

## Brain stroke computed tomography images analysis using image processing: A review

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### ABSTRACT

Stroke is the second-leading cause of death globally; therefore, it needs immediate treatment to prevent the brain from damage. Neuroimaging technique for stroke detection such as computed tomography (CT) has been widely used for emergency setting that can provide precise information on an obvious difference between white and gray matter. CT is the comprehensively utilized medical imaging technology for bone, soft tissue, and blood vessels imaging. A fully automatic segmentation became a significant contribution to help neuroradiologists achieve fast and accurate interpretation based on the region of interest (ROI). This review paper aims to identify, critically appraise, and summarize the evidence of the relevant studies needed by researchers. Systematic literature review (SLR) is the most efficient way to obtain reliable and valid conclusions as well as to reduce mistakes. Throughout the entire review process, it has been observed that the segmentation techniques such as fuzzy C-mean, thresholding, region growing, k-means, and watershed segmentation techniques were regularly used by researchers to segment CT scan images. This review is also impactful in identifying the best automated segmentation technique to evaluate brain stroke and is expected to contribute new information in the area of stroke research.

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## 1. INTRODUCTION

Brain is a hugely complex and fascinating organ in the human body composing of cerebrum, cerebellum, and brainstem that being protected by the skull [1]. This organ is composed of a number of support networks and billions of connected nerve cells. The brain is having complex space-time patterns characteristic. That is the reason the brain is considered the most complex system, where the degree of correspondence between structural and functional connectivity depends on time scales and spatial resolution [2]. The brain has the ability to control intelligence, creativity, emotion, and memory. The brain is also divided into parietal, frontal, temporal and occipital lobes which interconnect with the body through the spinal cord as well as twelve pairs of cranial vessels through blood circulation as shown in Figure 1. The cranial vessels for smell and vision originate in the cerebrum. Therefore, good blood circulation in the vessels

is important to avoid neuronal damage and subsequent neurological deficits that will lead to cell death [3], [4].

Stroke is the world's second-leading cause of mortality, according to data [5]–[7]. It needs immediate treatment to minimize the risk of death or serious long-term disability. It is a medical condition where a blood vessel bursts or is blocked. As a result, blood flow to a part of the brain is reduced. As shown in Figure 2, stroke can be categorized into hemorrhagic and ischemic stroke. An ischemic stroke happens when there is a blockage in the blood vessel that leads to abrupt occlusion of a cerebral artery while hemorrhagic stroke (brain bleed) occurs when a blood vessel breaks [8]–[11]. When a stroke happens, in each minute, millions of nerve cells and billions of synapses die [12]–[14]. This problem amplifies the notion as “time is brain”. Despite a critical need, there is no established automatic system for stroke, although several automated systems in other fields, including mammography and chest, are among others [15]–[18]. Furthermore, based on studies on computed-aided diagnosis (CAD) systems and technology, it shows that the diagnostic accuracy of radiologists can be improved by using CAD [19]–[29].

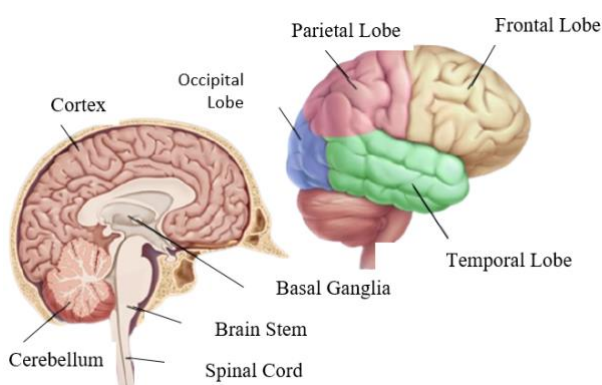


Figure 1. Anatomy of human brain

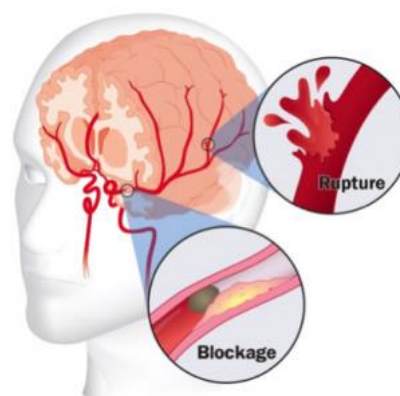


Figure 2. Types of stroke

Computed tomography (CT) scan is one imaging modality that uses multiple X-ray sources and detectors to determine emergency life-threatening neurocranial pathology [30]–[38]. There are two parts inside the CT scanner: a sensor and an X-ray tube to rotate the frame. X-ray beam is generated when the rotating frame rotates the X-ray tube and detector around the patient. One image will be obtained each time the X-ray tube and detector make one complete cycle. The volume data set can then be computer reconstructed to provide three-dimensional (3D) images of complex structures [39]. In cases of trauma and emergent situations, CT performs better as compared to other imaging modalities. It offers better bone detail and has a high sensitivity for acute hemorrhage. CT has become a critical tool in medical imaging to supplement X-rays, medical ultrasonography (USG), and MR imaging. Despite being more cost-effective [40], CT is preferred in the early screening of diseases, especially for patients with a high risk of stroke. CT scans are typically used to detect brain infarct, bleeding, and skull fracture in patients with a better scan time [41]. The image of a CT scan is shown in Figure 3. However, CT has the disadvantages of exposure to ionizing radiation and the potential to misdiagnose certain diseases [42].

In this paper, a review of brain stroke CT images according to the segmentation technique used is presented. Segmentation techniques, includes threshold, fuzzy C-means, region growing, watershed, and k-means segmentation are proposed. Furthermore, as to the best of our knowledge, this paper is the first attempt to review the most relevant brain stroke structure segmentation. As for literature, the primary databases: Scopus, IEEE Xplore, PubMed, and Scholar using systematic literature review (SLR) are searched. The technique is the most efficient way to review papers in which the results are based on a qualitative level instead of a quantitative one. The key three search strategy concepts are mainly brain stroke, CT imaging modality, and segmentation technique. Initially, the works that were out of the scope of this review, such as various brain infarct segmentation techniques, other image modalities, or different segmentation approaches are omitted, while keeping only the works that strictly proposed on segmentation for brain stroke in CT image modality. To retrieve other relevant research work, the reference lists of the selected publications are surveyed, and those related research works to the objective are included.



Figure 3. CT image [43]

## 2. SEGMENTATION TECHNIQUES

Signal processing and machine learning (ML) techniques have been successfully applied to several fields [44]–[62]. Furthermore, the digital signal processing (DSP) technique is always applied to extract the features of the signals and use it with related MLs [63]–[68]. In medical imaging applications, machine learning techniques suffer from several limitations due to the variety of possible shapes, locations, and intensity inhomogeneity [69]–[75]. These techniques relied heavily on manual functions developed by doctors and neuroradiologists in the field [76]. Every patient might have different observed data, and the interpretation of the data depends on the experience of those skilled in the art, this can lead to errors within and between observers [77]. Segmentation ensues by dividing digital images into multiple segments into non-overlapped areas that share characteristics such as shape, intensity, or texture to locate and identify objects and boundaries in an image [18], [78]–[89]. In further parts of this paper, the various techniques of segmentation are discussed and compared.

### 2.1. Threshold based segmentation

Ali *et al.* [90] discussed that threshold based technique is the simplest and computationally efficient approach to segment brain stroke because only intensity values need to be considered and rejects other pixels with values less than the threshold. This process is repeated twice, and the median filter is applied to obtain a smooth image and less noise.

Badriyah *et al.* [91] discussed the concept of stroke segmentation using the thresholding technique. They found out that this technique needs optimization to remove the brain skull image so that the cerebral scalp is invisible and sharpens the edges of the brain. The best output can be obtained by combining the Binary and Otsu thresholding techniques.

Flotmann *et al.* [92] differentiated between threshold-free probabilistic and traditional threshold techniques. The traditional technique exhibited more error on infarct volumes, whereas the probabilistic technique gave consistent prediction mean infarct volumes nearer to the actual volumes value and with higher accuracy. The comparison of the original image and after been segmented using threshold segmentation technique as shown in Figure 4.

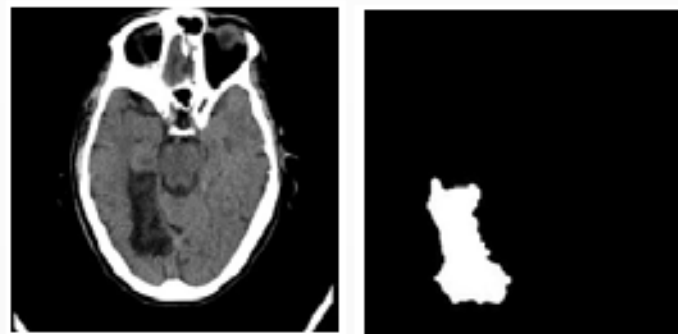


Figure 4. Original and segmented image using threshold technique [26]

## 2.2. Fuzzy c-means (FCM)

Kumar *et al.* [93] proposed a newly improved FCM technique that combined skull removal, automatic selection of cluster, FCM, thresholding and edge-based active contour techniques. The proposed technique has higher accuracy as compared to FCM clustering and manual fuzzy based active contour. Kaur *et al.* [12] estimated that FCM could cater vague and ambiguous CT images. In [12] concluded that the extended FCM (EFCM) has the highest efficiency compared to other image segmentation technique.

Bhadauria and Dewal [94] proposed a technique that combines the FCM technique with the region-based active contour technique for detecting haemorrhage with accuracy and minimum timeframe. The result showed that the proposed technique achieved the highest average dice coefficients, which is 0.8748, compared with conventional FCM and region based technique. In addition, this technique is better suited for CT images that have intensity inhomogeneities. This is due to the intensity information in the local regions to assist the contour towards the hemorrhage boundaries for higher accuracy and robustness [95]. Figure 5 shows the comparison of the original image and after been segmented using FCM segmentation technique.

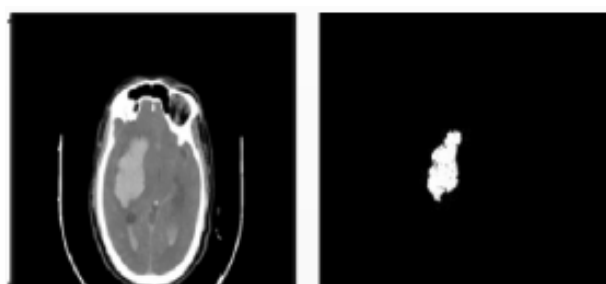


Figure 5. Original and segmented image using FCM technique [21]

## 2.3. Region growing segmentation

Biratu *et al.* [96] and Ali *et al.* [97] described the technique that can segment based on the similar pixel at the ROI and divides CT image into several areas with homogeneity properties. This technique's performance highly relies on the initial seed point selection and the similarity measure used between neighboring pixels. Matesin *et al.* [98] proposed a rule-based technique to segment CT images by the identification at the head symmetry axis based on moments. Other than that, to recognize various areas with rule-based region labeling and uniform brightness, seeded region growing (SRG) is used. SRG has the advantages of being fast, robust, and easy to tune the parameters once seeds are placed. Furthermore, this technique is able to follow the natural boundaries of CT images closely.

Bhadauria and Dewal [94] examined a combination of region growing technique with fuzzy c-mean technique, which gives a robust and accurate detection of hemorrhagic regions to be compared against experts' manual segmentations. Gupta and Mittal [99] and Saini and Banga [100] presented that region growing segmentation technique has the advantage of generating better ROI for brain stroke segmentation. However, Gupta and Mittal [99] proposed homotopic region-growing technique to reduce noise sensitivity and region extraction disconnection.

## 2.4. Watershed segmentation

Watershed segmentation is a technique based on region segmentation. This technique starts with origins in mathematical morphology [101]. For this segmentation technique, the topological surface, mainly the 2D grey-scale image represents each pixel corresponds to a "position" whereas the intensity refers the "altitude" [102].

Ajam *et al.* [103] proposed the marker controlled watershed technique that can reduce the over-segmentation problem due to noise. The over-segmentation usually occurred when the standard watershed technique is used. The newly proposed technique spot the foreground images by using morphological operations which are "opening-by-reconstruction" and "closing-by-reconstruction" that creates maxima contrast for each object.

Arasan *et al.* [104] discussed the efficacy of watershed segmentation technique to detect gray scale and accurately multiple regions simultaneously. Other than that, the proposed technique does not require contour joining, as it produces complete contour of the segments. Nivedhitha and Sankar [105] proposed "hemorrhage detection system using watershed segmentation" which contributed for detecting CT images

with and without haemorrhage. A precise segmentation and classification of haemorrhage stroke regions are essential for correct detection and diagnosis. Features are extracted using watershed segmentation to get a smooth image and able to cater to multi-classification problems. Experiments have been conducted to achieve the promising with an accuracy of 97% after segmentation. Figure 6 illustrates the comparison of the original and segmented image using watershed segmentation technique.

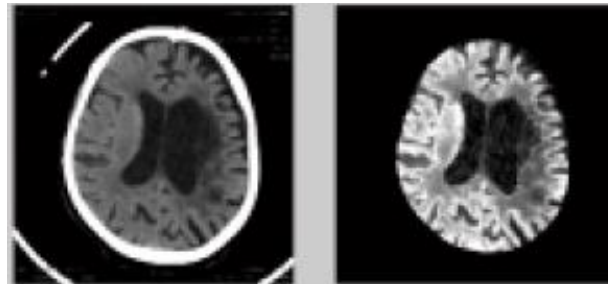


Figure 6. Original and segmented image using watershed technique [101]

## 2.5. K-means segmentation

K-means segmentation techniques are based on partition clustering segmentation techniques [106] that are more suitable and practical for biomedical images such as CT images [36]. According to Vankayalapati *et al.* [107], for a large number of data, K-means offers high computational time. Purohit and Joshi [108] proposed a new technique for producing the cluster centre without sacrificing implementation time. They also stated the initialization of k value plays a vital role in producing a good result in each cluster as it generates stability and reduces the mean square error. According to the studies, it shows the accuracy result is more for dense datasets as compared with sparse datasets.

Lee *et al.* [109] proposed a segmentation technique using EM clustering and k-means. The paper uses several segmentation techniques to divide the brain into 3 clusters: cerebrospinal fluid, abnormal regions, as well as brain matter. The techniques that have been used in their experiment are decision tree, k-means and expectation-maximization (EM) technique.

Rajini and Bhavani [110] proposed a k-means segmentation technique to detect ischemic stroke in CT scan images, texture features and outlining midline shift algorithm. They concluded that their technique could generate precise quantitative results suitable for clinical use. It has been proved by the result of the average precision, average overlap metric, and average recall are 0.99, 0.98 and 0.98, respectively.

## 3. RESULTS

Various techniques are used for brain stroke segmentation using CT scan even though there is a lack of existing studies and research work in databases for evaluation. Comparison summary of the above segmentation techniques is shown in Table 1. Furthermore, based on this review, research work on the segmentation using magnetic resonance imaging (MRI) modality is relatively routine compared to CT imaging modality [111]. All the segmentation techniques purposed is to achieve an efficient and precise system.

Table 1. Comparison of segmentation techniques

Technique	Characteristics	Pros	Cons
Threshold	Based on the histogram analysis [112]	Simplest technique, No need for previous information [91]	Not suitable when ROI and the unwanted area has similar intensity [113]
FCM	Based on partition into homogeneous clusters [12]	Fuzzy uses partial membership and is better for real problems [93]	Determining membership function is not easy [114]
Region Growing	Selection of initial seed point and examine neighboring pixels [115]	Capable of noise resistance, applicable when it is easy to identify similarity criteria [116]	Manual selection of homogeneity criterion [117]
Watershed	Viewed on topological surfaces [118]	Results are more computationally efficient, detected continuous edges [119]	Can lead to over-segmentation [118]
K-means	Divide into k clusters to define k-centroid value of each cluster [107]	Simple and suitable for large data sets [110]	Clustering data of varying sizes and density [120]

The clustering technique is mostly used for segmentation process. K-means has the advantage of less computational time as compared to fuzzy c-means [121]. Fuzzy c-means able to separate different tissue types using a small number of the cluster [93], but K-means uses many clusters for different tissue types [120]. Fuzzy c-means detect abnormalities more accurately than k-means by keeping more information from the original image [122]. Even though computer-aided detection/diagnosis (CAD) can significantly impact automating the image processing and analysis process, it will never replace doctors and radiologists.

#### 4. CONCLUSION

This paper has presented a systematic literature review about brain stroke computed tomography images analysis using image processing. This review was aimed to identify, critically appraise, and summarize the brain stroke segmentation using CT scan. Throughout the entire review, segmentation method such as thresholding, FCM, region growing, k-means, and watershed segmentation techniques have been deeply observed. All the segmentation techniques are purposed to achieve an efficient and precise system. It is easy to determine infarct with maximum accuracy in a shorter time. From the review, the clustering technique is mostly used for segmentation process. Both k-means as well as fuzzy c-means clustering shows an approximately same result, but k-means has the advantage of less computational time, and fuzzy c-means is superior to separate different tissue types. Fuzzy c-means is better to detect abnormalities than k-means, even though computer-aided detection/diagnosis (CAD) can significantly impact automating the image processing and analysis process.

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