MRI Brain Abnormalities Segmentation using K-Nearest Neighbors (k-NN)

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***Abstract*—Segmentation of medical imagery remains as a challenging task due to complexity of medical images. This study proposes a method of k-Nearest Neighbor (k-NN) in abnormalities segmentation of Magnetic Resonance Imaging (MRI) brain images. A preliminary data analysis is performed to analyze the characteristics for each brain component of "*membrane*", "*ventricles*", "*light abnormality*" and "*dark abnormality*" by extracting the minimum, maximum and mean grey level pixel values. The segmentation is done by executing five steps of k-NN which are determination of *k* value, calculation of Euclidian distances objective function, sortation of minimum distance, assignment of majority class, and determination of class based on majority ranking. The k-NN segmentation performances is tested to hundred and fifty controlled testing data which designed by cutting various shapes and size of various abnormalities and pasting it onto normal brain tissues. The tissues are divided into three categories of "*low*", "*medium*" and "*high*" based on the grey level pixel value intensities. The overall experimental result returns good and promising segmentation outcomes for both light and dark abnormalities.**

Keywords-k-Nearest Neighbor (k-NN); brain abnormalities segmentation, Magnetic Resonance Imaging (MRI)

I. INTRODUCTION

Human have extraordinarily large and complex brains. The anatomy of the brain is complex due its complicate structure and function [1]. The brain is the part of the central nervous system. It is the centre to control the mental processes and physical action of a human being. Brain abnormality is a symptom where motor impairment and neuropsychological problems affect the central nervous system. It is an abnormal growth of cells within the brain, which can be cancerous or non-cancerous [2]. To date, numerous researches of brain abnormality detection had been conducted due to its important roles in identifying anatomical areas of interest for diagnosis, treatment, or surgery planning paradigms [3].

Magnetic Resonance Imaging (MRI) is a primary medical imaging modality that commonly uses to visualize the structure and the function of human body [4]. It provides rich information for excellent soft tissue contrast which is especially useful in neurological studies [5]. In previous years, MRI is observed to play an important role in brain abnormalities research in determining size and location of affected tissues [6].

Image segmentation refers to a process of assigning labels to set of pixels or multiple regions [7]. It plays a major role in the field of biomedical applications as it is widely used by the radiologists to segment the medical images input into meaningful regions. Thus, various segmentation techniques in medical imaging depending on the region of interest had been proposed [8]. Medical image segmentation problems has been approached with several solution methods by different range of applicability such as Particle Swarm Optimization [9], Genetic Algorithm [7], Adaptive Network-based Fuzzy Inference System (ANFIS) [10], Region Growing [11], Self Organizing Map (SOM) [12] and Fuzzy c-Means (FCM) [13].

However, segmentation of medical imagery remains as a challenging problem due to the complexity of the images. Brain tissue is a particularly complex structure and its segmentation is an important step for studies in temporal change detection of morphology [14]. Success of MRI in the detection of brain pathologies is very encouraging. However, diagnosis and locations of abnormality are made manually by radiologists. It consumes valuable human resources, error sensitive [15] and making it prone to error [16]. Tool is needed to save time as manual segmentation is tedious, less accurate and require long time to complete [17]. Therefore, extensive effort is needed in order to find reliable and accurate algorithms to solve this difficult problem.

K-Nearest Neighbor (k-NN) classification technique is the simplest technique conceptually and computationally that provides good classification accuracy [18]. The k-NN algorithm is based on a distance function and a voting function in k-Nearest Neighbours, the metric employed is the Euclidean distance [19]. The k-NN has higher accuracy and stability for MRI data than other common statistical classifiers, but has a slow running time [20]. Yet, the issues of poor run time performance is not such a problem these days with the computational power that is available [21].

Therefore, this paper proposes a technique of k-NN in segmenting MRI brain abnormalities as it is found as a relevant method for our problem. A preliminary data analysis is performed to analyze the characteristics for each brain component of “membrane”, “ventricles”, “light abnormality” and “dark abnormality” by extracting the minimum, maximum and mean grey level pixel values. The segmentation is done by executing four steps of k-NN which are determination of k value, calculation of Euclidian distances objective function, sortation of minimum distance, assignment of majority class, and determination of class based on majority ranking. The accuracy of the segmentation performances are then statistically measured using Receiver Operating Characteristic (ROC) analysis.

The organization of the rest of this paper is as follows: Section II presents our methods, including the overview of k-NN methods and descriptions of the algorithm structure. Section III discusses our results and discussions. Finally, we present our conclusion in Section IV.

II. METHODS

In this study, the proposed segmentation algorithm consists of four main stages which are data acquisition, preliminary data analysis, segmentation of brain abnormalities using k-NN and result analysis as illustrated in Fig. 1.

A. *Data Acquisition*

Hundred and fifty secondary data of Fluid Attenuated Inversion Recovery (FLAIR)-MRI brain images are acquired from Hospital Kuala Lumpur (HKL). These images are then pre-processed to strip the brain skull. Skull stripping is an important pre-processing step in neuroimaging analyses because brain images must typically be skull stripped before other processing algorithms [3]. The skull is stripped using a technique of region growing as the region may affect the outcome of segmentation performances. Fig. 2 depicted sample of original FLAIR-MRI before and after skull stripping.

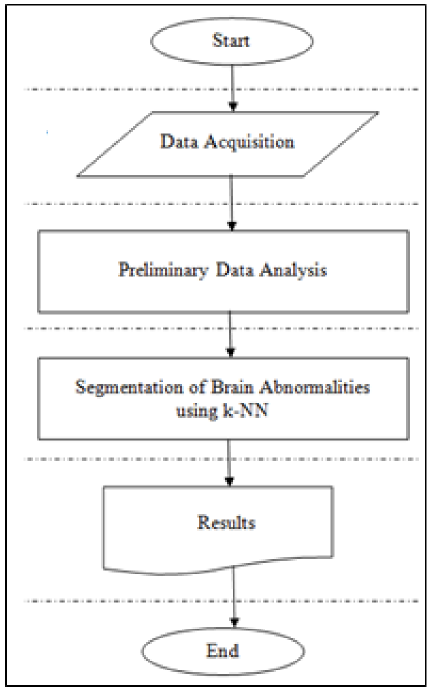
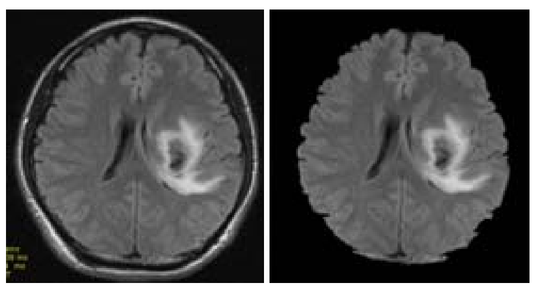


Figure 1. Proposed segmentation algorithm



(a) (b)

Figure 2. Original FLAIR-MRI brain image (a) and Skull stripped FLAIR-MRI brain image (b)

B. Preliminary Data Analysis

A preliminary data analysis is performed to analyze the characteristics for each brain component of “membrane”, “ventricles”, “light abnormality” and “dark abnormality” by extracting the minimum, maximum and mean grey level pixel values.

Region of interest (ROI) are extracted from 150 FLAIR-MRI brain images for distinguishing the patterns and characteristics of each brain component as shown in Fig. 3.

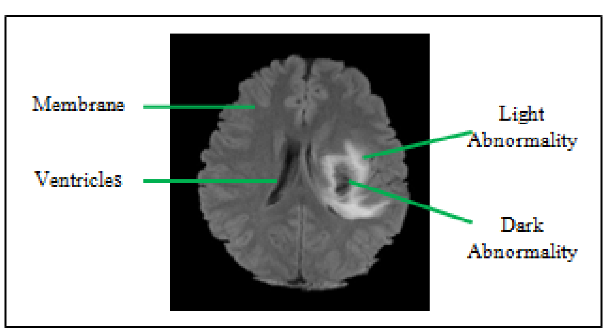


Figure 3. Proposed areas of brain ROI

The data analysis results are then tabulated into a reference table that produced the minimum, maximum and mean range of grey level pixel values for each brain component. Table I tabulates the summary of reference table produced.

TABLE I. SUMMARY OF REFERENCE TABLE

Brain Component	Minimum Range	Maximum Range	Mean Range
Ventricle	1 - 45	15 - 60	10 - 50
Dark Abnormality	5 - 65	15 - 80	10 - 95
Membrane	65 - 120	75 - 130	70 - 120
Light Abnormality	120 - 205	130 - 230	120 - 215

C. Segmentation of Brain Abnormalities using k-NN

The proposed brain abnormalities segmentation method is based on k-NN paradigm. The k-NN rule is used to construct a lookup table of class, indexed by pixel value.

As illustrated in Fig. 4, the proposed k-NN segmentation is divided into six important steps which are:

1) Determination of k value: an important parameter affecting both the accuracy and execution time of the k-NN classification rule is *k*, the number of nearest neighbouring pixels to consider. The choice of variable *k* in k-NN classification is dependent on the relation between the number of features and the number of cases. A small value of *k* may influence the result by individual cases, while a large value of *k* may produce smoother classification outcomes. After a few testing performed, the most suitable value of *k* for this study is *k* = 10.

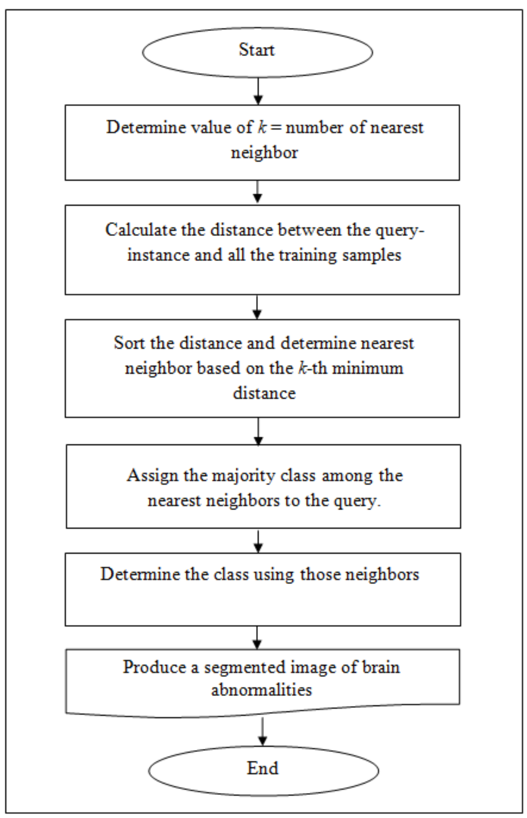


Figure 4. Proposed steps of k-NN segmentation

2) Distance calculation between the query instance and the training samples: the calculation of distance are executed between the query instance and 150 training samples. The formula of Euclidean distance as in (1) is used as the objective function, which the equation is as follows:

$$d_{ij} = \sum_{k=1}^{n} \left(x_{ik} - x_{jk} \right)^2 \qquad (1)$$

where x_{ik} is refers to the instance pixel points, whereas x_{jk} is concerns with the values of training samples. Table II tabulates a few samples of Euclidean distance calculation which the value of minimum, maximum and mean grey level values of the query instance is 54, 77 and 79.

TABLE II. SAMPLES OF EUCLIDEAN DISTANCE CALCULATIONS

Minimum value	**Maximum value**	**Mean value**	**Sum of square distance**
25	57	36	$[(54-25)^2 + (77-57)^2 + 79-36)^2]$ = 3090
67	78	69	$[(54-67)^2 + (77-78)^2 + (79-69)^2]$ = 270
45	73	54	$[(54-45)^2 + (77-73)^2 + (79-54)^2]$ = 722
14	35	21	$[(54-14)^2 + (77-35)^2 + (79-21)^2]$ = 6728
34	59	44	$[(54-35)^2 + (77-59)^2 + (79-44)^2]$ = 1910

3) Sortation of distance based on the k^{th} minimum distance: after all the Euclidean distances for each query instance are calculated, the distances are then sorted out. As shown in Table III, the square distance are sorted according to the most minimum square distance produced.

TABLE III. SORTATION VALUES OF SQUARE DISTANCE

Minimum value	**Maximum value**	**Mean value**	**Sum of Square Distance**	**Rank**
67	78	69	270	1
45	73	54	722	2
34	59	54	1910	3
25	57	36	3090	4
14	35	44	6728	5

4) Assignment of majority class: the first 10 (value of *k*) of query instances are then ranked based on the most minimum square distances produced. It will often make sense to assign more weight to the nearest neighbours in deciding the class of the query. Classifying component is based on highest rank [22]. Table IV shows the result of brain component.

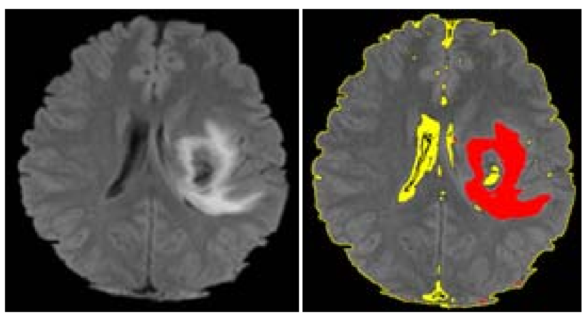
TABLE IV. ASSIGNMENT OF MAJORITY CLASSES

Brain component	Min value	Max value	Mean value	Sum of Square Distance	Rank
Dark Abnormality	67	78	69	270	1
Dark Abnormality	45	73	54	722	2
Ventricle	34	59	54	1910	3
Membrane	25	57	36	3090	4
Light Abnormality	14	35	44	6728	5

5) Determination of class: each query instance is then classified based on the majority categories of brain component it belongs to. From the sample discussed, it can be determined that the query instance is belongs to "ventricles".

6) Segmentation of brain abnormalities: after each query instance from the overall part of brain image are classified, the brain abnormalities are then identified and segmented.

Fig. 5 shows a sample of k-NN abnormalities segmentation. The red colour of segmentation represents the light abnormality, whereas the blue colour of segmentation depicted the dark abnormality region.



(a) (b)

Figure 5. Skull stripped FLAIR-MRI brain image (a) and Skull stripped FLAIR-MRI brain image after k-NN segmentation (b)

D. Result Analysis

The performances of k-NN abnormalities segmentation is tested to 150 controlled testing data. The data is designed by cutting various shapes and size of various abnormalities and pasting it onto normal brain tissues. The tissues are divided into three categories of "low", "medium" and "high" based on the grey level pixel value intensities as shown in Table V.

TABLE V. BACKGROUND IMAGES

Background Image	**Intensity**	**Minimum pixel value**	**Maximum pixel value**	**Size in pixels**
	Low	30	114	12144
	Medium	39	145	12144
	High	56	202	12144

Fig. 6 shows the process to produce the testing data of abnormality images in different background intensities.

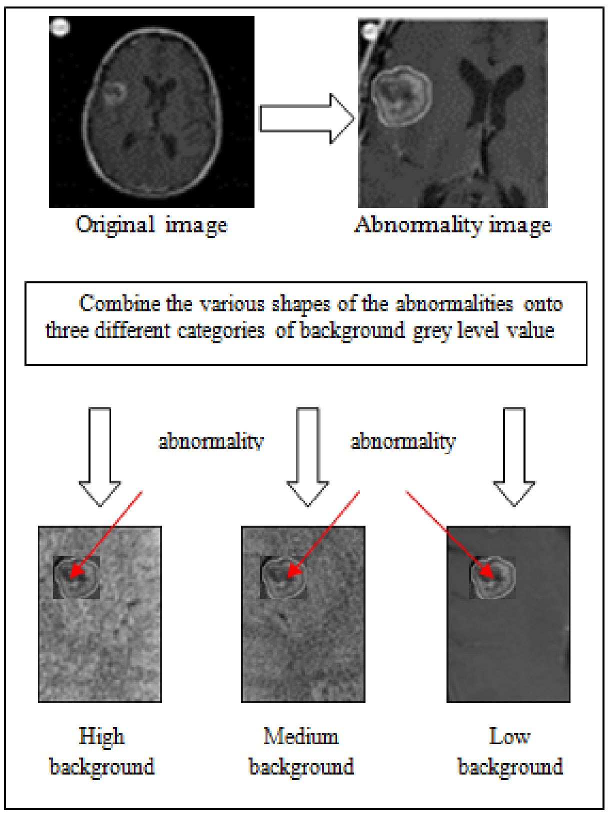


Figure 6. Testing data creation

A statistical method of Receiver Operating Characteristic (ROC) analysis is employed to quantify the k-NN segmentation accuracy. ROC analysis is a plot of the true positive fraction versus the true negative fraction that produced by classifying each data point as positive and negative according to outcome [23].

In this paper, the numbers of pixels of the raw MRI brain testing images are compared with the segmented abnormality area. ROC is used to measure the value of false positive, false negative, true positive and true negative. The sample of four conditions areas of false positive, false negative, true positive and true negative during the segmentation are illustrates in Fig. 7, while the explanation and of each condition is tabulated in Table VI.

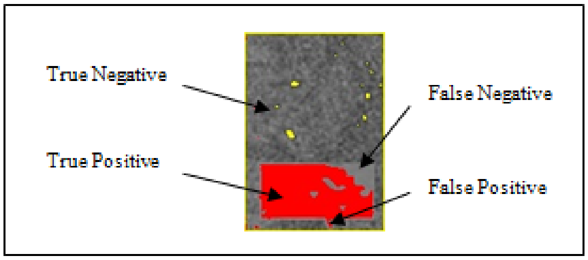


Figure 7. Primary conditions of ROC analysis

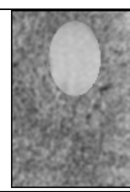
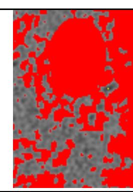
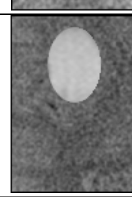
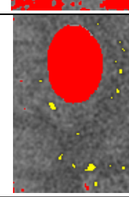
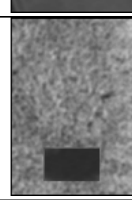
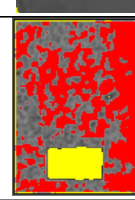
TABLE VI. CONDITIONS OF ACCURACY

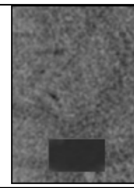
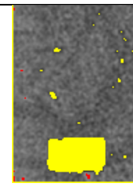
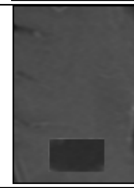
Condition	Description
False Positive	the normal areas that are incorrectly detected as abnormality
False Negative	the abnormality areas that are not detected
True Positive	the abnormality areas that are correctly detected
True Negative	the normal areas that are correctly undetected

III. RESULTS

Hundred and fifty testing images had been tested in measuring the performances of the proposed k-NN segmentation technique. Table VII tabulates a few samples of light and dark abnormalities segmentation of testing data produced.

TABLE VII. SAMPLES OF TESTING DATA SEGMENTATION

Abnormality	Background Intensity	Testing Image	k-NN Segmentation
Light	High		
	Medium		
	Low		
Dark	High		

	Medium		
	Low		

The segmentation accuracy performances are statistically measured using ROC analysis. This statistical result is important to determining the efficiency and effectiveness of the proposed k-NN technique in segmentation for brain abnormalities. The summary of ROC analysis for k-NN segmentation is tabulated in Table VIII.

TABLE VIII. SUMMARY OF ROC ANALYSIS OF K-NN SEGMENTATION

Abnormality	**Background Gray Level Value**	**Mean of False Positive**	**Mean of False Negative**	**Mean of True Positive**	**Mean of True Negative**
Light	High	0.446	0	1	0.554
	Medium	0.001	0.063	0.937	0.999
	Low	0	0.107	0.893	1
Dark	High	0.004	0.064	0.936	0.996
	Medium	0.023	0.005	0.995	0.977
	Low	0.073	0	1	0.927

From the Table VIII, the k-NN is observed to produce almost excellent segmentation performances in medium background grey level value for light abnormality. The statistics show that the combination of light abnormality within the medium background grey level value produced the highest mean values for both true positive and true negative, which are the most important conditions in producing good quality of segmentation. These conditions proved that the k-NN segmentation results showed some potential as the mean values of false positive and false negative are kept at a perfect rate as well. The combination of light abnormality within the low background grey level value is also monitored to produce high mean values for true positive and true negative, although they are slightly less performed than the medium background grey level value. The combination of light abnormality within high background grey level value produced poor segmentation performances since it appears as the highest mean value of false positive compared to medium and low background grey level value. This is found to be caused by the similarity of texture for both light abnormality and high background grey level value that leads the neighboring pixels to grow outside the abnormality areas.

In contrast, the dark abnormalities segmentation is also successfully performed in medium background grey level value. The combination of dark abnormality within medium background grey level value tend to produce the highest mean values of true positive and true negative as compared to the low and high background grey level values. The combination of dark abnormality within the low background grey level value is also cannot be underestimated as it produced high mean values for both true positive and true negative as well. The result of high background grey level value also produced good segmentation although a small occurrence of false positive mean value is observed.

IV. CONCLUSION

This paper has presented a technique of k-Nearest Neighbours (k-NN) for abnormalities segmentation of FLAIR-MRI brain images. The overall experimental result returns good and promising segmentation outcomes for both light and dark abnormalities, which makes the proposed k-NN technique as a potential technique in solving the segmentation problem in medical imagery. The k-NN segmentation is observed to produce good segmentation outcomes in both medium and low background grey level values for light and dark abnormalities. However, the segmentation performances for light and dark abnormalities within the high background grey level value are found to be unsatisfactorily especially for light abnormality. These may results from the confusion of distinguishing the similar texture of high background grey level value with the light abnormality. Therefore, several improvements are needed to enhance the segmentation outcomes in future.

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