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A Systematic Review of Current Advances in Ischemic Stroke Detection and Segmentation

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Abstract

Ischemic stroke is now one of the vital factors for disability and mortality that globally affects millions of individuals each year in accordance with the World Health Organization (WHO) contrast to hemorrhagic stroke. Treatment for an ischemic stroke as soon as possible can assist to limit prolonged damage and even decreases the risk of mortality. The diagnosis is based on a neurologist's visual observation, which may differ from one to another. On the other hand, Manual segmentation is a tedious and instinctive procedure that has a conspicuous impact on Acute ischemic stroke encountered patient's prognosis. Numerous automated computer Aided Diagnosis (CAD) systems dependent on many statistical learning algorithms of machine learning (ML) and multi-neural network architecture of deep learning (DL) were considered to reduce the complexity of prediction and lesion segmentation in ischemic stroke and also lower the time required for the manual procedure. This paper contemplates the Imaging modalities, Pre-processing techniques, and segmentation algorithms of ischemic stroke, as well as their performance based on comparing different evaluation parameters and their disadvantages. It highlights the current needs, preferred modality, and possible research ideas in the stroke sector.

Keywords

Brain MRI, Deep Learning, Ischemia, Machine Learning, Pre-Processing.

INTRODUCTION

Cerebrovascular accidents (CVA), popularly known as stroke, are a group of brain disorders caused by cerebrovascular diseases (CVDs), like cerebral ischemia, intracerebral hemorrhage, and interventricular hemorrhage. Stroke is the world's second leading cause of disability and death. Every year, there are expected to be 15 million new Cerebrovascular accident cases and a probability of 5 million deaths[1]. Ischemic stroke and hemorrhagic stroke are the two important types of strokes, which accounts for 87 percent and 13 percent of all Cerebrovascular Accidents respectively [2]. This review assessment makes the following contributions: (i) A complete summary of the various ischemic neuroimaging multi-modalities, their properties, and requirements. We examine the most well-known ones among other modalities and make comments on their applicability, accessibility, and feasibility. (ii) An encompassing overview of a variety of new strategies for stroke classification, identification, and lesion segmentation, organized by methods employed, datasets used, and obstacles addressed.

Ischemic Stroke

Ischemic stroke is engendered by thromboembolism that blocks or seals the brain, retina, and spinal cord blood vessels. Figure 1 Staging the illustration of ischemic stroke. Large artery atherosclerosis, atrial fibrillation, and heart disorders are significant origins of embolism.

Small vessel dysfunction, which is linked to hypertension and diabetes mellitus is another source of ischemic stroke[3], [4]. Patients who encountered ischemic stroke must be treated adequately within 3-4.5 hours after the emergence of symptoms[5].

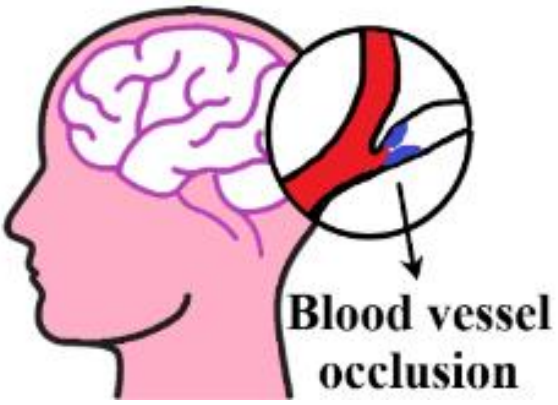
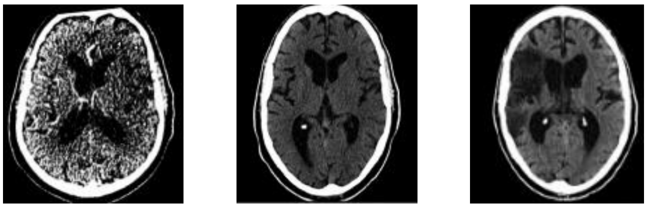


Figure 1. Ischemic stroke

Ischemic Stroke Imaging

The cerebral hemodynamics of ischemic stroke is represented by multimodal Computed Tomography (CT) and Magnetic resonance imaging (MRI), which are exploited to make treatment decisions and also predict expected outcomes[6]. Table 1 Interprets the multimodal imaging techniques used for acute ischemic stroke detection. Computed Tomography combines advanced computer technology with specialized x-ray equipment to generate multiple medical images in any inside part of the body, which includes fat, muscles, bones, internal organs, and blood vessels.



(a) (b) (c)

Figure 2. (a) Computed Angiography-Source Image (CTA-SI); (b) Non-Contrast CT (NCCT); (c) Ischemia on CTA-SI compared to NCCT

Non-contrasted Computed Tomography (NCCT), Computed Tomography Venography (CTV), Computed Tomography Angiography (CTA), and Computed Tomography Perfusion (CTP) are some of the CT imaging modalities used to diagnose a stroke caused by blood clots or bleeding inside the brain. Figure 2 shows the improved conspicuousness of ischemia on Computed Tomography Angiography source images (CTA-SI) compared to Non-contrasted Computed Tomography (NCCT).

Even though Computed Tomography is the most commonly available and fastest imaging modality, several comprehensive stroke centers prefer simplified MRI imaging over CT for two viable reasons. Firstly, Magnetic resonance imaging (MRI) is significantly more sensitive for detecting ischemic stroke and more precise for determining the core volume of infarction. Secondly, Magnetic Resonance Imaging (MRI) has less radiation dose and beam hardening artifacts are absent when compared to Computed Tomography (CT)[7]–[10].

Magnetic resonance imaging (MRI) sequences used for ischemic stroke detection includes functional MRI (fMRI), T1-Weighted Magnetic resonance Imaging, T2-Weighted Magnetic Resonance Imaging, Diffusion-Weighted Magnetic Resonance Imaging (DWI), Fluid-Attenuated Inversion Recovery (FLAIR) MRI and Gradient Record Magnetic Resonance Imaging (GRE)[11]–[16]. Figure 3 shows the axial view of a normal brain's Magnetic Resonance Imaging (MRI) sequences. When compared to various imaging techniques especially Computed Tomography (CT), Diffusion Weighted Imaging was more efficient in detecting acute ischemic stroke and more sensitive for finding more than 33% of Middle Cerebral Artery involvement. Diffusion Weighted Imaging (DWI) measurements of lesion size, as well as Apparent Diffusion Coefficient (ADC) values, are possible indicators of clinical outcomes in ischemic stroke patients[17], [18].

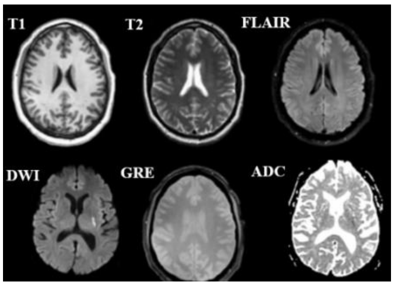


Figure 3. MRI sequences of normal brain

Table 1. Description of multimodal imaging for ischemic stroke detection

Imaging Modalities	Description
NCCT	NCCT generates soft tissue and bone images
CTA	CTA is applied to find thrombus as well as helps for intra-arterial thrombolysis
CTP	CTP is used to identify the parts of the brain that are sufficiently perfused with blood
T1w MRI	T1 imaging characterizes the brain tissue by smaller relaxation time based on the excitation state of protons in the water nucleus of the tissue a. Cerebrospinal fluid and inflammation appear dark b. Light white matter appearance c. Gray cortex appearance
T2w MRI	T2 imaging characterizes the brain tissue by a larger relaxation time based on the excitation state of protons in the water nucleus of the tissue a. Cerebrospinal fluid and inflammation appear bright b. Dark gray white matter appearance c. Light gray cortex appearance
FLAIR-MRI	It has a huge relaxation time than T2 weighted imaging to characterize tissue a. Dark Cerebrospinal Fluid appearance b. Dark gray white appearance c. Bright inflammation appearance d. Light gray cortex appearance
DWI-MRI	Recognize the random motions of water protons. It's a highly sensitive way of detecting strokes. The ADC (Apparent Diffusion Coefficient) quantifies the amount of water-molecule diffusion in the tissue.

Hemorrhagic stroke

Hemorrhagic strokes take place when an artery all of a sudden start bleeding inside the brain. As a consequence, the segment of the body which is controlled by the injured portion of the brain is unable to function properly. Intracranial hemorrhage (ICH) and subarachnoid hemorrhage (SAH) are the two types of hemorrhagic strokes[19], [20]. Figure 4 shows the illustration of hemorrhagic stroke. Both Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are utilized for detecting Hemorrhagic stroke[21].

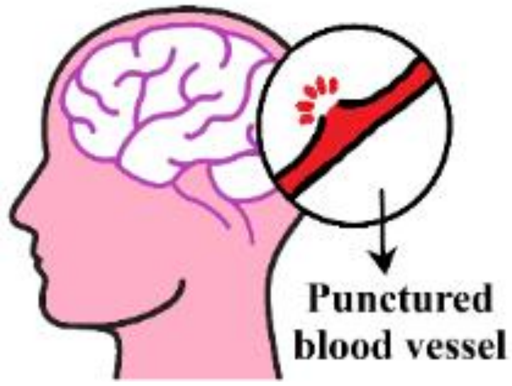


Figure 4. Hemorrhagic stroke

DATA ACQUISITION

In general, the accuracy of ischemic stroke detection algorithms is intimately linked to the data sets to which they were applied. As a result, the creation of a publicly accessible benchmarking system, such as Ischemic Stroke Lesion Segmentation (ISLES): SISS and SPES, ENIGMA- stroke recovery: ATLAS lesion datasets, Interuniversity Consortium for Political and Social Research (ICPSR): stroke datasets, Neuroimaging Tools and Resources Collaboratory (NITRC): Autism Brain Imaging Data Exchange (ABIDE), is used to ease the examination of current trending ML and DL application [22], [23].

Compared to other open-source datasets of ischemic stroke ISLES intends to provide a forum for comparing multiple segmentation for ischemia lesion segmentation from multispectral Magnetic Resonance Imaging (MRI) data fairly and directly. For the following two tasks below, a common dataset of various ischemic stroke instances will be made accessible, as well as an appropriate automatic evaluation procedure: Sub Acute Ischemic Stroke Detection (SISS) and Stroke Perfusion (Penumbra) Estimation (SPES[24]). Table 2 shows the data partitioning, number of centers, and number of expert segment details of each SISS and SPES case in the 2015 ISLES challenge.

Uncompressed Neuroimaging Informatics Technology Initiative (NIFTI) image data formats will be applied for SISS and SPES images. Partitioning the datasets into training and testing data that contains single focal and multifocal cases and also small lesion and large lesion cases. The data layout of SISS and SPES of each case comes with its respective own folder which contains different types of Magnetic Resonance Imaging (MRI) sequences.

Table 2. Dataset details of SISS and SPES

Data Types	Number of cases	Number of medical centers	Number of experts
SISS	28 Training 36 Testing	1 for Training 2 for Testing	1 Training 2 Testing
SPES	30 Training 20 Testing	1 for Training and Testing	1 Training and Testing

MRI sequences for SISS data are Fluid-Attenuated Inversion Recovery Magnetic Resonance Imaging (FLAIR), T2-Weighted Magnetic Resonance Imaging(T2-MRI) Turbo Spin Echo (TSE) which rephases the pulse sequences, T1-Weighted Magnetic Resonance Imaging(T1-MRI) TSE/Turbo Field echo (TFE) that rephases the gradient echo pulse sequences for contrast enhancement, Diffusion-Weighted Magnetic Resonance Imaging (DWI)[25], [26].

PRE-PROCESSING TECHNIQUES

To remove undesired artifacts and convert the data into the graded format, Magnetic Resonance Imaging (MRI) data must be pre-processed. The most predominant pre-processing technique in stroke images is image scaling also referred to as image resizing or image intensity scaling. Incrementing or decrementing the pixel values of rows and columns of an image is the working function of image intensity scaling. It helps to overcome the difficulties faced in the scrutiny of MRI [27].

The RGB format of the input images generated from medical imaging increases the computation time, memory size, and coding difficulty, to avoid such difficulties gray level conversion was introduced. It consists of two gray levels: 0 For black and 1 for white, it converts the RGB (Red, Green, Blue) image into a gray level image[28]. Skull stripping is one of the important Medical imaging pre-processing procedures that distinguish the brain tissues from other region tissues like the skull and non-brain area[29]–[31] in Magnetic Resonance Imaging (MRI) of the brain for stroke followed by the Bias field correction procedure that is exclusively used to solve the problem created by the presence of low-frequency field which blurs image components like contours, edges, and pixel intensity in brain Magnetic Resonance Imaging (MRI) images[32]. To annihilate noise from MRI images, many filtering methods are utilized, including the mean filter, median filter, adaptive median filter, weighted median filter, wiener filter, and so on[33]. To make ischemia region segmentation easier image registration was instigated to correlate two or more images in distinct MRI multimodalities it also differentiates the variations and identifies the anomalies manifested in the images then helps to convey esteemed data in more than a single MRI modality[34].

ROLE OF ARTIFICIAL INTELLIGENCE IN STROKE DETECTION AND LESION SEGMENTATION

Artificial intelligence (AI) is divergent from computer science and endeavors to replicate human intelligence to solve problems[35]. Machine learning (ML) is a type of AI that makes intelligent choices based on what has been learned from parsed input. Deep learning (DL) is a type of machine learning that uses an ANN (Artificial Neural Network) to generate intelligent decisions without using pre-set inputs[36]–[38].

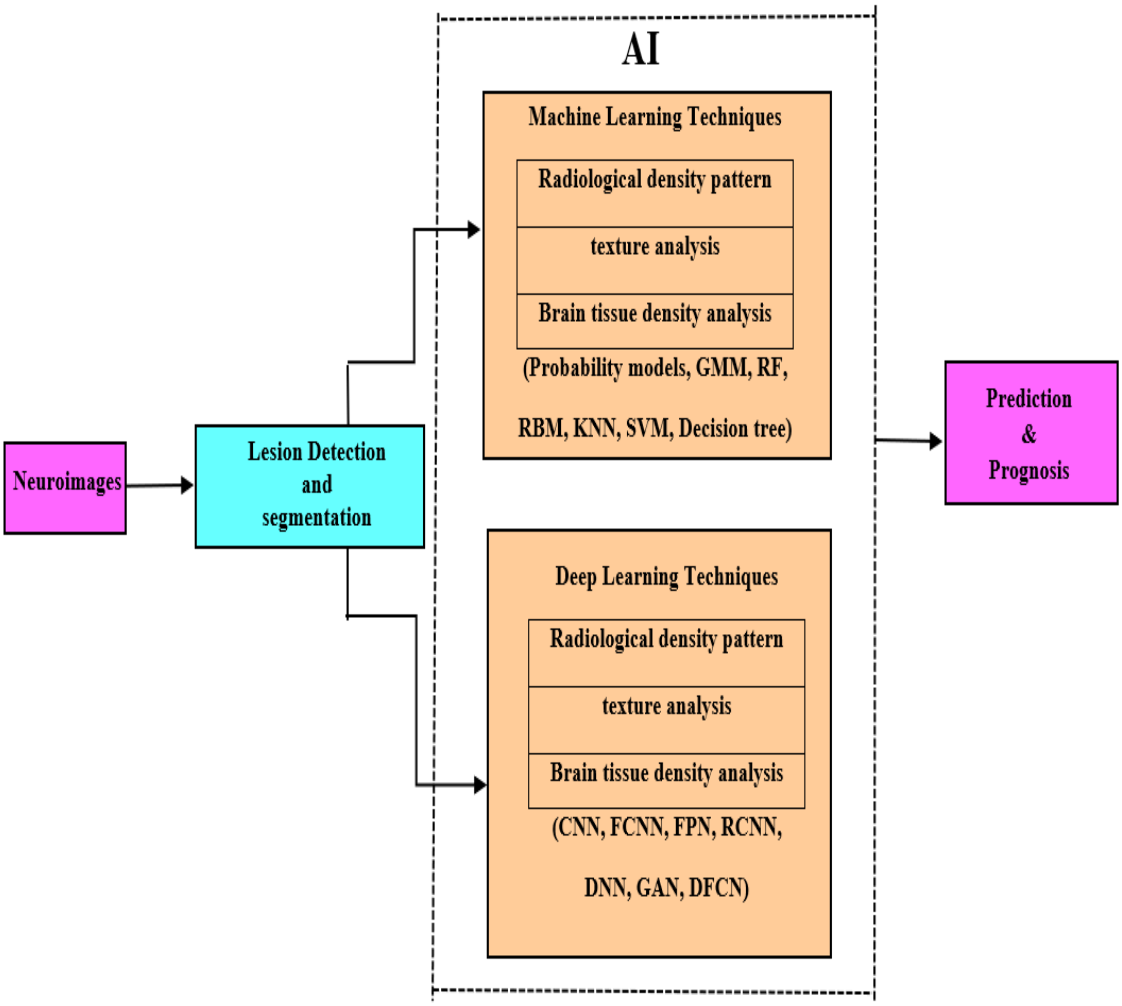


Figure 5. Role of AI in ischemic stroke

An ischemic stroke emerges on CT imaging as a dark attenuation patch that contrasts strongly with its surroundings. Manually processing by a clinical specialist has typically been the most successful for early diagnosis, although it consumes more time. As a result, machine learning approaches are being used for automatic detection. Figure 5 shows the role of Artificial Intelligence in stroke management

Rajini et al. established a texture analysis as well as midline shift tracing algorithm-based segmentation method using Machine learning where Cerebrospinal fluid (CSF) volume changed and acted as a cerebral edema biomarker[39]. Guberina et al. used machine learning to detect early signs of infarction in the Alberta stroke program[40]. Lin et al. researched to evaluate the quality and predict possible erroneous measurements triggered by an anomaly. Then examined and approved the density-based detection practicality. [41]. We see a lot of ML approaches used with MRI since the feature extraction from it gives better results. In the instance of acute ischemic stroke, Teruyuki et al. discovered that a mismatch of anomalies between perfusion–weighted Magnetic Resonance Imaging (MRI) and Diffusion Weighted Imaging (DWI) images could aid in the identification of the penumbral region[42]. Maier et al. published a study comparing alternative machine learning-based classification algorithms for lesion segmentation[43]. In order to segment lesions, Mitra et al. researched the Bayesian–Markov random field (MRF) probabilistic technique and employed random forests (RFs) to determine the location of lesion volumes[44]. Bharathi et al. investigated how handmade and unsupervised techniques, as well as derived features, may be used to improve segmentation quality[45]. In order to help in the decision to administer reperfusion therapy whenever stroke symptoms initially emerged, Yoo et al. conducted research to determine the ideal thresholds for Neuroimaging modality parameters [46]. Maier et al. suggested an effective algorithm for voxelwise categorization based on additional tree forests, with a priority on reproducibility and noise resilience[47]. Mark et al. used five machine learning techniques to identify intense cerebral ischemia tissues that can recuperate after reperfusion, including the generalized linear model, adaptive boosting model, Support Vector Machine, additive model, and random forests[48]. To enhance probability maps, Chen H. et al. proposed RFs which make use of dense sparse fields [49]. To train Radial Basis Function (RBF) kernel SVM model and Artificial Neural Network (ANN), Karthik et al. used discrete curvelet transformation over various scales of features. Pereira et al. implemented a Restricted Boltzmann Machine (RBM) to learn lesion features [50]. Delaunay triangulation (DT) was used by Subudhia et al. to optimize delineation, and FODPSO was used to determine the parameters [51].

A new paradigm for stroke diagnosis has emerged as a result of the development of deep learning. A quicker and more effective network for feature extraction was put forth by Hu et al[52]. Islam et al. suggested an adaptive learning-based training segmentation technique that would find and regulate higher-order conflicts among ground–truth and mapped segments. The model is made up of a conceptive, which demonstrates the synthesized, and racially discriminatory model, that calculates the probability of samples drawn from real-world data[53]. For voxel-wise region detection, Bertels et al. Designed an Convolutional Neural Network (CNN) architectural model using data from an adjacent voxel[54]. Dou et al. suggested a cascade framework-based automated 3D CNN model for executing a detection operation[55]. To get higher image quality for precision, Wang et al. developed a DWI synthesized using perfusion maps[56]. To detect hyper-intense locations in FLAIR and T2w imaging, Li et al. proposed a 2D Faster-CNN-based architecture[57]. Wielding a generative adversarial network (GAN), Alex et al. devised a semi-supervised method for segmenting brain lesions[58]. To effectively segment the acute ischemic stroke location using multi-modality Imaging studies, Liu et al. suggested a DCCN (Res–CNN). Utilizing multimodality enhances segmentation performance in comparison to the single modality variant[59]. For an accurate reconstruction, Karthik et al. presented a supervised Deep Fusion Clustering Network (DFCN) that employed an activation unit as ReLU in the last two layers of the network[60].

CHALLENGES AND FUTURE ORIENTATIONS

Evaluation is very challenging for all Computed Aided Diagnosis approaches, implementations, and strategies we came across while assessing the stroke area because they were all based on different datasets. Although several techniques claimed to be entirely automated, they nevertheless required human input or contact for setting up parameters. A robust intelligent system would be necessary for a fully automated procedure that can adjust and alter in accordance with the current state of the patient and the severity of their symptoms. It would open up a number of possibilities in terms of the potential for artificial intelligence. We discovered less research on the classification of stroke subclasses and paucity on the effectual progression of stroke lesion volume extraction across time. For better study and a clearer understanding of their impact, a diverse collection including images from different datasets should be developed

There are various possible directions for future research: (i) Artificial Intelligence-based automated system that greatly enhances ischemic stroke early detection (ii) Creating a massive heterogeneous public database (iii) Developing Graphical User Interface (GUI) for acute ischemic stroke (AIS) detection and segmentation by utilizing effective ML and DL Approaches (iii)Designing a prototype to monitor stroke encountered patients using predictive AI-models on this basis cloud.

CONCLUSION

In this systematic review, a distinct segmentation approach emphasizing infarct cores and penumbra estimation of ischemic stroke was presented. From brain images, the offered algorithms could identify the existence of a stroke lesion. It's difficult for academics to create a more reliable algorithm because of the computation time and accuracy requirements. The segmentation of the stroke lesions alone achieves the accuracy of approximately 81% to 99.1% contemplated in above section 4. Additionally, the gap appears when all state-of-the-art approaches are insufficiently applied in clinical settings. It may be possible for the medical and engineering fields to collaborate to develop an accomplishing end-to-end automatic generic framework for recognizing stroke lesions.

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