

# Automated Stroke Lesion Detection and Diagnosis System

N. Mohd Saad, N. S. M. Noor, A.R. Abdullah, Sobri Muda, A. F. Muda and N. N. S. Abdul Rahman

**Abstract**—This study proposes a technique for automated detection and diagnosis of stroke lesions based on diffusion-weighted imaging (DWI). The technique consists of several stages which are pre-processing, segmentation, feature extraction, and classification. The proposed analytical framework of this study is based on Fuzzy C-Means (FCM) segmentation, statistical parameters for features extraction and rule-based classification. The three-dimensional (3D) view is developed to enable observing directions of the gained 3D structure along the three axes. The segmentation results have been validated by using Jaccard and Dice indices, false positive rate (FPR), and false negative rate (FNR). The results for Jaccard, Dice, FPR and FNR of acute stroke are 0.7, 0.84, 0.049 and 0.205, respectively. The accuracy for acute stroke is 90% and chronic stroke is 70%, while the sensitivity and the specificity is 84.38% and 83.33%, respectively.

**Index Terms**—Diffusion-Weighted Imaging (DWI), Segmentation, Fuzzy C-Means, Three-Dimensional Reconstruction

## I. INTRODUCTION

STROKE is a major health burden in Malaysia as well as worldwide. It is also one of the top five leading causes of death in Malaysia [1]. National Stroke Association of Malaysia (NASAM) stated that one of six people worldwide will suffer from the stroke in their lifetime and it is the third leading cause of adult disability [2]. Stroke is a clinical symptom that happens when the blood vessel is blocked or burst due to a blood clot. All the oxygen and nutrients supply will be cut off causing a syndrome characterize by rapidly developing symptoms or sign of focal neurologic

dysfunction due to a vascular cause [3]. Urgent treatment is needed to obtain less debilitating of stroke and for better recovery. Detection and diagnosis of brain stroke are the keys to implementing successful therapy and treatment planning. However, the diagnosis is a very challenging task and can only be performed by professional neuroradiologists [4].

Computer Aided Diagnosis (CAD) is needed to assist radiologists in interpreting medical images by using dedicated computer systems to provide a second opinion for clinical validation [5]. Studies on CAD systems and technology show that CAD can help to improve the diagnostic accuracy of radiologists. Today, diffusion-weighted imaging (DWI) of the brain has become common in emergency setting, such that it is considered as a key sequence for stroke imaging, and essential in the proper evaluation of most pathologic conditions [6]. This imaging technique provides high lesion contrast compared to other magnetic resonance image (MRI) sequences [7].

DWI measures diffusion of water molecules within the tissue structure on a pixel basis. Tissues in which water diffusion is reduced can, therefore, be readily detected as a hyperintense on DWI images, which has become the hallmark of detection of recent stroke lesion. Manual detection and segmentation of different tissues are very time-consuming compared to computer-aided techniques [8]. However, automatic image segmentation is still a troublesome issue with larger part of utilization due to the presence of noise and intensity inhomogeneity.

Fuzzy C-Means (FCM) is a popular technique proposed by many researchers for segmentation of medical images [8]. However, because of noises and intensity inhomogeneity, FCM technique fails in producing accurate results. Although, the original FCM algorithm provides superior results for segmenting noise free images, but its accuracy is low when the image is corrupted with noises. Therefore, FCM algorithm is modified to improve the segmentation results [9, 10, 11].

The purpose of this research is to develop an automatic method to detect and segment the brain stroke lesions from DWI images and to visualize the brain scan in three-dimensional (3D) view. The ability of MRI scan in converting the 3D brain images into multiple two-dimensional (2D) image slices in a various way may lead to certain necessary information being lost. This problem has attracted researchers to continuously seek towards the 3D reconstruction. The availability of 3D imaging has made disease diagnosis and surgical planning successful, which resulted in saving precious patient lives [12].

The proposed analytical framework of this study is based

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on FCM segmentation technique, statistical parameters for features extraction and rule-based classification. Finally, the performances of the proposed segmentation technique are evaluated based on Jaccard and Dice indices, false positive rate (FPR) and false negative rates (FNR). Acute and chronic stroke lesions have been evaluated through this analysis. For the classification performances, accuracy, sensitivity and specificity are evaluated. The three-dimensional (3D) view of the brain is created to visualize the segmented area of the stroke lesion.

## II. METHODOLOGY

### A. Proposed Analysis Framework

Fig. 1 shows the flow process of the proposed analysis framework. The process begins with DWI data collection, followed by pre-processing stage. After that the segmentation is applied to extract the region of interest (ROI) of the lesion. Then, the parameters for features extraction are calculated to be fed as input to a classifier. Finally, three-dimensional (3D) reconstruction is created.

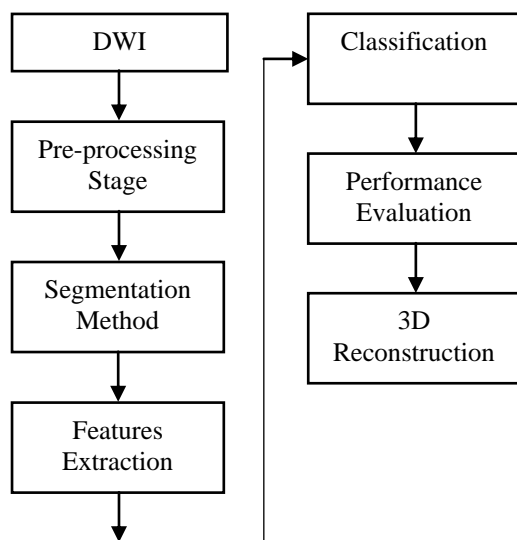


Fig. 1. Flowchart of Analysis

### B. Imaging Parameter

The DWI are gained from General Hospital of Kuala Lumpur using 1.5T MRI scanners Siemens Magnetom Avanto. The diffusion-weighted parameters obtained from this scanner are time echo (TE), 94ms; time repetition (TR), 3200ms; pixel resolutions, 256x256; slice thickness, 5mm; gap between each slice, 6.5 mm; of diffusion weighting known as b value, 1000s/ intensity mm<sup>2</sup> and total number of slices, 19. The data is encoded in 12-bit DICOM (Digital Imaging and Communication in Medicine) format. The dataset consists of 30 samples of acute stroke and 20 samples of chronic stroke. Overall, 50 images were taken for this analysis.

### C. Pre-processing Stage

The pre-processing stage is developed to acquire better segmentation results [13]. Three algorithms are applied which are image normalization, background removal, and image enhancement. Detail descriptions about pre-

processing stage is explained previously in [4].

### D. Fuzzy C-Means Segmentation

The flowchart of the proposed FCM segmentation is shown in Fig. 2. The segmentation begins with selecting a data point in three clusters which are the low, middle and high cluster. This algorithm functions by assigning membership to each data point corresponding to each cluster center on the basis of distance between the cluster and the data point. Fuzzy partition works based on minimizing an object function by iteratively updating membership function and cluster centers.

The iteration allows the data that belong to two or more clusters with different membership coefficients to become clusters. The process begin with generating the initial fuzzy partition matrix and then calculating the initial fuzzy cluster centers. The cluster centers and the membership grade point in each step of the iteration are updated, and the objective function is minimized to find the best position for the clusters. The process stops when the maximum numbers of iterations is reached, or when the objective function improvement between two consecutive iterations is less than the minimum specified amount of improvement. Morphological operation and correlation template are then utilized to dispense the dissonance in the image after the segmentation process. The details for the proposed segmentation algorithms are discussed in [13].

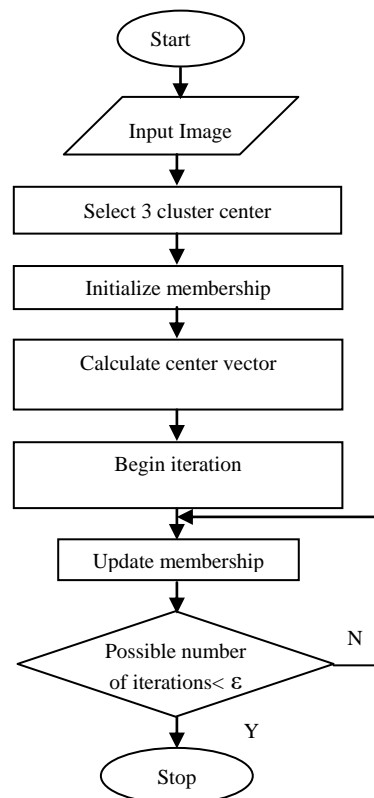


Fig. 2. Flowchart of FCM Algorithm

### E. Features Extraction

In this work, statistical features analysis in spatial domain are used to quantitatively describe the region pixels. Due to the small number of pixels count in the segmented regions, the calculation involve only one scale representations of the pixels and do not consider any spatial pixel's dependence. Meanwhile, the differential diagnosis in DWI images is mainly dependent on the signal intensity. Therefore, mode, standard deviation, mean, median and mean boundary are calculated as the parameters from the features for the stroke regions. The equations are given as follows:

$$\text{Mode} = \frac{|\text{mode} - \mu|}{\sigma} \quad (1)$$

$$\text{Standard Deviation} = \sqrt{s^2} \quad (2)$$

$$\text{Mean} = U = \frac{\sum x}{N} \quad (3)$$

$$\text{Median} = \frac{1}{2}(n+1)^{\text{th}} \text{ value} \quad (4)$$

### F. Classification

The overall process of classification is shown in Fig. 3. Rule-based classification is chosen in this study due to its simplicity for implementation as well as its ability to classify the stroke based on the given features.

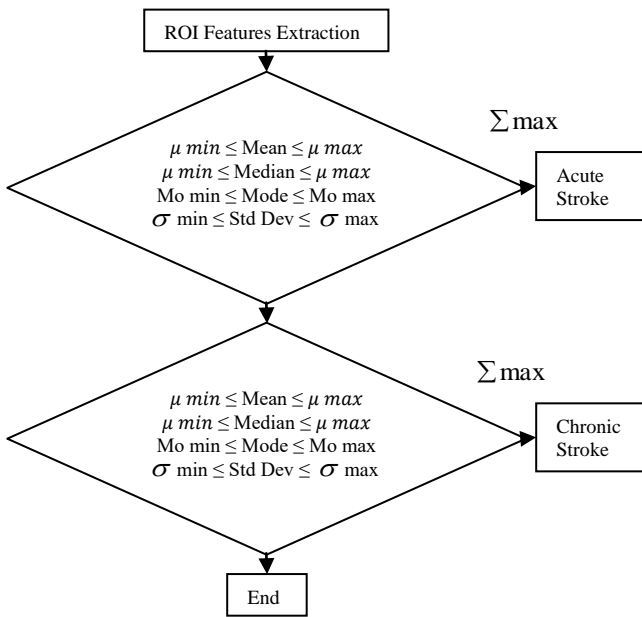


Fig. 3. Rule Based Classifier

### G. Performance Evaluation

Performance of the segmentation results is evaluated by comparing the results obtained from the analysis with the manual reference image which has been visually inspected by neuroradiologists. Jaccard, Dice, false positive rate (FPR), and false negative rate (FNR) are used as the performance metrics. FPR and FNR are used to quantify over-segmentation and under-segmentation results, respectively. High Jaccard and Dice, and low FPR and FNR

indicate high accuracy of the segmentation results. These metrics are computed by using the following equations [13]:

$$\text{Jaccard} = 100 \times \frac{A \cap G}{A \cup G} \quad (5)$$

$$\text{Dice} = 100 \times \frac{2|A \cap G^c|}{|A| + |G|} \quad (6)$$

$$\text{FPR} = \frac{A \cap G^c}{A \cup G} \quad (7)$$

$$\text{FNR} = \frac{A^c \cap G}{A \cup G} \quad (8)$$

The accuracy, sensitivity and specificity of the stroke classification is evaluated by using the equations as below [13]:

$$\text{Accuracy} = \frac{\sum \text{correct classification}}{\sum \text{number of sample}} \times 100 \quad (9)$$

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN}) \quad (10)$$

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP}) \quad (11)$$

The sensitivity of a classification are defined as the probability that a diagnostic test is positive, given that the person has the disease, while the specificity is a probability that a diagnostic test is negative, given that the person does not have the disease. The true positives (TP) is defined as correctly classified positive cases, true negatives (TN) is correctly classified negative cases, false positives (FP) is incorrectly classified negative cases, and false negatives (FN) is incorrectly classified positive cases.

### H. Three-Dimensional Reconstruction

Three-dimensional (3D) reconstruction is performed to display, analyze the regions and identify the location of the stroke lesions. The 3D images of the brain have unique characteristics and can be viewed in sagittal, frontal and transverse. Fig. 4 shows the flow process for constructing the 3D image of the brain.

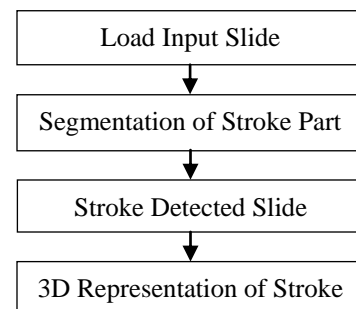


Fig. 4. Flowchart of 3D view

The steps are described as below:

*Step 1-* The brain MRI image slices are loaded using *dicomread* command.

*Step 2-* The stroke area present in the input image is automatically detected using the proposed segmentation technique.

*Step 3-* The brain and stroke slices, which are the output of the segmentation can be represented in the 3D view, which normally helps in finding out the exact shape and size of the stroke.

*Step 4-* The brain and stroke area is represented in the 3D view.

### III. RESULTS

#### A. Segmentation

The segmentation results of the original image from stroke lesions are shown in Fig. 5. The manual reference images are obtained from [4].

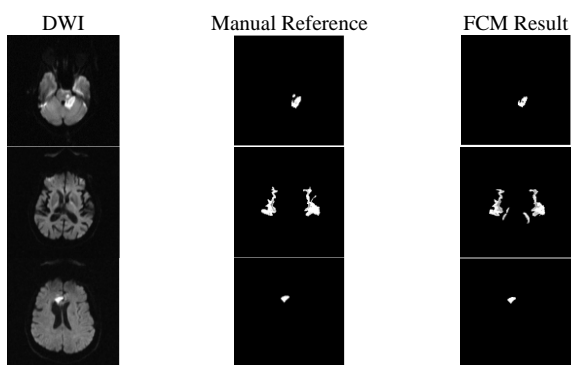


Fig. 5. The segmentation results of the original image from stroke lesion

Table I shows the average performance of the proposed FCM segmentation for 30 samples of acute stroke and 20 samples of chronic stroke. The performance of the algorithm is measured using the metrics such as Jaccard, Dice, FPR and FNR.

TABLE I  
PERFORMANCE ANALYSIS AND EVALUATION

Index	Acute Stroke	Chronic Stroke
Jaccard	0.7	0.4
Dice	0.84	0.53
FPR	0.049	0.284
FNR	0.205	0.273

Fig. 6 shows Jaccard index for the segmentation of acute stroke. Overall, 26 out of 30 patients able to achieve the segmentation results of above 0.5. The highest reading is 0.99 while the lowest is 0.41. Fig. 7 shows 7 out of 20 chronic stroke patient having above 0.5 with the highest rate is 0.86.

Fig. 8 and Fig. 9 show the results of Dice index for acute and chronic stroke samples, respectively. The highest index of acute stroke is 0.97 for Patient 9 and 19 while the lowest index is 0.34 for Patient 2. Fig. 9 shows that Dice index of a chronic stroke at the highest rate is Patient 11 with 0.97.

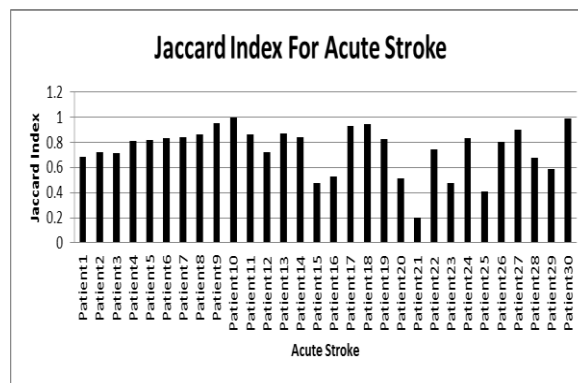


Fig. 6. Jaccard index of acute stroke

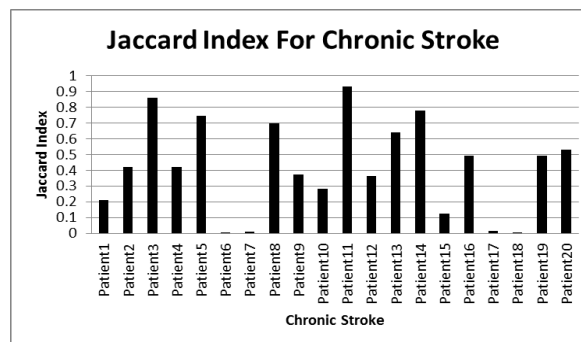


Fig. 7. Jaccard index of chronic stroke

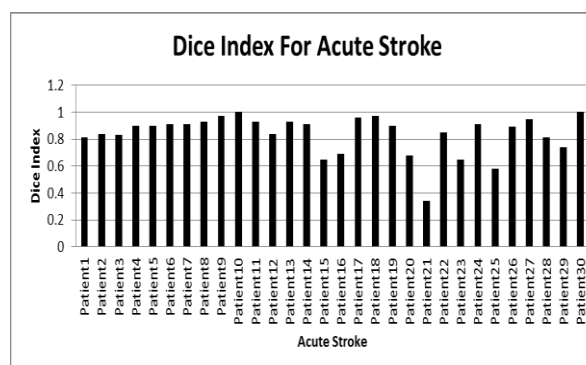


Fig. 8. Dice index of acute stroke

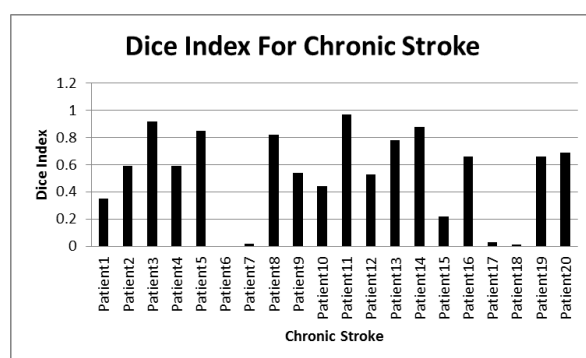


Fig. 9. Dice index for chronic stroke

#### B. Classification

The performances of the segmentation results have been evaluated to show the accuracy of the technique. The table of actual versus prediction cases in the classification of multiple classes is shown in Table II, which relates to the overall classification accuracy, sensitivity, and specificity of each class.

TABLE II  
CONFUSION MATRIX FOR CLASSIFICATION

Actual	Predicted		
	Acute Stroke	Acute Stroke	Chronic Stroke
	Acute Stroke	27	3
Chronic Stroke	5	15	

From Table II, the accuracy for acute stroke is 90% and for chronic stroke is 75%. The sensitivity of both cases is 84.3% and specificity is 83.33%.

C. Three-Dimensional Reconstruction

A proper graphical user interface (GUI) is designed which allow the system is used by simply clicking the buttons. In order to work with the brain images, the user needs to enter the path directory which holds the initial dicom format. After that, the user can view the 3D images, segmentation images and the details parameters of the features extraction. Fig. 10 shows the GUI for the proposed system. Fig. 11 visualized the image slices in axial view.

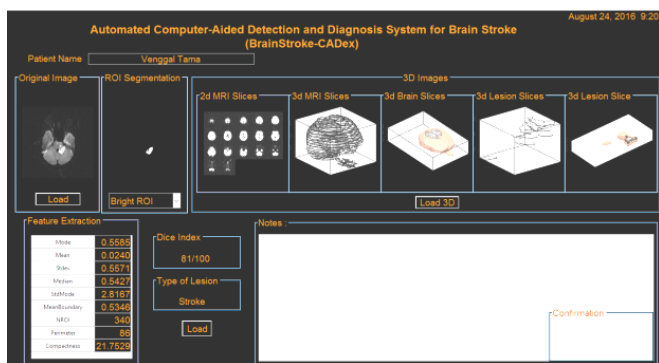


Fig. 10. Main GUI

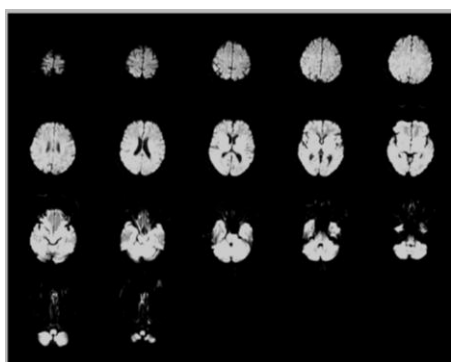


Fig. 11. The segmented brain outlier

Fig. 12 and Fig. 13 show the 3D view that shows the segmented stroke regions. For Fig. 8, the yellow color is the abnormal lesion in each slice of the brain and in Fig. 13, it shows the brain iso-surface of the stroke lesion.

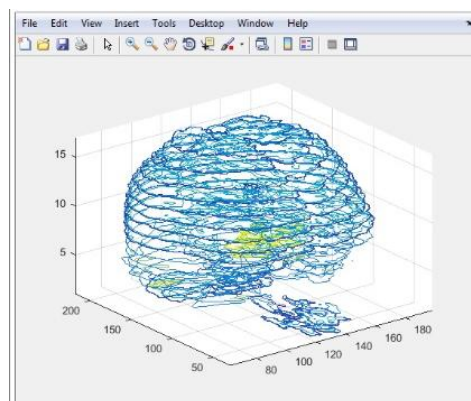


Fig. 12. 3D view to show segment of stroke in the brain

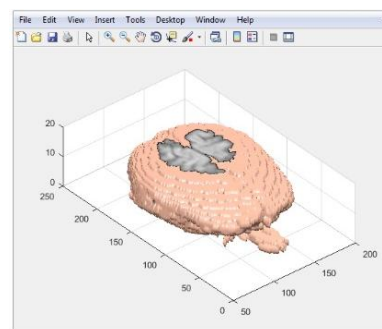


Fig. 13. The brain in 3D

Fig. 14 shows the movie player for the segmentation result of overall DWI slices of the patient. It contain 17 slices of the brain images. In this figure, slice 3 to slice 8 have abnormal stroke regions, while the rest slices are normal. Finally, Fig. 15 shows the segmentation outer of the stroke lesion for each slice in coordinate view.

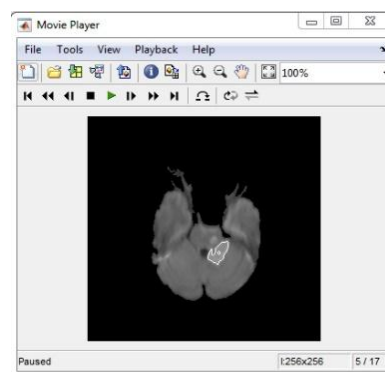


Fig. 14. Movie player to show the region of stroke lesion

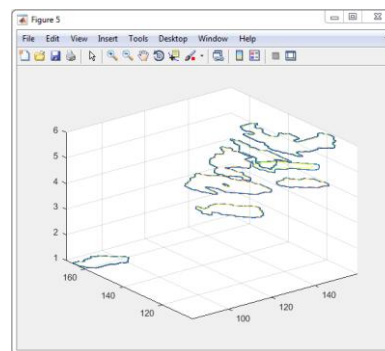


Fig. 15. The region of stroke lesion for each slice in coordinate view

#### IV. CONCLUSION

Diffusion-weighted imaging (DWI) is considered as the most sensitive technique in detecting stroke and is useful in giving details of the component of the stroke lesions. In this study, new approach for automatically detecting, segmenting and classifying of stroke from DWI are introduced. Fuzzy C-Means (FCM) algorithm is proposed to segment the stroke lesions in DWI. Jaccard, Dice, false positive rate (FPR) and false negative rate (FNR) are used as the segmentation performance evaluation metrics. The results demonstrated that the FCM algorithm provides better segmentation results in acute stroke lesion according to the high values of Jaccard and Dice indices and low values of FPR and FNR. The results for Jaccard, Dice, FPR and FNR of acute stroke are 0.7, 0.84, 0.049 and 0.205, respectively. The accuracy for acute stroke is 90% and chronic stroke is 70%, while the sensitivity of the lesion is 84.38% and the specificity is 83.33%. Finally, the DWI images have been reconstructed in three-dimensional (3D) view showing that it has a good visualization of the stroke lesions.

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