A Review on Image Segmentation Techniques for MRI Brain Stroke Lesion

Norhashimah Mohd Saad[1], Nor Shahirah Mohd Noor[2], Abdul Rahim Abdullah[3]
[1]*Faculty of Electrical and Electronic Engineering Technology, Universiti Teknikal Malaysia Melaka, Malaysia*
[2]*Faculty of Electronics and Computer Engineering, Universiti Teknikal Malaysia Melaka, Malaysia*
[3]*Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malaysia*
norhashimah@utem.edu.my

***Abstract*—One of the major categories of brain disorders is known as stroke, which it can affect the entire body. The ability to recover from a stroke depends on the severity of the stroke and how quickly the patients receive the medical treatment. Conventionally, the diagnosis of brain stroke is performed manually by professional neuroradiologists during a highly subjective and time-consuming process. This paper reviewed the techniques for automatic magnetic resonance imaging of brain lesions segmentation. The proposed review is important to identify more robust and accurate technique in segmenting the brain stroke lesion for computer-aided diagnosis. This could be an opportunity for the medical and engineering to collaborate in designing a complete end-to-end automated framework in detecting and segmenting stroke lesions.**

***Index Terms*—magnetic resonance imaging; segmentation; stroke.**

I. Introduction

Stroke also known as a cerebrovascular accident (CVA) is a part of the brain that loses blood supply and a part of the body that is controlled by blood-deprived brain cells stops working. This loss of blood supply can be ischemic because of lack of blood flow, or haemorrhagic because of bleeding into brain tissue [1]. Stroke is the leading cause of adult disability worldwide, with up to two-thirds of individuals experiencing long-term disability.

Neuroimaging studies have shown promise in identifying robust biomarkers of long-term stroke recovery following rehabilitation [2]. Stroke is not only the top five leading causes of death in Malaysia, but it is also occurred across the world [3]. Every year, an estimation of 40,000 people in Malaysia suffer from stroke [4]. National Stroke Association of Malaysia (NASAM) has been stated that one out of six people worldwide will be diagnosed with stroke and it is the third leading cause of adult disability [5].

Stroke is a medical emergency and clinical symptom that happens when the blood vessel is blocked or burst due to a blood clot (thrombosis). All the oxygen and nutrients supply will be cut off causing a syndrome characterized by rapidly developing symptoms or sign of focal neurologic dysfunction due to a vascular cause [6]. Urgent treatment is needed to treat the detrimental effects of stroke. A diagnosis of brain stroke is extremely crucial and only professional neuroradiologists can perform the task [7]. Therefore, early detection and diagnosis is the key to successful therapy and treatment planning for brain stroke.

Magnetic resonance imaging (MRI) is an imaging system extensively used for the diagnosis of stroke. The MRI sequence to respond to early detection of stroke is known as Diffusion-weighted Imaging (DWI). It is suitable for the detection of hyperacute and acute stroke [8]. It measures the diffusion of water molecules within the tissue structure on a pixel basis and provide high lesion contrast [9]. In recent stroke lesion detection, DWI becomes the indication of MRI sequences due to it is able to reduce the diffusion water to detect the tissue of hyperintense images. Although, DWI image has good ability in visualizing the stroke lesion, manual detection and diagnosis are very time-consuming compared to computer-aided diagnosis techniques [10].

A smart computer system such as computer-aided diagnosis (CAD) is needed for neuroradiologists in providing a second opinion or clinical validation. This advanced technology system is able to help neuroradiologists to improve the accuracy of their diagnosis [11]. CAD also helps to improve the performance of radiologists's interpretation by increasing the sensitivity rate in a cost-effective way [12]. The automatic image segmentation and classification can be developed in the development of CAD to improve the accuracy, preciseness, and speed of computation of segmentation approaches.

II. Brain Stroke Imaging

A. Stroke

Stroke is a serious healthcare problem that led to high mortality and long-term disability. A stroke occurs when the blood supply to part of your brain is interrupted or reduced, preventing brain tissue from getting oxygen and nutrients. Brain cells begin to die in minutes. It is a disease when the blood, oxygen or the nutrient are not supplied forcing the brain cells to stop working and sending information to the nerve cells. The disadvantage of this disease produces a harmful effect on the human body to act well. symptoms of stroke include trouble speaking and understanding what others are saying, paralysis or numbness of the face, arm, or leg, problems seeing in one or both eyes, headache, and trouble walking. Stroke is mainly classified into two parts which are ischemic and haemorrhagic stroke [13], [14]. Figure 1 shows the image of the brain stroke attacks the human brain from ischemic stroke and haemorrhage stroke.

When the blood, oxygen, and nutrient are not supplied in the human brain causing the structure of the blood vessel to become narrow and leads to blockage it is called an ischemic stroke. Ischemic stroke can happen in two categories which are thrombotic and embolic stroke [15]. A thrombotic stroke happens when the brain is blocked from the blood clot formed by a plaque of an artery. The embolic stroke happens when the blood vessel in the brain is blocked by the wandering clot from elsewhere around the body that was carried by the bloodstream.

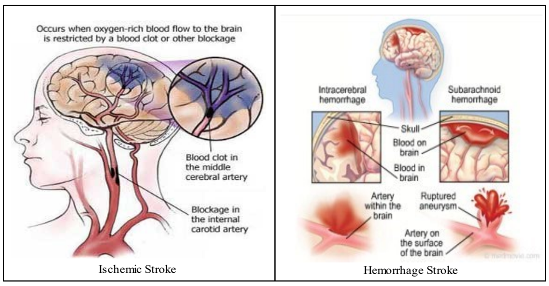


Figure 1: Types of stroke [14]

A ruptured blood vessel in the brain is called a haemorrhagic stroke. It is categorized into two categories which are intracerebral haemorrhage and subarachnoid haemorrhage [16]. Intracerebral haemorrhage occurs when the blood vessel bleeds or ruptures into the tissue deep within the brain. It is always caused by chronically high blood pressure or ageing blood vessels and sometimes caused by an arteriovenous malformation (AVM), where AVM is a cluster of abnormally formed blood vessels. With the form of this disease, the blood vessels are ruptured affecting the brain to bleed [17].

When an aneurysm occurred (a blood-filled pouch that balloons out from an artery) on or near the surface of the brain ruptures and bleeds into the space between the brain and the skull it is called a subarachnoid haemorrhage [18]. It is often caused by high blood pressure and other factors that increase the risk of haemorrhagic strokes which include cigarette smoking, use of oral contraceptives, excessive alcohol intake, and the use of illegal drugs.

B. Diffusion-Weighted Imaging

Diffusion-weighted imaging (DWI) is an MRI sequence that is produced based on the movement of water molecules known as Brownian motion. In the brain tissue, diffusion of water molecules follows the structure and properties of the brain where it can represent the normal brain and stroke lesion. The diffusion-weighted is generated based on the diffusion gradient, G_d and the dependent readout signal. Figure 2 shows the diagram of a spin-echo DWI sequence.

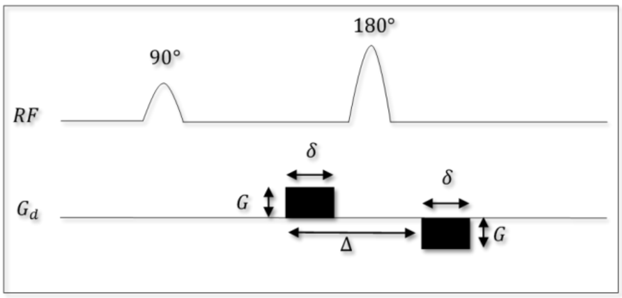


Figure 2: Diffusion-weighted sequence [19]

Diffusion weight consists of two G_d where each G_d is separated by a span of time, Δ. Data is acquired at some duration, δ of the G_d and this is a symmetry to the 180° RF pulse. The protons on the first gradient will dephase and the second gradient will rephase. If the proton diffuses resulting in a non-complete rephrasing of proton spin, signal attenuation is generated producing dark regions on DWI images. The signal attenuation is given by Stejskal-Tanner in Equation (1) [20].

$$S(b) = S_0 e^{-bD} \tag{1}$$

where S(b) is the signal received for the certain gradient value and S_0 is the signal strength of non-diffusion weighting, D is diffusion. The b is written in Equation 2:

$$b = \gamma^2 G^2 \delta^2 \left(\Delta - \frac{\delta}{3}\right) \tag{2}$$

where γ is the constant gyromagnetic ratio of hydrogen proton, given as 42.58 MHz/T, G is the magnitude of the applied gradient, δ is the duration of gradient and Δ is the time between the application of the two gradients. DWI is based on the signal that is dependent on the particle motion where this process can generate image contrast through exploiting the diffusion property of water molecules in water.

An important role in the progress of imaging treatment in finding the extent and location of the stroke lesion is at the stage of stroke imaging [21], [22]. Currently, DWI is mostly preferred as a stroke imaging at a very early stage because it can produce a signal that shows the characteristics of stroke lesion by the paramagnetic effects of the breakdown products of hemoglobin, the magnetic field strength, and the pulse sequence used [23].

Within the specific range of time, the DWI imaging tool stroke lesion is presented in five phases [24]. The stroke lesion appears in two conditions which is hyperintense and hypointense. Hyperintense can be seen in the stroke lesion from the MRI image with brighter image intensity while hypointense is presented in the MRI image with darker image intensity [25]. The presentation of hyperintense and hypointense are based on the breakdown products of haemoglobin and are characterized by the different oxidation states of iron and different magnetic properties.

For the ischemic stroke, the stroke lesion phase begins with early hyperacute that happen in 0 to 6 hours, followed by the late hyperacute within the range of 6 to 24 hours. At this phase, the signal intensity shown by the DWI image is still high. The stroke lesion became hyperintense in the acute phase when it is present within 24 hours to 1 week. The sub-acute is presented from 1 to 3 weeks. From the 10th day until the 14th day after of subacute, the appearance of stroke lesion became hypointense. The last phase of the ischemic stroke is present as hypointense at the chronic stroke stage which is after more than 3 weeks.

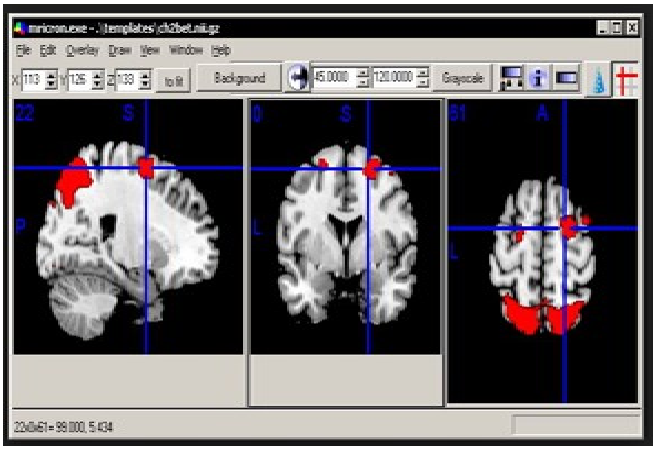
For the haemorrhage stroke, hyper acute stroke lesion is appeared in hyperintense in less than 12 hours. The stroke lesion changes into hypointense from acute to early subacute phase. It takes 12 hours to 2 days for the acute phase to present followed by the early subacute until day 7. The stroke lesion appears back in hyperintense at the late subacute from 8 days until 1 month. The last phase of stroke lesion is continued until years with the appearance of hypointense at the chronic phase [26].

III. Stroke Lesion Segmentation

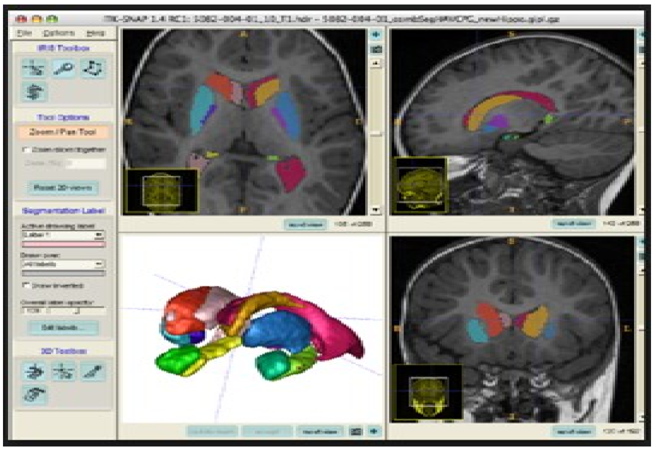
Brain image segmentation is an important procedure as it is useful to obtain some reliable information in the brain image such as the grey matter (GM), white matter (WM), cerebrospinal fluid (CSF), and abnormal brain tissues. This procedure involves the process of partitioning images into several parts without changing the features and the properties of the brain images. There are several ways in segmenting brain images such as manual segmentation, thresholding, region growing, clustering, active contour, and hybrid segmentation.

A. Manual Segmentation

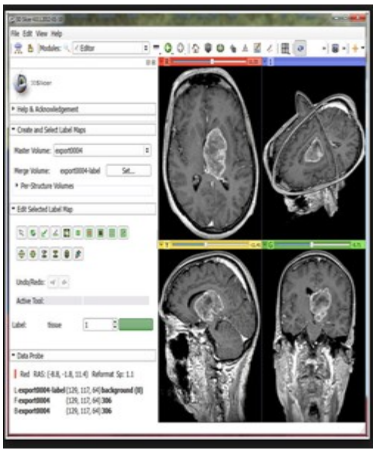
Segmenting brain images have several ways. Manual segmentation is one of the segmentations techniques have proposed. Manual segmentation is a task performed by an expert radiologist in segmenting brain images by the ability of his or her hand. It is a process that requires skilled tracers and can be prohibitively time-consuming and subjective [2]. It is performed diligently by an expert in order to get accurate and reliable delineate structures of the brain images [27]. However, as many as eighty slices of brain images with 512 x 512 size dimension from the MRI scanner is segmented to obtain the contour of the ROI [28].



(a) MRIcon



(b) ITK-SNAP



(c) 3D-Slicer

Figure 2.3.1 Semi-automatic segmentation software [43]

This task has difficulty reproducing an impossible and different result of the ROI based on their previous delineation. By the assessment of various inter and intra expert studies, also encourages prone errors [29], [30]. From time to time, the medical image tools are developed with the latest technology making manual brain image segmentation is not only tedious but also time-consuming [31] – [36].

Segmentation software such as MRIcon [37], ITK-SNAP [38], and 3D-Slicer [39] is shown in Figure 3(a)-(c), respectively. This software which is also known as semi-automatic segmentation helps the expert to analyse brain images and provide feedback response for the software computing to evaluate the performance of the brain image [40]. Although semi-automatic segmentation techniques can give faster results, it also comes into being different results from different experts or the same user at different times [41], [42].

Manual segmentation of different brain structures is a fundamental step in brain atlas formation and is used in segmentation approaches [44]. Nevertheless, manual segmentation is still intensively used for defining a delineation of the ground-truth image that is used for quantitative evaluation of automated segmentation techniques [45].

B. Automated Segmentation

Regarding the disadvantage of manual and semi-automatic segmentation techniques, automated segmentation is needed to diagnose the brain image. Basic segmentation techniques are also known as intensity-based segmentation which consists of three techniques which are thresholding, edge, and region-based segmentation.

Watershed segmentation is a gradient-based segmentation technique. It is first introduced by Vincent, Soille in the year 1991, and followed by Sethian in the year 1996. The watershed transformation considers the magnitude of the gradient of the image as a topographic surface. Pixels that have the highest gradient magnitude intensity (GMI) correspond to the water flow line, which represents the region's boundaries [46].

Water is placed on any pixel surrounded by flowing stream water that normally flows down to the minimum local average intensity. Pixel's flow into the same form as the catchment basin, which represents the segment. The significant limitation of the watershed transform is the tendency to over-segment the image. To overcome this limitation, the location of the object must be estimated with instance markers, which can guide the selection of a subset of these basins [47].

K-Means algorithm is the most popular clustering technique and is widely used in partitioned cluster algorithms. The purpose of this algorithm is to minimize the distance of all elements to their cluster centre. This algorithm increases the cluster repeatedly and runs in the loop so that it reaches the optimum solution [48]. The performance of the k-algorithm depends on the starting value of the cluster centre. Therefore, algorithms need to be tested for different results with different initial cluster centres with multiple runs. The main drawbacks of this technique are that the number of clusters is uncertain, and this technique is sensitive to the initial cluster centres. To overcome this limitation, statistical computation or cluster verification technique is required to estimate the number of clusters [49].

Clustering is a process where a set of data is replaced by a group of a cluster, which is a collection of data points that are "belong together". Specific criteria will be used depending on the image. Pixels in the image may belong together because they have similar color and/or similar texture and/or proximity.

Fuzzy C-Means (FCM) is effectively used in data analysis, pattern recognition, image segmentation, and fuzzy modeling. It is a popular soft clustering technique and one of the most promising fuzzy clustering techniques [50]. The fuzzy clustering techniques can be superior since they can represent the relationship between the input pattern data and clusters more naturally. In most cases, it is more flexible than the corresponding hard-clustering algorithm. Traditional clustering approaches generate partition, each pattern belongs to one and merely a single cluster. Because of that, the clusters in hard clustering techniques are dislodged. Fuzzy clustering enlarges this notion to connect each pattern with every cluster by means of a membership function. The outcome of such algorithms is clustering, although not a partition.

The Level-Set technique (LSM) is a conceptual framework that involve numerical analysis of surface and spaces. The advantage of LSM is that one can perform numerical calculations involving curves and surfaces on a fixed Cartesian grid without having to model this object [51]. The LSM can easily be followed from the topology of changing shape, for example, when the shape is split into two split forms or the shape develop some holes, or otherwise from these operations. The advantages and disadvantages of each segmentation techniques are shown in Table 1.

Table 1
Comparison for Segmentation Techniques

Segmentation Technique	Advantages	Disadvantages
Manual Segmentation	Reliable to delineate structures of the brain images.	Depending on human skill ability, time-consuming and produce different results of the ROI.
Edge Detection	Correctly segment region with the same properties and generating connected region.	Difficult to represent object-level information.
Thresholding Technique	Simple and computational fast.	Limited applicability to segment region with overlap homogeneity.
Watershed Transform	Segments multiple regions at the same time. It produces a complete contour of the images and avoids the need for many contour joining.	Easily produce over-segmentation.
Fuzzy C-Means	Defines sharp boundary for segmented region.	Noise sensitive.
k-Means	Faster computation than hierarchical clustering, if keep k value smalls.	The number of clusters is uncertain.
Level Set	Topological changes are naturally possible.	Computationally expensive.

IV. TRENDS IN STROKE SEGMENTATION TECHNIQUES

Abdel-Maksoud (2015) stated that image segmentation is considered the most essential and crucial process for facilitating the delineation, characterization, and visualization of ROI in any medical image [52]. A hybrid clustering technique was proposed by the researchers using the k-Means clustering technique integrated with the FCM algorithm using T1, T2, and proton density weight images. This technique is proposed for the FCM technique in reducing the number of iterations done by initializing the right cluster centres to obtain qualitative segmentation results with less execution time. It is followed by thresholding and level set segmentation stages to provide an accurate brain tumor detection by removing the remaining noise from the clustering technique. The results show that the k-Means obtain 92.49% and FCM obtains 95.23% accuracy.

Zhang (2015) proposed a segmentation technique by using a deep convolutional neural network to segment the infant brain tissue images which involve WM, GM, and CSF. The MRI images involved in this technique were T1, T2, and DWI images. In the proposed approach, multiple intermediate layers were added such as convolution, pooling, normalization to capture highly nonlinear mapping between inputs and outputs. The drawback of this technique was the patches that were extracted from each tissue type of each patient were not homogenized resulting in bad prediction performance. The results show that the Dice coefficient for 10 DWI sample patients is in the range of 0.8 [53].

Haeck (2015) proposed an automated model-based segmentation for ischemic stroke lesions. An expectation-maximization approach was used for estimating intensity models for both normal and abnormal brain regions using DWI and FLAIR images. A level-set formulation was adopted, that eliminates the need for manual initialization of the level-set. The performance of the technique for segmenting the ischemic stroke was summarized by an average Dice score of 0.51 [54].

Reza (2015) proposed a segmentation technique for ischemic stroke lesions using local gradient and texture features. The MRI images involved in this technique were T1, T2, DWI, and FLAIR images. The framework of the technique proposed consists of local texture feature extraction, intensity inhomogeneity correction, structure tense based local gradient feature, and feature selection. The average Dice result obtained for the MRI images by the technique proposed was 0.59 [55].

Chen (2015) proposed a novel framework for ischemic stroke lesion segmentation in multi-modality MRI images using random forest (RF). The MRI images involve in this technique were T1, T2 FLAIR, and DWI images. The framework of the proposed technique was image normalization, features extraction, classification, and post-processing. The feature extraction involves the features which are extracted from the patch intensity. The features were employed in the RF classifier to classify the dataset whether the brain image contains a lesion or not. The average result obtained by this technique was 0.55 [56].

Telrandhe (2016) propose a technique for detecting brain tumours from benign and malignant classes using MRI images [57]. The detection involved the segmentation technique from the k-Means algorithm and the classification technique from SVM. The brain image was preprocessed with median filter, morphological operation and wavelet transform before segmenting the brain tumour using the k-Mean technique. Histogram-oriented gradient (HOG) was proposed to extract the ROI from the noises and the features of the ROI were used as the classifier input of the SVM technique. From the segmentation and classification technique, the percentage accuracy obtains from the proposed technique is 80%.

Robben (2016) proposed a voxel-wise, cascade classification approach to segment the stroke lesion using T1, T2, and DWI images. The dataset was first pre-processed using Random Forest inhomogeneity before being normalized using the histogram to improve the pathology robustness. A voxel-wise classification approach was implemented to classify the set of features of a voxel whether the voxel contains a lesion or not. The classification approach was implemented using a cascade classifier where the classifier decides with a remarkably high probability that the voxel does not contain lesion or not. The limitation of the approach was the number of features is limited and the computation time is large. The average Dice index result obtained by the researchers was 0.57 [58].

Adam (2016) presented an approach using features of the infarction incidence in classifying the ischemic stroke from embolic, thrombotic, and haemorrhagic using the decision tree technique. The technique proposed has improved the classification process of each type of stroke to help medical doctors in monitoring ischemic stroke patients. From the classification technique proposed, the overall sensitivity obtained was 0.99 [59].

Kiranmayee (2017) proposed an effective analysis for MRI brain tumours using hybrid data mining techniques. In the proposed approach, segmentation and classification techniques were applied. The segmentation technique applied is the k-Means and the classification technique that applied are the nearest neighbor with generalization (NNge), Best-First decision tree (BFTree), decision tree, LADtree, and random forest. These techniques were able to classify the type of abnormal and normal region include tumour region from the brain data set. The performance of the proposed techniques was analyzed using true positive rate (TPR), false positive rate (FPR), receiver operating characteristic (ROC), Area and accuracy. The accuracy for NNge, BFTree, decision tree, LADtree and random forest is 96.3%, 66.7%, 66.7%, 85.2% and 96.3%, respectively [60].

Havaei (2017) proposed Deep Neural Networks (DNNs) that were able to segment 75 patients with brain tumours using T1, T2, and fluid-attenuated inversion recovery (FLAIR) images. In the proposed approach, the CNN is designed with a two-pathway architecture that learns about the local details of the brain as well as the larger context. The researchers also proposed a two-phase training procedure which is critical to deal with imbalanced label distributions. The result gains from the proposed technique are the CNN was able to distinguish the boundaries between tumour sub-class and improve the Dice index on all tumour regions. However, the drawback of this technique it consumed high processing time. Therefore, high-performance GPU was mandatory. Based on the proposed technique, the dice coefficient, sensitivity, and specificity obtain are 0.84, 0.88, and 0.84, respectively [61].

Batra and Kaushik (2017) proposed an automatic segmentation and classification technique to detect the Gliomas in the MRI brain tumour. The segmentation technique proposed involved the FCM technique and the classification technique involved the SVM technique. The MRI brain tumour was segmented, and the lesion was categorized into two types which are malignant and benign. The SVM classifier was chosen to classify the tumour. Based on the proposed technique, the results for the automatic segmentation and classification were 98.18%, 97.5%, and 100% for the accuracy, sensitivity, and specificity, respectively [62] .

Saad (2017) proposed the FCM segmentation technique to segment the stroke lesion of acute and chronic ischemic stroke. Due to the failure of the FCM technique to separate chronic stroke lesions with CSF, a correlation template was integrated with the FCM technique to separate the lesion. For the classification technique, the rule-based classifier was used to classify the type of stroke based on the features extracted from the segmentation area. The results of accuracy, specificity, and sensitivity were 84%, 83.33% and 84.38%, respectively [7].

El-Melegy (2018) proposed an automatic brain tumour segmentation from a machine learning classifier including random forest, LDA, and SVM using MRI modality from T1, T2, and FLAIR images. The researcher segments the whole tumour, tumour core, and active core by involving the processing, feature extraction training and classification stage. The proposed technique shows that the Dice score obtained was in the range of 0.8 with the highest score is from the random forest classifier with 0.89 [63].

Subudhi (2018) proposes an automatically delineated ischemic stroke lesion from DWI using a watershed-based segmentation algorithm. The algorithm was incorporated with the fuzzy connectedness to detect the edges of the brain structure without applying a threshold value. The fuzzy connectedness sharpened the edges of the brain structure which help to improve the gradient between the lesion and the normal tissue. The lesion was extracted for the random forest classifier to classify the partial anterior circulation system (PACS) and lacunar syndrome (LACS) stroke type. The accuracy obtained from the proposed technique is 80% [64].

Ruba (2020) proposed with modified semantic segmentation networks (CNNs) based method has been proposed for both MRI and CT images. Classification is also employed in the proposed work. In the proposed architecture brain images are first segmented using a semantic segmentation network which contains series of convolution layers and pooling layers. Then the tumour is classified into three distinct categories such as meningioma, glioma, and pituitary tumour using the GoogLeNet CNN model. The proposed work attains better results when compared to existing methods [65].

Díaz-Pernas (2021) present a fully automatic brain tumour segmentation and classification model using a Deep Convolutional Neural Network that includes a multiscale approach. One of the differences in his proposal with respect to previous works is that input images are processed in three spatial scales along different processing pathways. This mechanism is inspired by the inherent operation of the Human Visual System. The proposed neural model can analyze MRI images containing three types of tumours: meningioma, glioma, and pituitary tumour, over sagittal, coronal, and axial views and does not need preprocessing of input images to remove skull or vertebral column parts in advance. The performance of the method on a publicly available MRI image dataset of 3064 slices from 233 patients is compared with previously classical machine learning and deep learning published methods. In the comparison, the method remarkably obtained a tumour classification accuracy of 0.973, higher than the other approaches using the same database [66]. The summary for review of the MRI segmentation techniques proposed by other researchers is shown in Table 2.

Table 2
Summary of Segmentation Results

Author	Lesion	Technique	Results
Saad (2017, [7])	Acute & Chronic Stroke	FCM	Accuracy = 84%
Abdel-Maksoud (2015, [52])	Tumour	• k-Means • FCM	k-Means = 92.49% FCM = 95.23%
Zhang (2015, [53])	Infant brain tissue	• Deep CNN	Dice = 80%
Haeck (2015, [54])	Ischemic stroke	• Expectation maximization • LSM	Dice = 0.51
Reza (2015, [55])	Ischemic stroke	• Local gradient • Texture	Dice = 0.59
Chen (2015, [56])	Ischemic stroke	• Random Forest	Dice = 0.55
Telrandhe (2016, [57])	Tumour	• k-Means • SVM	Accuracy = 80%
Robben (2016, [58])	Ischemic stroke	• Voxel-wise	Dice = 0.57
Havaei (2017, [61])	Tumour	CNN	Accuracy = 81%
El-Melegy (2018, [63])	Tumour	• Random Forest • LDA • SVM	Random Forest = 89% LDA = 85% SVM = 88%
Subudhi (2018, [64])	Ischemic stroke	• Watershed • Random Forest	Accuracy = 95%
Ruba (2020, [65])	Tumour	• CNN • GoogLeNet CNN	Accuracy Meningioma=99.57% Glioma =99.78% Pituitary Tumours. =99.56%
Díaz-Pernas (2021, [66])	Tumour	Deep CNN	Accuracy =97.30%

V. CONCLUSIONS

This paper has reviewed the MRI brain segmentation and classification techniques for brain stroke. From the review, it has been known that DWI measures the strength of molecular motions of diffusion within a tissue structure or boundaries of WM and GM brain tissues, CSF and brain lesions which have their own diffusion criteria and can be restricted by the diseases. While the image contrast depends on the diffusivity, where chronic stroke with high diffusion (watery tissues) appears dark (hypointense), and acute stroke with low diffusion appears bright (hyperintense). Conventionally, the differential diagnosis of brain lesions is performed manually by professional neuroradiologists during a highly subjective, time-consuming process. In response, computer-aided detection/diagnosis (CAD) has been developed for accurate diagnosis and to reduce the time required.

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