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Review

Automatic brain ischemic stroke segmentation with deep learning: A review

Hossein Abbasi [a,*], Maysam Orouskhani [b], Samaneh Asgari [c], Sara Shomal Zadeh [d]

[a] Islamic Azad University, South Tehran Branch, Tehran, Iran
[b] Department of Radiology, University of Washington, USA
[c] Islamic Azad University, Karaj Branch, Karaj, Iran
[d] Department of Civil and Environmental Engineering, Lamar University, USA

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ABSTRACT

The accurate segmentation of brain stroke lesions in medical images are critical for early diagnosis, treatment planning, and monitoring of stroke patients. In recent years, deep learning-based approaches have shown great potential for brain stroke segmentation in both MRI and CT scans. However, it is not clear which modality is superior for this task. This paper provides a comprehensive review of recent advancements in the use of deep learning for stroke lesion segmentation in both MRI and CT scans. We compare the performance of various deep learning-based approaches and highlight the advantages and limitations of each modality. The deep learning models for ischemic segmentation task are evaluated using segmentation metrics including Dice, Jaccard, Sensitivity, and Specificity.

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1. Introduction

Stroke is a medical emergency characterized by the interruption of blood supply to the brain, resulting in the deprivation of oxygen and nutrients to brain cells [1]. It is a leading cause of mortality and long-term disability worldwide, emphasizing the need for effective diagnosis and treatment strategies. Ischemic stroke and hemorrhagic stroke are the two main types of strokes, each with distinct underlying causes and characteristics. Ischemic stroke, accounting for approximately 80% of all stroke cases, occurs when a blood clot or plaque build-up obstructs or narrows a blood vessel, leading to a reduction or complete blockage of blood flow to a specific area of the brain [2]. The lack of blood supply results in the deprivation of oxygen and nutrients, causing the death of brain cells in the affected area. On the other hand, hemorrhagic stroke occurs when a blood vessel ruptures, leading to bleeding within the brain. This rupture can be due to factors such as high blood pressure, weakened blood vessel walls, or abnormal blood vessel connections [2].

Stroke segmentation plays a crucial role in stroke diagnosis as it enables the identification and delineation of the regions affected by stroke. The importance of stroke segmentation lies in its ability to provide quantitative and spatial information about the extent and location of the stroke-related abnormalities within the brain. Magnetic resonance imaging (MRI) and computed tomography (CT) are two commonly used imaging modalities in the context of stroke segmentation. MRI offers excellent soft tissue contrast and is particularly advantageous for detecting acute ischemic strokes. Diffusion-weighted imaging (DWI) in MRI provides sensitive detection of early ischemic changes, helping to identify the core infarct region [3] all types are demonstrated in Fig. 1, [4]. Additionally, perfusion-weighted imaging (PWI) can assess the extent of the perfusion deficit, aiding in the identification of the ischemic penumbra, which represents potentially salvageable tissue [5].

On the other hand, CT imaging is widely available, relatively fast, and essential for the initial evaluation of stroke patients. Non-contrast CT is often performed to rule out hemorrhagic stroke and detect early signs of infarction, such as hypoattenuation in the affected brain regions [6]. CT angiography can provide information about vessel occlusion, guiding treatment decisions, while CT perfusion imaging can assess the extent of the ischemic core and penumbra [7]. Both MRI and CT have their respective strengths and limitations, and the choice of imaging modality depends on factors such as availability, patient condition, and specific clinical requirements in stroke segmentation studies.

Artificial intelligence (AI) has aroused widespread interest in medical imaging. Especially with rapid progress in deep learning (DL), AI has turned into one of the hot topics of medical images analysis. While manual analysis of medical images is a challeng-

* Corresponding author.
E-mail addresses: Hossein.abbasi48@gmail.com (H. Abbasi), maysam@uw.edu (M. Orouskhani), smnhasgari@gmail.com (S. Asgari), sshomalzadeh@lamar.edu (S.S. Zadeh).

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Fig. 1. Ischemic Stroke on CT, MRI, and diffusion weighted MRI. [4].

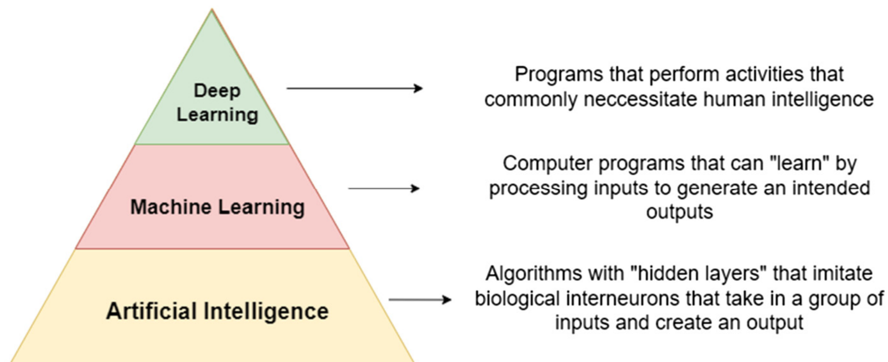

Fig. 2. Classification of artificial intelligence architectures.

ing task for radiologists, AI-based techniques made it automated and easier than before. Deep learning models, which have recently exhibited exceptional performance in medical images analysis, can be considered a subfield of machine learning (Fig. 2) focus on the development and application of deep neural networks to perform tasks by analysing large amounts of labelled data and identifying patterns and relationships within the data. While traditional machine learning algorithms are given the features as input, the main advantage of deep learning is its ability to automatically learn and extract high-level features from raw data, without the need for manual feature engineering. Deep learning has achieved remarkable success in various medical imaging, including lesion segmentation, image synthesizing, and disease early-stage detection [8]. In the literature, deep learning with different architectures including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), U-Net, Deep Convolutional Neural Networks (DCNNs), and Autoencoders have been used in stroke segmentation task. CNNs as one of the popular types of deep learning architectures employed in medical images analysis, use convolutional layers to detect features within an image and can learn how to classify important patterns for identifying stroke lesion. On the other hand, RNNs suitable for sequential data such as time series data from stroke patients, learn to recognize patterns and relationships within the data and can be used for predicting stroke outcomes. The U-Net architecture is a type of CNN that is used for medical image segmentation. It uses a contracting pathway to capture context and a symmetric expanding pathway to localize and refine the segmentation. DCNNs, on the other hand, are a type of CNN that are designed to process larger and more complex datasets. Lastly, Autoencoders were used for unsupervised learning tasks such as feature extraction and dimensionality reduction.

Through this review, we aim to provide researchers and clinicians with insights into the current state of deep learning-based ischemic stroke segmentation, its potential clinical implications, and future research directions in this rapidly evolving field. This paper divides the articles by imaging modality including CT and MRI. For each article, purpose, data source, algorithm type, outcome metrics, and qualitative results are evaluated and reported using descriptive statistics.

2. Search strategy

An initial systematic literature search following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for systematic review was conducted in 7 stages, using PubMed and Web of Science databases. Boolean search terms included any of the following: "deep learning" OR "neural network" OR "Convolutional Neural Network" OR "U-Net" in combination with any the following terms: "Stroke" AND "Segmentation" OR "Detection". A PRISMA diagram is shown in Fig. 3. We followed a seven-step filtering process to identify the most relevant publications. First, we found 764 papers, 225 publications were filtered from a set of 764 publications based on the title, hemorrhagic stroke, and unavailable papers or irrelevant titles. Second, we filtered 142 publications from a set of 225 publications, based on their focus on classification. Then, we employed a full-length study to understand the details and implementation aspects of the deep learning method and eliminated low Dice similarity coefficient and total of 22 publications were finally included in our review. As a result, we excluded articles published in non-English, abstracts and conference proceedings that were not published in peer-reviewed journals.

3. Deep learning-based medical image segmentation

Medical segmentation plays a vital role in various clinical applications, facilitating accurate delineation and characterization of anatomical structures and pathological regions. Deep learning methods have revolutionized medical image analysis by providing robust and effective tools for automated segmentation. A typical workflow for lesion segmentation using deep learning can be considered as:

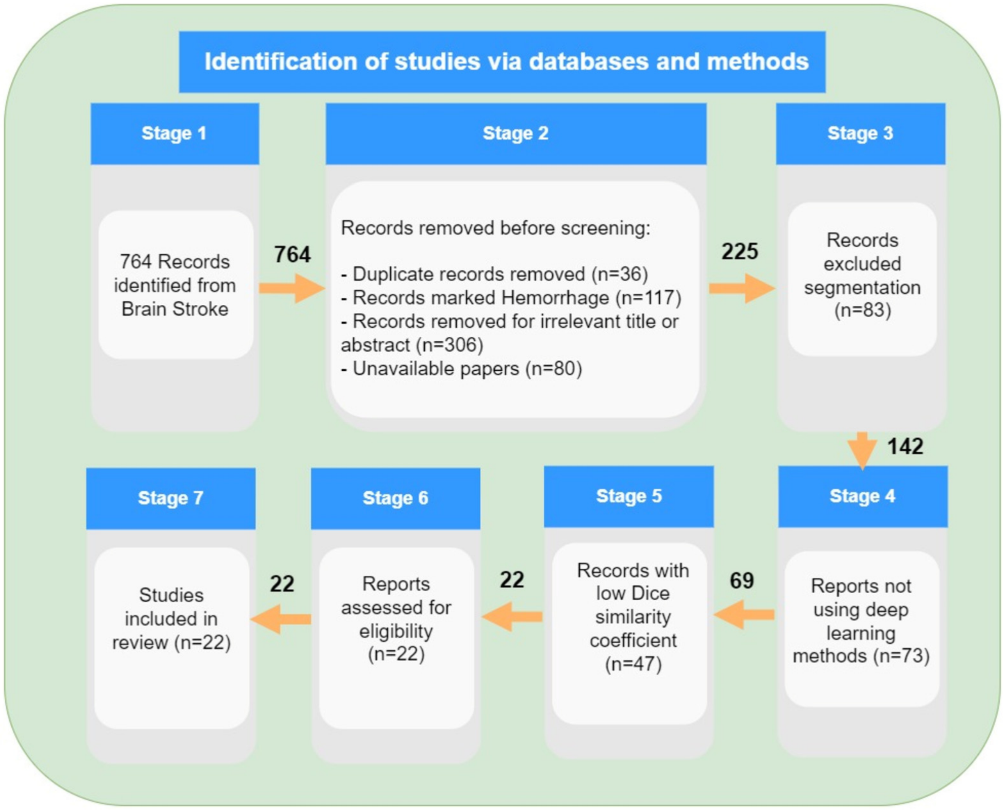

Fig. 3. PRISMA for Systematic Review Flow Diagram.

The first step is the acquisition of medical images data, such as magnetic resonance imaging (MRI) and computed tomography (CT). These images are often acquired in multiple modalities and may require pre-processing steps, including noise reduction, intensity normalization, and spatial alignment to ensure consistency across the dataset.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in medical segmentation. Various architecture designs, such as U-Net [9] V-Net [10] or 3D variants, are tailored to handle the complexities of medical imaging data and capture contextual information effectively. These models are trained using annotated medical images, where expert-defined labels serve as ground truth for the desired segmentation. The training phase involves feeding the prepared dataset into the deep learning model. The model learns to generate pixel-level segmentation masks by optimizing a suitable loss function, typically based on a comparison between the predicted and ground truth labels. Techniques such as transfer learning, where pre-trained models on large-scale datasets are fine-tuned, are often employed to overcome the challenges of limited medical data availability. Evaluation of the trained model is crucial to assess its performance. Metrics such as Dice coefficient, sensitivity, specificity are commonly used to quantify the accuracy and robustness of the segmentation. Cross-validation or independent testing on unseen datasets can provide further validation and ensure generalization capabilities. Once the model is deemed satisfactory, it can be deployed for segmenting new images. The inference process involves feeding unseen images into the trained model, which generates segmentation maps or masks. Post-processing techniques, including morphological operations, region growing, or graph cuts, can be applied to refine the segmentation results and enhance their clinical utility.

4. Stroke segmentation with deep learning models

In this section we review the recent works concentrating on ischemic stroke segmentation with deep learning models. Most papers in stroke segmentation use CNNs and U-Net model as the segmentation framework. CNNs use convolutional layers to extract features from the input image and pooling layers to reduce the spatial dimensionality of the feature maps. These features are then passed through fully connected layers to perform the segmentation task. In addition to CNNs, U-Net architecture, Fig. 4, consists of an encoder and decoder network with skip connections between them, and uses contracting and expanding pathways to capture context and localize and refine the segmentation. The U-Net architecture has shown promising results for medical image segmentation tasks and is widely used in the research community. Attention mechanisms are a recent addition to deep learning models that can improve their performance by focusing on relevant regions of the input image. Attention mechanisms allow DL models to selectively attend to certain parts of the input image and ignore others, depending on their relevance to the task at hand.

We divide the articles by imaging modality including MRI and CT as follows:

4.1. MRI

MRI plays a crucial role in stroke segmentation by providing detailed and high-resolution images that enable the accurate identification and characterization of stroke-related lesions. Generally, the benefits of MRI in stroke segmentation include its high soft tissue contrast, time sensitivity, differentiation of stroke types, and long-term follow-up. These benefits enhance the accuracy of stroke segmentation, contribute to better understanding of stroke pathology, and assist in clinical decision-making for optimal patient management. To take the advantages of MRI in stroke segmentation, some

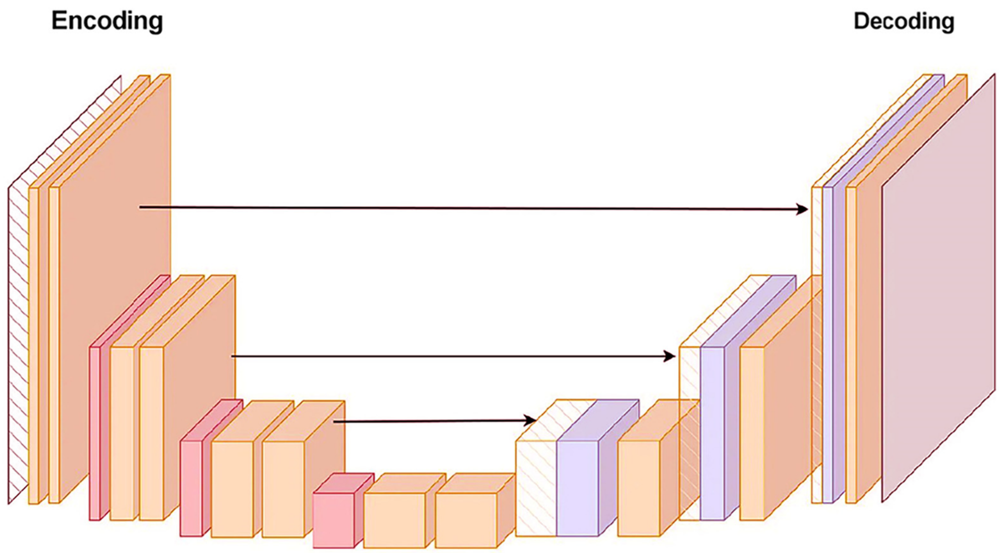

Fig. 4. U-net architecture.

deep learning models with MR images have been proposed. The deep learning models utilize various architectures, including residual ConvLSTM U-Net, ensemble of two DeconvNets, self-similar fractal networks, deep symmetric 3D convolutional neural network, and deep residual neural networks. The models are trained on multimodal MRI scans, including DW-MRI, PWI, FLAIR, and T1-weighted MRI scans, to improve accuracy and efficiency. The studies also address challenges such as class imbalance, complex geometry of the lesion shape, and variable textural representation.

Clèrigues et al., [11] proposed a deep learning methodology for acute and sub-acute stroke lesion segmentation using multimodal MR imaging. The authors pre-processed the data to facilitate learning features based on the symmetry of brain hemispheres and use a combination of small patches with a balanced training patch sampling strategy and a dynamically weighted loss function to tackle class imbalance. They also used a U-Net based CNN architecture and high degree of overlapping patches to reduce the need for additional post-processing. The proposed method was evaluated by two public datasets from the 2015 Ischemic Stroke Lesion Segmentation challenge (ISLES 2015). These involve the tasks of sub-acute stroke lesion segmentation (SISS) and acute stroke penumbra estimation (SPES) from multiple diffusion, perfusion and anatomical MRI modalities. The performance achieving a DSC for the SISS, sub-acute stroke lesion segmentation (DSC=0.59 $\pm$ 0.31) and SPES, acute stroke penumbra estimation (DSC=0.84 $\pm$ 0.10), respectively.

A composite deep learning model based on the self-similar fractal networks and the U-Net model was proposed for automated acute stroke lesion segmentation [12]. The proposed Classifier-Segmenter network (CSNet) involves a hybrid training strategy with a self-similar (fractal) U-Net model that is explicitly designed to perform segmentation. The authors exploited the benefits of both models by combining them into one hybrid training scheme and developing the concept of a cascaded architecture, which further enhances the model's accuracy by removing redundant parts from the Segmenter's input. A voting mechanism is also employed to enhance the overall segmentation accuracy.

Nazari et al., [13] presented a fully automated model for localizing and segmenting acute ischemic stroke (AIS). The method is based on the Crawford-Howell t-test and comparison of stroke images to healthy controls. A classifier to discriminate the images into stroke or non-stroke categories was designed following the lesion segmentation. Results showed model's high potential to improve the accuracy and efficiency of AIS lesion segmentation in routine clinical practice, as it can be easily integrated into the diagnostic workflow and does not require high computational resources.

A deep residual neural network was developed for automated segmentation of chronic ischemic stroke lesions on T1-weighted MRI scans [14]. The study utilized 3D deep convolutional segmentation models with residual learning and a novel zoom-in and out strategy. To train the models efficiently, a two-stage zoom-in and out strategy was employed, where the models were first trained on small volumes and then finetuned on larger volumes. This strategy allowed for regularizing the models, utilizing sub-optimal GPUs, and improving the robustness of the models by learning from the broader context of input images. The models were evaluated using manual tracing of lesions as the reference standard, and the results showed that the models had an average Dice similarity coefficient (DSC) of 0.64, an average symmetric surface distance (ASSD) of 3.6 mm, and an average Hausdorff distance (HD) of 20.4 mm.

Another residual model, ConvLSTM was proposed by Alis et al., [15] to segment acute ischemic lesions on diffusion-weighted imaging (DWI). The study found that the median Dice scores is 0.85 for the internal tests and 0.84 on the external tests which were non-inferior to the radiologist's performance on the external tests. They demonstrated non-inferior performance compared to a radiologist in delineating borders of ischemic lesions when applied to previously unseen images derived from the same manufacturer on which the models were previously trained.

To take the advantages of symmetric 3D convolutional neural network, DeepSym-3D-CNN was proposed by Cui et al., [16] for automated diagnosis of acute ischemic stroke (AIS) using diffusion-weighted imaging (DWI) images. The authors collected DWI and Apparent Diffusion Coefficient (ADC) images from 190 study subjects (97 AIS and 93 Non-AIS) and split 3D DWI brain images into left and right hemispheres, inputting them into two paths. After the features computed from two paths are subtracted through L-2 normalization, four multi-scale convolution layers produce the final prediction. They construct three comparative models using DWI images, including MedicalNet with transfer learning, Simple DeepSym-3D-CNN and L-1 DeepSym-3D-CNN. The method's ability to identify AIS automatically via DWI images and its potential for extension to other diseases with asymmetric lesions suggest its wider applicability in clinical practice.

Dense convolutional networks were also used for stroke detection. Oksuz I. [17] combined Dense CNN with residual U-net architecture for correcting motion-related brain MRI artifacts. The presence of image artifacts is a significant challenge in clinical practice as it can lead to low diagnostic image quality. The proposed pipeline generates synthetic artifacts using an MR physics-based corruption strategy. The detected artifacts are corrected using a residual U-net network trained on corrupted data. The results show that the algorithm can improve both image quality and segmentation accuracy. Furthermore, reduce the influence of low image quality on the final prognosis. Small size of dataset and absence of external validation are limitations of this paper.

Wei et al., [18] leveraged deep learning models to segment, classify, and map lesion distributions of acute ischemic stroke (AIS) using MRI images. The authors evaluated brain MRI images of AIS patients from 2017 to 2020 and developed the Semantic Segmentation Guided Detector Network (SGD-Net), composed of two models - the first U-shaped model for segmentation in diffusion-weighted imaging (DWI) and the second model for binary classification of lesion size (lacune vs. non-lacune) and circulatory territory of lesion location (anterior vs. posterior circulation). They modified the two-stage deep learning model into SGD-Net Plus by automatically segmenting AIS lesions in DWI images and registering the lesion in T1-weighted images and the brain atlases. The authors conclude that the domain knowledge-oriented design of artificial intelligence applications can deepen our understanding of patients' conditions and strengthen the use of MRI for patient care. SGD-Net and SGD-Net Plus are practical tools that meet the clinical needs and enrich educational resources of neuroimage.

Wong et al., [19] developed and evaluated a deep learning model for the automatic segmentation of acute ischemic stroke lesions in diffusion-weighted magnetic resonance imaging (DW-MRI) scans. The model was developed based on a rotation-reflection equivariant U-Net architecture and grouped convolutions to ensure robustness to rotation and reflection. The study also evaluated the use of segmented stroke volumes in different brain regions for predicting 90-day modified Rankin Scale outcome. The results showed that the model achieved a competitive segmentation performance in the hold-out testing cases, and the location-specific stroke volume segmentations combined with clinical factors demonstrated high accuracy and area under the curve for 90-day modified Rankin Scale outcome prediction.

Nazari et al., [20] explored the use of a deep convolutional neural network (DCNN) model trained with diffusion-weighted imaging (DWI) to predict final infarct volume and location in acute stroke patients, without the need for perfusion-weighted imaging (PWI). The goal is to estimate tissue at risk of infarction in the absence of timely reperfusion, without adding time and expense to the acute stroke imaging workup. The authors trained and validated an attention-gated (AG) DCNN using DWI, apparent diffusion coefficients (ADC) maps, and thresholded ADC maps with values less than 620 × 10-6 mm2/s as input channels. The output was a voxel-by-voxel probability map of tissue infarction. The authors conclude that the AG-DCNN model using only diffusion information upon admission was able to predict infarct volumes at 3-7 days after stroke onset with comparable accuracy to models that consider both DWI and PWI. This suggests that using a DCNN model trained on DWI alone could enable treatment decisions to be made with shorter stroke imaging protocols, without the need for PWI.

A novel autoencoder architecture with cross-attention mechanisms and hierarchical deep supervision was proposed by Gómez et al., [21] for delineating brain lesions from MRI studies. The cross-attention deep autoencoder focuses on the lesion shape through a set of convolutional saliency maps and skip connections to preserve the morphology of affected tissue. A deep supervision training scheme is used to induce the learning of hierarchical lesion details, and a weighted loss function is used to alleviate the negative impact of class imbalance. The study shows that deeply supervised cross-attention autoencoders, trained to pay more attention to lesion tissue, are better at estimating ischemic lesions in MRI studies.

Praveen et al., [22] proposed an unsupervised feature learning approach using a stacked sparse autoencoder (SSAE) framework. The framework consists of sparse autoencoder (SAE) layers followed by a support vector machine (SVM) classifier. They designed a five-layer SSAE architecture by training a SVM classifier in a supervised manner. Each image patch to be classified is fed into the SSAE model, which extracts features and classifies the image patch into ischemic stroke lesion or normal class. Their results were high record on the Ischemic Stroke Lesion Segmentation (ISLES) 2015 dataset and achieve high precision, dice coefficient of 0.94, recall of 0.92, and accuracy of 0.9.

Zhang et al., [23] introduced a novel method for segmenting acute ischemic stroke from diffusion weighted images (DWIs) using deep 3-D convolutional neural networks (CNNs). The study dataset consisted of 242 subjects, with 90 for training, 62 for validation, and 90 for testing. The proposed method achieved impressive results on various metrics: a Dice similarity coefficient of 79.13%, lesionwise precision of 92.67%, and lesionwise F1 score of 89.25%. These results outperformed other state-of-the-art CNN methods by a significant margin. To address the challenge of training a very deep 3-D CNN, the network was equipped with dense connectivity to allow unimpeded propagation of information and gradients throughout the network. The model was trained using a Dice objective function to combat the severe class imbalance problem in the data. The method also underwent evaluation on the ISLES2015-SSIS dataset, where it demonstrated strong generalization capacity and achieved highly competitive performance.

4.2. CT

While MRI provides superior soft tissue contrast, CT offers fast imaging in the acute setting, excellent detection of hemorrhages, and widespread availability. A variety of approaches were used, including CNNs with attention mechanisms and U-Net architectures, all of which demonstrated high accuracy on stroke lesion segmentation in CT images. These studies address different aspects of stroke diagnosis and segmentation, such as the use of different imaging modalities, the design of deep learning architectures, the handling of class imbalance, and the validation of automated methods against clinical standards. However, most of these studies have some limitations, such as small sample sizes, single-center studies, or lack of external validation. Further research is needed to validate the proposed methods in larger and more diverse datasets and to evaluate their clinical utility in routine practice.

Wang et al., [24] introduced a novel framework based on synthesized pseudo Diffusion-Weighted Imaging (DWI) from perfusion parameter maps to obtain better image quality for more accurate segmentation. The proposed framework consists of three components based on Convolutional Neural Networks (CNNs) and is trained end-to-end. First, a feature extractor is used to obtain both a low-level and high-level compact representation of the raw spatiotemporal Computed Tomography Angiography (CTA) images. Second, a pseudo DWI generator takes as input the concatenation of CTP perfusion parameter maps and the extracted features to obtain the synthesized pseudo DWI. To achieve better synthesis quality, the authors propose a hybrid loss function that pays more attention to lesion regions and encourages high-level contextual consistency. Finally, the lesion region is segmented from the synthesized pseudo DWI, where the segmentation network is based on switchable normalization and channel calibration for better performance.

A 3D U-Net architecture with squeeze-and-excitation blocks and a restrictive patch sampling to alleviate the class imbalance problem and handle intra-ventricular strokes in stroke segmentation with CT images [25]. The study also analysed the effects of patch size, different modalities, data augmentation, and loss functions on the segmentation results. Small size of dataset is one limitation of this study.

The ISLES challenge (Ischemic Stroke Lesion Segmentation) is a global competition that enables teams to develop advanced tools for stroke lesion analysis with machine learning. The aim of ISLES-2018 was to segment infarcted tissue on computed tomography perfusion (CTP) based on diffusion-weighted imaging as a reference standard. The data consisted of 103 cases of acute anterior circulation large artery occlusion stroke from 4 centres, with 63 cases for training and 40 for testing. Hakim et al., [26] reviewed the best methods and concluded that machine learning methods predict infarcted tissue from CTP with improved accuracy compared with threshold-based methods used in clinical routine. Overall, the ISLES challenge provides a platform for advancing stroke lesion analysis with machine learning and improving accuracy in identifying infarcted tissue on CTP, which can be critical in determining eligibility for late-time-window thrombectomy.

The objective of Naganuma et al., [27] was to validate deep learning-based Alberta Stroke Program Early Computed Tomography Score (ASPECTS) calculation software that utilizes a three-dimensional fully convolutional network-based brain hemisphere comparison algorithm (3D-BHCA). The authors retrospectively collected head non-contrast computed tomography (CT) data from 71 patients with acute ischemic stroke and 80 non-stroke patients. The results for ASPECTS on CT assessed by five stroke neurologists and by the 3D-BHCA model were compared with the ground truth by means of region-based and score-based analyses. They conclude that the automated ASPECTS calculation software they developed using a deep learning-based algorithm was superior to orequal to stroke neurologists in performing ASPECTS calculation in patients with acute stroke and non-stroke patients.

Li et al., [28] proposed a multi-scale U-Net to a faster ischemic stroke segmentation from non-enhanced CT images. To achieve this, the researchers used a multi-scale U-Net deep network model to segment image features of 30 stroke patients. They utilized the Dice loss function training model to address the data imbalance problem. The motion time of automatic segmentation was less than 20 ms, indicating that this method can meet the real-time clinical needs for diagnosing acute ischemic stroke and providing thrombolytic therapy. Because artificial intelligence technologies require large databases to function effectively, imaging data must be collected systematically. Another U-Net stroke segmentation, introduced by Soltanpour et al., [29] was designed to segment objects in different scales and unusual appearances. The proposed method also used contra-lateral and corresponding Tmax images to enrich the input CTP maps.

Mäkelä et al., [30] developed and evaluate a convolutional neural network (CNN) algorithm for detecting and segmenting acute ischemic lesions from CT angiography (CTA) images of patients with suspected middle cerebral artery stroke. The algorithm's performance was compared to the volumes reported by widely used CT perfusion-based RAPID software (IschemaView). The CNN model was trained on 50 CTA volumes with manually delineated targets, and the severity of false positives and false negatives was assessed visually to guide the method's development. The results showed that the CNN model corresponded to the manual segmentations with voxel-wise sensitivity of 0.54, precision of 0.69, and Dice coefficient of 0.61. The study suggests that detecting anterior circulation ischemic strokes from CTA using a CNN-based algorithm can be feasible when accompanied by physiological knowledge to rule out false positives. Using of small size dataset is critical limitation of this survey for external validation.

Based on the Shi et al., [31] the authors proposed a novel deep learning network called C2MA-Net for segmenting acute ischemic stroke (AIS) lesions from CT perfusion (CTP) maps. The network incorporates a cross-modal and cross-attention (Cˆ2 MA) mechanism, which establishes spatial-wise relationships between different modal features and performs dynamic group-wise recalibration through a group attention block. The Cˆ2 MA -Net has a multipath encoder-decoder architecture, where each modality is processed in different streams on the encoding path, and the pair related parameter modalities are used to bridge attention across multimodal information through the Cˆ2 MA module. This study demonstrates the advantages of applying Cˆ2 MA -network to segment AIS lesions, which yields promising segmentation accuracy, and achieves semantic decoupling by processing different parameter modalities separately. The significance of this study lies in proving the potential of cross-modal interactions in attention to assist in identifying new imaging biomarkers for more accurately predicting AIS prognosis in future studies.

Chen et al., [32] proposed a novel framework that automatically segments stroke lesions in DWI. This framework consists of two convolutional neural networks (CNNs). The first CNN, known as the EDD Net, is an ensemble of two DeconvNets and is responsible for detecting the lesions. The second CNN, called the MUSCLE Net, evaluates the detected lesions by the EDD Net and removes potential false positives. They attempted to solve this problem using both CNNs, and the results demonstrate very good performance. The framework was validated using a large dataset of DW images from 741 subjects. The mean accuracy, measured by the Dice coefficient, is 0.67 overall. Additionally, the mean Dice scores for subjects with small and large lesions were 0.61 and 0.83, respectively. The lesion detection rate achieved was 0.94.

Briefly, the results show that deep learning models can accurately segment ischemic lesions and predict patient outcomes, with Dice scores ranging from 0.36 to 0.94. The models can also improve image quality and reduce the influence of low image quality on prognosis. The studies suggest that deep learning models have the potential to improve stroke diagnosis, prognosis, and treatment planning in routine clinical practice.

4.3. Evaluation metrics

Quantitative evaluation metrics are essential for assessing the segmentation performance of deep learning methods. These metrics provide a quantitative measure the performance characteristics of the models. There are several evaluation metrics commonly used for stroke lesion segmentation, including the Dice similarity coefficient (DSC), the Jaccard similarity coefficient (JSC), the sensitivity, and the specificity. The DSC is a commonly used metric that measures the overlap between the predicted segmentation and the ground truth segmentation, ranging from 0 (no overlap) to 1 (perfect overlap).

It is computed as follows:

$$DSC = \frac{2 \times TP}{((2 \times TP) + FP + FN)} \tag{1}$$

where TP, FP, and FN represent the true positives, false positives, and false negatives, respectively. The higher the DSC value, the better the segmentation accuracy. The JSC is another metric that measures the similarity between the predicted segmentation and the ground truth segmentation, ranging from 0 (no similarity) to 1 (perfect similarity). It is computed as follows:

$$JSC = \frac{TP}{TP + FP + FN} \tag{2}$$

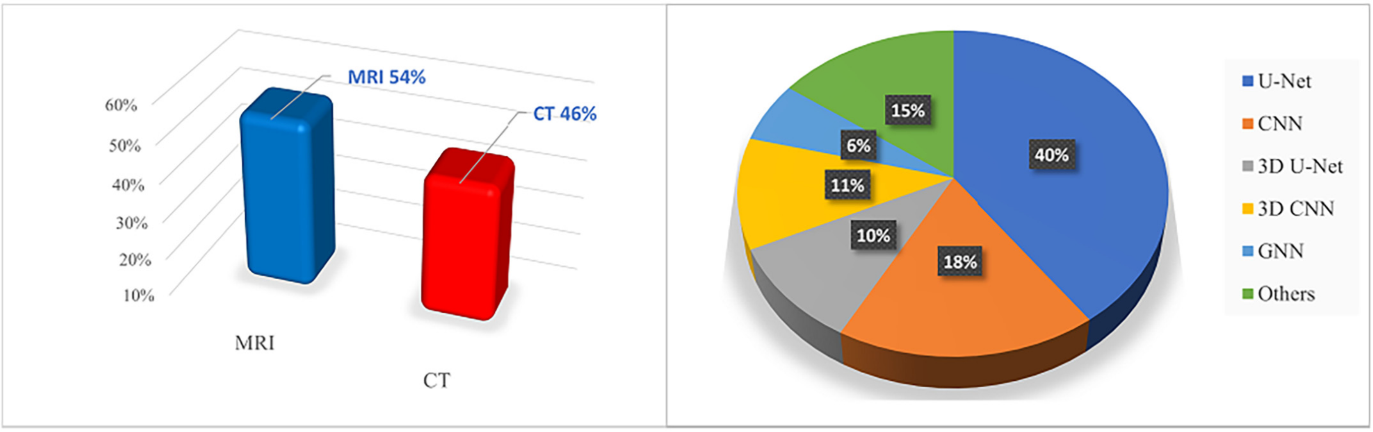

Fig. 5. Modality and neural network model distribution in stroke segmentation research.

The sensitivity measures the proportion of true positives among all positive samples, while the specificity measures the proportion of true negatives among all negative samples.

Sensitivity measures the proportion of true positives among all positive samples, while specificity measures the proportion of true negatives among all negative samples. These can be calculated using the following formulas:

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

5. Discussion

In this study, we identified recent articles about ischemic stroke segmentation with deep learning using MRI (54%) and CT (46%) images. These papers used Dice similarity coefficient (91%), Accuracy rate (23%), Jaccard index (10%), Sensitivity (84%), Specificity (84%), Hausdorff distance (2%), PPV (4%) and NPV (3%) metrics as performance evaluation. Some papers utilized several metrics in a paper, so the sum of the percentages may be greater than 100%. The reported results vary depending on the study, the model used, and the metric measured. Mean Dice coefficients range from 0.36 to 0.94, mean sensitivities range from 0.54 to 0.84 (mean: 0.7), and mean specificities range from 0.69 to 0.97 (mean: 0.83). Other metrics such as PPV, NPV, Jaccard index, Hausdorff distance, and accuracy used few, so statistically these are not comparable here.

Researchers used U-Net (40%), 3D U-Net (10%), CNN (18%), 3D CNN (11%), GAN (6%) as deep learning architectures and 15% of them used another model. Only 50% of papers have dataset more than 100 image scans and 27% have dataset lower than 60 image scans. Only 22% of papers passed external validation. These findings limit model generalizability, because the quality and size of reported datasets may significantly influence results, findings drawn from limited or internal data sources may not reflect true algorithm quality when tested against external resources. We suggest that deep learning researchers to share the source code of their algorithms, enabling other researchers to gain ideas from similar studies and provoke a new wave of deep learning advancements. These statistical data is provided in Fig. 5.

Table 1 shows the Comparison of deep learning-based methods for stroke lesion segmentation in MRI and CT scans. Deep learning-based methods, such as 3D CNNs and U-Net networks, have shown high accuracy and excellent soft tissue contrast in MRI and CT image segmentation tasks. However, they can be computationally intensive and require large amounts of training data. Other methods have also shown potential for clinical applications but may be less accurate than deep learning-based approaches. Table 2 demonstrates that the SGD-Net method appears to be the most accurate for stroke lesion segmentation in MRI, achieving an accuracy of 99% and a mean DSC of 0.82. The Residual ConvLSTM U-Net and 3D U-Net CNN + zoom-in & out strategy also showed promising results with high accuracy and DSC. For CT, the 3D U-Net and MultiRes U-Net based CNN methods reported the highest DSC.

Advantages and limitation of CT and MRI that derived from papers that given in Table 1 are shown in Table 3. MRI provides high soft tissue contrast, multi-parametric imaging, functional imaging, diffusion-weighted imaging, and spectroscopy, which can help in accurate lesion segmentation. However, it has limitations such as high cost, long scan times, limited availability, contraindications (e.g., pacemakers, metallic implants), motion artifacts, limited spatial resolution, and limited availability of contrast agents. CT, on the other hand, provides high spatial resolution, fast scan times, wide availability, low cost, bone imaging, CT angiography, CT perfusion, and low sensitivity to motion artifacts. However, it has limitations such as ionizing radiation, limited soft tissue contrast, limited functional imaging, limited diffusion-weighted imaging, limited spectroscopy, bone artifact, contrast agent-related risks, and limited availability of CT perfusion and CT angiography.

6. Limitations and future directions

Despite the promising results of deep learning, there are still challenges to overcome. Future works on deep learning models in ischemic stroke segmentation can focus on several areas to advance the field and address current limitations. Here are some potential future directions:

(a) Development of robust and interpretable models: Future research can focus on developing deep learning models that are not only accurate but also provide interpretable results. Exploring techniques such as attention mechanisms, explainable AI, and uncertainty estimation can enhance the transparency and trustworthiness of the segmentation models, allowing clinicians to understand and validate the model decisions.

(b) Integration of multimodal imaging: Incorporating multiple imaging modalities, such as MRI, CT, and perfusion imaging, can provide a more comprehensive understanding of ischemic stroke. Future work can explore fusion strategies and network architectures that effectively leverage the complementary information from various modalities, enabling more accurate segmentation and better characterization of stroke lesions.

(c) Data augmentation and domain adaptation: Obtaining large, annotated datasets for training deep learning models in stroke segmentation can be challenging. Future research can focus on exploring effective data augmentation techniques to augment the avail-

Table 1
Stroke segmentation by deep learning approaches.

Reference	Year	Modality	Dataset Size	Model	Results
Alis et al., [15]	2021	diffusion-weighted MR imaging (DWI)	Dataset A: 2986 Dataset B: 3951 Training (80%), Validation (10%), test (10%)	Residual ConvLSTM U-Net	DSC of A: 0.858 DSC of B: 0.857
Clèrigues et al., [11]	2020	multimodal MRI	SISS: 28 training 36 testing cases. SPES: 30 training, 20 testing cases	U-Net based CNN	DSC for SISS: 0.59 ± 0.31 DSC for SPES: 0.84 ± 0.10
Kumar et al., [12]	2020	MRI	SISS: 28 training, 36 test cases SPES: 30 training, 20 test cases ISLES 2017: 43 training, 32 test	Classifier-Segmenter Network (CSNet), involving a hybrid training strategy with a self-similar (fractal) U-Net	DSC for SISS:0.83 SPES:0.79 ISLES2017:0.89
Nazari et al., [13]	2020	MRI	192 multimodal 3D-MRI images, including 106 stroke and 86 healthy cases	Crawford-Howell	Accuracy: 73% Precision: 0.77% Sensitivity: 84% Specificity: 69%
Nazari et al., [20]	2023	DWI	445 cases with 5-Fold cross validation	AG-DCNN	DSC: 0.5 AUC: 91% Sensitivity: 60% Specificity: 97%
Cui et al., [16]	2021	DWI	190	DeepSym-3D-CNN	Accuracy: 85% AUC: 0.864
Oksuz I., [17]	2021	MRI	28 cases	U-Net based CNN	Accuracy: 97.8%
Tomita et al., [14]	2020	MRI	239 MRI scans	3D U-Net CNN + zoom-in & out strategy	DSC: 0.64
Wei et al., [18]	2022	MRI	216 Patients 80% for training, 20% for testing	Semantic Segmentation Guided Detector Network (SGD-Net)	Accuracy: 99% Mean DSC of 0.82
Wong et al., [19]	2022	DWI	875 Patients	rotation-reflection equivariant U-Net	Mean DSC: 0.88 AUC: 0.8
Gómez et al., [21]	2023	MRI	51 stroke patients (ISLES2017)	cross-attention mechanisms	DSC: 0.36 Precision: 0.42%
Praveen et al., [22]	2018	MRI	ISLES 2015	SSA+SVM	DSC: 0.94 Accuracy: 90%
Zhang et al., [23]	2018	MRI (DWI)	242 cases, 90 training, 62 validating, 90 testing	3D CNN	DSC: 0.79 Precision: 0.92% F1-score: 0.89
Hakim et al., [26]	2021	CT perfusion (CTP)	103, 63 training and 40 testing (ISLES challenge 2018)	Generative Adversarial Network (GAN)	DSC: 0.51 Hausdorff: 10.1 mL
Mäkelä et al., [30]	2022	CT angiography (CTA)	50 CTA	CNN	DSC: 0.61 Precision: 0.77% Sensitivity: 54% Specificity: 69%
Naganuma et al., [27]	2021	CT	71 patients + 80 non-stroke patients	3D CNN	DSC: 0.9 Sensitivity: 80% Specificity: 97%
Li et al., [28]	2021	CT	30 patients	multi-scale U-Net	DSC: 0.86
Shi et al., [31]	2022	CT perfusion (CTP)	94 training and 62 test cases	C2MA-Net	DSC:0.55 F1-score: 0.59 F2-score: 0.66
Soltanpour et al., [29]	2021	CT perfusion (CTP)	103, 63 training and 40 testing (ISLES challenge 2018)	MultiRes U-Net based CNN	DSC: 0.68, Jaccard score: 57%
Wang et al., [24]	2020	CT perfusion (CTP)	103, 63 training and 40 testing (ISLES challenge 2018)	CNN	DSC: 0.82
Chen et al., [32]	2017	CT	741 cases	CNN (EDD+ MUSCLE NET)	DSC: 0.67

Table 2
Comparison of deep learning-based methods for stroke lesion segmentation in MRI and CT scans.

Modality	Method	Advantages	Limitations	References
MRI	Residual ConvLSTM U-Net, SGD-Net	High accuracy, multi-parametric imaging	Limited spatial resolution, high cost, long scan times, limited availability, computationally intensive, requires large amounts of training data	[15] [18]
MRI	3D U-Net CNN + zoom-in & out strategy	High DSC	Limited spatial resolution, high cost, long scan times, limited availability, computationally intensive, requires large amounts of training data	[14]
CT	3D U-Net	High DSC, bone imaging, low sensitivity to motion artifacts	Limited soft tissue contrast, limited functional imaging, ionizing radiation, contrast agent-related risks, limited availability of CT perfusion and CT angiography	[25]
CT	MultiRes U-Net based CNN	High DSC, low sensitivity to motion artifacts	Limited soft tissue contrast, limited functional imaging, ionizing radiation, contrast agent-related risks, limited availability of CT perfusion and CT angiography	[29]

Table 3
Advantages and limitations of MRI and CT scans for stroke lesion segmentation.

Modality	Advantages	Limitations
MRI	High soft tissue contrast, multi-parametric imaging, non-ionizing radiation, no bone artifact, functional imaging, diffusion-weighted imaging, perfusion imaging, spectroscopy	High cost, long scan times, limited availability, contraindications (e.g., pacemakers, metallic implants), motion artifacts, limited spatial resolution, limited availability of contrast agents
CT	High spatial resolution, fast scan times, wide availability, low cost, bone imaging, CT angiography, CT perfusion, low sensitivity to motion artifacts	Ionizing radiation, limited soft tissue contrast, limited functional imaging, limited diffusion-weighted imaging, limited spectroscopy, bone artifact, contrast agent-related risks, limited availability of CT perfusion and CT angiography

able datasets and create diverse and representative training samples. Additionally, investigating domain adaptation methods that can improve the generalization of models across different datasets or clinical sites can enhance the applicability of deep learning models in real-world settings.

(d) Clinical validation and prospective studies: While deep learning models have shown promising results in ischemic stroke segmentation, future work should focus on conducting rigorous clinical validation studies. Prospective studies involving large patient cohorts and comparison with existing standard-of-care methods can provide insights into the clinical utility and impact of deep learning-based segmentation in routine stroke diagnosis and treatment decision-making.

(e) Real-time and clinical deployment: To facilitate clinical adoption, future work can focus on developing real-time segmentation models that can operate efficiently within clinical workflows. Integration of deep learning models into existing clinical systems and validation in real-world clinical environments are crucial steps toward the practical deployment of these models.

7. Conclusion

This study has explored the recent advancements in ischemic stroke segmentation using deep learning models. The utilization of deep learning techniques, particularly convolutional neural networks (CNNs) and U-Net-based models has shown great promise in accurately and automatically segmenting ischemic stroke lesions from medical imaging data. These models can effectively handle the complexity and variability of stroke lesions by learning from large-scale datasets, capturing intricate patterns, and extracting meaningful features. Moreover, deep learning models have demonstrated impressive generalization capabilities, enabling them to perform well across different imaging modalities, such as MRI and CT. This versatility makes them applicable in diverse clinical settings and enhances their potential for widespread adoption in routine clinical practice.

Human and animal rights

The authors declare that the work described has not involved experimentation on humans or animals.

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Author contributions

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Declaration of competing interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

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