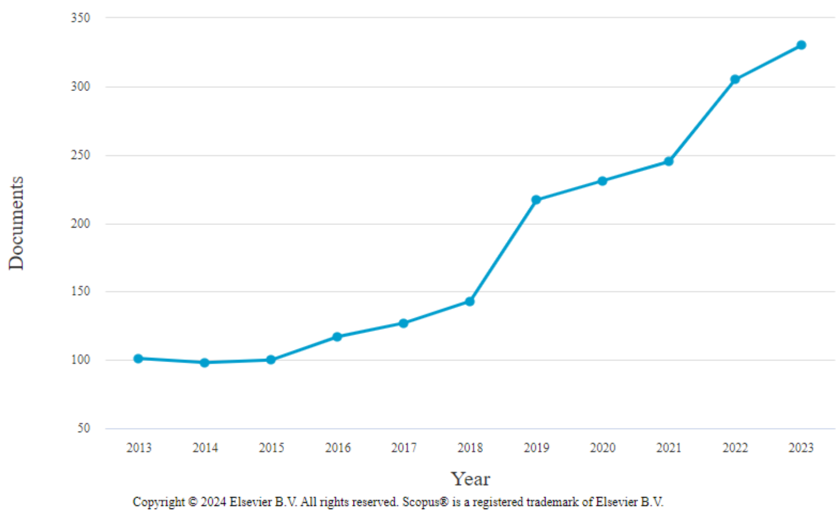

Figure 2. Evolution of scientific production

3.2. The most relevant publication sources

Table 1 highlights the primary sources of variation over the past decade. It shows that "Lecture notes in computer science, including the subseries lecture notes in artificial intelligence and lecture notes in bioinformatics," is the most prolific source, with 27 publications in 2019. This is followed by "Frontiers in neurology," which published 15 articles in 2023.

The data from Table 1 are presented in Figure 3. It shows the variation in document production over our research period “Lecture notes in computer science including subseries lecture notes in artificial intelligence and lecture notes in bioinformatic” which comes first in 2019 with nearly 30 publications, followed by “Frontiers in neurology” with around 15 documents, “NeuroImage clinical” and “communications in informatics and computers in biology and medicine” with 9 and 8 respectively documents. After examining the annual production by source, we focused on the most relevant publications.

Figure 4 shows the leading research institutions in the field of image segmentation. At the top is the University of Calgary with 48 publications, followed by the Chinese Academy of Sciences with 41 publications, and Massachusetts General Hospital with 37 publications. The seven other listed institutions each have between 30 and 26 publications.

Table 1. The most relevant publication sources

Source	Publications										
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Frontiers in neurology	0	0	0	0	2	3	4	5	6	5	15
NeuroImage clinical	2	2	3	2	3	2	8	3	4	5	4
Computers in biology and medicine	0	0	0	0	2	4	3	2	5	7	8
Lecture notes in computer science including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics	7	5	8	20	8	9	27	15	16	8	22
Biomedical optic and imaging proceedings of SPIE	8	6	4	2	6	5	6	6	4	5	5

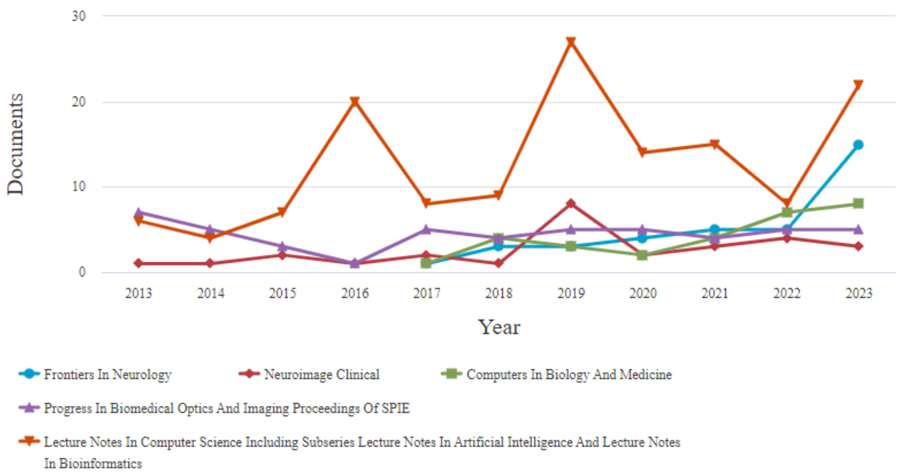

Figure 3. Production per year by source

3.3. The most relevant authors

The Figure 5 shows the authors who have published the greatest contribution to publishing in the field of Stroke image segmentation. The author with the most publications in this field is N. D. Forkert with 18 documents, followed by B. K. Menon, W. Qiu, and Rueckert with respectively 17, and 14 published documents. Meanwhile, the other six authors have each published between 13 and 11 documents in this research area.

3.4. The most relevant countries

Figure 6 shows the 10 countries with the highest number of contributions to document editing in the field of the segmentation of stroke imaging with China as the first country with 450 publications, followed by the United States with 420 publications, and India which comes in third position with 251 publications. The other countries, namely the United Kingdom, Germany, Canada, Netherlands, France, South Korea, and

Italy, published between 160 and 60 documents. This data highlights the global interest and research activity in stroke imaging segmentation across multiple regions.

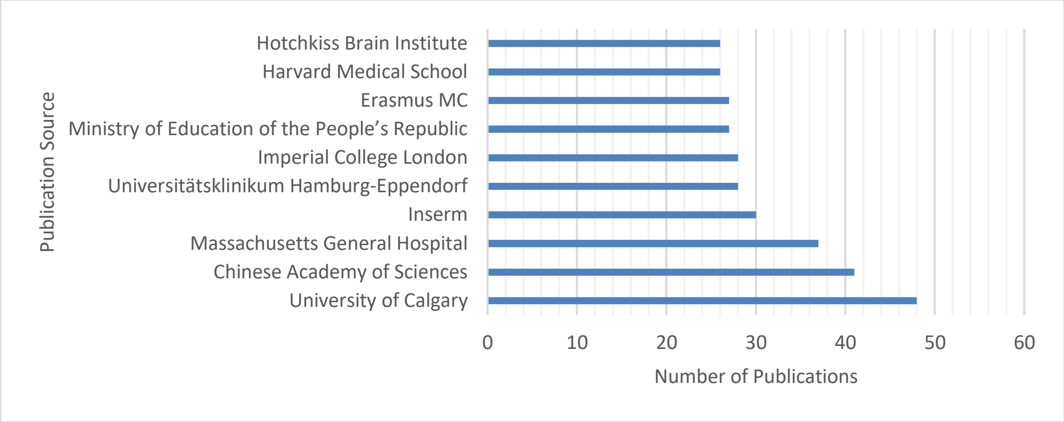

Figure 4. The most relevant publication sources

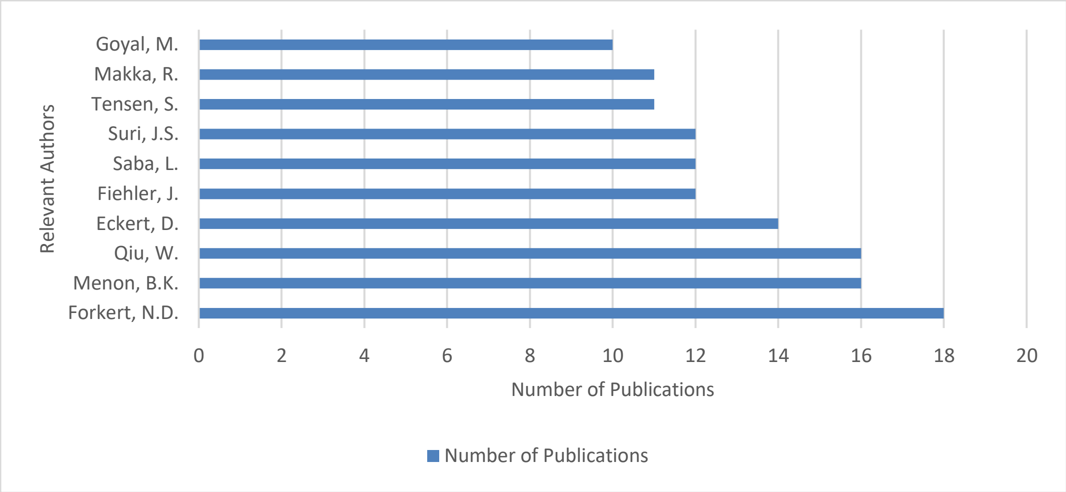

Figure 5. Most relevant authors

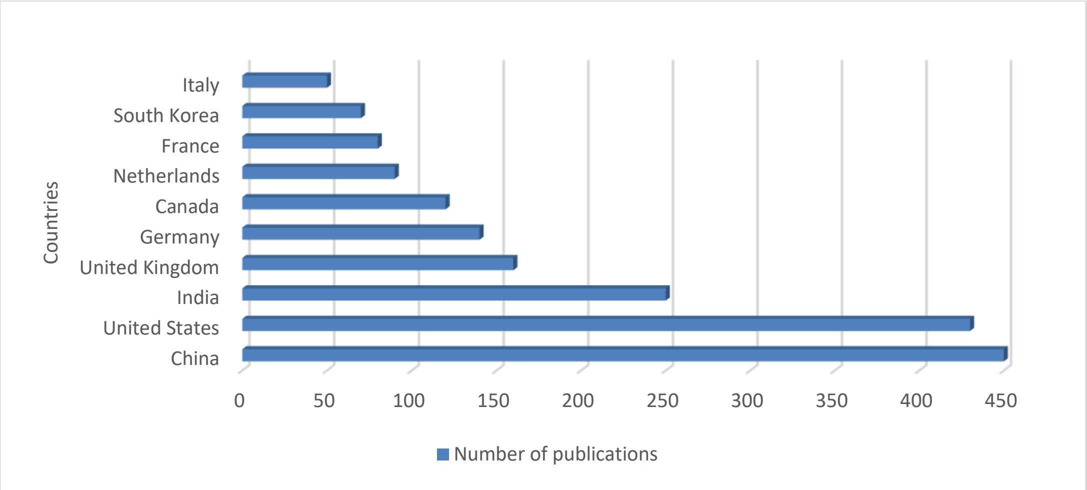

Figure 6. Most relevant countries

3.5. Analyze funding sponsor

Figure 7 presents the list of funding institutions that most actively contribute to studies related to stroke image segmentation. Leading the rankings are the National Natural Science Foundation of China, with 215 publications, followed by the National Institutes of Health, with 125 publications, and the National Institute of Neurological Disorders and Stroke, with 55 publications. The remaining seven identified institutions supported between 48 and 32 publications.

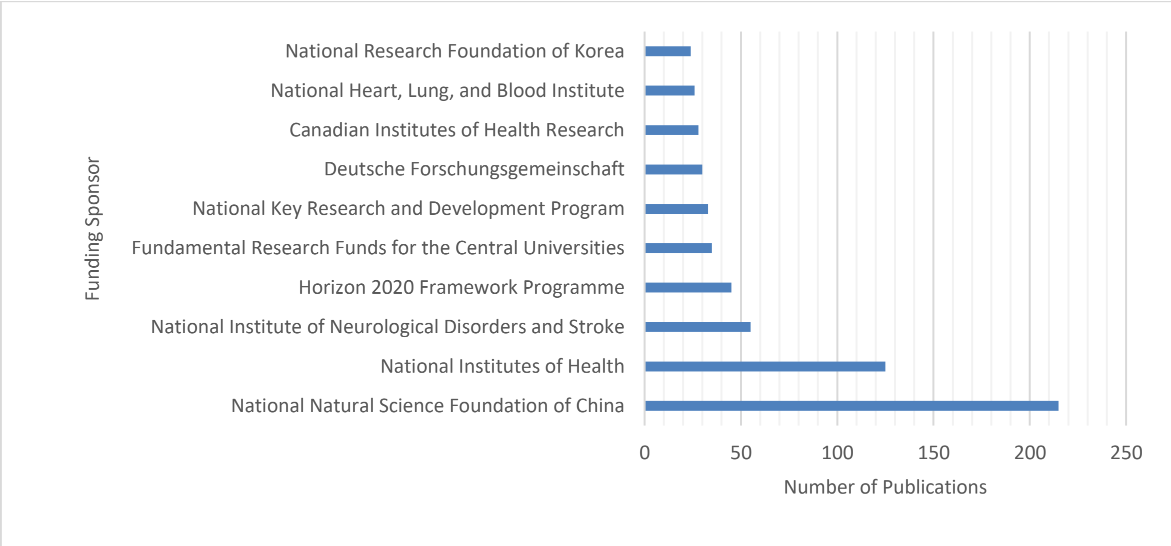

Figure 7. Number of documents analyze-fundingsponsor

4. STATE-OF-THE-ART

To gain a deeper understanding of the ecosystem surrounding medical image segmentation for ischemic strokes, we conducted a literature review. In this article, we highlight the most relevant studies from the 40 reviewed. Image segmentation, a technique in computer vision, involves automatically dividing an image into regions where pixels belong to the same class of objects. This method has numerous applications, especially in medical imaging. For instance, Gajanayake *et al.* [10] from the Department of Statistics and Computer Science demonstrated that the Otsu thresholding method is the most effective for segmenting brain tumors in magnetic resonance images. Zhang *et al.* [11] from Neuroimage has proposed a data augmentation method, called CarveMix, to improve the segmentation of brain lesions using convolutional neural networks (CNN). This study showed that CarveMix improves the quality of brain lesion segmentation compared to other data augmentation methods and obtains good results on several datasets. One limitation of this method is its reliance on existing training data and the performance of the underlying CNN. Additionally, results can vary based on the quality of the initial annotations. Yu *et al.* [12] conducted a study in 2021 to identify and quantify calcification in major cerebral arteries, investigating the correlations between quantitative calcification parameters, hemorrhagic transformation, and prognosis in patients who underwent intravenous thrombolysis for ischemic stroke.

The study included patients with acute ischemic stroke with anterior circulation who received intravenous thrombolysis. CT scans were performed before thrombolysis and 24 hours afterward. Third-party software, ITK-SNAP, was used to segment and measure calcification volume. Hemorrhagic transformation was determined according to the ECASS II classification criteria. Of the 242 patients included, 214 presented calcification. Thirty-one patients developed hemorrhagic transformation. The volume of clacification on the lesion side was associated with hemorrhagic transformation, with a p-value of 0.004 and an OR of 1.504. Ninety-six patients had a poor prognosis, and this group had more calcified vessels than the group with a favorable prognosis. Zhou [13] worked to solve the brain tumor segmentation problem using multimodal magnetic resonance imaging (MRI)s even when MRI modalities are missing due to various practices. Svecic *et al.* [14] published in their journal a deep learning model for tracking the evolution of tumor anatomy as well as interfractional variations for head and neck cancers. This model was trained with 337 cases and tested with 50 distinct patients using sequential CT and associated dosimetric data, with the probabilistic framework yielding a Dice score of 92% and a global dose difference of 1.2 Gy in organs at risk and tumor volume over the course. Khoshkhabar *et al.* [15] presents a model of a technique based on deep learning to segment liver tumors and identify liver organs on CT maps. Its study was conducted on the LiTS17 database. The suggested technique includes four convolutional layers of the Chebyshev graph and one fully connected layer, capable of accurately segmenting the liver and liver tumors. Thanks to this model it obtained an accuracy of up to 99.1%. Özcan *et al.* [16] implemented a hybrid segmentation model based on convolutional networks called the inception module-unet (AIM-Unet). This model was used to experiment with four different liver CT image datasets. The results of this study show better performance with a Dice DSC of 97.86% and a Jaccard similarity coefficient of 96.10%. Manjunath and Kwadiki [17] implemented a ResUNet-based deep learning algorithm to segment the liver and its tumors from abdominal CT scan images. The results of this study achieved similarity coefficients of 96.35% and an accuracy of 99.71%. In a study, Chlebus *et al.* [18] implemented a method for segmenting liver tumors from CT scan images based on fully convolutional 2D neural. His work works on two methods cascading two models operating on a voxel. It achieved an accuracy rate of up to 85%.

Zhang *et al.* [19] contributed to improving the feature pyramid network (FPN) [20] to detect lung nodules by adding an squeeze-and-excitation (SE) module with a channel attention mechanism to improve the detection performance. This made it possible to optimize the 3D FPN architecture to detect pulmonary nodules. The results obtained were validated with a LUNA16 database with a competition performance metric (CPM) of 89.34%. The authors in [21]-[23] who worked on a healthy atlas and the detection of lesions based on discrepancies in the appearance of tissues between the patient and the atlas image. Due to image quality, lesions can cause significant structural deformations that can lead to poor segmentation. The authors in [24], [25] solved this problem of segmentation and registration tasks.

Liu *et al.* [26] showed that low-rank decay recording results in abnormal structures in sparse components as a by-product, although this may not be precise enough for the detection of small lesions. It should be noted that CNN [27], [28] have achieved promising results after being applied to a variety of biomedical fields imaging problems. Ciresan *et al.* [29] had the privilege of having implemented the first GPU of a two-dimensional CNN to segment neural membranes. Based on subsequent CNN-based work, the methods in [30]-[32], the latter being the best-performing automatic approach in the BRATS 2015 challenge [33]. These methods are based on 2D CNNs, which have been widely used in image segmentation applications. Here, the segmentation of a 3D brain scanner is obtained by processing each 2D slice separately, which undoubtedly constitutes a non-optimal use of large quantities of medical image data. Giancardo *et al.* [34] developed a deep learning approach including a novel weighted gradient-based approach to achieve stroke core segmentation with image-level labeling, specifically the size of the central stroke volume acute. This approach outperforms segmentation approaches trained on voxel-level data computed tomography-perfusion (CTP) estimation.

Felfeliyan *et al.* [35] have implemented a trained Mask-region-based convolutional neural network (RCNN) architecture to locate the distortion location and recover the pixels from the original image. This pre-trained model gains knowledge about relevant texture in images from self-supervised pre-training on unlabeled imaging data. This approach was proposed to improve the Dice score by up to 18% compared to training the models using only the annotated data. Camacho *et al.* [36] have developed a 3D CNN approach to detect Parkinson's disease from structural images of the brain.

The results obtained from this model achieved 79.3% accuracy and 80.2% precision on the test set while performing similarly on an independent training set. Zeng *et al.* [37] proposed a correspondence-based generative Bayesian deep learning (C-GBDL) model to capture data distributions with better generalization. This matching-based generative Bayesian deep learning model for semi-supervised volumetric medical image segmentation, when 20% of the training data is labeled, this model outperforms the optimal Dice score of existing models, the Wang and Lukasiewicz [38], the 95% Hausdorff distance (95HD) score, average surface distance (ASD) score and the Micro F1 which are respectively 0.002, 0.007, 0.11, 0.27, 0.002. To solve interoperability problems of invariant features on prostate images by Gao *et al*. [39] proposed an interpretable Bayesian framework (BayeSeg) through Bayesian image modeling. The results of their segmentation work on the images showed the effectiveness of the proposed method.

According to the data presented in the comparative table as shown in Table 2, the model developed by Svecic *et al.* [14] stands out with the highest performance, achieving a precision rate of 99.99%, followed by the model proposed by Khoshkhabar *et al.* [15], which reaches a dice similarity coefficient (DSC) of 97.86%. It is worth noting that these results are exclusively derived from models based on advanced deep learning architectures. The notable absence of traditional methods in this analysis highlights their limited performance in medical image segmentation. This implicit omission reflects their inability to meet the precision requirements demanded in complex clinical contexts, such as the identification of ischemic stroke lesions. This observation underscores a significant methodological shift in recent literature toward modern approaches that are more robust and better suited to the variability of medical data.

Table 2. The five most performant models

Source	Method	Result	Limit
Svecic *et al.* [14]	Deep learning model for liver tumor segmentation	Precise segmentation achieving up to 99.1% accuracy	Dependence on annotated data; Generalization issues; High computational; resource requirements; Lack of interpretability; Risk of overfitting.
Khoshkhabar *et al.* [15]	AIM-Unet model for hybrid liver segmentation based on convolutional networks	High performance with a DSC of 97.86% and a Jaccard similarity coefficient of 96.10%	Risk of overfitting on small or non-diverse datasets; Complex neural network, making it challenging to understand decision-making processes; Can be time-consuming, delaying deployment in real-time applications
Özcan *et al.* [16]	ResUNet algorithm for automatic segmentation of the liver and its tumors from CT scans	Similarity coefficients of 96.35% and an accuracy of 99.71%	requires a substantial amount of high-quality annotated data. Limited or subpar data can impact its performance.
Manjunath and Kwadiki [17]	Method based on 2D CNN for liver tumor segmentation	Accuracy reaching up to 85%	These methods require large amounts of high-quality annotated data for effective training. Insufficient or poor-quality data can degrade model performance.
Chlebus *et al.* [18]	Optimization of the 3D FPN network for pulmonary nodule detection	Improved detection performance with a CPM of 89.34%	Handling 3D medical imaging data involves large volumes of data, which can complicate data management and processing.

5. DISCUSSION AND PERSPECTIVES

5.1. Analysis of trends and emerging models

The conducted bibliometric study reveals significant trends in the field of medical image segmentation, with a particular focus on ischemic strokes. A substantial increase in research activity has been observed, characterized by a concentration of efforts within prestigious institutions such as the University of Calgary, the Chinese Academy of Sciences, and Massachusetts General Hospital. This concentration indicates a notable commitment from these establishments to the development of innovative solutions for image segmentation.

The analysis of the methodologies employed reveals a predominance of approaches based on CNNs and deep learning. Advanced models such as ResUNet and AIM-Unet have demonstrated high performance in quantitative evaluations. However, it is crucial to emphasize that the quality of annotated data and training datasets remains a major constraint. The lack of high-quality labeled datasets limits the models' ability to generalize effectively. Therefore, it is essential to enhance annotation practices and diversify datasets to optimize model performance.

5.2. Perspectives for future research

This study identifies several promising areas of research to advance the field of medical image segmentation. The integration of multimodal data, including information from CT, MRI, and genetic data, represents a potentially fruitful direction. This approach could enable more precise lesion detection and improve segmentation outcomes.

Furthermore, optimizing model architectures and exploring emerging techniques, such as transfer learning, could lead to significant advancements in accuracy and efficiency. It would also be relevant to evaluate a model based on Bayesian capsules and compare it to existing models to analyze the potential advantages of this approach over traditional segmentation methods, whether manual or semi-automated. Finally, the development of segmentation models specifically designed for clinical use could enhance the impact of this research on medical practice.

6. CONCLUSION

Image segmentation is one of the fundamental steps in digital image processing and computer vision. A review of the literature on the segmentation of ischemic stroke images highlighted the ecosystem of article production on segmentation from 2013 to 2023. Current studies have achieved good results in segmenting ischemic stroke CT images. The article also showed that the majority of ischemic stroke image segmentations are performed on MRI images. The most commonly used methods are deep learning methods. However, very few authors have worked on image segmentation using Bayesian methods, and even fewer with Bayesian capsules. To explore and evaluate the performance and accuracy of image segmentation with

Bayesian capsules, it would be interesting for future work on CT image segmentation for the identification of ischemic strokes to be conducted using Bayesian capsules.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study does not involve the use of human subjects or animal experimentation. Therefore, no institutional ethical approval was required.

DATA AVAILABILITY

The data used in this study consists of scientific articles available through the Scopus database. These publications were selected using our customized query string, which is described in the methodology section. The extracted metadata (titles, abstracts, keywords, authors, publication years, etc.) are available from the corresponding author upon reasonable request.

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