# COMPUTED TOMOGRAPHY IMAGE SEGMENTATION FOR ISCHEMIC STROKE LESION DELINEATION: A COMPREHENSIVE BIBLIOMETRIC ANALYSIS AND ADVANCED METHODOLOGICAL REVIEW

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**ABSTRACT**

Ischemic stroke remains a leading cause of global morbidity and mortality, necessitating rapid and accurate diagnosis for effective treatment. Computed Tomography (CT) imaging is a primary modality for initial assessment, particularly for distinguishing ischemic stroke from hemorrhagic stroke. Accurate, automated segmentation of ischemic stroke lesion areas from CT images is crucial for guiding clinical decisions, evaluating treatment efficacy, and predicting patient outcomes. This article presents a comprehensive bibliometric analysis of research trends from 2013 to 2023 and an in-depth survey of contemporary methodologies employed for CT scan image segmentation to identify ischemic stroke lesion areas. We meticulously explore the evolution of techniques from traditional image processing to advanced deep learning approaches, highlighting key trends, challenges, and future directions. The bibliometric analysis, encompassing over 2,000 publications, reveals a surging interest in the field, with significant contributions from China, the United States, and India. The methodological review emphasizes the dominance and superior performance of deep learning models, particularly Convolutional Neural Networks, while also addressing persistent challenges such as data scarcity, lesion subtlety, and model interpretability. The analysis underscores the critical need for robust, generalizable, and automated segmentation tools to improve diagnostic workflows and ultimately enhance patient care.

**Keywords:** CT scan; Image segmentation; Ischemic stroke; Stroke image; Deep learning; Convolutional Neural Networks; Bibliometric analysis; Medical imaging; Computer-aided diagnosis; Lesion delineation.

## INTRODUCTION

Stroke, defined as the rapid onset of neurological symptoms due to a disturbance in the blood supply to the brain, represents a significant global health crisis [1, 2]. It is broadly classified into two main types: ischemic stroke, accounting for approximately 80-85% of cases, caused by a blockage in a blood vessel supplying the brain; and hemorrhagic stroke, resulting from bleeding into the brain tissue or the spaces surrounding it [1]. The consequences of stroke are profound, ranging from motor deficits, sensory loss, and cognitive impairment to language disorders, leading to long-term disability and being the second leading cause of death worldwide [2, 3]. The global burden of stroke continues to escalate, disproportionately affecting low- and middle-income countries where incidence and case-fatality rates are notably higher, often striking individuals at a younger age and frequently linked to systemic hypertension and challenges in healthcare access and quality [3, 4, 5, 6]. Despite these disparities, the distribution patterns of ischemic strokes in these regions do not markedly differ from those observed in developed nations. This critical

health issue underscores the urgency for prompt diagnosis and intervention, rendering medical imaging an indispensable component of acute stroke management.

Computed Tomography (CT) imaging stands as the cornerstone imaging modality for the initial evaluation of patients presenting with suspected stroke symptoms. Its widespread availability, rapid acquisition time, and exceptional ability to differentiate between ischemic and hemorrhagic stroke make it the preferred first-line diagnostic tool. This distinction is paramount, as the presence of hemorrhage contraindicates thrombolytic therapies (e.g., tissue plasminogen activator - tPA), which are the primary treatments for acute ischemic stroke. While non-contrast CT (NCCT) can identify early signs of ischemic changes, such as subtle hypodensity or effacement of sulci, these manifestations are often very subtle in the hyperacute phase, especially within the first few hours following symptom onset. This subtlety poses considerable challenges for accurate and timely manual delineation of lesion areas by radiologists, who must interpret these nuanced findings under immense time pressure. Inaccurate or delayed identification of ischemic

stroke lesion areas can directly lead to suboptimal treatment decisions, potentially excluding eligible patients from life-saving reperfusion therapies or exposing inappropriate candidates to treatment risks, ultimately resulting in adverse patient outcomes.

The precise and reproducible segmentation of ischemic stroke lesions from CT images holds immense clinical and research significance for several critical applications:

● Treatment Guidance: Accurate lesion segmentation enables clinicians to differentiate between the irreversibly damaged core infarct and the surrounding penumbra (tissue at risk but potentially salvageable). This distinction is vital for guiding reperfusion strategies, including intravenous thrombolysis and mechanical thrombectomy, aiming to salvage the penumbral tissue and improve functional outcomes.

● Prognosis Prediction: The precise volume, location, and evolution of the ischemic lesion are powerful predictors of a patient's long-term functional recovery and overall prognosis. Automated segmentation provides objective quantitative measures that can inform clinical counseling and rehabilitation planning.

● Research and Clinical Trials: Standardized, objective, and reproducible lesion quantification is fundamental for conducting robust research studies, evaluating the efficacy of novel therapeutic interventions, and comparing outcomes across different patient cohorts and treatment protocols. Manual segmentation, being time-consuming and subject to inter-observer variability, significantly impedes large-scale research efforts.

Historically, lesion delineation has relied heavily on the manual outlining performed by expert clinicians, a process known to be time-intensive, subject to considerable inter-observer variability, and often impractical within the narrow time windows demanded by acute stroke care [7]. This inherent limitation has catalyzed extensive research into the development of automated and semi-automated image segmentation techniques. Building upon fundamental advancements in general image processing and computer vision, including early work on gradient-based learning for document recognition [27] and breakthrough developments in deep convolutional neural networks for image classification [28, 29], the field of medical image analysis has witnessed rapid progress. While substantial achievements have been made in segmenting other medical images, such as brain tumors from Magnetic Resonance Imaging (MRI) [8, 10, 13, 21, 23, 24, 25, 26, 30, 31, 32] and liver tumors from CT scans [15, 16, 17, 18], the unique challenges associated with ischemic stroke lesion segmentation on CT remain a dynamic and critical area of investigation. These challenges include the subtle nature of early ischemic changes, varying lesion sizes and

locations, and the presence of image artifacts. This comprehensive article aims to provide a detailed bibliometric overview of the current research landscape and an in-depth survey of the state-of-the-art methodologies employed for CT scan image segmentation, specifically targeting the identification and delineation of ischemic stroke lesion areas, thereby addressing the pressing need for advanced, automated solutions in clinical practice.

2. Methods

This comprehensive study employs a two-pronged methodological approach to thoroughly investigate the landscape of CT scan image segmentation for ischemic stroke lesion identification: a detailed bibliometric analysis to map global research trends and a systematic survey of the contemporary methodologies.

2.1. Bibliometric Analysis

The bibliometric analysis was designed to provide a quantitative overview of the scientific output in this specific research domain over the past decade.

● Search Strategy and Data Collection: The analysis commenced with a meticulous search across major scientific databases, including Scopus, PubMed, Web of Science, and IEEE Xplore. A predefined search string was constructed using a combination of keywords to ensure comprehensive coverage: "(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)." The search was intentionally limited to publications released between January 2013 and December 2023 to capture recent research and technological advancements.

● Inclusion and Exclusion Criteria: To ensure the relevance and scientific rigor of the dataset, specific criteria were applied:

○ Publication Period: Only documents published within the stipulated 2013-2023 timeframe were included.

○ Language: Publications were restricted to English or French to ensure accessibility for an international scientific audience.

○ Document Type: The selection focused on scientific journal articles, systematic reviews, and indexed conference proceedings. Editorials, non-indexed abstracts, unpublished theses, and books were excluded.

○ Peer Review: Only peer-reviewed publications were retained to uphold scientific quality.

○ Thematic Scope: Documents had to explicitly address medical image segmentation within the context of ischemic stroke.

An initial search without filters identified 2,059 publications. After applying these stringent inclusion and exclusion criteria, the refined dataset comprised 2,014 relevant publications.

● Data Analysis Tools: Data extracted from the search results included publication year, authors, affiliations, keywords, citation counts, and funding information. For the quantitative analysis and visualization of bibliometric networks, specialized software and tools were utilized. The analytical tools available within the Scopus interface were used for initial trend identification. Furthermore, the VOSviewer application [9] was employed to facilitate the visualization of bibliometric networks, enabling the identification of intricate associations among researchers, institutions, countries, publication volumes, frequently used keywords, and emerging research collaborations. The bibliometrix package in RStudio also complemented the analysis by providing additional quantitative metrics. It is important to note that this analysis primarily focused on quantitative aspects (e.g., publication volume, temporal trends, leading sources, keywords, and contributing countries) and did not include a deep qualitative analysis of citation content or detailed co-author collaboration dynamics.

2.2. Methodological Survey

A systematic review of the methodologies employed for CT scan image segmentation in ischemic stroke was conducted, drawing upon selected articles identified through the bibliometric analysis and other pertinent literature.

● Selection Criteria for Methodological Review: The selection for the in-depth methodological survey prioritized studies that met the following criteria:

o Primary focus on the segmentation of ischemic stroke lesions from CT images. This included non-contrast CT (NCCT), as well as advanced modalities like CT perfusion (CTP) and CT angiography (CTA) where relevant for lesion identification [34].

o Published in high-impact, peer-reviewed journals or reputable international conference proceedings.

o Provided a clear, reproducible, and sufficiently detailed description of the segmentation methodology.

● Categorization of Methodologies: The identified segmentation methodologies were broadly categorized based on their underlying algorithmic principles to provide a structured overview:

o Traditional Image Processing Approaches: This category encompasses classical computer vision techniques that rely on explicit image properties (e.g., intensity, texture, shape) or predefined models. Examples include intensity thresholding (e.g., Otsu's method), region growing, active contours (snakes), statistical shape models, and atlas-based segmentation methods [10, 21, 22, 23, 24, 25, 26].

o Classical Machine Learning Approaches (non-deep learning): These methods typically involve a feature extraction step (handcrafted features) followed by a classification algorithm. Common classifiers include Support Vector Machines (SVMs), Random Forests, k-Nearest Neighbors (k-NN), and ensemble methods.

o Deep Learning Approaches: This category represents the most recent and dominant paradigm in medical image segmentation. It specifically focuses on Convolutional Neural Networks (CNNs) and their numerous architectural variations and extensions [7, 11, 13, 18, 19, 20, 27, 28, 29, 30, 31, 32]. This broad category was further subdivided to capture the nuances of modern deep learning for segmentation:

■ Supervised Learning: Models trained extensively on large datasets with pixel-wise ground truth annotations.

■ Semi-Supervised Learning: Approaches that leverage both a limited amount of labeled data and a larger pool of unlabeled data to improve model generalization [37, 38, 39].

■ Self-Supervised Learning: Techniques where models learn representations from unlabeled data by formulating "pretext tasks" that do not require manual annotations, generating their own supervision signals [35].

■ Weakly Supervised Learning: Methods that utilize less precise or incomplete annotations (e.g., image-level labels instead of pixel-level masks) to train segmentation models [34].

■ Network Architectures: Specific CNN architectures frequently adapted for medical image segmentation, such as U-Net and its variants (e.g., AIM-Unet [16]), Feature Pyramid Networks (FPNs) [19, 20]), and models incorporating attention mechanisms [19] or Bayesian approaches [8, 38, 39].

● Evaluation and Analysis: For each identified method, the following aspects were critically analyzed: the type of CT images employed (e.g., NCCT, CTP, CTA), the specific algorithms and architectural choices, characteristics of the datasets used for training and testing (e.g., size, source, disease characteristics), the evaluation metrics reported (e.g., Dice Similarity Coefficient (DSC), Jaccard Index, Hausdorff Distance, Accuracy, Precision), and the reported performance. Particular attention was given to how these techniques addressed common challenges inherent in medical image segmentation, such as limited annotated data, the high variability of stroke lesions in terms of size, shape, and location, and the increasing demand for model explainability and interpretability in clinical settings.

## 3. RESULTS

The comprehensive bibliometric analysis and systematic

methodological survey provide a detailed overview of the research landscape concerning CT scan image segmentation for ischemic stroke lesion identification.

3.1. Bibliometric Analysis Findings

The quantitative analysis of publications between 2013 and 2023 reveals a robust and continuously growing interest in the field of medical image segmentation for ischemic strokes. This surge in scientific production underscores the clinical importance of accurate stroke detection and the transformative impact of evolving deep learning techniques.

● Evolution of Scientific Production: As depicted in Figure 2: Evolution of Scientific Production, there has been a remarkable increase in annual scientific productivity. In 2013, less than 20 articles were published on the subject. This number saw a significant and consistent rise, reaching a peak of approximately 350 publications in 2023. This trajectory clearly indicates an escalating engagement from researchers globally, reflecting the urgency and complexity of the research subject.

| Year | Number of Documents |
|------|---------------------|
| 2013 | ~100 |
| 2014 | ~95 |
| 2015 | ~100 |
| 2016 | ~120 |
| 2017 | ~120 |
| 2018 | ~140 |
| 2019 | ~220 |
| 2020 | ~230 |
| 2021 | ~245 |
| 2022 | ~300 |
| 2023 | ~350 |

(This data can be visualized as a line chart, showing the increasing trend of publications over time.)

● Most Relevant Publication Sources: Table 1: Most Relevant Publication Sources and Figure 3: Production per Year by Source (which is a line chart representation of Table 1's data) highlight the leading publication venues disseminating research in this domain. "Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)" emerged as the most prolific source, notably publishing 27 documents in 2019, and consistently contributing significantly throughout the decade. "Frontiers in Neurology" also demonstrated strong contributions, with 15 articles in 2023. Other prominent sources include "NeuroImage Clinical" and "Computers in Biology and Medicine," reinforcing the interdisciplinary nature of this research, spanning computer science, artificial intelligence, and clinical neurology.

**Table 1: Most Relevant Publication Sources (2013-2023)**

| Source | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 |
|--------|------|------|------|------|------|------|------|------|------|------|------|
| Fron | 0 | 0 | 0 | 0 | 2 | 3 | 4 | 5 | 6 | 5 | 15 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| tiers in neurology | | | | | | | | | | | |
| Neurolm age 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 | 7 | 5 | 8 | 20 | 8 | 9 | 27 | 15 | 16 | 8 | 22 |

| notes in bioinformatics | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Biomedical optic and imaging proceedings of SPIE | 8 | 6 | 4 | 2 | 6 | 5 | 6 | 6 | 4 | 5 | 5 |

(This data can also be represented as a line chart, showing the variation in document production per source over time.)

● Leading Research Institutions: Figure 4: Most Relevant Publication Sources (by Institutions) identifies the primary global players. The University of Calgary stands at the forefront with 48 publications, followed closely by the Chinese Academy of Sciences with 41 publications, and Massachusetts General Hospital with 37 publications. Several other institutions, including Hotchkiss Brain Institute, Harvard Medical School, Erasmus MC, Imperial College London, and various European research institutes (e.g., Inserm, Universitätsklinikum Hamburg-Eppendorf), also demonstrate substantial commitment, each contributing between 26 and 30 publications. This concentration of research within leading academic and medical centers underscores a concerted effort towards innovative solutions in image segmentation.

Most Relevant Publication Sources (Number of Publications by Institutions)

● University of Calgary: 48

● Chinese Academy of Sciences: 41

● Massachusetts General Hospital: 37

● Inserm: 30

● Universitätsklinikum Hamburg-Eppendorf: 28

● Imperial College London: 28

● Ministry of Education of the People's Republic: 27

● Erasmus MC: 27

● Harvard Medical School: 26

● Hotchkiss Brain Institute: 26

(This data can be visualized as a bar chart, showing the number of publications by institutions.)

● Most Relevant Authors: Figure 5: Most Relevant Authors identifies the most prolific authors in the field of stroke image segmentation. N.D. Forkert leads with 18 documents, followed by B.K. Menon with 17, and W. Qiu and Rueckert each with 14 publications. Other key contributors include J.S. Suri, L. Saba, J. Fiehler, D. Eckert, M. Goyal, R. Makka, and S. Tensen, each with 10-13 publications. These authors represent influential voices driving advancements in the field.

Most Relevant Authors (Number of Publications)

● N.D. Forkert: 18

● B.K. Menon: 17

● W. Qiu: 14

● D. Eckert: 14

● J. Fiehler: 12

● L. Saba: 12

● J.S. Suri: 12

● S. Tensen: 11

- R. Makka: 11

- M. Goyal: 10

(This data can be visualized as a bar chart, showing the number of publications by authors.)

- Geographical Distribution of Research: Figure 6: Most Relevant Countries illustrates the global distribution of research contributions, highlighting the leading countries. China is the most dominant contributor with 450 publications, followed by the United States with 420 publications, and India in third place with 251 publications. Other significant contributors include the United Kingdom, Germany, Canada, the Netherlands, France, South Korea, and Italy, each publishing between 60 and 160 documents. This data signifies the widespread international interest and collaborative research activity in stroke imaging segmentation across multiple continents.

Most Relevant Countries (Number of Publications)

- China: 450

- United States: 420

- India: 251

- United Kingdom: 160

- Germany: 130

- Canada: 120

- Netherlands: 90

- France: 80

- South Korea: 70

- Italy: 50

(This data can be visualized as a bar chart, showing the number of publications by countries.)

- Analysis of Funding Sponsors: Figure 7: Number of Documents - Funding Sponsor Analysis presents the list of funding institutions that most actively contribute to studies related to stroke image segmentation. The National Natural Science Foundation of China is the top funding body, associated with 215 publications, followed by the National Institutes of Health (USA) with 125 publications, and the National Institute of Neurological Disorders and Stroke (USA) with 55 publications. Other notable sponsors include the Horizon 2020 Framework Programme (EU), Deutsche Forschungsgemeinschaft (Germany), and various national research foundations from Canada and Korea, reflecting substantial governmental and organizational investment in this critical area.

Number of Documents - Funding Sponsor (Number of Publications)

- National Natural Science Foundation of China: 215

- National Institutes of Health: 125

- National Institute of Neurological Disorders and Stroke: 55

- Horizon 2020 Framework Programme: 48

- Fundamental Research Funds for the Central Universities: 45

- National Key Research and Development Program: 40

- Deutsche Forschungsgemeinschaft: 35

- Canadian Institutes of Health Research: 35

- National Heart, Lung, and Blood Institute: 32

- National Research Foundation of Korea: 32

(This data can be visualized as a bar chart, showing the number of publications by funding sponsors.)

- Key Research Clusters and Trends: The bibliometric analysis consistently highlights the central role of "deep learning" and "convolutional neural networks" as dominant keywords, signifying the paradigm shift towards AI-driven solutions. The ISLES (Ischemic Stroke Lesion Segmentation) challenge, initially focusing on MRI data [33], has played a crucial role in promoting dataset standardization and establishing benchmarks, although a comparable large-scale public CT dataset for ischemic stroke lesion segmentation remains a significant unfulfilled need. Recurring research clusters include:

o Methodological Innovation: Continuous development of novel deep learning architectures, training strategies, and integration of advanced computational techniques.

o Clinical Translation: Efforts to bridge the gap between research and clinical practice, focusing on validating automated methods for real-time performance, generalizability, and user-friendliness in acute settings.

o Addressing Data Challenges: Intensive research into techniques for overcoming limitations posed by scarce annotated data, including various forms of data augmentation and semi-supervised/self-supervised learning.

3.2. Survey of Methodologies

The methodological survey categorizes and critically examines the various approaches employed for segmenting ischemic stroke lesions from CT images, from traditional techniques to state-of-the-art deep learning models.

3.2.1. Traditional Image Processing Approaches

Early efforts in segmenting stroke lesions from CT images were primarily rooted in classical image processing techniques. These methods often leveraged fundamental image characteristics like pixel intensity, spatial proximity, and predefined anatomical knowledge.

● Intensity-Based Methods: Acute ischemic lesions often manifest as subtle areas of hypodensity (lower attenuation) on non-contrast CT scans. Therefore, methods like intensity thresholding were among the first to be explored. Otsu's method, for instance, is a well-known global thresholding technique that automatically determines an optimal threshold to separate foreground (lesion) from background (normal brain tissue) by maximizing inter-class variance [10]. However, these methods are highly sensitive to image noise, partial volume effects (where a pixel represents a mixture of tissue types), and the inherent low contrast of early ischemic changes.

● Region Growing: This technique starts from a seed point within the suspected lesion and iteratively adds neighboring pixels that meet certain homogeneity criteria (e.g., similar intensity, gradient). While simple and intuitive, region growing algorithms are highly dependent on the initial seed selection and the defined homogeneity criteria, making them susceptible to leakage into surrounding normal tissues or premature termination within the lesion.

● Active Contours (Snakes): These deformable models evolve a curve or surface towards object boundaries by minimizing an energy function that combines internal forces (smoothness of the curve) and external forces (image gradients). Active contours can capture more complex shapes than thresholding or region growing, but they often require good initialization and can get stuck in local minima, especially in the presence of weak or noisy boundaries.

● Statistical Models: Methods based on statistical models, such as Hidden Markov Fields [23] or Gaussian Mixture Models, attempt to classify pixels into different tissue classes (e.g., normal brain, edema, infarct) based on their intensity distributions. These models can account for intensity variations within tissue types but may struggle with the high variability and ill-defined boundaries of ischemic lesions.

● Atlas-Based Segmentation: This approach involves registering a pre-labeled anatomical atlas (containing normal brain structures and lesion templates) to the patient's CT image [24, 25, 26]. The anatomical labels from the deformed atlas are then transferred to the patient's image to segment the lesion. While atlas-based methods can provide anatomical context, they face significant challenges when dealing with large lesions or pathological deformations, as the registration process can become inaccurate [24, 25]. Furthermore, the initial atlas might not perfectly represent the patient's anatomy, leading to errors. Some frameworks for brain tumor segmentation based on outlier detection [21] or automated detection of white-matter lesions [22] have also provided foundational concepts that could be adapted for stroke lesion identification.

● Limitations of Traditional Methods: While these traditional image processing techniques provided foundational insights and proved useful in simpler segmentation tasks, their performance in the complex context of acute ischemic stroke CT is often limited. Key drawbacks include: sensitivity to noise and artifacts, reliance on handcrafted features, difficulty in capturing complex lesion morphology, susceptibility to inter-patient anatomical variability, and the need for significant manual intervention or parameter tuning, rendering them less practical for rapid, large-scale clinical application. The subtle nature of early ischemic changes means these methods frequently fail to differentiate affected tissue accurately from healthy brain, especially in the absence of clear hypodensities.

### 3.2.2. Deep Learning Approaches

The emergence and rapid advancement of deep learning, particularly Convolutional Neural Networks (CNNs), have fundamentally transformed the landscape of medical image segmentation [7, 29, 30, 31]. Inspired by groundbreaking successes in natural image classification [28] and pattern recognition [27], CNNs have demonstrated unparalleled capabilities in automatically learning complex, hierarchical features directly from raw image data, obviating the need for laborious handcrafted feature engineering.

● Core Principles of CNNs for Segmentation: Unlike traditional methods, CNNs can learn intricate spatial hierarchies and contextual information. For segmentation, a common approach involves an encoder-decoder architecture. The encoder pathway progressively reduces spatial dimensions while extracting higher-level features, and the decoder pathway reconstructs the full-resolution segmentation mask from these features. Skip connections between encoder and decoder layers help retain fine-grained spatial details lost during downsampling.

● Supervised Learning and Architectures: The vast majority of deep learning approaches for ischemic stroke lesion segmentation operate under a supervised learning paradigm. This necessitates extensive datasets of CT images meticulously annotated with pixel-wise ground truth masks by expert radiologists.

○ U-Net and its Variants: The U-Net architecture [16], characterized by its symmetric U-shaped design with skip connections, has become a de facto standard in biomedical image segmentation due to its remarkable effectiveness with relatively small datasets. Its ability to combine high-level semantic features with low-level detailed spatial information is crucial for accurately delineating lesion boundaries. Numerous variants of U-Net have been proposed and successfully applied to various medical segmentation tasks, including liver and tumor segmentation from CT scans [16]. For instance, the AIM-Unet, a hybrid model, integrates inception modules to enhance feature extraction, demonstrating improved performance for liver segmentation [16].

o    Feature Pyramid Networks (FPNs): FPNs address the challenge of segmenting objects at multiple scales by constructing a pyramid of features with strong semantic information at all levels [19, 20]. This is particularly relevant for stroke lesions, which can vary significantly in size. By incorporating attention mechanisms, such as the squeeze-and-excitation (SE) module, into 3D FPNs, models can enhance their focus on relevant features for tasks like pulmonary nodule detection, an approach transferable to stroke [19].

o    Other CNN Architectures: While U-Net is dominant, other CNN-based architectures, including those built upon ResNet backbones or fully convolutional networks (FCNs), have also been explored for medical image segmentation [18]. Initial breakthroughs in brain tumor segmentation from MRI using deep CNNs [30, 31, 32] provided a strong impetus for applying similar principles to CT-based stroke segmentation. However, directly transferring these successful MRI-based methods to CT requires careful consideration of CT's unique characteristics, such as lower soft-tissue contrast and susceptibility to specific artifacts.

●    Addressing Data Scarcity and Annotation Burden: A pervasive challenge in medical image segmentation is the prohibitive cost and time required to acquire large, high-quality, expert-annotated datasets. This is particularly acute for rare pathologies or modalities like acute stroke CT, where lesions are often subtle and highly variable. To overcome this limitation, researchers have explored innovative learning paradigms:

o    Data Augmentation: Techniques like geometric transformations (rotation, scaling, flipping), intensity variations, and more advanced methods like CarveMix [11] artificially expand the diversity and size of training datasets. CarveMix, proposed for brain lesion segmentation, synthesizes new training examples by mixing features from different images, thereby improving generalization and robustness with limited initial data [11].

o    Semi-Supervised Learning (SSL): SSL methods leverage a combination of a small labeled dataset and a large amount of readily available unlabeled data. The core idea is to use the labeled data to initiate learning and then use the model's predictions on unlabeled data (often with a confidence measure) to further refine the model. Techniques such as reciprocal learning [37] and various Bayesian deep learning methods [38, 39] have demonstrated improved segmentation performance. Bayesian models, like BayeSeg [39], offer the added benefit of providing uncertainty estimates alongside predictions, enhancing interpretability and generalizability. Wang and Lukasiewicz [38] re-examined Bayesian deep learning for semi-supervised volumetric medical image segmentation, showing promising Dice scores and Hausdorff distances even with only 20% of training data labeled.

o    Self-Supervised Learning (SSL-II): This emerging paradigm trains models to learn meaningful representations from unlabeled data by formulating "pretext tasks" that do not require manual annotations. For example, a model might be trained to predict missing patches, reconstruct images from noisy inputs, or recognize spatial relationships. Once a robust feature extractor is learned through self-supervision, it can be fine-tuned with a small amount of labeled data for the downstream segmentation task. Self-supervised RCNNs have been successfully applied to medical image segmentation, demonstrating significant improvements in Dice scores compared to purely supervised models when labeled data is scarce [35].

o    Weakly Supervised Learning (WSL): WSL reduces the annotation burden by using less precise or incomplete labels. For instance, instead of pixel-wise masks, models might be trained with image-level labels (e.g., "stroke present/absent") or bounding box annotations. Giancardo et al. [34] developed a deep learning approach for acute stroke infarct core segmentation using only image-level labels on CT-angiography data, outperforming methods trained on voxel-level CT perfusion estimations, demonstrating the potential of WSL to reduce annotation costs significantly.

●    3D Segmentation: Given that CT scans are inherently volumetric (3D), applying 2D CNNs slice-by-slice can lose crucial inter-slice spatial context. Consequently, 3D CNNs have gained prominence for directly processing volumetric images. These networks can capture complex spatial relationships across slices, leading to more consistent and accurate 3D segmentations [19].

●    Attention Mechanisms: Integrating attention mechanisms into CNN architectures allows models to dynamically focus on the most relevant regions or features within an image, enhancing their ability to discern subtle lesion boundaries and improve segmentation accuracy, particularly for small or ill-defined lesions [19].

●    Performance Metrics and Comparison: As highlighted in Table 2: Top Five Best Performing Models, advanced deep learning models consistently achieve superior performance compared to traditional methods. For instance, Svecic et al. [14] reported a remarkably high precision rate of 99.99% for a deep learning model in a related medical image analysis task (tumor tracking), emphasizing the potential of such models. For liver tumor segmentation, models like AIM-Unet [16] achieved Dice Similarity Coefficients (DSC) of 97.86% and Jaccard similarity coefficients of 96.10%, while ResUNet-based algorithms [17] reported accuracy rates up to 99.71% and similarity coefficients of 96.35%. Even fully convolutional 2D neural networks for liver tumor segmentation reached 85% accuracy [18]. While these examples are primarily from liver and brain tumor segmentation (as specific large-scale CT stroke segmentation benchmarks are less common in the literature), they illustrate the power and

precision afforded by modern deep learning architectures. The consistent absence of traditional methods in the top-performing models in recent comparative analyses (as implicitly shown in Table 2) further underscores their limited capacity to meet the high precision demands of complex clinical contexts like ischemic stroke lesion identification.

**Table 2: Top Five Best Performing Models**

| Source | Method | Result | Limitation |
|---|---|---|---|
| Svecic et al. [14] | Deep learning model for liver tumor segmentation | Precise segmentation | 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 | Achieving up to 99.1% accuracy | Risk of overfitting on small or non-diverse datasets. |
| Özcan et al. [16] | 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% | Complex neural network, making it challenging to understand decision-making processes; Can be time-consuming, delaying deployment in real-time applications. |
| Manjunath and Kwadiki [17] | 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. |
| Chlebus et al. [18] | 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. |
|---|---|---|---|
| Zhang et al. [19] | Optimization of the 3D FPN network for pulmonary nodule detection | Improved detection performance with a CPM of 89.34% | This method relies on existing training data and the performance of the underlying CNN. Additionally, results can vary based on the quality of the initial annotations. |

## 4. DISCUSSION

The detailed bibliometric analysis and methodological survey reveal a dynamic and rapidly evolving field, driven by critical clinical needs and significant technological advancements. The dramatic shift from traditional image processing techniques to sophisticated deep learning models marks a pivotal turning point, fundamentally improving the accuracy, efficiency, and automation of CT scan image segmentation for ischemic stroke lesions.

4.1. Transformative Impact of Deep Learning

Deep learning models, particularly Convolutional Neural Networks, have demonstrated a superior ability to learn complex, hierarchical features directly from raw medical image data. This eliminates the laborious and often suboptimal process of handcrafted feature engineering that characterized earlier methods. Their capacity to discern subtle density variations and diffuse early ischemic changes on non-contrast CT, which can be easily overlooked by the human eye or simpler algorithms, represents a major leap forward in diagnostic capability. The integration of advanced architectures like U-Net and its numerous derivatives, along with Feature Pyramid Networks and attention mechanisms, has enabled these models to achieve high levels of precision and robustness in capturing diverse lesion morphologies across different scales. The quantitative results reported for various medical segmentation tasks, as highlighted in our survey (e.g., high Dice coefficients, accuracy, and precision rates), underscore this transformative impact.

4.2. Persistent Challenges and Limitations

Despite these remarkable advancements, several formidable challenges continue to impede the widespread clinical deployment and optimal performance of automated CT stroke lesion segmentation tools:

● Subtlety and Low Contrast of Early Ischemic Changes: The inherent low contrast and subtle nature of early ischemic signs on non-contrast CT remains a primary challenge. In the hyperacute phase, distinguishing ischemic tissue from normal brain parenchyma can be extremely difficult, even for expert radiologists. This low signal-to-noise ratio makes robust automated detection and precise delineation particularly arduous.

● Image Artifacts: CT scans are susceptible to various artifacts, including beam hardening, motion artifacts (especially in agitated stroke patients), partial volume effects, and streaking from metallic implants. These artifacts can significantly degrade image quality, obscure lesion boundaries, and introduce spurious patterns that deep learning models may misinterpret, leading to erroneous segmentations.

● Data Scarcity and Annotation Burden: A critical bottleneck in the development of robust deep learning models for medical imaging is the scarcity of large, high-quality, and diverse annotated datasets. The process of manually delineating stroke lesions pixel-by-pixel is exceptionally labor-intensive, time-consuming, and demands specialized medical expertise, often leading to smaller and less diverse datasets compared to those available for general computer vision tasks. This limitation directly impacts the generalizability and robustness of trained models across different patient populations, scanner types, and clinical protocols.

● Lesion Variability: Ischemic stroke lesions exhibit immense variability in terms of size, shape, location (cortical, subcortical, brainstem, cerebellum), and appearance depending on the time since onset. This high inter-patient and inter-lesion heterogeneity makes it challenging for models to learn a universally applicable representation for all types of ischemic lesions.

● Generalizability and Robustness: Models trained on specific datasets may not perform well when applied to data from different hospitals or scanners (domain shift). Ensuring generalizability across diverse clinical settings and patient demographics is paramount for clinical utility. This issue is compounded by the lack of large, publicly available, standardized CT datasets specifically for ischemic stroke, unlike the ISLES challenge for MRI [33].

● Explainability and Interpretability (XAI): As AI systems become more integrated into critical clinical decision-making, the demand for explainability and

interpretability has grown [36]. Clinicians require an understanding of why a model makes a particular segmentation decision to build trust, validate its output, and identify potential errors, especially in life-threatening conditions like stroke. Most deep learning models, however, operate as "black boxes," making their internal decision processes opaque. Developing more transparent and interpretable AI models for stroke lesion segmentation is an active area of research.

● Computational Resources and Real-time Performance: Training complex deep learning models can require substantial computational resources (e.g., high-performance GPUs, cloud computing). Furthermore, in acute stroke settings, real-time or near real-time processing is crucial for guiding immediate interventions. Ensuring that these sophisticated models can operate efficiently within clinical timelines is a practical challenge.

4.3. Future Research Directions and Perspectives

The trajectory of research in CT scan image segmentation for ischemic stroke points towards several promising avenues that can further enhance diagnostic capabilities and clinical impact.

● Advanced Deep Learning Architectures: Continued exploration and development of novel deep learning architectures are essential. This includes:

○ Hybrid Models: Integrating the strengths of different architectures (e.g., transformers for long-range dependencies, graph neural networks for connectivity analysis) with CNNs to capture more nuanced features.

○ Uncertainty Quantification: Incorporating Bayesian deep learning methods [38, 39] not only for improved segmentation accuracy, particularly with limited data, but also to provide robust estimates of prediction uncertainty. This uncertainty information can be invaluable to clinicians in assessing the reliability of automated segmentations, especially in ambiguous cases.

○ Generative Models: Exploring Generative Adversarial Networks (GANs) or diffusion models for data augmentation, synthetic data generation, or image-to-image translation tasks that can improve segmentation robustness.

● Harnessing Limited Data: Given the persistent challenge of data scarcity, continued emphasis on methods that can effectively learn from limited annotations is critical:

○ Advanced Semi-Supervised and Self-Supervised Learning: Further development and refinement of techniques like reciprocal learning [37] and self-supervised RCNNs [35] will be crucial. This involves designing more effective pretext tasks, developing robust consistency regularization schemes, and exploring novel ways to leverage unlabeled data effectively.

○ Federated Learning: Investigating federated learning approaches where models can be collaboratively trained on decentralized datasets from multiple institutions without direct data sharing, thus addressing data privacy concerns and increasing data volume.

○ Transfer Learning and Domain Adaptation: Developing robust strategies for transferring knowledge from large publicly available datasets (even if for different organs or pathologies) to smaller, specific stroke datasets, and adapting models to new scanner types or patient cohorts with minimal effort.

● Multi-Modal and Multi-Parametric Integration: The current focus on NCCT is primarily due to its frontline role. However, integrating information from other modalities like CT perfusion (CTP) and CT angiography (CTA) can provide richer physiological and vascular information, enabling more precise lesion delineation and differentiation of core infarct from penumbra [34]. Future research should explore sophisticated fusion strategies that combine data from these modalities effectively within deep learning frameworks.

● Explainable AI (XAI) for Clinical Trust: Moving beyond "black-box" models, future research must prioritize the development of interpretable and explainable AI models [36]. This includes techniques like saliency maps, attention visualizations, and concept-based explanations that allow clinicians to understand the rationale behind a model's segmentation. Building trust through transparency is paramount for widespread clinical adoption.

● Clinical Integration and Workflow Optimization: Translational research focused on seamless integration of automated segmentation tools into existing clinical workflows is essential. This encompasses:

○ User-Friendly Interfaces: Developing intuitive and clinician-centric interfaces that present segmentation results clearly and allow for easy review and potential correction.

○ Real-time Performance Optimization: Engineering models and algorithms for rapid inference to meet the time-sensitive demands of acute stroke diagnosis.

○ Prospective Validation: Rigorous prospective clinical validation studies are necessary to assess the real-world performance, generalizability, and impact of these tools on patient outcomes across diverse populations and clinical environments.

● Standardized Benchmarking and Public Datasets: The establishment of large-scale, publicly accessible, and expertly annotated CT ischemic stroke datasets, similar to the impact of ISLES for MRI [33], would significantly accelerate research and facilitate robust benchmarking of new algorithms, leading to more comparable and reliable results across studies.

● Personalized Stroke Care: Ultimately, the goal is to move towards personalized stroke care. Advanced

segmentation, combined with clinical data and patient-specific biomarkers, could enable more precise prognostication, tailored treatment plans, and optimized rehabilitation strategies for individual patients.

## 5. CONCLUSION

Accurate and timely segmentation of ischemic stroke lesion areas from CT images is a cornerstone of effective acute stroke management. The evolution from rudimentary image processing methods to highly sophisticated deep learning approaches, particularly Convolutional Neural Networks, has revolutionized the field, offering unprecedented levels of accuracy and automation. This comprehensive bibliometric review underscores the increasing global research focus on this critical area, driven by the profound clinical need for rapid and efficient diagnostic tools. The analysis highlights a consistent upward trend in publications, with major contributions from leading institutions and countries worldwide, fueled by significant funding.

Despite these transformative advancements, the field continues to grapple with persistent challenges. The inherent subtlety of early ischemic changes on NCCT, the omnipresence of image artifacts, and the fundamental scarcity of large, high-quality annotated datasets remain significant hurdles. Moreover, the imperative for model interpretability and generalizability in clinical practice is gaining increasing prominence.

Future research efforts must strategically focus on developing more robust and generalizable deep learning architectures, particularly those that can effectively learn from limited and weakly supervised data. The integration of multi-modal imaging information (e.g., CT perfusion, CT angiography) holds immense promise for more precise lesion characterization. Concurrently, a strong emphasis on Explainable AI (XAI) is crucial to foster clinician trust and facilitate seamless clinical adoption. Ultimately, the translation of these technological innovations into tangible improvements in acute ischemic stroke care will hinge on continued rigorous research, collaborative efforts to build standardized datasets, and a sustained focus on real-world clinical validation and integration. The ongoing progress in this domain holds the potential to significantly enhance diagnostic workflows, optimize treatment strategies, and ultimately improve the lives of millions affected by ischemic stroke globally.

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