

# **Classification of Brain Hemorrhage using Textural Analysis**

by

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Dissertation submitted in partial fulfilment of

the requirement for the

Bachelor of Engineering (Hons)

(Electrical and Electronics)

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CERTIFICATION OF APPROVAL  
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In partial fulfilment of the requirement for the  
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(ELECTRICAL AND ELECTRONICS)

Approved by,

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TRONOH, PERAK

JANUARY 2015

## **CERTIFICATION OF ORIGINALITY**

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledges, and that the original work contained herein have not been undertaken or done unspecified sources or persons.

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Frenchlyn Maglinao Duran

## ABSTRACT

In order to assist in fast diagnosis of brain hemorrhage, computer-aided diagnosis have been developed in recent years. Image processing and analysis is considered to be an important area as technological tool for medical evaluation and diagnosis. With this, we decided to venture in the image processing and analysis of brain hemorrhage. Image processing comprises of different techniques and phases, wherein each techniques intend to contribute to the accuracy of medical diagnosis. With only few studies on image processing for the diagnosis of brain hemorrhage, there is a need to improve the algorithm of image processing for accuracy and robustness.

This project presents an algorithm that is able to classify the type of hemorrhage for each CT scan images that will be tested. The methodology comprises of three main processes which are; segmentation, feature extraction and classification using Neural Network in MATLAB. Morphological reconstruction as the technique used for segmentation of brain hemorrhage region was very time consuming since it is supervised type of segmentation. Supervised segmentation is when you continually change the parameters of structure elements that you want to extract from the image. Automation is a challenge due to the diversity of brain hemorrhage in size and shape. Four textural features which are entropy, mean, variance and inverse difference moment feature were chosen from Haralick texture features which are calculated based on gray-level co-occurrence matrix. These four textural features are known to have the best accuracy when combined. The proposed algorithm is effective in classifying between the four types of brain hemorrhage(cerebellar, extradural, intraventricular and subdural), however improvements can still be done to increase the accuracy of the system.

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# CHAPTER 1

## INTRODUCTION

### 1.1 Background

Neurovascular hemorrhage or in other term brain hemorrhage is a condition wherein blood vessels burst or ruptured and cause spillage within brain or the space between the brain and skull (Liebeskind, 2014). The breakage in the wall of blood vessel is either due to traumatic injury, high blood pressure, vascular malfunctions, aneurysm or usage of medication for thinning of blood.

Identifying the type of brain hemorrhage is crucial in the approach of appropriate treatment. According to Sharma et al. (2008), the accuracy of the diagnosis of a physician can be considered moderate to good, with of course lower reliability when it comes to less experienced and less confident examiners. In order to help in increasing the clinician's confidence in oneself ability in the analysis of neurovascular images, computer-aided diagnosis (CAD) have been developed in the recent years. It is claimed that assessing neurovascular images differ from person to person. Duncan and Ayache (2000) highlighted that with the goal to help in clinical analysis and studies, multiple researches have been conducted in the field of medical image analysis. The introduction of CAD leads to the drastic reduction of work load for the radiologists. Peng et al. (2008) and Guld et al. (2007), emphasize that with the use of CAD system for digital medical imaging, the demand for well-organized medical image processing techniques has increased.

Image processing and analysis is considered to be an important area as a technological tool for medical evaluation and diagnosis (Kucheryavski, 2007). In summary, image processing comprises of different techniques and phases, wherein each techniques intend to contribute to the accuracy of medical diagnosis. Therefore in this research

work, we aim to develop a simple system using Neural Network in MATLAB that can characterize between four types of brain hemorrhages which are; cerebellar, extradural, intraventricular and subdural hemorrhage.

## **1.2 Problem Statement**

Computed Tomography (CT) is known as a non-invasive technique used to scan the human body (Seletchi & Dului, 2007). It is done by the use of radiation that is detected by series of sensors (Cicala, 1999). Due to the sensitivity of the sensors used, CT scan is able to show the structure of the brain, blood vessels and other tissues within the skull. CT is known for its convenience for unconscious patients. Since majority of unconscious patients have unstable vital signs, magnetic resonance imaging (MRI) is not possible. CT scan images of the brain contain little information thus requiring more computations (Seletchi & Dului, 2007). Each pixel of CT image convey its corresponding gray value. Thus, regions can be identified in CT images based on the difference of gray value. CT scan images in different angles are used for analysis for abnormalities present.

Common problem of researchers is the limitation of CT scanning for head images. The limitations are known to be due to partial volume effects which affect the edges produce low brain tissue contrast and yield different objects within the same range of intensity. Since each pixel in a CT image represents the attenuation properties of a specific material volume, if that volume is comprised of a number of different substances then the resulting CT value represents some average of their properties. This is termed the partial-volume effect. Furthermore, because of the inherent resolution limitations of CT, all material boundaries are blurred to some extent, and thus the material in any one voxel (graphic information that defines a point in three dimensional space) can affect CT values of surrounding voxels. Although these factors can make CT data more problematic to interpret quantitatively, they also represent an opportunity to extract unexpectedly fine-scale data from CT images (High resolution X-ray CT Facility, 2014). With these elaborated limitation, image segmentation based on intensity value will not be efficient enough.

Medical experts stated that segmentation of CT scan images of brain is very significant; however on the contrary is very time consuming. To aid in the aforementioned problem, the best way to solve by automating this process even though we can see a struggle due to the variations of brain hemorrhage in different locations. However, since doing an automation system for classifying between the four subtypes of hemorrhagic stroke needs more time than what is allotted, we have decided to just analyze the CT scan images in a simple diagnosis system by segmentation and classification between the four types of brain haemorrhage using Neural Network toolbox in MATLAB.

### **1.3 Objectives**

In general this project aim, to classify the images of brain hemorrhage using image processes and analysis in MATLAB. The approaches are divided into three parts:

- i. To execute brain hemorrhage CT scan image analysis (segmentation and classification) using MATLAB.
- ii. To present an approach to distinguish the four types of brain hemorrhage using Neural Network toolbox in matlab.
- iii. To verify the accuracy of the system in classifying brain hemorrhage by testing external images (not from the database used in training the system).

The result of the image segmentation and classification should be useful for further or higher implementation.

### **1.4 Scope of Study**

In order to describe the boundaries of the research and basically point out what needs to be done, it is crucial to point out the scope of study. In this research, the scope of study is mainly on the image analysis methods which are the following:

- a) Segmentation
  - Skull Extraction

- Hemorrhage region extraction
- Superimpose both extracted regions
- b) Feature extraction
  - Extract textural features based on the chosen optimal combination of texture features.
- c) Classification using Neural Network Classifier
  - Using extracted textural features as input
- d) Evaluation of accuracy of the system
  - Testing the system with external images.

## **1.5 Relevancy and feasibility**

According to A.D.A.M. (2011), heart related sickness and stroke (ischemic stroke and hemorrhagic stroke) are considered to be the main reason of death. Trauma, vascular malformations, tumour related hemorrhage and hypertension are the factors that can possibly influence the occurrence of brain hemorrhage that lead to stroke. Within the mentioned factors anyone of us can be a victim due to any accidents, hereditary diseases that gives the possibility of having brain hemorrhage. However, no matter what are the main factors that cause the brain hemorrhage, the crucial first step is to diagnose it first. Determining the type of brain hemorrhage as mentioned earlier means analysing the neurovascular image of the patient. Thus, doing computer-aided diagnosis or medical image analysis researches is a stepping stone of saving lives. Texture analysis on neurovascular image has important implications in diagnosis and treatment of brain hemorrhage. Having a computer based system that uses textural feature in characterizing the clot or blood rupture for the hemorrhage region may lead us in determining the severity and cause of the brain hemorrhage. Therefore studies on the account of medical image analysis are significant to the recognition and categorization of the hemorrhage.

The classification and segmentation will be done using MATLAB. Since, we are having difficulty in finding CT scan brain image database therefore, we decided to use online images. With this limitation in the quality and number of CT scan brain images, it is possible that this may reduce the efficiency of our system.

## **CHAPTER 2**

### **LITERATURE REVIEW**

In order to differentiate between the four types of brain hemorrhage and to identify other conditions, neuroimaging is required. However, there is no specified type of neuroimaging modality. Mostly it depends on its availability, eligibility and the presence of patient contraindications. However having mentioned that, the most common and used neuroimaging modality is the CT scan due to its convenience and availability.

Our focus is on the classification of brain hemorrhage based on the textural features of the four chosen subsets of intracranial hemorrhages. We can classify each as either intra-axial (within the brain) or extra-axial hemorrhage (space between the brain and skull) named derived from their respective location of injury. Intra-axial hemorrhage subset types include cerebellar, intraventricular, lobar, and pontine hemorrhage whereas extra-axial hemorrhage subset types includes extradural hemorrhage, subdural hemorrhage and subarachnoid haemorrhage (Goel & Gaillard, n.d.). Each of the subsets of hemorrhage have different aetiology, demographics, treatment and prognosis (Skandhan & Jones, n.d.). Within these subsets of brain haemorrhage, we chose to characterize between four types of brain hemorrhage which are; cerebellar, extradural, intraventricular and subdural hemorrhage. Cerebellar hemorrhage is primarily rooted from poorly controlled hypertension and also by an underlying lesion like any vascular malformation (Gaillard, n.d.). While intraventricular hemorrhage (IVH) indicates the presence of blood in the ventricular system of the brain. This occurrence is responsible for the development of hydrocephalus in many cases of patients (Knipe & Jones, n.d.). On the other hand extradural hemorrhage (EDH) is known to be the accumulation of blood between the outer layer of dura and the skull. EDH is quite distinct due to its typical biconvex in shape. EDH is commonly

associated with patients with trauma and skull fracture (Gaillard, n.d.). Whereas subdural hemorrhage (SDH) is the accumulation of blood in the space between the dura and arachnoid mater of the meninges around the brain. Similar with EDH, it is usually caused by head trauma. The classic appearance of SDH is a crescent-shaped that spread diffusely over the affected hemisphere (Muzio & Gaillard, n.d.). Stroke caused by brain hemorrhage may catch you unaware for it can happen suddenly, develop quickly and can damage the brain within minutes. In some cases, a stroke may continue to develop for several hours to a day or two. Stroke symptoms may sometime be very confusing for physicians and patient. In order for patients to be suitable in receiving therapy depends solely on the accuracy and immediate evaluation of the cerebrovascular disease. In other words, physicians must quickly assess the person with suspected stroke since they cannot afford to lose the narrow time window that they have for the effectiveness of surgery and therapy.

Imaging techniques that are used in evaluating hemorrhage includes CT scan, MRI scan and ultrasound B scan. CT scan wherein its stroke protocol includes; non-contrast, CT angiography, and perfusion. While MRI scan stroke protocol includes; Diffusion Weighted Imaging and Apparent Diffusion Coefficient. CT scan images are known to be good in detecting mass lesions like brain abscess and acute hemorrhage. However, it is not that good in detecting ischemic stroke (Duncan & Ayache, 2000). The main goal of CT scan is to distinguish the stroke mimics and detect hemorrhages. On the other hand, MRI have better sensitivity and resolution than that of CT scan thus it is good in detecting ischemic stroke unlike CT scan (Padma and Sukanesh, 2011).

We have decided to use CT scan as most free downloadable images online are those of CT scan images and because it is also good in detection of hemorrhage.

Texture is considered to be the most important features when classifying images. In order to optimize the analysis of texture, choosing multiple varied features are needed based on the properties of texture images. Thus, designing a method which is efficient in classifying textures associated or rooted from the textural properties and characteristics will surely aid in the design of a system for classifying texture.

Segmentation and classification are possible like as done in human vision system when using texture together with brightness information collectively known as textone

(Textons, 1981). Functionality of human vision system includes recognition of objects; perception of depth; and identification of different textures.

## **2.1 Related Works and Cross-referencing**

### **2.1.1 Segmentation Techniques**

Dividing a digital image into group of pixels is what segmenting of images is all about. Most applications does require accurate and time saving techniques in segmenting images. The data gathered from segmentation are helpful in characterization and analysis purposes. Challenges regarding automatic segmentation of the CT brain images have many different approaches. Both Richard et al. (2007) and Zhang et al. (2001) proposed a technique in segmentation of images which is called recognition technique by statistical pattern. While Kaiping et al. (2007) presented an adequate particle swarm optimization algorithm to segment brain images and to point out both cerebro spinal fluid (CSF) and neglecting abnormal regions. On the other hand, Loncaric et al. (1997) and Matesn et al. (2001) recommended the rule based approach in order to show the regions with hemorrhage, calcification, and stroke lesion which are known to be abnormal regions. Another technique which is segmenting CSF from CT scan images was suggested by Ruthman et al. (1993) by using local thresholding technique. This technique is rooted from maximum entropy principle. Luncharic et al. (1993) suggested the use of both k means clustering and Neural Networks for segmenting CT scan images into skull, brain, calcification and background. Whereas Tong et al. (2009) recommended to segment same parameters including CSF by the use of two stages unsupervised clustering.

With these different types of segmentation techniques, we chose to use the local thresholding technique to extract the skull first hand. Then we proceed with marking of foreground objects using morphological reconstruction to retrieve hemorrhage regions. At the end, the segmented images of the skull and hemorrhage regions are superimposed and will be used to extract its textural features to be fed into the Neural Network classifier.

### **2.1.2 Feature extraction and classification**

The goal of pattern recognition is to determine the patterns and sub patterns present in a given image. According to Jain et al. (2000), an algorithm used for pattern recognition comprise of the following subsystems; 1) subsystem to determine the region of interest, 2) subsystem to extract selected features and 3) subsystem for classification. The region of interest which is in this case is the combination of the skull and hemorrhage region which is normally defined in supervised mode. Having the region of interest only present in a resulting image, the desired features will be extracted from it and finally will be fed in the classification subsystem.

There are three primary approaches for feature extraction and classification for pattern recognition based on types of features known as: 1) statistical approach, 2) syntactic or structural approach, and 3) spectral approach. Comparing these three approaches leads to a deduction where spectral approach is less efficient and that statistical method is more efficient for random patterns. On the other hand, syntactic approach is much useful for complex patterns (Sharma et al., 2008).

In this work, we have decided to use the features extracted using co-occurrence matrix method based on statistical description of gray level of an image. In addition, deciding the textural features to be used for the Neural Network Pattern recognition is based on the promising results of Padma and Sukanesh (2011) research wherein they primarily used 13 textural features in different combinations for classification. As a result, they found that only a combination of four features namely: entropy, energy, variance and inverse difference mean feature, gives the highest accuracy and that employing more than 5 features will decrease the accuracy.



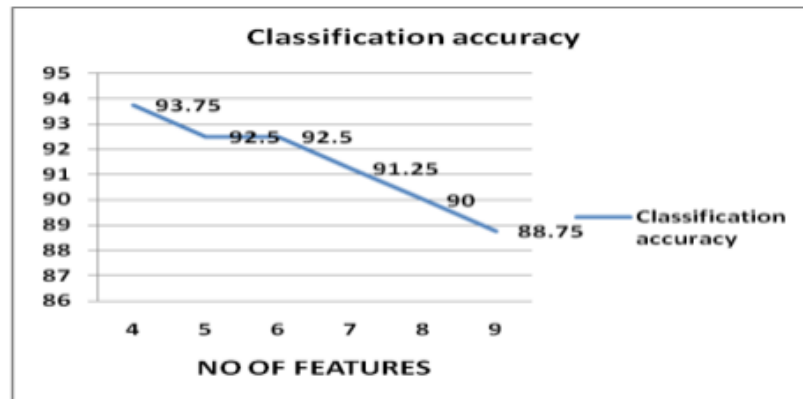


Figure 1. Classification accuracy with respect to different number of textural feature combinations.

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Therefore, in this research we will use only the four textural feature parameters (see section 3.4) that gives the highest classification accuracy in the previous research mentioned.

## CHAPTER 3 METHODOLOGY

### 3.1 Computer Based Texture Analysis System Algorithm

The main objective of this research is to present an algorithm that will be tested in classification of brain hemorrhage. Presented below is the proposed algorithm which is composed of three main processes: i) segmentation, ii) feature extraction, and iii) classification using Neural Network toolbox in MATLAB.

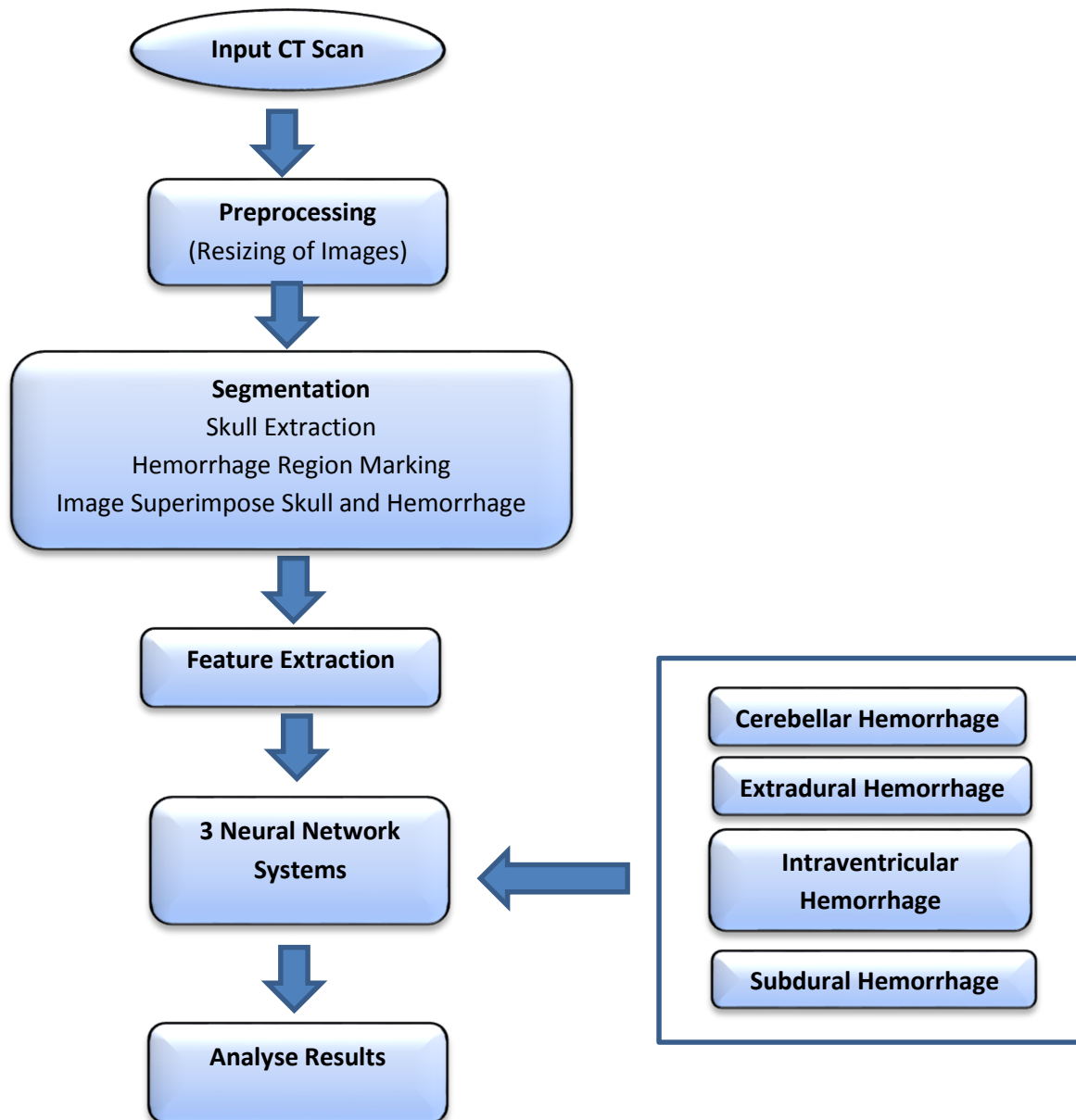


Figure 2. Texture Analysis Algorithm

### 3.2 Use of MATLAB for image processing

Based on Qidwai and Chen (2010), a picture or an image is a group of values arranged in the form of a matrix. Since MATLAB is well known to be good in operations regarding matrices, therefore it makes it very suitable for operation related to image analysis. MATLAB have Image Processing Toolbox wherein it has all the needed tools to perform or operate multiple geometric, logical, arithmetic and many other higher level transformations on images. The toolbox is also good in manipulating or processing color and grayscale images. However, most of the image processing is focused on grayscale images. Figure 3 and figure 4, below shows example of pixel values for grayscale image and black & white image consecutively.

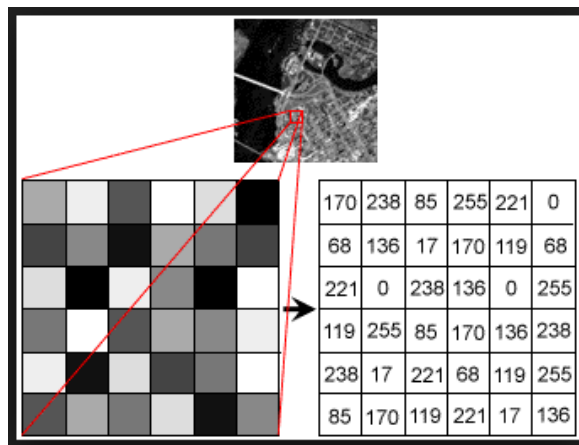


Figure 3. Pixel values of a grayscale image.

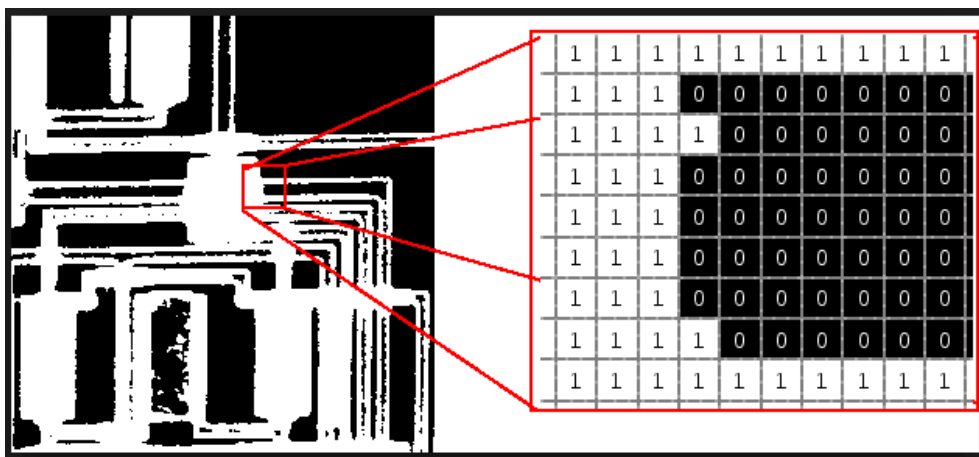


Figure 4. Pixel values of a black and white image.

### 3.3 Segmentation technique

On the other hand, segmentation as mentioned earlier is a valuable stage wherein it divides the image into portions with the same particulars. Examples of those properties or parameters used in dividing image into sections are gray level, color, texture, brightness, contrast and many more. Segmentation techniques can either be contextual or non-contextual. Non-contextual techniques doesn't bother about the association between features in an image. In non-contextual technique, pixels of an image are simply clustered or grouped based on some global attributes like its gray level. While in contextual techniques, it somehow look through the connection between the feature in the image. Therefore, contextual techniques have the possibility of grouping pixels that have the same grey levels and are connected and close to each other. Figure 5 below shows the operations that consist segmentation process.

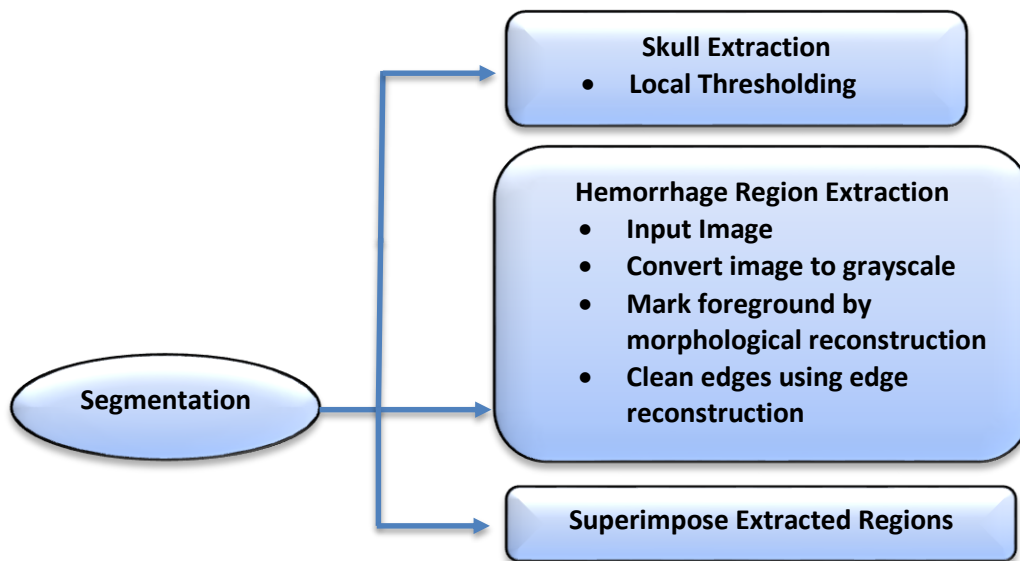


Figure 5. Segmentation Algorithm

#### 3.3.1 Skull Extraction

In this phase, we primarily used basic global pixel-based segmentation technique which is image thresholding. This type of segmentation is accomplished by scanning the image pixel by pixel and labeling each pixel as object or background, depending on whether the grey level is greater or less than the value of  $T$ .

$$g(x, y) = \begin{cases} 0 & f(x, y) < T \\ 1 & f(x, y) \geq T \end{cases}$$

Thresholding is very effective when using grey level histogram of the image to separate or group pixels of the background and the object into two dominant groups. At the same time, a threshold  $T$  can be easily chosen between the groups. Picking the threshold includes;

- 1) Human operator decided the threshold.
- 2) Use mean gray level of the image.
- 3) A fixed proportion of pixels are detected (set to 1) by the thresholding operation.
- 4) Analyzing the histogram of an image.

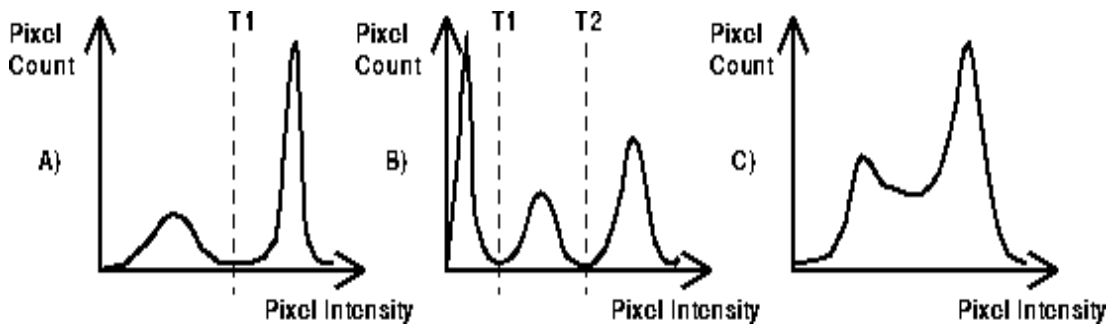


Figure 6. Examples of histogram.

The figure above consist of three different cases of histogram where A) is a classic bi-modal intensity distribution, wherein the image can be accurately segmented using a single threshold T1. Whereas B) is a bit more complex. Here, we assumed that the central peak is the region that we would like to separate segment and so threshold segmentation requires two thresholds: T1 and T2. In C), since the two peaks of a bi-modal distribution have run together and so it is not possible to successfully segment this image using a single global threshold.

Thresholding may be viewed as an operation that involves tests against a function  $T$  of the form:

$$T = T[x,y,p(x,y),f(x,y)]$$

Where  $f(x,y)$  is the gray level , and  $p(x,y)$  is some local property. This thresholding scheme is known to be Global Thresholding wherein it compares each pixels gray level with single global threshold.

If  $T$  depends on both  $f(x,y)$  and  $p(x,y)$  then this is referred to as local thresholding.

According to Ferrari (2012), an algorithm used to obtain  $T$  automatically for global thresholding is as follows :

- 1) Estimate initial value for  $T$ .
- 2) Using the estimated  $T$ , segment the image. Therefore it will segment an image into two groups of pixels:  $G1$  compose of all pixels with gray level values  $>T$  and  $G2$  compose of pixels with values  $<T$ .
- 3) Calculate the mean gray level values  $\mu1$  and  $\mu2$  for the pixels in regions  $G1$  and  $G2$ .
- 4) Calculate a new threshold value:  $T = \frac{1}{2}[\mu1 + \mu2 ]$
- 5) Perform steps 2 until 4 until the difference in  $T$  in successive iterations is smaller than a predefined parameter  $To$ .

Using this procedure, we will easily isolate the skull. Which we plan to superimpose with the hemorrhage region.

### 3.3.2 Hemorrhage Region Extraction

Morphology is the study of shapes and structures based on a general scientific perspective. Morphological filtering is a nonlinear transformation in order to transform geometric features of images. The original image will be transformed into another image through iteration with another image of certain shape and size which is known to be as the structuring element (Serra, 1982).

A set of structuring element is used to identify the shape that makes up an input image. The common morphological operations are known to be the morphological opening and closing with structuring elements. These operations have some inconveniences wherein if undesirable features are removed, the rest of the structures will be modified.

However, by using reconstruction it makes it possible to remove the undesirable structures without affecting the desirable structures.

Therefore by using the morphological image reconstruction it enables us to attain better results than the basic morphological opening and closing algorithm. The segmentation method provides as a resulting images wherein its foreground markers are the region that we are trying to segment. At the same time, segmentation method is applicable to gray-scale images.

In order to remove the undesirable regions we need to mark those regions that require segmentation, however it is hard to achieve appropriate markers automatically without any interaction by the user.

The algorithm we used in extracting the hemorrhage region is as following:

- 1) Read the color image and convert to gray scale.
- 2) Mark the foreground object or region using morphological reconstruction.
- 3) Clean the edges of markers using edge reconstruction and ‘bwareopen’ function.
- 4) Superimpose the foreground marker (hemorrhage region) with the extracted skull.

In this work, we decided to create foreground markers with the use of morphological image reconstructions. As mentioned, reconstruction-based opening and closing algorithm is good at removing blemishes without affecting the overall shapes of the objects. In short, the technique used is actually an erosion followed by a morphological reconstruction. In extracting the foreground marker, we will use structuring element (‘strel’) function specifically disk as the shape parameter, wherein size has to be adjusted by the user depending on the size of the hemorrhage. Using erosion to smoothen the extracted region tends to leave some stray isolated pixels that must be removed. We can remove all blobs that are lesser than a certain number of pixels using ‘bwareopen’ function. Calculating the regional maxima of these reconstructed images is done to get smooth edge foreground objects.

### 3.4 Feature extraction

The two classes of techniques that are extensively used for classification are the following: a) based on gray level and b) based on textural feature. Based on studies, gray level technique of classification will not give favourable results especially on medical images, whereas analysis based on texture are mostly used instead.

As decided, we are going to use the optimal design texture features combination with the highest classification accuracy based from the research of Padma and Sukanesh (2011) which are the following:

- i. Entropy – measure of randomness.

$$\text{Entropy: } H = - \sum_{i=0}^{G-1} P(i) \log_2 [P(i)] ;$$

- ii. Energy – measure of homogeneity.

$$\text{Energy: } E = \sum_{i=0}^{G-1} [P(i)]^2$$

- iii. Variance – measure of how much grey level area vary from mean.

$$\text{Variance: } \sigma^2 = \sum_{i=0}^{G-1} (i - \mu)^2 P(i)$$

- iv. Inverse difference median – measure of local homogeneity.

$$\text{Inverse difference: } = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{P(i,j)}{1+(i-j)^2}$$

The above features are extracted statistically from Gray Level Cooccurrence Matrix (GLCM). A GLCM is a matrix where the number of rows and columns is equal to number of gray levels,  $G$ , in the image. From  $P(i, j/\Delta x, \Delta y)$ , which is the matrix element with relative frequency with which two pixels are separated by a pixel distance  $(\Delta x, \Delta y)$ , occur within a given neighbourhood, one with intensity  $i$  and other with intensity  $j$ .

Therefore the following notations above are;

$G$  - the number of gray levels in image.

$i$  - intensity level.

$j$  - intensity level.

$\mu$  - mean value of  $P$ .



GLCM is a technique using statistics of inspecting texture that considers the spatial connection of pixels. This is also known as gray-level spatial dependence matrix. The GLCM function characterizes the texture of an image by computing how frequent pairs of pixels with specific values and in a specified spatial connection appear in an image, creating a GLCM ( Albreghsen, 2008). We then extract statistical measures from this matrix. After creating the GLCM, you can get several statistics using the ‘graycoprops’ function. These statistics provide information about the texture of an image as shown in Figure 7 below. Each column shows the four textural feature values for each image. The row consist of energy, entropy, variance and inverse difference median values accordingly. These sets of values are called the training sets which will be fed into the Neural Network for training purposes.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.0898	0.3597	0.1571	0.2382	0.3660	0.4041	0.1356	0.1256	0.3983	0.1075	0.1750	0.0778	0.3881	0.2984	0.3590	0.2341	0.2888	0.4022	0.2210	0.1
2	3.1338	1.9642	2.9477	2.5155	1.9838	1.8847	2.8802	2.9650	1.8790	2.8677	2.5085	3.2091	1.8527	2.2415	2.1818	2.5581	2.4034	1.8338	2.3804	3.4
3	44.9876	30.1858	39.6231	49.93...	39.1...	30.1920	55.66...	40.70...	37.12...	65.3930	58.4504	63.9990	34.45...	33.6848	27.2...	34.5257	30.0...	27.4764	48.5808	52.9
4	0.9651	0.9737	0.9456	0.9368	0.9569	0.9806	0.9632	0.9585	0.9783	0.9777	0.9784	0.9677	0.9819	0.9679	0.9648	0.9632	0.9572	0.9754	0.9765	0.9
5																				
6																				

Figure 7. Sample of extracted four textural feature for each images.

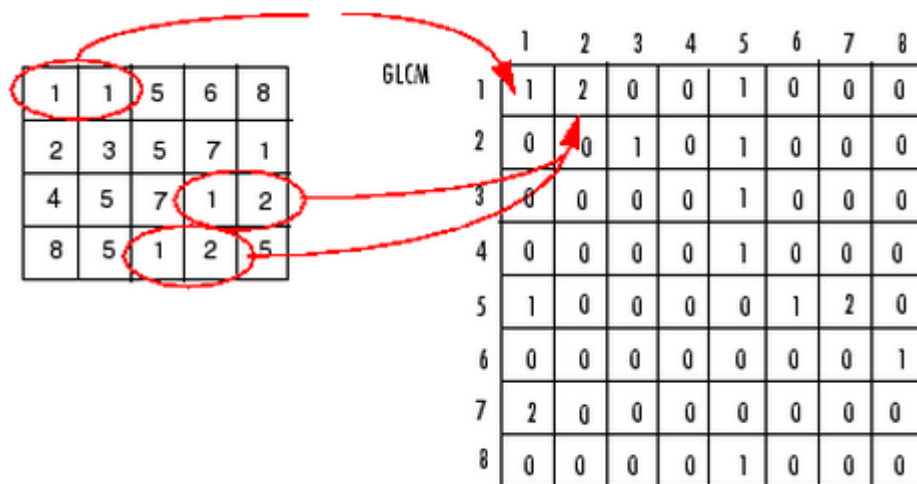


Figure 8. Process used to create GLCM

Based on Figure 8 above, the following elaborate how the gray co-matrix computes the first three values in a GLCM. In the GLCM matrix, element (1,1) composed of value 1 because there is only one occurrence in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. Whereas the element (1,2) contains the value 2 because there are two occurrences where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the GLCM has the value 0 because there is no occurrence of two horizontally adjacent pixels with the values 1 and 3. Continuously, 'graycomatrix' keeps on processing the input image, going through the image for pixel pairs  $(i,j)$  and recording the sums in the corresponding elements of the GLCM.

### 3.5 Classification Algorithm

These textural features from GLCM are further extracted for all images of the four types of haemorrhage, to be used as the database, and then they will be fed into the Neural Network for pattern recognition and classification.

The Neural Network is used for pattern detection; it receive the inputs(training set) and targets and generate a relationship between them. In this project, the Neural Network is used in detecting the difference between the four types of hemorrhages which the are cerebellar, extradural, intraventricular and subdural haemorrhage. Each of these inputs will be designated a certain target value to distinguish between the types. For example in 1 versus 1 (cerebellar versus extradural), cerebellar is set as '1' and extradural is set as '0'.

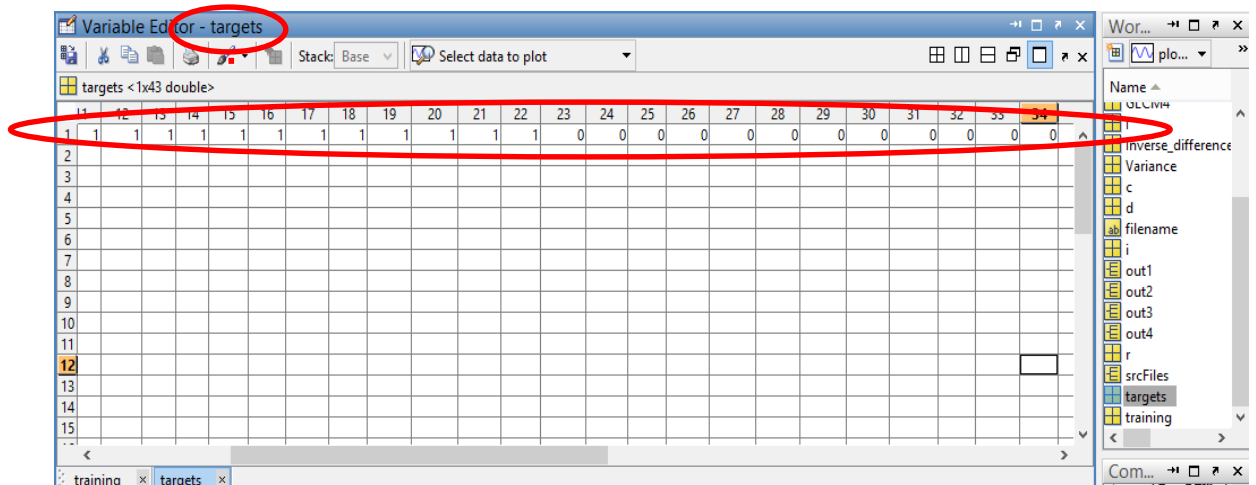


Figure 9. Each image are fixed as target value 1 or 0.

As shown in Figure 10, we will create Neural Network System based on both values of training set shown in Figure 5 and target values shown in Figure 7.

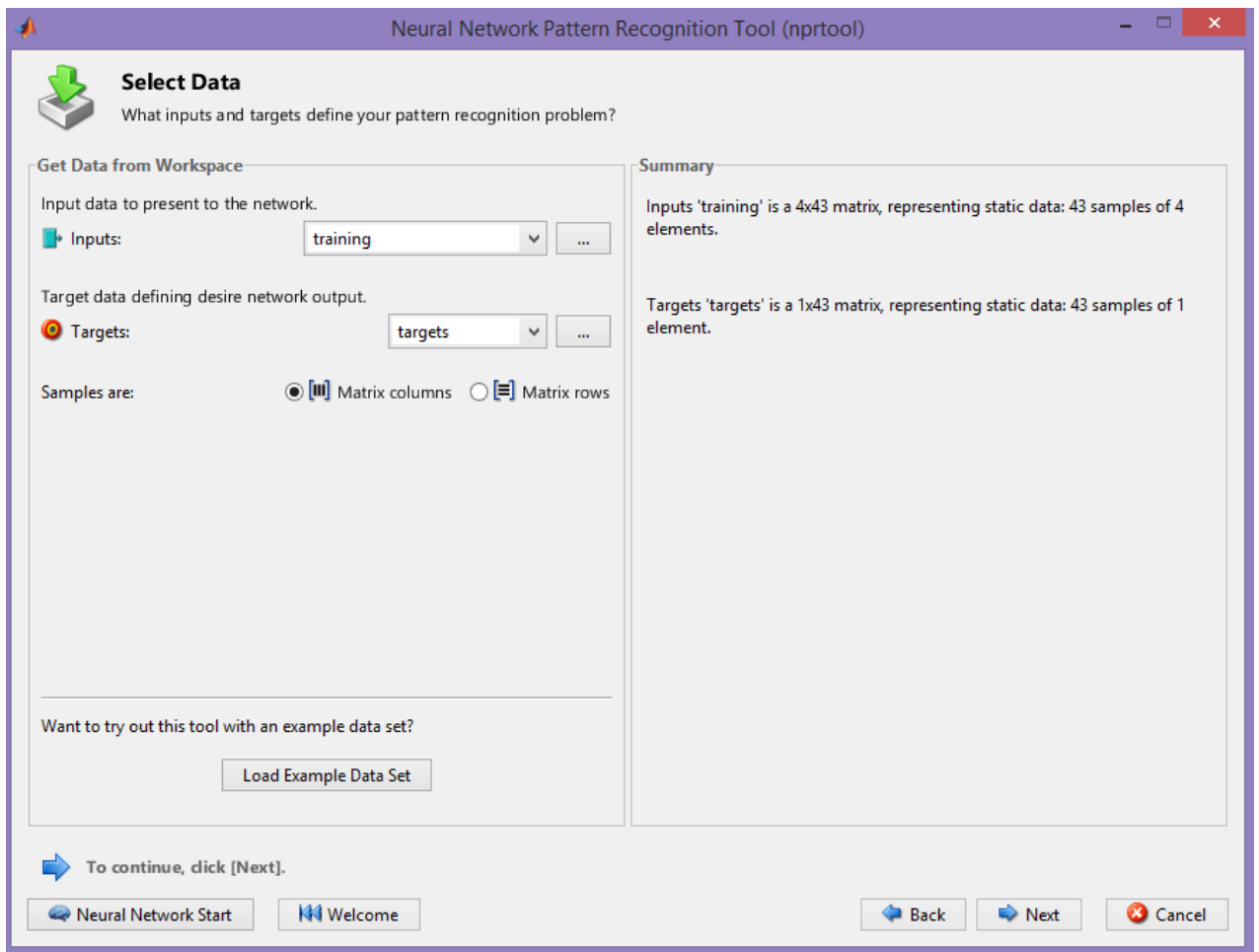


Figure 10. Creating Neural Network using Training values (Textural Feature vector of each image) and Target Values of each image.

The efficiency of the Neural Network solely depend on the input data, if the input data is not sufficient to extract the relation between the training sets and targets then the efficiency of the system will be low. Thus in order to obtain a better result, a large database of images is needed.

### 3.6 Project Activities and Key Project Milestone

The timeline for this research is divided into two parts since the span of time for the completion of this study is allotted for two semesters.

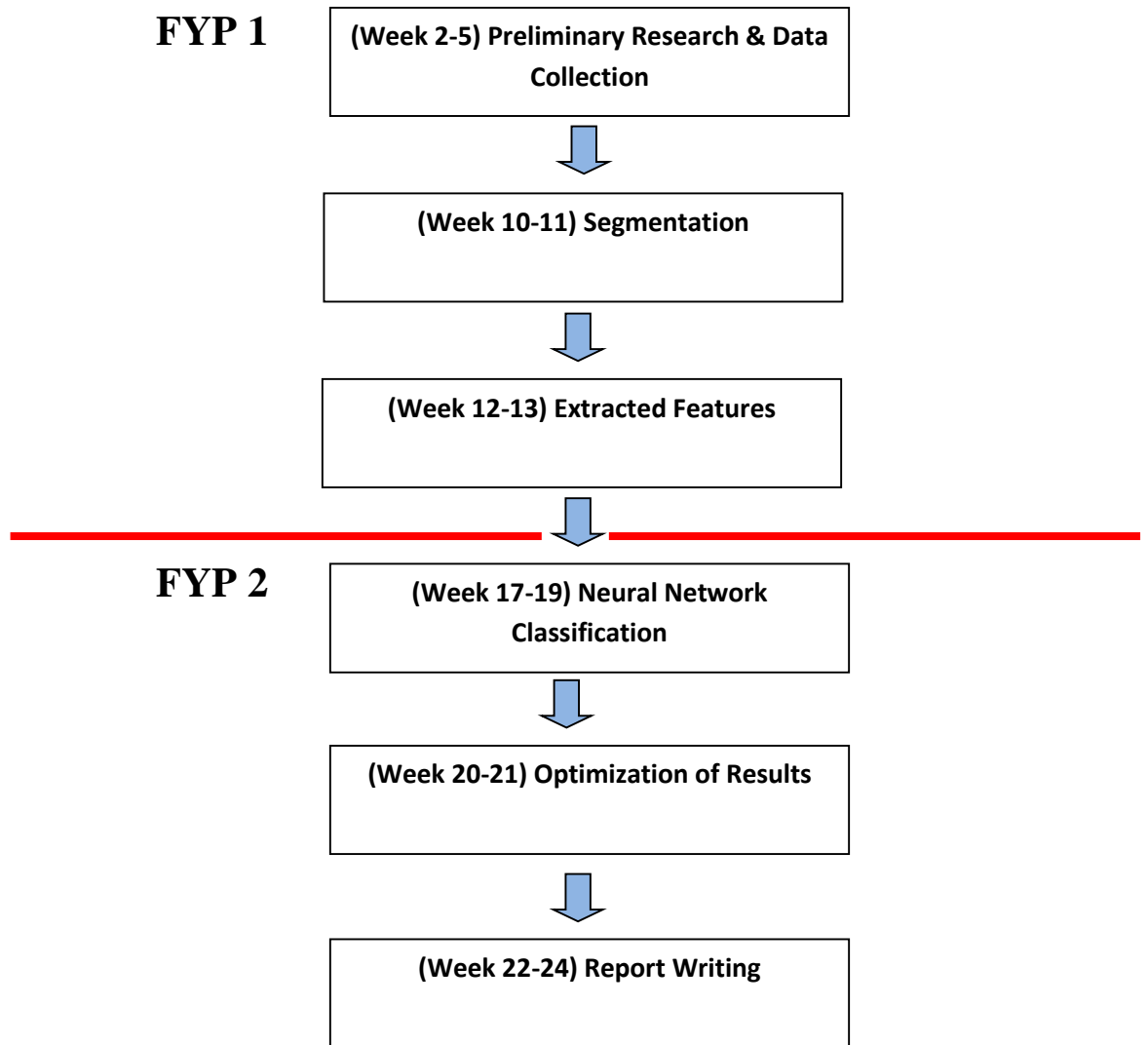
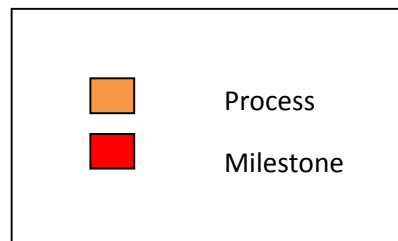


Figure 11. Project Activities and Key Project Milestone

### 3.7 Gantt Chart

Looking at the Gantt Chart, process is shown in orange bar while project milestone is shown in red bar.

No	Detail/Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	FYP Topic Selection	Process	Process												
2	Prelim. Research/Info Gathering		Process	Process	Process	Process									
3	Extended Proposal Submission						Milestone								
4	Design Segmentation Algorithm							Process							
5	Proposal Defense								Process	Process					
6	Employ Segmentation Algorithm Develop the Classification System										Process	Process			
7	Develop the Classification System												Process		
8	Interim Draft Report Submission													Milestone	
9	Interim Report Submission														Milestone



## **CHAPTER 4**

### **RESULTS & DISCUSSIONS**

Within the allotted time, we were able to do the following; 1) extracted the skull, 2) attain the foreground marker which is the hemorrhage region, 3) superimpose the foreground marker with the skull, 4) extracted textural features and 5) feed in the values of the textural features for each image in the database to create 12 Neural Network since there are 3 Neural Network for each of the four types of hemorrhage (see Table 6). Lastly, we successfully tested external CT scan images and classify the images between four types of brain hemorrhage which are the following; 1) cerebellar, 2) extradural, 3) intraventricular and 4) subdural hemorrhage.

#### **4.1 Segmentation**

The first part of segmentation is done by thresholding based on histogram as elaborated earlier in methodology wherein we manage to extract the skull first. Followed by retrieving the hemorrhage region alone and then superimposing both the extracted image. The reason for this is to remove the unwanted objects and only analyse the region of interest which is the hemorrhage region and the skull.

##### **4.1.1 Skull Extraction and Hemorrhage Region Extraction**

After the skull extraction by using thresholding and hemorrhage region extraction using morphological reconstruction, we were able to successfully segment both the skull and hemorrhage region from every CT scan images that we want to use to create 3 Neural Network system for each type of hemorrhage, thus having 12 Neural Network system all in all. Each of the hemorrhage type has distinct shape and location, thus the whole process of hemorrhage extraction was completed through full supervision by changing the parameters in the 'strel'(structuring element) function. As mentioned earlier, 'strel' function is where you can extract a specific structure in the image that

we want to extract. Supervision is needed to control the size of the structure that we want to extract from each of the image. 'Strel' function has the following syntaxes;

- SE = strel (shape, parameters)
- SE = strel ('arbitrary', NHOOD)
- SE = strel ('arbitrary', NHOOD, HEIGHT)
- SE = strel ('diamond', R)
- SE = strel ('disk', R, N)
- SE = strel ('line', LEN, DEG)
- SE = strel ('octagon', R)
- SE = strel ('pair', OFFSET)
- SE = strel ('periodicline', P, V)
- SE = strel ('rectangle', MN)
- SE = strel ('square', W)

Since hemorrhage region is mostly shaped as disk, we decided to use the syntax SE = strel ('disk', R), where R is the radius. Radius is the parameter that is being supervised and changed for each image that is to be segmented depending on the size of hemorrhage region.

The following figures are examples of the segmented images for each type of brain hemorrhage.

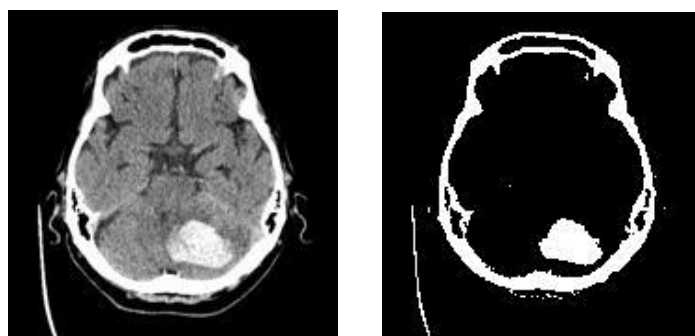


Figure 12. A) Original Image for Cerebellar Hemorrhage, B) Segmented Skull and Hemorrhage Region

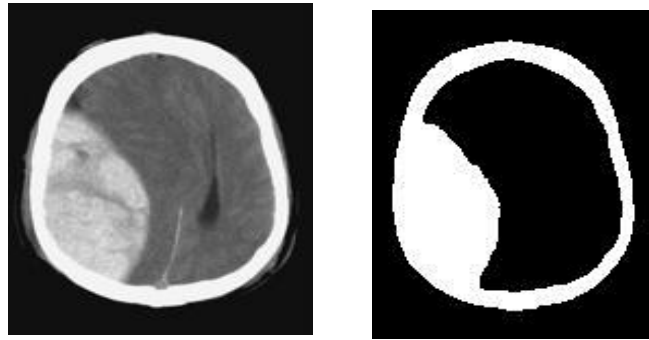


Figure 13. A) Original Image for Extradural Hemorrhage, B) Segmented Skull and Hemorrhage

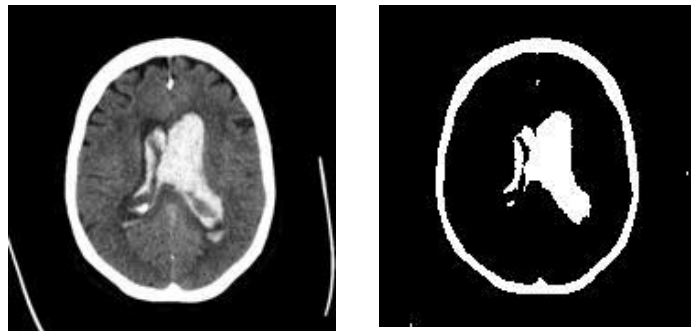


Figure 14. A) Original Image for Intraventricular Hemorrhage, B) Segmented Skull and Hemorrhage

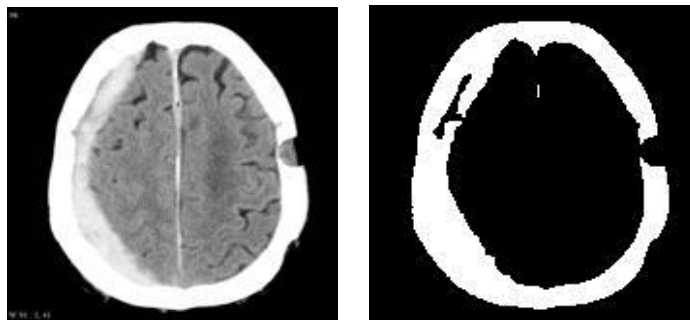


Figure 15. A) Original Image for Subdural Hemorrhage, B) Segmented Skull and Hemorrhage

#### 4.1.3 Extraction of features

We managed to develop the code in extracting the needed features from the images that will mainly be used for training and testing of the Neural Network. The relationship of having plenty of images to the effectiveness of the system is due to having more input values that Neural Network will use to characterize each images based on its calculated texture features. Thus, the more images there is for training and testing, the more the Neural Network can compare between these values and understand which type of image belongs to which type of brain hemorrhage. The



figures below are examples of extracted features for each images of a particular haemorrhage type, each are used to create one versus one Neural Network system.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.5903	0.4602	0.5867	0.7694	0.5308	0.6753	0.5708	0.6372	0.7320	0.5635	0.6502	0.7086	0.6935	0.5118	0.4998
2	0.9153	1.1157	0.8702	0.5477	0.9866	0.7224	0.8786	0.7720	0.6364	0.9588	0.7906	0.6868	0.7111	0.9942	1.0802
3	29.9866	48.7308	36.9241	21.1327	44.7371	30.17...	46.3610	37.2351	18.8302	33.1472	28.49...	21.5895	22.89...	52.3266	42.4520
4	0.9356	0.9202	0.9456	0.9741	0.9438	0.9636	0.9610	0.9660	0.9564	0.9318	0.9521	0.9569	0.9538	0.9506	0.9312
5															
6															

Figure 16. Extracted features for images which belongs to cerebellar haemorrhage type.

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.5168	0.7180	0.6201	0.6602	0.7852	0.7485	0.5558	0.7025	0.5922	0.6965	0.5681	0.6759	0.7462	0.7875	0.7149
2	0.9607	0.6352	0.8194	0.7316	0.5184	0.5909	0.8994	0.6333	0.8318	0.6926	0.8921	0.7223	0.6056	0.5143	0.6601
3	54.6...	27.0667	36.67...	34.1609	19.82...	22.0358	49.36...	33.2650	44.9...	25.3...	44.6214	30.1...	19.9984	18.9261	24.1...
4	0.9555	0.9705	0.9595	0.9668	0.9758	0.9692	0.9610	0.9799	0.9653	0.9597	0.9565	0.9639	0.9640	0.9745	0.9635
5															
6															

Figure 17. Extracted features for images which belongs to intraventricular haemorrhage type.

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.6025	0.5698	0.6274	0.7305	0.5803	0.5317	0.7461	0.5482	0.7546	0.5685	0.6492	0.7997	0.5088	0.6275	0.6947
2	0.7576	0.8891	0.7922	0.6371	0.8782	0.9479	0.6039	0.9557	0.5864	0.8894	0.7631	0.4778	0.9860	0.7835	0.6784
3	50.7...	44.9886	37.64...	20.6778	42.29...	47.6163	18.11...	42.1010	20.6...	45.3...	34.1702	20.0...	50.9015	38.8908	29.3...
4	0.9786	0.9579	0.9634	0.9610	0.9564	0.9471	0.9586	0.9443	0.9683	0.9586	0.9639	0.9806	0.9442	0.9661	0.9680
5															
6															

Figure 18. Extracted features for images which belongs to intraventricular haemorrhage type.

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.6025	0.5698	0.6274	0.7305	0.5803	0.5317	0.7461	0.5482	0.7546	0.5685	0.6492	0.7997	0.5088	0.6275	0.6947
2	0.7576	0.8891	0.7922	0.6371	0.8782	0.9479	0.6039	0.9557	0.5864	0.8894	0.7631	0.4778	0.9860	0.7835	0.6784
3	50.7...	44.9886	37.64...	20.6778	42.29...	47.6163	18.11...	42.1010	20.6...	45.3...	34.1702	20.0...	50.9015	38.8908	29.3...
4	0.9786	0.9579	0.9634	0.9610	0.9564	0.9471	0.9586	0.9443	0.9683	0.9586	0.9639	0.9806	0.9442	0.9661	0.9680
5															
6															

Figure 19. Extracted features for images which belongs to subdural haemorrhage type.

## **4.2 Characterization using Neural Network**

Furthermore, after segmentation and having the superimposed skull and hemorrhage region in an image. We extracted the values of the four chosen textural features for each image in each type of brain hemorrhage. Having the 4 types of hemorrhage, we created three (one versus one) Neural Network system for each type of the brain hemorrhage. Therefore having a total of 12 Neural Network systems. Listed down are the 12 (one versus one) Neural Network, three for each of the four brain hemorrhage types:

- i) Cerebellar vs Extradural (CE)
- ii) Cerebellar vs Intraventricular (CI)
- iii) Cerebellar vs Subdural (CS)
- iv) Extradural vs Cerebellar (EC)
- v) Extradural vs Intraventricular (EI)
- vi) Extradural vs Subdural (ES)
- vii) Intraventricular vs Cerebellar (IC)
- viii) Intraventricular vs Extradural (IE)
- ix) Intraventricular vs Subdural (IS)
- x) Subdural vs Cerebellar (SC)
- xi) Subdural vs Extradural (SE)
- xii) Subdural vs Intraventricular (SI)

### **4.2.1 One versus three (1 versus 3) Neural Network System**

However before doing the one versus one system, we first attempted to use one versus three Neural Network system for each of the hemorrhage type, however the results were very disappointing. We tested five images of the main hemorrhage type in each of the one versus three system and the results are in the following table. When the value is greater or equal to 0.5 then it means the image that we tested belongs to the main hemorrhage type in the system that we tested it in.

Below are the following results for the one versus three Neural Network systems.

Table 1. Cerebellar as the main hemorrhage type against the other three types.

<b>Cerebellar vs (Extradural, Intraventricular and Subdural)</b>		
<b>IMAGE</b>	<b>VALUE</b>	<b>RESULT</b>
Cerebellar 1	0.9423	Correct
Cerebellar 2	0.5699	Correct
Cerebellar 3	0.2700	Fault
Cerebellar 4	0.2986	Fault
Cerebellar 5	0.7460	Correct
<b>TOTAL</b>		<b>3 out of 5</b>

Table 2. Extradural as the main hemorrhage type against the other three types.

<b>Extradural vs (Cerebellar, Intraventricular, and Subdural)</b>		
<b>IMAGE</b>	<b>VALUE</b>	<b>RESULT</b>
Extradural 1	0.3436	Fault
Extradural 2	0.5214	Correct
Extradural 3	0.5029	Correct
Extradural 4	0.3981	Fault
Extradural 5	0.3118	Fault
<b>TOTAL</b>		<b>2 out of 5</b>

Table 3. Intraventricular as the main hemorrhage type against the other three types.

<b>Intraventricular vs (Cerebellar, Extradural, and Subdural)</b>		
<b>IMAGE</b>	<b>VALUE</b>	<b>RESULT</b>
Intraventricular 1	0.2390	Fault
Intraventricular 2	0.3225	Fault
Intraventricular 3	0.2433	Fault
Intraventricular 4	0.2668	Fault
Intraventricular 5	0.3480	Fault
<b>TOTAL</b>		<b>0 out of 5</b>

Table 4. Subdural as the main hemorrhage type against the other three types.

<b>Subdural vs (Cerebellar, Extradural, and Intraventricular)</b>		
<b>IMAGE</b>	<b>VALUE</b>	<b>RESULT</b>
Subdural 1	0.1880	Fault
Subdural 2	0.1206	Fault
Subdural 3	0.4806	Fault
Subdural 4	0.0759	Fault
Subdural 5	0.1838	Fault
<b>TOTAL</b>		<b>0 out of 5</b>

Therefore by looking at the poor results of the system, we decided to try to use the one versus one Neural Network system to check its accuracy with respect to the one versus three Neural Network system in classifying the type of hemorrhage.

#### 4.2.2 One versus one (1 versus 1) Neural Network System

Below is an example of plot confusion that shows the accuracy of the Neural Network system.

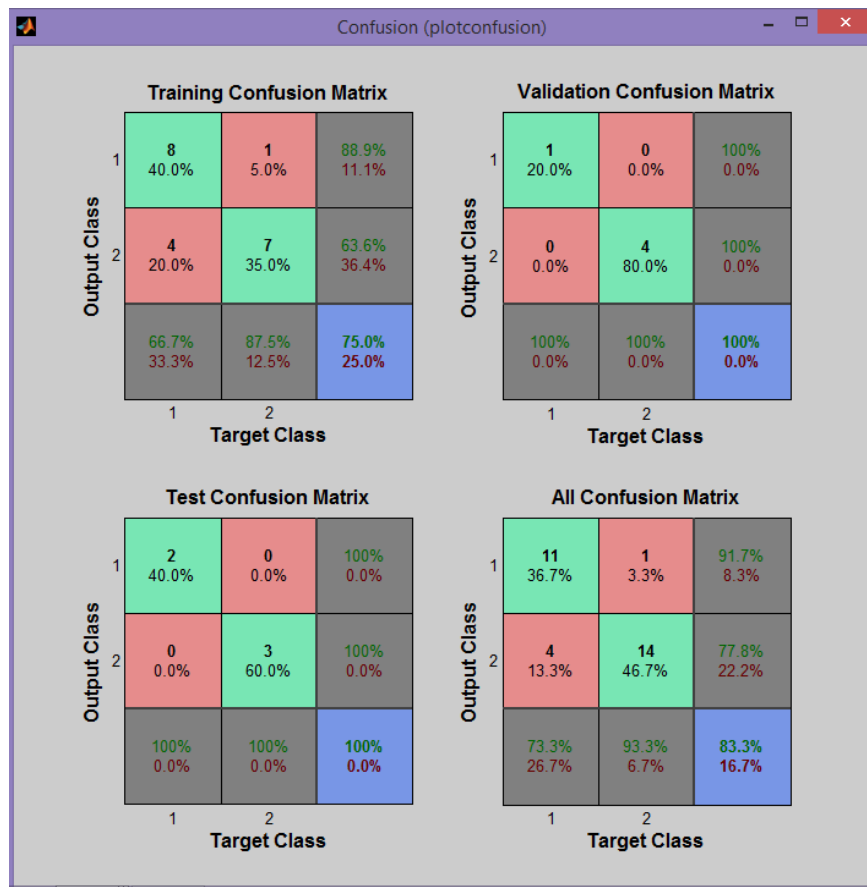


Figure 20. Example of Plot Confusion for Cerebellar versus Extradural Hemorrhage.

The interpretation of the plot confusion is that out of 30 segmented images ( 15 images of Cerebellar and 15 images of Extradural), 20 of those images were used for the training of the system, while 5 of those image for validation and the rest were used for testing. Internal testing with the use of the 5 input images used in creating the Neural Network system itself resulted to 100 percent in accuracy. However the all confusion matrix which includes training, validation and testing sums up to only 83 percent of accuracy. Table 5 shows the result of the all confusion matrix from plot confusion for each of the 12 (one versus one) Neural Network system.

Table 5. All Confusion Matrix for each of the Neural Network system.

<b>1 vs 1 Neural Network Systems</b>	<b>All Confusion Matrix (%)</b>
Cerebellar vs Extradural (CE)	<b>83.3</b>
Cerebellar vs Intraventricular (CI)	<b>83.3</b>
Cerebellar vs Subdural (CS)	<b>83.3</b>
Extradural vs Cerebellar (EC)	<b>83.3</b>
Extradural vs Intraventricular (EI)	<b>83.3</b>
Extradural vs Subdural (ES)	<b>76.7</b>
Intraventricular vs Cerebellar (IC)	<b>83.3</b>
Intraventricular vs Extradural (IE)	<b>83.3</b>
Intraventricular vs Subdural (IS)	<b>83.3</b>
Subdural vs Cerebellar (SC)	<b>86.7</b>
Subdural vs Extradural (SE)	<b>70</b>
Subdural vs Intraventricular (SI)	<b>86.7</b>

The accuracy of Neural Network is dependent on the number of input images we use in creating the Neural Network system. The more input images we used, the more input values are available for the Neural Network to understand and compare between the hemorrhage types. Since we only use 30 images for each of the systems to train, validate and test, it is quite expected to have slightly lower accuracy than using more than 30 images as the input images.

Each type of hemorrhage have 3 (one versus one) Neural Network systems that will be used to verify the hemorrhage type of the image being tested. By testing one specific image of a particular type of hemorrhage to these 12 (one versus one) Neural Network system, the image belongs to a certain haemorrhage type if all 3(one versus one)

Neural Network systems of a particular brain haemorrhage obtain values that are  $\geq 0.5$ .

Table 6. General testing using external images.

1 vs 1 Neural Network Systems	Classification of CT Images			
	Cerebellar Hemorrhage	Extradural Hemorrhage	Intraventricular Hemorrhage	Subdural Hemorrhage
CE	0.7461	0.5295	0.5808	0.9032
CI	0.6396	0.9779	0.2514	0.9884
CS	0.7020	0.2991	0.7802	0.4383
EC	0.2494	0.6689	0.2622	0.2119
EI	0.1204	0.9922	0.0429	0.9848
ES	0.4182	0.8410	0.3841	0.1558
IC	0.4257	0.0147	0.6915	0.0129
IE	0.8464	0.0319	0.9481	0.2376
IS	0.9488	0.0314	0.9714	0.0694
SC	0.0641	0.2772	0.0106	0.7716
SE	0.3582	0.2602	0.4158	0.9431
SI	0.1569	0.9758	0.0289	0.9857

Looking at the results that are highlighted in red, we verify that the algorithm works well in classifying between the four types of hemorrhage. For example as shown above in Table 6, when we tested an image which is known first-hand to belong to cerebellar hemorrhage type, the values obtain for the 3 (one versus one) Neural Network system pertaining to cerebellar haemorrhage type, have values  $\geq 0.5$ . Same goes to images tested that belongs to extradural, intraventricular and subdural haemorrhage type, all obtain values  $\geq 0.5$  to each of their specific 3(one versus one) Neural Network systems.

One versus one have more promising results compared to one versus three because the Neural Network can distinguish more between just two hemorrhage compared to four types of hemorrhage at once. These values can still be improved by increasing the number of input images and by having good quality of input images.

## **CHAPTER 5**

### **CONCLUSION & RECOMMENDATION**

Throughout the semester, we have managed to do the needed processes (segmentation, extraction of textural features) for the characterization of the brain hemorrhage images based on textural analysis using Neural Network classification system. Our goal for the second half of research period includes the optimization of the segmentation technique. At first we were just using thresholding, but since thresholding is not that effective in extracting the hemorrhage region, we have decided to use the thresholding for extraction of skull only and used morphological reconstruction for the extraction of the hemorrhage region in the image. Therefore, we successfully optimize the segmentation technique by using morphological reconstruction which consist of 'strel' function that specify what shape of structuring elements with specified radius are to be extracted each time segmentation is done for an image.

We also planned to add more input images for all types of brain haemorrhage, however barely succeeded on this because of limited source. Neural Network is used for pattern recognition and classification, however it mainly depend on the input data. As discussed earlier, the more targets or input we put in the Neural Network the more it understand and learn. Thus, efficient classification between the images can be achieved by increasing the database of image as targets in the Neural Network. At the same time this is highly needed for the Neural Network to have greater generalization. However, since we are just getting images online, the small number of images is the primary limitation that we have for the success of this research.

In the beginning of the second half of research period, we were able to use different amount of images as input for each type of hemorrhage to create (one versus three) Neural Network system. Through observation, we concluded that the system which has the highest amount of images has the highest chance of getting high resulting



values which leads to the inaccuracy of the result. The unequal distribution of numbers of input images leads to inaccuracy. Thus, we decided to equalize the number of images in each Neural Network system. Still after doing so, the one versus three Neural Network system were not that accurate. Thus, we changed our approach and decided to execute the one versus one Neural Network system to compare its accuracy with respect to one versus three Neural Network system with of course equal numbers of images as input. We can conclude from the results shown on the previous chapter that one versus one Neural Network has succeed to classify the tested external images accordingly.

Upon fulfilling the above needs like adding more images in the database or using high quality and high number of images as the database, the efficiency of the network can be highly improve.

Overall, we manage to execute image analysis through segmentation, feature extraction and classification of CT scan images using MATLAB. At the same time, we succeed in presenting and verifying an algorithm of a system that is capable of classifying between the four types of hemorrhage.

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## APPENDIX I

### Sample Matlab Coding for Segmentation

```
%first Segmenting skull only..

I = imread('C:\Users\Frenchlyn\Documents\MATLAB\Segment
ROI\cerebellar_hemo-22\1.jpg');
[r c d] = size(I);
if (d==3)
I = rgb2gray(I);
end

c12=[196 255]; %skull
c2=[255 255 255];

c13= [0 196]; %background
c3 =[0 0 0];
[r c]=size(I);
y=I;
%segmentation of skull only..
for i = 1:r
    for j = 1:c
        if (I(i,j))>= c12(1) && I(i,j)<=c12(2))
            cc=c2;
        else
            cc = c3;
        end

        for k =1:3
            y(i,j,k)=cc(k);
        end
    end
end

%figure;imshow(y);

% using abit of erosion
se=strel(ones(5,5));
fm=imerode(y,se);
%figure;imshow(fm);

% Start with Foreground marking

hy = fspecial('sobel');
hx = hy';
Iy = imfilter(double(I), hy, 'replicate');
Ix = imfilter(double(I), hx, 'replicate');
gradmag = sqrt(Ix.^2 +Iy.^2);
%figure;imshow(gradmag,[]), title('Gradient magnitude (gradmag)')
```

```

%just for the show of direct watershed
L = watershed(gradmag);
Lrgb = label2rgb(L);
%figure, imshow(Lrgb), title('Watershed transform of gradient
magnitude (Lrgb)')

%...Marking of foreground objects step 3a opening
se = strel('disk',5);
Io = imopen (I,se);
figure
%imshow(Io), title ('Opening(Io)')

%...Marking of foreground objects step 3b opening by reconstruction
Ie = imerode(I, se);
Iobr = imreconstruct (Ie, I);
%figure
%imshow(Iobr), title( ' Opening by reconstruction(Iobr)')

%step 3c..just for show comparison with standard without reconstr..

Ioc = imclose (Io, se);
%figure
%imshow(Ioc), title('Opening closing(Ioc)')

% step 3d..editing like dilating and complementing..
Iobrd = imdilate (Iobr, se);
Iobrcbr = imreconstruct(imcomplement (Iobrd), imcomplement(Iobr));
Iobrcbr = imcomplement(Iobrcbr);
%figure
%imshow(Iobrcbr), title('Opening closing by reconstruction with
dilation, complementing (Iobrcbr)')

%step 3e...regional maxima to have a good foreground object...
fgm = imregionalmax(Iobrcbr);
%figure
%imshow(fgm), title('Regional maxima of opening closing by
reconstruction (fgm)')

%step 3e... good foreground object superimposing with skull...

bw=im2bw(fm);
I2=bw;
I2(fgm)=255;
%figure
%imshow(I2), title('Regional maxima superimposed on skull (I2)')

% step 3f ...modifying it to look nicer in edge
se2 = strel(ones(5,5));
fgm2 = imclose (fgm, se2);
fgm3 = imerode (fgm2, se2);
fgm4 = bwareaopen (fgm3 ,30);
I3=bw;
I3(fgm4) = 255;
figure
imshow(I3), title('Modified regional maxima superimposed on skull
(I3)')

imsave

```

## APPENDIX II

### Sample Matlab Coding for Feature Extraction

```
srcFiles = dir('C:\Users\Frenchlyn\Documents\A 4th 2nd\FYP 2\NN
equalize number of pictures\1 vs 1 segmented ROI\Cerebellar vs
Extradural\cerebellar hemo-15\*.jpg'); % the folder in which ur
images exists
for i = 1 : length(srcFiles)
    filename = strcat('C:\Users\Frenchlyn\Documents\A 4th 2nd\FYP
2\NN equalize number of pictures\1 vs 1 segmented ROI\Cerebellar vs
Extradural\cerebellar hemo-15\',srcFiles(i).name);
    I = imread(filename);
    %figure, imshow(I);
[r c d] = size(I);
if (d==3)
I = rgb2gray(I);
end
GLCM1=graycomatrix(I, 'Offset', [0 4]); %0 degree
GLCM2=graycomatrix(I, 'Offset', [-4 4]); %45 degree
GLCM3=graycomatrix(I, 'Offset', [-4 0]); %90 degree
GLCM4=graycomatrix(I, 'Offset', [-4 -4]); %135 degree
[out1] = GLCM_Features1(GLCM1,0);
[out2] = GLCM_Features1(GLCM2,0);
[out3] = GLCM_Features1(GLCM3,0);
[out4] = GLCM_Features1(GLCM4,0);
Energy = (out1.energ+ out2.energ + out3.energ +out4.energ)/4;
Entropy = (out1.entro+ out2.entro+ out3.entro+ out4.entro)/4;
Variance = (out1.svarh + out2.svarh + out3.svarh + out4.svarh)/4;
Inverse_difference_median = (out1.idmnc + out2.idmnc + out3.idmnc +
out4.idmnc)/4;

training(:,i)=[Energy,Entropy,Variance,Inverse_difference_median];
targets=ones(1,15);
end

srcFiles = dir('C:\Users\Frenchlyn\Documents\A 4th 2nd\FYP 2\NN
equalize number of pictures\1 vs 1 segmented ROI\Cerebellar vs
Extradural\extradural - 15\*.jpg'); % the folder in which ur images
exists
for i = 1 : length(srcFiles)
    filename = strcat('C:\Users\Frenchlyn\Documents\A 4th 2nd\FYP
2\NN equalize number of pictures\1 vs 1 segmented ROI\Cerebellar vs
Extradural\extradural - 15\',srcFiles(i).name);
    I = imread(filename);
    %figure, imshow(I);

[r c d] = size(I);
if (d==3)
I = rgb2gray(I);
end
GLCM1=graycomatrix(I, 'Offset', [0 4]); %0 degree
GLCM2=graycomatrix(I, 'Offset', [-4 4]); %45 degree
GLCM3=graycomatrix(I, 'Offset', [-4 0]); %90 degree
GLCM4=graycomatrix(I, 'Offset', [-4 -4]); %135 degree
[out1] = GLCM_Features1(GLCM1,0);
```

```
[out2] = GLCM_Features1(GLCM2,0);
[out3] = GLCM_Features1(GLCM3,0);
[out4] = GLCM_Features1(GLCM4,0);
Energy = (out1.energ+ out2.energ + out3.energ +out4.energ)/4;
Entropy = (out1.entro+ out2.entro+ out3.entro+ out4.entro)/4;
Variance = (out1.svarh + out2.svarh + out3.svarh + out4.svarh)/4;
Inverse_difference_median = (out1.idmnc + out2.idmnc + out3.idmnc +
out4.idmnc)/4;

training(:,15+i)=[Energy,Entropy,Variance,Inverse_difference_median]
;
targets(1,15+i)=0;
end
```



## APPENDIX III

### Sample Matlab Coding for General Testing

```
I = imread('C:\Users\Frenchlyn\Documents\A 4th 2nd\FYP 2\NN equalize
number of pictures\1 vs 1 segmented ROI\Cerebellar vs
Extradural\testing\10.jpg');
[r c d] = size(I);
if (d==3)
I = rgb2gray(I);
end
GLCM1=graycomatrix(I, 'Offset', [0 4]); %0 degree
GLCM2=graycomatrix(I, 'Offset', [-4 4]); %45 degree
GLCM3=graycomatrix(I, 'Offset', [-4 0]); %90 degree
GLCM4=graycomatrix(I, 'Offset', [-4 -4]); %135 degree
[out1] = GLCM_Features1(GLCM1,0);
[out2] = GLCM_Features1(GLCM2,0);
[out3] = GLCM_Features1(GLCM3,0);
[out4] = GLCM_Features1(GLCM4,0);
Energy = (out1.energ+ out2.energ + out3.energ +out4.energ)/4;
Entropy = (out1.entro+ out2.entro+ out3.entro+ out4.entro)/4;
Variance = (out1.svarh + out2.svarh + out3.svarh + out4.svarh)/4;
Inverse_difference_median = (out1.idmnc + out2.idmnc + out3.idmnc +
out4.idmnc)/4;

vect=[Energy,Entropy,Variance,Inverse_difference_median];
y=sim(cenet,vect')
```