Artificial Intelligence for Diagnosing Acute Stroke: A 25-Year Retrospective

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Submitted to: Journal of Medical Internet Research
on: April 20, 2024

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Abstract

Background: Stroke is a leading cause of death and disability in the world. Rapid and accurate diagnosis is crucial for minimizing brain damage and optimize treatment plans.

Objective: This review aims to summarize the methods of artificial intelligence (AI) assisted diagnosis of acute stroke and the assessment of stroke prognosis over the past 25 years, providing an overview of common performance metrics and the development trends of algorithms. It also delves into existing issues and future prospects, intending to provide a comprehensive reference for clinical practice.

Methods: Method: A total of 33 representative articles published between 1999 and 2024 on utilizing AI technology for acute stroke diagnosis were systematically selected and analyzed in detail. Results: Results: The segmentation of acute stroke lesions from 1999 to 2024 can be divided into three stages. Prior to 2012, research mainly focused on brain white matter segmentation using thresholding techniques. From 2012 to 2016, the focus shifted to stroke lesion segmentation based on machine learning (ML). After 2016, the emphasis was on deep learning (DL) based stroke lesion segmentation, with a significant improvement in accuracy observed. For the classification and prognosis assessment of strokes, both ML and DL have their advantages, achieving a high level of accuracy. Conclusions: Conclusion: Over the past 25 years, AI technology has shown promising performance in segmenting, classifying, and assessing the prognosis of acute stroke lesion.

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(JMIR Preprints 20/04/2024:59711)
DOI: https://doi.org/10.2196/preprints.59711

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Abstract

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Keywords: Acute stroke, Machine learning, Deep learning, Lesion segmentation, Stroke classification, Stroke prognosis

1 Introduction

Stroke is a globally significant public health issue, ranking as the second leading cause of death and the third leading cause of disability and death. One in every four people over the age of 25 will experience a stroke in their lifetime. 11.6% of deaths are due to stroke, and both the incidence, mortality and disability rates of stroke are on the rise [1-3].

Acute stroke refers to the clinical pathological state caused by the acute disruption of cerebral blood vessels. It can result in either the interruption of blood supply to the brain or the rupture of brain vessels, leading to damage to brain tissue. Ischemic strokes account for about 80% of all strokes, while hemorrhagic strokes make up about 20% [4]. Ischemic stroke is caused by reduced blood flow or blockage in the cerebral vessels, leading to oxygen and blood deprivation in brain tissue, while hemorrhagic stroke results from bleeding due to rupture of cerebral vessels. Symptoms typically appear within minutes and can lead to severe neurological deficits [5].

Research has found that artificial intelligence (AI) technology plays a positive role in reducing brain damage and improving patient prognosis [5]. AI is a new technological science that studies and develops theories, methods, technologies, and application systems for simulating, extending, and expanding human intelligence. It aims to emulate human cognition and information processing through various algorithms, with outstanding applications in analyzing and processing high-dimensional complex medical images, disease assessment, and diagnosis [6]. Through machine learning (ML) and deep learning (DL) algorithms, automatic analysis of medical images is performed to achieve automatic identification of lesions and predict patient prognosis, which can assist doctors in diagnosing diseases and establishing treatment plans [7].

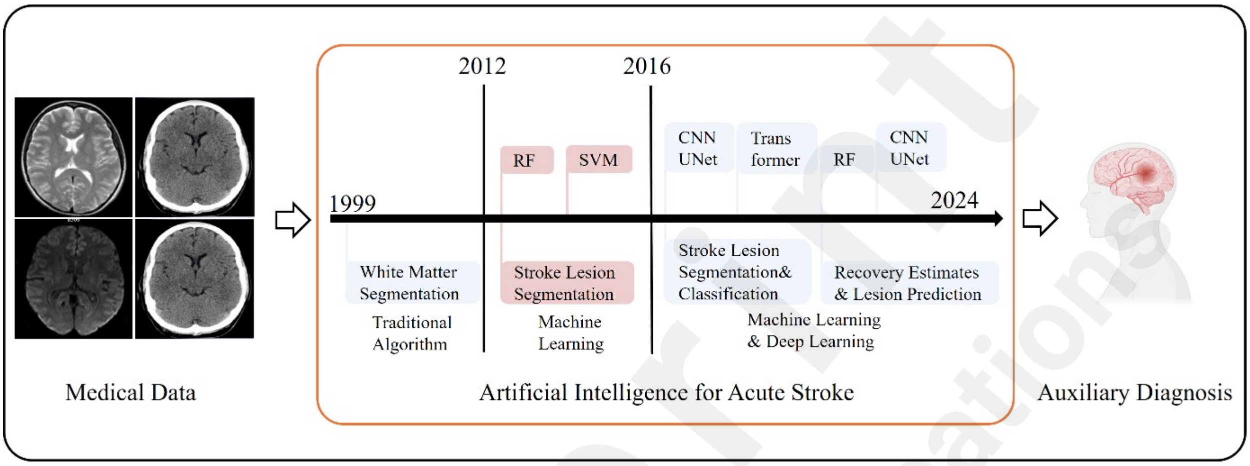

Fig.1 AI for diagnosing acute stroke.

Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are the most commonly recommended imaging methods for the clinical diagnosis of acute stroke. MRI has higher clarity and clinical sensitivity, offering better soft tissue contrast, but it typically requires a longer imaging time, usually more than 30 minutes [8]. Common MRI imaging techniques used for brain examinations include T1-weighted Imaging (T1WI), T2-weighted Imaging (T2WI), Fluid Attenuated Inversion Recovery (FLAIR), and Diffusion-Weighted Imaging (DWI), eta. Each imaging technique has its unique applications and advantages. T1WI provides excellent anatomical detail, but it is not very sensitive to early changes in acute stroke. T2WI can highlight increased water content in brain tissue and is commonly used for evaluating the subacute and chronic stages of stroke, although the images may be blurry and have artifacts. FLAIR can suppress cerebrospinal fluid signals, making it suitable for detecting white matter lesions and identifying lesions near the cerebrospinal fluid pathways. However, it has a longer scanning time and is not sensitive enough for detecting small infarcts. DWI is highly sensitive to early acute cerebral ischemia, but DWI images have lower resolution and are not sufficiently sensitive to small infarcts [9]. Compared to MRI imaging, CT is faster and commonly used for detecting early signs of infarction. CT Angiography (CTA) can provide information about vascular occlusion to guide treatment decisions, while CT Perfusion Imaging (CTP) can assess the extent of ischemic core and penumbra areas [10]. The 2018 American Heart Association and American Stroke Association Guidelines (AHA/ASA 2018) indicate that non-contrast CT (NCCT) and CTA are recommended within 6 hours of acute stroke onset, while MRI and CTP are recommended for the 6 to 24-hour window [11]. (Fig2)

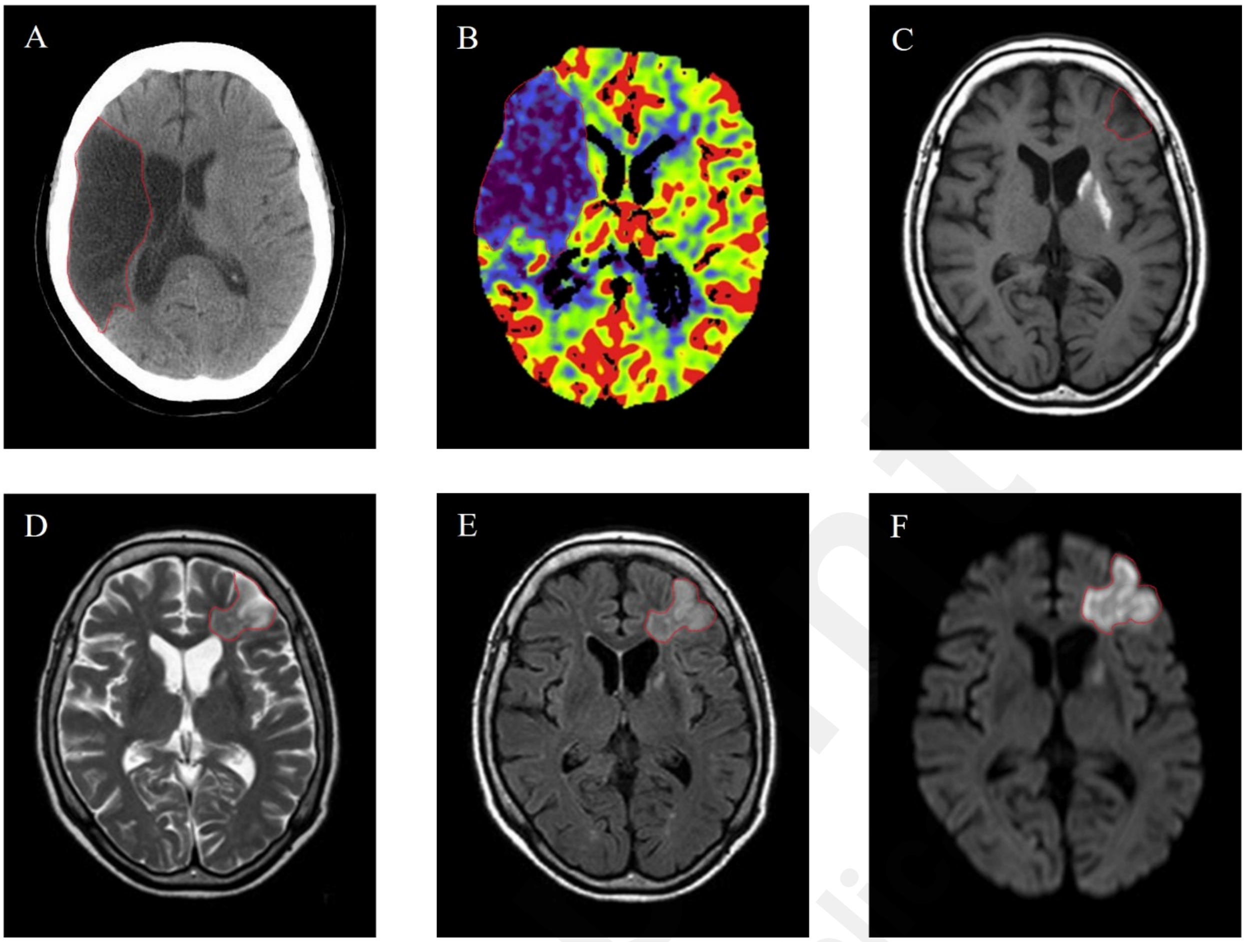

Fig.2 Stroke lesions detected by different imaging modalities. (A)NCCT; (B)CTP; (C)T1WI; (D)T2WI; (E)FLAIR; (F)DWI. Stroke lesion areas are marked with red lines and the images are not paired.

The main contributions of this article are as follows: Firstly, it summarizes the common applications of medical imaging in the assessment of acute stroke. Secondly, it outlines the development trends of AI algorithms for acute stroke image segmentation and prognosis prediction from 1999 to 2024, including an analysis of the data sources, types of algorithms, outcome metrics, and qualitative results described in each article. Thirdly, it discusses the clinical significance and existing challenges, as well as future research directions in this rapidly advancing field.

This review aims to provide researchers and clinicians with insights into the current state of acute stroke image segmentation based on DL, offer a comprehensive reference for clinical practice, and assist in the formulation of more effective acute stroke treatment and triage strategies.

2 Methods

This article conducted a literature search from January 1999 to February 2024 in databases such as Web of Science, PubMed, IEEE Xplore, and Google Scholar, etc. The investigation focused on the application of AI technology in identifying acute stroke lesions from medical images and predicting patient prognosis. Keywords used for the search included combinations such as "artificial intelligence," "machine learning," "deep learning," "ischemic stroke," "hemorrhagic stroke," and "acute stroke." After screening, a representative selection of 33 articles over 25 years was included in the study.

3 Evaluation Metrics

To assist readers in gaining a clearer understanding of these articles, we will explain the model evaluation metrics featured in this review, as shown in Table 1.

Table1 Equations and significance for evaluation metrics

Metrics	Equations	Significance
Dice Similarity Coefficient (DSC) [12]	$\frac{2\vee X\cap Y\vee ¿}{¿X\vee+¿Y\vee}$	The degree of overlap between image segmentation results and labels.
Hausdorff Distance (HD) [13]	$max\left[\check{H}(A,B),\check{H}(B,A\right.$	The maximum dissimilarity between two sets of points.
Area Under the Curve (AUC) [14]		Classification performance unaffected by threshold variations.
Positive Predictive Value (PPV, Precision) [15]	$\frac{TP}{TP+FP}$	The proportion of true positive samples among those predicted as positive.
Recall (Sensitivity) [15]	$\frac{TP}{TP+FN}$	The model's ability to identify positive class samples.

TP: True Positive; FP: False Positive; TN: True Negative; and FN: False Negative; X and Y represent the segmentation result and label, respectively; $\check{H}(A,B)$ denotes the directed Hausdorff distance from set A to set B.

4 Results

4.1 Segmentation and classification of stroke lesions

Imaging examinations are typically included in the admission tests for acute stroke patients [16,17]. Segmentation of stroke lesions can determine the location, size, and shape of the stroke lesions [18]. Classification of stroke lesions allows for the rapid identification of stroke type, facilitating patient triage [19]. This supports disease diagnosis, assists physicians in making treatment plans based on the patient's condition and lesion location, and provides accurate references for surgical or pharmacological treatments.

4.1.1 Stroke lesion segmentation based on ML

Stroke lesion segmentation is a challenging task. The blurred boundary between stroke lesions and surrounding normal tissues, especially in hemorrhagic strokes, making it difficult for segmentation algorithms to accurately delineate lesion boundaries, which may lead to missegmentation. The boundaries of stroke lesions are more clearly delineated in MRI images compared to CT scans, offering greater contrast and clarity for the observation of stroke lesions[20].

Due to the blurred boundaries of stroke lesions, traditional threshold-based algorithms cannot achieve accurate segmentation of stroke lesions. Therefore, before 2012, there was limited research on automatic segmentation algorithms for stroke lesions, with most studies focusing on traditional methods for white matter segmentation [21,22].

From 2012 to 2016, stroke lesion segmentation algorithms were primarily based on ML algorithms, with common segmentation methods mainly utilizing Support Vector Machines (SVM) [23], Random Forests (RF) [24], and Naive Bayes (NB) [25], eta. Due to the limited feature extraction capabilities of ML segmentation algorithms, the segmentation algorithms primarily use MRI images during this period.

Mitra et al. utilized a Bayesian-Markov Random Field for the preliminary classification of FLAIR images, then analyzed multimodal MRI data (including T1WI, T2WI, FLAIR, and DWI) along with contextually relevant features using RF to identify areas highly likely to be lesions.

Lesion segmentation was ultimately achieved by thresholding the RF probability maps. In experiments conducted with 36 patients, the automated method showed a Sensitivity and PPV of 0.53 ± 0.13 and 0.75 ± 0.18, respectively compared against manual segmentation by experts [26].

Maier et al. proposed a multi-spectral MRI image segmentation method for ischemic stroke lesions based on SVM. By extracting local features from multi-modal MRI data, SVM was used to classify lesions in unknown images. The method was evaluated with leave-one-out cross-validation, and the average DSC was 0.74 in 8 test datasets [27].

One year later, Maier et al. proposed another method for segmenting subacute ischemic stroke lesions in multi-modal MRI images using Extra Tree forests. This approach utilized Extra Trees for voxel-level classification and incorporated intensity-derived image features. This method achieved an average DSC of 0.65 on 37 clinical cases [28].

Pustina et al. proposed an automatic segmentation algorithm for stroke lesions in T1WI images, employing RF combined with multi-resolution neighborhood data analysis to enhance efficiency and reduce observer dependency. Using 60 cases of left-sided chronic stroke as the training set and 45 cases as the test set, the average DSC was 0.696 ± 0.16, with a HD of 17.9 ± 9.8 mm [29].

Griffis et al. employed a stroke lesion segmentation approach based on the Gaussian Naive Bayes (GNB) classifier. By utilizing probabilistic tissue segmentation and image algebra to create feature maps, they encoded information about missing and abnormal tissues. The author used the leave-one-out method for cross-validation. The average DSC was 0.66 on T1WI images from 30 patients [30].

4.1.2 Stroke Lesion Segmentation Based on DL

After 2016, with the emergence of Convolutional Neural Networks (CNNs), particularly U-Net, there has been a leap in the capabilities of DL for medical segmentation and feature extraction. DL has gradually replaced ML as the main force in stroke image segmentation [31]. During this period, there were more stroke lesion segmentation algorithms than between 2012 and 2016. Additionally, due to the improved feature extraction capabilities of DL, algorithms for stroke lesion segmentation based on CT scans emerged.

Goncharov et al. proposed a method integrating U-Net with T-Net in a CNN framework. In each network, simple convolutional layers are replaced with residual blocks, and an initial convolution layer is added, enhancing the deep network's learnability. On the ISLES2018 dataset, comprising 94 training images and 62 testing images, they achieved an average DSC of 0.53 ± 0.01 and a HD of 23.29 ± 0.02mm [32].

Clèrigues et al. proposed a 3D CTP segmentation method based on a 2D asymmetrical residual encoder-decoder CNN. By enhancing training, symmetric modality augmentation, and uncertainty filtering, they addressed issues such as small sample size, class imbalance, and overfitting, improving performance and achieving fast inference. On the ISLES2018 dataset consisting of 94 training images and 62 testing images, they achieved an average DSC of 0.49 ± 0.31, PPV of 0.51 ± 0.36, Sensitivity of 0.57 ± 0.35, and HD of 11.3 ± 31.6mm [33].

Wang et al. proposed a multimodal 3D CTP segmentation method based on CNNs. They extracted features from CTA images, synthesized pseudo-DWI, and used an innovative loss function to focus on lesion areas, improving segmentation accuracy. On the ISLES2018 dataset, the DSC was 0.51 ± 0.31, Precision was 0.55 ± 0.36, and Recall was 0.55 ± 0.34 [34].

Kuang et al. proposed a DL approach named EIS-Net, combining a 3D Triple CNN (T-CNN) and a Multi-Region Classification Network for automatic segmentation of early ischemic strokes and ASPECTS scoring on NCCT in patients with acute ischemic stroke. On 160 training images and 70 test images, the DSC was 0.448 [35].

Soltanpour et al. proposed an improved version of the U-Net network called MultiRes U-Net for automatic segmentation of ischemic stroke lesions in CTP images. The algorithm utilizes multi-scale convolutional blocks and incorporates contralateral CT images as references, estimating lesion locations using Tmax heatmaps. On the ISLES2018 dataset, the DSC was 0.69, PPV was 0.67, and Sensitivity was 0.68 [36].

Luo et al. proposed an acute ischemic stroke NCCT lesion segmentation method called UCATR. This method combines ResNet-50 and Transformer encoders and introduces a Multi-Head Cross Attention (MHCA) module in the decoder to improve the accuracy of spatial information recovery. On 293 cases of acute ischemic stroke, the DSC was 0.7358, significantly surpassing the traditional U-Net (DSC = 0.4938) [37].

Vries et al. proposed a DL model called PerfU-Net for directly estimating the infarct core area in patients with acute ischemic stroke from CT perfusion source data. This model uses a symmetry-aware spatio-temporal convolutional structure, exploiting the dynamics of cerebral microperfusion, while decoding static segmentation maps for infarct core assessment. Moreover, PerfU-Net employs attention modules in the skip connections of the encoder and decoder to reduce the time dimension, propagating only the most informative features. On the ISLES2018 dataset, the DSC was 0.564 [38].

Kuang et al. proposed a Hybrid CNN-Transformer network based on circular feature interactions and bilateral difference learning. It consists of a Hybrid CNN-Transformer encoder, a recurrent feature interaction module, and a shared CNN decoder with bilateral difference learning modules. The proposed method achieved DSC scores of 0.6139 and 0.4674 on the AISD and private datasets, respectively [39].

Compared to CT-based stroke lesion segmentation, MRI-based stroke lesion segmentation achieves higher segmentation accuracy.

Chen et al. proposed a CNN network composed of two parts: Ensemble of DeconvNets (EDD Net) and Multi-Scale Convolutional Label Evaluation Net (MUSCLE Net). EDD Net utilizes two DeconvNets for initial segmentation, while MUSCLE Net is used to evaluate and eliminate false positives of small lesions. The study achieved an average DSC of 0.67 on a large DWI dataset comprising 741 patients [40].

Zhang et al. proposed a 3D FC-DenseNet model based on CNN for segmenting acute stroke lesions in DWI medical images. This model combines dense connections and multiscale context on top of 3D CNN to address common issues in DWI such as noise, artifacts, and variations in lesion size and location. On a self-built DWI dataset comprising 242 cases, the DSC achieved 0.7913 [41].

Karthik et al. proposed an improved FCN network that employs the concept of the U-Net architecture and applies Leaky ReLU activation in the last two layers of the network for a precise reconstruction of the ischemic lesion. This enables the network to learn additional features not considered in the U-Net architecture. Experiments on the ISLES 2015 dataset with 22 multimodal MRI training data and 6 test data achieved an average DSC of 0.70 [42].

Building upon the U-Net architecture, Clèrigues et al. addressed class imbalance issues and enhanced segmentation performance by employing symmetric modality enhancement, balanced training sample strategies, and dynamic weighted loss functions. On the publicly available multimodal MRI datasets from the two subtasks (SISS and SPES) of the ISLES 2015 challenge, they achieved DSC scores of 0.59 and 0.84, respectively [43].

Wu et al. introduced a lesion boundary rendering method named TransRender. This method utilizes Transformers to capture global information during the encoding phase and employs multiple renderings to effectively map encoding features of different levels to the original spatial resolution. Additionally, the method supervises the rendering module in generating points by adaptively selecting points to compute boundary features based on point-wise rendering, enabling TransRender to continuously refine uncertain regions. On the ATLAS dataset with 60 training and 30 testing datasets and the ISLES2022 dataset with 250 training and 150 testing datasets, it achieved DSC scores of 0.5979 and 0.8537, respectively [44].

In the same year, Wu et al. proposed a two-phase brain multimodal MRI lesion segmentation method called W-Net. This method acknowledges the similarity in grayscale features of tissue structures and imaging modes in medical images, while recognizing that stroke lesion segmentation is affected by complex backgrounds and noise interference. It utilizes CNN and Transformer-based approaches as the backbone networks and introduces a Boundary Deformation Module (BDM) and Boundary Constraint Module (BCM) to tackle the challenges of ambiguous boundaries. Additionally, a multi-task learning loss function is designed to optimize W-Net from both regional and boundary perspectives. On the ATLAS and ISLES2022 datasets, it achieved DSC scores of 0.6176 and 0.8560, respectively [45].

Soh et al. proposed an algorithm for stroke image segmentation named Hybrid U-Net Transformer (HUT). The HUT comprises two parallel pipelines, one based on UNet and the other on Transformer. During training, the Transformer-based pipeline utilizes feature maps from the intermediate layers of the U-Net decoder. On the ATLAS12 dataset, with 212 training and 27 testing instances, it achieved a DSC of 0.737 [46].

Table2 Segmentation Methods and Performance

Researcher	Year	Image	Dataset	Methods	Metrics	Performance
Machine Learning						
Mitra et al. [26]	2014	MMRI	36	SVM	Recall PPV	0.53 ± 0.13 0.75 ± 0.18
Mitra et al. [27]	2014	MMRI	——	SVM	DSC	0.74
Mitra et al. [28]	2015	MMRI	37	Extra Tree Forests	DSC	0.65
Pustina et al. [29]	2016	T1WI	60/45	RF	DSC	0.696 ± 0.16

					HD	17.9 ± 9.8
Griffis et al. [30]	2016	T1WI	30	GNB	DSC	0.66
Deep Learning (CT)						
Goncharov et al. [32]	2018	CTP	94/62	UNet + TNet	DSC HD	0.53± 0.01 23.29± 0.02
Clèrigues et al. [33]	2019	CTP	94/62	CNN	DSC HD	0.49 ± 0.31 11.3 ± 31.6
Wang et al. [34]	2020	CTP CTA	94/62	CNN	DSC HD	0.51 ± 0.31 0.55 ± 0.34
Kuang et al. [35]	2021	NCCT	160/70	T-CNN	DSC	0.448
Soltanpour et al. [36]	2021	CTP	94/62	MultiRes U-Net	DSC	0.69
Luo et al. [37]	2021	NCCT	293	Resnet-50 Transformer	DSC	0.7358
Vries et al. [38]	2023	CTP	94/62	PerfU-Net	DSC	0.564
Kuang et al. [39]	2024	NCCT	——	CNN + Transformer	DSC	0.6139 0.4674
Deep Learning (MRI)						
Chen et al. [40]	2017	DWI	741	EDD Net + MUSCLE Net	DSC	0.67
Zhang et al. [41]	2018	DWI	242	FC-DenseNe	DSC	0.7913
Karthik et al. [42]	2019	MMRI	22/6	FCN	DSC	0.70
Clèrigues et al. [43]	2020	MMRI	——	UNet	DSC	0.59 0.84
Wu et al. [44]	2023	MMRI	60/30 250/150	TransRender	DSC	0.5979 0.8537
Wu et al. [45]	2023	MMRI	60/30 250/150	CNN + Transformer	DSC	0.6176 0.8560
Soh et al. [46]	2023	T1WI	212/27	UNet + Transformer	DSC	0.737

MMRI represent multimodal MRI.

4.1.3 Stroke classification

The initial step upon admission for acute stroke patients typically entails stroke triage, a process aimed at identifying the specific stroke variant affecting the patient. For patients with acute ischemic stroke who meet the criteria for thrombolytic therapy, they should be promptly referred to a thrombolytic center for treatment. Otherwise, they should be admitted for observation and monitoring, with intervention therapy as necessary. For patients with hemorrhagic stroke, neurosurgical intervention is often required, and they should be urgently referred to a medical facility capable of providing appropriate treatment [17]. Acute ischemic stroke classification is typically based on CT imaging. Within the first few hours of symptom onset of ischemic stroke, CT images may not show significant abnormalities, with affected areas later appearing as low-density regions (dark areas). Hemorrhagic stroke appears as high-density (white areas) regions on CT images [47-

49].

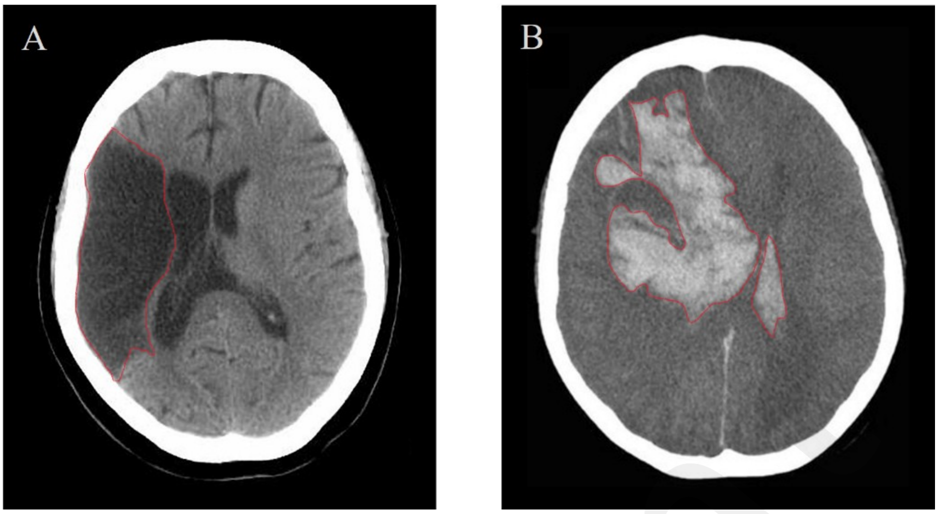

Fig.3 Ischemic stroke and hemorrhagic stroke. (A) Ischemic stroke; (B) Hemorrhagic stroke. Stroke lesion areas are marked with red lines and the images are not paired.

Adam et al. proposed a classification model based on Decision Tree (DT) and K-Nearest Neighbors (KNN) algorithms, utilizing a dataset of 400 cases collected from several hospitals. The study found that the DT algorithm outperformed KNN in classification, and that certain features, such as whether the patient is agitated, has seizures, presents with facial drooping, and the results of CT scans, could be directly used to determine the type of stroke [47].

Gautam et al. proposed a CNN model for classifying hemorrhagic and ischemic stroke CT images. They improved the quality of CT images by using a multi-focus image fusion preprocessing technique, and then inputted the processed images into a 13-layer CNN architecture for classification. Experiments were conducted on two different datasets, achieving classification accuracies of up to 0.9877 [48].

Chen et al. utilized hyperparameter optimization and transfer learning to identify stroke conditions in brain CT images. The optimized CNN and ResNet-50 models demonstrated high accuracy in distinguishing between normal, hemorrhagic stroke, ischemic stroke, and other lesions. Although ResNet-50 exhibited the highest accuracy, it required more time for processing [49].

4.2 Stroke Prognosis

Stroke prognosis refers to predicting long-term outcomes such as recovery status, quality of life, and survival rates of patients based on medical imaging and clinical records. ML and DL algorithms can quantify the extent of brain tissue damage, assess patients' prognostic situations, and provide benchmarks for long-term rehabilitation [50].

4.2.1 Stroke recovery estimates

Clinical records can assist in estimating stroke recovery. The size and location of the stroke are critical factors in predicting recovery. Patients with extensive brain damage or strokes affecting critical brain areas generally have a poorer prognosis. Combining patient clinical records with stroke scales can also help estimate recovery [51].

Bentley et al. utilized SVM to predict whether acute ischemic stroke patients would develop symptomatic intracerebral hemorrhage after thrombolysis. Through a retrospective analysis of clinical records and CT brain images of 116 patients who received intravenous thrombolysis treatment for acute stroke, the study found that SVM outperformed traditional prediction scoring systems, such as Stroke with Early Decompressive Surgery (SEDAN) scores, in predicting SICH [52].

Monteiro et al. investigated the use of ML methods to predict functional recovery in ischemic stroke patients three months after the event. The study examined the performance of five different classifiers, among which RF exhibited the best performance with an AUC value of 0.93 [53].

Cheon et al. constructed a Deep Neural Network (DNN) model combined with Principal Component Analysis (PCA) for feature extraction. The model demonstrated high predictive ability with an AUC of 0.8348, based on medical records from 15,099 stroke patients [54].

Kuang et al. proposed an automated evaluation method for the Alberta Stroke Program Early CT Score (ASPECTS) in NCCT images of patients with acute ischemic stroke. This method utilizes texture features to train a RF classifier, modeling on training data from 157 patients, then evaluating the model on 100 test cases. The results showed good agreement between the automated ASPECTS and DWI ASPECTS scores, with a consistency of 0.76, and performed well in identifying large areas of early infarction [55].

Scrutinio et al. utilized a RF algorithm enhanced with Synthetic Minority Over-sampling Technique (SMOTE) to predict the 3-year mortality rate of patients with severe stroke, significantly outperforming the logistic regression model. The SMOTE RF model achieved an AUC of 0.928, demonstrating high sensitivity and specificity [56].

Brugnara et al. integrated clinical, multimodal imaging, and angiographic features using ML to predict the clinical outcomes of patients with acute ischemic stroke after endovascular treatment. The predictive accuracy based on baseline clinical and routine imaging features was 0.71, which slightly improved with the addition of CTP features. Further inclusion of CTA and postoperative clinical features significantly enhanced predictive performance, achieving an accuracy of 0.80 [57].

4.2.2 Final lesion estimation

Acute stroke lesions tend to expand over time, and some researchers have used DL to predict the final infarct lesions of strokes.

Yu et al. proposed a U-Net-based model for predicting final infarct lesions in patients with acute ischemic stroke. The model utilizes initial MRI data as input without requiring additional perfusion information and can predict the size and location of infarct lesions 3-7 days later. The model demonstrated good predictive performance across all patients, with an AUC of 0.92, DSC of 0.53, and volume error of 9 mm [58].

Pinto et al. proposed a method combining an unsupervised learning module (using Restricted Boltzmann Machine(RBM)) and a supervised learning module (based on U-Net and Gated Recurrent Unit(GRU)) to predict the final stroke lesion in patients with acute ischemic stroke after 90 days. Each RBM learns features from different MRI parameter maps, then these features are merged with the original maps and fed into a convolutional and recurrent neural network architecture for supervised learning. This method was evaluated on the ISLES 2017, achieving a DSC of 0.38 and an HD of 29.21mm [59].

Nielsen et al. utilized a deep CNN (CNNdeep) to predict final lesion, demonstrating higher accuracy compared to General Linear Models (GLM), a CNN based on Tmax, and an Apparent Diffusion Coefficient (ADC) threshold method. CNNdeep was more effective at integrating information from multimodal MRI data, providing a more precise evaluation of stroke progression. It also identified the impact of treatment strategies on the disease course, achieving an AUC of 0.88[60].

Kelvin et al. developed a DL-based method for automatic segmentation of infarct volume in MRI of patients with acute ischemic stroke. This approach utilized networks with rotation and reflection variants, trained on a large dataset of patient images. The model could incorporate clinical variables to predict patients' 90-day modified Rankin Score, achieving an AUC of 0.80 and an accuracy of 0.75[61].

5 Discussion

Over the past 25 years, significant developments have been achieved in the field of AI-assisted detection of cerebral infarctions and in assessing patient prognosis. This technological evolution has empowered physicians to make swift diagnoses and enhance patient outcomes effectively.

In clinical practice, CT and MRI are the prevalent imaging modalities employed for the diagnosis of acute stroke. CT demonstrates lower sensitivity in identifying early changes of acute ischemic stroke but higher sensitivity in detecting significant high-density lesions characteristic of hemorrhagic stroke [62]. Compared to CT, MRI has higher contrast and a stronger ability to differentiate between brain tissues. The DWI sequence can detect minor changes in brain tissue just minutes after ischemia occurs. MRI is clearer in identifying minor hemorrhages, differentiating between intracerebral hemorrhage and ischemic areas, and can provide more detailed information about the extent and type of brain tissue damage following a stroke [63]. However, MRI is associated with higher costs and longer scan times. In actual clinical practice, the choice between MRI and CT depends on the specific conditions of patients.

Before 2012, brain segmentation algorithms were primarily based on traditional methods for brain white matter segmentation. There are few studies focusing on the segmentation of stroke lesions in this period [21,22]. Between 2012 and 2016, segmentation algorithms for ischemic stroke lesions were primarily based on ML. Due to the blurred boundaries between stroke lesions and surrounding normal tissue in CT images, algorithms from this period mainly relied on MRI imaging. The accuracy of segmentation algorithms during this time generally did not exceed 0.75, and the algorithms were complex with weak generalization capabilities, unable to match manual segmentation [20-30]. After 2016, with the emergence of CNNs, particularly U-Net, segmentation algorithms for stroke lesions have primarily relied on DL [31]. During this period, due to the remarkable advancement in DL feature extraction capabilities, segmentation algorithms for ischemic stroke lesions based on CT images emerged. However, the accuracy of these segmentation algorithms based on CT commonly did not surpass 0.75 [32-39]. Algorithms for segmenting ischemic stroke lesions based on MRI have shown better accuracy, enough to be comparable to manual segmentation. Some algorithms have achieved accuracies up to 0.85 [40-47]. To facilitate the triage of patients with acute stroke, given the urgency of the condition, classification of stroke types primarily relies on CT images. Current algorithms had achieved high accuracies, generally exceeding

0.9, indicating promising application prospects [47-49].

Data preprocessing is important for medical image segmentation. Preprocessing aims to standardize image quality, enhance valuable features, and reduce segmentation difficulties. References [33,43] employed symmetry-enhanced modalities, leveraging the high bilateral symmetry exhibited by the human brain in its natural state. This approach provides clearer and more accurate information for subsequent steps such as feature extraction, lesion detection, and image segmentation. For complex segmentation tasks such as stroke lesion segmentation, the introduction of multimodal approaches can significantly enhance algorithm performance by extracting complementary information from different imaging techniques. References [26,34] are particularly representative. Reference [26] employs multimodal MRI data including T1WI, T2WI, FLAIR, and DWI, along with context-aware features. Reference [34] extracts feature from CTA images and synthesizes pseudo-DWI for use in CTP segmentation methods.

Additionally, numerous studies have employed multi-stage algorithms, combining coarse and fine-grained approaches to achieve better segmentation performance. For instance, reference [26] uses a Bayesian-Markov Random Field model for preliminary classification of FLAIR images and employs RF for multimodal MRI segmentation. Reference [40] utilizes EDD Net for initial segmentation and employs MUSCLE Net to evaluate and eliminate false positives of small lesions, achieving commendable results on large datasets and proving the algorithm's generalizability.

Since 2021, various attention mechanisms and Transformers have been widely applied in the field of medical image segmentation, leading to further improvements in the performance of stroke lesion segmentation algorithms. Transformers leverage self-attention mechanisms, enabling neural networks to capture global information and exhibit excellent performance when processing long sequence data [64]. Reference [38] introduces attention mechanisms on the skip connections between the encoder and decoder, reducing the time dimension and only propagating the most informative features. References [37,39,44-46] all incorporate the concept of Transformers, leading to significant improvements in algorithm performance.

Recently, the emergence of models such as Segment Anything Model (SAM) [65], Vision Mamba (VMamba) [66], and multimodal large models [67] has provided new directions for stroke lesion segmentation. SAM boasts a large parameter count and introduces pre-trained weights from Vision Transformer (VIT), resulting in excellent generalization performance for medical image segmentation [65]. Multimodal large models can integrate different modal data, enabling a more comprehensive and accurate understanding of patient conditions and prognosis [68,69]. VMamba represents a further improvement and upgrade of the Transformer architecture. It can capture global information while maintaining linear computational complexity, addressing the performance bottleneck caused by the quadratic computational complexity of Transformers [66]. Whether VMamba can achieve a leap in performance for stroke lesion segmentation algorithms similar to Transformers remains to be seen and will require further evaluation over time.

For predicting recovery status, DL methods have not shown significant superiority over ML [70]. DL models require a large amount of data for training to learn sufficiently complex features and avoid overfitting. This also explains why the deep models (DNN) in [54] achieved better performance after being trained on 15,099 medical records, while acquiring a large amount of high-quality clinical data for stroke prognosis may be challenging. When handling stroke prognosis tasks, RF and its variant models have shown better performance compared to other ML algorithms [53, 55, 56]. Although the existing final infarct estimation may not achieve high DSC, the metrics such as volume error, AUC have reached high levels, indicating good practical value [58-61].

6 Conclusion

This article has reviewed and explored the development trends, current status, and challenges of AI in acute stroke lesion segmentation, stroke classification, recovery status prediction, and final infarction estimation over the past 25 years. AI-assisted diagnosis and prognosis assessment for acute stroke have now shown good performance, assisting physicians in making rapid diagnoses and improving patient outcomes. With the development of new computer vision technologies such as SAM, LLMs, and VMamba, AI-assisted diagnosis of acute stroke will have higher accuracy and stability in the future, making it more beneficial for clinical application and widespread adoption.

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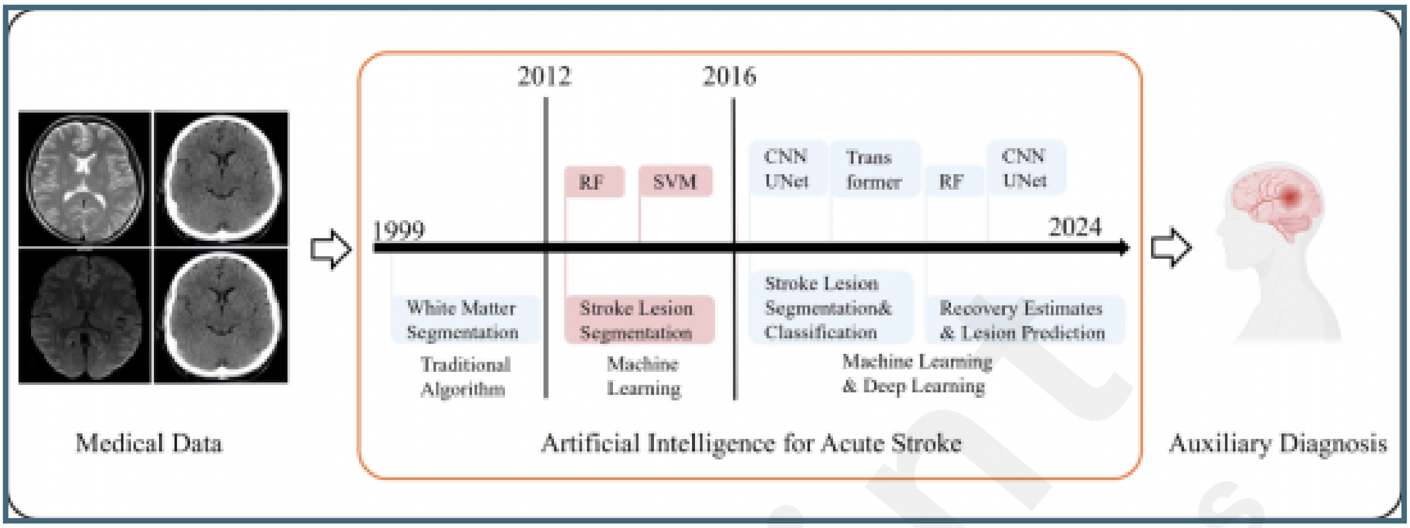
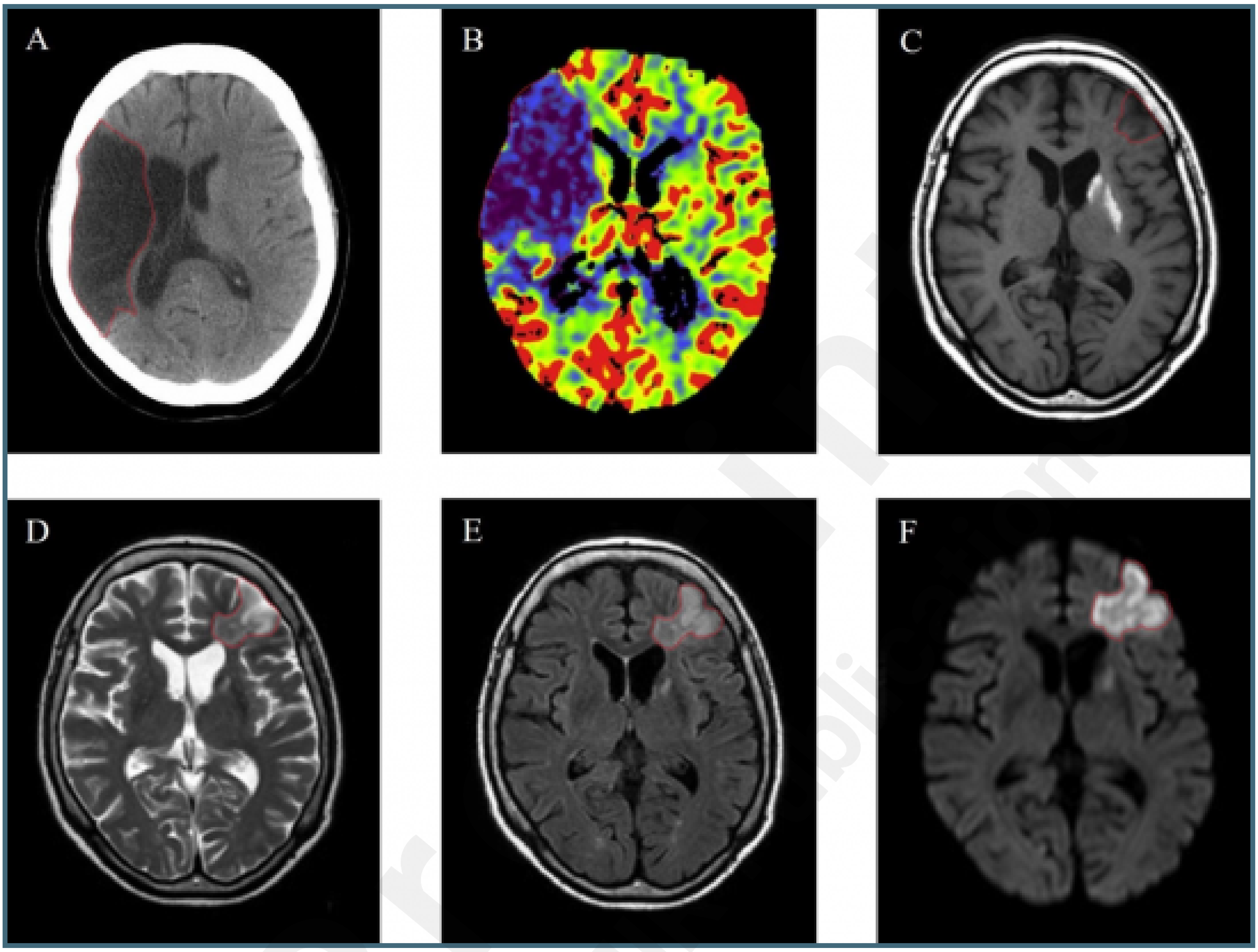
Supplementary Files

Figures

AI for diagnosing acute stroke.



Stroke lesions detected by different imaging modalities. (A)NCCT; (B)CTP; (C)T1WI; (D)T2WI; (E)FLAIR; (F)DWI. Stroke lesion areas are marked with red lines and the images are not paired.



Ischemic stroke and hemorrhagic stroke. (A) Ischemic stroke; (B) Hemorrhagic stroke. Stroke lesion areas are marked with red lines and the images are not paired.