Segmentation and classification techniques used to detect early stroke diagnosis using brain magnetic resonance imaging: a review

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ABSTRACT
Stroke is a leading cause of disability and death worldwide. Early diagnosis and treatment are crucial in reducing the risk of stroke-related complications. Brain magnetic resonance imaging (MRI) is a common diagnostic tool used for stroke evaluation. However, manual interpretation of MRI images can be time-consuming and subjective. Machine learning (ML) algorithms have shown promise in automating and improving stroke diagnosis accuracy. This article focuses on classification and segmentation techniques used to detect early stroke diagnosis using brain magnetic imaging. The diagnosis, treatment, and prognosis of complications and patient outcomes in a number of neurological diseases are currently made possible by ML through pattern recognition algorithms. However, the use of MRI is limited because of its high cost and significant operational and processing time. More importantly, MRI is contraindicated in some patients who are claustrophobic or have pacemakers due to the potential for damage.

Recent studies have shown that treatment within six hours of a stroke can save a patient's life. Unfortunately, Malaysia is facing a shortage of neuroradiologists, hampering efforts to treat its growing number of stroke patients.

Keywords:
Cardiac pacemakers
Claustrophobia
Computed tomography scan
Disc disease
Magnetic resonance images
Qualitative losses

1. INTRODUCTION
Stroke is the second leading cause of death worldwide and requires immediate treatment to avoid serious long-term disability and death. It occurs when a blood clot blocks a blood vessel or ruptures, blocking blood flow to an area of the brain. As shown in Figure 1, stroke can be classified as ischemic stroke (as shown in Figure 1(a)) and hemorrhagic stroke (as shown in Figure 1(b)). Ischemic stroke, in which a blood vessel suddenly blocks an artery in the brain [1], and hemorrhagic stroke (cerebral hemorrhage), in which a blood vessel ruptures [2].

Stroke has a major impact on public health, resulting in significant costs for primary care, rehabilitation, and treatment of chronic diseases. In 2015, 6.3 million of his deaths worldwide were due to stroke, making it her second leading cause of death after ischemic heart disease. In June 2019, the Institute...
for Health Metrics and Evaluation reported that stroke was still her third leading cause of death in Malaysia (Institute for Health Metrics and Evaluation, 2017) [3]. It is estimated that approximately 1.9 million neurons and 14 billion synapses die every minute during a stroke, and the ischemic brain ages by approximately 3.6 years every hour. This difficulty reinforces the notion that “time is the brain”. Despite the dire need, there are no computer-aided diagnosis (CAD) systems for stroke, but there are numerous CAD systems for other fields such as mammography and thorax. In addition, research on CAD systems and techniques shows that the use of CAD can improve the diagnostic accuracy of radiologists.

Reperfusion injury plays an important role in the outcome of ischemic stroke patients when blood flow is restored [4]. For this reason, much attention has been paid to cardio protection by ischemic preconditioning, perconditioning, and postconditioning, with differing results regarding possible treatments [5]. Timely restoration of local blood flow helps to rescue the threatened tissue, reduce cell death, and ultimately reduce patient disability. Successful recanalization increases the likelihood of a favorable outcome by a factor of 4 compared to patients without recanalization. In addition, mortality in patients with successful recanalization is reduced by a factor of four [6]. Strategies for recanalization include the use of thrombolytic drugs, such as IV drugs (eg, tissue plasminogen activator (tPA)), and/or mechanical interventions, such as distal or proximal thrombectomy or stent retrievers method. Thrombectomy is the removal of blood clots using a long catheter with a mechanical device attached to the tip. The short intervention time, high recanalization rate, and potential for rapid and efficient restoration of blood flow make the use of thrombectomy attractive. However, the risks associated with thrombectomy must be considered, and only patients with specific indications, such as large circumference, small infarct, and good collateral circulation, should undergo such a procedure. I have. In other words, advanced patient selection based on pretreatment imaging is critical to achieving high rates of good outcomes with mechanical recanalization [7].

The brain is one of the most complex organs in the human body. This organ consists of billions of nerve cells interconnected with a series of supporting networks. The brain is characterized by complex spatiotemporal patterns. For this reason, the brain is considered to be the most complex system in which the degree of correspondence between structural and functional connections depends on spatial resolution and temporal scale [8]. The brain has the ability to control intelligence, creativity, emotions and memory. The brain, protected by the skull, consists of the cerebrum, cerebellum, and brainstem. Figure 2 shows the structure of the human brain. The brain is also divided into several lobes:

− The frontal lobe is responsible for problem-solving, decision-making, and motor skills.
− The parietal lobe controls sensation, handwriting, and posture.
− The temporal lobe is involved in memory and hearing.
− The occipital lobe contains the brain’s visual processing system.

The brain communicates with the body through 12 pairs of cerebrovascular vessels through the spinal cord and blood flow. Ten of the 12 pairs of cerebral vessels that control hearing, eye movements, facial sensations, taste, swallowing, and movements of the muscles of the face, neck, shoulders, and tongue originate in the brainstem. The cerebral blood vessels responsible for smell and vision originate in the cerebrum. Therefore, good blood circulation in blood vessels is very important to avoid neuropathy leading to nerve cell damage and subsequent cell death [9].

The collateral circulation is an auxiliary vascular network that is dynamically recruited upon arterial occlusion. In recent years, many studies have emphasized the importance of preoperative evaluation. Peripheries and infarct areas are readily discernible on clinical maps generated from angiographic scans.

Figure 1. Types of strokes: (a) ischemic stroke and (b) hemorrhagic stroke [1]
including measurements of cerebral blood flow and volume. A collateral circulation is defined as an auxiliary vascular network that is dynamically recruited when a region loses its regular blood supply due to occlusion of a major arterial trunk [10]. Parallel blood vessels in the human brain that carry blood to the same target tissue or cell. Cerebral blood flow follows the cerebral perfusion gradient. A “pressure boundary zone” develops between two vessel regions when there is an upstream flow obstruction [11]. The collateral circulation can be divided into lateral cranial collateral circulation and medial cranial collateral circulation. As shown in Figure 3, the lateral cranial collateral circulation is supplied by external carotid artery anastomoses leading to many branches of the neck that are potential sources of collateral blood flow [12]. The cranial collaterals can be further divided into primary and secondary collaterals as shown in Figure 4. The primary pathway involves the arterial segments of the circle of Willis and the secondary pathway involves the leptomeningeal anastomosis connecting the distal portions of the cerebral arteries.

![Figure 2. Anatomy of human brain](image)

![Figure 3. Extracranial collateral circulation](image)  
![Figure 4. Intracranial collateral circulation](image)

The Willis circuit, shown in Figure 5, is a critical connection of arteries at the base of the brain that allows adequate blood flow from the arteries to both the anterior and hemispheres. A structure located in the central part of the brain that contains the pituitary stalk and other important structures. There are two arteries called carotid arteries. The carotid arteries supply blood to the brain and flow down both sides of the neck and connect directly to the circle of Willis. Each carotid artery branches into an internal carotid artery and an external carotid artery. The internal carotid artery then branches into the cerebral arteries. This structure allows all blood from the two internal carotid arteries to flow through the circle of Willis.
Segmentation and classification techniques used to detect early ... (Shaarmila Kandaya)
(classification success rate). Due to the simplicity of obtaining data from brain analyses, support vector machines (SVMs), k-nearest neighbours (k-NN), and decision trees are well known as classification methods of MRI brain pictures in machine learning. [15].

3. EARLY STROKE SEGMENTATION TECHNIQUES

Image segmentation is very important because radiologists need to know the exact location, size, intensity, and other details of lesions to make conclusions and diagnoses. Segmentation involves recognizing and marking meaningful regions within specific image data. Five different image segmentation methods are analyzed: adaptive threshold, fuzzy C-means, region-growing, marker-controlled watershed, and k-means.

3.1. Adaptive threshold

The segmentation technique of adaptive thresholding converts a grayscale image with a fixed value into a binary image. Thresholding is the process of converting a grayscale image to a black-and-white image by precisely setting pixels whose values are above a certain threshold to white and those below it to black [16]. Adaptive thresholding assigns an image threshold for each pixel with reference to the gray-level intensities of neighboring pixels, given by (1).

\[ G(x, y) = \begin{cases} 
1 & \text{if } I(x, y) \geq \tau \\
0 & \text{otherwise} 
\end{cases} \]  

(1)

3.2. Region growing

Region growing is a basic and common image segmentation method used to segment homogeneous regions with the same intensity value. It requires no prior knowledge of the shape, so it can be implemented on objects of various shapes [17]. The main working principles include that each pixel must be in a specific region, that pixels within a region must be connected and satisfy certain similarity conditions, that regions are disjoint, and that there are two different It includes that regions must not have the same properties [18]. It is initialized with the starting point of each region of interest, which can be selected manually or automatically. Neighboring pixels or regions are then connected to seed points according to some predefined similarity criteria. This process continues until all pixels in some regions have been classified, preserving the connectivity of all pixels grown from the seed point. Contains local relationships between pixels. Its computational simplicity improves the use of this method. However, it is sensitive to seed initialization and noise. It does not work well with images that have adjacent regions that share similar intensities and regions that do not vary smoothly, such as textured images. It can be applied to images subject to lighting changes, but requires proper preprocessing.

The partial volume effect is also an important factor limiting the accuracy of segmentation as it obscures the difference in intensity at the boundary of two tissue types, thereby leading to voxels representing multiple tissue types [19]. This has been overcome with the introduction of modified region growing method (MRGM) by using gradient information to identify borders, and MRGM has been proven to provide better tumor segmentation results in 3D T1-MRI images [20]. Effective choice of threshold for selecting similarity conditions between two regions is important in efficient segmentation by minimizing the variance between uniform regions and maximizing the gradient along the boundary [21]. The seed region growth method for tumor segmentation uses a fixed threshold along with some pretreatments and yields satisfactory results. However, adaptive thresholds may prove more reliable. Only strength constraints were considered, but the inclusion of a directional constraint [22] improved the results. An extended version of traditional regional cultivation was developed [23]. Brain MRIs are processed from the generation of brain MRI T2 thresholds and PD images using a seed region growth algorithm, which are further processed by a Markov algorithm and classified based on the presence of tumors.

3.3. Marker-controlled watershed

Watershed segmentation is a gradient-based segmentation technique. In this study, watershed segmentation locates watersheds and watershed ridges by assigning intensity levels as surfaces, high intensity to bright pixels and low intensity to dark pixels [24]. Based on the edge detection method, the magnitude of the gradient is calculated from the foreground and background markings of the image. Morphological operations and watershed edges are then applied. A watershed transformation is formed based on the represented edges of the watershed [25]. The input image \( I(x,y) \) and the gradients along the x and y axes are computed based on (2) and (3).

\[ I_x = \frac{\delta I}{\delta x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \]  

(2)
\[ I_y = \frac{\delta f}{\delta y} = (z_3 + 2z_6 + z_9) - (z_4 + 2z_4 + z_7) \]

Then the gradient of the image is defined as (3):

\[ \nabla I(x, y) = \frac{\delta f}{\delta x} i + \frac{\delta f}{\delta y} j = I_x i + I_y j \]  \quad (3)

where \( i \) and \( j \) are unit vectors along \( x \) and \( y \) axis respectively. The magnitude of gradient is given by (4).

\[ g(x, y) = |\nabla f(x, y)| = \sqrt{g_x^2 + g_y^2} \]  \quad (4)

In order to address issues such as noise and irregularities that can lead to over-segmentation in the image, morphological surgical techniques can be employed. These techniques involve applying morphological operations, such as erosion or dilation, to modify the image and reduce the impact of gradients. By selectively removing or expanding certain image components, the surgical techniques aim to achieve a more accurate segmentation result and overcome the challenges posed by noise and irregularities.

4. EARLY STROKE CLASSIFICATION TECHNIQUES

4.1. Discriminant analysis model

The model of discriminant analysis as shown in Figure 7. This model uses a Gaussian distribution to classify the dataset within its categories. Gaussian generates data from each category, finds a linear combination of features, and computes the boundaries of the data between each category. Determine categories of new data by collecting linear combinations of features that can be formed from linear or quadratic functions.

4.2. SVM analysis model

The SVM analytical model shown in Figure 8 allocate facts with the classification beside finding a linear decision boundary (hyperplane). If the data can be linearly separable, the hyperplane best suited for SVM has the widest margin between the two categories \[ \text{[26]} \]. If the data cannot be linearly separable, use function loss to penalize points on opposite sides of the hyperplane. Transformation kernels can be utilized by SVM to alter nonlinearly separable data into higher dimensions, where linear decision boundaries can be identified.

4.3. k-NN analysis model

The k-NN analysis model is illustrated in Figure 9, and it classifies data into its respective category by examining the nearest neighbors. Data points that are close to each other are deemed to have similar characteristics and are classified as belonging to the same category \[ \text{[27]} \]. To identify class parameters, k-NN calculates distance metrics, such as Euclidean, city block, cosine, and Chebyshev.

4.4. Decision tree analysis model

A decision tree analyzes data with its categories by constructing predictions. It determines the tree diagram concept. To make a prediction, the process starts from the root of the tree and moves towards the node leaf as shown in Figure 10 \[ \text{[28]} \]. The routes produce branches, and a split is made by selecting predictor values that can be differentiated using trained weights. The number of branches and weight values are determined during the training phase. Additional modifications or simplifications can be made to the model.

5. RESULTS AND DISCUSSIONS

Different methods are employed to segment and classify brain strokes using MRI scans, despite the limited amount of research available for assessment in databases. Tables 1 and 2 summarize the comparative
analysis of these segmentation and classification techniques. In addition, based on this review, MRI is a more common imaging modality for segmentation research than CT. The primary objective of all these segmentation techniques is to create a system that is both efficient and accurate. In this part, using machine learning various techniques demonstrated for segmentation and classification, those are adaptive thresholding, marker-controlled watershed using correlation template, FCM, region growing, k-means, discriminant analysis model, SVM analysis model, k-NN analysis model and decision tree analysis model. Segmentation results describes k-means using the fast marching technique (FMM). Table 1 presents a summarized comparison of the segmentation techniques discussed above. Additionally, according to the review, the use of magnetic resonance imaging (MRI) for segmentation research is more commonplace than that of CT imaging [29]. Overall, the aim of all these segmentation techniques is to develop an accurate and effective system.

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Characteristics</th>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold</td>
<td>Threshold Method based on analyzing the histogram</td>
<td>Simplest technique, does not require prior information [36]</td>
<td>Not effective when the Region of Interest (ROI) and the unwanted area have similar intensity [40]</td>
</tr>
<tr>
<td>FCM</td>
<td>FCM Method based on partitioning data into homogeneous clusters [31]</td>
<td>Fuzzy logic allows for partial membership, better for real-world problems [37]</td>
<td>Determining the membership function is difficult [41]</td>
</tr>
<tr>
<td>Region Growing</td>
<td>Region Growing is the selection of an initial seed point and examination of neighboring pixels [32]</td>
<td>Effective at noise resistance, applicable when it is easy to identify similarity criteria [38]</td>
<td>Manual selection of the homogeneity criterion [42], [43]</td>
</tr>
<tr>
<td>Watershed</td>
<td>Watershed Method based on topological surfaces [33]</td>
<td>Results are computationally efficient, detects continuous edges [33]</td>
<td>Can lead to over-segmentation [33]</td>
</tr>
<tr>
<td>K-means</td>
<td>K-means Method that divides data into k clusters to define k-centroid values of each cluster [34], [35]</td>
<td>Simple and suitable for large datasets [39]</td>
<td>Challenges with clustering data of varying sizes and densities [44]</td>
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</tr>
</thead>
<tbody>
<tr>
<td>Discriminant Analysis Model</td>
<td>Discriminant Method has an efficient method for feature extraction and dimension reduction [45]</td>
<td>Assigns exact values to outcomes of various actions [45]</td>
<td>It is restricted to one output attribute [45]</td>
</tr>
<tr>
<td>SVM Analysis Model</td>
<td>SVM Method is a best classifier for categorising two or more categories [46]</td>
<td>Provides better accuracy compare to other classifier easily handle complex nonlinear data points and easily handle complex nonlinear data points [47]</td>
<td>It is expensive [47]</td>
</tr>
<tr>
<td>k-NN Analysis Model</td>
<td>k-NN Method is a nonparametric learning set of a classification algorithm that categorises objects based on the closest pixel [48]</td>
<td>It is easy to implement [48]</td>
<td>Sensitive to noise and requires large storage space [48]</td>
</tr>
<tr>
<td>Decision Tree Analysis Model</td>
<td>Decision tree Method minimizes the ambiguity of complicated decisions [49]</td>
<td>It handles both numerical and categorical data [49]</td>
<td>It is an unstable classifier, for example performance of classifier is depend upon the type of dataset [49]</td>
</tr>
</tbody>
</table>

The clustering technique is commonly used during the segmentation process. K-means is computationally faster than fuzzy c-means [50]. K-means employs several clusters to distinguish different tissue types, whereas fuzzy c-means uses a smaller number of clusters [37]. Fuzzy c-means is better at detecting anomalies with greater accuracy by preserving more information from the original image compared to k-means. Although computer-aided detection/diagnosis (CAD) has a substantial impact on automating image processing and analysis, it will never fully substitute medical professionals such as radiologists and doctors. Apart from that, the SVM is normally used during the classification process because it provides better accuracy compare to other classifier easily handle complex nonlinear data points and easily handle complex nonlinear data points.

6. CONCLUSION

In the nutshell, the researchers focused at MRI brain segmentation and brain stroke classification systems. Based on the research, DWI evaluates the capacity of molecular diffusion movements in a tissue structure, including the boundaries between white matter and gray matter brain tissues, cerebrospinal fluid, and brain lesions. These regions have distinct diffusion criteria that may be affected by illnesses. These boundaries can also be found in WM and GM brain tissues. Diffusivity affects picture contrast; a chronic
stroke with high diffusion (watery tissues) appears dark (hypopointense), but a recent stroke with less diffusion seems dazzling (hyperintense). At last, different diagnosis of brain lesions is traditionally execute manually by skilled neuroradiologists, which is a very internal and time-consuming method.

ACKNOWLEDGEMENTS

The study is funding by Ministry of Higher Education (MOHE) of Malaysia through the Fundamental Research Grant Scheme (FRGS), No: FRGS/1/2022/5SKK06/UTM/02/1. The authors also would like to thank Faculty of Electrical Engineering, Universiti Teknologi Malaysia Melaka (UTeM) and to all team members of Advanced Digital Signal Processing Group (ADSP), Centre of Robotic & Industrial Information (CeRIA), for their contribution and suggestion to successfully complete this paper.

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